



Kent Academic Repository

Rizzi Raymundo, Caroline, Johnson, Colin G., Fabris, Fabio and Vargas, Patricia A. (2016) *A Situation-Aware Fear Learning (SAFEL) Model for Robots*. Neurocomputing, 221 . pp. 32-47. ISSN 0925-2312.

Downloaded from

<https://kar.kent.ac.uk/58076/> The University of Kent's Academic Repository KAR

The version of record is available from

<https://doi.org/10.1016/j.neucom.2016.09.035>

This document version

Author's Accepted Manuscript

DOI for this version

Licence for this version

CC BY-NC-ND (Attribution-NonCommercial-NoDerivatives)

Additional information

Versions of research works

Versions of Record

If this version is the version of record, it is the same as the published version available on the publisher's web site. Cite as the published version.

Author Accepted Manuscripts

If this document is identified as the Author Accepted Manuscript it is the version after peer review but before type setting, copy editing or publisher branding. Cite as Surname, Initial. (Year) 'Title of article'. To be published in *Title of Journal*, Volume and issue numbers [peer-reviewed accepted version]. Available at: DOI or URL (Accessed: date).

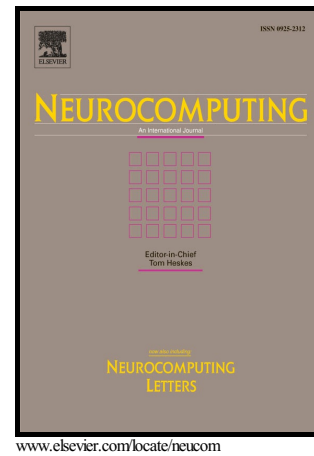
Enquiries

If you have questions about this document contact ResearchSupport@kent.ac.uk. Please include the URL of the record in KAR. If you believe that your, or a third party's rights have been compromised through this document please see our [Take Down policy](https://www.kent.ac.uk/guides/kar-the-kent-academic-repository#policies) (available from <https://www.kent.ac.uk/guides/kar-the-kent-academic-repository#policies>).

Author's Accepted Manuscript

A Situation-Aware Fear Learning (SAFEL) Model
for Robots

Caroline Rizzi, Colin G. Johnson, Fabio Fabris,
Patricia A. Vargas



PII: S0925-2312(16)31052-9
DOI: <http://dx.doi.org/10.1016/j.neucom.2016.09.035>
Reference: NEUCOM17564

To appear in: *Neurocomputing*

Received date: 18 December 2015
Revised date: 13 July 2016
Accepted date: 14 September 2016

Cite this article as: Caroline Rizzi, Colin G. Johnson, Fabio Fabris and Patricia A. Vargas, A Situation-Aware Fear Learning (SAFEL) Model for Robots, *Neurocomputing*, <http://dx.doi.org/10.1016/j.neucom.2016.09.035>

This is a PDF file of an unedited manuscript that has been accepted for publication. As a service to our customers we are providing this early version of the manuscript. The manuscript will undergo copyediting, typesetting, and a review of the resulting galley proof before it is published in its final citable form. Please note that during the production process errors may be discovered which could affect the content, and all legal disclaimers that apply to the journal pertain

A Situation-Aware Fear Learning (SAFEL) Model for Robots

Caroline Rizzi^{a,*}, Colin G. Johnson^a, Fabio Fabris^a, Patricia A. Vargas^b

^a*School of Computing, University of Kent, Canterbury, UK*

^b*Robotics Laboratory, School of Mathematical and Computer Sciences, Heriot-Watt University, Edinburgh, UK*

Abstract

This work proposes a novel Situation-Aware FEAR Learning (SAFEL) model for robots. SAFEL combines concepts of situation-aware expert systems with well-known neuroscientific findings on the brain fear-learning mechanism to allow companion robots to predict undesirable or threatening situations based on past experiences. One of the main objectives is to allow robots to learn complex temporal patterns of sensed environmental stimuli and create a representation of these patterns. This memory can be later associated with a negative or positive “emotion”, analogous to fear and confidence. Experiments with a real robot demonstrated SAFEL’s success in generating contextual fear conditioning behaviour with predictive capabilities based on situational information.

Keywords: Contextual Fear Conditioning, Brain Emotional Learning, Temporal Pattern, Affective Computing, Autonomous Robotics, Amygdala and Hippocampus Modelling

1. Introduction

Learning to fear unpleasant or harmful stimuli from the environment is ubiquitous in nature. Fear can be defined as a brain’s mechanism for automatic learning and memorization of potential threats to one’s survival. It offers exceptional advantages over conscious-rational thinking during critical situations due to its involuntary and automatic responses, leading to faster decision-making and reaction in the face of danger [1, 2], as well as increased focus and attention [3]. Fear learning is also an important ally for environmental adaptation as the brain constantly associates fear with newly experienced dangers. Hence, it assists animals to learn and react to the new patterns and threats of unfamiliar environments.

Fear learning supports not only survival and environmental adaptation, but also social adaptation (i.e., one’s ability of adjusting its behaviour to the rules of its own society). The concept of society applies to many animal species, where individuals feel an instinctive need to be accepted by others of its kind. As belonging to a community can highly increase one’s chances of survival,

the brain of many animal species evolved to process social rejection as an aversive environmental stimulus. Consequently, the brain triggers fear learning when an individual observes disapproval from others towards its actions.

By being real agents that inhabit the physical world and interact with human beings, autonomous robots are also susceptible to environmental threats and to social adaptation. Hence, autonomous robots could also take advantage of a mechanism inspired by fear learning. Robot companions [4–7], for instance, are gaining more space in our society as social entities and have shown a great potential for applications in many areas (e.g., healthcare [8]). However, a common issue with long-term robot companions is the rapid loss of interest from their users, who get frustrated and lose motivation over time as companions continue to perform pre-defined and repetitive behaviours [5]. This poses a challenge to the broad development and practical use of robot companions.

From the HRI (Human-Robot Interaction) point of view, robots’ social interaction becomes more believable and natural as they become more adaptable and responsive to environmental cues [4, 6, 9]. As humans, we expect others to be able to identify environmental factors that can represent unpleasantness or danger to themselves and act accordingly. Therefore, being able to properly express fear responses could highly increase

*Corresponding author

Email addresses: cr519@kent.ac.uk (Caroline Rizzi), C.G.Johnson@kent.ac.uk (Colin G. Johnson), ff79@kent.ac.uk (Fabio Fabris), p.a.vargas@hw.ac.uk (Patricia A. Vargas)

the believability of a long-term robot companion [9].

Fear learning has been a strong source of inspiration for developing more flexible and adaptive artificial intelligence [10–13]. The potential of artificial intelligence based on fear-learning models is demonstrated by its successful contribution to a variety of engineering and robotic applications [14–29]. Despite its advances, research on artificial fear-learning is still in its infancy and has several aspects with margin for improvement, among which we can highlight *situation appraisal*.

In the real world, people react not only to individual environmental stimuli (e.g. pain, smells, noises, location, light levels, etc.), but also to contextual variation over time, also known as *situation*, which is characterized by the temporal order and intensity variation of all appraised stimuli in a given period of time (e.g., being in a forest at night, with impaired visibility, and hearing animals' noises). Here, we define the emotional outcome and evaluation of a situation as *situation appraisal*.

To the best of our knowledge, artificial fear-learning models proposed to date do not substantially address situation appraisal, which is a significant part of the brain's fear-learning system, and essential for an organism to predict outcomes and adapt to threats and environmental changes [30].

This paper proposes a novel hybrid computational model, named SAFEL (Situation-Aware FEAr Learning), which is based on the brain's fear-learning system and incorporates the concept of situation awareness from expert systems. SAFEL builds on our fear-learning model, proposed in [31], which is inspired by three brain regions essential in fear learning: the sensory system, the amygdala and the hippocampus, along with a cognitive function of the brain known as the working memory [2]. Here, we discuss the implementation of SAFEL's hippocampus and working memory modules, which are responsible for simulating situation appraisal regarding fear. Experiments with a NAO robot demonstrate that SAFEL has successfully generated fear-conditioning behaviour with predictive capabilities based on situational information.

The main contributions of this work as compared to the state of the art are:

1. Integration of a fear learning model with the concept of temporal context. SAFEL performs threat predictions based on complex temporal and contextual information. Existing fear memory models either focus in the contextual or the temporal aspect, overlooking the need of both skills for an artificial intelligent agent to properly react to real-

world threatening situations.

2. SAFEL is focused on real-world applications for artificial and autonomous intelligence in robotics. Many existing fear-learning models that are inspired by the real mechanisms of the brain focus on providing a close-to-real emulation of brain functions without addressing the practical usage of the model for artificial intelligence.
3. The successful integration of a symbolic rule-based platform for situation management with a classification algorithm for memorizing and predicting threats based on complex temporal context.

This paper is organised as follows: Section 2 discusses related work. Section 3 summarizes the biological background and neuroscientific findings that have inspired SAFEL. Section 4 presents SAFEL's modelling and implementation. Experimental methodology and results are discussed in Sections 5 and 6, respectively. The paper concludes with Section 8, and also suggests future work.

2. Previous Models of Contextual Fear Conditioning

The idea of using models of emotion for improving autonomous learning in artificial systems started with Picard's research in 1995 [32, 33]. Picard's work originated one of the most recent branches of computer science: *affective computing*. According to Picard [33], affective computing tackles three aspects of artificial intelligence: (1) the ability of machines to recognize and express emotions, (2) the ability of machines to respond intelligently to human emotion, and (3) the capability of machines to regulate and utilize emotions in order to behave more intelligently and effectively. In this work, we focus on the latter aspect of affective computing, though all the three aspects are indirectly addressed.

A large range of approaches have been proposed for simulating emotions in artificial agents, such as affective space models [34, 35], motivation-driven models [13], neuro-inspired models [10, 12, 36–38], hormonal or homeostatic systems [39–42], among others [43, 44] (for a broader review on the varied approaches and challenges of affective computing, we refer the reader to [45]). Here, we are particularly interested in approaches addressing the temporal properties of context applied to fear conditioning for providing robots with fast, efficient and flexible decision-making.

One of the most influential works in artificial fear conditioning is the brain emotional learning (BEL) model, proposed by Morén and Balkenius [10]. Their model (Fig. 1) consists of interconnected modules of

artificial neural networks (ANNs) that simulate the role of neural circuitries involved in fear learning. It receives two types of inputs – environmental neutral stimuli and a reward signal – that are processed by four simulated neural regions: the thalamus, the sensory cortex, the amygdala and the orbitofrontal cortex.

The thalamus and sensory cortex simply relay input information to the orbitofrontal cortex and amygdala and, together, compose the “low and high roads” to the amygdala, respectively [2]. The sensory cortex receives information from the thalamus, which in turn receives information directly from the environment. As the thalamic pathway is shorter, it provides the amygdala with low latency information about environmental stimuli. On the other hand, information projected through the thalamic-cortical pathway takes longer to reach the amygdala, but provides a higher-level and more accurate representation of the sensed world.

The amygdala is responsible for assessing and predicting the emotional value of stimuli, based on the significance of the accompanied reward. Finally, the orbitofrontal cortex is responsible for inhibiting emotional associations of the amygdala that are no longer valid. This model has been tested for the most basic effects of classical conditioning – such as *fear acquisition*, *fear extinction*, *blocking*, *habituation* and *spontaneous recovery* – showing satisfactory results.

