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A non-holonomic, highly human-in-the-loop
compatible, assistive mobile robotic platform
guidance navigation and control strategy

By

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MSc BEng

A thesis submitted in fulfilment of the requirements for the degree of
Doctor of Philosophy of the University of Kent

Engineering and Digital Arts

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Abstract

The provision of assistive mobile robotics for empowering and providing independence to the infirm, disabled and elderly in society has been the subject of much research. The issue of providing navigation and control assistance to users, enabling them to drive their powered wheelchairs effectively, can be complex and wide-ranging; some users fatigue quickly and can find that they are unable to operate the controls safely, others may have brain injury resulting in periodic hand tremors, quadriplegics may use a straw-like switch in their mouth to provide a digital control signal.

Advances in autonomous robotics have led to the development of smart wheelchair systems which have attempted to address these issues; however the autonomous approach has, according to research, not been successful; users reporting that they want to be active drivers and not passengers. Recent methodologies have been to use collaborative or shared control which aims to predict or anticipate the need for the system to take over control when some pre-decided threshold has been met, yet these approaches still take away control from the user. This removal of human supervision and control by an autonomous system makes the responsibility for accidents seriously problematic.

This thesis introduces a new human-in-the-loop control structure with real-time assistive levels. One of these levels offers improved dynamic modelling and three of these levels offer unique and novel real-time solutions for: collision avoidance, localisation and waypoint identification, and assistive trajectory generation. This architecture and these assistive functions always allow the user to remain fully in control of any motion of the powered wheelchair, shown in a series of experiments.

Acknowledgements

My thesis has been a journey through my chosen academic field of guidance navigation and control within the school of electronic engineering at the University of Kent under the European Union INTERREG two-seas cross-border SYSIASS project. I have chosen to investigate control architecture and sub-component structures which include suitable human-compatible trajectories and intuitive collision avoidance for non-holonomic mobile robotics. This can be mainly applied within the healthcare arena to provide assistance to powered wheelchair users. The journey turned out to be much longer than I expected, and one which I could not have undertaken without the considerable support of my family and friends, and in particular the unquestioning support that I received from the academics, technicians, and support staff of the electronics department at the University of Kent.

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Hashal Osa.....Friend and fellow student
Gareth Howells.....Main supervisor
Sarah Spurgeon.....Second supervisor
IT technicians, electronic lab technicians, and workshop technicians

Declaration

I declare that I have composed this thesis in entirety by myself and that this thesis describes my own research.

Publications and presentations

Academic publications:

- Highly efficient Localisation utilising Weightless neural system. ESAAN Conference Bruges Belgium April 2012
- Real-time Sensor Data for Efficient Localisation Employing a Weightless neural system. ICSCS Conference Lille France August 2012
- Weightless Neural System Employing Simple Sensor Data for Efficient Real-Time Round-Corner, Junction and Doorway Detection for Autonomous System Path Planning in Smart Robotic Assisted Healthcare Wheelchairs. EST Conference Lisbon Portugal September 2012
- Real-time Doorway Detection and Alignment Determination for Improved Trajectory Generation in Assistive Mobile Robotic Wheelchairs. EST Conference Cambridge England September 2013
- Floor Covering and Surface Identification for Assistive Mobile Robotic Real-Time Room Localization Application. December 17, 2013, Sensors Journal 2013, 13, 17501-17515
- Système universel à bas coût d'aide à la conduite d'un fauteuil roulant électrique. HANDI-CAP, July 2014
- Powered wheelchair platform for assistive technology development. 2014 Fifth International Conference on Emerging Security Technologies (EST). IEEE, September 2014

Academic poster presentations:

- Robust real time control for an autonomous robot. EDA School Conference Canterbury Kent England January 2012

- Doorway passing smooth trajectories for non-holonomic assistive mobile robotic devices. EDA School Conference Canterbury Kent England January 2014

Public presentations:

- Real-time Assistive, Adaptive and Intelligent Mobile Robotic Control for the Powered Wheelchair. Conference on Recent Advances in Assistive Technology & Engineering, November 26th 2012 Warwick UK
- Exhibition of the assistive PWC hardware and the collision avoidance doorway passing demonstration at the SYSIASS closing conference, Lille, France June 2014
- Exhibition of the assistive PWC hardware and the collision avoidance doorway passing, and corridor following demonstration at CareTECH conference, ESIGELEC, ROUEN, France December 2-3, 2014

Abbreviations

Assistive robot transport for youngsters (ARTY)

Canadian occupational performance measure (COPM)

Controller-area network (CAN)

Dynamic window approach (DWA)

Empowerment of disabled people through ethics in care and technology (EDECT)

Electric powered indoor/outdoor chair (EPIOC)

Global positioning satellites (GPS)

Grey-level co-occurrence matrix (GLCM)

Graphical user interface (GUI)

Hue-saturation-value (HSV)

Inertial measurement unit (IMU)

Liquid crystal display (LCD)

Micro-electromechanical systems (MEMS)

National Health Service (NHS)

Partially observable Markov decision process (POMDP)

Pattern recognition (PR)

Powered wheelchair (PWC)

Radio detection and ranging (Radar)

Red, green, blue (RGB)

Sound navigation and ranging (Sonar)

Surface quality (SQUAL)

SYStème Intelligent et Autonome d'aide aux Soins de Santé (SYSIASS)

Vector force-field histogram (VFH)

Wireless fidelity (Wi-Fi)

Weightless neural networks (WNN)

List of figures

- Figure 1.1 Otto Bock C2000 off-road all-terrain PWC
- Figure 1.2 Invacare Pronto M51 indoor mid-wheel drive PWC
- Figure 1.3 Invacare Storm Series 3G Ranger rear-wheel drive EPIOC
- Figure 1.4 Invacare FDX mid-wheel drive EPIOC
- Figure 1.5 Golden Motors lightweight rear-wheel driven transportable PWC
- Figure 3.1 Sensor–motor connection arrangements for Braitenberg vehicles
- Figure 3.2 Complex behaviour of a Braitenberg vehicle
- Figure 3.3 Traditional robotic architecture
- Figure 3.4 Subsumption Architecture
- Figure 3.5 Behaviour-testing mobile robot
- Figure 3.6 Human-in-the-loop control architecture, for assistive mobility devices
- Figure 4.1 A representation of the potential field gradient surface of a workspace
- Figure 4.2 Typical Voronoi collision avoiding paths
- Figure 4.3 A representation of highly localised potential fields
- Figure 4.4 Generic schematic and reference frame for platform
- Figure 4.5 Elliptical PWC platform obstacle avoidance model
- Figure 4.6 Zonal application of elliptical obstacle avoidance model
- Figure 4.7 Narrow corridor
- Figure 4.8 Lane following
- Figure 4.9 Fast approach to doorway
- Figure 4.10 Various doorway approaches

- Figure 4.11 Fast approach towards an obstacle
- Figure 4.12 Medium velocity approach towards an obstacle
- Figure 4.13 Low velocity approach towards an obstacle
- Figure 4.14 Obstacle slalom
- Figure 4.15 Dead-end or docking
- Figure 4.16 Obstacle course
- Figure 5.1(a) Mouse camera with laser illumination and colour sensor with white LED
- Figure 5.1(b) Shows improved and final configuration with mouse camera
- Figure 5.2(a) Coarse sandpaper mouse sensor image
- Figure 5.2(b) Medium sandpaper mouse sensor image
- Figure 5.2(c) Fine sandpaper mouse sensor image
- Figure 5.3(a) Pixel 3D mapping of coarse sandpaper image
- Figure 5.3(b) Pixel 3D mapping of medium sandpaper image
- Figure 5.3(c) Pixel 3D mapping of fine sandpaper image
- Figure 5.4(a) LDC webcam colour and texture confusion bitmap
- Figure 5.4(b) LDC RGB colour sensor and mouse registers confusion bitmap
- Figure 5.4(c) LDC RGBW colour sensor and mouse registers confusion bitmap
- Figure 5.5 Typical patterns for junction determination
- Figure 5.6 Generating the Weightless Neural Network input matrix
- Figure 5.7(a) 1-NN Classifier Confusion Bitmap Matrix for initial doorway testing
- Figure 5.7(b) 1-NN Classifier Confusion Bitmap Matrix for approach angles
- Figure 6.1 Doorway approach angle too great for platform to pass
- Figure 6.2 Non-holonomic platform alignment trajectories for parking in a box
- Figure 6.3 Human slalom PWC trajectories
- Figure 6.4 Human turn PWC trajectories
- Figure 6.5 Several types of sigmoid functions
- Figure 6.6 Exponential sigmoid compared with human trajectories
- Figure 6.7 Exponential curve compared with human turn trajectories

- Figure 6.8 PWC platform frame of reference and kinematic
- Figure 6.9 Doorways coordinate reference frame
- Figure 6.10 Developing a workspace
- Figure 6.11 Doorway offset angle
- Figure 6.12 Plot of doorway approach angle against
- Figure 6.13 A system generated slalom showing the controller following the trajectory
- Figure 6.14 Combining the collision avoidance layer to correct the small errors
- Figure 6.15 Four slalom trajectories used to better align the platform with the doorway
- Figure 6.16 Six turn trajectories used to better align the platform with the doorway

List of tables

Table 3.1	Summary of mobile robotic sensors available for assistive PWC
Table 4.1	Results of NASA load index
Table 4.2	Perception results of participant questionnaire
Table 4.3	Trajectory assistance when passing through doorway
Table 5.1	Optical mouse sensor data registers
Table 5.2	Flooring material test results, and room localisation test results
Table 5.3	Background lighting test results
Table 5.4	Classification thresholds
Table 5.5	Door and junction detection classification and WNN results
Table 5.6	Initial doorway testing
Table 5.7	Doorway approach angle and displacement
Table 5.8	Various doorway(s) and approach angles combined

Contents

Abstract	ii
Acknowledgements	iii
Declaration	iv
Publications	v
Abbreviations	vii
List of figures	ix
List of tables	xii
1. Introduction	1
1.1 Requirements for a human-compatible assistive system.....	4
1.2 Thesis layout.....	7
<i>1.2.1 Background of the developments in smart PWC.....</i>	<i>8</i>
<i>1.2.2 Technology required for the assistive system.....</i>	<i>9</i>
<i>1.2.3 Collision avoidance.....</i>	<i>10</i>
<i>1.2.4 Localisation and waypoint identification.....</i>	<i>11</i>

1.2.5	<i>Assistive trajectories</i>	12
1.2.6	<i>Conclusion</i>	13
1.3	Contribution of this thesis	13
1.4	Conclusion	15
2.	Background of the developments in smart PWC	16
2.1	The current state of the art of assistive PWCs	17
2.2	The PWC user perspective	24
2.3	Current problems for the PWC user	26
2.4	Assistive PWC evaluation	27
2.5	Approaches to collaborative control assistance	29
2.6	Conclusion	30
3.	Technology required for the assistive system	31
3.1	Requirements for developing an assistive system	32
3.2	Braitenberg vehicles and the Subsumptive Architecture	34
3.3	The human-in-the-loop assistive architecture	38
3.4	A review of potential robotic sensors for an assistive PWC	44
3.5	Determining the sensor suitability for the assistive PWC	51
3.6	Data fusion	54

3.7 Pattern recognition for waypoint detection.....	55
3.9.1 Suitable features for fast identification.....	56
3.9.2 Classification.....	57
3.10 Technology requirement conclusion.....	57
4. Collision avoidance	61
4.1 Obstacle avoidance requirements for an assistive system.....	62
4.2 Developing the adjustable localised force-field method.....	63
4.3 The PWC platform kinematics.....	68
4.4 Platform dynamic modelling development.....	70
4.5 Assistive PWC collision avoidance model development.....	73
4.6 Testing the collision avoidance method.....	77
4.7 Participant evaluation of collision avoidance method.....	86
4.8 Conclusions of collision avoidance method.....	91
5. Localisation and waypoint identification	94
5.1 Navigational requirements for an assistive system.....	95
5.2 Localisation for the assistive PWC.....	96
5.2.1 Room Localisation for an assistive PWC.....	97
5.2.2 Floor feature determination.....	99
5.2.3 Hardware.....	100

5.2.4	<i>Results and discussion</i>	106
5.2.5	<i>Experimental conclusions</i>	112
5.3	Junction identification for an Assistive PWC	113
5.3.1	<i>Weightless artificial neural architectures</i>	114
5.3.2	<i>Junction detection experiment</i>	116
5.3.3	<i>Experimental conclusions and discussions</i>	118
5.4	Doorway approach angle identification for an assistive PWC.	118
5.4.1	<i>Sensor choice and methodology</i>	119
5.4.2	<i>Doorway features and classification</i>	119
5.4.3	<i>Doorway approach angle results and discussion</i>	120
5.5	Localisation and waypoint conclusions for assistive PWC	124
6.	Assistive trajectories	128
6.1	Waypoint alignment assistance requirement	129
6.2	The non-holonomic problem and peg through the hole	131
6.3	Modelling the non-holonomic problem	133
6.3.1	<i>Kinematic constraint on the trajectory</i>	138
6.3.2	<i>Doorway frame of reference</i>	140
6.3.3	<i>Determining the workspace</i>	142
6.3.4	<i>Defining the heuristics</i>	144
6.3.5	<i>Generating the trajectory</i>	145

6.3.6 Keeping the human in the control loop	148
6.4 Experimental results	150
6.5 Conclusion	154
7. Conclusions	156
7.1 Summary of the thesis.....	157
7.2 Meeting the technical challenges.....	159
7.3 Addressing the research question.....	161
7.4 Future developments for the assistive system.....	162
References	165

Chapter 1

Introduction

As of September 2010 there were 10 million adults and 770,000 children in the United Kingdom with long-term ability problems, of which 8 million were in the working-age bracket. Nearly 8% (770,000) of all the registered disabled individuals use a wheelchair [1]. Over a ten-year period between 1986 and 1996 wheelchair use doubled to 710,000, the reasons for which were social and family dependency changes, healthcare policy, and economic improvements: users had been using family pass-me-downs—re-using old equipment—and changes in health authorities' wheelchair allocation to individuals rather than, traditionally, hospital wards [2]. In order to identify the issues, research by Woods and Watson suggests that a social constructionist approach needs to be undertaken to understand the relationship between users' needs and technological requirements [3], and how society views the wheelchair, and its user, and their needs, not a predisposition to accept that the current social and technological solutions must be the best.

Significant challenges exist for many powered wheelchair users; their mental and physical ability will change with time. For example, the ability to use the wheelchair joystick (the prime human-machine interface) and to drive safely progressively deteriorates for users with Muscular Sclerosis or Motor Neurone Disease. This means that for maintaining user-independent mobility the powered chair will require adjustment over time to suit the user's needs. Currently, adjustments to the control system result in the user having to wait several weeks for appointments with clinicians, therapists,

and technicians. The consequence of this wait means the user losing independent mobility which can be detrimental to their quality of life and that of their carers, friends and family.

There has been much research and publication in the field of mobile robotic assistance to improve the quality of life for the disabled persons in society according to Simpson [4]. However reviewing the literature has found there has been much less consideration with regard to user input, user feedback, and user confidence, and indeed almost negligible consideration of the users' abilities and desires. Powered wheelchair operation in indoor environments has proved problematic. Users with significant physical disabilities can find accurate control of the powered wheelchair a major challenge. Collisions with objects and other persons can be highly detrimental to user rehabilitation, particularly if the option of independent powered wheelchair control, a highly therapeutic empowerment, has had to be taken away from them because an unacceptable risk level has been reached. Research for this thesis, undertaken with the cooperation of clinicians, users, carers, and therapists, has identified areas which require addressing through the use of technological assistance:

- reduction in the length of time required for user rehabilitation through technology
- improvement in the longevity of independent mobility for users with deteriorating abilities
- reduction in the collateral damage caused by accidental collisions
- prevention of accidental injury to users, carers and the public
- provision of mobility to patients currently excluded due to their disabilities
- reduction in the time carers and family need to provide assistance helping users to navigate
- reduction of the costs to the NHS, or family, for adapting and adjusting hardware to individual user's medical condition
- empowerment of PWC users to help themselves become more independent



Figure 1.1 Otto Bock C2000 off-road all-terrain PWC (Germany) Image credit: Commandeur RevalidatieTechniek Holland



Figure 1.2 Invacare Pronto M51 indoor mid-wheel drive PWC (USA) Image credit: Invacare Corporation USA



Figure 1.3 Invacare Storm Series 3G Ranger rear-wheel drive PWC (USA) Image credit: Invacare Corporation USA



Figure 1.4 Invacare FDX mid-wheel drive PWC (USA) Image credit: Invacare Corporation USA



Figure 1.5 Golden Motors lightweight rear-wheel driven transportable PWC (China) Image credit: Golden Motor Technology Co Ltd China

There are several terms used to describe the electric powered wheelchair, mainly because there are four main types:

- outdoor use only such as the one depicted in Fig 1.1
- indoor use only as shown in Fig 1.2
- indoor/outdoor PWCs alternatively called EPIOCs shown in Figs 1.3 and 1.4
- transportable, usually by folding/collapsing so that the device is easily carried as normal luggage rather than requiring special transportation, Fig 1.5

The powered wheelchair differs from the manual wheelchair with the drive wheels on the PWC being usually much smaller. The need for heavy batteries means that the PWC is often quite heavy, sometimes exceeding 100kg. The PWC is therefore usually quite bulky and unlike the small compact manual wheelchairs can be cumbersome to manoeuvre, particularly in confined spaces and on inclines where the risk of toppling over becomes a serious safety consideration.

1.1 Requirements for a human compatible assistive system

Most research has considered autonomous solutions in undefined public locations not in familiar surroundings such as the users' home or work place, a location they are comfortable with and thus confident in their use of powered wheelchairs. In general navigation in the robotic arena can be described as the guiding of a robot towards a goal whilst avoiding obstacles; however those tasks must be undertaken with consideration to the platform kinematic constraints and platform dynamic behaviours. When we consider assistive, or semi-autonomous, robotics with the human in the loop, such as robotic wheelchairs and remote tele-operated platforms, we are required to remove the need for the robot to perform high-level path planning and targeting, or goal seeking. In reality, there is likely to be a conflict of interest, such that the platform may calculate some trajectory when the user, who is the more intelligent component of the human-in-the-loop system [5], can see that some other course

of action is necessary and, as a result of not being able to override the machine, some injury or damage may be caused in the worst case, or in the best case inconvenience or confusion may occur to the user and other people.

Mobile robotics techniques have been applied to developing PWC assistance since 1986 [6] and some examples are reviewed in Chapter 2. According to this research what has been lacking in the art is an intuitive, real-time, low-cost, adjustable and tuneable system which can meet the needs of a wide range of users of PWCs or other mobility devices. The research conducted for this thesis has made significant progress in working towards answering this hitherto unaddressed requirement. According to the literature surveyed about smart assistive PWCs and previous technical trials and evaluations [5, 7-28]; identifying users' needs through direct approach and involvement in the technological development is a definitive requirement for the successful adoption of any assistive system. Common issues identified for most users, be summarised as follows:

- non-intrusive system assistance
- knowledge of what the system is doing, or about to do, given as feedback to user
- adjustable assistance, not all users have the same requirements, desires, or needs
- different levels of assistance depending on needs, users may require more assistance at times for different tasks
- collision avoidance without denial of access to tight spaces, the user should be able to override the system when it fails
- ability to manoeuvre close to objects safely, the system should not deny the user from approaching objects, a requirement for getting into bed for example
- reliable and robust hardware suitable for the daily hard use required by users
- simple to operate and maintain, technical help should be minimised for daily use devices
- suitable for carers or family to use when taking over control from users

Furthermore from the literature surveyed [5, 7-28] it was clearly identified that for the assistive system to be practically useable at any location the following must also be applied to any assistive mobility device:

- independence from the requirement for specialised infrastructure; as will be fully demonstrated in this thesis
- system power consumption should not greatly affect the driving range limit of PWC; use of embedded hardware throughout the development to support this thesis ensures low power consumption
- system should not require communication with external agents to function; all methods developed and demonstrated in this thesis can be run on embedded localised hardware
- system should fail safe and when disconnected or switched off should still leave the PWC motor control system able to be operated with manual control; the human element described in the control architecture allows the user to remain in control throughout, making the intelligent decisions
- any assistive element should be adaptable and adjustable to new situations and places, not simply fixed at some initial setting by some technician, this concept has been the ultimate goal of the system presented in this thesis, which remains to be addressed by future work
- settings and adjustment should be modifiable by user and system within a safe range which has been determined that the user can cope with, therefore the initial set-up provided by a technician under clinical advice will set upper and lower limits of the manufacturer's mapping profile as is currently the safe practice, and will also set the assistance boundaries, again this remains to be addressed by future work

For any robotic system to provide assistance in real-time and online, novel and unique methods need to be developed. Suitable low computational cost hardware, particularly sensors, needs to be designed or adapted so that the platform system can be operated safely in the human environment, and

that those who live and work around the device and the user are not endangered. Therefore the following technical developments that may be deemed as appropriate for developing such a system, which are addressed in this thesis are as follows, to develop:

- and employ reliable low-cost obstacle detection sensors; *fully demonstrated on the system used for the research presented in this thesis*
- non-complex reliable indoor localisation; *developed and demonstrated later in this thesis*
- real-time waypoint (doorway, turn, junction) detection; *developed but not implemented*
- top-down bottom-up layered adjustable assistance; *proven in concept and demonstrated between the obstacle avoidance level and the assistive trajectory level*
- better modelling of the platform and obstacles; *fully implemented and demonstrated in real-time situations*
- suitable assistive steering trajectories; *developed and partially demonstrated*

1.2 Thesis layout

This thesis may be equally applied to all types of mobility devices, although throughout reference is mainly made to the assistive robotic PWC platform which specifically refers to an electric powered wheelchair which is driven by dual electric motors, one on each side, with differential drive steering. An alternative mobility device using a single drive motor and manually steered is also described in Chapter 4, and all novel methods described in this thesis could equally apply to this platform. The user, attendant, carer or human in the loop refers to the person operating the platform that may, or may not, also be the payload. The PWC is usually controlled by a human input device. This can be a proportional joystick or digital push button, or one of many specialist devices particularly designed for a specific user disability such as eye-gaze systems and palate devices for quadriplegics. However, all these devices essentially provide some measure of human desired direction of travel, digital or

analogue, into the PWC drive controller; the input is mapped according to some predetermined dynamic profile obtained empirically when setting up the PWC by technicians. This mapped profile becomes a feed-forward PWC control system. Attempts to provide feedback to the system, such as preventing drift over rough terrain by using a MEMS gyroscope have been implemented by manufacturers [29]. However this device does not function indoors due to the fabric and contents of the building affecting the magnetic compass normally used to stabilise the integration error drift which occurs in the MEMS gyroscope. This problem is reviewed in Chapter 3. There exists, therefore, a need to provide a method for wall or lane following in the human indoor environment which this thesis addresses in Chapter 4. This novel collision avoidance method utilises low-cost sensors such as those reviewed in Chapter 3 to produce a low-cost system which can be taken to market [14]. Currently a prototype PWC has been developed which utilises the avoidance system described in Chapter 4 and has this directly integrated into a manufacturer's standard PWC control system [30].

1.2.1 Background of the developments in smart PWC

The state of the art in assistive/smart PWC development is reviewed in this chapter. The first section looks at the current position for the development of smart PWCs. The second section describes the assistive PWC platform from the user's perspective. The third section looks at the problematic hazards and dangers faced by users of the PWC which have not yet been satisfactorily addressed by technology. In section 2.4 a range of assistive smart PWC research from early to current and the technologies employed are reviewed to establish the latest position in the art. The chapter then moves on to the evaluation methodologies employed to test the effectiveness of these smart PWCs, which are rather limited due to being at an early stage of development. Approaches as to how control should be, or could be, shared are reviewed at the end of the chapter. This chapter motivates the work of this thesis, which seeks to provide a suitable strategy for an intuitive and compatible system for a non-holonomic human-in-the-loop assistive mobile robotic platform.

1.2.2 Technology required for the assistive system

This chapter introduces the technology required to provide an assistive system in accordance with the requirements identified previously in this chapter. Research carried out during this thesis involving the collaboration and participation of PWC users, clinicians, and other assistive technology stakeholders has identified the need to maintain the user as the intelligence in the system with overall control. This is also supported from other evidence obtained from trials and research undertaken in parallel to this research under the SYSIASS project [27, 31]. This chapter now presents the development of a structured or layered control architecture where different levels, or types, of assistance behave in a complementary nature yet are commutative such that the human-in-the-loop has their assistive requirements fully met. The first section of this looks at the early research into the modelling of the obstacle avoiding assistance layer system using basic biological reactive desires and those needs required to navigate around a cluttered environment. Researching this biological behaviour-based logic has led to the development of the novel collision avoidance method presented in Chapter 4 intuitive for any human-in-the-loop and far less intrusive when providing assistance. This leads into second section of this chapter which introduces the sensors required to provide information about the environment.

Real-time operation for any assistive system must rely upon sensors to provide data about the state of the environment. This chapter continues presenting the technology by detailing the research undertaken to determine the suitability of individual sensors with regard to the requirements identified earlier. For example, the cost of the sensors can be the deciding factor when considering any potential of taking the technology to market and therefore major consideration must be given to utilise the optimal arrangement of sensors for maximum return from minimum outlay. The inherent problems faced by each type of sensor as well as their advantages are investigated. This is followed by a section on data fusion techniques which are used to combine the data from several different types of sensors to obtain optimal information by eliminating poor data from one sensor and replacing that data with more robust data from another type of sensor. The chapter concludes by introducing the concept of

pattern recognition to identify obstacles such as waypoints and locations such as rooms. This leads in Chapter 5 to the important re-use of data from some of the sensors used for the obstacle avoidance presented in Chapter 4. Pattern recognition and classification techniques can be quite intuitive and function similar to the brain in the biological world and therefore are ideal for real-time application in identifying rooms, waypoints, and doorway approach angles as will be demonstrated in this thesis.

1.2.3 Collision avoidance

Assistive technology developments such as smart electric wheelchairs are drawing mobile robotic interactions, traditionally bound to carefully controlled workspaces, increasingly towards the uncertain complex human environment. Seamless crossover between human-defined desired trajectories and traditional autonomous system-aided trajectories is required, human assistive systems have the intelligent user in the loop [12, 32] and require stochastic and semantic based workspaces [33]. Methods commonly employed in the Euclidean geometric domain, such as covariance ellipses indicating location and object uncertainty, now for assistive technologies require weighted nuances; obstacles and targets having a spectrum of importance. Therefore the functional levels of assistance in the control architecture need to be separated and their complexity reduced, for example: the mapping and localisation needs to relate in a semantic way with human terminology; the features used to identify waypoints and objects need to have a common grounding between the human user and the assistive machine. These reduced-complexity layers require robust low-cost sensors with multiple redundancy in order to ensure reliability and safety are maintained. This is necessary for any practical assistive system to be adopted by manufacturers who, even then, will still have to meet a significant number of challenges complying with legislation, type approval, and clinical suitability. Even after meeting these requirements the medical suppliers and ultimately the prescribing clinicians need to be persuaded that the assistive system is safe and beneficial. Therefore in order to develop a collision avoidance system which has any hope of reaching the end users, the entire process requires that all stakeholders have an involvement from the beginning.

Navigation in the robotic arena can be described as the guiding of a robot towards a goal whilst avoiding obstacles. However these tasks must be undertaken with consideration to the platform's kinematic constraints and dynamic behaviours. In the case of the assistive PWC, the kinematic is non-holonomic. In other words the PWC platform is not free to move about all of its body axes. The relationship between heading velocity and rotational velocity are coupled in the case of the differential drive PWC such that any translation in the restrained axis of the platform has to be at the expense of some motion in the one axis it has freedom to move along. The mechanically-steered single motor-driven platform is not so coupled but has a restricted turning circle and is not free to rotate about the body axis as can the differential drive; these relationships are detailed in Chapter 4.

In the first section of Chapter 4 navigation strategies for a real-time reactive system are reviewed. This is followed by a review of obstacle representation. The fourth section presents the dynamic model of the assistive PWC which builds upon previous work. This modified model is highly suited to an assistive PWC system and in particular will prevent tipping over of the platform when implemented, a serious issue identified in Chapter 2. This chapter then presents a highly novel and unique advancement in the art for the dynamic modelling of collision avoidance, following on from previous work in the field and addressing the unsolved issues. Experimentation and evaluation of the collision avoidance methodology are then presented and safe intuitive and human compatible platform motions are proven, solving the issues that are identified from the literature review and user participation highlighted at the beginning of this chapter and in Chapter 2. This forms the first major contribution to the thesis.

1.2.4 Localisation and waypoint identification

Autonomous robotic systems function well in a carefully defined workspace. However, assistive devices such as robotic wheelchairs need to consider user requirements whilst negotiating highly dynamic and varied arenas, particularly as indoor activity is highly room-correlated. Thus, for any effective assistive system a robust degree of real-time localisation becomes essential. Obtaining and

maintaining online coarse self-localisation would allow assistive systems to select appropriate navigation strategies such as when approaching doorways and waypoints or following corridors, and to know precisely when room boundaries are crossed; more importantly maintaining coarse localisation allows the system and human to converse using the exact same terms and to communicate that information to other automated systems or human assistants.

Localisation and mapping requirements for a human-in-the-loop mobile robotic assistance system have been identified, through research performed for this thesis, as the need to identify waypoints such as doorways and junctions. This enables the system to monitor and potentially predict the current and intended trajectory, quickly determining whether that trajectory is within the bounds of the kinematic and dynamic constraints of the platform. If the trajectory is not feasible, the system can then warn the user allowing them to make corrections. This chapter demonstrates a robust method of identifying rooms and waypoints and the approach angle to doorways which forms the second contribution to the thesis. Waypoint identification and approach angle solutions for an assistive system would then allow the system to calculate a system-steered trajectory, with the user remaining in control of any motion along that system-generated path. This work is a fundamental requirement for the trajectories presented in the next chapter.

The methods presented in this chapter use the low-cost sensors identified and developed from the research presented in Chapter 3 to provide data from which it is possible to obtain, using pattern recognition techniques, identifying features and thus signatures of rooms and waypoints. The need for localisation is reviewed and the requirements for room localisation and waypoints are identified and described. Solutions meeting those requirements are then provided.

1.2.5 Assistive trajectories

A significant problem for correctly aligning PWCs to the doorway exists due to the non-holonomic nature of the platform because the wheelchair width is not much narrower than a standard doorway. This is a major issue for users of PWCs also commonly observed with manual wheelchair operation;

this may result in apprehension or refusal to operate the wheelchair for both user and carer. Therefore any assistive system must run real-time monitoring in the background ready to assist robustly, warning what corrective measures are required and what intervening action the system can take, if any, thus empowering users [28, 29]. This chapter addresses the issue and presents a novel and unique methodology for determining assistive trajectories following on from the early identification of waypoints and doorway approach angles given in the previous chapter. This forms the third contribution to the thesis.

The generation of short, localised trajectories to manoeuvre through doorways or turn at junctions in passageways can be obtained from ranging sensor data. This level of assistance comes into operation when the user is unable to pass through a waypoint, or doorway, or to enter a lift because the collision avoidance level has prevented passage. The platform is then stationary and the user can then ask for assistance. This chapter presents these trajectories and the safe method of the human in the loop remaining in control.

1.2.6 Conclusion

Application of the unique and novel methods presented in this thesis have led to further research possibilities, at the date of completing this thesis, which are presented in this chapter. The control strategy is discussed in light of future work and how that may develop into a system capable of meeting the needs of a wide range of users, with their collaboration. The final section summarises the contribution to the art that this thesis has made and reflects upon the research journey.

1.3 Contribution of this thesis

Currently, the inability to avoid colliding with objects or other persons can deter the user from driving or may even cause the option of independent powered control to be removed because of unacceptable risk to the user themselves, other people and the environment. This user exclusion can lead to a

feeling of disempowerment, worthlessness, and lost social opportunities, especially for the younger user. This thesis has answered that key question in Chapter 4 by providing a collision avoidance method for an assistive mobile robotic device with specific regard to the PWC. The platform response is therefore not to oppose the user-desired input but to damp or restrict motion in the direction of the obstacle and not the other directions, identified as a serious issue during the research carried out for this thesis.

In practice, the wheelchair user is likely to spend more time in familiar surroundings such as their home or work place. The home environment is unlikely to have a sophisticated infrastructure, such as wireless radio location beacons, therefore providing assistance for the user to navigate using an assistive steering trajectory, a more complex problem than the reactive collision avoidance method presented in Chapter 4. This thesis has, therefore, answered another key question, that of providing a solution to the localisation and waypoint identification problem using low-cost sensors and sparse data in Chapter 5. Pattern recognition suitable for real-time application is used in an original way to identify locations [34], waypoints [35], and doorway openings [36] such that the assistive system is ready to offer the unique assistive trajectories presented in Chapter 6 should the user desire them.

This thesis has answered the hitherto unanswered problem of human compatible short trajectories for narrow doorway passing in Chapter 6. Another important and new consideration proposed in this thesis is that the user always remains in control. Therefore the solution has been to develop a corrective doorway passing trajectory, one which closely corresponds to the one they would have naturally chosen yet failed to implement correctly. The method presented in Chapter 5 follows the collision avoidance developed in Chapter 4 with which it is fully compatible, and with which it also functions in conjunction. The assisted steering operates by generating a geometric trajectory based upon the waypoint approach angle, identified by the contribution presented in Chapter 4, the user then uses the forward proportional velocity input to travel along that trajectory, the system providing the steering; therefore the user always remains in control of the stop-go motion and the proportional velocity.

This is a key consideration for any robust and safe operation; a certain requirement for assistive mobile devices operating in the human dynamic workspace, legal issues such as liability may become a serious problem in the near future, if they are not addressed at an early stage.

The problems resolved in this thesis have brought the prospect of developing an effective design of a mobile non-holonomic assistive robotic device, capable of interacting intuitively with a human operator in the loop closer to a desirable and marketable product [14, 30]. The contributions can be summarised as follows:

- low-cost sensors modified or employed re-using data for localisation, waypoint identification, obstacle detection, and trajectory generation
- a control architecture based upon the human not being overridden for safety
- unique room localisation using robust flooring features
- safe non-positive acting collision avoidance navigation methodology
- assistive localised trajectory generation for manoeuvring of a non-holonomic PWC through a doorway which only acts to steer whilst the human in the loop is in control of motion

1.4 Conclusion

This chapter has presented an introduction to the thesis identifying the research topics and unsolved problems. The thesis layout was then described with a synopsis of each chapter presented. Having identified the research issues required to be solved for providing a non-holonomic, highly human-in-the-loop compatible, assistive mobile robotic platform guidance navigation and control strategy, the following chapter reviews the current state of the art of the smart assistive PWC.

Chapter 2

Background of the developments in smart PWCs

This chapter investigates the state of the art of the assistive PWC and starts with some general facts about the current research position. Before reviewing any of the technical literature it is important to understand that the PWC user is also part of the system and that their perspective needs to be carefully considered, after all the technology is meant to assist them. A number of problems faced by PWC users are then identified from the literature and from having users, clinicians, suppliers, and manufacturers involved in supporting the SYSIASS project. This led to a realisation that little navigational assistance had been made available to the end users and therefore in order to better understand why, a full review of the literature is undertaken. Some of the important current and past projects are presented in this chapter and a review of the current assistive PWC evaluation methods are also presented, the chapter finishes by drawing together the findings.

Developing intelligent assistive systems is a challenge for the research community. Finding solutions which assist the user with collision avoidance/assisted navigation is required to help maintain the independent mobility of the PWC user, increasing their quality of life whilst reducing collateral damage, and reducing carer costs. For many users, powered wheelchair operation in enclosed environments such as buildings, has proved problematic. A major unmet need for all users is to be able to drive in such environments with minimal collisions, particularly for those users with significant physical disability accurate control of the chair may be a seemingly impossible challenge.

2.1 The current state of the art of assistive PWCs

Although there has been significant research in the technological field of smart powered wheelchairs there has been much less research consideration with regard to user input, user feedback, and user confidence, and negligible consideration of the users' abilities and desires. An extensive review of intelligent and assistive wheelchair literature was undertaken in 2005 by Simpson [4]; another independent review of the literature was undertaken by Faria in 2014 [15]. Some of the research projects mentioned in 2005 have continued to influence research [14, 37-39], while other new platforms have emerged [21, 22, 40, 41] and some 4,018 papers have been published between 2005 and 2013. Despite this significant research, little has been done to bring smart PWCs to the end users according to Garcia et al. [42]. They argue that most research is carried out in the lab without recourse to the stakeholders, in particular the users. They go on to say that one particular problem has been the availability of suitable sensors, and another is the lack of a standard platform.

Another significant issue with assistive PWC development is the lack of any standard testing procedure according to Yanco (2002), in particular it is important that when evaluating the performance of any assistive robotic system it is necessary to demonstrate that the system is safe and useable [10]. Most research has not fully considered these issues [5, 14] and what may be considered by researchers as appropriate may not address users' needs or worse may not be considered safe when applied to real-world applications. Considering the somewhat complex requirements of the individual user in the loop of the robotic PWC system most research has concentrated on addressing specific issues rather than attempting to define the general problem and then to seek a solution as proposed in the introduction chapter of this thesis. Consequently there is a considerable gap in the art between the typical research PWC platform and a manufactured end product [14]; therefore a suitable assistive platform needs to be developed.

The history of the smart or intelligent PWC development can be presented by the examination of previous projects and publication. There follows a chronological description of a selection of these projects and issues identified solved and remaining:

Madarasz was an early smart wheelchair first presented in 1986. It had a micro-computer and used a digital camera and an ultra-sound scanner with wheel encoder position feedback enabling it to move autonomously around in the human dynamic workspace [6]. The objective of this research was to develop a PWC platform for users with physical difficulties who find operating the PWC difficult. This smart PWC development focused on being able to travel around in peopled environments with minimal collisions. Madarasz et al. [6] determined that the platform should be able to move from room to room using path-planning whilst avoiding obstacles in real time. Importantly they stated that the technology employed should be self-contained within the platform, not requiring any infrastructure. The ranging was obtained by scanning the environment with single sonar, which they report was problematic: false distance readings caused by the sound wave being bounced away from the sensor and echoes in corridors, also the wide field of view causing objects to appear larger.

The most important conclusion from this research, for this thesis, is the identification that autonomous operation *'may not ultimately be practical, nor desirable'*. The motion in the environment was only partly successful suggesting that there were many issues to be identified and overcome.

VAHM was introduced in 1992 by Pruski and Bourhis [43] as a concept of applying mobile robotics to powered wheelchair assistance and has continued over the years: 1993 [19], 1996 [44], 1998 [45], 1999 [46]. The initial environment detecting hardware consisted of eight sonar ranging sensors, eight infrared ranging devices, and a ring of optical-contact sensing devices. This project incorporated a similar approach to the robot architecture as proposed by Brooks [47], called the Subsumption Architecture, this has a layered structure where a series of actions in increasing complexity, with simplest at the bottom, such that the action of higher levels can subsume behaviours of lower levels.

The VAHM architecture introduced the human into the process as the top layer with tight cooperation between the human and the autonomous system. The system generated a collision-free trajectory for the platform control to follow by taking into account some of the geometry of the platform. In 2002 a behaviour-based-approach control architecture was introduced; for example the user defines the direction vector whilst the system performs a wall-following behaviour such that minor deviations are smoothed over by the general vector heading and obstacles are avoided according to the reactivity behaviour [48]. This development improved upon the control architecture bringing in a generic behaviour-based element, these three behaviours were: stop, reflex, and vector following. If sensors detected an obstacle then depending on parameters a decision would be made: stop would bring the platform to a halt, reflex used the method of the Vector Field Histogram [49] to guide the platform around obstacles, and polar vector following employs fuzzy logic to enact behaviours such as wall-following.

This symbiotic system incorporates the user's directional intent, obtained from the joystick data, combined with the detected obstacles, in order to attempt to predict the intended path. This 'adapted system structure' was based upon multi-agents: behavioural, cognitive, and environment. Version 3 (VAHM-3) demonstrated the symbiotic architecture; Pruski et al. reported that the system had an acceptable reliability [50]. The system has been designed for the very highly disabled PWC user, and even though the system has a symbiotic approach, by incorporating the user desired vector into the decision making, the user is not in control of the motions of the platform, it is still autonomous.

