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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

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Abstract

Human assistive devices need to be effective with real-time assistance in real world situations: powered wheelchair users require reassuring robust support, especially in the area of collision avoidance. However, it is important that the intelligent system does not take away control from the user. The patient must be allowed to provide the intelligence in the system and the assistive technology must be engineered to be sufficiently smart to recognize and accommodate this. Robotic assistance employed in the healthcare arena must therefore emphasize positive support rather than adopting an intrusive role. Weightless Neural Networks are an excellent pattern recognition tool for real-time applications. This paper introduces a technique for look-ahead identification of open doorways and junctions. Simple sensor data in real-time is used to detect open doors with inherent data uncertainties using a technique applied to a Weightless Neural Network Architecture.

1. Introduction

For many users, powered wheelchair operation in enclosed environments such as buildings, has proved problematic. A major need is to be able to drive in such environments with minimal collisions. For those users with significant physical disability accurate control of the chair is a major challenge. 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, others and the environment. Therefore an intelligent system which assists the user with collision avoidance/assisted navigation would help maintain the independent mobility of the user affecting an increase in their quality of life. To do this requires flexible assistance which, despite the recent advances in autonomous robotic technology is still an open question. A further requirement of any interventional system is that the level of user control must be maximized [1]. This requirement for adaptable user control has been often been forgotten in research arenas, according to Nisbet (2002) [1], where research projects have concentrated mainly on robotic autonomy. User exclusion can lead to a feeling of disempowerment and the removal of the opportunity for that user, especially the younger user, to develop their contribution to path planning, decision making, and maneuvering control processes [1].

One major problem to be solved for any smart adaptive wheelchair system is maneuvering through a doorway. One less-abled participant in a doorway passing experiment only completed the task when maneuvering assistance was engaged [2]. Furthermore on average 2.27 crashes occurred per participant per trial [2]; however, analysis also highlighted participants concern regarding system intervention feedback when denied passage through the door because of incorrect approach angle [3]. Therefore any trajectory assistance would require look-ahead perception in order to: better inform the user, and align the wheelchair to the doorway.

Look-ahead identification provides system and operator feedback for feed-forward predictive planning; promising smoother optimal approach trajectory generation and system-operator integration. 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. The way

in which it is planned to do this is now presented in the following section on Sensor choice and deployment array.

We determine from simple pattern recognition using the application of a weightless neural network, open doorways, and corners, and turns, and dead-ends, and therefore propose a simple real-time early door and junction detection approach for assistive navigation systems. We additionally propose that this method also enables a degree of perceptive round corner obstruction detection compared with traditional methods.

2. Weightless artificial neural architectures

Weightless Neural Networks (WNNs) are Neural networks without weights between the inputs and nodes, spurred from initial work by Bledsoe and Browning [4] (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 [5]. 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. [5] detected various obstacles, corners and corridors identified from sonar data with an execution time of 0.25μs 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) [6]. 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.

3. Sensor choice and deployment array

Infrared ranging for indoor robotic application removes the incident angle limitation inherent with sonar sensors [7]. Previous work by Nurmani et al (2009) [5] relied solely on sonar sensors whereas data fusion between infrared and sonar, Flynn (1988) states [7], can remove the negative aspects of each improving the overall result. However; for this experiment we only use infrared ranging as comparative, their very narrow beam angle introduces sharp edge detection, a potential requisite for better discernibility between clutter, furniture, obstacles; and building fabric, such as corners and doors. Ceiling height was found to be consistent and a good localization indicator [8] therefore implemented to detect doorway crossing; hence bounding room and linking passages.
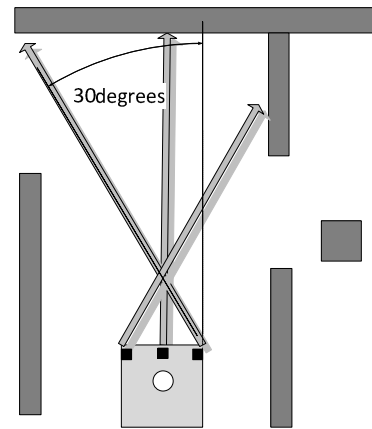
Figure 1. Three angled 5m infrared ranging sensors (black squares) and one zenith pointing 5m sonar ranging sensor (white circle).

Sharp GP2Y0A710K0F infrared (0.1m-5.0m) distance measuring units were used for angled distance ranging and an LV-MaxSonar®-EZ2™ with 0.05m resolution at 3m for doorway ceiling to lintel detection.

A typical corridor was chosen to best determine sensor angle for horizontal door and junction approach, an angle of plus and minus 60 degrees was chosen shown in Fig. 1 in order to detect openings some 2.0m distance ahead of the wheelchair when passing down a 1.8m wide corridor.