The BEL model was later improved in [46], with the addition of a module that simulates the contextual processing performed by the brain’s hippocampal regions. BEL’s hippocampus module has four main components:

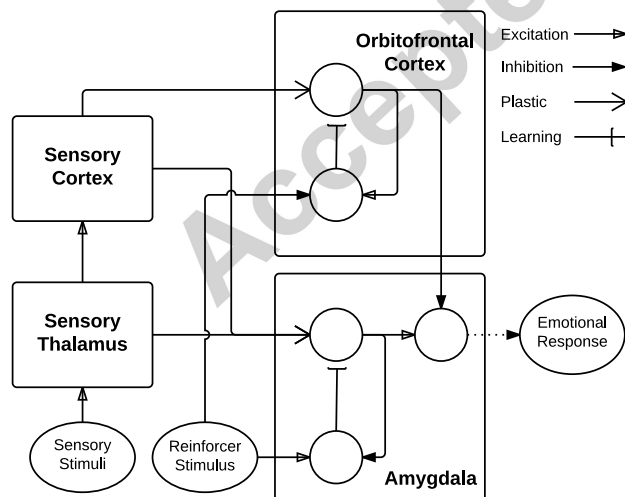


Figure 1: Fear-learning model proposed by Morén and Balkenius [10]. Each component of their model represents an ANN. Circles represent individual ANNs internal to the respective component.

the *Bind subsystem*, the *Mem system*, the *Match system* and the *Context system*. The Bind subsystem is responsible for binding stimuli that are simultaneously detected. The Mem system generates expectations about stimuli manifestation at specific locations. These expectations are later compared with the actual stimuli in the Match system. Lastly, the Context system combines information from the Match and Bind systems to generate a contextual code that feeds the amygdala and orbitofrontal cortex.

With the aid of the hippocampal module, BEL is able to express fear responses based on contextual information. For example, one of the experiments performed in [46] consisted on presenting two different stimuli, CS0 and CS1, sometimes separately and sometimes together. All single presentations of either CS0 or CS1 were followed by a reinforcing signal, whereas all simultaneous presentations were followed by nothing. The model gradually learned to differentiate between single and joint stimulus presentation. Further experiments in [46] with other patterns of stimulus presentation and location were also successful.

Despite BEL’s success in discriminating sets of simultaneously presented stimuli, a few important questions were left unanswered. For instance, what would happen if the reinforcing signal was presented only after CS0 was followed by CS1 (represented by CS0→CS1)? Would the model understand that CS1→CS0 is different from CS0→CS1? According to Morén [46], context “can be either an abstract sequence of stimuli or a place defined by a number of stimuli at different locations around the animal”. It is clear that temporal factors are not considered in Morén’s conceptualization of context, which is possibly the reason why the temporal order of stimulus presentation is never evaluated in his experiments.

The simplest version of the BEL model (i.e., the version proposed in [10], which has no hippocampus module) became more popular among researchers. Based on the BEL model [10], Lucas, Shahmirzadi and Sheikholeslami [11] proposed a Brain Emotional Learning Based Intelligent Controller (BELBIC), which was later applied (somewhat adapted) to a large range of industrial [14–18], engineering [19–23] and robotics [24–29] applications. Most of these works have compared their BELBIC controllers with conventional controller approaches (e.g. PID, MLP, ANFIS and LLNF) and observed meaningful improvements in varied performance aspects when using BELBIC.

In 2010, Beheshti and Hashim [47] published a review on BELBIC systems and demonstrated its performance for engineering ends. They compared BEL-

BIC with a range of conventional controller approaches (such as PID, ANFIS and feedback linearization controller) for several engineering applications (such as micro heat exchanger, intelligent control of washing machine, dynamic power management, intelligent predictor for geomagnetic activity, and speed and flux control of an induction motor). Their analysis concluded that BELBIC showed better performance and results than the tested conventional approaches for real time control and decision systems.

BELBIC's popularity and performance improvement over traditional approaches in several application areas demonstrates its great potential as a controller. We believe that such success could be even greater if BELBIC was based on the improved version of BEL [46], as well as if it considered the temporal aspects of context.

Rudy and O'Reilly [36] have also proposed a contextual fear-conditioning model that relies on a theoretical framework [48] based on the cortical and hippocampal regions of the brain. In their model, the cortex represents context as a set of independent features, whereas the hippocampus binds these features into an unitary representation. Rudy and O'Reilly have implemented their framework on an artificial neural network model, which was evaluated on a scenario that simulates a context fear-conditioning experiment performed with rats. The experiment aimed at evaluating the model regarding its capability to (1) enhance fear conditioning via pre-exposure to context and (2) induce pattern completion (when a subset of a learned pattern can recover the entire pattern).

Although successful in reproducing many fear conditioning effects, the contextual fear-conditioning model of Rudy and O'Reilly [36] also disregards the temporal properties of context. According to Rudy and O'Reilly [36], "either context can be represented as a set of independent features (the features representation view) or these features can be bound into an unitary encoding that represents their co-occurrence (the conjunctive representation view)". This implies that their unitary representation of context considers features that co-occur only, which excludes a large range of temporal possibilities between distinct features that are essential for a thorough contextual perception.

A model that considers temporal sequences has been designed by Harrison et al. [30]. Their study aimed at evaluating hippocampal responses to changes in probabilistic context by submitting subjects to a first-order Markov sequence, where the current event E_t is conditionally dependent on the previous event E_{t-1} , and the probability of transition between them is given by $p(E_t|E_{t-1})$. To model the task, they assumed that the

subject was an ideal Bayesian observer, who starts with the belief that all events are equally likely and consecutive events are independent. As samples of events are sequentially presented, this ideal observer constructs a transition matrix consisting of the probabilities of transition between consecutive events.

Their model is similar to ours in the sense that learning and prediction are based on the temporal relationship of events. However, the design of the task given to their subjects, which reflects on their model of an ideal observer, considers that every event consists of only one stimulus. Although sufficient for the purpose of their experiment, which is analysing hippocampal responses to temporal context, this simplistic design does not reflect real world situations, in which events may consist of many simultaneous stimuli.

Among recent research, we highlight the work of Subagdja and Tan [37]. They propose a model for *episodic memory*, which is a type of long-term declarative memory mainly processed by the hippocampus, using an extended adaptive resonance theory (ART) network. They argue that the accuracy of memory retrieval depends on the order and latency between memory cues, which matches the conceptual foundation of our work. They evaluate their approach on a transitive inference problem, which is a classical logical problem of comparing the value of things (e.g., given that A weighs more than B and B weighs more than C, then it can be inferred that A weighs more than C).

Amongst the related work, Subagdja and Tan [37] may be the most similar to our proposed model with regards to temporal context. For instance, their definition of situation (which they call an *episode*) is equal to ours. However, our approaches differ in the final purpose of temporal context. We are mostly concerned with predicting aversive events by creating a link between the "feeling of fear" and the events that preceded an aversive stimulus in a past experience. This would provide robots with the chance to react and prevent unpleasant (possibly harmful) situations, as well as to increase their adaptation capabilities. On the other hand, the work of Subagdja and Tan addresses neither fear conditioning, nor danger prediction/prevention. In their work, events' order is not associated with any emotion. Their main focus is to facilitate retrieval, creation and update of neutral (non-aversive) contextual memory.

3. Biological Background

This section discusses the main biological concepts behind SAFEL's model. We begin introducing SAFEL's inspiration: fear conditioning, the phenomenon behind

fear learning. Next we discuss the brain mechanism responsible for fear learning and memory, based on the model proposed by LeDoux [2, 49].

3.1. Fear Conditioning

In *classical fear conditioning* [50], associative learning is induced by repeatedly pairing a *neutral stimulus* (NS) with an aversive *unconditioned stimulus* (US). An aversive US is any stimulus that naturally elicits fear or anxiety in the animal. In other words, the animal is born with the knowledge that such stimulus is aversive, like a “hard-coded” knowledge. Some examples of aversive US are pain, hunger, sensory impairment (such as losing visibility in dark places), aggressive facial expression of other animals, etc.

By pairing a NS and an aversive US (i.e., by presenting these stimuli simultaneously to the animal), the NS acquires emotional value and becomes able to trigger fear reactions by itself, even in the absence of the US. Since the NS did not trigger fear reactions before, we say that the animal has learned to fear it through a conditioning procedure. As consequence, the NS becomes a *conditioned stimulus* (CS).

The classical foot-shock experiment with rats demonstrates this phenomenon. In the experiment, a rat is placed into an apparatus and receives auditory cues paired with electrical shock in its feet. The shock naturally elicits fear in the rat, which freezes in response. After repeating this procedure a few times, the rat associates the stimuli and starts to freeze in response to the auditory cue even in the absence of an electrical shock. Because the CS did not elicit the defensive response before, it is said to be a *conditioned emotional response*.

Nevertheless, in this experiment, fear expression has been observed not only in response to the auditory cue, but also to the background context, which in this case is the apparatus where the shock was induced. The phenomenon of expressing defensive responses in the presence of a specific combination of stimuli (e.g., a situation or place) under which a US has been previously induced is known as *contextual fear conditioning* [51].

Although both types of conditioning lead to the same fear responses, their perception and processing mechanisms in the brain are very different. In classical fear conditioning, the CS is restricted to an individual stimulus that belongs to a specific sensory modality (smell, touch, taste, hearing or vision), whereas in contextual fear conditioning, the CS is composed of a collection of stimuli, which may belong to different sensory modalities [51]. This set of stimuli is bound into an unitary representation of context that depicts not the stimuli *per se*, but the relationship between them [2].

3.2. Fear Learning in the Brain

Considerable evidence points the amygdala as the main brain region involved in fear learning and memory [2, 49, 51, 52]. Although the amygdala is essential for both classical and contextual fear conditioning [51], it is in the hippocampus where context processing mainly takes place [2, 53], including the association of events across time [54]. Research has shown that lesions to the amygdala interfere with fear responses to both types of fear conditioning, while lesions to the hippocampus interfere with fear responses in contextual fear conditioning only [51, 55].

These findings reinforce the model of the brain’s fear-learning process proposed by LeDoux [2, 49]. According to LeDoux, fear learning relies mainly on three brain regions: the sensory system, the amygdala and the hippocampus, as well as a cognitive function known as the working memory.

The sensory system, composed by the thalamic and cortical pathways, is responsible for providing the amygdala with information on different levels of abstraction and accuracy. The amygdala, in turn, processes the emotional significance of sensed stimuli. In other words, it is the brain region responsible for fear appraisal. It is also where classical fear conditioning takes place, i.e., where neutral stimuli are associated with aversive stimuli during the conditioning process.

The hippocampus is where we begin to leave the purely perceptual reasoning about the world and enter the conceptual domain of the brain. In the hippocampus, sensory information is put together in order to form an unitary representation of the current state of affairs. Unlike information processed in the amygdala, representations formed in the hippocampus are not just visual, auditory or olfactory, but all of these at once, and includes the way these sensations relate to each other both in intensity and temporal order.

The amygdala and hippocampal systems work in parallel, forming what LeDoux calls, respectively, as *emotional memory* and *memory of emotion* [2]. When you remember a traumatic situation, in addition to the state of affairs, the hippocampus will also remember you as a cold fact that you were afraid at that time, providing you with an unemotional *memory of emotion*. The amygdala, in turn, will trigger bodily and brain responses (muscles’ tense up, increased heart rate, hormone release, etc.) that allow you to re-experience the fear felt during the trauma, thus providing you with an *emotional memory* of the episode.