Although Pruski et al. conclude that future work should concentrate on minimising system intervention and take more account of user's desires; importantly this system does not have the user as the intelligence in overall control. The symbiotic system takes account of the user's desire and performs its own motion. This system is not assisting the user to carry out their desire; instead, crucially, it takes away control from the user and attempts to take a predicted action.

Omnidirectional Intelligent Wheelchair (1993) incorporated a modular control architecture which allowed the PWC to be controlled at different levels of abstraction. This research concentrated on providing a solution to the kinematic constraints of the PWC by developing a smart PWC which could manoeuvre in confined spaces due to the Mecanum wheels [51]. These wheels allow motion to occur sideways, forward/backward, and to rotate, therefore allowing users three degrees of freedom in a plane. Hoyer and Hoelper [52] concluded that having a modular open control structure allowed for flexible configurations of self-organising control modules: the communications unit which handled the data flow between modules, the functional unit which contains algorithms to control the PWC position, the sensor module which provides obstacle position data, and an inference mechanism module which provides the rule-based decision making. The information flow between modules consisted of data specific to the needs of the algorithms in each of the individual modules. This system operated with low-level embedded hardware; however the high-level processing was provided by a Unix PC/Laptop over either infrared wirelessly or via a RS-232 interface.

Although this development used a new type of wheel, allowing motion with three degrees of freedom, this motion was slow and the wheels are without pneumatic tyres, furthermore the control architecture still provides for autonomous operation which removes the motion control from the user. This development has however introduced a modular system with each module handling data specific to the modules function, a concept which this thesis incorporates.

NavChair was presented in 1994 by Bell et al. [53]. This smart PWC was equipped with 12 ultrasonic sensors and an on-board computer. The VFH [49] obstacle avoidance method was employed to modify the user joystick input signal before returning it to the power module of the wheelchair. This method used a localised obstacle vector approach to determine the obstacle position certainty. Modelling the PWC as a disk was a significant problem identified by the research. This, they report, did not represent the actual platform geometry when in motion. The research concluded that there were significant issues with doorway passing due to the modelling and due to the problems with detecting the doorway using sonar ranging sensors and the VFH method.

Attempting to solve these issues the research continued, and in 1999 the NavChair employed three operating modes: obstacle avoidance, door passage, and automatic wall following [54]. The VFH method was refined to allow better doorway passing; however the platform was not able to pass through a doorway if the approach angle was not close to the centreline of the doorway. This problem has been addressed in this thesis. Levine et al. [55] conclude that the platform provides a means for developing shared control, which is a move away from assistive and back towards autonomous.

TinMan was developed as a research platform by Miller and Grant in 1994 [56] at the KISS Institute for Practical Robotics. A standard PWC was used upon which sensors were mounted: drive wheel encoders, contact sensors on a bumper, 12 SUNX infrared proximity sensors, six ultrasonic range sensors, and a fluxgate magnetometer for detecting the geomagnetic field. The control system used a separate joystick for the user input and modified that signal according to any obstacles detected by the sensors using a small Motorola microcontroller. The altered trajectory was then returned by use of two electromechanical servo-motors attached to the joystick of the standard PWC. In 1998 Tin Man presented more advanced characteristics such as storing navigation information and returning to the starting point [57].

Wheelesley (a TinMan supplied by the KISS Institute for Practical Robotics) was introduced in 1995 by Yanco et al. [58]. The research established the need for using a semi-autonomous concept, and makes a significant point that there is a very clear distinction between the autonomous robot moving from goal to goal using a map and that of the smart PWC which must interact with the user. Yanco et al. [58] identify the issue of doorway passing as being a fine navigational requirement, and that maps are not required, and that the system should operate without external infrastructure. The research then presents a system which uses a graphical interface to allow the user to ask the system to pass through the doorway in front of it. The on-board computer uses a 68332 Motorola microprocessor with the user interface running on a Macintosh PowerBook. The robot used the Subsumption

Architecture [47] to switch between hallway and doorway mode [58] with the user being the instigator of that switching, which according to Yanco et al. [58] improved upon the problems of doorway passing encountered in the NavChair project [53]. The platform was used in 1997 [59] to test electrodes placed on the skin of a user, near the eyes, providing a directional input for the system rather than the traditional joystick human-input device.

RoboChair was initially developed by Pires et al. in 1998 [60] and aimed to be an open framework for assistive applications with a modular design based upon open standards. The system used a MC68332 microcontroller running a Linux operating system; 14 infrared ranging sensors, sonar ranging, and contact sensors all provided obstacle feedback, human-desired trajectory information was provided by voice and joystick input, and a fuzzy logic controller [61]. Initial research identified that most current developments (1998) have not been accepted by PWC users [60] and that the motion of the smart PWC *'must be coherent and inspire confidence to the user'*.

SmartChair project between 2004 and 2007 developed by Parikh et al. [9, 38] used a shared-control framework with the human operator able to interact with the intelligent chair whilst carrying out autonomous tasks. Infrared ranging sensors were employed for detecting the proximity to obstacles, an omnidirectional camera and laser range finder were employed for path planning, and wheel encoders used for trajectory dead-reckoning. This system used a human override to interrupt the autonomous trajectory and provided reactive intervention from sensor-detected obstacle feedback. Whilst this research presents a reactive and planned system combination the user is considered as an addition to the autonomous system who can interrupt the motion.

Intellwhells was a research platform developed in 2008 by Braga et al. [21] to be compatible with a multimodal human machine interface (voice, head movements, joystick, keypad and simple facial expressions) using a laptop computer, sonar and webcam sensors for navigation and collision avoidance with trajectory feedback from wheel encoders. The concept was to provide a platform to enable

the easy development of intelligent powered wheelchairs [21, 62]. In 2012 a new modular prototype was developed with improved multimodal interface and automatic patient adaptation capabilities [22, 63]. Although this platform uses a standard Sunrise Powertec PWC as the base, the laptop and webcam processing adds a level of sophistication, inherent complexities, and cost. However the modular hardware structure and the layered control architecture are retained.

MIT Intelligent Wheelchair Project has been a recent project following on from an earlier project called Wheelesley (1995) [58] and an updated Wheelesley called Wheely (2007) [64] which used stereo cameras for mapping and localisation. The current intelligent wheelchair project continues with the aim of enhancing an ordinary powered wheelchair, using sensors, to allow a smart control system to perceive the wheelchair's surroundings. A speech interface has been used to interpret user commands, and a wireless room localisation device employed allowing the research to concentrate on providing assistive narrated guided tours [65]. However the system is an autonomous one.

RADHAR, 2012, has the objective of developing an assistive PWC system which incorporates environment perception. Inherently uncertainty exists in measuring the environment and this project seeks to improve autonomous perception to predict and then assist the user trajectory by fusing user intent and environmental information [66]. Three Hokuyo laser range finding scanners were used to map the environment, one haptic joystick for user input and system feedback to the user, a touch screen with a GUI, four Kinects with one looking at the user's face, two wheel encoders, and Xsens IMU, all controlled by a PC. Demeester et al. [66] report that further work was required to integrate the system components.

ARTY project, presented in 2012 by Soh and Demiris [67], focuses on developing an intelligent PWC for paediatrics using a shared control. The collision avoidance combines the merits of the Combined Vector Field [68] and the Dynamic Window Approach [69] to form the hybrid shared-control.

The platform has three Hokuyo URG-04LG laser ranging scanners and five bump sensors connected to a small PC. Importantly this platform system interacts with the manufacturer's CAN bus which connects all the PWC system components together. The research reported that when the system was evaluated seven of the eight participants preferred the hybrid shared-control over a safe-guarding method which moderated the platform velocity in the vicinity of obstacles. It was reported that the user who did not like the system behaved in such a way that *'when the wheelchair swerved to avoid an obstacle, he stopped completely or issued fast "corrective" movements'*.

One existing technology which has been available to end users since 1996 [70] has been the collision avoiding line-following CALL Centre assistive PWC; however each individual needs to be uniquely accommodated into the system, and there exists no easily tuneable system [67]. Despite this the system operates on a line-following principle with collision avoidance sensors and bumpers to maintain a robust and safe operational device suitable for deployment in the highly dynamic environment such as schools and hospitals. Adapting to the users' changing needs is not an easy task therefore most research has concentrated on purely mobile robotic compatible solutions rather than establishing a suitable methodology which is able to deal with a wide range of users and their varying needs over time [5, 14]. There does however exist a trend in the art towards better consideration of the users' desires and incorporating them into the system decision making [7, 7, 9, 18, 37, 38, 41, 48, 71, 72]. There is therefore lacking in the art a methodology and system suitable for adapting to a wide range of PWC user's needs, helping them to negotiate complex cluttered and dynamic environments. Some measure of the complexities and problems can be inferred from the following sections.

2.2 The PWC user perspective

A PWC user may either be suffering from neurological trauma/disease or have some muscular/skeletal trauma/disease and may be of any age range, although increasingly people are living longer and

require mobility assistance for longer time spans thereby increasing the number of older people using PWC at any one time. There exists no typical PWC user, therefore it could be said that the requirements for providing assistive mobile technology to aid rehabilitation or to maintain a reasonable quality of life is a considerable challenge. One publication by May and Rugg in 2010 [73] highlighted the complexity of the issues; the researchers summarised that the literature was sparse with regard to PWC user quality of life and occupational performance (the ability to self-maintain) according to Reed and Sanderson [74]); their study found that all participants, after being issued with a PWC for the first time, had significant improvement to their performance and satisfaction scores on COPM. This evaluation method is a measure of the care receiver's perception of their own self-care and living capabilities; the test is being usually administered over a 30-minute period, developed by Law et al. in 1994 [75, 76].

According to research into PWC needs for young people (2003) [11] further study into the implications of providing mobility, and maintaining that mobility, at an early stage are required, particularly as the research indicated that many needs were not being met. Earlier research (1999) [77] indicated that children using PWCs had better spatial awareness and cause-and-effect skills than non-PWC users. More recent research into young people's experiences with EPIOCs (2006) [16] concluded that greater physical and social opportunities brought about by the increased mobility were of benefit to users and their families, 'making life easier', although they report most users had a back-up chair due to damage and reliability issues, and lengthy repair times experienced.

The first study of the elderly PWC user (2007) suggests that the immediate benefits from the use of the PWC are an increased independence and well-being [16]. They go on to state that despite this many elderly users were apprehensive when going outdoors. They discuss this and suggest that this may be due to social stigma, or a fear of accidents, particularly tipping over, and reliability issues such as being stranded if the technology fails. Furthermore they report that elderly users had dissatisfaction with the wheelchair service: long waiting times and concerns about the chair not meeting

their changing needs over time were mentioned. These findings were supported by similar feedback from stakeholders involved in the research undertaken for this thesis.

2.3 Current problems for the PWC user

Although there are complex issues surrounding assisting PWC users, their requirements for mobility assistance remain within a manageable range. A report on the introduction of the supply of EPIOCs by the NHS to users, published by Frank et al. in 2000 [78], obtained 113 PWC users' feedback four months after first-time supply of a PWC. They reported that there were six users who were tipped out of their PWC, three who fell during a transfer to or from the PWC and 44 users' PWC had component failure. Despite this, 96 users thought their life was made easier by using the PWC. Most problems, according to the literature [13, 16, 78, 79], can be listed as follows:

- causing injury to pedestrians
- damage to infrastructure
- learning to drive the PWC safely
- manoeuvrings in tight spaces
- inability for users to see behind/sides
- tipping over
- reliability of equipment
- adjustability and adaptability of system/equipment to changing needs

Some of these problems will be made worse due to the specific condition of the PWC user. However a key single common thread for all users is the need for an adjustable, reliable, robust assistance to

avoid collisions; whether those collisions are with people, other PWCs, furniture, building infrastructure, doorways, or pets they are nonetheless based upon the need for assistance with observing the dynamic human-world environment and manoeuvring around in that environment. Currently a low-cost robust assistive solution to this problem does not exist.

One article written by Nisbet in 2002 [5] draws attention to the reason most assistive or smart powered wheelchairs have not been brought to market: this research concludes that the most intelligent part of the system is the human, *‘and that the most important design aim should be to develop systems which complement, maximise and augment the pilot’s skills, not replace them,’* claims Nisbet. There is therefore an existing challenge to develop an assistive human-in-the-loop mobile robotic PWC which can avoid obstacles and manoeuvre in confined environments, and which is adjustable, low cost, reliable, non-complex to operate and maintain, and that is intuitive to use.

2.4 Assistive PWC evaluation

Evaluation of smart PWCs has no associated standard and benchmarks. Driving around a course which may include corridors and doorways assessing the number of collisions and time taken is usually adopted as a method of evaluating the performance of an assistive robotic PWC. One test in 2002 involved 14 non-disabled participants using the Wheelesley platform [10]. When asked to complete an obstacle-strewn course, participants were able to reduce their time taken by an average 25% when using the assistive system rather than the manual. Furthermore the number of collisions was on average reduced from 0.25 using manual to 0.18 per person when in assistive mode. The users reported on a scale of 1-10, where 10 represented the best, that the system rated 8.7 and manual 3.5 on average. The researchers were keen to note that the results were analysed using the ‘Analysis of Variance’ method; however an important consideration was overlooked: the user had a digital input, such that they clicked a button to go forward, backward, and turn, therefore in manual mode the driving performance would have been zigzag-like and not smooth, whereas the assistive system

would have had some proportional smoothing as part of the collision-avoiding function. In all likelihood this would have a significant effect on the user's perception of the performance of the system. In addition:

1. the system, although reducing the number of collisions, still failed to eliminate them
2. the system spent time scanning for commands
3. one of the testers was the researcher who tested for the optimal performance, rather than using an impartial experienced user
4. the tester was also able-bodied and was therefore not representative of an experienced disabled user

Another example of assessing smart PWCs is the ARTY project; researchers sought to test their smart PWC using eight non-disabled children aged 11 on a simple obstacle course, forward and reverse (2012) [67]. The test consisted of trialling two assisted control modes (safeguarding and assistive) and did not appear to include a non-assisted comparison. Although the assistance was helpful when reversing, the researchers reported little difference in the forward test. Interestingly when the respondents were asked after the trial if 'it felt natural driving the wheelchair' there was little distinction between safeguarding, assistive, or both. The researchers went on to test the system with a five-year-old boy who had physical and cognitive disabilities, and who was considered by his occupational therapist not to be ready to learn to operate a PWC. They reported that he was able to operate the PWC with the assistive method to a level that his occupational therapist thought was successful as he drove around safely. An experienced PWC user repeated the exercise given to the five-year-old boy and both joystick inputs were recorded for comparison. When analysing the data higher orders (jerk m/s^3 and snap m/s^4) were used to compare the experienced and inexperienced user. As expected, movements were rapid and jerky similar to an adult inexperienced user. This interesting piece of research indicates that humans, even when cognitively disabled, totally inexperienced, and very young are fully capable of controlling a mobility device when given navigational assistance.

2.5 Approaches to collaborative control assistance

Collaborative or shared control methods have been evaluated, with varying degrees of success. These methods depend on the quality of the user joystick input to the system, whereby the user is given more or less control depending upon the quality of their input. However, system intervention is not always intuitive and users are not always aware of what the system is doing or even why [7, 71]. One collaborative control approach presented in 2010 [7] was based upon a measure of user efficiency. A reactive sensor-based navigation scheme was used based upon the repulsive nature of potential fields [80] to give the user more freedom of movement if they were more efficient at avoiding obstacles. Although this method takes into account the variation in the user's ability over time the researcher reported that there was a lack of smoothness due to the human actions affecting the system corrections. They state that this would be improved by a more efficient reactive algorithm however they note that with their method this would decrease the human control element.

Another collaborative control method (2010) [41, 71, 81-83] was developed over a number of years at Imperial College London by Tom Carlson; their model, called DLOA, uses local obstacles detected in the vicinity of the user's intended direction (obtained from the joystick) and the system shaped the trajectory to avoid the obstacle or pass through a doorway. If the collaborative controller determines a mismatch between the approach path and a system-generated path, then the system takes over control. Their system uses a layered approach: beneath this trajectory assistance they employ a virtual bumper using sonar ranging sensors to avoid localised collisions. This layered structure is a common theme also having been employed in the VAHM [43] and Wheelsley [58] projects for example.

2.6 Conclusion

Having determined in this chapter that most developments, by 1998, had not been accepted by PWC users [60] and that the motion of the smart PWC '*must be coherent and inspire confidence to the user*'; according to Garcia et al. in 2013 these problems had yet to be overcome [14], they note that

recent research was applying modern robotic method and the projects reviewed in this chapter tend to confirm this. However earlier research by Madarasz et al. [6] had identified that autonomous operation *'may not ultimately be practical, nor desirable'*. Nisbet had also identified that *'the most important design aim should be to develop systems which complement, maximise and augment the pilot's skills, not replace them'*. Having identified the smart PWC was not the same as a robotic system, Yanco et al. [58] went on to state the issue of doorway passing as being a fine navigational requirement, that mapping would not be required, and that the system should operate without external infrastructure. However despite all these early findings the research has still moved towards autonomous robotic systems, with complex mapping and path-planning, far from the requirements of a real-time system. The only human consideration in these autonomous systems has been that of shared control, not assistive; a very important distinction. Therefore there is a significant lack in the research for an assistive system with the human user fully integrated into that system.

In summary the literature has revealed that there are a number of fundamental problems remaining: modelling of the platform was identified as being problematic; obstacle detection was uncertain, proper alignment with doorways another problem, an effective obstacle avoidance method is lacking, and taking away control from the user is considered of negative benefit, finally most proposed solutions are not financially viable for the end users or the suppliers/issuers.

The next chapter evaluates the technology required for developing an assistive PWC; this involves determining suitable control structures and sensors. A modular embedded hardware system is then proposed which uses a human-in-the-loop control architecture to provide a layered level of assistance with each layer compatible with the others.

Chapter 3

Technology required for the assistive system

The previous chapter reviewed the art with regard to the development of the smart PWC. It was identified that an assistive system, which empowers the PWC user, was lacking. The specific list of problems that were identified were: a lack of suitable sensors, an absence of a suitable control system for keeping the user in control, assistance with manoeuvring through waypoints and doorways in particular, a real-time navigation and collision avoidance, and the automatic identification of waypoints. This chapter investigates the technology to be used for the assistive PWC system and develops the assistive control architecture.

The chapter begins with investigating and defining the requirements for developing an assistive system. Reactive behaviour-based robotics are investigated experimentally in order to determine human-compatible intuitively reactive responses, such that the motion of the platform is natural and safe. This leads to a new control architecture with the user remaining in control of any platform motion. Having identified sensor hardware has been problematic an analysis of available sensors is then undertaken and experimentation is then performed to determine the sensors most appropriate for the assistive PWC system. This leads to the final section which explains how through the use of pattern recognition techniques the obstacle avoidance sensor data can be reused to also identify those obstacles. The conclusion then brings the chapter developments together.

3.1 Requirements for developing an assistive system

According to the literature research in the previous chapter and in consultation with PWC users, clinicians, prescribers of the PWC, and a manufacturer, (called the stakeholders) consideration must be given to safety: any collision avoidance method must act with robust sensory feedback, the user must be in control of any motion and that motion should be compatible and intuitive with what action the user would have taken themselves. Furthermore it was also identified from those consultations that the user would require a structured assistance: sometimes no assistance would be required, other times assistance with avoiding obstacles would be needed, and on other occasions a short trajectory to help align with and pass a waypoint or doorway would be needed, and sometimes a room-to-room assistance may be necessary.

Providing assistance to help the user decide which level of assistance they require is not covered in this research and would involve considerable user participation: an important observation that was noted by Carlson [71] during experimentation was that sometimes users would think their performance was much better than it actually was. This suggests that feedback with warnings and advisory actions may initially be a better option.

A common approach for smart PWC systems has been to form a layered structure which contains different assistive and autonomous behaviours, VAHM [43], Wheelsley [58], DLOA [83], ARTY [67] are a few examples. These layered structures can offer different behavioural responses depending upon some criterion being reached; and as we move up the layers each layer provides more complexity. Crespi in 2008 [84] compared top-down with bottom-up strategies in multi-agent robotics and found that they overlapped sufficiently, suggesting building robotic systems upwards from non-complex methods and behaviours (such as insect-like) could meet highly complex methods and

behaviours (such as human) when dealing with common tasks. Therefore in order to develop a human-in-the-loop intuitive system these layers would need to be complimentary, the outcome and input of each assistive layer being compatible with, and benefiting from, neighbouring layers in a seamless and smooth top-down bottom-up approach with each layer having flexible adjustment. This should be based upon the following caveats:

- that the human is always the instigator of any positive action
- that the human is informed of any corrections necessary
- that the system should have adjustable assistance
- that the system should have multiple levels of assistance
- that the system should fail safe, returning to some manual mode
- that the system should prevent injury to pedestrians
- that the system should prevent damage to infrastructure
- that the system should allow manoeuvrings in tight spaces
- that the system should be adjustable and adaptable to changing needs

Extensive consideration regarding the type of technology required for obtaining information about the environment has been undertaken during the research for this thesis. Existing PWC systems were reviewed in the previous chapter leading to a good understanding of the sensors previously used. There is however a significant problem: the more that complex information was required, the more that the sensors cost and the more that computational-processing was required. During the consultation with the PWC stakeholders it became clear that there were significant issues, but not complex and unsolvable:

- the system and hardware should be easy to set up, and be adjustable and adaptable
- the robustness of sensors and hardware must be sufficient for long term application

- the physical dimensions of the hardware should be minimal, thus being unobtrusive
- the hardware and system should be compatible with existing infrastructure
- the system should be assistive and not preventative
- the system should be easy to use and intuitive
- the user must know what the system is doing
- the user must be able to disable the system should the need arise

3.2 Braitenberg vehicles and the Subsumptive Architecture

In order to better understand the nature of a human-like reactive mobile platform, such that the platform behaviour is less intrusive and more intuitive, we need to review the simplest type of goal-achieving robots, developed by Valentino Braitenberg [85]. These robots were based upon a type of ‘synthetic-psychology’ according to Braitenberg [85], utilising a direct sensor to actuator connection to produce simple biological-like behaviours. The simplest vehicle Braitenberg proposed was one which comprised a single sensor and a single motor, taking the sensor as a thermocouple and that the motor would be mapped to turn at a rate directly proportional to the temperature; then the behaviour exhibited would be to slow down in cold places and speed up in warm places.

The next vehicle Braitenberg suggested was one which had two motors and two sensors such that it was a simple differential rear-wheel driven device as depicted in Fig 3.1. The next simplest behaviour Braitenberg describes is one of fight or flight: Fig 3.1a shows the actuator sensor connection arrangement which will mimic aggression, following the previous example of directly proportional temperature, and using a small heat source such as a lamp. Then the robot will turn to head towards the source speeding up as it nears, eventually colliding with it. The second method of connecting the

sensors to the motor, shown in Fig 3.1b, causes the robot to turn away; the closer the robot is to the source the quicker the robot turns away and Braitenberg describes this behaviour as fear. Using the same thermal sensor and proportion only this time making it proportionally negative, then the next behaviour shown in Fig 3.1c would be that of love: the robot would turn towards the heat source and slow down and stop when it reached it. Alternatively if the sensor motor connections are crossed as in Fig 3.1d then we see a different behaviour: assuming the robot has some set max velocity then it will move about, slowing as it nears the heat source and slowly turning away, getting close but not touching, as if exploring or curious.

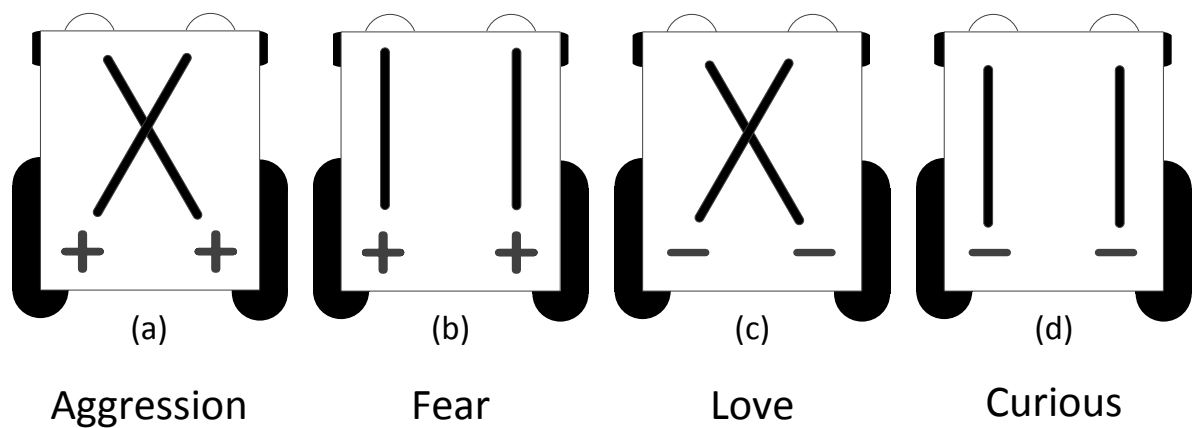


Figure 3.1 Sensor–motor connection arrangements for Braitenberg vehicle 2 a) aggression and b) fear Braitenberg vehicle 3 c) love and d) curious

In order to reproduce more complex biological goal-seeking behaviours Braitenberg imagined a network of wires which connected either the sensor to the actuator or across the two. These wires had special imaginary properties. Mnemotrix Wire represents a simple form of associative memory with threshold weighting allowing the analogue proportional signal to be passed or not passed. Ergotrix Wire has a capacitive nature and weighted such that it performs a predictive temporal function allowing the analogue proportional signal to be either delayed because some other behaviour is active or, if some behaviour has happened for an amount of time, then triggering some other behaviour.

Using these wires Braitenberg describes more complex behaviours using combinations of the multiple behaviours, describing one of the vehicles with this complex behaviour as similar to McCulloch-Pitts neurons which emulate the biological neuron [86].

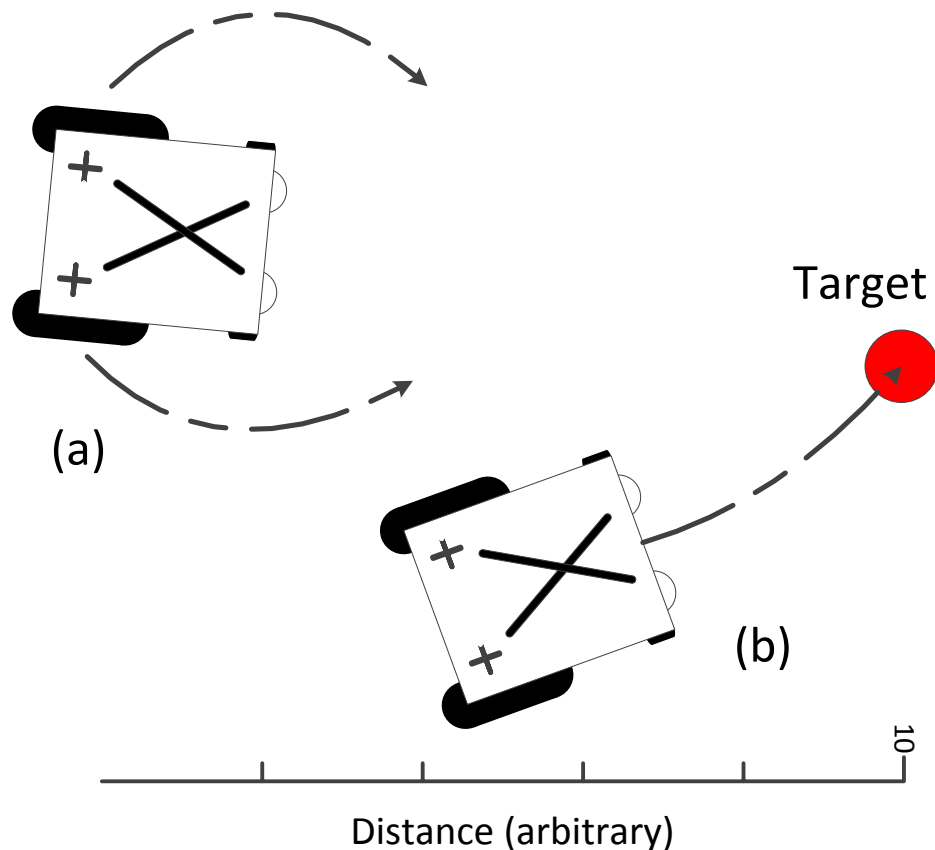


Figure 3.2 Complex behaviour of a Braitenberg vehicle

More complex behaviours, for example, can be obtained from the same basic set-up as shown in Fig 3.1 if there is some threshold or delay using the hypothetical wires described above. Fig 3.2 shows how this might work using the aggressive configuration shown in Fig 3.1a such that until some threshold is reached the robot swings about from side to side looking for ‘suspicious’ targets Fig 3.2 (a); when the target increases its thermal output above the threshold the robot turns rapidly and heads toward the target Fig 3.2 (b). These multiple-behaviour robots can perform in a realistic and biological-like way when using one robot as the prey and another as the predator, for example.

A similar and compatible approach to breaking down a control structure into behaviours which are specific to a task was proposed by Brooks around the same time [47], and was called the Subsumption Architecture. This method provides a powerful tool for representing intelligent robotic control mechanisms through the use of a structure of simple behaviours. Rather than trying to mimic biological and psychological behaviour using simple mechanisms and devices the Subsumption Architecture provides a more formal approach for building complex robotic systems. The oldest architecture is the Deliberative Control Architecture [87] as shown in Fig 3.3 which uses sensors to provide feedback to the high level; this level passes down the behaviour in a top-down manner.

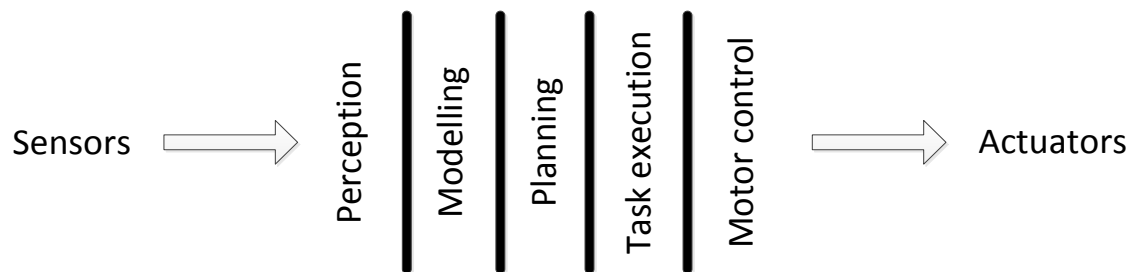


Figure 3.3 Traditional robotic architecture

The Subsumption Architecture, shown in Fig 3.4, is a structure of individual behaviours carrying out specific tasks where each of those behaviours in the structure is a complete stand-alone control system from sensor inputs to actuator outputs. Higher levels of behaviour can subsume the lower levels of behaviour by suppressing their outputs. This, Brooks reports, results in a robust and flexible robot control system: lower levels function independently as higher levels are added. If no suppression from higher levels occurs then the lower levels become the dominant current behaviour. Although this structure can be used to develop complex robotic behaviours, due to the nature of the self-contained task achieving layers, the decision-making information is not necessarily shared with the other layers. Improvements have been made to refine the interconnection between layers which provides new layers with access to the complete structure rather than the layer below, improving flexibility and expanding the number of possible behaviours [88].

These methods have evolved from these early reactive architectures into a more complex field of artificial intelligence [89], although Brooks has extended the concept to the construction of robots which are more creature-like [90]. However this reactive sensor-actuator nature is commonly used in the real world where a direct sensor-actuator principle is used for safety critical devices, stopping a machine when a barrier is open for example, or a more complex stand-alone system, which is part of a more complex architecture, such as for example anti-lock braking and traction control on vehicles. More specifically for this thesis the Subsumption Architecture has been used in the development of intelligent PWCs [10, 58, 91].

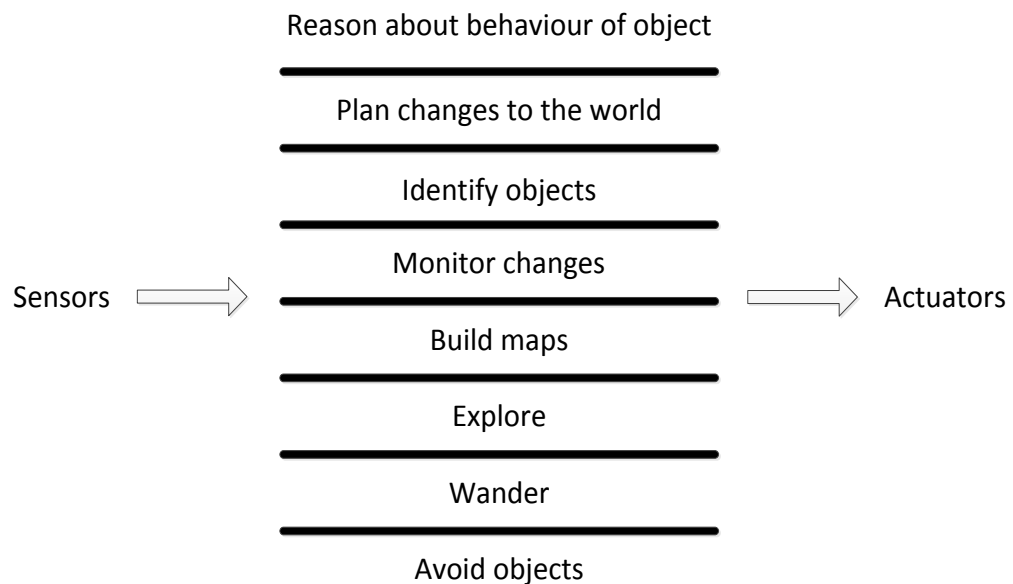


Figure 3.4 Subsumption Architecture

3.3 The human-in-the-loop assistive architecture

Having described the biological, and human, like behaviours of simple direct connected mobile robots, a simple robot was constructed for the purpose of examining these behaviours. This robot was constructed in a similar fashion to that described by Braitenberg and is shown in Fig 3.5. The sensors chosen were of the infrared ranging type (Sharp GP2Y0A41SK0F) with a detection range between 40mm and 300mm.

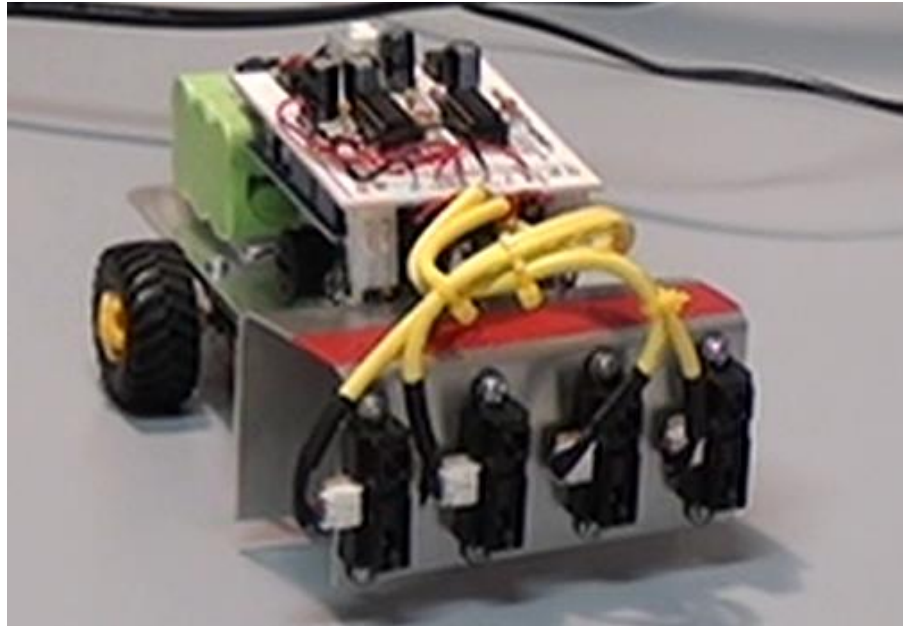


Figure 3.5 Behaviour-testing mobile robot

Various behaviours were examined experimentally, wall following and goal seeking had difficulties when presented with a changing environment, the best reactive-responses were all of those shown in Fig 3.1, although one other response that looked promising was free-space floor-following (head towards the open space) which was modified to stop if the floor dropped or rose up. This was to detect for stairwells and walls. This experimentation finally resulted in identifying one of the behaviours which performed in a manner closest to the requirements identified at the beginning of this chapter; and that was the love model Fig 3.1c. This configuration allows the mobile robot to move up to objects and stop but not collide with them. Further adjustment to suit a more complex behaviour was obtained when the sensors were mounted at an angle, two on each side, and the repulsion was set as non-linear rather than switched, as was the case with the example in Fig 3.2. This allowed the robot to follow walls and steer around obstacles. It was observed that the mobile robot responded in a more natural and intuitive fashion consistent with what might be expected from a human-controlled mobile device.

The research into the provision of assistive mobility devices to the severely disabled, those who would not qualify for a NHS PWC driving licence, has prevailed in the art. However this excludes

the majority of users. The ARTY project [67] identified that young people had also been sparsely considered. The researchers reported that a young highly-disabled participant managed to operate the PWC safely with collision avoidance provision. This indicates that the user, even when very young and highly disabled, is fully capable of moving about safely. During testing the participant was able to 'visit' friends and socialise, this lends more weight to Nisbet's advocacy the user is the intelligence in the assistive system [5]. The robustness and safety requirements, described earlier in the chapter, necessary for any human-in-the-loop mobility assistive system means that the user must therefore have ultimate control over the mobility device; their decision and judgement must be the overriding authority with the assistive system never fully taking over control, instead the user must be part of any positive acting decision.

A review of robotic control architectures, and their effectiveness, in 2011 [92] identified that reactive architectures performed significantly better than the deliberate in the uncertain and dynamic environment; however in order to achieve comprehensive navigation a reactive robot would require a real-world representation, perception, and decision making. Combining the Deliberative Control Architecture and the Subsumption Architecture forms the Hybrid Control Architecture proposed by Arkin in 1989 [93] thus allowing the top-down directives to provide the higher level dictates, such as real-world navigation and decision making, and allowing the reactive architecture to pass back to the upper layers when unable to resolve the situation locally. This combined hybrid architecture; Nakhaeinia [92] reports, provides a much better solution to autonomous robotic navigation.

Taking the network concept for providing a better interconnected Subsumption Architecture [88] and combining this with the Hybrid Control Architecture [93] then introducing the human into the network, it is proposed that a robust architecture can be described by the one represented in Fig 3.6. This architecture provides a full interconnection between the higher layers and lower layers, in a top-down and bottom-up directive, unlike the previously-mentioned architectures. This architecture prevents the higher levels from subsuming the lower layers if the lower levels are still active. By this it

is meant that the collision avoidance layer will not be overridden by the assistive trajectory level if there is an unpredicted interruption or undetected obstacle. Instead the collision avoidance layer overrides the assistive trajectory layer, or alters the trajectory in a complementary fashion, whilst informing the user and higher levels, thus keeping the human in the loop.

The collision avoidance layer should provide the user with an adjustable zone which causes the PWC to avoid the obstacles in a localised and non-linear fashion. This was something identified in the experimentation performed in section 3.3 from the non-linear infrared ranging sensors. The damping nature of the love behaviour, Fig 3.1c, was also identified as suitable for non-intrusive intervention which can be used to gently steer the platform away from obstacles. The experimentation also identified that a local and shaped (from the angled sensor array mentioned in section 3.3) collision avoidance zone should be employed. This could then be adjusted by sensor feedback, as well as having user refinement, for example the higher waypoint identification layer could pass down a directive to adjust the zone according to the shape of the waypoint or obstacle. More specifically the user may have instructed the path-planning layer to keep to the left in a particular corridor; therefore the dictate is then a human desired adjustment of the collision avoidance.