Table 1: Door and junction detection classification and WNN results

	WNN architecture									
	1		2		3		4		5	
	Percentage class identification and sample quantity									
Class	%	Qty	%	Qty	%	Qty	%	Qty	%	Qty
Dead end slow	85.2	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**

4. Parsing into the weightless neural network

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.

4.1. Classification

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. 2. Confirmation and adjustments were made during initial range and free space floor to ceiling (zenith) testing. Classification was then determined as listed in Table 1.
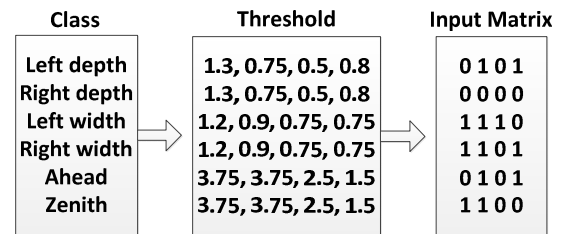
Table 2: Classification thresholds

Class	Boundary /metres			
	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	>0.90	>0.75	<0.75
Right width	>1.2	>0.90	>0.75	<0.75
Ahead	>3.75	<3.75	<2.5	<1.5
Zenith	>3.75	<3.75	<2.5	<2.1

Range and angle data are used to obtain Cartesian body frame co-ordinates thus depth into opening and width.

4.2. WNN matrix generation

These threshold classified results of ranging data are now in a 6x4 binary format suitable to be parsed into an input matrix, shown in Fig. 2, comprising 5 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 identifying 15 examples of class.

Class	Threshold	Input Matrix
Left depth	1.3, 0.75, 0.5, 0.8	0 1 0 1
Right depth	1.3, 0.75, 0.5, 0.8	0 0 0 0
Left width	1.2, 0.9, 0.75, 0.75	1 1 1 0
Right width	1.2, 0.9, 0.75, 0.75	1 1 0 1
Ahead	3.75, 3.75, 2.5, 1.5	0 1 0 1
Zenith	3.75, 3.75, 2.5, 1.5	1 1 0 0

Figure 2. Generating the WNN input matrix

5. Results

Several 1.8m wide corridors around a University research department were examined and used to provide sensor data for WNN junction and doorway determination. The method of collecting those data was representative of a wheelchair user exiting a room negotiating a corridor and entering/exiting another room, in comparison with experimentation by others [2, 3].

Identification of these test classes listed in Table 1 were 94% successful for classification, and briefly summarized, Table 3, were 93% for object identification.

Table 3: Door and junction detection summary

Percentage correctly identified for each WNN architecture and sample quantity

	Qty	%1	%2	%3	%4	%5
Door	6	66.7	66.7	16.7	16.7	66.7
Turn clear	7	100	100	100	100	85.8
T-Junction	1	0	0	100	0	100
Dead-end	5	100	100	100	100	100
No turn	2	100	100	50	100	100
Door crossing	3	100	100	100	100	100
Corner	2	100	100	100	100	100
Total	**26**	**81**	**81**	**81**	**66.7**	**93**

When comparing the results with a similar experiment, Nurmani et al (2009) [5] reported 94% for classification and 95% for identification. However in this experiment class detection was achieved using 3 infrared sensors compared with 8 sonar sensors and their classification consisted of 9 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.

It should be noted that the representative wheelchair user path did not pass any left corners, and only one T-Junction was negotiated. Results tabulated in Table 3 combine left and right categories for ease of display, although correctly identified, "no turn" (false turn) represents correctly identified "open corridor" when passing an alcove; hence an obstructed turn identified. WNN architectures labeled 1-5 in Table 1 and Table 3 represent various neuron layer configurations.

6. Conclusions

Advanced, "look-ahead", junction and doorway detection were successfully demonstrated at a distance of 1.5m; significantly greater than previously demonstrated using sonar [5]. Thus allowing sufficient time to schedule any smooth trajectory change if required, and provide effective user feedback. Furthermore simple doorway crossing detection was demonstrated which effectively bounds rooms; thus locations become simpler to map in a dimensionless, or loose, yet logical manner.

Simple smaller low cost sensors, infrared (0.1m-5.0m) distance measuring units, are less prone to mechanical wear and accidental damage than scanning sensors: Carlson reported sensor damage from collisions when more expensive mechanical larger laser range scanner sensors were employed [2].

This perceptive look-around corner technique can be employed to provide wheelchair users advance warning, due to sensor position and angle, before they see it, thus potentially allowing earlier velocity and trajectory modification when approaching hazards and turns.

7. Acknowledgements

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