Exposure to stimuli that were present during the trauma activates both the amygdala and hippocampal

systems, which work in parallel to retrieve emotional and contextual memory about the event, respectively. Because these two memories are simultaneously recovered in response to the same stimuli, they are experienced as if they were one single memory.

These two memories are fused and consciously experienced in the working memory. LeDoux [49] defines the working memory as “a serially organized mental workspace where things can be compared and contrasted and mentally manipulated”. A variety of studies indicate pre-frontal cortex areas and the anterior cingulate region as involved in working memory functions [49, 56, 57]. Newly sensed stimuli and stored hippocampal representations are integrated in working memory through interactions between pre-frontal and hippocampal areas. In the case of an aversive stimulus, similar interactions are triggered, which inform the working memory of the fact that the amygdala has activated fear responses. In other words, the working memory allows the association of explicit contextual memory formed in the hippocampus with implicit emotional memory formed in the amygdala.

4. SAFEL: A Situation-Aware Fear Learning Model

SAFEL is a situation-aware computational system capable of endowing a companion robot to learn and predict threatening situations to itself through a fear-conditioning-like procedure. Nevertheless, we emphasise that, although we have chosen robotics as our main application, SAFEL has the potential for being used in any other areas that require machine learning and adaptation.

This work is based on the fear-learning model of the human brain and contemplates part of a more ambitious fear-learning architecture proposed in [31]. This architecture is inspired by the LeDoux model [2, 49], discussed in Section 3.2. SAFEL’s complete architecture [31] is divided into four hybrid modules that work in an integrated and parallel manner: the sensory system, the amygdala system, the hippocampal system and the working memory.

Fig. 2 depicts the complete model proposed in [31], illustrating how the four main modules of the architecture are interconnected. The sensory system pre-processes environmental stimuli detected by the robot (e.g., by means of sensors’ input or direct user input), which is relayed to the amygdala and hippocampal systems. The amygdala system is responsible for predicting and associating environmental stimuli to imminent danger. It also provides emotional feedback to the hippocampal system. In parallel, the hippocampal sys-

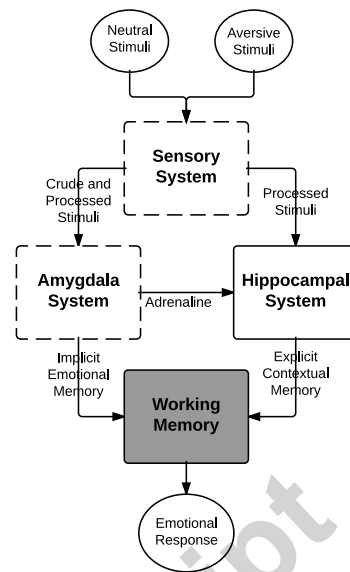


Figure 2: The complete model of the fear-learning architecture proposed in [31]. Dashed boxes represent the modules of the architecture that we have not yet implemented. White boxes represent areas of the brain, whereas grey boxes represent cognitive functions of the brain. The system receives neutral and aversive stimuli as input, and outputs the corresponding emotional response.

tem generates complex contextual representations of the environment based on the processed sensory information projected by the cortex. Finally, implicit memories from the amygdala system and explicit memories from the hippocampal system meet in the working memory, where contextual information is associated with emotional information to produce emotional responses.

Note that this model does not attempt to capture all the real neural circuits involved in the brain’s fear learning system, which are far more complex and have not yet been completely understood by neuroscientists. It also does not attempt to perfectly mimic all aspects of the real fear learning. The proposed model seeks to capture the aspects of the fear learning system that are relevant for improving a robot’s learning, adaptation and believability competencies.

In this paper, we model, implement and evaluate the hippocampus and working memory modules. The implementation of the sensory and amygdala systems are part of our future work.

4.1. Hippocampus Module

In the following, we present both theoretical and practical foundations for implementing situation awareness in the hippocampus module of SAFEL.

The hippocampus module is responsible for SAFEL’s contextual processing and is based on the concepts of

situation-awareness proposed by Dey [58], which is discussed in Section 4.1.1. In order to address Dey’s definition of situation awareness, we have modelled and implemented SAFEL’s hippocampus module on the JBoss Drools rule engine and CEP (Complex Event Processing) platform [59], which we introduce in Section 4.1.2. Finally, Section 4.1.3 presents the design of the hippocampus module.

4.1.1. Situation Awareness

Context has many definitions among different areas of study. Dey [58] was one of the first to propose a context definition from the perspective of expert systems. According to Dey, “context is any information that can be used to characterise the situation of an entity. An entity is a person, place, or object that is considered relevant to the interaction between a user and an application, including the user and application themselves” [58].

Dey’s definition of context, however, does not incorporate temporal properties. This is because, according to Dey, the temporal aspects associated with the status of an entity are part of an extended conceptualization of context called *situation*. A situation describes a collection of states of relevant entities, where each state depicts those entities’ context in a given point in time. In this sense, the term *situation awareness* could be understood as the act of being aware of the variations in an entity’s context during a particular period of time.

To the merge of situation-awareness with emotional evaluation we give the name of *situation appraisal*. Here, we define situation appraisal as one’s capability of not only being situation aware, but also being able to make emotional evaluations and associations over perceived situations. This is not to be confused with the *appraisal approach of emotion*, in which emotional states are usually defined by rule-based techniques on a set of appraisal variables [12, 60]. Although the hippocampus module is based on rules and event management, the link between situations and emotional states is not defined through rules, and is performed in the working memory module, as we explain later in Section 4.2.

The hippocampus module of SAFEL is based on Dey’s conceptualization of situation awareness for computing. In other words, the hippocampus module is responsible for collecting, understanding and managing the states of the robot over time, so that other modules of SAFEL, such as the working memory, can make proper use of this information at a higher level of abstraction.

4.1.2. Underlying Technology

Rule-based languages are based on the model of human cognitive process of conscious decision-making,

which is guided by the rules and facts learned during an individual’s life [61]. This makes rule-based techniques suitable for simulating the hippocampal functions in the brain.

The hippocampus module of SAFEL is based on JBoss Drools [59], which is a robust rule management platform. Drools also provides CEP (Complex Event Processing) management and greatly fulfils the design requirements of the hippocampus module.

Drools has its own rule-based language, the DRL (Drools Rule Language), consisting of a set of *when-then* statements that can be applied to a set of *facts*. Facts, in turn, are information representing immutable entities of the world. For example, “John”, “Mike” and “Mary” are instances of the fact “person”, which can have “age” as an attribute. An example of a rule (in natural language) would be “*when* a person older than 60 years enters the bus, *then* apply ticket discount”. Code 1 shows a simple example of how this rule could be written in DRL.

Drools’ *inference engine* (or *rule engine*), is responsible for evaluating facts against rules’ patterns through a process known as *pattern matching*. When one or more facts satisfy a rule’s condition (the *when* part), the inference engine executes the actions defined in the rule’s *then* part and we say that the rule has been *fired*. When a rule is fired, the execution of its actions may fire other rules, leading to a cascade effect.

Drools also has an embedded CEP platform, which allows for the detection and management of events. *Events* are defined as records of significant changes in the domain’s state at a given point in time [59]. Some examples of events are “A person has entered the bus”, “Mary has left the room”, etc. Besides facts, an event can also consist of other events, when it is said to be a *complex event*.

Because events have intrinsic temporal properties, they can be compared with each other by means of *temporal operations*. Drools implements all 13 temporal operators defined by Allen [62, 63]. Some examples are “before”, “after”, “during”, “finished by”, etc.

Code 1: Example of Drools rule.

```

1 rule "Ticket Discount" // rule name
2 when // condition
3     person : Person(age > 60)
4 then // action
5     BusSystem.applyTicketDiscount();
6 end

```

An example of rule using a temporal operation would be “when a person enters the meeting room *before* the meeting time, *then* ask to wait outside”.

While events represent punctual changes in the state of affairs, such as “Mary has entered the room”, *situations* represent changes in the state of affairs that have duration and can be either current (e.g., “Mary has been in the room since 6AM”) or past (e.g., “Mary was in the room for 5 hours”). SAFEL is inspired by SCENE’s situation management modelling [64, 65] to implement situation-awareness. According to SCENE’s conceptualization, situations are “composite entities whose constituents are other entities, their properties and the relations in which they are involved” [64].

In SCENE, general characteristics of situations are defined by their *situation type*. For example, “John is in the meeting room” and “Mary is in the living room” are examples of instances of the situation type “Person is in the room”. A situation instance is *activated* when entities whose properties satisfy the restrictions of the respective situation type are detected. A situation instance is said to be a *current situation* while these restrictions are satisfied. The situation instance is *deactivated* when its type restrictions are no longer satisfied, and it is said to be a *past situation*. *Situation duration* is the period of time between the activation and deactivation of a situation. Therefore, only inactive situations (i.e., past situations) can have a closed duration.

Our situation management differs from SCENE’s approach regarding the moment of situation detection, i.e., the moment when the system becomes aware of the existence of the situation. According to SCENE, situations are always detected at their activation time. However, SAFEL’s design requires certain types of situation to be detectable at or after their deactivation time. The reason for this design decision is explained next, in Section 4.1.3.

4.1.3. Hippocampus Model

The hippocampus module receives two input types: *neutral stimulus* and *adrenaline signal*. Neutral stimuli are real values representing environmental stimuli detected by the robot’s sensors that, initially, have no emotional meaning for the robot. On the other hand, the adrenaline signal is a value in the range $[0, 1]$ representing the system’s level of fear based on the detection of aversive unconditioned stimulus (US).

Analogously to aversive US in the brain, an aversive US for SAFEL is any stimulus that is known to be harmful to the robot and, thus, can be hard-coded as aversive US in the robot’s fear-learning system. In the same

sense that animals are born with knowledge about aversive US, robots should also start their life-cycle with a set of well-known aversive US (e.g., collision, low light/visibility level, low battery, etc.), which are pre-configured parameters of SAFEL.

In the complete architecture of SAFEL (Fig. 2), the amygdala module is responsible for assessing the emotional value of sensed stimuli and outputting an adrenaline signal. The adrenaline informs the hippocampus about the presence or not of aversive stimuli. However, as previously mentioned, the amygdala module has not yet been implemented in the current version of SAFEL. To deal with the absence of the amygdala, we simplify the process of adrenaline management by setting it high whenever a pre-defined aversive stimulus (i.e., an US) is detected, and setting it low otherwise.

This solution, though, is temporary and has the only purpose of evaluating the hippocampus and working memory modules. Thus, it is not intended to replace the amygdala module. The amygdala is an important module in SAFEL’s architecture, which performs essential tasks other than managing adrenaline levels. For example, the amygdala is also responsible for detecting and memorizing new potential aversive stimuli that are not US (i.e., are not pre-defined), which may have been neutral in the past, but became dangerous in a currently new environment.

Situation management in the hippocampus module is based on the following definitions:

Definition 1. An event \mathbf{e}_t is a collection of all stimuli detected by the robot’s sensors at time t , so that $\mathbf{e}_t = \{s_1^t, s_2^t, \dots, s_n^t \mid n \in \mathbb{N}\}$, where s_i^t is a normalized real value $s_i^t \in [0, 1]$ representing the intensity of stimulus of type i detected at time t .

Definition 2. A situation S is composed of the sequence of events occurring during its active period, so that $S_j = \{\mathbf{e}_{a_j}, \mathbf{e}_{a_j+1}, \dots, \mathbf{e}_{d_j} \mid a_j < d_j, [a_j, d_j] \in [\mathbb{N}, \mathbb{N}]\}$, where a_j and d_j are, respectively, the times of activation and deactivation of situation j .