A dynamic model is required to allow the platform behavioural response zone to be adjusted by sensor feedback and by user desires, different users may wish to use the PWC and they may have different masses and inertia profiles. Therefore some small adjustments are required; usually these are required to be set in the manufacturers' mapped profile for each individual shown in blue in Fig 3.6. The dynamic model layer shown in Fig 3.6 allows some fine adjustment to be made without recourse to remapping the profile. Furthermore a dynamic model would better express the behaviour of the non-holonomic platform than kinematics alone.

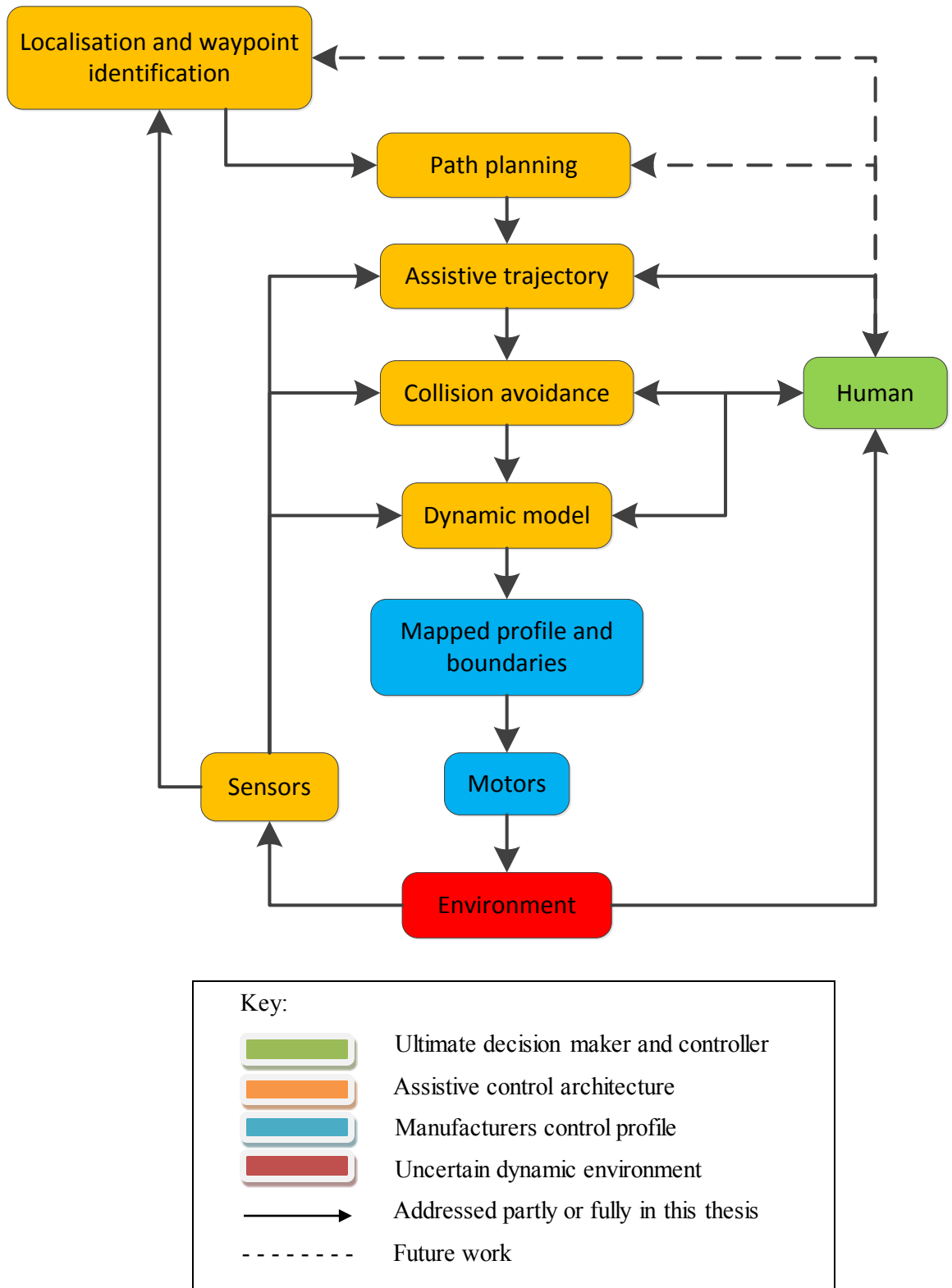


Figure 3.6 Human-in-the-loop control architecture for assistive mobility devices

The methodology of this architecture allows it to sit upon the layer of control provided by the manufacturer of the PWC; these layers are the mapped profiles and boundaries, and the time-based ramps for the motor drivers. Therefore the PWC can be set up to respond within a safe dynamic envelope. These various time-based ramps are used together with boundary limits imposed on the joystick, or digital, user inputs such that the platform responds in a safe controllable manner, therefore the layers above can never send a false directive to the motors unnecessarily loading them.

The localisation and waypoint identification layer will be required to provide real-time room identification, and which waypoint it is approaching. The user would have some input to initially supervise the training of the system and to assign labels to the rooms and waypoints, or when re-training the system should changes occur over time. The user would also have the ability to correct or override the identification if the system notifies the user incorrectly. The system would then be able to detect incorrect approaches to a specific doorway, for example, and warn the user. If the user then required assistance this information would be passed to the path-planning layer. This layer is not developed in this thesis and might in future have some predictive nature and the ability to combine trajectories to assist the user room-to-room, but for now it simply passes the information about the immediate workspace around the platform and what action is required, such as doorway alignment, to the assistive trajectory layer.

Assistive trajectories are required to help the user negotiate narrow doorways and to enter lifts, and to negotiate other waypoints. These trajectories would be generated when the user has sought assistance from the path-planning layer, the system detects the waypoint approach angle and range and then calculates a geometric path for the PWC platform. The user then has control of the velocity, stop and start, and the system uses feedback from sensors to follow that path providing the steering input to the layer beneath which takes care of any uncertainties, small errors, and dynamic changes. These are short assistive trajectories and the system passes back steering to the user after passing through the waypoint.

3.4 A review of potential robotic sensors for an assistive PWC

Avoiding obstacles, localisation, recognising waypoints, and generating assistive trajectories require the use of sensors which give some information about the environment in which the robotic device operates. There are two types of sensor: the first type are proprioceptive which deal with a mobile robot's internal measurements such as acceleration, rotation, and battery voltage, the second type of sensor are exteroceptive which measure the interaction with the environment such as the proximity to obstacles, or the distance travelled across the surface in the case of a mobile robot. These exteroceptive sensors can also be divided into two categories, active and passive. Active sensors make physical contact with the environment by either emitting energy, such as laser light, and using the returned signal to make some measurement. Passive sensors on the other hand make use of external energy, such as a using a pressure sensor to determine altitude in an atmosphere. Having reviewed the sensors used on other PWC platforms in the literature, Chapter 2, a summary of the types of sensor can be as:

- ranging sensors which return the distance from the sensor to some object
- absolute position sensors which return the position of the sensor in terms of the workspace that it operates
- environmental sensors which return information about the environment such as the properties of objects
- inertial sensors which return the platform body rates of change of the mobile robot

Mobile robotic sensors are inherently noisy, they are difficult to model, and they return incomplete and sometimes false data about the environment, these uncertainties can be significant if not taken into account.

Inertial Measurement Unit

The IMU usually has at least six degrees of freedom being sensed: this usually consists of an accelerometer mounted on each of the three body axes (x, y, z) and gyroscopes mounted on each of those axes to measure the body rotation about those axes (ϕ , θ , ψ).

The accelerometer usually consists of a mass suspended in a frame; when the frame accelerates the inertia of the mass creates strain in the support structure, this strain can be measured and provides a proportional representation of the acceleration. Accelerometers are usually designed to operate in a single axis only and can be very small MEMS devices or more complex high-accuracy devices using piezoelectric materials to support the mass. Measuring the acceleration can be very accurate even though MEMS devices suffer with electronic noise. The real problem with these devices is the need to integrate the signal to get velocity, then again to get position; therefore every integration calculation has a DC element (constant) which causes the velocity to appear to increase slowly over time and the position to drift over time.

Gyroscopes are usually based upon either mechanical rotating devices using low-friction bearings, which work on the principle of the conservation of angular momentum, or they can be based upon vibrating tuning forks using the principle of the Coriolis Effect. These vibrating tuning fork devices are usually a MEMS based device. There are more accurate gyroscopes such as the laser ring gyroscopes, and the fibre optic gyroscope which operates on the principle of the Sagnac effect. However all gyroscopes will suffer from some form of drift due to the accumulation of errors, with the low-cost MEMS devices having a significant drift whereas very expensive gyroscopes using the Sagnac effect can have extremely low drift rates.

Magnetic and gravity vector

The aforementioned accelerometer can act as a gravity vector measurement as this can simply use the direct measurement of the acceleration due to gravity without any accumulative errors; other

methods include using a conductive liquid in small vessel with contact sensors on the walls to measure the tilt of the platform. Knowing the gravity vector is very important in mobile robotics because of the risk of toppling over; this is something discussed earlier in this thesis as a major contribution to PWC accidents.

The Earth's magnetic field lines can also be used to find the gravity vector and to orientate the platform with respect to the real world; these devices are again usually MEMS and rely on the principle of measuring the Lorentz-force acting upon a current flowing in a conductor; although there are many other approaches for example, using a magnetometer, or a Hall effect sensor. These devices suffer badly from localised metal objects altering the lines of the Earth's magnetic flux and from lines of flux given off by electromechanical devices. Because the Inertial Measurement Unit suffers from inherent drift, using the magnetic field of the Earth can provide a fix to inertial frame in the real-world frame [94], therefore the low-cost MEMS device may be suitable for inclusion in the PWC for outdoor use only.

Sonar

Sound has been used in nature by various creatures to echo navigate and some animals manage to use this method in the air and underwater with remarkable accuracy. Replicating this process has been quite simple; a piezo crystal is resonated at a high frequency 40-50 kHz, above human hearing, and the time between the emitted pulse and the return pulse is measured to determine the range to the obstacle. These transducers can be small and very low cost; they have the advantage of being able to detect narrow and small obstacles in a wide-angle field of view, being therefore appropriate for safety critical object detection. They do however have several major negative aspects; they have a limited rate of data collection, and the signal can reflect off flat objects at angles $>\pi/4$ away from the centreline of the transducer, this results in the object not being detected. Another problem this causes is if that reflected signal is then reflected back off another object back down the same path then a false reading is returned. There is also another issue of cross-talk with other transducers.

Infrared

The infrared Sharp ranging devices are based upon a principle of triangulation [95]. There is a focused infrared dot projected from the emitter and a focused linear receiver. As the distance from the object changes the reflected light illuminates more or fewer pixels in the linear receiver array. These devices are not as low cost as the sonar and also suffer with cross-talk, they are also highly non-linear, suffer highly with statistical variation in the measurements due to electronic noise, and the measurements depend upon the reflectivity of the materials, and background illumination from the sun and other infrared sources causes false readings [96]. There is also one other major disadvantage; when the device is close to an object the linear array is fully illuminated and therefore if the object comes any closer the centre of the Gaussian cone of returned light now moves off the other end of the array giving a reading that equates to the object being moved further away, therefore giving a false reading that the object is further away than it actually is [96].

Radar

Although traditionally radar has been expensive, requiring bulky equipment, recent advances in research, such as at the University of Melbourne [97] mean that there now exists the possibility of using small low-cost MEMS full radar on chip solutions for obstacle detection and ranging. The nature of the radar means that the velocity of the object relative to the platform can be directly measured using the Doppler shift, and the range to the object can be determined from the time of flight if the signal is pulsed. The negative aspect of this sensor is the wide-angle narrow beam, acting to detect objects in one plane only.

Laser

The laser rangefinder [98] works on the principle of either triangulation, time of flight, or is phase based. These devices usually function in a single plane and mechanically scan the environment; the more expensive devices can scan in both planes forming a 3D data array, although the Microsoft

Kinect functions by using multiple laser dots [99]. Mechanical scanning usually means that the device can only return data from the same point a few times a second. These devices may seem suitable for PWC use; however when reviewing the literature, and in consultation with users, it is clear that these devices are not suitably robust or cost effective for any realistic PWC application.

GPS

Satellite-based positioning has been fully functional since 1995 [100] and has proved to be a well-received technology used in mobile phones, shipment tracking, military use (intended purpose), construction, astronomy, rescue, anti-theft, mobile robotics, Unmanned Aerial Vehicles, rocket launching, aviation, and maritime navigation, as just a few examples. These devices are well suited to the application of assisted PWCs; however they do not provide very local information (partly due to military restriction of precision) required when moving about in a dynamic environment, and they do not work well, if at all, in the indoor environment due to nature of how the system functions.

Optical

The camera is the obvious device listed in this category; however computational requirements can be quite high, although the camera could provide the user with overlaid feedback whilst the system uses the data for navigation assistance. There are other alternatives, for example an Avago MEMS colour sensor [101] can be used to identify the colour of an object helping to identify quickly it or to allow the PWC to follow a coloured line in a similar fashion to the existing CALL Centre assistive PWC. Another type of sensor, the Avago optical computer mouse camera [102] uses optical flow algorithms to determine relative velocity [103] and has been used in mobile robotics to zero the velocity drift in inertial measurement units [104] and to identify surface qualities [105].

Encoders

The wheel or shaft encoder is usually a small glass disk which has a series of black lines etched upon the surface radiating from the centre like spokes, a small light source is mounted on one side of the disk and a light detector on the other side. As the disk rotates the dark lines cross the sensor and trigger a pulse; there are usually two of these sensors offset from each other so that the direction of rotation can be determined. These encoders then provide a proportional count of a section of the circumference of the wheel when it rotates; as the wheel is in contact with the ground this provides a measure of the distance travelled. Although usually large and bulky some encoders, including those PWCs, are built into the motor to make an integrated unit adding only a small amount more to the overall cost.

When indoor mobile robots move from one point in the human dynamic workspace (x, y) to another point in the workspace $(x + \Delta x, y + \Delta y)$ they can suffer from measurement error and drift [106]. The mobile robot can believe that it has carried out the instruction successfully whereas the reality can be quite different. These errors can be from wheel slippage and slide, or tyre inflation imbalance from one side to the other. Furthermore translation of non-holonomic mobile robots about the workspace does not have the simplicity of the point-to-point motion, therefore the kinematics of the platform need to be considered; the pose (rotation orientation) is a significant consideration when undertaking path planning and navigation which can suffer greatly from these errors of measurement [107]. Despite the drawbacks the wheel encoders can provide a good short distance track of position and a velocity feedback to the system to correct for accelerometer drift.

Table 3.1 Summary of mobile robotic sensors available for assistive PWC

<i>Sensor</i>	<i>Advantages</i>	<i>Disadvantages</i>
IMU	Low cost Compact dimensions	Accelerometer drift Gyro walk Electronic noise
Magnetic	Full global reference frame	Susceptible to other magnetic fluxes and metals Requires adjustment to localised field lines
Gravity vector	Nadir/zenith global reference frame	Some devices contain mercury Prone to false readings if vibrated or shaken
Sonar	Wide area coverage Low cost Robust High accuracy	Low data rate False reporting Temperature, humidity and altitude dependant
Infrared	Small area of detection, good for mapping and detecting edges	Susceptible to interference Suffers with electronic noise Affected by infrared light from sky Materials and colour affect the reflected signal Not low cost Glass not detected
Radar	Much faster sampling rate than sonar New low-cost MEMS devices Velocity and range	2D planar detection
Laser	High resolution Good accuracy Low noise	Mechanical scanning 2D planar detection Low sample rate
GPS	3D real-world position 3D real-world velocity Low cost	Requires line of sight to satellites, not indoors Requires large processing power for fast data flow
Camera	Low cost Multi-dimensional data Wide area coverage	Complex processing
Optical sensors	Low cost	Simple processing Rapid data rates Low resolution Small area of detection
Encoders	Accurate position measurement Simple processing	Error due to wheel slip Expensive to buy Bulky Resolution dependant on cost Maximum data rate and dynamic range dependant on processor rate.

The summary of the various sensors available in the mobile robotics arsenal given in Table 4.1 lists the advantages and disadvantages of each. In order to provide a safe robust assistive PWC there will be a need to employ multiple sensor types to ensure that obstacles are not overlooked or incorrect distances given. Combining multiple sensor data can be quite complex.

3.5 Determining the sensor suitability for the assistive PWC

According to the literature reviewed in the previous chapter the most commonly used sensors for smart PWC collision avoidance were:

- camera based
- sonar
- wheel encoders
- laser ranging

During discussions with PWC stakeholders it was determined that there were various issues and problems, some of those are listed at the beginning of this chapter. The main problems were that of size and reliability, these were deemed to be the stumbling-block to moving the smart PWC from a development concept to a potential practical marketable solution. Bulky sensors and equipment tended to get knocked or broken, according to these discussions, and scanning devices such as laser ranging with delicate moving parts would not be sufficiently robust for the everyday use of the PWC, experienced by SYSIASS project partners working in parallel. There was also concern raised by the PWC stakeholders with regard to the significant amount of processing power which had hitherto been required for most of the previous smart PWCs they had evaluated. What was really wanted, they reported, was a small compact box with robust sensors that plugged into an existing system to help PWC users navigate without collision.

The only available sensors that could be used in such a compact system were sonar and infrared ranging devices, another two sensors which were identified as potentially useful were thermal and line cameras. The thermal sensor could measure radiated heat and therefore identify if the obstacle was alive and not permanently static. The line camera is essentially a single row of CMOS photo-detectors; these are commonly used to detect edges in mechanised production lines. A series of investigations and experiments was undertaken to determine the characteristics of the sensors, their limitations, and modifications to improve them.

The initial results of sensor experimentation determined that the sonar gave a very accurate range unlike the infrared ranging. However when multiple sensors were tested the cross-talk, or unwanted echoes, became a significant issue with regard to false readings. Firing all of the sensors at the same time made a substantial improvement and it was decided this was the best method. A much later improvement was to reduce the range, amplitude, of the sonar. Another issue with the sonar is that the sound wave is only reflected back from a smooth surface when the incident angle is less $<\pi/4$ and therefore fails to detect the obstacle.

The Sharp infrared ranging sensors have a number of problems; some are listed in Table 4.1, the main problems were the statistical variation of the returned value and the non-linearity of the range measurements [96, 108]. Considerable iterative research was undertaken to improve these characteristics. However a considerable number of samples were required to obtain a stable reading equivalent to that of the sonar. Filtering required extra processing and was considered best left as a future option. A suitable ranging, 0.9 of the stability of the sonar, was obtained from a smaller sample using a median value filtering which gave a 10:1 sample rate of infrared to sonar using a small form factor ATmega2560 16 MHz microprocessor (Atmega). This was deemed suitable for a real-time collision avoidance application.

Combining the sonar ranging and the infrared ranging meant that the false reading of the sonar could be mitigated [108, 109]. However another significant issue was the area of obstacle detection. The sonar had a wide field of detection and almost any obstacle from the ground up to the head height of a PWC user could be detected; whereas the infrared had a very small area of detection (1-2cm). When the combined sensor arrangement was used in a practical environment it turned out that the infrared had an advantage of being able to follow the contour of walls and furniture giving a much better resolution of typical obstacles. It was therefore determined that the two sensors should be combined in a different way, a voting method was chosen such that the closest range was deemed to be the true nearest obstacle distance. This was to prove important when negotiating confined spaces and doorways.

Many orientations of sensor arrangement were attempted before the final arrangement used for the collision avoidance developed in the next chapter. However these experiments did determine the resolution of obstacles in front of the platform needed to be much better presented if doorways and lifts were to be negotiated by the PWC. The solution to this was to modify two line cameras such that they operated in the infrared and to illuminate the obstacles with infrared light. This gave a clear edge to the doorway.

Measuring the platform position with respect to the environment was another significant issue which required careful sensor evaluation. Initially considerable research was undertaken, as it was thought necessary to develop a velocity sensor for collision avoidance, to use a modified mouse camera [102] to provide a velocity feedback to the system. It was found that laser light speckle when reflected off of any surface, uneven or not, back along the same axis and into the modified mouse camera allowed the velocity of the platform relative to that surface to be accurately determined. This was able to be achieved at some distance from the surface (>140mm) and depended upon the focal point to keep the speckle size small.

Identifying the obstacles and waypoints were other considerations of the research undertaken in this thesis; low-cost thermal sensors were used to differentiate a dynamic obstacle, such as a human, from static, such as a chair, this functioned well and can be used to modify/adjust the collision avoidance system developed in the next chapter. Identifying waypoints, junctions, and doorways is necessary to be able to either generate a trajectory or adjust collision avoidance. Previous research had used sonar for identifying junctions [110] and infrared ranging sensors have been used successfully for statistical object identification (100%) [111] and accurate mapping [112].

3.6 Data fusion

There are random variations in all sensor measurements due to electronic noise. This noise can be thermal in nature, called Johnson–Nyquist noise, which is usually the random motion of electrons and modelled as a Gaussian probability function, or it can be due to quantum events such as occur in discrete components, and external noise from many other sources. There is also the issue of sensor non-linearity and environmental variation; all these uncertainties give rise to a statistical variations and deviations from the true when making measurements. If the sensors can be modelled such that these errors are all Gaussian in form, then the peak of the Gaussian represents statistically the best measurement value. There are also the issues of accumulating DC biases such as with accelerometer drift and encoder wheel slip. However if more than one sensor is used then the weaknesses of one can be overcome by the strength of the other, this is called data fusion.

The best known data fusion method is the Kalman filter [113] which uses an optimal recursive least squares method to reduce the uncertainties, providing the errors are almost Gaussian and the sensor models are linear. If the model is non-linear then the extended Kalman filter is used which attempts to linearise the model first by using the Jacobian and then by using that linear approximation in the

Kalman filter. The Kalman gain element in the filter allows the weighting of each data input according to how much it can be trusted for a particular measurement. This can however still lead to divergence from the true value and therefore some form of voting mechanism can also be employed which can then bias the weighting in the filter. There are also other means of data fusion such as particle filters which can be better suited to some tasks. Some of the current (2009) methods of combining different multi-sensor data are reviewed by Dong et al. [114].

3.7 Pattern recognition for waypoint detection

As the robotic device moves around the environment it needs to know where it is to navigate. The usual method is to employ the use of maps such that the robot can compare the sensed location and pose with that of a stored map, the path is then planned and a trajectory calculated. The robot then follows that path to a target or next waypoint. This method usually employs some pattern recognition if only to compare the detected surroundings with the map. However significant problems exist; first is the need for the robot to wander around and map the environment; secondly having mapped the environment the robot then needs to stop and calculate, off-line, where it is and where it is going. These problems are not suitable for a real-time reactive system such as a human-in-the-loop system proposed in this thesis. There has been one solution proposed which combines moving about in the environment whilst simultaneously building a map and using the map to determine pose and position within that environment, called SLAM [115]. This method has gained much popularity in mobile robotics; however this method is more suited to autonomous systems even though there is an intuitive human-like element [116]. Rather than store the environment as a map, it is suggested in this thesis that a series of updateable stored patterns represent the environment where due to the nature of the dynamic environment they can be quickly updated by the human in the loop. Having determined in the previous section in this chapter that sonar and infrared ranging sensors can be used to identify obstacles, waypoints, and junctions it follows that re-use of this ranging data to form these patterns would seem appropriate. Room identification could also be obtained from geometric features.

The human dynamic workspace is not best suited to mobile robotics: furniture is moved, people become mobile obstacles, and clutter is produced, all of which make the environment highly confusing for the techniques commonly employed in autonomous mobile robotics. However the human-in-the-loop system described earlier incorporates the human in the feedback loop: for example if we apply pattern recognition to a particular waypoint and there has been a re-arrangement of furniture or addition of clutter then the human in the loop is informed of a pattern mismatch, the user then simply informs the system, to update the training patterns stored by the system; which is described by the control architecture presented previously in this chapter.

3.9.1 Suitable features for fast identification

Following on from the previous section the criteria for the real-time assistive PWC localisation and waypoint recognition level can be summarised as follows:

- the ability to reuse data from ranging sensors if possible
- if not, sensors should be robust and low cost
- that sensors should not rely upon time-consuming scanning
- and that data from sensors should require minimal processing
- all features should be compatible with human methods of recognition
- and these features need to be stable and non-changing for long time spans
- also feature representation needs to be suitable for fast classification for real-time operation

Identifying features which may be suitable for real-time pattern recognition requires some investigation, and this research and development will be presented in Chapter 5.

3.9.2 *Classification*

Classification can be described as the problem of identifying to which category a new observation is attributed. The categories can either be a set of patterns determined by supervised training, which have a human determined label assigned to them, or unsupervised learning. This is called clustering, without the human labelling and training, which involves the grouping of data into categories according to some similarity or feature distance. A list of typically-used classifiers is given below:

- Bayes-Normal [117]
- Fisher's linear discriminant [118]
- Logistic regression [119]
- Naive Bayes classifier [120]
- Perceptron [121]
- Support vector machines [122]
- Least squares support vector machines [123]
- Quadratic classifiers [117]
- k-nearest neighbour [124]
- Decision trees [125]
- Neural networks [126]
- Learning vector quantisation [127]

3.10 **Technology requirement conclusion**

Developing a system which has suitable hardware to solve the problems identified earlier in this thesis, without prior example, involved considerable iterative research. The work presented in this chapter sets out the technology required for the assistive human-in-the-loop PWC. Some of this technology requires further refinements and possibly the application of new sensors to the system

developed so far, such as using radar-on-a-chip. The research and developments in this chapter have led to answering some of the requirements identified at the beginning of the chapter such:

- that the human is always the instigator of any positive action
 - which has been addressed by the control strategy developed in this chapter and which will be addressed further in the next chapter and in Chapter 6
- that the human is informed of any corrections necessary
 - which has been proposed by the control strategy in this chapter, Chapter 5 develops the waypoint and room identification such that information is available for that feedback to be later developed
- that the system should have adjustable assistance
 - which has been addressed by the control strategy developed in this chapter and which the next chapter develops
- that the system should have multiple levels of assistance
 - which has been fully addressed by the control strategy developed in this chapter
- that the system should fail safe, returning to some manual mode
 - which has been partly addressed by the control strategy developed in this chapter
- that the system should prevent injury to pedestrians
 - development in this chapter provided a means of identifying pedestrians for the purpose of adjusting the collision avoidance developed in the next chapter
- that the system should prevent damage to infrastructure
 - which has been proposed by the control strategy in this chapter, the next chapter develops the obstacle avoidance
- that the system should allow manoeuvrings in tight spaces

- developed in the next chapter
- that the system should be adjustable and adaptable to changing needs
 - which has been addressed by the control strategy developed in this chapter and which will be addressed further in the next chapter, Chapter 5 and in Chapter 6
- that the human is always the instigator of any positive action
 - which has been addressed by the control strategy developed in this chapter and which will be addressed further in the next chapter and in Chapter 6
- that the system and hardware should be easy to set up, and be adjustable and adaptable
 - which has been proposed by the control strategy in this chapter
- that the robustness of sensors and hardware must be sufficient for long term application
 - robust sensors have been evaluated in this chapter
- that the physical dimensions of the hardware should be minimal, thus being unobtrusive
 - small form factor sensor have been identified and evaluated in this chapter
- that the hardware and system should be compatible with existing infrastructure
 - future work
- that the system should be assistive and not preventative
 - which has been addressed by the control strategy developed in this chapter and which will be addressed further in the next chapter, Chapter 5 and in Chapter 6
- that the system should be easy to use and intuitive
 - which has been partly proposed by the control strategy developed in this chapter and which will be addressed further in the next chapter and in Chapter 6
- that the user must know what the system is doing
 - which has been proposed by the control strategy in this chapter, Chapter 4 provides

trajectory alteration which can be fed back to the user by haptic or visual means, Chapter 5 develops the waypoint and room identification such that this information is available for the user (to be later developed), and Chapter 7 generates a trajectory which is available for display to the user, again future work

- that the user must be able to disable the system should the need arise
 - which has been fully addressed by the control strategy developed in this chapter

The next chapter develops a new method of modelling the platform and then a novel collision avoidance system using sensors identified and evaluated during the technology development in this chapter. This methodology is evaluated with regard to the issues of behavioural coherence and system-inspired confidence for the user, as summarised in the conclusion of the previous chapter. The problem of providing a safe non-positive acting collision avoidance navigation strategy which acts in an intuitive fashion is thus presented.

Chapter 4

Collision avoidance

In the last chapter the technology required for developing an assistive PWC to meet the needs of the users and other stakeholders was investigated and a control strategy proposed. The lower level of this control architecture, shown in Fig 3.6, requires a real-time collision-avoidance method to be developed for the dynamic human environment. This chapter now presents that development which solves the issue of providing an adjustable localised collision avoidance zone which travels with the platform, one which is based upon a real-time adjustable dynamic model, such that the system intervention is intuitive and compatible with human behaviour, and safe.

This chapter begins with identification of the navigational requirements for an assistive system and then develops the first contribution to the thesis in this chapter, the localised potential force field. The platform kinematic is then described and this leads to the next novel developments in this chapter, that of the adjustable dynamic modelling of the platform and the modelling of the repulsive zone around the platform. Only the nearest obstacle each side, in the direction of travel, acts to damp steering keeping the platform from colliding with obstacles. This produces a more natural intuitive trajectory as identified and evaluated in the previous chapter. This chapter then presents experimentation and evaluation of the collision avoidance developed in this chapter. The chapter then concludes that the unique methodology presented in this thesis is suitable for use in the human dynamic environment as a real-time human-in-the-loop assistive navigation aid.

4.1 Obstacle avoidance requirements for an Assistive System

Having determined in Chapter 1 that assistive technology developments such as smart electric wheelchairs are drawing mobile robotic interactions, traditionally bound to carefully controlled workspaces, increasingly towards the uncertain complex human environment; then seamless crossover between human-defined desired trajectories and traditional autonomous system-aided trajectories are necessary. Having also determined that human assistive systems must have the intelligent user in the control loop [12, 32]; then according to Matuszek et al. [33] a stochastic and semantic based workspace will be required. This means that for developing a collision avoidance assistive technology weighted nuances are potentially required where obstacles and targets have a spectrum of importance. Additionally having determined previously in Chapter 3 that the user will require various levels of assistance with increasing complexity in the control architecture then these will also need to have a seamless cross-over. Therefore the requirements for the collision avoidance level in the control architecture can be identified as needing to be real-time reactive model with adjustments depending upon dynamics, user desires, obstacles, and environmental changes.

Having set out the requirements for an assistive human-in-the-loop system, at the beginning of the previous chapter, there is no need to repeat them here. However the following must also be taken into account: in an autonomous system a conflict of interest may well occur, such that the smart system takes some trajectory when the user desires some other, possibly as a result causing some injury or damage [26]. One particular issue called ‘sudden acceleration’ has been something which the motor car industry recognises [128, 129]. Therefore any adjusted trajectory must be smooth and locally-acting to damp over-action, not sensible action, such as to maintain user flexibility of use. This action must not restrict freedom or be obtrusive, and certainly not overpowering, as has been the case with solutions associated with autonomous robotic systems [5, 7, 71]. This collision avoidance level must also be compatible with the levels above, as described in the top-down bottom-up strategy of the control architecture presented in Chapter 3.

4.2 Developing the adjustable localised force-field method

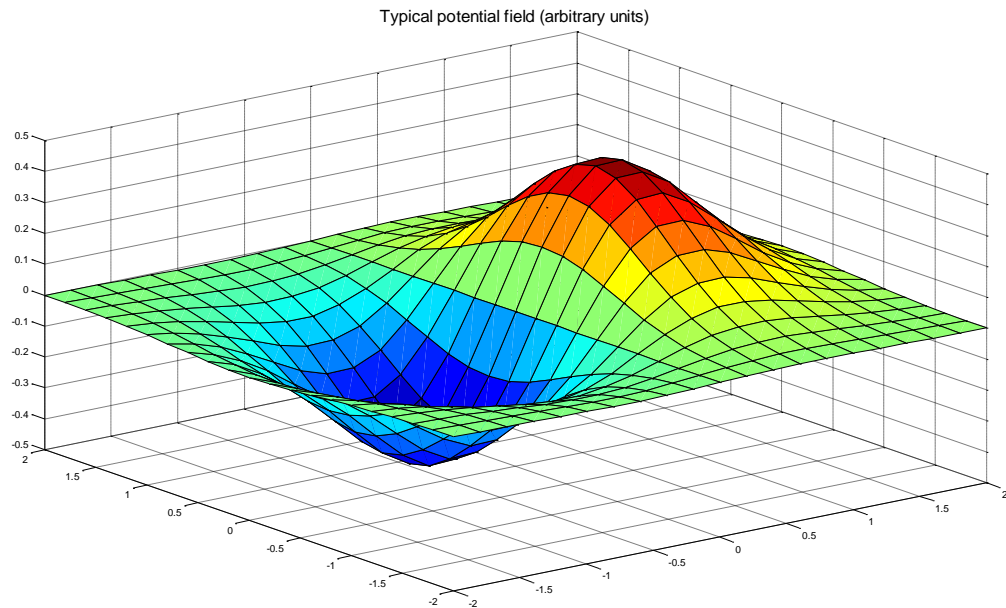


Figure 4.1 A representation of how the potential field gradient surface of a workspace would look if goal was located at the bottom of the dark blue well and the obstacle centred on the dark red hill

Rather than identifying and mapping all objects and the geometries in the vicinity of the mobile robot, it is much easier to simplify the representation as free-space and occupied areas. There are several methods widely adopted in autonomous robotics, one such method of representing obstacles and the goal or target is to use a 'potential field', first suggested by Katib [80]. This concept combines the principle of positive attractive forces acting at the goal, or target, and negative repulsive forces emanating from obstacles. A gradient surface then forms between the target and the current position of the robot; this forms the descent trajectory from current position to the target which avoids all the known obstacles. A typical potential field gradient surface of a small workspace arrangement is shown in Fig. 4.1 where the attractive potential is the lower potential (minimum in dark blue) and the repulsive potential (maximum in dark red) such that a potential gradient surface exists between them, and thus any motion can be said to be a form of gradient of descent over that surface. This approach is highly suitable for real-time application because, at any time if another object is detected,

the field is changed by this object and then the descent trajectory becomes altered to avoid that obstacle. There are a number of problems [130] with this method, and they are namely:

- a local minima, or false goal, can trap the robot before it reaches the target
- a prevention of passage between closely spaced obstacles
- oscillations in the presence of closely spaced obstacles
- oscillations in narrow passages

The harmonic dipole potential is one solution to the local minima problem based upon electrostatics [131]. This introduced the concept of representing obstacles as point charges within circular security zones, which are inside ellipsoidal gradients. This method considered the nearest obstacle, and used weighting to avoid discontinuities when switching between zones. This nearest obstacle approach, rather than combining the effect of all the obstacles, has been used in the obstacle avoidance method developed in this chapter. Another solution to the local minima problem used a human robot interaction for the manipulation of potential fields [132] in order to navigate around obstacles. They used the human interaction to shape the potential field such that the two sides of the trap were modified by the human operator such that they were ‘pulled’ into a convex boat like shape driving the robot out of the trapped situation.

An early method of integrated navigation and steering for autonomous vehicles introduced by Kroug and Thorpe [133] sought to combine potential fields with a path relaxation method. This used sensor feedback in the direction of travel together with *a priori* information to generate a global series of critical waypoints as sub goals, whilst the potential field approach generated a local goal and collision avoidance path; this type of approach is suited to the smart PWC requirements previously identified earlier in this thesis. In particular this lends to the argument that using local collision avoidance between waypoints is suitable to be combined with short trajectories, and that these waypoints can then be used as part of a simplified global map.

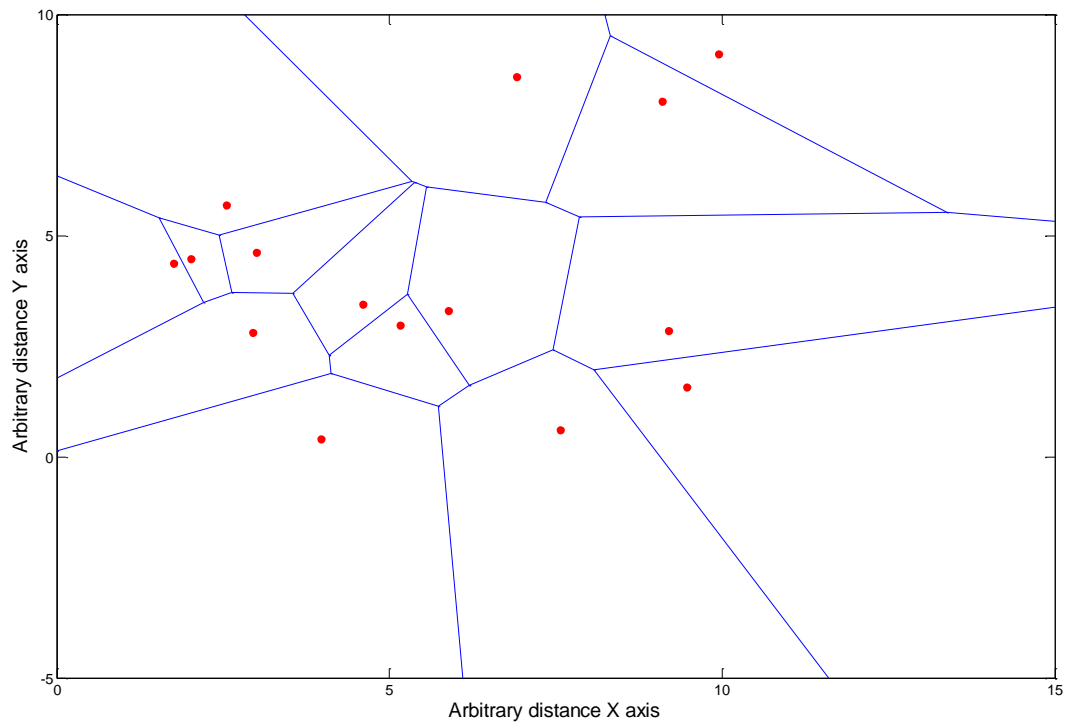


Figure 4.2 Typical Voronoi collision avoiding paths

Another method of representing the free-space is by the application of Voronoi Diagrams to the obstacle avoidance problem [134]. These diagrams are used to form a skeleton-like map of obstacle free passages around the workspace, Fig 4.2, or in our case habitation such that a simple roadmap is formed. The paths tend towards the midway distance between obstacles and therefore represent a trajectory that the robot can take without collision. There is no gradient surface so the robot must have some other driving mechanism. This method is suitable to be combined with the waypoint pattern recognition developed in the next chapter such that a collision-free path can be generated through the waypoint.

The Virtual Force Field [49] method introduced in 1989 as real-time obstacle avoidance for fast robots utilises a two-dimensional Cartesian grid, or active window, centred on the vehicle centre point which moves with the platform in the real-world reference frame, thus effectively reducing the world frame area in size to the immediate vicinity of the platform. Ultrasound ranging measurements can

then be used to determine the existence of obstacles by using certainty values for each of those measurements in a histogram grid [135] from which a repulsive force vector can be determined. The resultant force vector driving the robot is then the summation of the repulsive vector and the target attractive vector.

The ARTY researchers in 2012 [67] attempted to use two methods of navigational assistance for their smart PWC: the first method used the VFH [136] which proved difficult to tune and adjust, non-intuitive, and which relies upon the model of the platform being expressed as a point object; the second method used the DWA [69] which is a better representation for taking into account platform dynamics and modelling and was easier to tune and adjust. However this method was computationally expensive taking too long to compute solutions. The researchers adopted a novel hybrid approach which provided an approximate solution to the DWA.

In order to develop a better model, more suited for a human-in-the-loop assistive obstacle avoidance system, some of the best attributes of all the aforementioned methods need to be identified:

- the concept of only the nearest obstacle acting on the PWC platform
- the repulsive element of the potential field concept only
- the concept of the human-in-the-loop and system being able to adjust the potential field
- the workspace area moving along with the platform

The initial development began with a new and novel method of representing the repulsive field around the obstacle as an exponential, shown in Fig 4.3. This allowed the PWC user to drive the platform in close proximity around obstacles in a cluttered environment yet preventing collision with those obstacles. The traditional potential field would have acted to prevent users from approaching close to an obstacle, this would be problematic when getting out of a wheelchair and into a bed. This new localised representation can now allow that to happen. Because the repulsive force field is steep-sided and localised the problem of the traditional potential field no longer apply.