We have defined four situation types in the hippocampus module: *aversive*, *predictive*, *safe* and *unknown*. The rules under which these situations are instantiated are defined in a DRL file and are constantly matched against the current adrenaline signal and existing situations instances in Drools’ memory. When information in Drools’ memory satisfies the constraints of these rules, new situations are instantiated, whose type depends on which rule was executed.

Code 2 shows the rule responsible for instantiating new aversive situations, whose conditions are defined in

the *when* block (lines 3 to 5). This rule is satisfied when the last adrenaline signal received (line 3) has level above a given threshold (line 4) and there is no aversive situation currently active (line 5). If these conditions are satisfied, the actions listed in the *then* block are executed, which in this case is creating a new instance of aversive situation and insert it into Drools' memory (line 7). The properties of events (e.g. *Adrenaline*) and situations (e.g. *AversiveSituation*) are defined in Java objects.

It is also possible to perform temporal operations between situations. Code 3 shows a snippet of the rule responsible for instantiating predictive situations. Observe in the conditions of this rule, keywords such as *before* and *after* (lines 5 and 6). These keywords represent temporal operations and allow creating conditions based on the temporal order of situations' activation and deactivation.

The properties and constraints of each situation type in the hippocampus can be summarized as follows:

- *Aversive situation*: An aversive situation indicates the periods of time in which the system was (or is, if it is a current situation) exposed to aversive stimuli.

Code 2: Drools rule for instantiating an aversive situation.

```

1 rule "Aversive Situation"
2 when
3     adrenaline : Adrenaline() over
4         window:length(1)
5     Adrenaline(this == adrenaline, level >=
6         adrThreshold)
7     not AversiveSituation()
8 then
9     insert(new AversiveSituation());
10 end

```

Code 3: Example of temporal operation.

```

1 rule "Predictive Situation"
2 when
3     (...)
4     aversive : AversiveSituation ()
5     unknown : UnknownSituation(this before
6         aversive)
7     not (exists UnknownSituation(this after
8         unknown, this before aversive))
9     (...)
10 then
11     (...)
12 end

```

uli. It is activated when the adrenaline signal rises above a given threshold (meaning that the robot has detected an aversive stimulus), and is deactivated when the adrenaline signal returns to normal levels (meaning that the aversive stimulus is no longer present).

- *Predictive situation*: Predictive situations are those that precede aversive situations. Because they have preceded an aversive situation once, if they reoccur, it is probable that they will precede a similar aversive situation again. By recognizing the pattern of predictive situations, the robot increases its chances to predict the imminent exposure to aversive stimuli. Because predictive situations can only be detected on the activation of the respective aversive situation, i.e., after their own deactivation, they are always past situations (see Section 4.1.2) for the system.
- *Safe situation*: Safe situations are those that do not precede or co-occur with aversive or predictive situations. This means that the robot is not being exposed to aversive stimuli at the current moment, and has no expectations to be exposed to aversive stimuli in the near future. The only way to ensure that a given situation is safe is to look at the situations occurring right after it in order to confirm that they are neither aversive nor predictive. Hence, like predictive situations, safe situations can only be detected when they are already past situations.
- *Unknown situation*: An unknown situation is any situation that is not aversive, and cannot yet be considered safe or predictive (since these can only be detected after their deactivation). Unknown situations can become either safe or predictive in the future, depending on the events occurring in a given time interval after their deactivation.

Fig. 3 shows an example of situations' life-cycle over time, where Fig. 3a shows the adrenaline signal over time, and Fig. 3b, 3c and 3d show situations' status in the system at time t_{10} , t_{13} and t_{14} , respectively. In Fig. 3b, for instance, situation S_1 has activation time $a_1 = t_1$ and deactivation time $d_1 = t_5$, situation S_2 has activation time $a_2 = t_2$ and deactivation time $d_2 = t_6$, and so on. Analogously, $S_1 = [e_{t_1}, e_{t_2}, e_{t_3}, e_{t_4}, e_{t_5}]$, $S_2 = [e_{t_2}, e_{t_3}, e_{t_4}, e_{t_5}, e_{t_6}]$, and so on.

Observe that situations can overlap each other. For example, situation S_2 is activated while situation S_1 is active; situation S_3 is activated while situations S_1 and S_2 are active, etc. Consequently, two or more situations

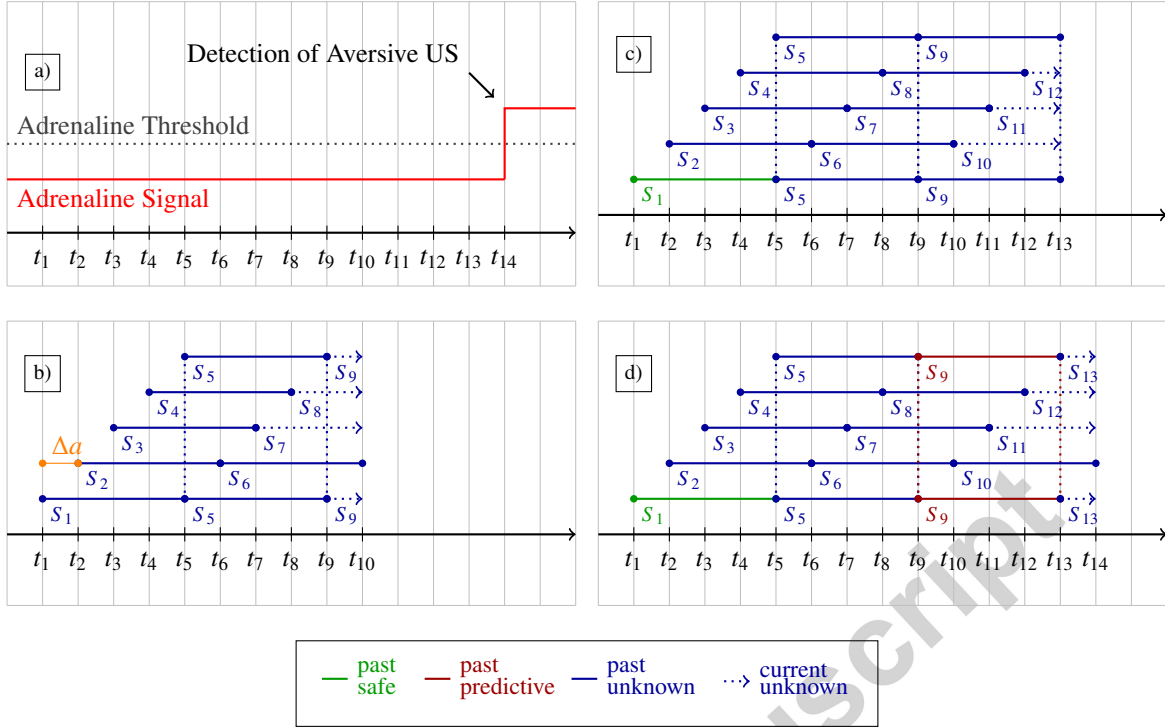


Figure 3: Example of situations' status over time. In Fig. (b), (c) and (d), the horizontal axis indicates the time step, and overlapping situations are disposed vertically, for the sake of readability. (a) Behaviour of adrenaline signal over time. In this example, the adrenaline is below the pre-defined threshold, and instantly goes above it when an aversive US is detected. (b) Status of situations' type at time t_{10} . At this moment, all situations are still considered unknown. (c) Status of situations' type at time t_{13} . At this moment, situation S_1 can no longer become a predictive or aversive situation. As consequence, it leaves the status of unknown situation and becomes a safe situation. (d) Status of situations' type at time t_{14} . At this moment an aversive US is detected and, consequently, adrenaline levels rise above the pre-defined threshold (see Fig. a). Because situation S_9 is the last unknown situation to happen before the elevation of the adrenaline signal, it becomes a predictive situation.

can contain the same event. For instance, event e_{t_4} belongs to situations S_1, S_2, S_3 and S_4 .

A new unknown situation is activated every Δa time steps (Fig. 3b), where Δa is a parameter of SAFEL, called *situation detection delay*, that defines the period of time between the activation of a given situation and the activation of its predecessor situation. Unknown situations can be either current or past. For instance, in Fig. 3b, situations from S_1 to S_6 are past because they have already finished by time t_{10} , while situations S_7, S_8 and S_9 are current because they are still occurring at time t_{10} .

Unknown situations may become safe or predictive in the future, but only if certain constraints are satisfied at the current moment, otherwise they continue to be considered unknown. For instance, all situations detected in Fig. 3b are still unknown, since nothing can be said about them at time t_{10} . To be considered safe, a situation must be past and be followed by at least two consecutive past unknown situations. This is to ensure it will never precede or co-occur with any predictive or aver-

sive situation. To be considered predictive, a situation must precede a peak in the adrenaline level. Considering that at moment t_{10} none of these conditions have been matched, all situations are still unknown at that moment.

At moment t_{13} in Fig. 3c, however, the conditions for detecting safe situations are satisfied by the current status of situation S_1 . At time t_{13} , situation S_1 is past and is followed by a past situation (S_5) that, at this point, can no longer become predictive. Thus, at time t_{13} , situation S_1 leaves the status of unknown and becomes a safe situation. Similarly, the conditions for detecting predictive situations are also satisfied by the current status of situation S_9 at time t_{14} in Fig. 3d, when the adrenaline level rises above the specified threshold (as seen in Fig. 3a). Because S_9 is the last past unknown situation before the raise of adrenaline, it leaves the status of unknown situation and becomes a predictive situation.

Safe and predictive situations are immediately sent to the working memory module at their detection time, while unknown situations are sent at their deactivation

time. Consequently, every factually safe and predictive situation is sent twice to the working memory: first when it has just finished and is still unknown; and then again a few time steps later, when the hippocampus is able to determine whether it is actually safe or predictive. In the example of Fig. 3, for instance, situation S_1 is sent to the working memory at time t_5 as unknown and at time t_{13} as safe. Analogously, situation S_9 is sent to the working memory at time t_{13} as unknown and at time t_{14} as predictive. The dual submission of the same situation instance, but with different situation types, is essential for the working memory to perform its task, which is discussed in the next section.

4.2. Working Memory Module

The working memory is the place where emotional memory (formed in the amygdala) and contextual memory (formed in the hippocampus) are fused to create “emotional contextual memories”. The goal is to provide the robot with the capability to recover fear memories and predict an imminent unpleasant event by experiencing again a situation that preceded that unpleasant event in the past.

In this section we discuss the working memory module regarding the main algorithm behind its associative learning (Section 4.2.1) and its modelling (Section 4.2.2).

4.2.1. Underlying Technology

The working memory’s associative learning is implemented using MATLAB’s *binary classification tree* [66], which is used to classify situation patterns into safe or predictive. In a binary classification tree, each node corresponds to a binary predicate on one attribute, where one branch from the node represents positive instances of the predicate and the other branch represents negative instances. Each leaf node is labelled by a class. To predict the type of an input situation pattern, a path to a leaf from the root is found depending on the value of the predicate at each node that is visited.

MATLAB creates a classification tree by first analysing the training dataset and examining all possible binary splits on every attribute. Then, the first node is split according to its *impurity gain*, which is calculated using the *Gini Diversity Index* (GDI), also known as *Gini Impurity Criterion* [67]. The GDI of a node is given by

$$1 - \sum_i p^2(i), \quad (1)$$

where $p(i)$ is the proportion of cases of class j at the respective node. A node with just one class (a pure node)

has Gini index 0; otherwise the Gini index is positive. To split the node, MATLAB selects the attribute variable that maximizes the impurity gain (i.e., that maximizes the purity of the node). This process is recursively repeated for the child nodes, stopping when it finds a pure node or when it reaches a stopping criteria, such as a maximum number of splits or maximum tree depth.

The following design reasons led us to adopt the binary classification tree:

- *Interpretable*: classification trees are white box algorithms, thus allowing one to easily interpret the logic behind the robot’s learning and emotional response to stimuli.
- *Insensitive to outliers*: classification trees are built by dynamically selecting the most informative features, and ignoring information that is irrelevant for the predictions. This is an essential feature for the working memory module, because in most cases only a subset of the robot’s sensors will provide valuable information about the pattern of a specific situation. For instance, a robot may require a camera, face recognition algorithms and sonar sensors to detect that a person is nearby, but many other sensor information (e.g., internal temperature, accelerometer and battery level) would not give valuable information in this case. It is essential that the classifier of the working memory module be able to ignore information that is irrelevant for characterizing the pattern of predictive situations.
- *Fast training and classification*: classification tree is an algorithm well known by its fast training and classification processes [68]. This is important because SAFEL’s emotional learning greatly relies on constantly retraining the classifier of the working memory module. The slower the re-training and classification processes are, the more time the robot would take to present an emotional reaction.
- *Non-parametric*: classification trees are non-parametric algorithms, meaning that they do not require specifying parameters that depend on the distribution of data. One of SAFEL’s goals is to be of general purpose. To be applicable to a variety of environmental characteristics, SAFEL’s learning must be independent of data shape.

4.2.2. Working Memory Model

In the working memory module, situation instances coming from the hippocampus module pass through a

feature extraction process in order to generate compacted versions of situational information. This phase consists of extracting relevant information that characterizes the fluctuation pattern of each stimulus over the situations' duration.

From Definitions 1 and 2, and supposing that $a_j = 1$ and $d_j = m$, and that the robot has n sensory inputs, we have that:

$$S_j = \begin{pmatrix} \mathbf{e}_1 \\ \mathbf{e}_2 \\ \vdots \\ \mathbf{e}_m \end{pmatrix} = \begin{pmatrix} s_1^1 & s_2^1 & \cdots & s_n^1 \\ s_1^2 & s_2^2 & \cdots & s_n^2 \\ \vdots & \vdots & \ddots & \vdots \\ s_1^m & s_2^m & \cdots & s_n^m \end{pmatrix}. \quad (2)$$

From Eq. 2 we can say that

$$S_j = [\mathbf{s}_1, \mathbf{s}_2, \dots, \mathbf{s}_n], \quad (3)$$

where $\mathbf{s}_i = [s_i^1, \dots, s_i^m]^T$. Then, the new situation information S'_j generated from S_j is given by

$$S'_j = [\bar{s}_1, \dots, \bar{s}_n, \gamma_1, \dots, \gamma_n, \eta_1, \dots, \eta_n], \quad (4)$$

where \bar{s}_i , γ_i and η_i are, respectively, the mean, skewness and number of local maxima of \mathbf{s}_i (Eq. 3). The mean value provides the average intensity of each sensed stimulus along the situation's duration. The skewness provides the approximate time interval when each stimulus was more intense during the respective situation. Finally, the number of local maxima provides the detection frequency of each stimulus during the situation.

The main goal of performing this feature extraction procedure is to create approximated representations of situation instances that aid on the generalization aspect, thus preventing overfitting of situation patterns. The new piece of information generated by this process is analogous to the unitary representation of context created in the brain, discussed in Section 3.2.

This feature extraction phase is also useful for data compression, since it can reduce the volume of information about situation j from a matrix S_j of size $n \times m$ to a vector S'_j of size $3n$. This is especially efficient when $m \gg n$, which is in fact the most common case, as the number m of time steps in a situation is usually much larger than the number n of sensory inputs a robot may offer.

As mentioned in Section 4.1, every factually safe and predictive situation is sent in two time-steps from the hippocampus to the working memory: first when it is still unknown and later when it is either factually safe or predictive. Therefore, at time d_j (i.e., when situation j has just been deactivated), S_j will be sent as an

unknown situation to the working memory, where it is transformed into S'_j and submitted to the binary tree for classification. The tree will classify that situation into safe or predictive based on past situation experiences of the robot. Then, at time t_n , where $t_n > d_j$, situation information S_j will be sent to the working memory once again, but this time labelled as either safe or predictive. The generated situation pattern S'_j and its type (safe or predictive) will now be used for retraining the classification tree, providing it with one more situation experience where to base its future predictions.

For example, in Fig. 3b, situation S_1 is sent to the working memory as an unknown situation at time $d_1 = t_5$. Then, the working memory compacts S_1 into S'_1 , which is later classified as either safe or predictive. At time t_{13} in Fig. 3c, the same situation S_1 is submitted again to the working memory, but now as a safe situation. This time, S'_1 is used for retraining the classification tree, thus reinforcing that the pattern of S'_1 represents a safe situation and indicates that no aversive stimulus is expected to occur in the near future.

Similarly, situation S_9 is sent as unknown for prediction to the working memory at time $d_9 = t_{13}$ (Fig. 3c). If the robot has experienced other situations that are similar to S_9 in the past, then the binary tree will very likely classify S'_9 as a predictive situation, meaning that an aversive stimulus is about to occur. Knowing at time t_{13} that something "bad" is about to occur is advantageous, as the system can use this information to prevent or minimize the outcome of the aversive stimulus occurring at time t_{14} , if possible. Then at time t_{14} (Fig. 3d), when the aversive stimulus occurs (making it possible to affirm that S_9 is indeed a predictive situation), situation S_9 is sent again to the working memory and is used for retraining the classification tree to recognize the pattern of S'_9 as a predictive situation.

The dataset used to train the decision tree starts empty, with no knowledge about the current environment. As the robot explores the environment and experiences new aversive situations, the dataset grows and the tree is retrained. Therefore, the robot's capability to predict imminent aversive events improves with experience, as it explores the environment. In addition, because the tree is constantly retrained, the robot can adapt itself even when it is moved from one environment to another. If a particular situation that was safe in a previous environment is now predictive in the new environment, the classification tree will be constantly retrained in this new environment to recognize that situation as predictive, consequently gradually forgetting the previous association of that situation with safety.

5. Experiments with a Humanoid Robot

In terms of predictive performance, we understand that comparing BEL [10] and SAFEL with focus on temporal reasoning would be unfair, because unlike SAFEL, BEL is not designed to process temporal sequences of events. Although BEL has similarities with SAFEL, these are mostly conceptual, such as being inspired by real brain mechanisms. Instead, we focus on experiments showing the efficacy of SAFEL for predicting aversive events based on temporal context.

The experiments have been conducted using a NAO humanoid robot, model T14 (Fig. 4). NAO is one of the most widely used robots in the HRI field of research [69]. By using NAO, we hope to facilitate the reproduction of our work, as well as the implementation of future comparative studies.

In addition, by using a physical robot in this experiment, we aim at exposing SAFEL to noises and reading failures characteristic of real robot sensors. In a virtually simulated environment, the quality of sensor reading could be greatly improved in comparison to real sensors, providing smoother data and possibly facilitating SAFEL's predictions. As the goal of SAFEL is to be of practical use in real world scenarios, we decided to test it with data collected through real robot sensors. For this reason, all sensor noises and detection failures were preserved during this experiment, so to analyse how it would affect SAFEL's prediction performance.

We have used four types of sensor readings to represent NAO's perception of environmental stimuli, which are:

- s_1 : light level,
- s_2 : number of human faces detected,
- s_3 : identification of *NAOmarks*, which are landmark images with specific patterns that NAO robots can recognize and identify (Fig. 5),
- s_4 : sound detection confidence, which is a number in the range $[0,1]$ depicting NAO's confidence that a particular detected sound is real.

In this experiment, the aversive stimulus is represented by darkness, which is an analogy to the natural fear and stress that most animals experience when they become unable to see. Hence, before running the experiment, SAFEL was configured to increase adrenaline levels whenever NAO detected low light levels. The remaining environmental stimuli (i.e., human faces, NAOmarks and sound detection) were initially neutral.

We highlight that this experiment focuses on observing the robot's emotional response rather than its behavioural response. In fear conditioning, the behavioural response of an individual is a reflex of its emotional response. The emotional response, in turn, is the most important feedback in order to verify that the individual is under fear, as well as to evaluate the success of fear learning. Thus, in this experiment we focus on studying the robot's emotional response to different stimulation in order to verify that it can in fact learn and predict aversive events based on situational information. In future work (Section 8), we plan to perform a robust case study which will evaluate the behavioural response of the robot, as well as how it affects the robot success into accomplishing a given task.

In order to create a controlled test environment, where we could analyse the influence of the same set

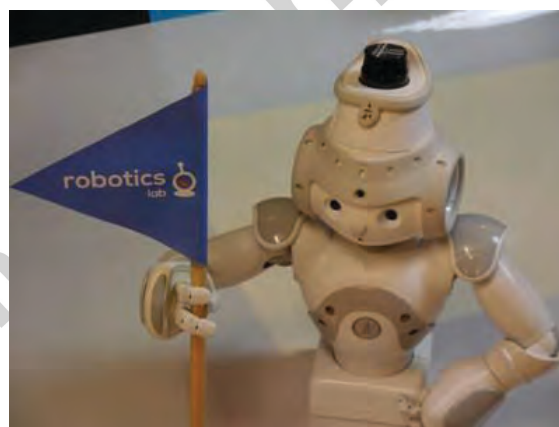


Figure 4: The NAO robot used in the experiment.

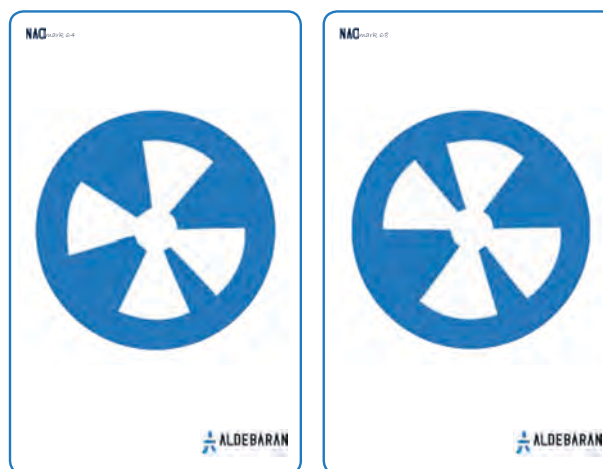


Figure 5: Examples of NAOmark.

of situations under different parameter settings, we have separated the experiment into three phases. First we collected data, by repeatedly presenting the above-listed stimuli to NAO and then storing NAO's sensor readings. In the second phase, we assembled the collected data in a specific time line, creating a dataset that was reproduced for different parameters and configurations. Lastly, we ran SAFEL on each dataset independently, during which the instances of the datasets were presented sequentially to SAFEL, as if it was being executed in the robot at real time. In this section, we describe the first two phases in detail. The third phase is addressed in Section 6.