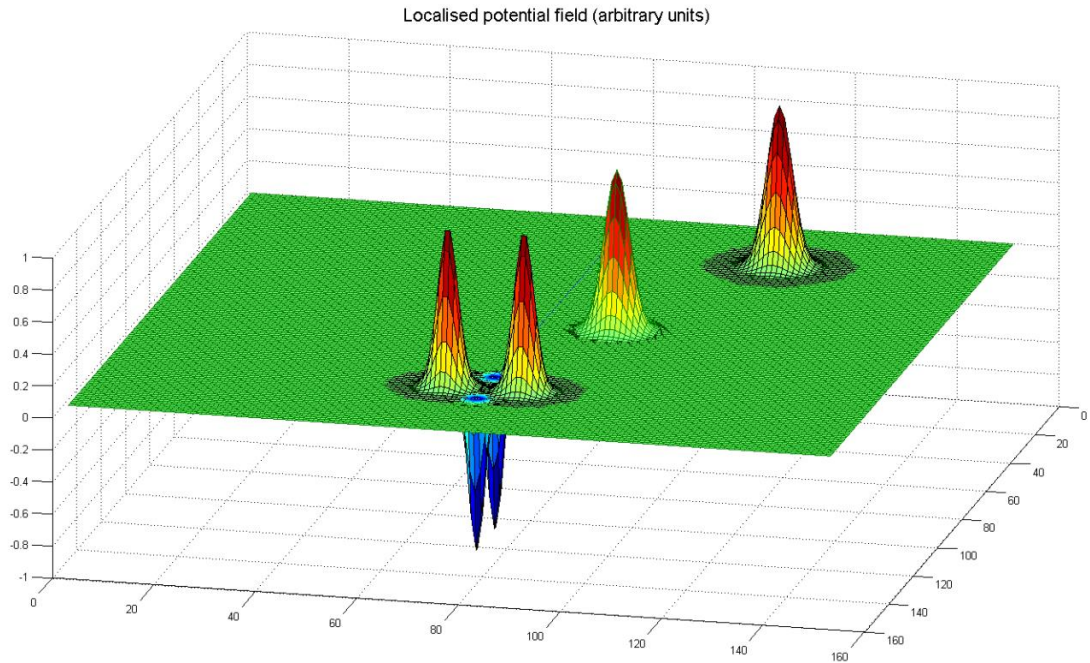


Figure 4.3 A representation of how a highly-localised potential fields field gradient surface of a workspace would look if goal was located at the bottom of the dark blue wells and the obstacles centred on the dark red hills

Furthermore this unique localised method allows the user to move about freely without restriction when not in the very near vicinity of any obstacle, whereas the traditional method shown on Fig.4.1 causes repulsion from all obstacles in the vicinity to have some effect on the motion at any point over the surface therefore restricting motion anywhere in the workspace. It is proposed that the assistive system would recognise the learned waypoints using pattern recognition techniques and adjust the fields accordingly also feedback from inertial sensors would be used to shape the field. The user could manually override the system and adjust the field themselves should it be necessary or they so desire. This adjustable localised potential force-field concept therefore fits well into the human-in-the-loop control architecture presented in Chapter 3 section 4 allowing the user to keep control of all actions where the system provides assistance.

4.3 The PWC platform kinematics

In order to make use of the localised potential field, the method of how the repulsion is applied to the platform to avoid the collision needs to be developed. First the behaviour of the platform must be described:

Human transport is largely based upon car-like vehicles, which can all be thought of as acting in a manner whose kinematic modelling can be described as a bicycle model [137]. Another alternative form of transport commonly used is the tank style, or differential drive wheels on the same axle, such as used on electric wheelchairs; this kinematic model can be thought of as a unicycle [138]. Both the unicycle and bicycle models can be expressed as follows [139]:

$$\dot{x}_{body} = v_{body} = \frac{v_{right} + v_{left}}{2} \quad (4.1)$$

$$\dot{x}_{body} = v_{body} \quad (4.2)$$

$$\dot{\theta}_{body} = \omega_{body} = \frac{v_{right} - v_{left}}{W} \quad (4.3)$$

$$\dot{\theta}_{body} = \omega_{body} = \frac{v_{rear}}{W} \tan \alpha \quad (4.4)$$

Where:

v_{right} and v_{left} are the velocities of the individually-driven rear wheels.

v_{rear} is the velocity of both rear wheels driven off the same fixed axle.

W is the distance between the rear driving wheels.

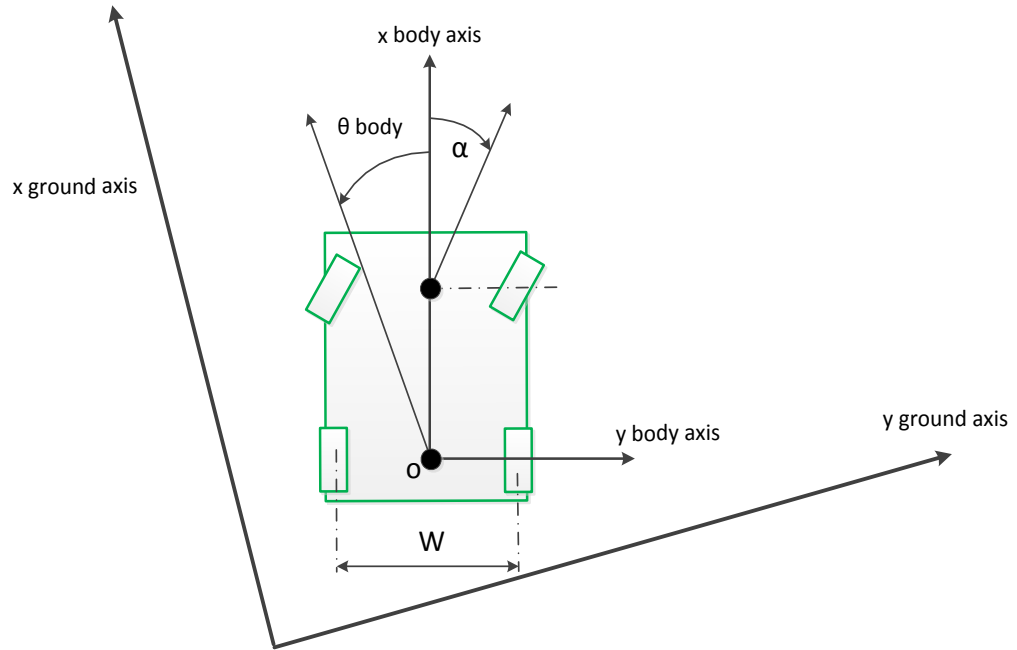


Figure 4.4 Generic schematic and reference frame for platform

Conventional use of the kinematic models [140] usually divides them such that unicycle-type robots obey Eqn (4.1) and Eqn (4.3) whilst bicycle-type robots obey Eqn (4.2) and Eqn (4.4). However it can be clearly seen that the form of both equations are very similar, for example unicycle robots could be represented as a front-wheel-driven tricycle, and six common wheel configurations, with 2-degrees-of-freedom or 3-degrees-of-freedom, have been given consideration [141]. However in all cases the effective real-world platform trajectory could be said to generally follow the mid-point between the two rear wheels, marked as 'o' in Fig. 4.4 where Eqns (4.1) and (4.2) are effectively the same and describe the platform forward velocity (v_{body}), and Eqns (4.3) and (4.4) describe the rate of body rotation (ω_{body}) about the z body axis on the x, y plane where θ is the instantaneous tangential heading angle at some time. It can be seen that the steering angle α can be effectively described as a bounded case of θ .

4.4 Platform dynamic modelling development

Having identified early on in this thesis that the assistive PWC platform must operate with a wide range of users (differing mass and inertia) under varying dynamic loads (laden with shopping or on slopes) then the platform kinematic must be modelled in a dynamic fashion. And following on from the dynamic model research presented by Viera et al. [142] a model suitable for a human-in-the-loop assistive PWC is further developed.

Taking our user input desire as a force vector, rather than a velocity vector, either taken from a joystick or some other human analogue interface device, or even some digital threshold value from another human interface, which is opposed by an obstacle force vector, then we need to develop the geometric kinematics function to one which better represents a truer model allowing dynamic adjustments to be made from feedback sensors; for example inertia and mass need to be considered adjustable due to loading, and the gravity vector in order to maintain a constant velocity driving up an incline, or conversely damping to prevent tipping over when turning on a slope.

The new development then proceeds by referring to our method and previous statement that the human input device in some way gives a desired force vector, then we can disseminate this into a force component and a torque component at some time, and in order to damp, or maintain, that platform motion we need to state the dynamic model in terms of left motor and right motor. If we take Eqns (4.1) and (4.3) and then re-arrange we can obtain those kinematic equations in terms of each motor as shown in Eqns (4.5) and (4.6).

$$v_{mr} = V_{body} + \frac{W\omega_{body}}{2} \quad (4.5)$$

$$v_{ml} = V_{body} - \frac{W\omega_{body}}{2} \quad (4.6)$$

Where v_{mr} and v_{ml} are the electrical inputs to the right and left motors.

And then inserting in terms of a dynamic model by Guerra et al. [138], following on from Viera, using Newton's second law where M and J represent platform mass and rotational inertia, and J_m represents the motor and gearbox inertia, and $\dot{\theta}$ represents the wheel rotational velocity rather than v which is the ground velocity, then our dynamic force and torque model for left and right wheel motor torques are given by Eqns (4.7) and (4.8):

$$J_m \dot{\theta}_{mr} = Mv_{body} + \frac{JW\omega_{body}}{2} \quad (4.7)$$

$$J_m \dot{\theta}_{ml} = Mv_{body} - \frac{JW\omega_{body}}{2} \quad (4.8)$$

It can be shown that the electrical energy input to the electric motors directly relates to the mechanical energy of the platform. Therefore losses and ratios can be empirically obtained and their respective sums are represented by constants k and, taking the voltage inputs to the motors as having an almost direct linear relationship to the electrical power, we can then say that e_m is the electrical voltage motor inputs to the motors which is then directly proportional to the respective desired wheel torque of each drive wheel, which in turn are directly proportional to the body velocity and body rate of turn expressed in Eqns (4.9) and (4.10).

$$k_e e_{mr} = k_m M v_{body} + \frac{k_j JW \omega_{body}}{2} \quad (4.9)$$

$$k_e e_{ml} = k_m M v_{body} + \frac{k_j JW \omega_{body}}{2} \quad (4.10)$$

We can then describe our improved adjustable dynamic model with terms of torque and force damping directly from the obstacle avoidance requirements, shown in Eqns (4.11) and (4.12) where independently the obstacle damping force acts uniquely on the left wheel F_r and on the right wheel F_l as exponential ratios (localised potential force field), bounded by Eqn (4.13) such that they drive their respective opposing side wheel velocities to zero in the presence of obstacles.

$$k_e e_{mr} = k_m F_r M v_{body} + F_r \frac{k_j JW \omega_{body}}{2} \quad (4.11)$$

$$k_e e_{ml} = k_m F_l M v_{body} + F_l \frac{k_j JW \omega_{body}}{2} \quad (4.12)$$

$$\begin{cases} 0 \leq F_r \leq 1 \\ 0 \leq F_l \leq 1 \end{cases} \quad (4.13)$$

The damping equations of each motor can also be re-arranged to be expressed in terms of the body heading velocity and body turning rate, Eqns (4.14) and (4.15).

$$v_{body} = k_e \left(\frac{F_l e_{mr} + F_r e_{ml}}{2Mk_m} \right) \quad (4.14)$$

$$\omega_{body} = k_e \left(\frac{F_l e_{mr} - F_r e_{ml}}{k_j JW} \right) \quad (4.15)$$

The nearest obstacle each side of the platform can now be said to act as a potential force-field which damps the motion of the drive wheel on the opposite side of the platform. This formalises the method developed and evaluated early in Chapter 3.

4.5 Assistive PWC collision avoidance model development

Following on from the localised potential force-field developed at the beginning of this chapter and formalising how that affects the platform dynamics developed previously, the application of the concept of a localised workspace travelling with the platform, which originated from the certainty grid [135] and later developed into the moving histogram grid [49], can be used to provide the starting point for the development of how the methods developed in this chapter can be applied to practical obstacle avoidance in real-time; the novel elliptical-shaped platform development follows.

Having undertaken evaluation and experimentation, using the robotic platform which was shown in Chapter 3 and also having developed a full-size test platform to conduct further extensive testing, it is proposed that a more effective way of modelling the region of interest around the platform, or local workspace, can be expressed in terms of a Euclidean ellipse which has a geometric relationship to the PWC platform dimensions. This region replaces the workspace and instead acts as a repulsive region around the PWC platform. Similar work in the art has looked at modelling obstacles as ellipses to improve the flow of potential field lines [143] and another has looked at modelling the obstacles as geometric shapes [144]. The inner ellipse represents the boundary of the platform and the outer ellipse the furthest extent of the repulsive region. One foci of the inner ellipse and outer ellipse marked in red and shown in Fig. 4.5 is located at the body coordinate origin marked 'o', also in Fig. 4.4, and the other foci of both ellipses being located along the x body axis, the inner ellipse coincides with the front steering axis, the outer ellipse moves outward from the inner foci location according to the adjustment of the region of repulsion. Therefore the inner ellipse shape is determined by dimensions A and B , where $2A$ is at least the length of the platform (including appendages) and $2B$ is

at least the width of the platform plus any overhang. The platform sits within the inner ellipse boundary as shown in Fig. 4.6. The outer ellipse can be extended along E_x and E_y shown in Fig. 4.5 yet is always equal to or greater than the inner ellipse dimensions.

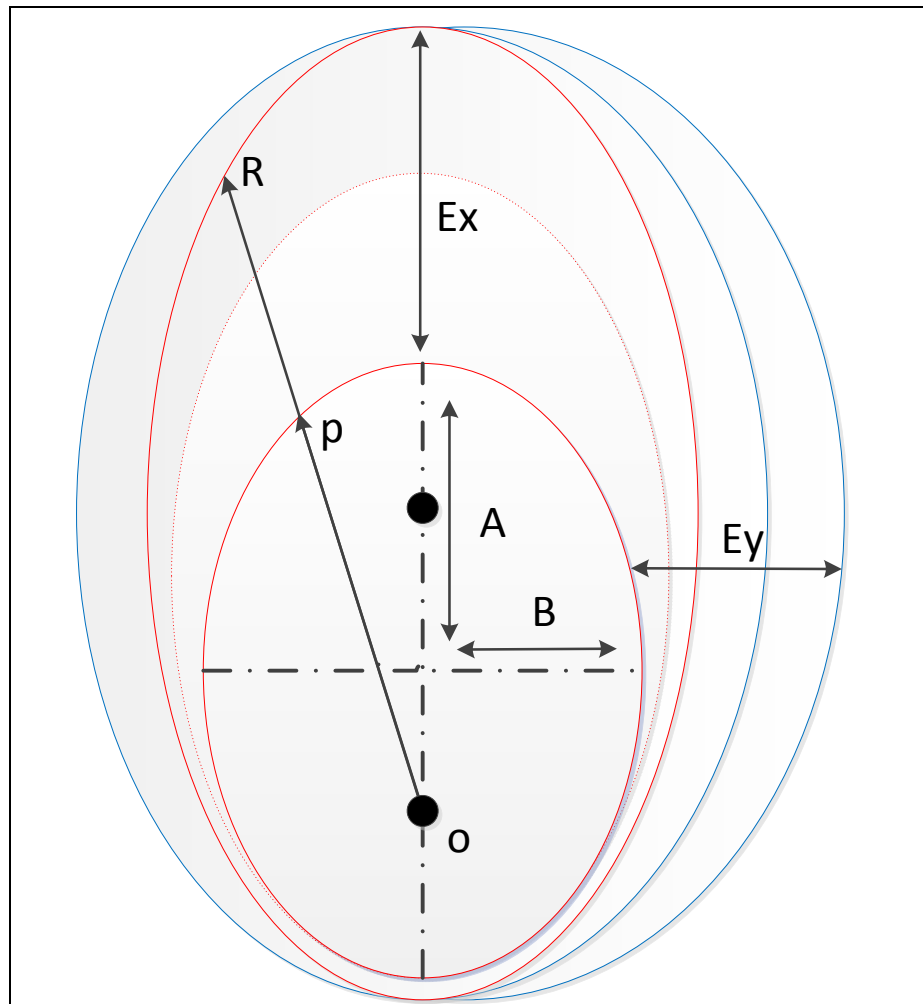


Figure 4.5 Elliptical PWC platform obstacle-avoidance model

Furthermore because the novel ellipse model can be separated into zones with different elliptical dimensions depending upon the navigational requirements then for example the right-hand side zone may have the inner ellipse extended along B and the outer ellipse along E_y (Fig. 4.5) such that the platform performs a corridor-following biased to one side behaviour. Another example would be to extend both the front left and front right zones along A and E_x proportionally to the platform velocity such that as velocity of the platform increases then the inner and outer ellipses are extended, not

necessarily equally. Therefore this method allows the repulsive elliptical zone surrounding the platform to be easily tuned to the task at hand, either by some other system or by the user.

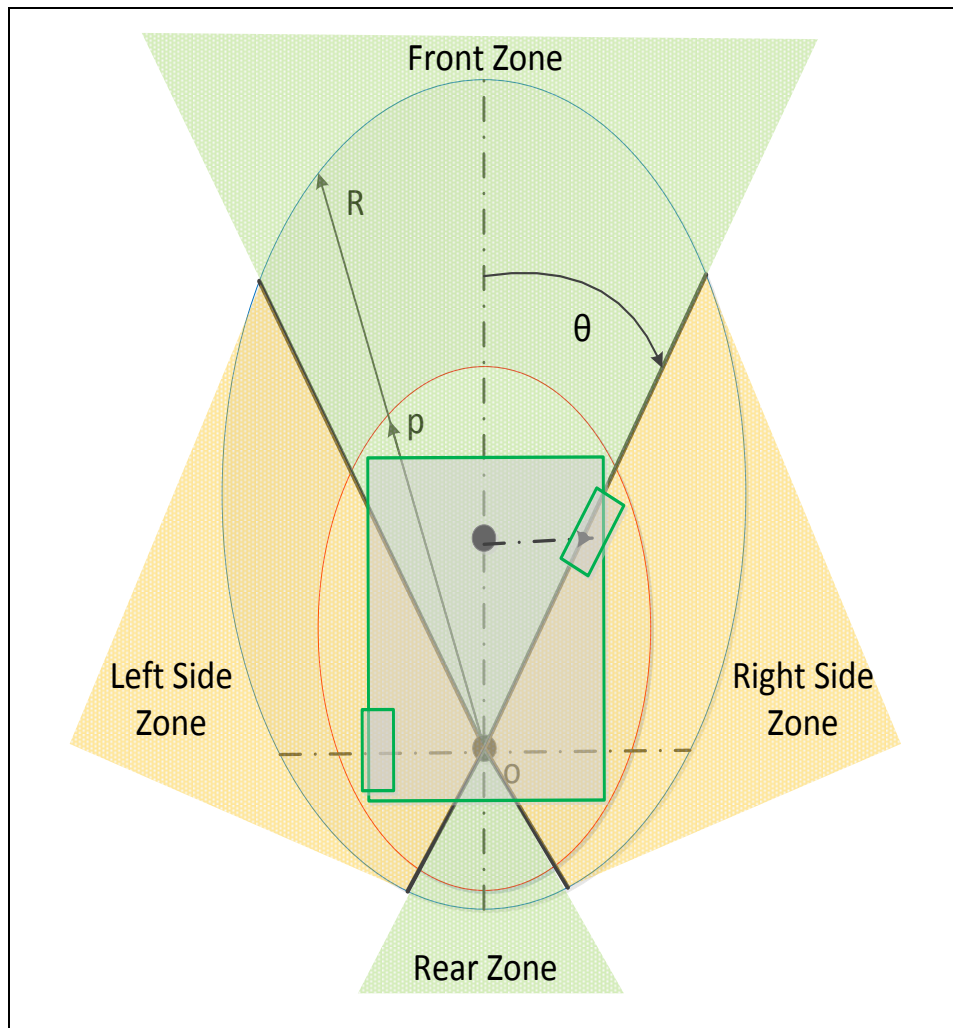


Figure 4.6 Zonal application of elliptical obstacle avoidance model

Sensors are mounted so as to radiate out from the platform, such that they provide ranging data along the lines marked R and p in Fig. 4.5 and Fig. 4.6. The repulsive force-field method is applied as a moderating input to the drive motors, as developed in the previous section, along ranging axis R between the inner and outer ellipses can be given in the general form of Eqn (4.16) nearest obstacle on each side specified by zone such that Eqns (4.17) and (4.18) represent the terms for the front left and right zones; the rear and side zones can be equally obtained. The frontal zone and similarly the

rear zone, Fig.4.6 shows the front right quarter angle as θ , represents the region covering the maximum platform steering angle ($\max \alpha$) whilst still moving forward, or reverse, such that the sensors in this region can be of a high resolution providing accurate range and angle, for example detecting doorway sides. The side zones are used to detect proximity to obstacles such as walls when translating in the x body axis, and obstacles when rotating about the z body axis in the special case of the unicycle or wheelchair kinematic model. Thus the novel ellipse model separates obstacles, and sensors, into zoned regions of interest; where depending on the direction of travel the nearest object in each zone acts to damp each drive motor.

The following innovative adjustable damping terms were developed, as part of this research, from numerous simulations and experimentations:

$$F = 1 - \frac{1}{\exp((R-p)/k_r)} \quad (4.16)$$

$$F_r = 1 - \frac{1}{\exp((R-p)/k_r)} \quad (4.17)$$

$$\text{Where: } \begin{cases} \theta \geq 0 \\ \theta \leq \alpha_{max} \end{cases}$$

$$F_l = 1 - \frac{1}{\exp((R-p)/k_l)} \quad (4.18)$$

$$\text{Where: } \begin{cases} \theta < 0 \\ \theta \geq -\alpha_{max} \end{cases}$$

The angle alpha (α) relates to the maximum steering angle of the platform such that both rear wheels either have the same velocity vector sign or one of the wheels has a magnitude of zero, the angle theta relates to the platform heading. It should be noted that these terms are not limited to this case. The term k_r allows the potential field slope to be adjusted/tuned.

The zones shown in Fig 4.6 are a simplification; the number depends upon the placement of suitable sensors. Each zone can be independently manipulated, moving the inner and outer ellipse further out or the outer closer in (if the inner is at the minimum range). Furthermore zones can be active or not, depending upon the requirements, usually zones would be active only in the direction of platform motion, side zones being either permanently activated or only when the platform is either rotating about the z body axis at point 'o' or when activated according to the task such as traversing corridors, or when lane following, or some other dynamic requirement. The equations for the side zones are the same as the forward and rear zones where the angular limitations are between the forward maximum steering angle and the rear steering angle respectively. Dynamic adjustment of the force-field for velocity should be through the use of extending both the inner and outer ellipses directly proportionally to the velocity, but not necessarily equally so.

4.6 Testing the collision-avoidance method

The experimental platform hardware consisted of a differential drive wheelchair, 0.68m (2B inner ellipse) width by 1.0m length (2A inner ellipse), with two 150W brushed DC motors, two 25A independent SyRen 25 motor drivers, a Hall Effect joystick human input device, four digital buttons, and an Atmel SAM3X8E ARM 32-bit microcontroller as the system processing unit. The two standard motor gearboxes were modified to each accommodate a 360-degree per turn resolution optical wheel encoder. An elliptical array of 4 Sharp GP2Y0A710K0F 5m range infrared ranging sensors were

mounted on the platform at 45° , 10° , -10° , -45° , and two, modified to function in the near infrared, 128 pixels TSL1411 line-scan imaging sensors, one covering the front left zone and the other the front right zone between -25° to 25° , infrared illumination was provided by two LED security camera arrays, thus the line-cameras provide a high resolution obstacle edge detection for doorway passing i.e. when the elliptical potential field has been adjusted to allow a non-collision passage through two closely-spaced obstacles.

A series of tests were conducted to experimentally evaluate the performance of the method:

- Narrow corridor
- Wide corridor keeping to a side i.e. lane keeping
- Different velocity approaches to an obstacle
- Several obstacles in path
- Closely spaced obstacles i.e. doorway
- Driving up to an obstacle and docking

A 1.1m wide narrow corridor was chosen for the first experiment, and only by adjusting the outer ellipse B value the platform was then able to pass down the centre of the narrow corridor, trajectory shown in Fig. 4.7a, with a platform clearance of 0.21m either side, and despite moving the joystick from side to side as if to steer into the walls (joystick voltage shown in Fig. 4.7b) little deviation from the centre is seen, and no collision with the walls occurs. Furthermore no oscillations occur as is often the case with potential field applications in mobile robotics [130].

Potential fields have been suggested for lane-keeping in mobile robotics [145] and this consideration is applied in the second experiment with a 1.7m wide corridor. In this experiment the right zone

ellipse was kept the same as the narrow corridor setting and the left ellipse zone set such that the platform again follows a path parallel to the corridor however this time a bias to the right is applied allowing a little wriggle room so that the platform could move a few centimetres off course, hence not damping the overall velocity as much as we did in the narrow corridor. The clearance to the right wall at the higher velocity was considered uncomfortable for the user and so adjustments to the two ellipses were made to move the trajectory away from the right wall a little more. The lane-following trajectory can be seen in Fig. 4.8a and the attempt to deviate vigorously from the lane following trajectory by moving the joystick side to side can be seen in Fig. 4.8b.

This experiment shows that one of the major problems, oscillating when passing close between two obstacles, which often occurs when implementing potential fields in mobile robotics, can be overcome by using this new method. The localised potential field kr was adjusted to change the shape of the slope to reduce the velocity with which the platform passed through the doorway and minimised the outer ellipse to allow a fast approach. The doorway opening in this experiment is 0.76m thus the clearance between doorway frame and platform is only 40mm each side. The platform trajectory can be seen in Fig. 4.9a being driven away from the ride side of the doorway whilst the joystick turn command remains zero. The approach velocity to the doorway is nearly 0.8m/s given in Fig. 4.9b and taken from the wheel encoder data, only slowing and manoeuvring in the last 0.75m which was faster than was comfortable for the experimenters. Several high speed passes of the doorway are shown in Fig. 4.10, the damping causing the platform to centre on the doorway as it approaches. Furthermore one of the trajectories (6), shown as a dashed line, can be seen to cause the platform to avoid the doorway, this is because at that approach angle there would not be sufficient clearance for the platform to pass through, thus preventing a collision with the doorway frame.

Applying potential field methods to obstacle avoidance has traditionally meant that the repulsive effect of an obstacle may not have sufficient effect to cause a deviation of the trajectory until the platform is close to that obstacle; this causes the platform to behave in a non-intuitive manner. Using the method proposed in this thesis, the user desired platform velocity vector magnitude, taken from the joystick input, (which is also treated independently as the force vector) or obtained from wheel encoder velocity feedback, and use that feedback to dynamically extend the inner and outer front zone ellipses. This manipulation of the field allows the platform to move out around the obstacle earlier thus leading to a smoother trajectory around that obstacle; at nearly 0.8 m/s the trajectory starts to deviate 2.5m from the obstacle shown in Fig. 4.11. When the obstacle is approached at a velocity of 0.6 m/s the trajectory starts to deviate at around 1.5m from the obstacle, shown in Fig. 4.12. Finally if the platform is driven up slowly to the obstacle, in this case <0.2 m/s, then the dynamic potential field allows the platform to be driven very close to the obstacle before diverting the trajectory away from the obstacle, shown in Fig. 4.13: such a requirement would be necessary when manoeuvring in highly-cluttered and confined environments.

A multiple obstacle experiment was run with four obstacles to evaluate the performance of the platform when negotiating slaloms. The obstacles were placed approximately 1.5m apart longitudinally and laterally approximately 0.5m apart. The trajectory can be seen in Fig. 4.14a and the joystick steering input can be seen in Fig. 4.14b. This shows the user trying to oppose the motion by deliberately driving the chair into the obstacles.

One inherent problem with obstacle avoidance methods is that by avoiding obstacles the robotic platform is prevented from docking or passing close by, for example when a human operator is on that platform he may wish to pull up to a desk. This problem can be solved using the method proposed; the previous experiments have shown the platform can pass through a doorway and pass close

to corridor walls, it has also been shown that the method allows dynamic feedback to alter the elliptical potential field. Therefore in this experiment both of the frontal zones are treated as the same zone (the nearest obstacle in either frontal zone acts on both drive wheels equally) and the joystick velocity demand has been used as a feedback to adjust both the inner and outer ellipses proportionally. When driving up to a wall in a dead-end, the period marked D of the joystick forward velocity command shown in Fig. 4.15b can be seen to be demanding the platform move, yet the period marked S in Fig. 4.15a clearly shows the actual platform velocity is zero during this period. It is only after the period D when the joystick demand is reduced to a very low level that the dynamic damping allows the platform to move forward with a very slow velocity until docking occurs and the demand is zeroed. This experiment shows that this method allows the platform to dock gently, and that excessive demand drives the platform velocity to zero, such as a digital switch remaining high or the joystick accidentally stuck in the forward position, or erratically operated due to platform-user motor co-ordination difficulties for example.