5.1. Data Collection

In SAFEL, a *situation pattern* is the set of main temporal aspects (such as average time delay and temporal sequence among stimuli) that characterizes a given situation. Hence, *situation instance* is the instantiation of a situation pattern, and must have all the properties that

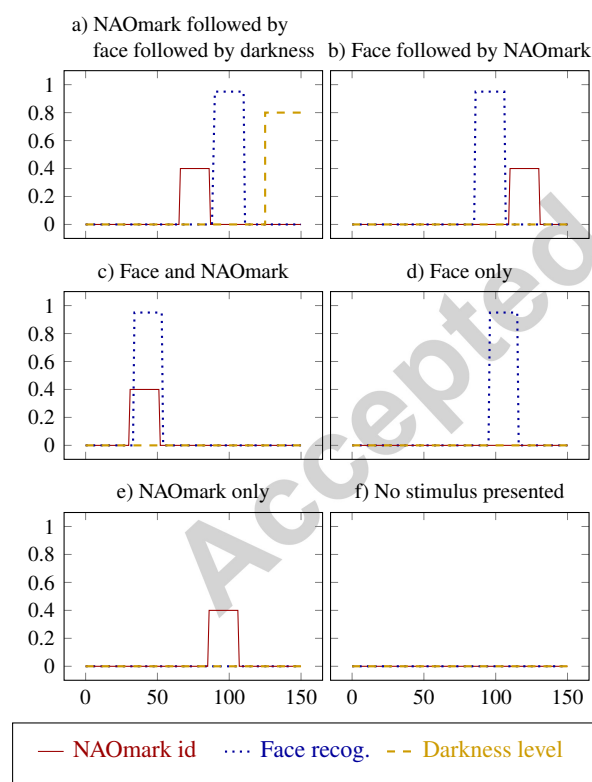


Figure 6: Example of situation instances for each of the six situation patterns induced in the experiment. Vertical axis depicts NAO's sensor input after normalization. Horizontal axis depicts the time line counted in numbers of events.

characterize that pattern (e.g., a specific order of stimulus detection).

We have collected data respecting six distinct situation patterns. Fig. 6 shows examples of NAO's sensor readings for each of the six situation patterns induced in the experiment. For example, the pattern of the situation observed in Fig. 6b is characterized by the detection of a human face followed by the detection of a NAOmark. To collect data of situation instances with this pattern, we first presented a human face to the robot for about five seconds, after which we hid this face and presented a NAOmark to the robot for about five seconds. This procedure has been performed at good light conditions, so the robot could easily detect both human faces and NAOmarks. The same procedure was then independently repeated several times in order to collect many different instances of this same situation pattern.

Analogously, to collect instances like the one seen in Fig. 6c, we presented the NAOmark and a human face at the same time to the robot at good light conditions for about five seconds, and then hid both. Again, we repeated this procedure several times in order to collect many different instances of this same pattern. The same sequence of steps was performed for collecting instances of the remaining situation patterns in Fig. 6.

Fig. 6a depicts an example of predictive situation followed by an aversive stimulus, which in this case

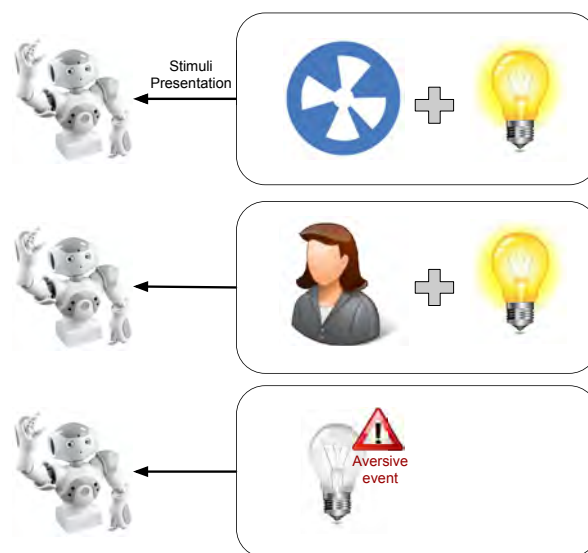


Figure 7: Procedure for presenting the aversive event to the robot. (a) Lights are kept on, while a specific NAOmark is presented to NAO for about 5 seconds. (2) With lights still on, the NAOmark is hidden, and then a human face is presented to the robot for about 5 seconds. (3) Both human face and NAOmark are hidden. Light is turned off.

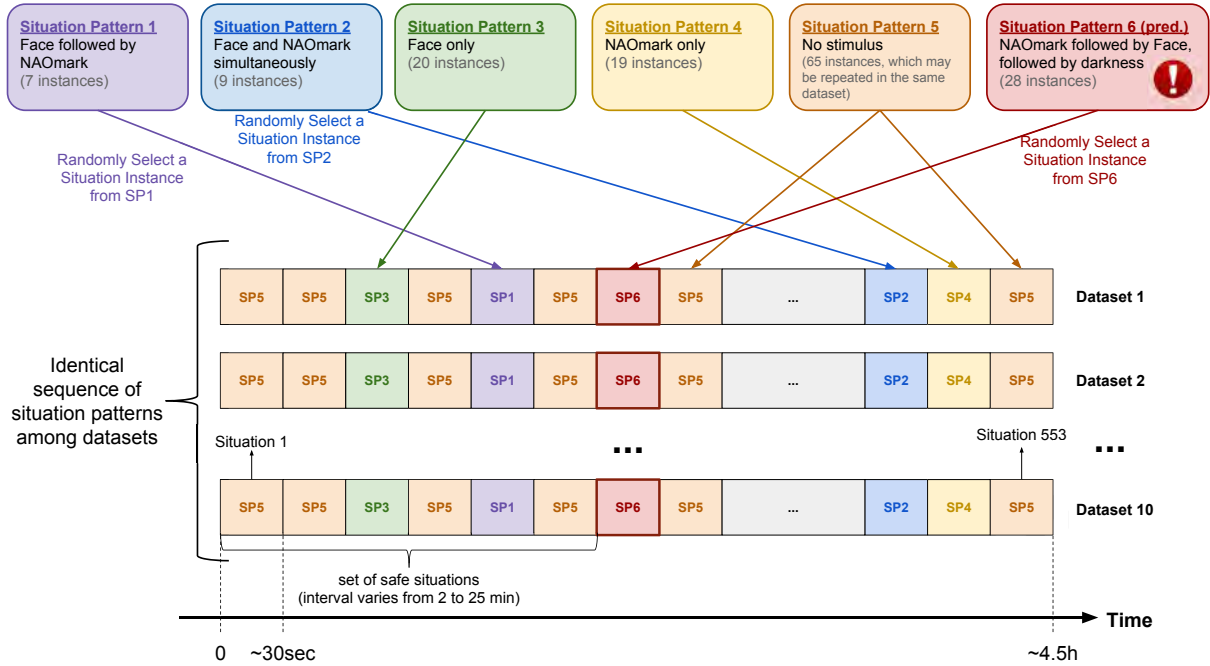


Figure 8: Dataset generation process. First, we individually collected a number of situation instances for each of the 6 situation patterns induced in this experiment. Then, for each pattern in the chosen sequence of situation patterns, we randomly select a situation instance of that pattern and concatenate it to the dataset. This procedure is repeated 10 times, so to generate 10 distinct datasets with the same temporal order of situation patterns.

is darkness. The predictive situation is characterized by the presentation of the NAOmark at good light conditions, followed by the presentation of a human face (demonstrated in Fig. 7). Because this pattern is always followed by the presentation of an aversive stimulus, it is then considered to be the pattern of a predictive situation. On the other hand, all the other patterns (Fig. 6b to 6f) represent safe situations, because they never precede any aversive event.

Observe that some situation patterns, such as the ones in Fig. 6b and 6c, are similar to the pattern of the predictive situation in Fig. 6a. This is because we desire to verify SAFEL’s capability to effectively differentiate safe situations from predictive situations, even when the patterns of these situations are similar.

Although exposition duration and delay of each stimulus was similar among data collections, it was not rigorously timed, as it is part of the experiment to evaluate SAFEL’s generalisation capability. Besides, in real world cases, situation instances of the same situation pattern may have similar temporal delays, but rarely equal.

5.2. Dataset Generation

Fig. 8 demonstrates the process for generating the datasets used in this experiment. We have generated 10 different datasets, which are composed of the situation instances collected through the process explained in Section 5.1. The individually collected situation instances were arranged in the datasets according to a specific temporal sequence of situation patterns, which is identical for all the 10 datasets.

To generate a dataset, we randomly selected a situation instance matching the first situation pattern of the chosen temporal sequence and concatenated this situation instance to the dataset. Then we repeated these steps for all the remaining situation patterns in the chosen temporal sequence (Fig. 8). Because all sensor noise and failures have been preserved during data collection, a few situation instances may present incomplete or fragmented data. To prevent the temporal positioning of a problematic situation instance influencing the result, we generated 10 datasets in total using the above-mentioned method.

Only situation instances with no stimulus presentation (with the pattern of Fig. 6f) were reused in the same dataset. Since they are basically the absence of stimula-

tion, situation instances of this pattern are highly similar to each other, and so they can be reused without affecting the integrity of the experiment. Situation instances of the remaining patterns (Fig. 6a to 6e) were not reused in the same dataset.

Each dataset is equivalent to about 4.5 hours testing and contains 28 aversive situations (and, consequently, 28 predictive situations), which are separated by intervals varying from 2 to 25 minutes representing the set of safe situations, which may comprise any of the situation patterns from Fig. 6b to 6f.

5.3. Validation Methodology

The generated datasets have been evaluated according to three factors. The first factor evaluates SAFEL's performance under different pre-defined situation durations. SAFEL has been analysed for three situation durations: 20 seconds ($\Delta a = 4$ sec), 30 seconds ($\Delta a = 6$ sec) and 40 seconds ($\Delta a = 8$ sec).

The second factor evaluates SAFEL's capability to ignore sensory inputs that are not relevant for predicting the occurrence of aversive stimuli. In this regard, we evaluated SAFEL on two versions of each generated dataset, one with and another without sound sensor input. Since there are no particular patterns in the sound information detected by NAO, it should have small influence in the final prediction. Thus, SAFEL's outcome should be similar for both dataset versions.

Finally, the third factor evaluates the impact of different values of *inter stimulus interval* (ISI) on SAFEL's performance. *Inter stimulus interval*, is the time interval between the offset of the predictive situation and the onset of the aversive event. For example, in this experiment, the ISI is the time interval starting right after the presentation of the NAOmark followed by a human face, and ending right before increasing the darkness level of the environment.

We have tested three values of ISI: 5, 10 and 15 seconds. The goal of testing different ISIs is to analyse whether the temporal position of relevant events in the predictive situation can influence SAFEL's performance.

Considering all dataset generations (10 datasets, 3 ISIs and 2 sets of stimuli input, with and without sound readings) and the 3 situation durations tested, this experiment contains 180 dataset samples in total.

6. Results

All 180 generated datasets were tested independently, and their instances were presented sequentially

to SAFEL, as if it was being executed in the robot at real time. For each run, we started measuring predictive performance after the classifier had processed the initial 20% of the respective dataset. This decision was made because we assume that the classifier would not have enough samples from each situation type (safe and predictive) to create a differentiation among them without learning the initial 20% of the datasets.

We have used the *f-measure* as performance metric to evaluate SAFEL's efficacy for classifying unknown situations into safe or predictive. The *f-measure*, also known as *f-score*, is the harmonic mean between precision and recall.

Fig. 9 shows SAFEL's performance regarding the three factors mentioned in Section 5.3, which are (1) situation duration, (2) input set and (3) ISIs. The generated dataset samples have been divided into groups within each factor that reflect the features under which they are being evaluated.

The first factor evaluates the influence of different values of the situation duration parameter on the classification performance. It has been divided into three groups of 60 samples (Fig. 9a). The first group comprises all dataset samples with situation duration equals 20 seconds, the second group comprises all samples with situation duration equals 30 seconds, and the third group comprises all samples with situation duration equals 40 seconds.