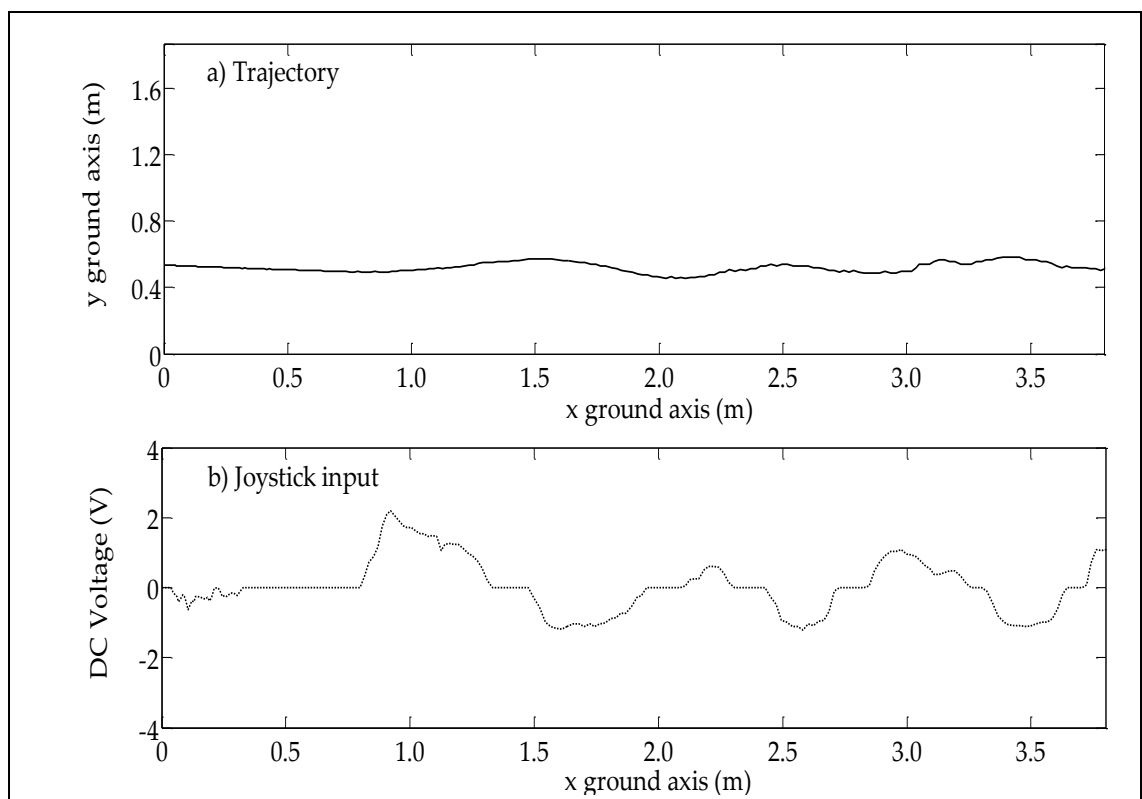


Figure 4.7 *Narrow corridor*

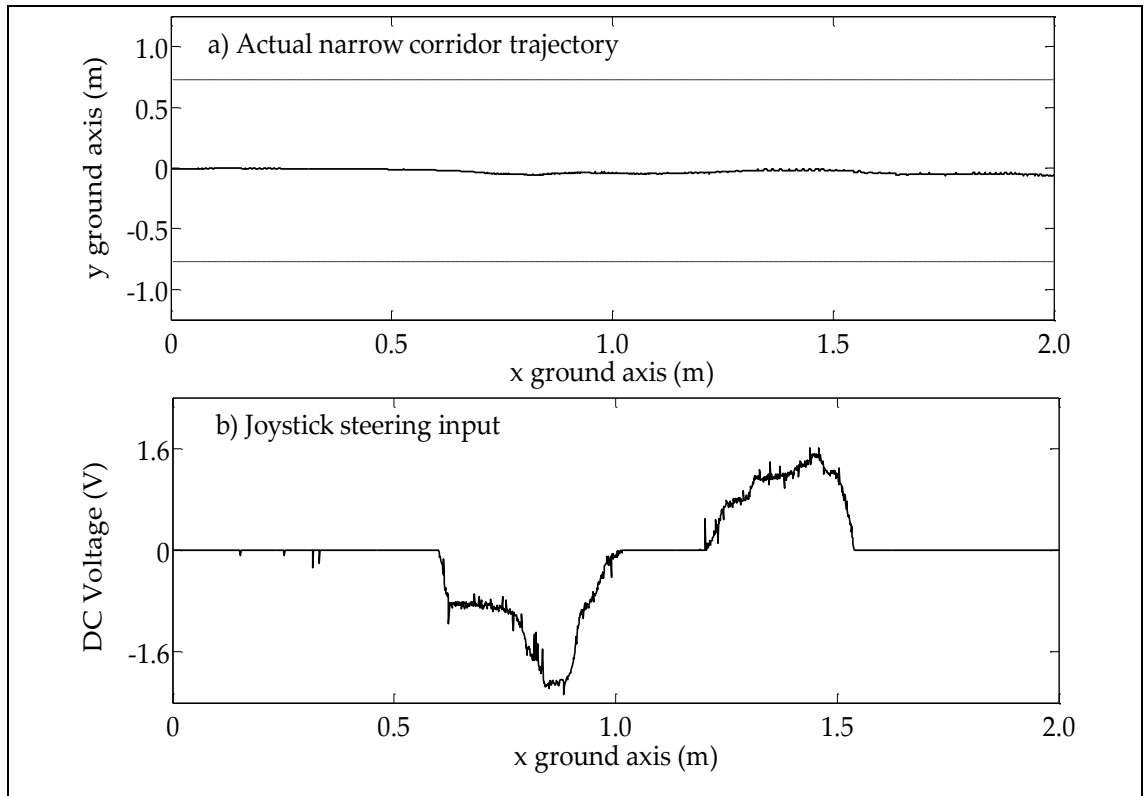


Figure 4.8 Lane following

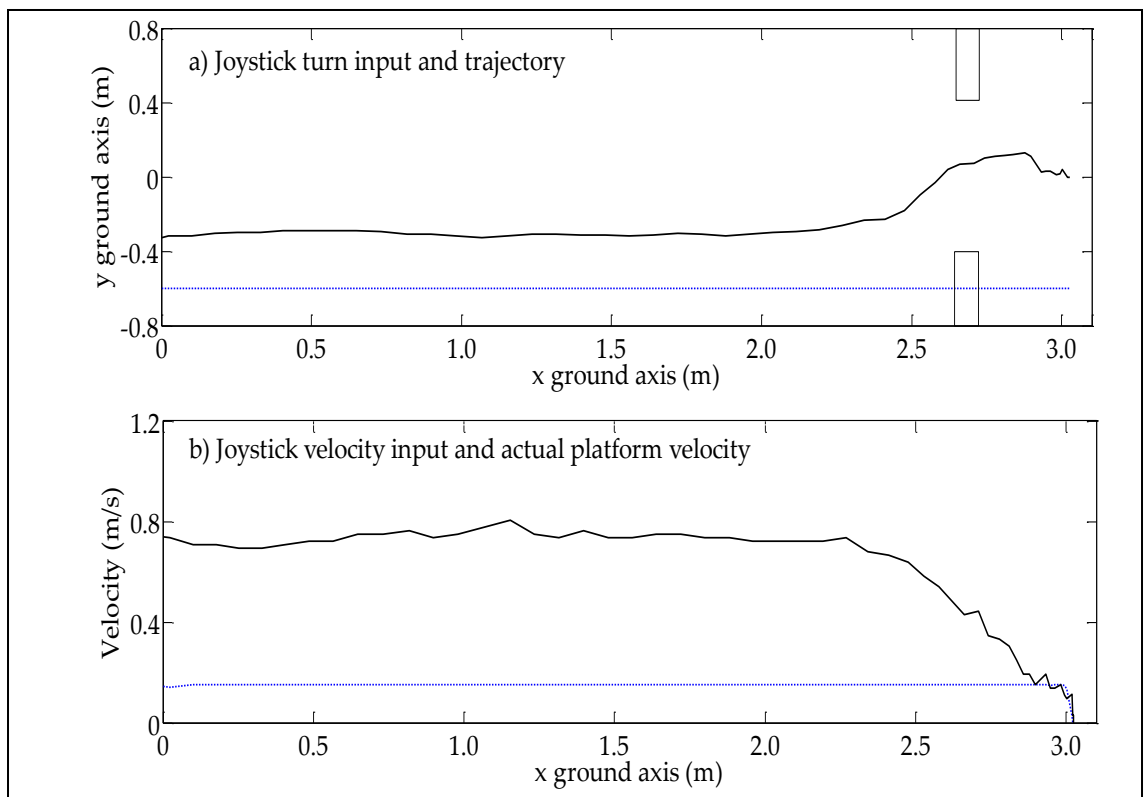


Figure 4.9 Fast approach to doorway

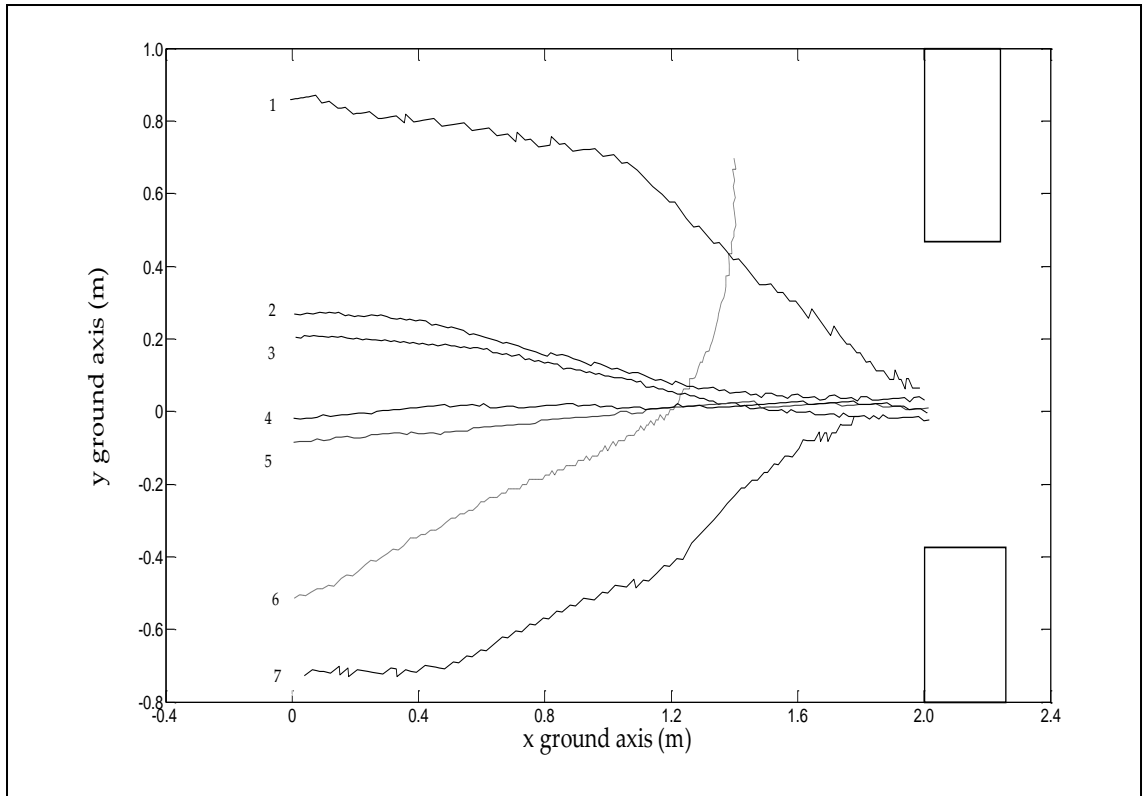


Figure 4.10 Various doorway approaches

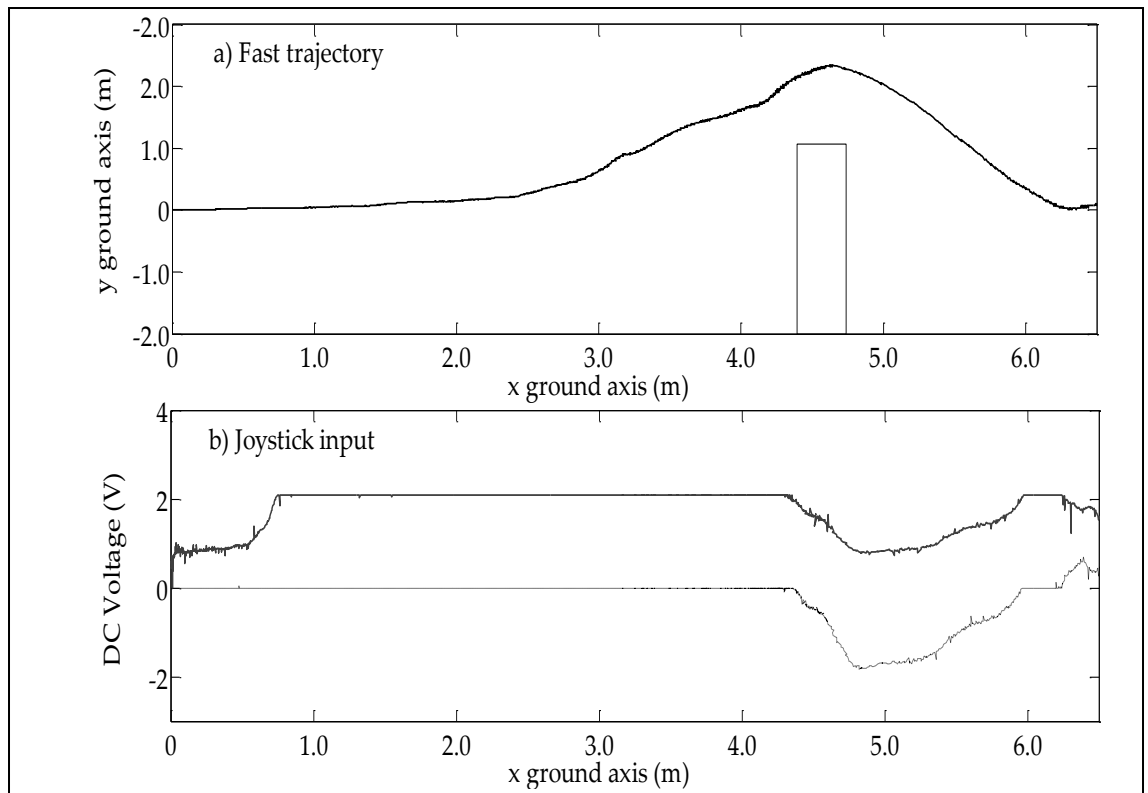


Figure 4.11 Fast approach towards an obstacle

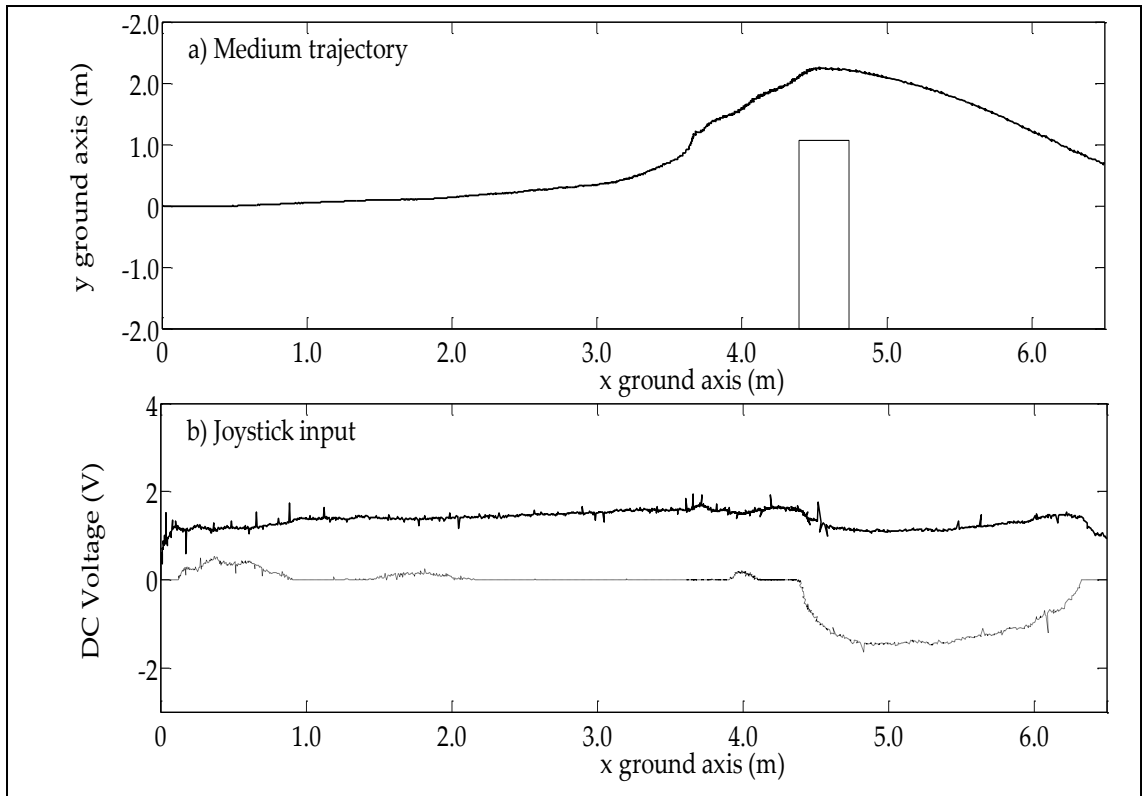


Figure 4.12 Medium velocity approach towards an obstacle

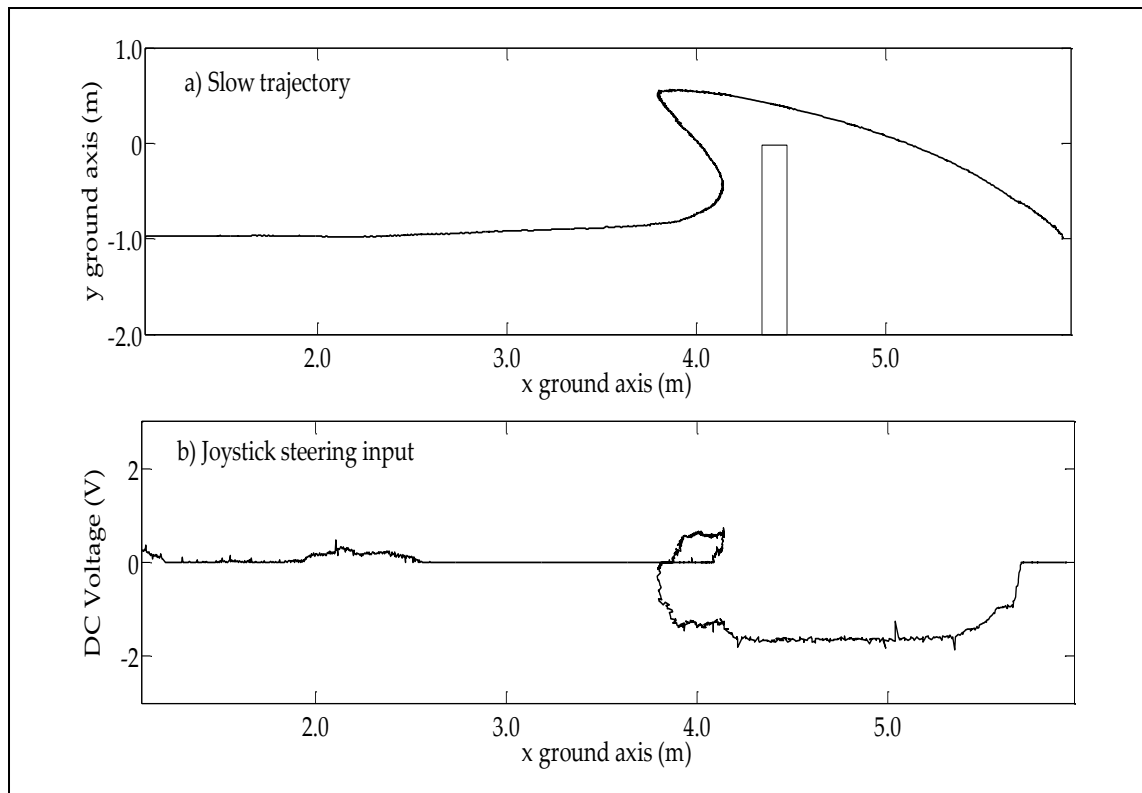


Figure 4.13 Low velocity approach towards an obstacle

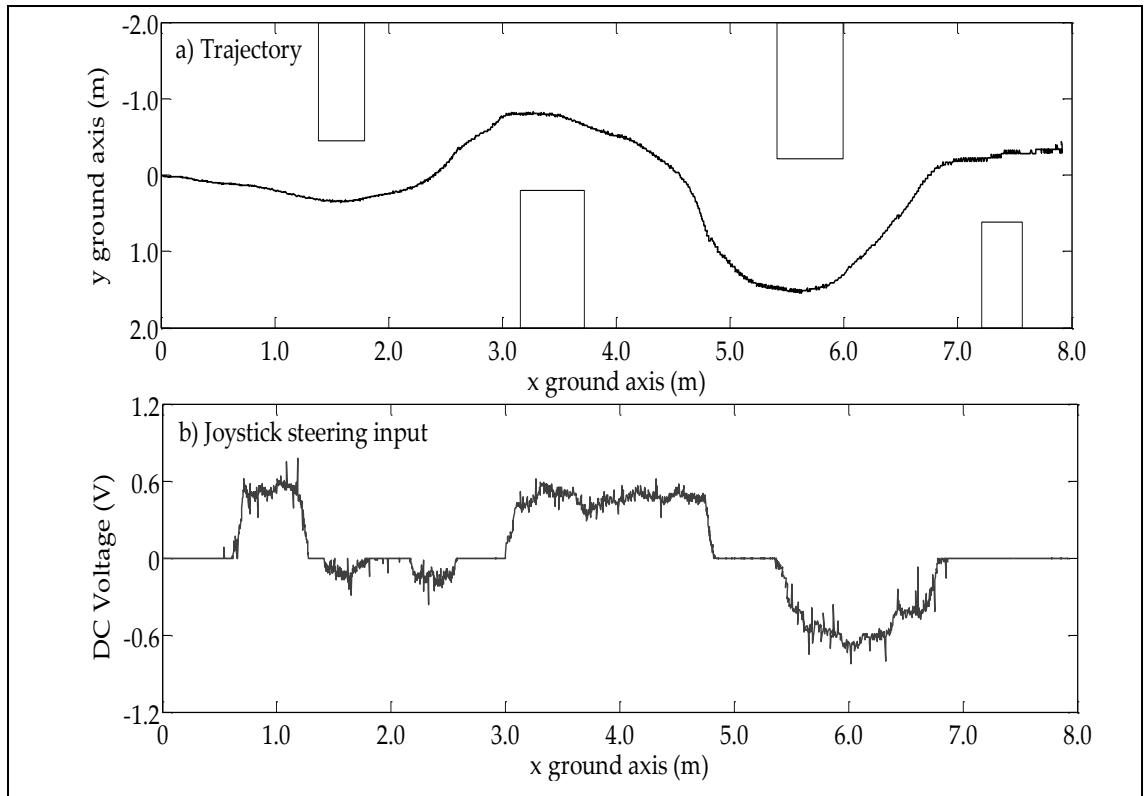


Figure 4.14 Obstacle slalom

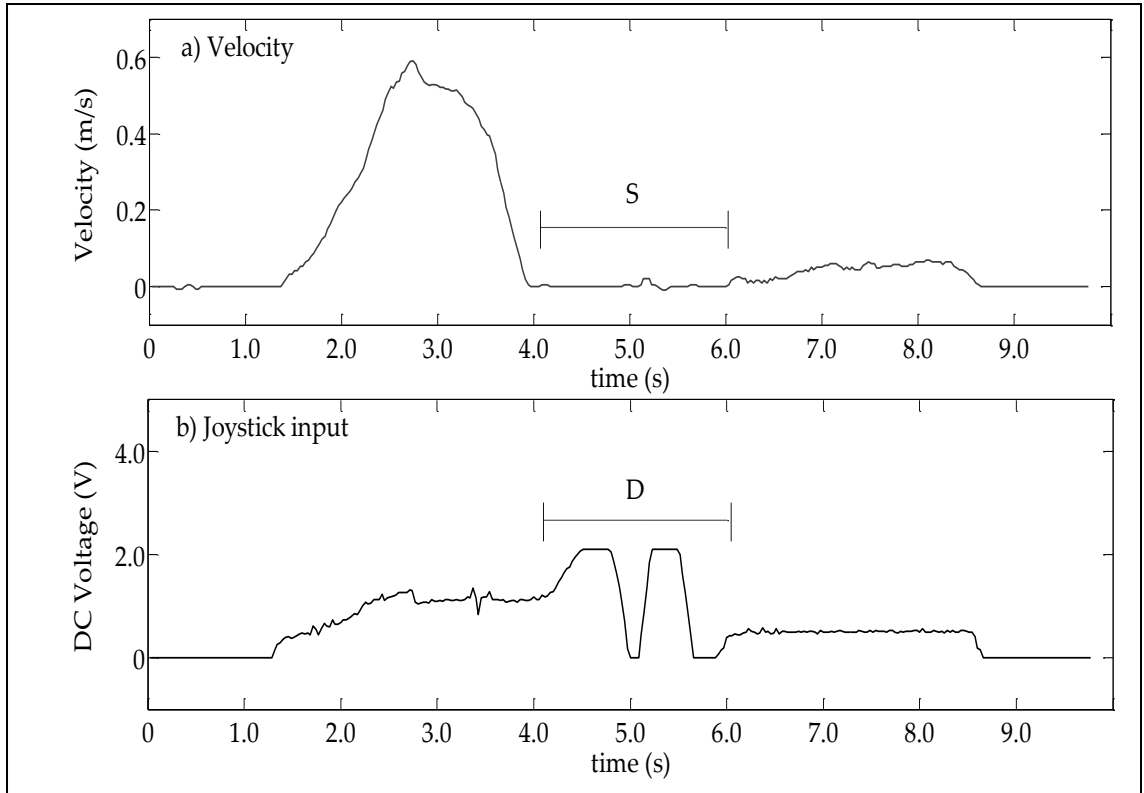


Figure 4.15 Dead-end or docking

4.7 Participant evaluation of collision avoidance method

A typical PWC user scenario was undertaken using 17 volunteers, of various levels of PWC driving abilities, in a controlled environment. They were given simple instructions on how to operate the wheelchair platform safely, told that they would be followed by someone with an emergency power cut-off switch and shown their own easily-accessible emergency stop button. The 17 participants comprised 14 males and 3 females; all male participants were given the joystick analogue input device, and all female participants used a digital button push input device.

The participants were all shown the obstacles and walked through the course; the obstacles were all light-weight cardboard and the doorway had collapsible fold-back sides to prevent any injury or need to stop. The course consisted of a narrow doorway and a series of obstacles as indicated in Fig. 4.16. The slalom was used to draw attention away from the doorway-passing element. The task consisted of each individual completing 12 consecutive circuits, the first two with assisted navigation on, then the next two without assistance, and so on. The subjects were all notified of the status of the assistance and data was collected by the system with regard to the amount of deflection given by the system assistance to the user's trajectory when passing through the doorway.

All participants were asked to complete a questionnaire (devised after consultation with PWC stakeholders), the first part of page 1, up to and including question A, before the testing and the remainder afterwards. This questionnaire contained a section based upon the NASA task load index [146], this section was aimed at checking that the participants had followed the instructions given to them in completing the task.

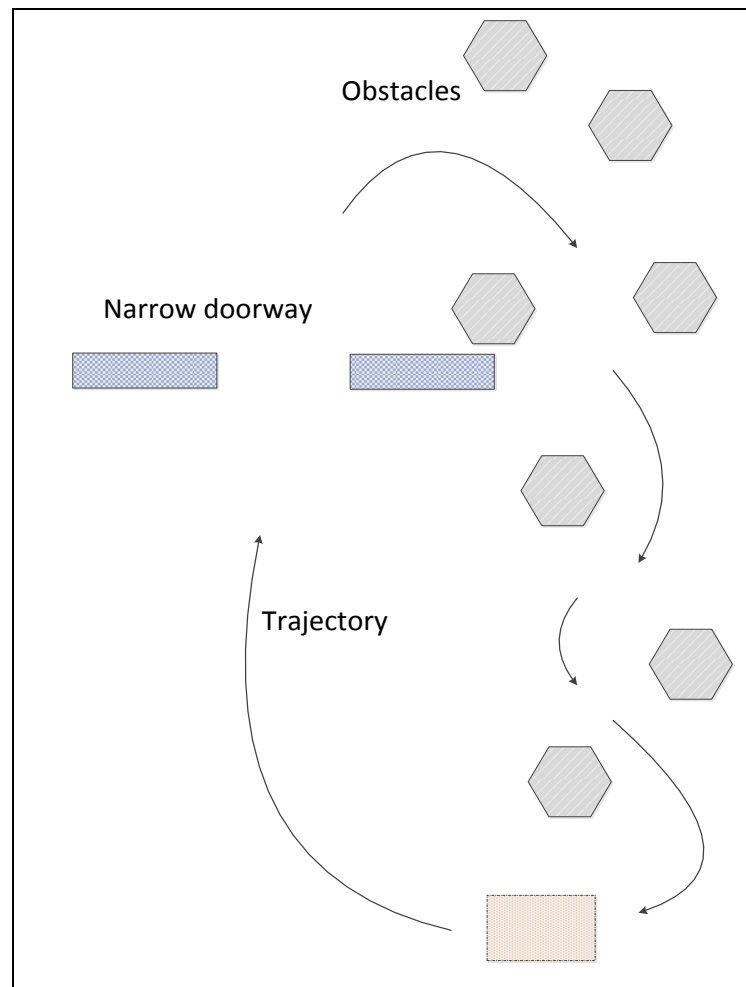


Figure 4.16 Obstacle course

NASA Task Load Index workload evaluation procedure is usually a two-part procedure which requires collecting an individual's rating and a weighting of each of the six perceptive categories:

- mental demand (MD)
- temporal demand (TD)
- performance (P)
- frustration (F)
- effort (E)
- physical demand (PD)

These perceptive responses are quantified into a 0 to 20 scale which are then used to produce an Overall Workload score; this method has been used for over 20 years on many diverse applications [147]. This method has been chosen for the purposes of checking consistent testing. The participants were informed that they should circumnavigate the course starting and stopping at the same place with the following strict caveats:

- repeat accurately the same path each time
- treat this test as if it were a driving test
- attempt your best competitive effort
- no stopping
- avoid all collisions
- complete each circuit as fast as possible as if in completion with others

Having preloaded the task it was felt unnecessary to use both parts of the NASA Task Index, therefore only the first part was applied. The results are given in Table 4.1 which shows that the participants did abide by the caveats, the tester did not guide the completion of the form, and some of the outliers were caused because the participants did not fully understand the context of the question: some thought that 'effort' meant how hard they tried to follow the caveats rather than how hard the actual task was. Similar confusion occurred with four individuals with regard to the mental demand and the temporal demand; some again believed these referred to driving the wheelchair rather than the task.

The participant questionnaire before and after questions was devised to assess the expectations of the participant towards the collision avoidance system. They were shown the course and the task was explained with a demonstration; then just prior to starting the task they were asked to respond on a scale of 1 to 5 how well they expected the system, and their performance, would be in completing that task. Having completed the task they were asked again to respond with their revised response to the task and how well they and the system performed.

Table 4.1 Results of NASA load index

User	MD	TD	P	F	E	PD
1	10	10	16	4	12	4
2	2	3	3	3	2	2
3	1	1	17	1	3	1
4	4	4	18	3	2	6
5	1	3	21	1	7	1
6	1	5	4	1	3	2
7	9	7	15	5	6	7
8	3	2	19	2	11	1
9	7	4	18	3	16	4
10	11	6	21	1	14	1
11	4	4	19	1	3	1
12	4	3	16	3	5	2
13	4	4	2	3	7	6
14	14	11	15	9	1	1
15	1	2	18	1	1	3
16	3	2	21	1	1	3
17	2	2	21	1	1	1
Median	4	4	18	2	3	2

The results of the personal perception are given in Table 4.2 which shows the mean personal rating after (PRA) is higher than the mean personal rating before (PRB), with only two individuals down-rating themselves. The mean system rating after (SRA) has also increased over the system rating before (SRB) with no down-rating by any individual. The last column (E) in Table 4.2 represents the results of being asked how obvious, quantitatively, they noticed the system was intervening. All participants were asked whether the intervention was intuitive and helpful or not, to which they all replied that it was. The first column (A) in Table 4.2 indicates the participant's previous experience of wheelchair driving and may be used to qualify the answers given.

Table 4.2 Perception results of participant questionnaire

User	A	PRB	PRA	SRB	SRA	E
1	5	4	4.5	4.5	4.5	5
2	3	5	5	5	5	3
3	5	5	4	5	5	2
4	2	3	5	4	5	1
5	1	3	4	4	4	1
6	1	1	3	4	4	4
7	1	3	4	4	4	4
8	1	4	5	5	5	3
9	3	3	4	4	5	4
10	2	3	5	4	5	1
11	1	3	5	3	5	2
12	2	4	4	3	5	4
13	1	3	4	4	5	2
14	5	5	5	5	5	3
15	1	3	4	4	5	1
16	1	3	5	2	5	4
17	1	5	4	3	4	3
Mean	2.11	3.53	4.38	3.97	4.74	2.76

There were no collisions with the doorway; in all six passes from all 17 participants when the assistance was enabled, shown in Table. 4.3. However there were four joystick input participants who collided once each with the doorway during the six passes without assistance. One of the three digital input participants collided on three of the six passes without assistance. The doorway passing trajectory assistance for each participant was recorded and again given in Table. 4.3. The three digital input participants (15-17) received consistently the most assistance, as would be expected. The other 14 analogue joystick input participants ranged from a good central alignment with no help (participant 13 pass 1) to one participant who decided to test the system by trying deliberately to crash (participant 1 pass 5) which required the system to intervene successfully more often.

Table 4.3 Trajectory assistance when passing through doorway

User	Trajectory assistance provided %					Number of Collisions		
	1	2	3	4	5	6	Sys on	Sys off
1	32	29	27	31	76	22	0	0
2	30	28	30	29	28	28	0	1
3	13	29	30	29	29	19	0	1
4	24	27	30	24	19	19	0	0
5	34	19	18	23	23	21	0	0
6	19	6	27	25	27	19	0	0
7	26	30	13	30	30	30	0	0
8	23	24	27	27	39	27	0	1
9	3	23	30	20	29	22	0	0
10	25	32	29	31	24	23	0	0
11	20	24	11	16	20	26	0	0
12	30	27	31	17	26	26	0	0
13	1	32	32	22	29	22	0	1
14	27	30	29	24	25	20	0	0
15	47	46	38	50	51	38	0	3
16	59	49	51	54	49	52	0	0
17	49	46	30	48	43	43	0	0

4.8 Conclusions of collision avoidance method

Developing assistive technologies can be divided into two distinct phases [148]: the technology and software development represents the first phase, and the second phase requires clinical trials with end users evaluating the technology. Powered wheelchair assisted navigation evaluation has no standard metric to apply [149]. Users' abilities can be wide ranging and vary over short time periods making the move from the first phase to the second phase difficult to implement [148]. The participants in our human trial were not disabled as the purpose of testing was to determine whether the method developed in this chapter could be said to be intuitive and not intrusive when driven under best conditions as a the first phase of evaluation. The second phase would require a much longer term

for evaluation using a platform system which is also much closer to one which could be readily adopted by manufacturers of assistive PWCs. However this chapter has fully developed a practical methodology which can be used on embedded hardware with low-cost sensors to provide a stand-alone, or part of a modular architecture, real-time collision avoidance system. It has been shown by experimentation that:

- When users try to pass through a narrow standard doorway with a powered wheelchair collision will occasionally occur for some users without robotic assistance.
- This collision-avoidance method prevents collision with narrow doorways and will not allow passage if the approach angle is such that the gap is too small.
- As evidenced from the user feedback, this method of assistance is intuitive and not so intrusive when the user needs that assistance.
- Oscillations around objects and in narrow corridors do not occur when using this method.
- Trajectory deviation can be adjusted according to the dynamics of the platform, or obstacle, allowing a more flexible human-in-the-loop assistive system to be developed.

This chapter has described a real-time reactive low-level collision avoidance methodology which is compatible with a layered assistive system described in Chapter 3. There has been a general acceptance in the art that real-time collision avoidance is a requisite for any assistive mobile robotic system, this was reviewed in Chapter 2 additionally this review determined that collision avoidance should be intuitive and unobtrusive, empowering the individual not disempowering or overpowering. The feedback from testing with humans in the loop, when asked whether they were comfortable with the assistance, unanimously reported that it was reassuring to know it was there, they all stated they preferred the system when it was active.

The literature reviewed in Chapter 2 pointed to the need for varying levels of assistance because users have differing needs at differing times. Therefore the next level up in the Human-in-the-loop architecture proposed in Chapter 3, above this collision avoidance layer, should be a layer offering more assistance, and this should be one that provides assistive steering for short trajectories to enable users to manoeuvre more accurately through waypoints; for example when the doorway has been approached wrongly and the collision avoidance layer has prevented passage through the doorway. However in order to determine the trajectory it is necessary to develop a method which avoids mapping, as identified by Yanco et al. [58], yet provides the necessary information for generating an assistive trajectory. The next chapter therefore develops the first step towards this by providing a real-time methodology for localisation and waypoint identification. This methodology uses pattern recognition and ranging histogram data to determine waypoint identification and a novel flooring recognition method for localisation is also developed. When combined the two methods result in providing a waypoint approach angle and position suitable for determining a trajectory. Uncertainties and small errors are assumed to be dealt with by the lower collision avoidance level.

Chapter 5

Localisation and waypoint identification

Having partly identified a number of suitable sensors in Chapter 3 for developing collision avoidance in Chapter 5, and following the identified need for re-using sensor data, this chapter now addresses the question of using real-time data and simple pattern recognition techniques to identify individual rooms, approaches to doorways, corners, turns, dead-ends, and other waypoints for navigational purposes. These are necessary requirements for generating a trajectory for the assistive human-in-the-loop mobile robotic system as developed in the next chapter of this thesis.

The chapter starts with an identification of the requirements for developing a real-time waypoint and room identification system. The chapter then moves on to describe the unique and novel solution for providing a means of fast room identification. Section 5.3 introduces a real-time method for the identification of junctions and doorways in corridors. The following section then presents a method for identifying doorways from inside rooms and determines the approach angle of the platform to that doorway. This unique research carried out to identify doorways, approach angles to those doorways, and junctions is complementary with the localisation method described in section 5.2, the summary of this chapter in final section collects together the research presented in this chapter and compares that to the requirements laid down for the assistive system and any potential future work.

5.1 Navigational requirements for an assistive system

One major problem to be solved for any smart adaptive wheelchair system is manoeuvring through a doorway. One disabled participant in a doorway-passing experiment only completed the task when manoeuvring assistance was engaged [71]. Furthermore on average 2.27 crashes occurred per participant per trial [71]; however, analysis also highlighted participants' concern regarding system intervention feedback when prevented from passing through the doorway because of an incorrect approach angle [7]. Therefore for any real-time non-reactive trajectory assistance to be offered, a predictive look-ahead perception would be required in order to better inform the user of their error. This would allow them to better align the wheelchair to the doorway preventing collision and allow passage through openings with narrow clearance to the platform. In order to accomplish forward prediction identification of waypoints (junctions and doorways) needs to be available to the assistive system in real time.

Having researched various methods and techniques and reviewed the literature in a cyclic process, a set of requirements for developing real-time localisation and waypoint identification for assistive real-time PWCs have been identified:

- using real-time pattern recognition techniques
- reuse of information from other sensors if possible
- sensors should be robust and low cost
- sensors should not rely upon time-consuming scanning
- data from sensors should require minimal processing
- features should be compatible with human methods of recognition
- features need to be stable and non-changing for long time spans
- feature representation needs to be suitable for fast classification for real-time operation

Look-ahead identification provides system and operator feedback for predictive planning; promising smoother optimal approach trajectory generation and system-operator integration, therefore sensors need to detect the obstacles at a sufficient distance in front of the platform as well as the system obstacle identification method functioning in real-time. Navigational assistance for any wheelchair user whilst negotiating doorways, round corners, or junctions, requires two critical problems to be addressed: the first is to develop advanced junction/doorway detection and identification, the second is to use this data in real time to modify the chair's trajectory so that it will pass through the doorway or round a corner without collision. In order to achieve the first goal it is necessary to collect appropriate sensor data and then to manipulate those data using pattern recognition techniques as identified in Chapter 3. The way in which it is planned to do this is now presented in this chapter.

5.2 Localisation for the assistive PWC

Localisation can be achieved using Global Positioning Satellites (GPS) or mobile telephone techniques. However, the degree of accuracy and loss of signal can present a real problem within buildings, particularly when there is a need to differentiate between small rooms as is common in domestic situations. Tracking and localisation within a room has been covered extensively within the literature [150, 151]. Current research favours optical methods [152] however Wi-Fi systems are widely employed and considered by many as a de-facto method [153]. Mobile robotic localisation research for systems employing limited short-range sensors is lacking in the literature [150]. Any robotic application must have an executable trajectory; autonomous robotic devices require reference points and maps for localisation and navigation, whether those data are *a priori* known or obtained dynamically whilst undertaking exploration. However assistive technologies such as electric wheelchairs are drawing mobile robotic interactions increasingly towards the uncertain and complex human environment. Seamless crossover between human defined-desired trajectories and autonomous system aided trajectories is required, human assistive systems have the intelligent user in the

loop [5, 12] which necessitates abandoning fixed definable workspaces—best suited to autonomous robotics—and instead adopting stochastic, and semantic-based workspaces [33]. Methods commonly employed in the Euclidean geometric domain, such as covariance ellipses indicating location and object uncertainty, now for assistive technologies require weighted nuances; obstacles and targets thus having a spectrum of importance. Whilst Cartesian maps provide a useful reference and must be accurate, allowing interaction with fixed infrastructure, localised dynamic interactions within the human environment are perceptual, subjective and instinctive and therefore any robotic assistive system must incorporate some form of learned localised perceptive temporal mapping in order to be effective. When the assistive device is first initialised, for example after powering down and then having been manually moved, localisation becomes the first dictate; current methods require some form of scanning or initial exploration to generate a map which is then compared with a stored map. However this approach requires some time and unnecessary motion, both undesirable features in any human assistive system. In addition a habitable room may be cluttered and dynamically varying hence geometric mapping will not remain consistent over time.

5.2.1 Room localisation for an assistive PWC

Whilst much work has been done in the field of robot self-localisation there remain significant difficulties with integration into the dynamic human world. Techniques have been introduced in the healthcare field to monitor patient and staff location such as Radio Frequency Identification (RFID) tags [154] and Wireless Fidelity (Wi-Fi) [17]. Rimminen et al. used capacitive RFID tags embedded in the shoes of nurses and an electric field floor sensor; they reported 93% successful localisation. Doshi-Velez et al. mounted devices on wheelchairs aiming to reduce the time spent locating patients in a residential home; they reported significant time saving, however they also indicated 8.9% false positives where the radio signal was not being bounded by walls. Yifei et al. developed an occupancy-clustering technique utilising Wi-Fi signatures for room distinguishability; they reported 95% successful location identification.

Most locations where wheelchair users frequent, such as their homes, offices, and other public places, or those of friends, are unlikely to have such infrastructure and even if domestic Wi-Fi is utilised there is a possibility of it being turned off, obstructed, or moved. Thus a more robust room identification solution, less reliant on specialised infrastructure, must be sought for any practical mobile robotics system particularly if it is to be effective in diverse and dynamic environments.

Ceiling lights and tiles [155-157] have all been used in the literature to provide a means of localisation within a room. However, lighting conditions can prove problematic and not all rooms have multiple lights and suspended ceilings. Other localisation techniques have involved sonar mapping [158]; these require room scanning, thus inducing unwanted motion and delay before identification is possible, as do laser range finding LIDAR methods. A well-established camera-based image feature matching method, Speeded-Up Robust Features (SURF) [159] employed by Murillo et al. [160], was used to localise a robot. The method compared the current omnidirectional image with stored images; they reportedly achieved a 95% robot tour room recognition rate.

Any assistive or autonomous robotic system requires localisation information prior to action; path planning can only be achieved from knowing the current location relative to other locations, and is thus an essential component for any trajectory generation or assistance. Localisation and tracking is often carried out through GPS and/or GSM, or other radio beacon systems. However loss of signal often occurs in buildings, and when available is usually limited to an oval probability footprint several metres by several metres, with little regard to room walls and boundaries. Therefore any radio-based system gives rise to false positives, and false negatives, when considering a specific room; thus any localisation system solely utilising these methods suffers susceptibility to false reporting. Other methods of localisation not involving radio systems require exploration time or delicate expensive rotating sensors and are thus unsuitable for human assistive devices; image processing localisation techniques are computationally expensive and have restrictive coverage. Therefore determining which room, for example in which house or apartment in a multi-storey terrace or block,

in real-time to an acceptably robust degree, in a highly dynamic environment, appears difficult if not impossible to achieve.

5.2.2 Floor feature determination

Flooring is usually laid for some considerable time without change, tends to be homogeneous in colour and texture patterning, and has variance upon location, particularly room-to-room in the home or living environment and is usually kept clean and free of obstacles and clutter. Whilst hospitals and public buildings may well have the same type of flooring throughout zones, there are usually some differences, in particular colour-coded strips running along the corridors of many hospitals guide people to traverse from place to place; other infrastructure may also be present or cost-effectively implemented. However offices, houses, flats, shops and restaurants are where people spend the majority of their time; all of these places would be unlikely to have the infrastructure necessary for robotic localisation, therefore using flooring as a localisation feature offers an additional tool in the human-assistive robotic localisation arsenal.

Flooring can be smooth as in the case of a hard surface such as linoleum or wood, or rough as in carpet providing a degree of texture and patterning is an important discriminator. Whilst it is entirely possible for a floor to be part-covered by a rug or to have a stain, these tend to be permanent features and the variance of these features could be said to be slowly changing over time, as wear and tear occurs for example; however any system reporting falsely could be easily retrained for that room, an occurrence in all likelihood equal to one introducing new locations and deleting old. Furthermore thresholds of rooms or doorways usually have carpet or flooring dividers thus further bounding the location.

Fast reliable classifying requires extracting suitable robust flooring features. Previous work classifying and cataloguing images in large datasets has been achieved by simply defining a ratio of the red,

green and blue RGB in colour space [161], thus effectively reducing an image to three single colour values and standard deviation. Most flooring is much less detailed and varying than human interest photographic images are, and therefore these features are highly suited to this application. Various statistical and structural methods defining texture have been reviewed [162, 163] however a true texture definition remains undefined; metrics of texture could be described as homogeneity, contrast, correlation and energy which can be obtained from a greyscale image. Therefore overall image reflectivity, contrast and homogeneity have been chosen as a metric of flooring texture.

Classification is used in statistics and machine-learning systems as a method of determining to which category some current observation (the testing data set) belongs when compared with some stored or learned observation (the training data set). The Nearest Neighbour (KNN-1) classifier is well understood and used extensively due to simplicity of operation [164]. KNN-1 functions well across different ranges and types of datasets; therefore it provides a good benchmark to test flooring features. However, in practice, when processing large datasets, for example too many different types of floor, statistical classifiers often perform better; therefore the linear classifier Bayes-1, and quadratic classifier Bayes-2, and the simplistic Naïve Bayes Classifier have also been used when testing feature sets. According to research [164] all these classifiers look promising for application in any real-time pattern recognition systems, particularly the statistical classifiers.

5.2.3 Hardware

There are numerous techniques for localisation utilising a range of hardware devices, for example vision-based pattern recognition systems typically use low-resolution webcams to obtain images which are then processed and parsed, with long computational time due to need for large numbers of comparative stored images, even with modern techniques [159], or lowering frame rates to improve accuracy, therefore hardware dependent problems exist for real-time human assistive systems [151].

The following are a list of some of the methods, hardware and their limitations:

- Wi-Fi and radio broadcast (personal and local area networks) offer only coarse localisation, are sensitive to interference, dynamic changes and propagation effects, require power level mapping, and suffer a difficulty to bound rooms effectively.
- RFID is limited by range and accuracy, requires installation therefore limited to identifying rooms with the devices installed.
- Photonic devices are sensitive to ambient conditions, reflection, and obstruction and may require some infrastructure, which are all problematic for a dynamic human environment.
- Image processing has high processing requirements, sensitive to ambient lighting conditions, and environmental changes, and obstructions, although good for room identification.
- Geometrics, such as sonar, laser and infrared ranging, usually require some degree of scanning or platform motion and all can be affected by dynamic conditions, cluttering, reflectance and scattering; although good for room identification some considerable time may elapse before identification is completed and thus not directly suitable for assistive robotic application.
- Inertial and mechanical sensors suffer from drift due to integration, noise, thermal differences, and alignment errors, hence they require periodic calibration; they also require accurate initialisation because any error in initial position is carried forward. Therefore these types of sensors are not suitable for initial system localisation but would work well with a system which periodically accurately determines some position, such as a room or floor-covering boundary.
- Geomagnetic sensors are strongly affected by electromagnetic fields and metallic objects and therefore highly unreliable indoors.

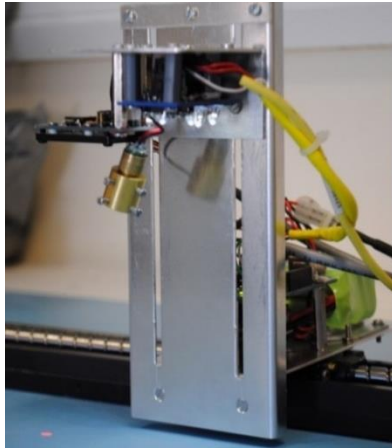


Figure 5.1(a) Mouse camera with laser illumination and colour sensor with white LED illumination

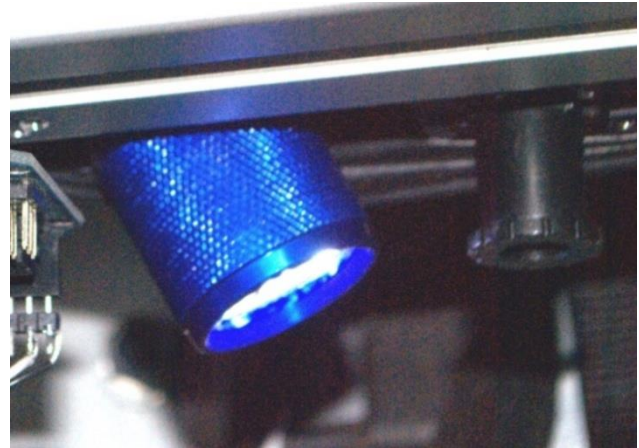


Figure 5.1 (b) Shows improved and final configuration with mouse camera and lens, and colour sensor both illuminated by white LEDs

Therefore for any real-time human assistive system computationally fast sampling hardware with easy-to-extract data must be employed for that system to succeed, and for this reason two high-speed low-cost sensors, one to extract the RGB colour features, and one to obtain the surface texture features were chosen. For the three-feature colour sensor an Avago ADJD-S311-CR999 [101] four-colour channel (RGB and White) surface mount photodiode array was used, comprising filters and front end analogue-to-digital converter with adjustable integrators and offsets. This was connected by serial interface to a small ATmega328 microcontroller programmed to read register information from the sensors and send those values to a laptop which was used to collect those spectral data. Illumination was provided by eight white LEDs mounted around and parallel to the sensor shown in Fig. 5.1.

Whilst the chosen colour sensor provides the spectral image processing element, a real-time monochrome texture sensor was required for the second sensor. Optical computer mice sensors are based upon compact high speed monochrome image processing, therefore an Avago ADNS-2610 1,500fps compatible [102] MCS-12086 simple small form factor 19x19 pixel array optical mouse sensor has been chosen for our texture feature sensor. This sensor conventionally uses the optical flow algorithm

[103] to return X and Y relative motion. The process of obtaining the relative motion requires hundreds of vector calculations, based upon comparing a moving pattern of each bright pixel's relationship to eight neighbouring pixels between two frames. These velocity vectors are fused over a number of frames to provide a low noise resultant velocity vector, which is available in component form from the device registers. Pixel integration time is carefully managed in order to preserve the feature patterns between frames, for example previous work has shown that the whole optical mouse image can be utilised, rather than many 3 x 3 matrices, as a feature pattern [165], in order to improve performance of the motion detection algorithm. Therefore the optical mouse provides a robust and stable image pattern of the surface over which it travels.

Table 5.1 Optical mouse sensor data registers

Register	Address	Range	Remarks
SQUAL	0x04	0-254	Number of features in current frame
Maximum Pixel	0x05	0-63	Maximum pixel value in current frame
Minimum Pixel	0x06	0-63	Minimum pixel value in current frame
Pixel Sum	0x07	0-159	Full sum of pixel values/128 current frame
Shutter Upper	0x09	0-254	Read first upper 8 bits of 16 bit integration time
Shutter Lower	0x11	0-254	Read second lower 8 bits of 16 bit integration time
Image	0x08	0-63	Actual 361 pixel value array dump

The data registers on the sensor provide datum information each clock cycle are shown in Table 5.1. This particular model only makes one image pixel magnitude of information available per clock cycle, thus 361 cycles or frames are required per accessible image. Each frame taken by the optical mouse is therefore directly representative of a form of surface texture, where backscattering of the light from an illumination source is dependent upon the surface irregularities [105].

The optical mouse sensor has a pin-hole lens restricting the focal point and the number of photons entering the device so that the mouse only functions when in very close proximity to a surface. The

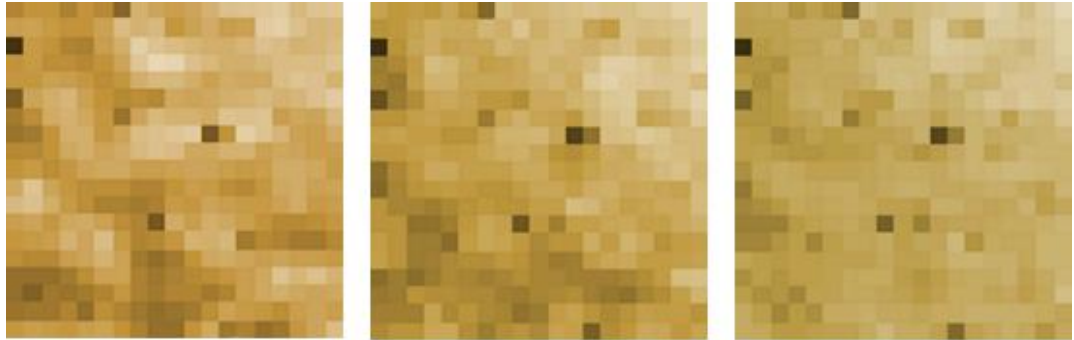
initial set-up used a laser for illumination in order to increase the distance from the surface that the optical mouse sensor was effective, Fig. 5.1a. However, for safety reasons and practical application it was later decided to modify the optical mouse sensor and utilise the illumination from the colour sensor thus effectively creating a single sensor package. The original optical mouse sensor pin-hole cover was replaced by a small webcam lens to give a wider field of view whilst also allowing more light into the sensor shown in Fig. 5.1b. Both laser and white light illumination proved equally successful as will be shown later. A standard 180 x 320 colour webcam was chosen to provide a comparison benchmark sensor when imaging the flooring materials.

The optical mouse camera and RGB sensor are able to be sampled at approximately 500 samples per second, using the ATmega328 microcontroller, although depending on the optical mouse sensor model 800 to 1500 frames per second can be achieved [102]. The colour sensor can be sampled at 10,000 times per second [101] although for the purpose of these tests either single samples or when in motion approximately 50 samples every second were recorded.

The mouse camera and colour sensor were mounted beneath the robotic platform together with the web camera and connected to a laptop to record the data. Calibration for the system was undertaken by using a variety of materials, dark to light in order to determine the optimum illumination level requirement, colour cards were used for the RGB colour. The web camera was positioned so as to centre in the captured image the same area that the mouse sensor and colour sensor observed.

The benchmark web camera was used simultaneously with the proposed system to image flooring samples. The collected web camera images had simplistic RGB channel colour median bin values extracted as the colour features. Texture was obtained from a greyscale mapping of the same colour image used to extract RGB features, each greyscale image was analysed as a grey-level co-occurrence matrix (GLCM), which is a statistical method that considers the relative spatial pixel

relationships. The result of the statistical analysis provides four image texture features; a relative degree of contrast, correlation, homogeneity, and energy.



*Figure 5.2 (a)
Coarse sandpaper
mouse sensor image*

*Figure 5.2 (b) Me-
dium sandpaper
mouse sensor image*

*Figure 5.2 (c)
Fine sandpaper mouse
sensor image*

All images were obtained, using a 30-degree angled white LED illumination source, from the re-lensed mouse sensor.

The colour sensor provides a single pixel for each of the RGB channels, thus comparable with the web camera RGB median binning method [166]. The complete optical mouse sensor image can be obtained from the sensor registers as a greyscale bitmap; Fig. 5.2 shows three 19x19 pixel images, from which we can also extract a GLCM and thus directly compare with the web camera. Additionally the optical mouse sensor also provides raw data which are directly representative of the surface irregularities due to the intrinsic properties needed to determine an overall velocity vector output.

One of the mouse sensor registers gives a value for surface quality (SQUAL): the value represents the total number of features identified; these features are essentially obtained by utilising a 3 x 3 pixel mask across the whole image, pixel by pixel, excluding the edge rows and columns. An overall brightness gradient may then be determined between the central pixels of each masked matrix to its neighbouring pixels within the mask; this gradient is then represented as a vector subsequently assigned to each central pixel. These feature vectors are then used by the optical flow algorithm to

determine an overall motion vector of the sensor in Cartesian form between frames. Therefore the brightness contrast between pixels needs to be significant in order to be trackable as a surface feature. However in the case of the modified mouse, where each pixel images a larger surface area than the standard mouse sensor, due to the lens change, rather than image the microscopic nature of surfaces, we can now image slightly more macroscopic. Fig. 5.2 shows three different, same colour, textured materials taken using the modified mouse sensor with a 30-degree illumination angle, the contrast or gradient between neighbouring pixels, and overall contrast, the angled illumination slightly exaggerates the surface profile which allows surfaces with homogeneous colour, hence un-patterned, to become discernible by a measure of surface roughness.

5.2.4. Results and Discussion

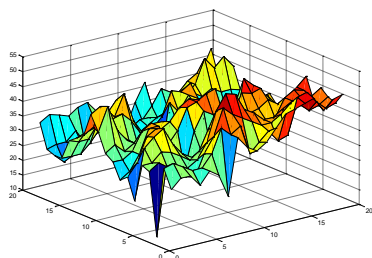


Figure 5.3(a) Pixel 3D mapping of coarse sandpaper image

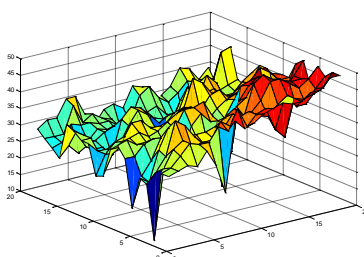


Figure 5.3 (b) Pixel 3D mapping of medium sandpaper image

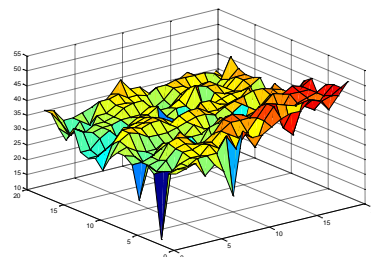


Figure 5.3 (c) Pixel 3D mapping of fine sandpaper image

A very simple measure of the surface texture can therefore be extracted from the mouse sensor registers; contrast, and relative brightness, can be obtained from the average, maximum, and minimum pixel values, also available from the registers each clock cycle, given in Table 5.1, particularly as the optical mouse sensor is intrinsically designed to maintain these relative magnitudes, by modulating the shutter period in order to keep the features consistent between frames. Surface roughness is

clearly discernible in Fig. 5.2: different grades of the same colour sandpaper, coarse in Fig 5.2a, medium in Fig. 5.2b and fine in Fig. 5.2c. This surface roughness, or equally-coloured patterning, shows correlation with the gradient between a pixel and its neighbours. This variation can be better quantified by the 3D mappings of the three sandpaper images, shown in Fig. 5.3, hence there is a direct relationship between the SQUAL count and the surface homogeneity.

Table 5.2 Flooring material test results, and room localisation test results

Features source	Percentage of correctly identified samples				Number of samples tested	
	<i>1-NN Classifier</i>	<i>Bayes-Normal-1</i>	<i>Bayes-Normal-2</i>	<i>Naive Bayes</i>	<i>Total</i>	<i>Average per floor class</i>
Initial floor covering test (52 classes) using the unmodified mouse sensor with new flooring materials in a controlled lighting environment						
RGB and Registers	91.1	87.0	94.8	68.8	2330	44
RGB	92.4	84.7	91.8	51.7	2330	44
Mouse Registers	34.1	38.7	33.2	27.7	2330	44
Second floor covering test (50 classes) using the modified mouse sensor with new flooring materials in a controlled lighting environment						
RGB and Registers	93.3	95.0	29.1	66.1	500	10
RGB	90.3	93.5	2.0	56.3	500	10
Mouse Image Texture	8.6	7.8	9.2	6.9	500	10
Mouse Registers	28.3	40.2	19.3	28.6	500	10
Webcam RGB+Texture	43.5	85.0	63.6	69.8	500	10
Webcam RGB	37.9	45.5	40.8	22.0	500	10
Webcam Texture	77.6	76.7	73.1	55.0	500	10
Room localisation testing (133 rooms and 35 classes of flooring), using the modified mouse sensor on flooring materials in various states of wear with uncontrolled random background lighting						
RGB and Registers	94.7	85.2	94.3	68.5	59797	1622
RGB	93.3	76.9	90.4	54.5	59797	1622
Registers	39.3	42.7	46.0	39.3	59797	1622

A series of 52 classes of different flooring materials were obtained for an initial testing, including tightly woven carpet through to long pile, various linoleum patterns and wooden flooring. Classes were manually selected to test the ability of the sensor to identify correctly individual flooring. A 60% training dataset and 40% testing dataset were obtained by a random splitting of the collected data samples, and testing, using PR Tools4 [167] Matlab toolbox for pattern recognition. A series of five complete runs, including random data splitting, were performed for each class and the average results tabulated in Table 5.2. Samples were taken uniformly across the surface of the initial flooring test using a motorised pre-programmed X/Y table with background consistent fluorescent lighting. These measures were undertaken to ensure repeatability. Tests were re-run to confirm this. The test sensor configuration is shown in Fig. 5.1a; a red laser is used for mouse camera surface illumination and white LEDs for the colour sensor surface illumination.

The results in Table 5.2 for the initial floor covering test, using the unmodified mouse sensor and red laser illumination, show that the mouse sensor registers values provide an identifying fingerprint for different flooring materials: the Bayes-Normal-1 classifier resulted in a 38.7% correct identification, the RGB colour sensor RGB features using the same classifier resulted in a 84.7% correct classification, and when those features are combined into one feature set a small improvement in correct classification occurs. These results were taken at a height from the surface of 70mm, which was equally comparable to other testing previously run at surface level [168]. The initial test was repeated, six months later, using as many of the original materials as possible and with the modified mouse sensor. This testing was static, unlike the previous dynamic test, to compare our sensor results with those of a webcam and also directly with the complete mouse sensor image.

The results shown in Table 5.2 suggest that the modified mouse sensor with white LED illumination performance is comparable and equivalent to that of the unmodified laser illuminated mouse sensor. The modified mouse sensor registers and colour sensor combined give a 95% correct identification flooring classification using the Bayes-1 classifier, which compares with the previous unmodified

mouse camera 87% correct Bayes-1 classification. The webcam image GLCM texture analysis and webcam colour RGB binning benchmark methods gave a correct identification Bayes-1 classifier result of 85%. Fig. 5.4a shows the confusion bitmap for the webcam RGB and texture combined features, Fig. 5.4b shows the mouse sensor registers and colour sensor RGB confusion matrix bitmap, and Fig. 5.4c shows the improvement in clarity between classes, not tabulated in the results, when the fourth colour channel white feature is added.

Table 5.3 Background lighting test results

Features source	Percentage of correctly identified samples			
	<i>I-NN Classifier</i>	<i>Bayes-Normal-1</i>	<i>Bayes-Normal-2</i>	<i>Naive Bayes</i>
Intense Background Daylight and Localised LED illumination, no other light				
RGB and Registers	94.1	98.2	90.9	82.7
RGB	90.5	99.5	97.7	78.2
Mouse Registers	35.9	51.8	29.1	39.1
Webcam RGB+Texture	93.6	91.8	85.0	88.2
Webcam RGB	93.6	94.1	93.2	80.0
Webcam Texture	64.1	62.3	81.4	62.3
Intense Background Incandescent and LED illumination, no other light				
RGB and Registers	81.8	88.2	78.2	76.8
RGB	78.6	80.5	45.9	65.0
Mouse Registers	27.3	26.4	33.2	32.3
Webcam RGB+Texture	78.6	97.7	85.9	94.1
Webcam RGB	79.5	80.0	79.5	66.8
Webcam Texture	65.5	70.9	68.2	62.3
Typical office Background Fluorescent and LED illumination, no other light				
RGB and Registers	90.3	78.0	87.1	55.9
RGB	85.6	58.8	83.8	42.6
Registers	30.0	32.1	37.9	29.1
Webcam RGB+Texture	84.1	95.0	85.5	90.0
Webcam RGB	85.0	87.3	80.9	75.5
Webcam Texture	88.6	94.5	90.5	78.6
All lighting sources combined and LED illumination				
RGB and Registers	94.7	85.2	94.3	68.5
RGB	93.3	76.9	90.4	54.5
Registers	39.3	42.7	46.0	39.3
Webcam RGB+Texture	84.1	82.0	92.0	86.2
Webcam RGB	82.3	54.9	74.5	58.9
Webcam Texture	66.8	38.5	63.2	51.4

The results clearly show that flooring material identification is consistently improved when colour features are combined with texture features, in some cases significantly. However the mouse camera complete image proved to be a poor method for texture determination using the GLCM method.

The inability to capture all pixels on one clock cycle simultaneously is thought to be one reason. The material illuminating source spectrum significantly affects the RGB reflected values, as does directionality; therefore testing was carried out under various exaggerated lighting conditions, so that the polluting light totally overwhelmed the localised illumination source, as if there were no shading by the robotic platform. Taking 500 samples, 10 per class, it was found that even when combining sampling taken across different lighting conditions, shown in Table 5.3, the ability to identify uniquely four grades of similar colour sandpaper and seven shades of colour paper remained at 85.2% for the mouse camera and colour sensor method, and 82% for the comparative webcam test. The mouse camera, whose spectral sensitivity sits closely around the 600nm peak [102], was more tolerant of the wavelength shift occurring with the fluorescent lighting test than the colour sensor; the features obtained from the mouse camera significantly improved the overall correct Bayes-1 classification result 19.2%. There are methods, not considered here, for the removal of unwanted lighting; one such mitigating method, utilising five different room layouts, reported a 75% correct room image identification when three different lighting conditions were used [169].

A robotic PWC platform with the sensors mounted beneath; hence partly shaded, was utilised to take extensive sampling, with no background lighting control, across 133 rooms where the flooring was in various conditions of wear. Flooring related to a university campus accommodation and other sites, which used the exact same flooring across many rooms/locations, giving a total of 35 classes of flooring in different states of wear, and varying levels and wavelengths of background illumination were available for testing. In all 59,797 samples were taken across all the rooms from two directions wall to wall. The results in Table 5.2 show that the Bayes-1 classifier identifies 76.9% correctly all classes of flooring using the colour sensor RGB features, and 42.7% correctly the mouse camera

register features, when combined correct identification increases to 85.2%. The 1-NN classifier combined features performed even better at 94.7%. Similar work identifying rooms using images reported home 1 with 3 classes correctly identified 85% and home 2 with 5 classes correctly identified 73% [170]. Other work 96% correctly identified 6 classes of floor surface materials, one example of each, 25 samples in 80:20 training-testing split, by using images in HSV colour space with a random tree classifier [171].

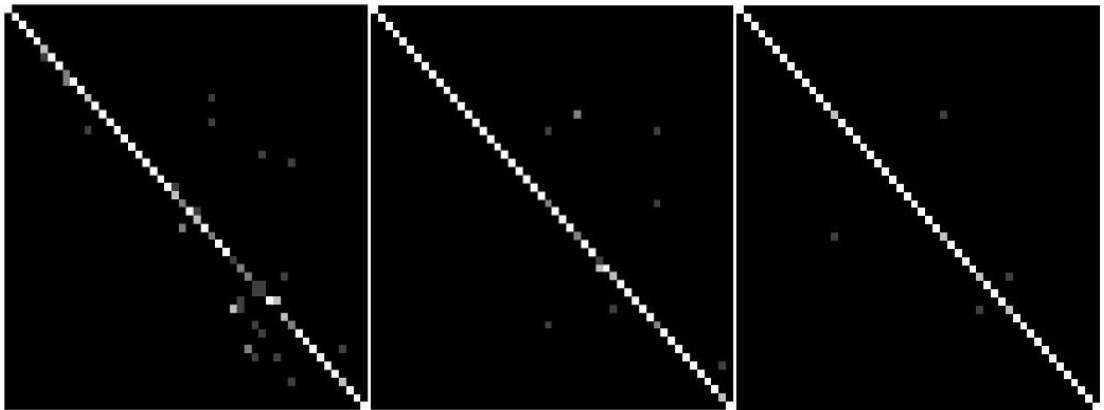


Figure 5.4 (a) LDC webcam colour and texture confusion bitmap

Figure 5.4 b) LDC RGB colour sensor and mouse registers confusion bitmap

Figure 5.4 (c) LDC RGBW colour sensor and mouse registers confusion bitmap

The vertical axes denote the classifier determined label and the horizontal axes denote the true label

The mouse sensor and colour sensor were tested with the platform in motion at various speeds from stationery up to 1m/s with no apparent surface identification performance difference. During the extensive room flooring testing it was found that the various states of wear of identical flooring generated a unique signature, sufficient to differentiate significantly 18 rooms with originally identical flooring 58.4% correctly using the Bayes-Normal-2 classifier. Testing was finalised by running a real-time classifier on a laptop mounted on the wheelchair. In real-time it was possible to detect the moment flooring boundaries were crossed, and when the joins between similar flooring were crossed.

5.2.5 *Experimental conclusions*

The simple features and sensors proposed in this thesis for flooring, and thus room identification, enable rapid processing techniques to be used. Standard pattern recognition techniques have been used in these experimentations which according to other research, when using modest feature sets, can be used for real-time system application [164]. This is a highly desirable requirement for human assistive robotic devices a requirement highlighted earlier in the thesis and repeated throughout.

Room identification through flooring identification comparison is possible to a high degree [151] of accuracy, although the final degree of accuracy is dependent upon the classifier chosen; according to the confusion matrices misidentifications were from similar classes or where flooring was too low in reflectivity. Other localisation methods such as those utilising radio waves or GPS often fail to define the boundaries of the room correctly, and may give a false reading for some considerable range outside of the room [17]. This method detects the moment flooring boundaries are crossed, an important requirement for correcting inertial sensor odometry drift, and our sensor arrangement covers less than 1cm² of floor at any one time, therefore small changes in platform position present entirely new floor area for sampling rather than, as with other methods, a need for significant movement around the room.

These experiments have also shown that from the optical mouse camera useful extractable data—surface quality, maximum pixel, minimum pixel, and average pixel values—can be successfully used as a simple form of surface texture identification, sufficient on its own as a surface identifier; across classifiers and lighting conditions a 19%-52% correct classification rate was obtained. Although not specifically, this and other work suggests that further work could be done with the mouse sensor, having identified the surface from previous known samples, to use this information as feedback for wheel encoder odometry error mitigation and traction control.

When the mouse sensor was combined with the four-pixel colour sensor using RGB colour space it was demonstrated that the combination of features improved the overall correct surface identification when compared with using the individual sensors alone. It was also demonstrated when lighting conditions vary, providing flooring training samples are updated, surface determination is maintained. This would be important in any user-in-the-loop system, when changes occur, such as new lighting or new floor stain: the user would be able to re-train the system by correcting system errors to which they can easily relate, thus creating a semantic symbiosis between user and robotic assistive PWC; this is also an important criterion for detecting waypoints in the next section.

5.3 Junction identification for an assistive PWC

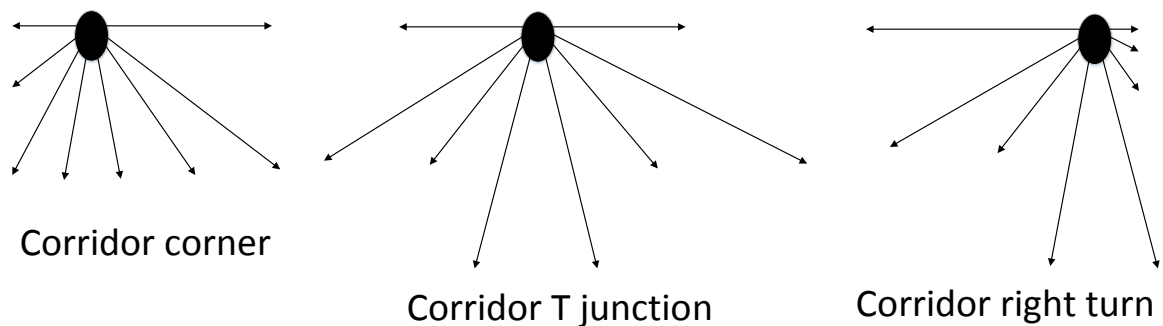


Figure 5.5 Typical patterns for junction determination showing the infrared ranging sensor array as mounted on the PWC test platform

An initial early experimentation was undertaken to determine junctions in a corridor utilising a Weightless Neural Network as a classifier to distinguish between classes of junction. The feature criteria is mentioned at the start of this chapter, the Sharp GP2Y0A710K0F infrared (0.1m-5.0m) distance measuring units, introduced in Chapter 3, which are used for collision avoidance and set out in an array as described in Chapter 4. These are used to determine a distance histogram pattern as the platform moves, an example of how this infrared ranging pattern looks for different waypoints in the real-world is shown in Fig 5.5; the following experimentation describes the method employed, results and conclusion.

5.3.1 *Weightless artificial neural architectures*

WNNs are Neural networks without weights between the inputs and nodes, spurred from initial work by Bledsoe and Browning [172] (1959) on n-tuple pattern recognition systems. These networks use simple binary values instead of the large amount of training and processing needed for a weighted network to converge, thus allowing WNNs to work on more simplistic hardware. WNNs use stored look-up tables while weighted networks use a system of complex weightings. The WNNs possess exceptional pattern recognition abilities, particularly optical character recognition; data can be easily binarised using threshold techniques [110]. Fast simple testing and training employed by WNNs mean efficient implement on hardware; thus ideally suited for application in mobile robotics.

WNN real-time execution successfully demonstrated by Nurmaini et al. [110] detected various obstacles, corners and corridors identified from sonar data with an execution time of 0.25 μ s on an Atmel AT89x55 with 256 bytes of RAM and 24.3 MHz clock speed; however using sonar has limitations due to reflection incidence angle. The system that will be used in this paper is the Generalized Convergent Network (GCN) [173]. The layers in these architectures are independent but connected. The GCN architecture has the following properties:

- A set of layers are created, dimensions of the input matrix match the number of neurons in each layer. If the input matrix is m by n, each layer is made up of mn neurons.
- Each layer has a 'connectivity pattern' which determines which neurons in each layer are connected to which. This pattern is relative to the position of each neuron, which is exclusive to a particular layer, meaning its relative location can be determined within the input matrix.
- Layers are grouped into two main parts within the architecture; 'Pre' and 'Main'.
- A merge operation is executed on those constituent layer outputs from each group; effected on matching positioned neurons within each layer.
- Output from the merge operation is an unaltered input into each layer of Main group.

- Constituent layers of each group vary in the choice of elements committed to the inputs of their constituent neurons; the ‘connectivity pattern’.
- The neurons within a single layer are connected in the same way relative to their location within the parsed code matrix, thus maintaining connectivity.

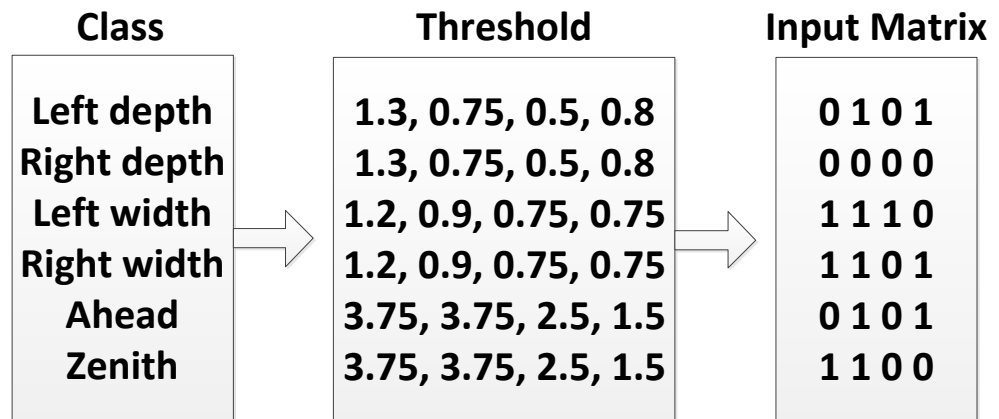


Figure 5.6 Generating the Weightless Neural Network input matrix

WNNs require binary input pattern matrices to process data, with similar distances represented by similar encoded data; therefore sensor measurements require threshold classifying to determine a comparative binary pattern suitable for WNN operation. Several 1.8m wide corridors around a university research department were examined and used to provide sensor data for WNN junction and doorway determination. Measurements of doors, and openings, and corners, and junctions, and standard wheelchairs were used to define pass/no-pass criterion and ease of passage threshold criteria listed in Table. 5.4. These threshold classified results are now placed in a 6x4 binary format suitable to be parsed into an input matrix, shown in Fig. 5.6, comprising five examples of each class for training and 20 testing sets in each of 22 tests. These can now be used by the WNN to determine the best fit in identifying 15 examples of class.

Table 5.4 Classification thresholds

Feature	Boundary/ m			
	1	2	3	4
Left depth	<1.3	<0.75	<0.5	>0.8
Right depth	<1.3	<0.75	<0.5	>0.8
Left width	>1.2	>0.9	≥ 0.75	<0.75
Right width	>1.2	>0.9	≥ 0.75	<0.75
Ahead	≥ 3.75	<3.75	<2.5	<1.5
Zenith	≥ 3.75	<3.75	<2.5	<1.5

5.3.2 Junction detection experiment

Infrared ranging for indoor robotic application removes the incident angle limitation inherent with sonar sensors [109]. Previous work by Nurmani et al. (2009) [110] relied solely on sonar sensors whereas data fusion between infrared and sonar, Flynn (1988) states [109], can remove the negative aspects of each improving the overall result. However; for this experiment we only use infrared ranging sensors as comparative: with their inherent very narrow beam angle allowing sharp edge detection, a potential requisite for better discernibility between clutter, furniture, obstacles, and between building fabric, such as corners and doors.

The assistive PWC platform was taken around the corridors previously described to collect a set of training data and several sets of testing data. The results of the experiment are given in Table 5.5. Doorway crossing was an additional feature that was initially used to determine the passage of the platform through a doorway using the ceiling height change as an additional feature; this was due to having undertaken this experiment before the localisation experiment.

Table 5.5 Door and junction detection classification and WNN results

	WNN architecture									
	1		2		3		4		5	
	Percentage class identification and sample quantity									
<i>Class</i>	<i>%</i>	<i>Qty</i>	<i>%</i>	<i>Qty</i>	<i>%</i>	<i>Qty</i>	<i>%</i>	<i>Qty</i>	<i>%</i>	<i>Qty</i>
Dead end slow	82.5	61	94.1	17	94.6	56	57.3	24	85.9	64
Dead end stop	100	6	100	6	100	6	100	6	100	6
Left turn caution	100	17	89.6	13	81.1	10	82.8	4	100	10
Left turn clear	100	13	100	17	92.7	17	100	19	100	15
Left turn door	100	1	100	1	0	0	0	0	100	1
Open corridor	100	243	100	257	99.2	227	91.8	248	100	222
Right corner caution	100	2	78.8	4	77	4	100	1	100	3
Right corner clear	100	9	98.4	9	98.7	7	100	9	100	8
Right corner door	100	2	80.7	3	81.5	2	100	3	100	2
Right turn caution	100	9	100	8	80.8	9	100	7	100	8
Right turn clear	100	15	99.2	17	93.8	15	100	15	100	15
Right turn door	100	5	100	8	49	3	100	2	100	4
T-junction	0	0	0	0	100	2	0	0	25	2
Door crossing	92.1	19	90	20	11.4	44	96.8	19	100	28
No door crossing	100	41	100	40	100	16	100	41	100	32
Total	91.8	443	88.7	420	77.3	418	81.9	398	94.1	420

5.3.3 *Experimental conclusions and discussions*

When comparing the results with a similar experiment, Nurmani et al. (2009) [110] reported 94% for classification and 95% for identification. However in this experiment class detection was achieved using three infrared sensors compared with eight sonar sensors and their classification consisted of nine classes compared to 15 (out of a possible 18) detected on this typical real-world representation. Additionally infrared does not suffer with excessive crosstalk, and noise limited range, which they reported occurred when using sonar. Furthermore their reported detection range was less than 0.4m compared to >1.5m obtained in this experiment.

5.4 Doorway approach angle identification for an assistive PWC

The doorway passing wheelchair problem may be considered a ‘peg-through-the-hole’ problem, where depth of the hole provides information for alignment purposes [174]. Depth in this case is minimal and therefore alignment difficult. Different algorithms and sensors may be used for general obstacle avoidance and user feedback than those imposed, harder constraints, required for doorway passing; thus doorway identification becomes a crucial issue.

Users may well not think they need assistance [7], thus early doorway detection offers real-time user trajectory correction feedback. This would improve orthogonal line-up and would thus maximise clearance between doorway and the wheelchair, leading to collision elimination. Additionally, if required, users could initiate an automated doorway passing system if they felt in need of assistance. These are all considerations identified earlier in this and previous chapters of this thesis as requirements for a human-in-the-loop assistive PWC.

5.4.1 *Sensor choice and methodology*

A suitable sensor arrangement must also be identified for doorway identification. Feature identification using geometric ranging information has been covered previously in the literature [111, 175-177]. Sonar has been used to detect corners and junctions [110], and doorways [176] although in this case detection was based upon wall-following/corridor methods as the robot passed the doorway rather than approaching from deep inside rooms.

Other sensors employed, such as the scanning laser, have succeeded [178] in locating doorways geometrically and generating trajectories. However laser scanning sensors require time to scan and are currently expensive and bulky. The infrared Sharp GP2Y0A710K0F ranging sensor is relatively inexpensive and has a maximum 5m range; these types of sensors have been used previously for statistical pattern recognition [111] and also in the previous section. Therefore in line with the introduction at the beginning of the chapter and the requirements described in earlier chapters the same oval-like sensor arrangement as used in the earlier junction detecting experiment and in the previous obstacle avoidance chapter will be employed to detect the doorway approach angle in this experiment.

5.4.2 *Doorway features and classification*

In order to provide a fast response system, after initial experimentation, binning from the ranging sensors was chosen as the features set using high resolution raw data (mm) initially, and then lower resolution raw data (cm), and finally a constrained binning where we simply take the difference between the highest range value and others to give an effective door shape dependent on platform rotation and translation with respect to the doorway. 1-nearest-neighbor (K-NN), Bayes-Normal-1, Bayes-Normal-2 and Naive Bayes classifiers were employed to test the doorway and approach position identification.

The experiment in this section uses a different classifier. Real-time consideration is paramount to any assistive system functioning well and similar pattern recognition work has been undertaken on embedded systems using online classifiers. Starzacher evaluated these processes [164] and found that using the K-NN classifier took 200 times longer than Bayes-Normal-2, which is often much faster than neural networks, the Bayes statistical classifiers were capable of running similar pattern recognition tasks in the microsecond range on a dual core 1500MHz 2GB RAM Microspace EBX (MSEBX945) small computer format board with 2000 sample training set and 100 features.

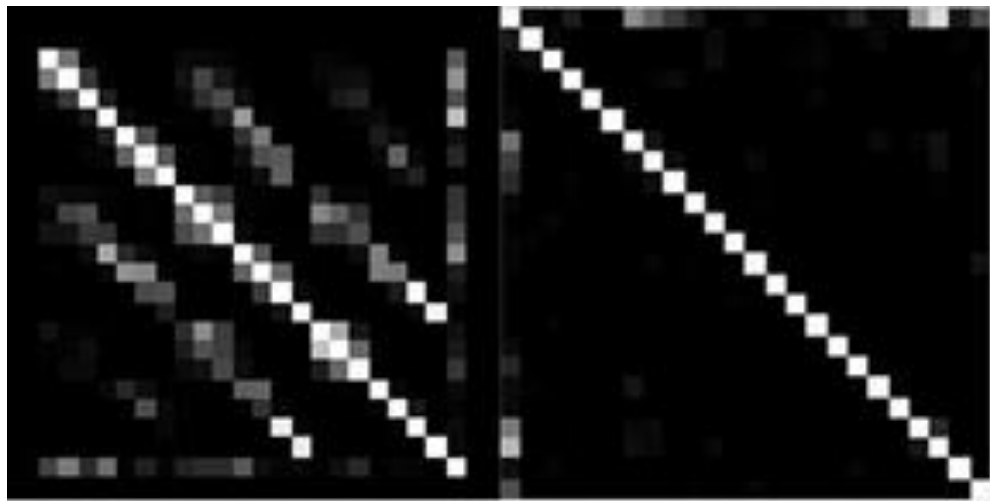
Table 5.6 Initial doorway testing

Feature tested	Percentage of correctly identified samples			
	<i>1-NN</i>	<i>Bayes-Normal-1</i>	<i>Bayes-Normal-2</i>	<i>Naive Bayes</i>
Left inward opening door				
7 approach angles	93.2	54.6	76.3	66.4
Non-doorway	93.6	63.7	79.4	58.5
Opening only no door				
7 approach angles	92.4	58.9	49.3	67.9
Non-doorway	94.0	67.4	47.0	66.4
Right inward opening door				
7 approach angles	94.9	70.8	58.4	83.8
Non-doorway	96.4	73.8	40.4	78.9
All three door openings				
Identify all 21 individual approach angles	87.0	39.8	26.7	46.9
Identify all 21 approach angles as doorway class v non-doorway	96.8	80.5	88.8	78.3

5.4.3 Doorway approach angle results and discussion

A room with multiple doorway configurations and a flat suitable for wheelchair user occupation together with several other typical office-like-rooms were tested for doorway profile and approach angle identification. Data were collected in real-time doorway approaches and rooms were thoroughly scanned for comparison. Re-testing was randomly undertaken at a later time confirming the results were consistent and true.

A standard doorway in a large cluttered room with three possible door openings was initially tested. Seven approach angles were used [-45, -30, -15, 0, 15, 30, 45 degrees] with respect to the doorway midpoint (2600 samples average) and the room extensively sampled (>18000) the data being split 60:40 (other ratios were examined without significant change) for training and testing respectively; ranging data was smoothed with mm resolution and sampled >200/s. According to the results listed in Table 5.6, the 1-NN classifier clearly outperforms the others with respect to identification of individual approach angles where consistency was lacking.



*Figure.5.7 (a) 1-NN Classifier
Confusion Bitmap Matrix for the
initial doorway testing*

*Figure.5.7 (b) 1-NN Classifier
Confusion Bitmap Matrix for various
doorways and approach angles*

*Axes are true label top left to bottom left (ordered) and determined label top left to top right,
white intensity represents sample count identified proportionally*

When all three door openings were combined, same doorway same room, the confusion matrix shown as a bitmap in Fig. 5.7a clearly indicates confusion between the three door-openings, thus implying the free space or surrounding shape is a more prominently distinctive feature than the door itself. Confusion with the room is minimal and indeed all classifiers performed well in this respect: the Bayesian classifiers, all door orientations combined, show significant improvement over individual door positions, re-enforcing the door opening or hole as the prominent feature, where poor statistical performance indicates a required feature separation improvement.

$$\bar{K} = K_{max} - K_i \quad \text{where } \left\{ \begin{array}{l} i = 1,2,3 \dots n \\ K_{max} = \max < K_i \end{array} \right\} \quad (5.1)$$

The feature set was improved by using a range histogram by taking the maximum range from all the sensors and subtracting their values from that to give a distinctive shape representative of the geometric door and opening (Eqn. 5.1).

This new pattern was tested using a standard door opening, with one correct angular and three correct translation approaches, and eight other incorrect angular approaches together with 10 incorrect translational approaches, all approaches were within a 2.5m range from and 2m width zone immediately in front of the door opening. Angular range was -35° to -15° , -15° to -5° , -5° to 5° , 5° to 15° and 15° to 35° offset such that each translation and the offset angles occupied a geometric area 30cm by 40cm each of the other angles represented a slice segmented every 40cm.

Table 5.7 Doorway approach angle and displacement

Feature tested	Percentage of correctly identified samples			
	<i>1-NN Classifier</i>	<i>Bayes-Normal-1</i>	<i>Bayes-Normal-2</i>	<i>Naive Bayes</i>
Approach positions/angles	86.6	51.7	72.7	62.6

All 22 positions and angles were tested against each other in a 60:40 training/testing split and four random re-tests at some other time consistently confirming correct labelling. These results in Table 5.7 show that each rotation and translation can be identified by 1-NN at 87% and by Bayes-Normal-2 at 73% correctly; the confusion matrix importantly determined that all of the errors were adjacent

zones. An average 3,000 samples were used for training and testing and for each of the 22 positions/angles.