The second factor evaluates SAFEL's capability to ig-

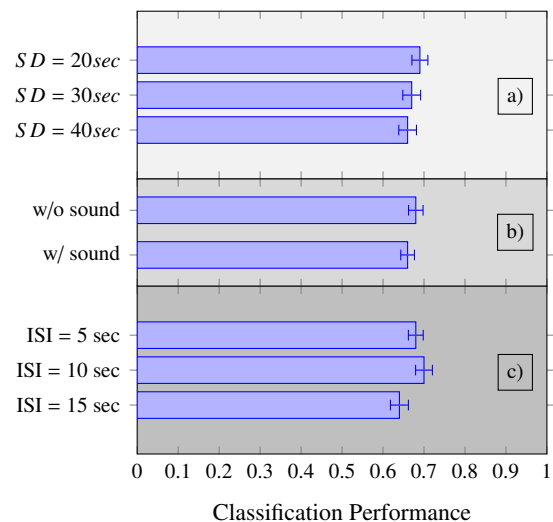


Figure 9: Average classification performance (f-measure) among dataset samples per group, where error bars show the 95% confidence interval of the respective group. Each graphic shows the results for one of the evaluated factors, which are (a) situation duration (SD), (b) input set (with or without sound input) and (c) ISI.

more sensory information that is irrelevant for the prediction. This factor is divided into two groups of 90 samples (Fig. 9b). The first group comprises all dataset samples without input from the sound sensor and the second group comprises all dataset samples with input from the sound sensor.

The third factor evaluates the influence of different values of ISI on the classification performance. It is divided into three groups of 60 samples (Fig. 9c). The first group contains all datasets with $\Delta p = 5$ seconds, the second group contains all datasets with $\Delta p = 10$ seconds, and the third group contains all datasets with $\Delta p = 15$ seconds.

In order to study the effects of these three factors on SAFEL's classification performance, we have used the *factorial analysis of variance* (factorial ANOVA), where the null hypothesis states that there is no statistically significant difference in the classification performance among groups within a given factor, and is rejected when $p \leq 0.05$.

Through the ANOVA test, we have analysed the significance of the main effects (i.e., the three factors independently) and of the two-way interactions between factors on the classification performance. The ANOVA test has not found statistically significant interaction between factors. The test also found no statistically significant difference between groups within the first and second factors, which are situation duration and input set, respectively.

This result indicates that there is no significant difference in the classification performance when varying the situation duration from 20 to 40 seconds, which reinforces the robustness of SAFEL for situation prediction. It also indicates that there is no significant difference in classification performance between datasets with and without sound sensor input. This demonstrates that SAFEL managed to mostly ignore sound information, as expected. Because sound input had no particular patterns regarding the presentation of aversive stimuli, if SAFEL had significantly considered it for classifying situations into safe or predictive, the second group of datasets in Fig. 9b could present much lower predictive performance.

On the other hand, the ANOVA test has found statistically significant difference in the classification performance among groups within the third factor ($p = 0.0001$), which evaluates the variation of the ISI. However, even though the ANOVA test has found statistically significant difference among groups, we can observe through the confidence intervals shown in Fig. 9c that such difference is minimal. We can assert with 95% confidence level that the (true) performance mean of the

three groups in Fig. 9c are, respectively, within the intervals [0.66, 0.7], [0.68, 0.72] and [0.62, 0.66]. The closeness of the confidence intervals indicates that, although the ISI can influence the classification performance, such effect is not substantial.

7. Discussion

In this section, we investigate how the positioning of the events of interest in the predictive situation can influence the classification performance. This has potentially led to the result observed in Fig. 9c. We also discuss SAFEL's performance over time, aiming at analysing how the prediction of aversive events improves as the robot enriches its knowledge about the surrounding environment.

7.1. Influence of the Events of Interest

Events of interest are those events that persistently precede aversive events, but are consistently absent in safe situations. Hence, events of interest are the set of events that can provide the most valuable information to differentiate a safe situation from a predictive situation. The proper detection and management of this information is, therefore, essential for consistently training the classification tree.

Fig. 10 demonstrates how a particular configuration of ISI and situation duration can affect the classification performance. In the performed experiment, the events of interest for predicting the aversive event are the presentation of a NAOmark for about 5 seconds (red lines in Fig. 10) followed by the presentation of a human face for about 5 seconds (blue lines in Fig. 10). The ISI is represented by dotted black lines, which may have 5, 10 or 15 seconds (Fig. 10a, 10b and 10c, respectively). Green lines represent the three tested durations of predictive situations, which are 20, 30 and 40 seconds.

Observe in Fig. 10 that predictive situations always contain all events of interest, except when $\Delta p = 15$ seconds and the situation duration is 20 seconds long (Fig. 10c). In this case, the first 5 seconds of the events of interest (i.e., the presentation of the NAOmark) are left out of the predictive situation. As consequence, an incorrect pattern of predictive situation is used to train the classification tree. Instead of NAOmark followed by face recognition (Fig. 6a), the tree is trained to recognized situations with face recognition only (Fig. 6d) as predictive. The problem is aggravated by the fact that some safe situations have the same pattern. As consequence, the tree is trained with inconsistent information, in which the same situation pattern is sometimes presented as safe and sometimes presented as predictive.

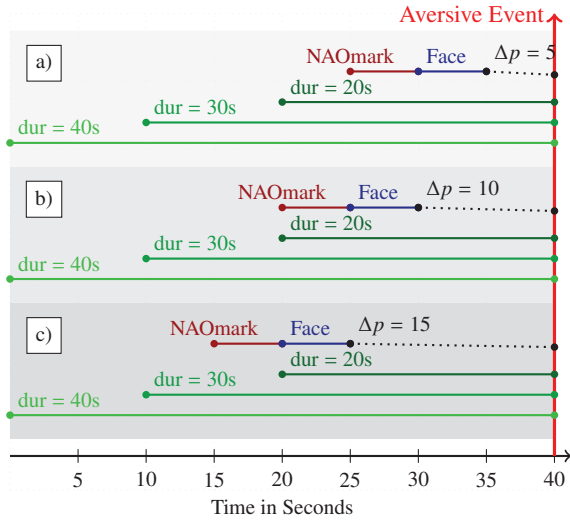


Figure 10: Time positioning of the events of interest during predictive situations. The diagram shows the possible scenarios considering all combinations of situation duration and ISI used in the experiment. Green lines depict the different situation durations (20, 30 and 40 seconds). The different values of ISI are represented by black dotted lines, which are (a) 5 seconds, (b) 10 seconds and (c) 15 seconds. Events of interest are depicted by red and blue lines, which represent the presentation of NAOmark and human face to the robot, respectively.

This could explain the difference in classification performance observed in Fig. 9c.

Fig. 11 shows the average performance for all evaluated datasets without sound input. Note that SAFEL has consistently demonstrated better performance for datasets where the situation duration is 20 seconds, except when $\Delta p = 15$ seconds, case in which we can observe the largest performance decay of the graphic. The result of Fig. 11 supports the explanation given above, indicating that the problem demonstrated by Fig. 10c is indeed the main reason for the discrepancy observed in Fig. 9c.

In addition, the higher performance obtained when situation duration equals 20 seconds (in comparison with the other situation durations tested) shows that keeping the length of the situation duration as close as possible to the length of the events of interest leads to better results (as long as it manages to cover all the events of interest). One can speculate that if the situation duration is too large, the classifier may start considering noise from other events (having happened long before the aversive event) that are not part of the events of interest.

In conclusion, the situation duration should not be too short, neither too large. The ideal scenario is to have the

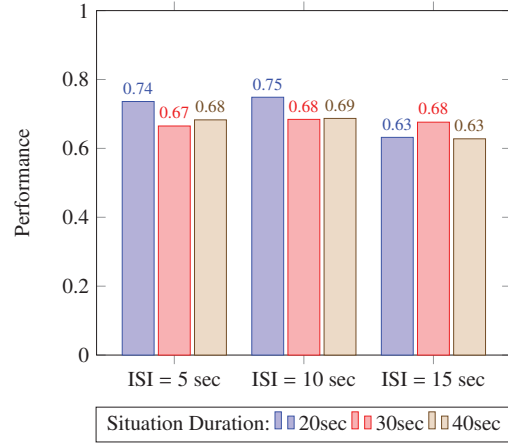


Figure 11: Mean classification performance (f-measure) among datasets generated without sound information, grouped by their situation duration and ISI.

situation duration just large enough to cover the events of interest. A way of tackling this problem is to create a mechanism that allows SAFEL to automatically adjust the duration of situations, which is an improvement that we will perform in future work (Section 8).

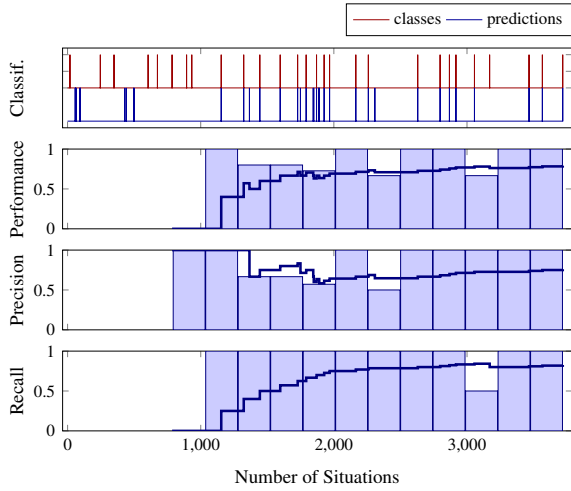
7.2. Performance Over Time

Through SAFEL, the robot learns continuously during its life cycle, thus improving its predictive capabilities with each newly detected stimulus. Fig. 12 shows the classification outcome and its performance over time for two of the 180 datasets tested with SAFEL. Fig. 12a depicts the most common result among the evaluated datasets and Fig. 12b depicts the worst-case scenario. We have generated similar graphics for each of the 180 datasets evaluated, which are available online¹.

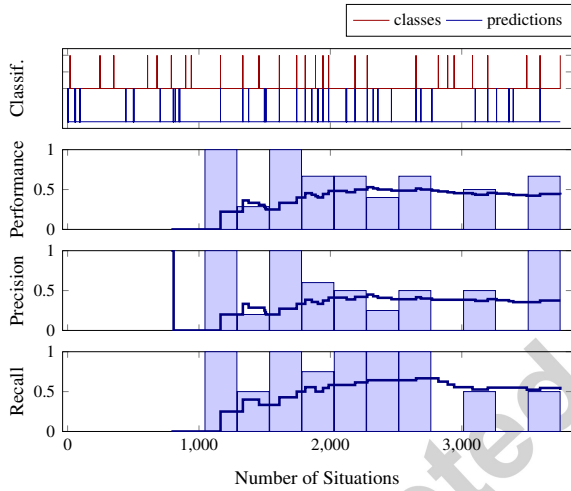
Since situations can partially overlap each other (as seen in Fig. 3), part of the events of interest for detecting an aversive event may be in more than one situation. Thus, it is reasonable that the working memory starts to predict an aversive event a few situations before the actual predictive situation. To take into account such cases, we have considered as true positive any situation classified as predictive that is in a range of five situations before the actual predictive situation.