Table 5.8 Various doorway(s) and approach angles combined

Feature tested	Percentage of correctly identified samples			
	<i>1-NN Classifier</i>	<i>Bayes-Normal-1</i>	<i>Bayes-Normal-2</i>	<i>Naive Bayes</i>
Approach positions/angles	96.3	67.8	85.0	66.8

Finally testing of the method involved driving the wheelchair around a series of six rooms and through each of the six doorways at 3-4 different angles. It was found possible to determine the unique identification of individual doorway trajectory when compared to each and all others and to all of the rooms given in Table 5.8. Very little confusion occurred, as shown in Fig.5.7b. Occasionally some trajectory samples were misidentified as room although they tended to be those at longer range. An average 1,000 samples for each approach angle and 6,500 samples for each room giving a 62,000 total sample size and the geometric pattern with eight features were employed.

Previous work has commonly used histogram grid map comparison. One such work combined sonar, image and digital infrared (fixed distance threshold not analogue as we have used) [175], identifying 24 features, compared to our eight, from all three sensor grid maps, and they achieved a 98% door recognition rate up to 2m into the room using a computationally more expensive 3-NN classifier, which is similar to our result of 96% from a 1-NN classifier. Other work when looking for door openings (the gap) rather than the profile [179], using laser scanning and Scale Invariant Feature Transform identifying objects from imagery, noted some false positives from the doorway detection, although a 93% to 97% trajectory correct classification success rate, whilst not directly and intentionally assessing doorway approach trajectories as we have done. However they note the process is

significantly slow and requires a 360-degree scanning laser and a camera adding complexity, cost, and vulnerability and, hence, being unsuitable for a real-time human interactive system.

5.5 Localisation and waypoint conclusions for assistive PWC

The methods presented in this chapter allow an assistive human-in-the-loop system the potential real-time ability to provide an intuitive and semantic response to the human dynamic world when identifying rooms and approaches to waypoints such as doorways as identified as a need in earlier chapters. This research has shown that rooms can now be labelled and described with human terms such as bedroom, bathroom, and kitchen, and approaches to waypoints and doorways can be simplified to phrases such as ‘too far to the left’ when giving feedback to the user.

It has also been shown that pattern recognition of doorway approach angles using simple low-cost ranging sensors, which would also be used for collision avoidance, can be easily utilised for the purpose of assisting users by identifying a potential mismatch in their approach angle and offer that user some form of corrective assistance by either informing them visually/aurally of the need for course correction or providing a suitable trajectory steering assistance if the user so desires. This research provides a unique solution to identifying bad approaches to doorways in a potential real-time system to warn users and prepare the system for a request to generate a doorway passing trajectory for example the problem of real-time localisation and waypoint identification described in Chapter 1.

Door openings have another component, the door, which makes detection difficult. In real situations however, most doors, when considering wheelchair users, either open automatically to a set point, or in the home, may be removed and, where not, would most likely be propped open when human assistance is unavailable. Therefore, utilising a pattern-recognition trained system; various doorway configurations can be stored. Pattern recognition systems can be easily trained in the field with unique locations and users; re-training if conditions change, such as door prop angles, or furniture location change, or clutter build-up, particularly in the case of sensor wear and mechanical misalignment.

The floor method for room localisation can be combined with the waypoint or doorway method in a combined voting way to introduce more robustness into the real-time system such that the user can be confident that the feedback warnings given by the system in the control architecture presented in Chapter 3 are reliable. For example the room localisation might identify the room as the lounge and when the user approaches the doorway the approach might also be recognised as the lounge doorway therefore the system becomes highly confident (removing confusion on doorway approach seen in Fig 5.7) that if the user requires assistance to pass the doorway then the assistive trajectory level in the control architecture (introduced in Chapter 3) can generate a door-passing trajectory (Chapter 6) to assist the user with negotiating the doorway. If the system is not confident then the false readings and changes in the dynamic environment can be used by the human in the loop to update the system by ‘supervising’ the re-training of the stored patterns.

The research presented in this chapter has contributed to the art and has answered the requirements for a human-in-the-loop assistive PWC system identified in earlier chapters and re-presented at the beginning of this chapter. They are summarised and answered as follows:

- re-use information from other sensors if possible
 - ranging sensor data has been re-used

- sensors should be robust and low cost
 - a very inexpensive colour sensor and mouse camera were used
- sensors should not rely upon time-consuming scanning
 - all sensors employed in the data collection were non-scanning
- data from sensors should require minimal processing
 - histogram-like features were used for waypoint identification
 - raw sensor feature data was used for floor identification
- features should be compatible with human methods of recognition
 - the waypoint pattern histogram represents a human-like pattern
 - floor identification was based upon the similar human colour and texture pattern identification method
- features need to be stable and non-changing for long time spans
 - flooring tends to be colour-fast and hard-wearing
- feature representation needs to be suitable for fast classification for real-time operation

Furthermore it can be said:

- the patterns used for classification are intuitively compatible with human thinking (I am in the hall with the dark wood floor and there is a T-junction at the end of the corridor)
- the standard classification techniques which are used can operate in the real-time realm
- the methods comply with the requirement for feedback to the human in the loop to be semantic; too far left, lounge, left turn ahead, and not possible to pass doorway

This chapter has provided the necessary research and solutions to provide the feedback in the control architecture, presented in Chapter 3, for the human in the loop and for the higher levels in the architecture. The key point of this level is to provide information for the lower levels. The obstacle avoidance level can be adjusted by identification of the specific waypoint, location, or junction; for example having identified that the platform is in a wide corridor the obstacle avoidance localised repulsive potential force field can be adjusted to keep to the left-hand side, or pass through a narrow passage, or doorway. This level also provides information which allows the trajectory level presented in Chapter 6 to provide geometric paths for '*steering*' assistance in manoeuvring through doorways or waypoints.

One interesting result of this research was to determine early that WNN classifier architectures were not necessary for the identification of rooms and waypoints, simpler statistical classifiers were sufficiently accurate which can be processed much quicker and therefore more suited to real-time application. It should also be noted that the WNN research component does not represent any contribution to this thesis.

The next chapter uses the waypoint and the approach angle identification developed in this chapter to provide a trajectory for better alignment with a doorway, an issue identified early in the literature search and reviewed in Chapter 2. A novel assistive steering trajectory enables the user to control their motion whilst the system provides the steering, thereby keeping the user in control of motion of the assistive PWC, a major issue identified by Nisbet [5]. Final doorway and waypoint approach misalignments are taken care of by the control architecture lower-level collision avoidance, this has been shown in Chapter 4 to correct approach angle errors up to $\pi/4$ radians.

Chapter 6

Assistive trajectories

Chapter 6 presents unique assistive trajectories, which can be generated when the localisation and waypoint identification layer, developed in the previous chapter, and the path planning layer of the assistive control architecture presented in Chapter 3, has detected and identified and warned the user, that the approach angle to a waypoint or doorway is incorrect. This chapter starts by defining the requirements for developing the assistive trajectories and then introduces the rationale in the first section. The chapter then moves on to describe the development of the trajectories for a non-holonomic PWC platform.

The dimensions of the PWC and other mobility devices are known prior to operation and remain fixed during use. Following on from Chapter 4 where it was stated that the modelling presented in this thesis would be generically suited to both differential drive steering and car-like steering in the case of the assistive steering trajectory, the same is applied in this chapter. The heading angle has been bounded between $\pi/4 > \theta > -\pi/4$. This allows any assistive trajectories to be within a safe range of steering, if the steering angle is greater than this on the differential drive PWC one of the wheels starts to rotate backwards as can be seen if Eqn 4.1 and Eqn 4.3 are examined.

The control architecture presented earlier in Chapter 3 of the thesis describes the user interaction with the system as being the definitive decision-maker therefore these steering assistance trajectories,

generated by the system, leave the user in full control of the velocity and motion along that assistive trajectory. Having regard to previous research and working closely with clinicians and user groups during the research undertaken in this thesis, a clear issue of safety has been identified which has been solved by this research. Namely, that the method presented in this chapter uniquely allows the motion of the platform to be terminated at any time if some safety issue arises, which is actioned by the user ceasing to provide a positive input to the system. In other words the platform only moves if the user gives the command, and at the rate the user also commands. This is usually by an analogue proportional joystick human-machine-interface, although a digital interface can be accommodated by appropriately pre-setting the values and boundaries to those with which the user feels comfortable.

The collision avoidance layer remains active beneath this layer, having shaped the repulsive elliptical zones described in Chapter 4 according to the waypoint identified by the localisation and waypoint identification layer using the novel methods presented in Chapter 5, such that any small errors and dynamic interruptions can be dealt with. Furthermore in keeping with the re-use of sensor data identified in Chapter 3, the free space available to the platform around the waypoint can also be easily obtained from the collision avoidance ranging sensors; thus an actionable trajectory can be generated.

6.1 Waypoint alignment assistance requirement

PWC users may become tired, disorientated, or have severe time-varying motor reflex abilities, as identified in the background research. Therefore all assistive mobile robotic systems will need to provide at some time, frequent or infrequent, some form of manoeuvring assistance above that of obstacle avoidance. This manoeuvring assistance will in all likelihood involve passing through a doorway or entering a very confined box such as a lift. These problems are well known in the field of robotics and are termed ‘peg-in-hole’ [174, 180]; which in the case of mobile robotics have additionally a peg-through-the-hole need. The mobile robotic problem may appear to be somewhat

simplified by the reduction to two dimensions however the non-holonomic nature of the PWC platform significantly complicates any solution, particularly when that solution has the human in the loop. The nature of the problem was identified in Chapter 2, and several solutions tried [23-26].

The assistive trajectory layer in the new human-in-the-loop control architecture presented earlier runs independently in the background. The novel localisation and waypoint layer described earlier in Chapter 5 is able to determine exactly where the platform is and what waypoint it is approaching. Additionally supporting this thesis, doorway approach angles were also determined from the same data; fulfilling a criterion for the assistive PWC determined earlier. Having identified where and what, this information is passed down to the planning level in the assistive architecture. It is proposed in the planning level that some human-machine semantic exchange would take place, and some agreed trajectory would be decided upon. This might be the system confirming with the user that it has identified where it is (lounge) and understands where the user has asked it to go (bathroom), in this case the path would be longer, consisting of a chain of smaller trajectories such as those presented in this chapter.

The typical user scenario might be: that the user has fatigued to a point where they are unable to use the obstacle avoidance level; the user may have approached the doorway too far to one side or at an angle that physically prohibits the passage of the platform such as shown in Fig 6.1, the user then requires the system to generate a short trajectory to assist them to steer a more appropriate approach path through the waypoint.

There will no doubt be errors of measurement and dynamic changes to the environment; however referring back to the control architecture presented in Chapter 3 this assistive trajectory layer provides a top-down input to the collision avoidance layer which will then reactively alter the assistive trajectory trajectories.

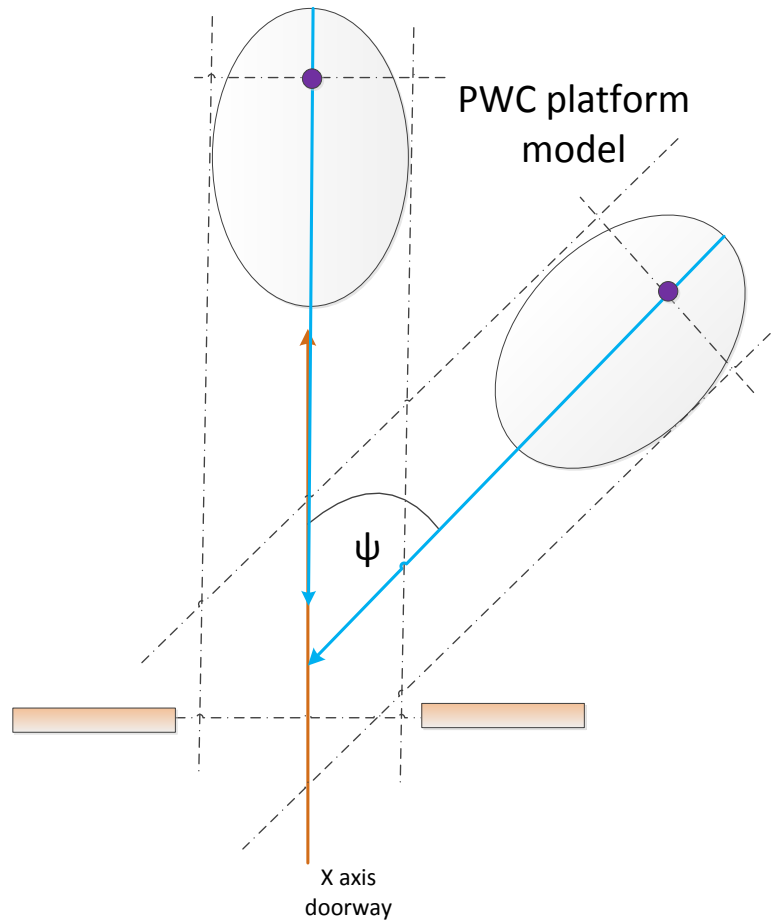


Figure 6.1 Doorway approach angle too great for platform to pass using Chapter 4 collision-avoidance method

6.2 The non-holonomic problem and peg through the hole

The non-holonomic mobile robotic doorway passing problem can be simply expressed in a two-dimensional plane as proper approach angle alignment. This is the key to collision-free passage. We can take the doorway as an opening in a wall which is in the same plane. Thus the doorway opening becomes the target frame of reference, and we are required to align the platform frame of reference so as to pass through the doorway such that the X body and X doorway axis are aligned and both Y axes are orthogonal to that line. It can be seen from Fig 6.1 that as the approach angle to the doorway, ψ , moves away from zero, the width of the platform soon becomes unable to pass through the doorway.

Therefore the problem of proper alignment becomes one of generating a suitable trajectory which takes into account the kinematics and dynamics of the platform. If we compare the peg through the hole scenario of Fig 6.1 and the peg-in-the-hole shown in Fig 6.2 it can be seen that the solution to both problems for the non-holonomic trajectory are the same, and that a human intuitive solution might be similar to either form of trajectory shown in Fig 6.2.

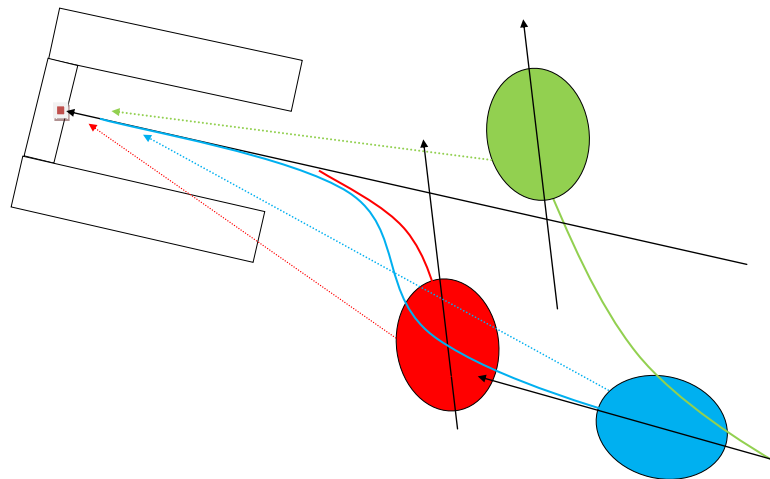


Figure 6.2 Non-holonomic platform alignment trajectories for parking in a box

In this chapter, the thesis argues that the solution to the non-holonomic doorway passing and the box parking are essentially the same proper approach alignment problems, and that there are two types of short assistive trajectories which are human-like, intuitive, and smoothly solve all rotational and translational requirements. They can be described as cornering or turning, and overtaking or slalom like lane change, as explored by Nelson in 1989 [181].

This thesis has assumed that the assistive mobile platform is fundamentally treated as car or bicycle like and therefore a similar trajectory is required. Jacobs and Canny [182] used circular curves to smooth a path-planning derived trajectory, Scheuer and Xie [183] used optimised continuous curves to join short paths, lines and clothoids, for car-like non-holonomic mobile robots. Liang et al. described a flexible trajectory using maximal-curvature cubic spiral [184].

6.3 Modelling the non-holonomic problem

Despite previous research a fresh approach was deemed necessary to better represent a human-like steering trajectory. Having assumed the kinematics of the steering are bound $\pi/4 > \theta > -\pi/4$ it is now assumed that the problem of proper alignment with regard to doorway passing and box or lift entering is a single problem solved by two types of trajectory. In order to develop a mathematical geometry describing these two trajectories significant observations were made of wheelchairs, cars, and mobility scooters manoeuvring into and out of boxed parking spaces with minimal clearance between vehicle and box. PWC user groups and clinicians who prescribe PWCs also contributed to assist with the understanding of the problem. A brief summary of that development follows.

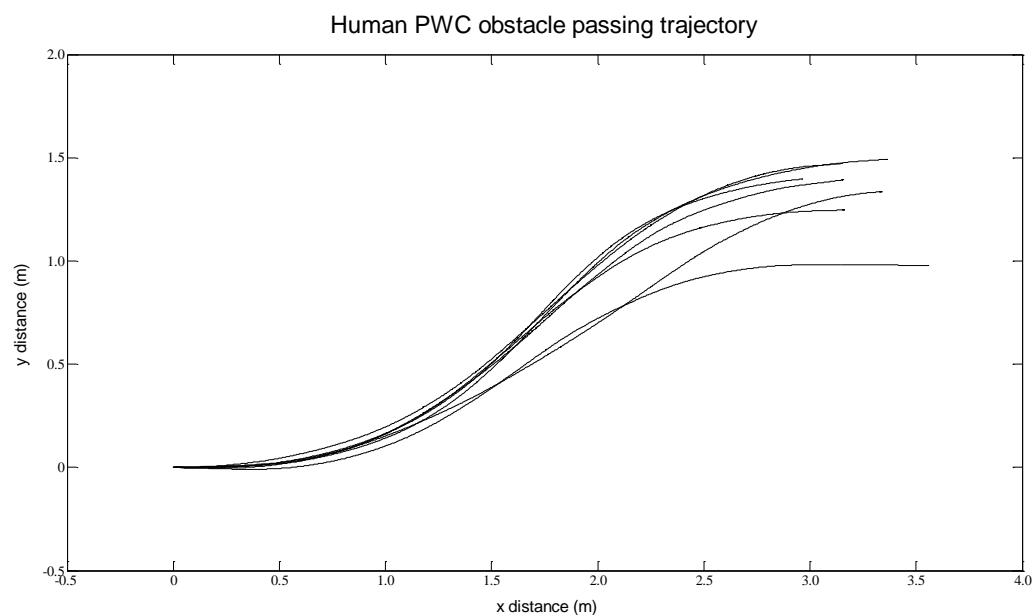


Figure 6.3 Human slalom PWC trajectories

The slalom, or lane change, was investigated first. A PWC fitted with wheel encoders, to measure the positional change of the platform, was employed to examine the typical human trajectory and Fig 6.3 shows seven of those human slalom trajectories. The PWC platform started at the same position each time and was driven along a straight corridor with the user moving out to pass around an obstacle located to the right side of the platform.

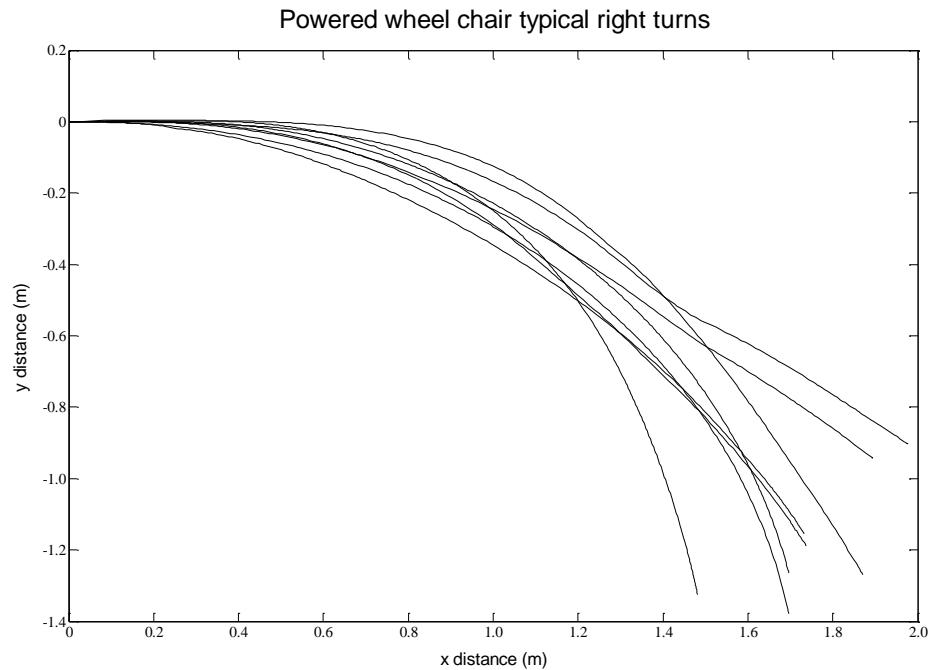


Figure 6.4 Human turn PWC trajectories

The next test examined the nature of a human right turn; eight examples are shown in Fig 6.4, and a typical corridor right turn corner was used. The slalom and turn experiments were undertaken by a non-disabled experienced operator of a PWC. The user of a PWC may have brain injury or some other physical disability and therefore each user will have some bias to their driving trajectory, in particular there will be a considerable difference between each trajectory collected from the same person therefore obtaining data of the average human trajectory would require extensive and exhaustive sampling. The example trajectories shown in Figs 6.3 and 6.4 have been assumed to be a reasonable representation for the purpose of the research in this thesis.

To provide an intuitive assistive trajectory, a mathematical function needs to be developed which closely represents that of the human PWC trajectory. After simulating several functions which resemble a slalom trajectory, shown in Fig 6.5, and then comparing these to the human slalom trajectories, thin black lines, it was determined that a best fit would be an exponential function which is shown in Fig 6.6 as the thick blue line.

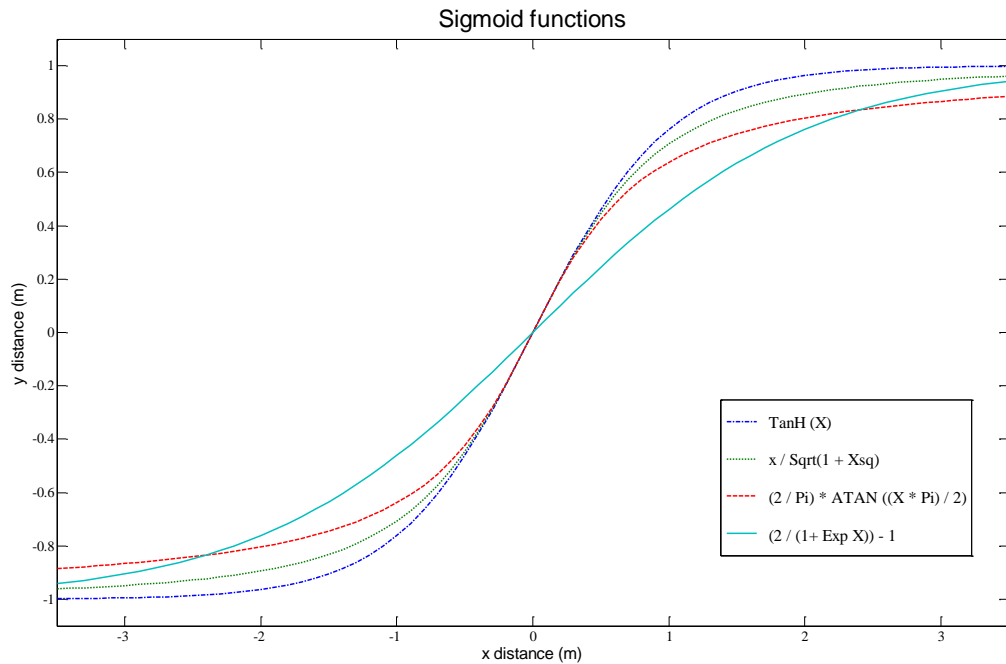


Figure 6.5 Several types of sigmoid functions

Having found a reasonable fit the next step was to develop the actual adjustable function required for any slalom; however before this, a function needed to be found for a turn. It was initially thought that a circular or elliptical path could be used; however after considerable experimentation and simulation, and a revisit to the human turn trajectory, it was realised that a human turn was not necessarily an orthogonal one. An exponential function, with the function shown in the inset box plotted as a thick blue line, was compared with the human trajectories, thin black lines, and shown in Fig 6.7. The function appeared to be a good fit. Having determined from previous research that harmonic functions can provide smooth interruptions to trajectories [185-187] the natural exponential function was deemed to be a good starting-point for the development of assistive trajectories, which would be highly compatible [185-187] with the exponential collision avoidance method in Chapter 4.

The next step was to determine the exact exponential functions that could be used and how they could be adjustable to negotiate specific turns and slaloms. Both of these trajectories can be used to negotiate waypoints, in particular doorway passing, in a similar fashion as shown in Fig 6.2.

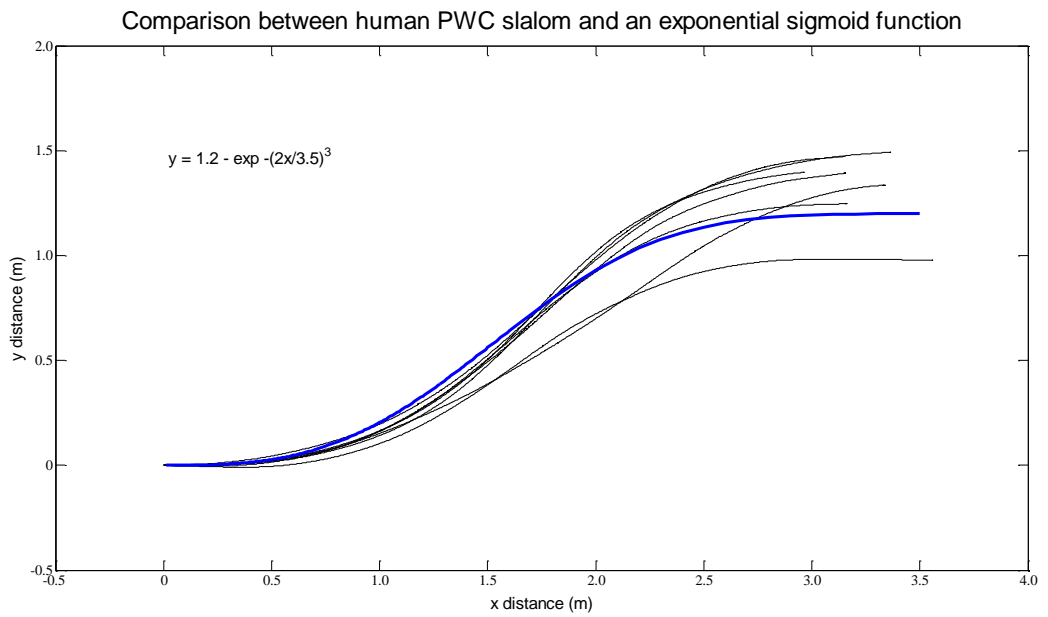


Figure 6.6 Exponential sigmoid compared with human trajectories

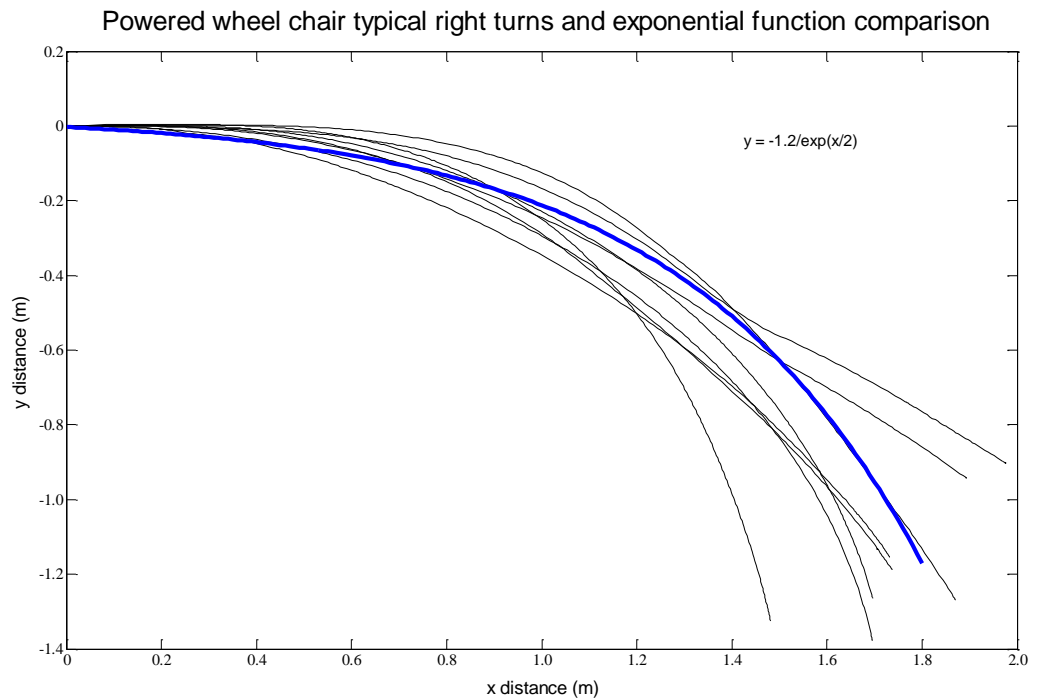


Figure 6.7 Exponential curve compared with human turn trajectories

Starting with the basic exponential equations a series of simulations were run each with different configurations and the most suitable adjustable trajectories have been developed which best fit the human trajectory:

$$f_y = y_d * (1 - \exp(-(2x_t/x_d)^3)) \dots \dots \dots (6.1)$$

$$f_y = y_d - \left(\frac{y_d}{\exp(\pi x_t/x_d)} \right) \dots \dots \dots (6.2)$$

Where (6.1) represents a slalom manoeuvre, (6.2) a turn and:

- f_y is the y real-world displacement in the body reference frame at some time
- y_d is the required y real-world displacement distance in the body reference frame
- x_d is the required x real-world displacement distance in the body reference frame
- x_t is the x real-world displacement in the body reference frame at some time

The turn exponential trajectory similarity to the human trajectory is limited to angles of ψ between:

$$\begin{cases} \pi/9 < \psi < 2\pi/5 \\ -\pi/9 > \psi > -2\pi/5 \end{cases} \dots \dots \dots (6.3)$$

If maps were to be avoided these trajectories needed to function in the body frame of reference, the development was then concentrated on short assistive trajectories which would help the user negotiate an immediate waypoint in front of them, and these algorithms are most suited to this.

6.3.1 Kinematic constraint on the trajectory

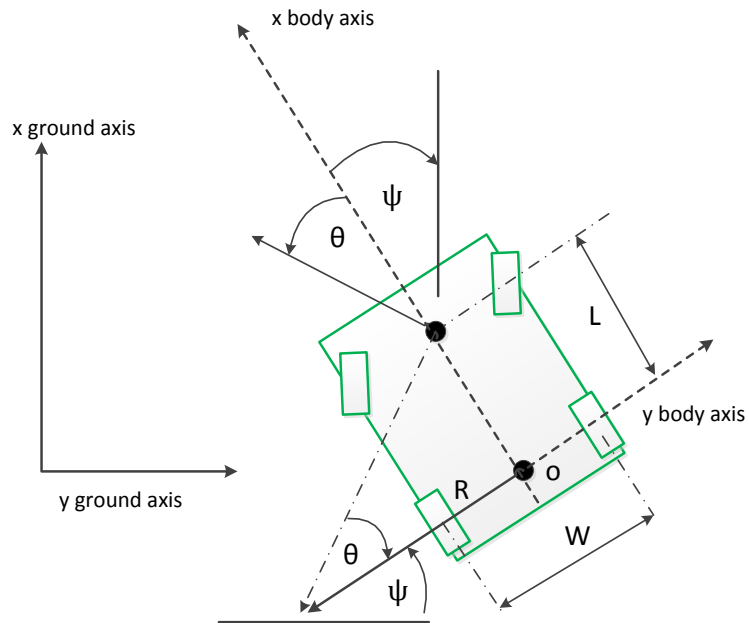


Figure 6.8 PWC platform frame of reference and kinematic

Having stated previously, and throughout this thesis, that for any assistive trajectory the differential drive wheel steered PWC heading angle θ and the car-like single drive motor mechanically steered platform heading angle α should be between $\pi/4 > \theta > -\pi/4$, outside this the collision avoidance method in Chapter 4 should be employed for the PWC. The path that the two types of platform generated can be said to be a function of the wheelbase length L and width W shown in Fig 6.8 which gives a curve transcribed by the origin $f1$ of the platform coordinates according to the radius R at some time.

Therefore taking our boundary conditions as the minimum turning radius of the platform and considering that platform kinematic is described by:

$$\tan \theta = \frac{L}{R} \dots \dots \dots (6.4)$$

Where R could be used to generate a curved trajectory for the platform to follow; however there is the additional problem of the platform width. Therefore if we refer to the platform model developed in Chapter 4, shown in Figs 4.5 and 4.6, the dimension p needs to be added:

$$R_{\min} = \left(\frac{L}{\tan \pi/4} \right) + p \dots\dots\dots (6.5)$$

It has been argued previously that these circular trajectories do not represent intuitive and smooth human-like trajectories. However minimum R can be used to provide a boundary to the trajectory Eqns 6.1 and 6.2. This is required to establish whether there is a real trajectory solution. Therefore the absolute minimum free space requirement in x and y world coordinates can be determined for turning as:

$$y_{\min} = x_{\min} = B + R_{\min} \dots\dots\dots (6.6)$$

And for slalom trajectories as:

$$y_{\min} = 2B + R_{\min} \dots\dots\dots (6.7)$$

$$x_{\min} = 2A + 2R_{\min} \dots\dots\dots (6.8)$$

Where:

A and B, shown in Fig 4.5, are the elliptical dimensions of the novel dynamic collision-avoidance model in Chapter 4.

6.3.2 Doorway frame of reference

The new assistive trajectories presented in section 6.3 have been developed to act in the body frame of reference; however in order to define the trajectory workspace the waypoint frame of reference with respect to the body frame of reference needs to be developed. For the purpose of solving the problem of doorway passing, or lift entering, in this thesis the doorway frame of reference will be defined as in Fig 6.9, although other waypoints and junctions could be similarly represented.

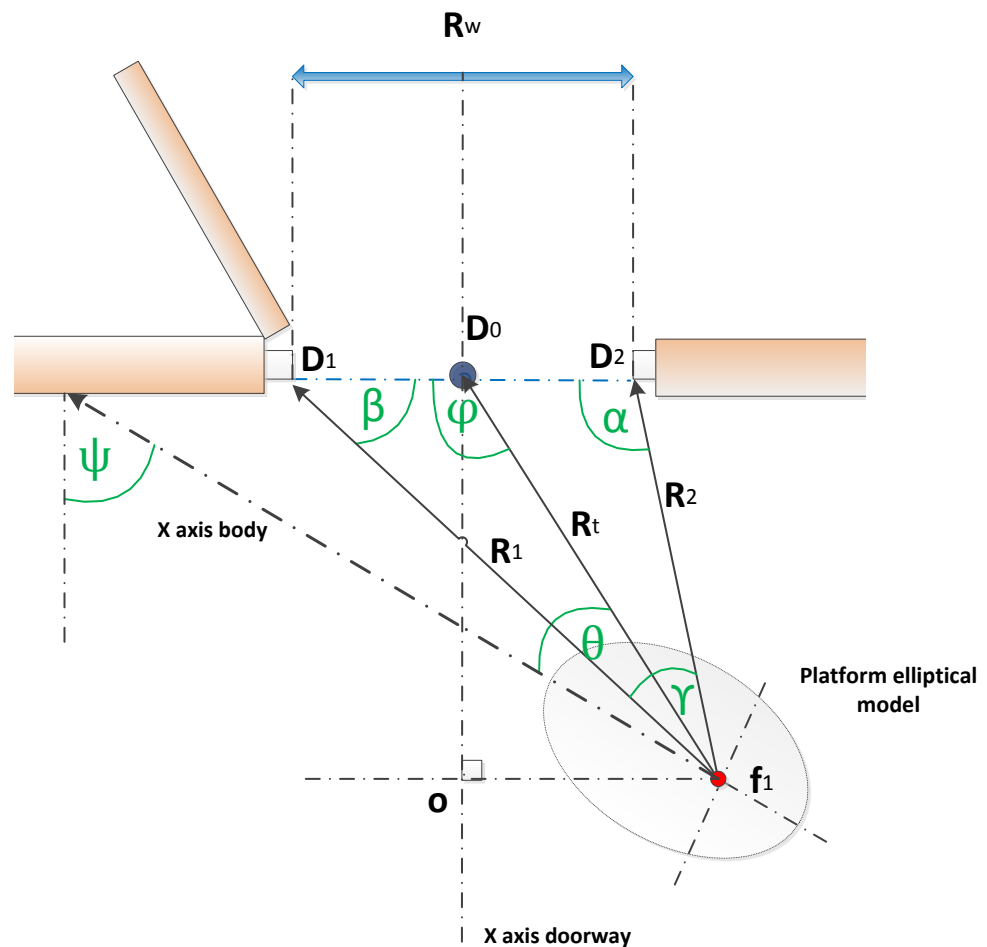


Figure 6.9 Doorways coordinate reference frame with respect to the innovative platform body frame of reference presented in Chapter 4

A method of determining the approach angle to doorways was presented in Chapter 5 for warning users that they may need to make adjustments to their trajectory. However there will be occasions when the user of the assistive PWC will find that they were unable to make that correction due to

illness or have misjudged the approach due to fatigue. For example the approach angle to the doorway ψ may be so great that the platform width $2B$ (Chapter 4) will not pass through such as is depicted in Fig 6.1.

The doorway frame of reference, Fig 6.9, origin is represented by $D0$ such that the line $D1 - D2$ represents the y doorway axis with the x doorway axis orthogonal and the platform axis origin is at $f1$ with the x body axis annotated and the y body axis orthogonal. R_w is the doorway width along the y doorway axis with the middle of the doorway aligned to $D0$. The platform heading angle to doorway y axis is shown as ψ and the origin of the doorway $D0$ is given by θ and R_t is the distance between the doorway frame of reference origin and the platform frame of reference origin.

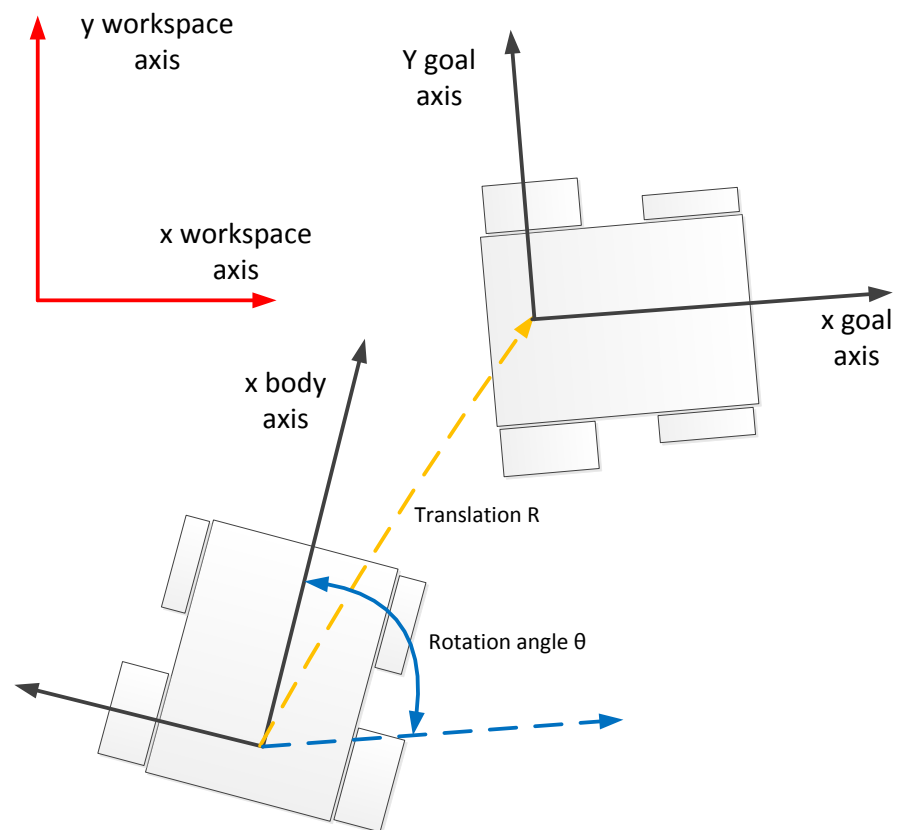


Figure 6.10 Developing a workspace in which the platform body reference frame can be related to the waypoint frame of reference

6.3.3 *Determining the workspace*

In order to determine how the trajectory equations can be applied, the workspace first needs to be defined. In mobile robotics the platform pose [107] is considered the rotational orientation of the platform reference frame with respect to the real-world reference frame. This can have considerable error attached to the estimation [107] although in the case of the indoor assistive PWC platform the fabric of the building provides a simple geometric identity for waypoints, as proven in the previous chapter. The obstacles and building fabric allowed the assistive PWC to use real-time reactive collision avoidance, developed in Chapter 4, to navigate the indoor environment successfully.

Having identified that the indoor assistive PWC has a much simpler navigation requirement, one without maps, then combining the waypoint frame of reference, Fig 6.9, with that of the platform, Fig 6.8, can be said to be simplified to the task of taking the current platform rotation θ and the translation R position with respect to the waypoint frame of reference and suitably aligning the two as shown in Fig 6.10 such that the platform is able to move along a trajectory which is compliant with the kinematic constraints.

To generate a trajectory the free floor space around the doorway must be determined. This may be obtained through use of the obstacle detection sensors, such as the method for waypoint identification in Chapter 5, and is assumed to be dealt with elsewhere for this thesis. It has been previously stated that doorway approach angles can be determined by various pattern recognition techniques, in Chapter 5. However for the purpose of re-enforcing the argument in this thesis a more traditional approach to determine the workspace will be presented re-using ranging sensor data only, whilst remaining compatible with the proposed control architecture. The dimensions in Fig 6.9 can be obtained from platform sensor position and by range obtained from the sensors as follows:

$$R_w = \sqrt{R_1^2 + R_2^2 - 2R_1R_2 \cos \gamma} \dots\dots\dots (6.9)$$

$$\alpha = \cos^{-1} \frac{R_2^2 + R_w^2 - R_1^2}{2R_2R_w} \dots\dots\dots (6.10)$$

$$\beta = \cos^{-1} \frac{R_1^2 + R_w^2 - R_2^2}{2R_1R_w} \dots\dots\dots (6.11)$$

$$R_t = \frac{R_1 \sin \beta}{\sin \varphi} \dots\dots\dots (6.12)$$

Although the angle φ is not derived it can be seen that this can be calculated in a similar fashion once the other three terms are calculated, and knowing $D0 - D1 = \frac{1}{2} R_w$. It also follows that the range along the x body axis to the doorway y axis can be obtained by ranging measurement and similar treatments will derive ψ . When the two frames of reference are combined to form the trajectory frame of reference the origin of the new frame of reference becomes the origin of the platform f1 and the distance between that point and the point O in Fig 6.9 becomes the maximum value of yd and the distance between O and $D0 + 2A$ becomes xd in Eqns 6.1 and 6.2.

The workspace for the trajectory equations can then be defined as the doorway frame of reference, or equally the corridor, or corner, such that the trajectory equations, in the case of the turn equation, use the f1 platform origin point as the start and the doorway origin D0 as the finish and f1 - O is the equation y axis and D0 - O is the equation x axis. The case of the slalom is the same with the exception that there is an offset from the y axis at the beginning of the trajectory.

6.3.4 Defining the heuristics

Having defined the work space and the trajectory equations, deciding which trajectory to generate, slalom or turn, or whether there is a trajectory compatible with the platform kinematic requires a set of boundaries and conditions to be imposed. It has already been stated in Eqn 6.3 that the turn trajectory is limited, and in some complex cases it may be that only the collision avoidance layer can be employed and the user needs to ‘wriggle’ out. In this thesis it is argued that for the correct passing of waypoints a more accurate alignment to that waypoint is required, and it is also argued that the user must remain in control of the platform, and furthermore that combining two or more trajectories, as implied in Fig 6.2, can be simply endlessly combined to solve all necessary path-planning requirements for the non-holonomic PWC platform, such as when even more assistance is required by assisting the user to get from room to room, or park the platform when not in use.

Platform kinematic constraints, bounding the turn trajectory, are:

$$R_t > R_{min} < y_d \dots\dots\dots (6.13)$$

$$-\pi/6 < (\theta_{body} - \psi) < \pi/6 \dots\dots\dots (6.14)$$

$$\pi/9 < \psi < 3\pi/7 \dots\dots\dots (6.15)$$

$$-\pi/9 > -\psi > -3\pi/7 \dots\dots\dots (6.16)$$

If equations 6.13 – 6.15 are not all true then the slalom trajectory is used. The slalom trajectory is

bound by:

$$R_t > 2R_{\min} \dots \dots \dots (6.17)$$

$$R_t > y_d \dots \dots \dots (6.18)$$

If neither turn nor slalom forward trajectories can be generated, then a reverse trajectory may be required, as the trajectories implied in Fig 6.2 show a reverse-forward trajectory combination. However due to lack of time the heuristic development has not been developed and presented here. This remains future work.

There are errors in determining the exact waypoint dimensions and other uncertainties; however the collision avoidance layer developed in Chapter 4 remains active. This acts to provide a fine alignment with the waypoint, an issue identified by Yanco et al. [58]. Furthermore when the platform has reached the end of the trajectory, such that $x_{\text{world}} \text{ at some time} = x_d$, then the trajectory steering assistance control simply hands back to the collision avoidance, the trajectory layer does not subsume the collision avoidance layer, instead it works with it and with the user.

6.3.5 *Generating the trajectory*

Having defined and measured the trajectory workspace, and knowing the constraints and single trajectory heuristics for this level of assistance, it will be taken that a suitable trajectory can be generated. Whilst this section describes the methodology that can be used to generate any turn, forward or reverse, the development shown relates to a right turn for brevity.

The workspace has been previously defined such that the origin in Fig 6.8 relates to the origin of the body frame of reference $f1$, and the termination of the trajectory relates to the doorway origin $D0$, and where the y_d axis is the displacement from $f1$ to O (Fig 6.9), and the x axis is O to $D0$. Therefore in order to generate a smooth trajectory the tangent of the trajectory must be equal to the doorway approach angle ψ . Having obtained the doorway approach angle from either the method developed in the previous chapter or the one developed in section 6.3.3, it is now required to develop a method of selecting the tangent parameter for the turn trajectory.

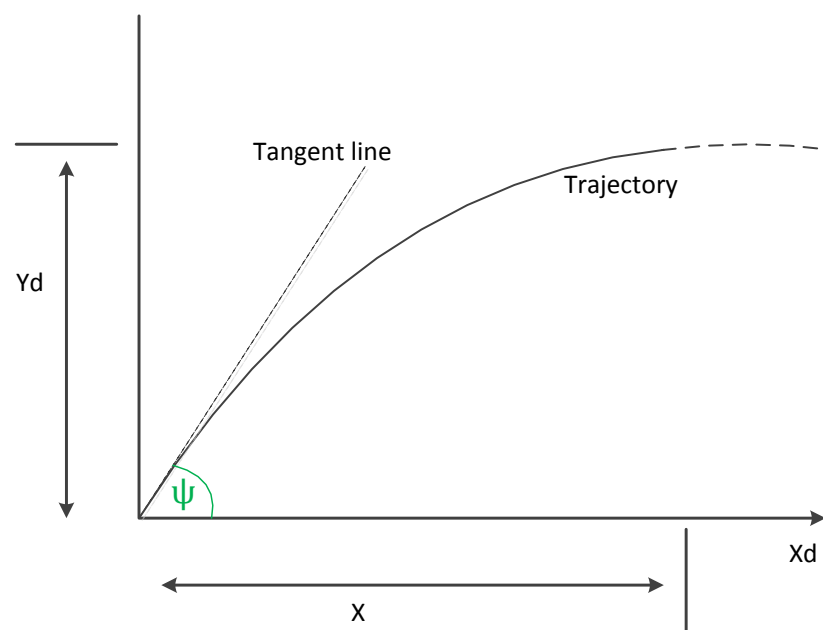


Figure 6.11 Doorway offset angle is defined as the same as the initial tangent of the trajectory, the end of the alignment trajectory x should end just before the doorway origin $D0$, then another trajectory may then be added or the system reverts back to collision avoidance only

Having determined the boundaries for the turn trajectory in the previous section a means of determining the tangent of the turn function Eqn 6.2 must be found such that the trajectory tangent is the same as the heading to doorway angle shown in Fig 6.11. Plotting the x_d distance against the turn angle for various values of y_d it can be seen in Fig 6.12 that an approximate linear function can be used to select the x_d value such that the tangent of the function = ψ .

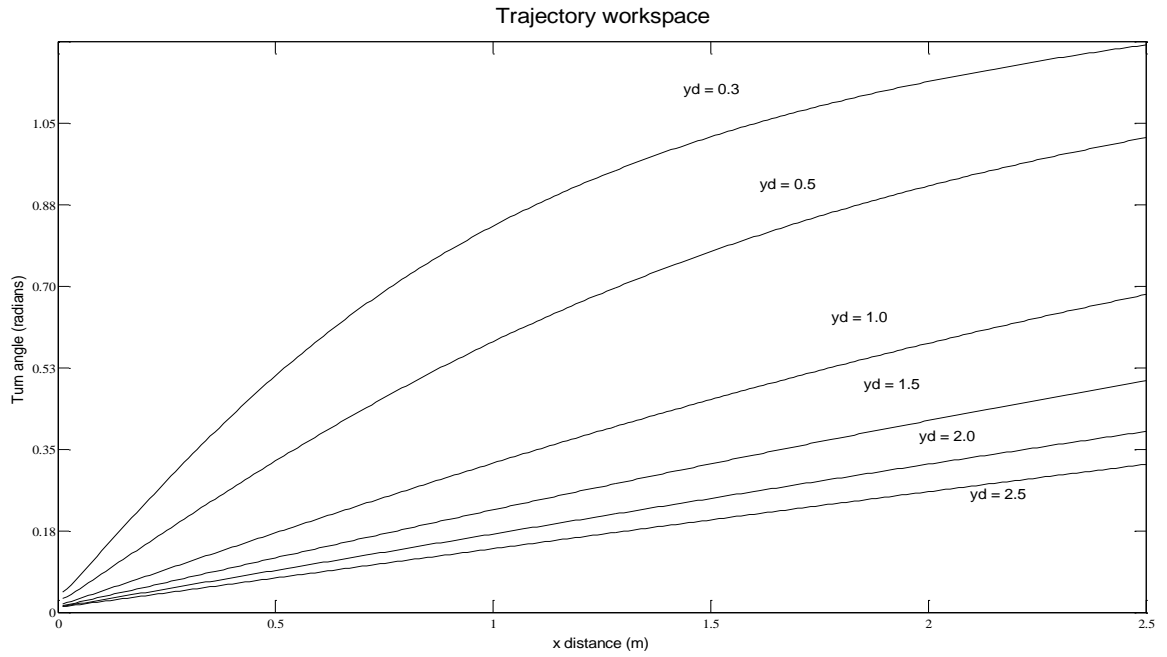


Figure 6.12 Plot of doorway approach angle against x for various values of yd

Plotting the function for various values of y , Fig 6.12, a look-up table can be generated such that the value of x along xd in Fig 6.11 can be calculated for any value of y and ψ so that the tangent of the trajectory function Eqn 6.2 is equal to the initial doorway approach angle ψ :

for $yd = 0.3$; $x \cong 1.068\psi$

for $yd = 0.5$; $x \cong 1.781\psi$

for $yd = 1.0$; $x \cong 3.705\psi$

for $yd = 1.5$; $x \cong 4.940\psi$

for $yd = 2.0$; $x \cong 6.413\psi$

for $yd = 2.5$; $x \cong 7.410\psi$ (6.19)

Further to this equation another condition must also hold true for the trajectory to be executable:

$$R_{\min} < x_d \dots\dots\dots (6.20)$$

If Eqn 6.19 is not true then once again a slalom trajectory must be first performed, this is the case when travelling down a corridor close to the side that has the doorway to the room that requires entering. The platform must move further out into the centre of the corridor first, by performing a slalom manoeuvre, before turning.

6.3.6 Keeping the human in the control loop

Having made the case earlier in this thesis for the user to remain in full control of the PWC it is required to present a new method of executing the trajectory generated in the previous section. It has been determined earlier in this thesis that for the user to remain in full control they must initiate any motion, control the velocity of the platform along the trajectory, and stop and re-start at any time without interruption from the system. Having defined constraints and boundaries previously it can be assumed that the PWC platform will be able to follow the assistive trajectory to an acceptable degree, and that any errors or dynamic interruptions can be dealt with by the collision avoidance method presented in Chapter 4.

For the user to control the PWC motion a further dynamic relationship of the platform needs to be defined; and that is the relationship between the steering angle, platform velocity, and geometry. Hence the resulting rate of turn is given by:

$$\omega = \frac{V}{L} \tan \theta \dots\dots\dots (6.21)$$

The dynamic model and the relationship between v and ω has been previously derived in Chapter 4 Eqns 4.11 to 4.14 and therefore it can be seen from Eqn. 6.20 that the dynamics of the platform turn rate is dependent upon the heading angle θ , and the front to rear axle wheelbase L . There is a limitation upon $+v$ and that is as previously stated to values of $|\alpha|$ less than $|\pi/4|$. Therefore v has a maximum value defined by $\tan \pi/4$.

Having defined our trajectory as a natural exponential function then the gradient of that function at some time is the height of that function which enables the desired heading to be easily obtained. The actual heading angle can be obtained from inertial sensors or through the direct use of wheel drive-shaft encoders and the following equation:

$$\theta = \frac{x_r - x_l}{W} \dots\dots\dots (6.22)$$

Where x_r is the ground distance travelled by the right wheel, x_l is the ground distance travelled by the left wheel, and W is the distance along the axle between the two rear wheels.

The development of the assistive trajectory controller follows; the heading error can then be expressed as a linear control to determine the body rotation rate at some time according to the desired velocity input:

$$\omega_{\text{body}} = k \frac{V_{\text{desired}}}{L} \sin (\alpha_{\text{des}} - \alpha_{\text{act}}) \dots\dots\dots (6.23)$$

Where k is some constant which is used to tune the turn rate to some comfortable rate the user is content with, the value of which can be obtained from practical observation of the performance when setting up the platform parameters. The user supplies the desired platform from the velocity input of

the joystick, v_{body} , the rate of turn, ω_{body} , is then dependent upon the error between the desired heading α_{des} and the actual heading α_{act} and the user velocity input. The platform velocity and turn rates are then returned to the dynamic model Eqns 4.11 and 4.12 from Chapter 4 collision avoidance. This is the obstacle avoidance level of the control architecture developed in Chapter 3 section 3.4. Therefore the assisted trajectories are able to be dynamically interrupted should a previously undetected obstacle arise, or should the need to correct small positional errors occur.

6.4 Experimental results

This section of the chapter applies the developments of the chapter, using the platform described in previous chapters, to conduct a series of experiments. The platform was set up to detect the doorway as described in section 6.3.3 and used four of the long range Sharp GP2Y0A710K0F infrared (0.1m-5.0m) distance measuring units to obtain the dimensions depicted in Fig 6.9.

The first experiment was to determine if the controller would be suitable for following the generated trajectory. The controller was set to use Eqns 4.9 and 4.10 which use the dynamic model but not the collision avoidance model. The platform was offset from the doorway and the system was asked to assist the user to align with the doorway. The user then moves the joystick forward, as the platform moves forward the controller turns the platform to follow the trajectory. Fig 6.13 shows the trajectory which was generated in blue (top line) and the red line shows the actual platform trajectory. The controller can be seen to follow the trajectory smoothly and closely and the platform body x axis at the end of the manoeuvre was almost perfectly aligned with the doorway x axis.

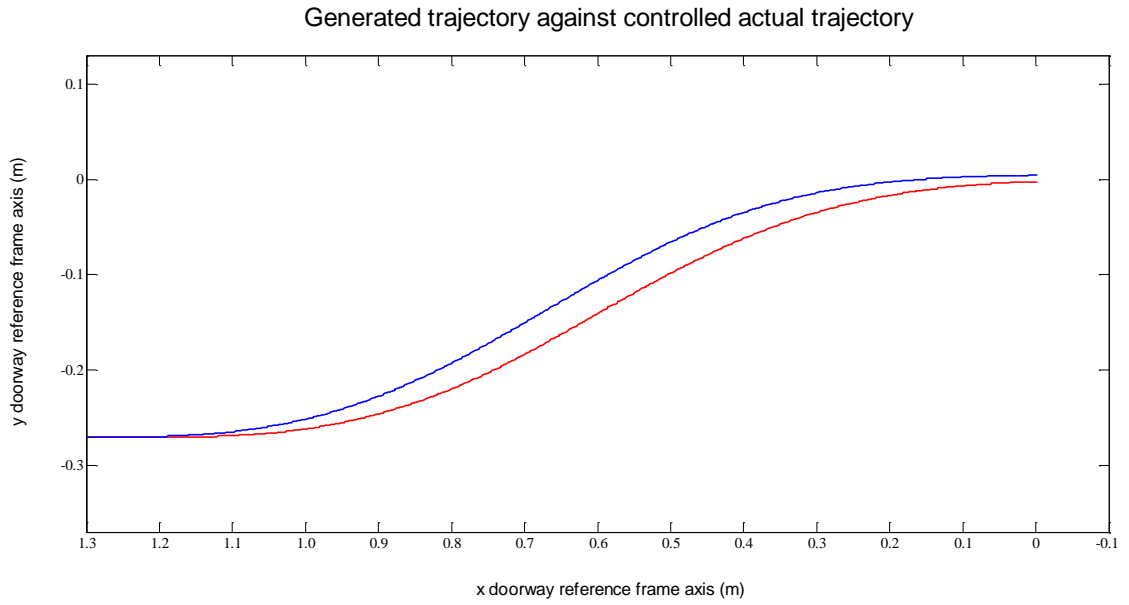


Figure 6.13 *A system generated slalom showing the controller following the trajectory as the user applies the platform user desired velocity*

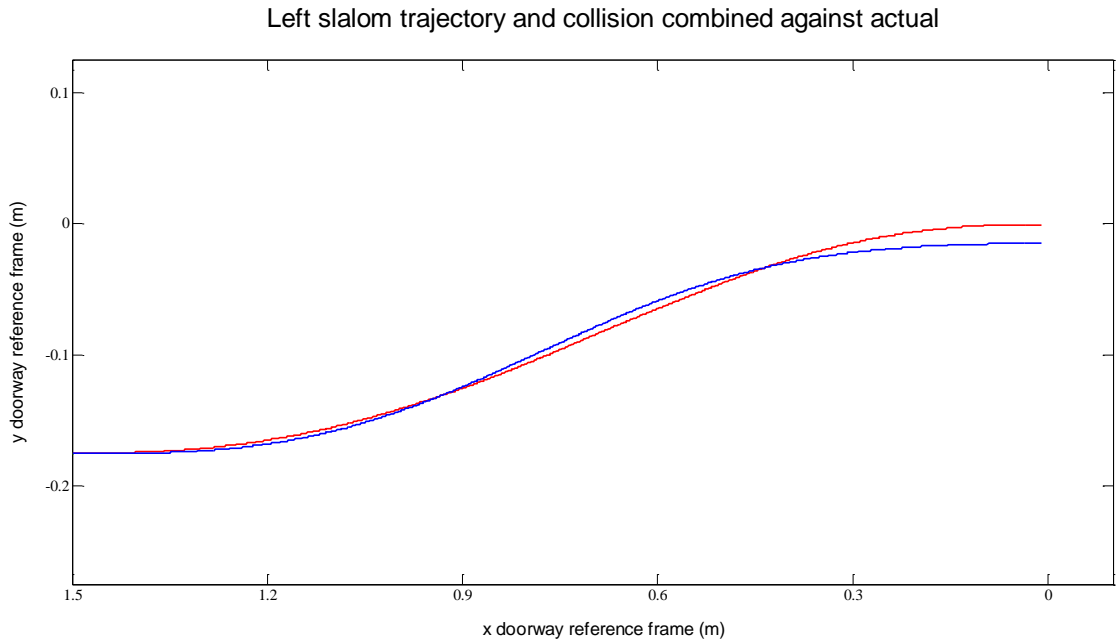


Figure 6.14 *Combining the collision avoidance layer to correct the small errors which occur in doorway approach angle measurement and current position measurement*

When the collision avoidance layer was added to the assistive trajectory layer, the controller now uses Eqns 4.11 and 4.12; Fig 6.14 shows the generated trajectory in blue and the actual trajectory in red. The small alignment error can be seen to be corrected as the platform trajectory has been shifted slightly away from the generated trajectory by the collision avoidance layer making adjustments for the sensor-detected doorway.

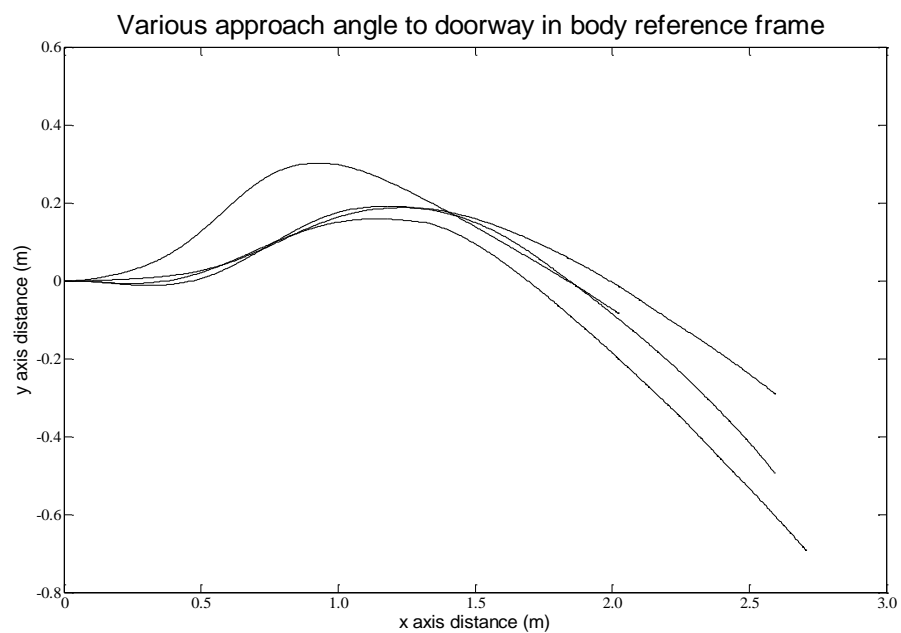


Figure 6.15 Four slalom trajectories used to align the platform with the doorway better, such that the collision avoidance can then take over to provide correctly aligned passage through a narrow doorway with 35mm clearance each side

Whilst it may be hard to determine from Fig 6.14 whether the collision avoidance layer smoothly interrupts the generated trajectory, and to also to test if the slalom trajectory can be employed without being combined with a turn trajectory, for example because of boundary constraints or some heuristic condition, then for the following experiment the trajectory has been set to terminate along the x doorway axis at a point which is a distance of L (Fig 6.8) away from D_0 the doorway origin (Fig 6.9). At the end of the trajectory the joystick input reverts to the collision avoidance layer, although for this experiment the joystick was kept in the forward position applying no turn.

The assistive test PWC was set at four angles between $\psi = \pi/4$ and $\psi = \pi/8$ from the doorway x axis and four different translations from the doorway origin D0. The system was asked to generate a trajectory for each of the start points and the PWC was then driven forward by the joystick velocity input. The system controller then followed each of the generated trajectories in turn. Fig 6.15 shows these four actual trajectories. The reference frame used is that of the PWC platform so the start appears to be at the same position and angle, whereas in reality the ends of the trajectories were all at the same real-world position and angle.

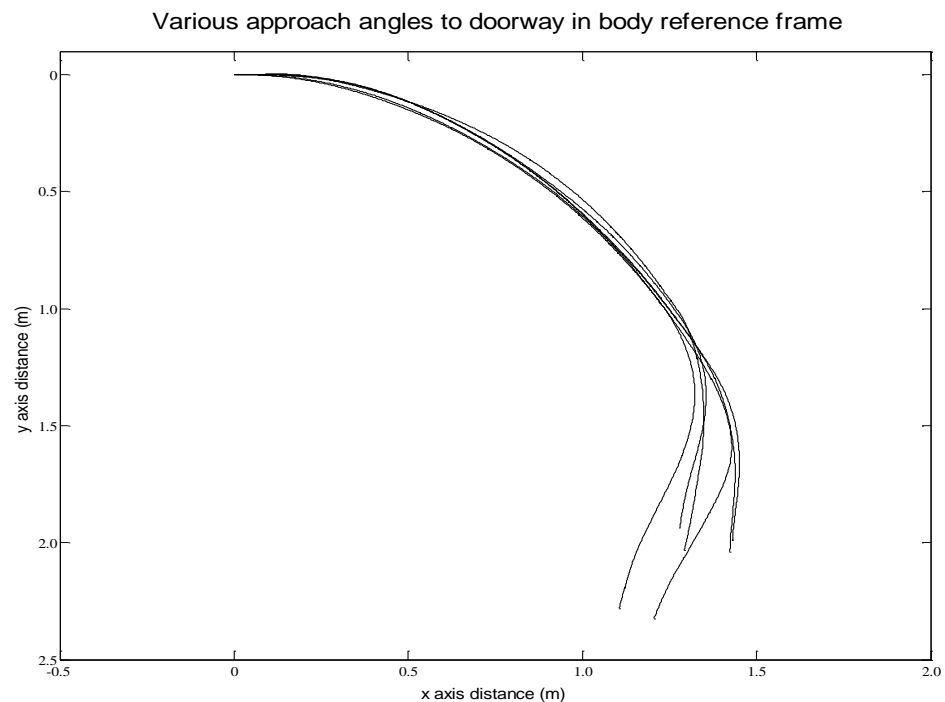


Figure 6.16 Six turn trajectories used to better align the platform with the doorway such that the collision avoidance can alter the trajectory to provide correctly aligned passage through a very narrow doorway with 35mm clearance each side with deliberate angular error introduced

The experiment was intended to demonstrate the smooth transition between the end of the assistive layer trajectory, and the taking over of the collision avoidance layer. In effect the collision avoidance layer has provided the turn element missing from the trajectory layer. This is a clear indication that the trajectories from the two layers are both compatible and complementary with each other. Furthermore the doorway was 0.75m wide and the platform was 0.68m wide, the platform origin f1 (Fig 6.8) passed through the doorway origin D0 (Fig 6.9) with equal clearance both sides.

The test was repeated with the turn trajectory, Eqn 6.2, and the same controller as Eqn 6.23 with α_{des} and α_{act} offset by ψ . The angle of approach to the doorway ψ was set at $\pi/4$ and the platform placed at six angles between $\pi/6$ and $\pi/3$ to ensure a significant angular error, as if the platform had been moved or the doorway incorrectly located. The results of the actual trajectories are given in Fig 6.16, and are in the body frame of reference; hence they appear to start at the same place and angle when conversely they end at the same point mid-way between the doorway such that $f1 = D0$ (Fig 6.9), as was the case in the previous experiment. These two experiments show that the collision avoidance method developed in Chapter 4 is capable of correcting significant error in either the user or system trajectory in a real-time application, where that error can be as much as $\pi/4$.

6.5 Conclusion

A novel set of trajectories for assisting PWC users to pass through a doorway, or other waypoint, has been developed in this chapter. The trajectories are compatible and complimentary with the collision avoidance real-time trajectory developed in Chapter 4. The control strategy developed in Chapter 3, aimed to solve the problem of keeping the user in control with the aid of assistance. This led to the development of a control method, in section 6.3.6, which leaves the user in full control of any motion. The system generates a human-like trajectory which allows the non-holonomic assistive PWC to be appropriately aligned with the doorway centre line such that the platform can pass through a doorway, or into a lift, with minimal clearance.

This chapter has therefore answered the question of keeping the user in control, a highly important requirement identified in this thesis as necessary to provide and maintain user empowerment and satisfy liability of use issues hitherto not addressed. Furthermore the difficult and complex challenge

of doorway passing is solved in this chapter through the development of two human-like trajectories. These trajectories were shown to improve the approach angle sufficient for the collision avoidance layer developed in Chapter 4 to provide a smooth final accurate alignment with a doorway, even when the initial trajectories were each given a significant error, which were far greater than the true small measurement errors shown in Fig 6.14. The result of combining these two assistive layers has been shown to provide a robust method of providing a precise alignment with a doorway such that a non-holonomic robotic platform can pass through with a very narrow safety gap with a human in the control loop.

The next chapter concludes this thesis and discusses future development of this work for solving the remaining issues, and needs faced by PWC users, potentially leading to an assistive system sufficiently robust for manufacturers to bring to the market place.

Chapter 7

Conclusions

This thesis has presented several contributions to the field of assistive mobile robotics. The first main contribution was the development of a collision avoidance method which developed a novel localised adjustable elliptical force field. This was then combined together with a further development of a dynamic model, which was then applied to a new elliptical zone developed again in Chapter 4 which moves with the platform like a dynamic window to produce an obstacle-negotiating method whose trajectory was intuitive and more natural than other methods previously employed, the human-in-the-loop remained in control of the positive motion of the platform at all times.

The second major contribution was the development of a method to localise the platform in the indoor environment using robust flooring features in a real-time method. Previous to this, wireless infrastructure was commonly used which did not always give the correct room location. Other contributions were to identify and determine waypoints and doorway approach angles using pattern recognition techniques.

Generating an executable trajectory for the PWC platform when the user has approached the doorway at an angle or translation which would not allow passage through that doorway is the third major

contribution to the art. These trajectories are compatible with the collision avoidance method developed earlier in Chapter 4 of this thesis such that any dynamic interruption or small errors in the trajectory generation and following layer are dealt with by this layer. Another contribution was the development of a control which takes the user velocity input and uses that to control the motion of the platform along the system-generated assistive trajectory keeping the user in control of the platform motion.

The overall contribution is to combine these developments into a novel assistive human-in-the-loop architecture developed in Chapter 3. This top-down bottom-up layered adjustable assistance control architecture is based upon the human command being a crucial part of the system for safety. The human command is top-down and the system feedback is high-level information assisting the user's decision making; system intervention is bottom-up with increasing magnitude, initially damping the platform motion in the presence of obstacles then, when more assistance is required, providing manoeuvring assistance around them by generating a collision-free trajectory. These two layers were proved to be compatible when combined in the previous chapter, and therefore highly suited to the control structure.

Other contributions to the field of assistive mobile robotics have been from: the low-cost sensors modified or employed, re-using of ranging data for localisation, waypoint identification, obstacle detection, and trajectory generation.

7.1 Summary of the thesis

Chapter 3 developed a control architecture which allowed the human in the loop to be the decision maker and instigator of all actions. Suitable hardware was evaluated to solve the problems identified

by working with PWC stakeholders; this involved considerable iterative research. Therefore the work presented in this chapter set out the technology required for the assistive human-in-the-loop PWC.

Chapter 4 has described the development of a real-time reactive low-level collision avoidance methodology which is compatible with a layered assistive system described in Chapter 3. The method of collision avoidance proved under testing to be intuitive and unobtrusive, empowering the individual not disempowering or overpowering. Participants in the trial when asked whether they were comfortable with the assistance, unanimously reported that it was reassuring to know it was there, they all preferred the system when it was active. Experimentation found that using the novel collision avoidance system a standard PWC was able to pass through a 0.76m doorway opening with an angle of approach $< \pi/4$ radians. The improved dynamic model introduced in this chapter can use a modified version of the collision avoidance method (by using it additionally in the vertical body axis) to provide a velocity damping when the platform is on an incline.

Chapter 5 developed a new and novel method of method for room localisation obtained from flooring features and a waypoint or doorway identification method using ranging data suitable for real-time assistive PWC. This provides the necessary feedback in the control architecture, presented in Chapter 3, for the human in the loop and for the other levels in the architecture. The key point of this level is to provide information for the lower levels. Having identified the waypoint, the obstacle avoidance level can therefore adjust the collision ellipse to suit the application; for example having identified that the platform is in a wide corridor the obstacle avoidance localised repulsive potential force field can be adjusted to keep to the left-hand side, or pass through a narrow passage, or doorway. This level also provides information which allows the trajectory level presented in Chapter 6 to provide geometric paths for '*steering*' assistance in manoeuvring through doorways or waypoints.

Chapter 6 developed unique trajectories for the correct alignment of the platform with doorways. These innovative trajectories that are presented in this chapter cover the approach angles not covered by the collision avoidance alone. The combination of the collision avoidance layer and the assistive trajectory layer in the system control architecture explained in Chapter 3 will allow the future development of more complex assistive layers such as path-planning assistance.

7.2 Meeting the technical challenges

Having defined the technical requirements in Chapter 3, after identifying the issues and problems faced by users in Chapter 2, the requirements for:

- *non-intrusive system assistance* was examined by:
 - participant evaluation in Chapter 4 section 4.7 which found that the method of the assistance collision avoidance developed in that chapter was intuitive not intrusive
- *knowledge of what the system is doing, or about to do, given as feedback to user* was provided by:
 - haptic feedback; vibrating the joystick when the trajectory was altered
 - a small screen depicting the range to an obstacle

(Neither were evaluated in the thesis as all participants did not feel the need to use them)

- *adjustable assistance, not all users have the same requirements, desires, or needs* was addressed by:
 - provision is made in the control architecture by employing layers of assistance where boundaries in each layer are each set
- *different levels of assistance depending on needs, users may require more assistance at times for different tasks* has had:

- provision made in the control architecture by employing layers of assistance each of which have been developed to be potentially adjustable
- *ability to manoeuvre close to objects safely, the system should not deny the user from approaching objects, a requirement for getting into bed for example has been answered by:*
 - the collision avoidance method in Chapter 4
- *reliable and robust hardware suitable for the daily hard use required by users has:*
 - been used throughout all developments presented in this thesis
- *simple to operate and maintain, technical help should be minimised for daily use devices;*
 - this research provides a building block for future implementation
- *suitable for carers or family to use when taking over control from users :*
 - having successfully tested the collision avoidance on novice PWC users provides a building block for future implementation
- *independence from the requirement for specialised infrastructure has been fulfilled:*
 - because no infrastructure has been used, or needed, in any of developments and none is included in the control architecture developed in Chapter 3
- *system power consumption should not greatly affect the driving range limit of PWC;*
 - the use of embedded hardware throughout the developments, and low-cost MEMS sensors evaluated in Chapter 3, ensures low power consumption
- *system should not require communication with external agents to function :*
 - all methods developed and demonstrated in this thesis can be run on local embedded hardware
- *The system should fail safe and when disconnected or switched off should still leave the PWC motor control system able to be operated with manual control:*

- the human element described in the control architecture allows the user to remain in control and also making the intelligent decisions in each of the three assistive layers presented in this thesis, therefore the system reverts to the lowest level which is currently the manufacturers' mapped profiles and boundaries

These considerable developments have needed to be undertaken in order to provide support for the development of the human-in-the-loop assistive system architecture.

7.3 Addressing the research question

Having met many of the technical challenges identified in the introduction of this thesis the initial question of developing a non-holonomic, highly human-in-the-loop compatible, assistive mobile robotic platform guidance navigation and control strategy can be assessed. The research undertaken for this thesis, with assistance of PWC stakeholders, enabled a set of criteria to be established which would be critical for any successful assistive PWC system development:

- *a reduction in the length of time required for user rehabilitation through technology:*
 - can be evidenced by evaluation of novices in Chapter 4 section 4.7
- *an improvement in the longevity of mobility for users with deteriorating abilities:*
 - is implied by the control architecture and the developments in this thesis
- *to reduce the collateral damage caused by accidental collisions:*
 - the collision avoidance method developed in Chapter 4 concluded so in section 4.8
- *for prevention of accidental injury to users, carers and the public:*
 - the collision avoidance method developed in Chapter 4 implied so in section 4.8

- *to provide mobility to patients currently excluded due to their disabilities:*
 - is significantly implied by all the developments in this thesis
- *to reduce the time carers and family need to provide assistance helping users to navigate:*
 - is implied by all the developments in this thesis
- *by reducing the costs, for adapting and adjusting hardware for individual users:*
 - is future work, although implied by the low-cost sensors and hardware developed and evaluated in Chapter 3
- *to empower PWC users to help themselves become more independent:*
 - will be a natural progression if the developments in this thesis are engaged

Keeping the user in control of the platform velocity; hence all motion, throughout all of the developments presented in this thesis has been based upon the need for the safety of the user, other people, and the environment. The assistive collision avoidance layer and the assistive trajectory layer has proven highly compatible with human trajectories, whilst observing the non-holonomic constraints.

7.4 Future developments for the assistive system

Whilst writing up this thesis; and following on from the research presented in this thesis, a prototype smart PWC was developed utilising highly localised non-linear adjustable virtual force fields which allow the user negotiating these obstacles far greater flexibility with manoeuvring around them. This embedded hardware and these low-cost sensors are mounted in small unobtrusive boxes which are fully functional and which interface with Dynamic Control's wheelchair control system (whose controllers are specified by the NHS wheelchair service). This hardware currently uses the algorithms

and methods presented in this thesis to assist powered wheelchair users to negotiate obstacles and doorways without collision in an intuitive fashion. Furthermore clinical trials are being undertaken through the East Kent Hospitals University Foundation Trust (EKHUFT) under the EDECT project which is following on from SYSIASS.

Further considerations:

- The user interface and feedback needs to be further researched in light of the evaluations carried out in Chapter 4.
- The pattern recognition of waypoints needs to be fully implemented in a stand-alone learning module, and a human-machine semantic interface needs to be developed.
- The short trajectory level of the architecture needs to be fully implemented. This can be achieved once the pattern recognition is fully functional. Further testing to determine where the failures occur such that the system can be given safe operational boundaries.
- The sensor technology needs to be re-evaluated to ensure interference from lighting and sensors employed by other wheelchairs do not lead to false readings. The adoption of the radar-on-a-chip sensor was suggested in Chapter 3 and the application of thermal sensors used to identify humans which can be used to modify the collision avoidance allowing the method to be used in a highly dynamic environment.
- The assistive control system needs to be developed such that it can be easily set up without requiring highly qualified and expensive technical support in order to meet the requirements of users and their needs. Therefore research involving the participation of PWC users and other stakeholders will be required to establish the range of adjustment required.
- any assistive element should be adaptable and adjustable to new situations and places, not simply fixed at some initial setting by some technician, this concept has been the ultimate goal of the system presented in this thesis, but remains to be addressed by future work
- settings and adjustment should be modifiable by user and system within a safe range with

which it has been determined that the user can cope, therefore the initial set-up provided by a technician under clinical advice will set upper and lower limits of the manufacturer's mapping profile as is currently the safe practice, and will also set the assistance boundaries

Further development of the work in this thesis could lead to the uptake of the technology by stakeholders; for this to happen, users, industry and the clinical prescribers would need to evaluate the system over a long period of time. The current state of the research would require the following future work to be undertaken:

- Evaluate the system robustness for full safety approval meeting the necessary legislative frameworks currently in force.
- Obtain relevant approvals from the relevant ethical bodies need to be obtained for the developed assistive system in addition to those obtained for the current trials.
- Develop a robust pre-production prototype which interfaces into the existing manufactured powered wheelchair control system which is able to flexibly adapt to the requirements of a range of patient needs.
- Exploit initial proof-of-concept algorithms and methodologies developed and use the usability feedback to adjust the algorithms to provide a more optimised system navigation performance to an individual user.
- Employ extensive feedback from public and patient opinion regarding their desires and needs to advise the development of the adaptable assistive system ensuring that ease of use and meeting the needs of the patient govern the technological developments.
- Use the proposed project partnership between academic, health-professional and importantly the equipment manufacturer to bring the product to market in a short a time as possible.

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