Observe in Fig. 12a that performance increases as the number of processed situations increases. Classification recall is low for the first third of the detected situations because SAFEL did not predict any of the aversive events happening during that period. Recall improved

¹<https://www.cs.kent.ac.uk/people/rpg/cr519/safel>



(a) Performance over time for the dataset without sound input, situation duration equals 30 seconds and prediction precedence equals 10 seconds.



(b) Performance over time for the dataset without sound input, situation duration equals 20 seconds and prediction precedence equals 15 seconds.

Figure 12: SAFEL’s performance over time for two of the 180 datasets. Figure (a) and (b) show four graphics each. The first graphic presents the result of SAFEL’s classification: read-line peaks indicate the occurrence of aversive events over time and blue-line peaks indicate SAFEL’s predictions for aversive events. The last three graphics show the f-measure, precision and recall of SAFEL’s classification over time, respectively. These graphics show two types of over-time measurement: the first, depicted by the blue line, is the cumulative performance over the integral test; the second, depicted by the bars, is a more “instantaneous” over-time measurement. In this case, the performance is cumulative only in the interval comprised by the respective bar. About 20% of each dataset was used exclusively for training, so the performance values shown in the last three graphics contemplate only the remaining 80% of the respective dataset.

for the second third of the detected situations, but precision was affected because SAFEL misclassified a few safe situations during that period. However, towards the end, both precision and recall improved as a result of SAFEL correctly classifying most situations in the final third of the dataset.

This demonstrates that SAFEL’s predictions get more accurate over time. The classification tree starts empty, with no knowledge about the current environment, which explains the low predictive performance in the beginning of the dataset. As the robot experiences different situations, the tree is fed with information about the environment and becomes able to provide better predictions. The more experience the robot gains about the environment, the higher the accuracy of SAFEL’s predictions.

The learning process described above is ubiquitous in nature. For example, most animals that have never seen or touched fire before could, by curiosity, naively try to interact with it. After touching it for the first or second time, they would be afraid of fire and would avoid touching it in the future. However, it is important to notice that “being afraid” of fire is only possible after the animal acquires the knowledge that fire can be harmful. And the more experiences the animal has with fire, the bigger its confidence that fire is indeed dangerous.

This learning pattern, in which prediction accuracy improves over time, is reflected in the majority of the experiments that we have performed with SAFEL, and the speed with which performance improves varies among datasets. The exception is the case described in Section 7.1, in which the classification tree is fed with incorrect patterns of predictive situations.

Fig. 12b shows an example of the performance over time when predictive situations happen to miss part of the events of interest (in our case, when the situation duration is 20 seconds and the ISI is 15 seconds). Fig. 12b shows a slow and modest performance improvement over time, which decays after 2000 situations. In addition, classification precision is poor from the beginning to the end of the experiment due to the large number of safe situations classified as predictive. As previously mentioned, this is because the tree is being trained with inconsistent information, where the same situation pattern is sometimes presented as safe and sometimes presented as predictive. Therefore, in this case, the classification tree has no basis for providing an accurate prediction.

7.3. Final Considerations

The experiments have demonstrated that, as long as all events of interest are captured by the predictive sit-

uations, the actual duration of these situations, as well as their ISI, do not meaningfully influence the classification performance. This means that SAFEL is capable of adapting to different temporal characteristics without performance decay. In addition, Fig. 9 shows that, although all sensor noises and detection failures have been preserved, SAFEL was capable of predicting aversive events based on situational information with 67% of classification performance (f-measure) on average.

8. Conclusion

In this paper we have proposed SAFEL, a situation-aware computational model capable of learning and predicting threatening situations through a fear-conditioning-like procedure. SAFEL is based on the fear-learning model of the human brain. Experiments with a NAO humanoid robot have been performed, which aimed at evaluating SAFEL regarding its capability to:

- identify events' temporal order;
- identify and differentiate patterns of situations;
- associate a particular situation pattern with the imminent occurrence of an aversive event;
- ignore environmental stimuli that are irrelevant for predicting aversive events; and
- adapt to varied temporal characteristics, such as different situation durations.

Experiment results were positive in all evaluated aspects, corroborating the potential of artificial fear-learning models when combined with concepts of situation awareness to improve a robot's adaptive behaviour.

Future work involves expanding SAFEL with additional modules. As mentioned in Section 4, the work discussed here implements part of a larger architecture [31], which includes an amygdala module in addition to the hippocampus and working memory. Next, we will implement an amygdala module, which would be responsible for accessing the emotional significance of stimuli (i.e., whether it is aversive). The amygdala module will then create associations between individual stimuli and signal its fear perception to other brain areas, such as the hippocampus.

We will also improve the existing hippocampus module. As mentioned in Section 7.1, the duration of situations may affect the classification performance if it is so short that part of the events of interest are left out of the

active period of predictive situations. In the same sense, very large situation durations may also lead the working memory to start considering events that are actually irrelevant for predicting aversive events. This could lead to low classification performance.

To address this issue, we will extend the current version of SAFEL by implementing either a search mechanism [70] or an evolutionary robotics approach [71] that would automatically adjust the duration of situations based on the values that yielded best classification performance in the past. This would reduce the set of pre-configured parameters of the system and considerably improve the prediction performance.

In addition, we expect to increase the believability of the robot's response by tuning the misclassification cost of predictive situations in the working memory module. Most animals that are capable of fear have evolved to overestimate danger, as the cost of underestimating a danger is usually much higher than overestimating it [2]. The same rule applies to real companion robots, since they inhabit the same world as us. In order to make SAFEL's fear responses more biologically plausible, we intend to mimic nature's tendency to overestimate danger, by increasing the misclassification cost of predictive situations in the working memory.

Finally, the experiments performed so far have evaluated SAFEL in relation to its main goal of simulating fear learning and predicting aversive events based on situational information. However, there are other aspects of SAFEL that we will also evaluate in further experiments. These include, but are not restricted to, SAFEL's capability to: associate multiple situation patterns with the same aversive event, associate multiple types of aversive events, and identify not only stimuli temporal order, but also intensity.

We will also perform a robust case study, in which the robot's success in accomplishing a complex task will greatly depend on its emotional learning skills, as well as its capability to predict threats and adapt to environmental changes.

Acknowledgement

The first and third authors are financially supported by CAPES, a Brazilian research-support agency (process numbers 0648/13-2 and 0653-13-6, respectively). We also thank Dr. Owen Lyne, from the School of Mathematics, Statistics and Actuarial Science in the University of Kent (England, UK), for the advice on the statistical analysis. Finally, we thank the Robotics Laboratory of the Heriot-Watt University (Edinburgh,

UK) for providing the resources necessary for the experiments.

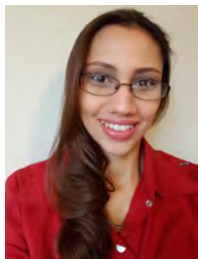
References

- [1] A. Damasio, *Descartes' Error: Emotion, Reason and the Human Brain*, Avon Books, New York, 1994.
- [2] J. LeDoux, *The Emotional Brain: The Mysterious Underpinnings of Emotional Life*, Phoenix, London, 1999.
- [3] N. Fragopanagos, J. Taylor, Modelling the interaction of attention and emotion, *Neurocomputing* 69 (1618) (2006) 1977–1983. doi:10.1016/j.neucom.2005.11.016.
- [4] K. Dautenhahn, *The Art of Designing Socially Intelligent Agents - Science, Fiction and the Human in the Loop*, *Applied Artificial Intelligence* 12 (7-8) (1998) 573–617. doi:10.1080/088395198117550.
- [5] W. C. Ho, K. Dautenhahn, M. Y. Lim, P. Vargas, R. Aylett, S. Enz, An Initial Memory Model for Virtual and Robot Companions Supporting Migration and Long-Term Interaction, in: *The 18th IEEE International Symposium on Robot and Human Interactive Communication (RO-MAN)*, 2009, pp. 277–284. doi:10.1109/ROMAN.2009.5326204.
- [6] P. A. Vargas, Y. Fernaeus, M. Y. Lim, S. Enz, W. C. Ho, M. Jacobsson, R. Aylett, Advocating an ethical memory model for artificial companions from a human-centred perspective, *AI & Society* 26 (4) (2011) 329–337. doi:10.1007/s00146-010-0313-3.
- [7] S. Enz, M. Diruf, C. Spielhagen, C. Zoll, P. A. Vargas, The Social Role of Robots in the Future - Explorative Measurement of Hopes and Fears, *International Journal of Social Robotics* 3 (3) (2011) 263–271. doi:10.1007/s12369-011-0094-y.
- [8] J. Kim, G. Gu, P. Heo, Robotics for healthcare, in: H. Jo, H. Jun, J. Shin, S. Lee (Eds.), *Biomedical Engineering: Frontier Research and Converging Technologies*, Vol. 9 of *Biosystems & Biorobotics*, Springer International Publishing, 2016, pp. 489–509. doi:10.1007/978-3-319-21813-7_21.
- [9] N. Lazzari, D. Mazzei, A. Zaraki, D. De Rossi, Towards a believable social robot, in: N. Lepora, A. Mura, H. Krapp, P. Verschure, T. Prescott (Eds.), *Biomimetic and Biohybrid Systems*, Vol. 8064 of *Lecture Notes in Computer Science*, Springer Berlin Heidelberg, 2013, pp. 393–395. doi:10.1007/978-3-642-39802-5_45.
- [10] J. Morén, C. Balkenius, Emotional Learning: A Computational Model of the Amygdala, *Cybernetics and Systems* 32 (6) (2001) 611–636. doi:10.1080/01969720118947.
- [11] C. Lucas, D. Shahmirzadi, N. Sheikholeslami, Introducing Belbic: Brain Emotional Learning Based Intelligent Controller, *Intelligent Automation & Soft Computing* 10 (1) (2004) 11–21. doi:10.1080/10798587.2004.10642862.
- [12] E. Lotfi, M.-R. Akbarzadeh-T., Practical emotional neural networks, *Neural Networks* 59 (2014) 61–72. doi:10.1016/j.neunet.2014.06.012.
- [13] M. A. Salichs, M. Malfaz, A New Approach to Modeling Emotions and Their Use on a Decision-Making System for Artificial Agents, *IEEE Transactions on Affective Computing* 3 (1) (2012) 56–68. doi:10.1109/T-AFFC.2011.32.
- [14] T. Babaie, R. Karimizandi, C. Lucas, Learning based brain emotional intelligence as a new aspect for development of an alarm system, *Soft Computing* 12 (9) (2007) 857–873. doi:10.1007/s00500-007-0258-8.
- [15] C. Lucas, R. M. Milasi, B. N. Araabi, Intelligent Modeling and Control of Washing Machine Using Locally Linear Neuro-Fuzzy (LLNF) Modeling and Modified Brain Emotional Learning Based Intelligent Controller (BELBIC), *Asian Journal of Control* 8 (4) (2006) 393–400. doi:10.1111/j.1934-6093.2006.tb00290.x.
- [16] M. R. Jamali, M. Dehyadegari, A. Arami, C. Lucas, Z. Navabi, Real-time embedded emotional controller, *Neural Computing and Applications* 19 (1) (2009) 13–19. doi:10.1007/s00521-008-0227-x.
- [17] R. Ravi, S. Mija, Design of Brain Emotional Learning Based Intelligent Controller (BELBIC) for Uncertain Systems, in: *2014 International Conference on Advanced Communication Control and Computing Technologies (ICACCCT)*, 2014, pp. 1089–1093. doi:10.1109/ICACCCT.2014.7019265.
- [18] M. K. Sharma, A. Kumar, Performance Comparison of Brain Emotional Learning-Based Intelligent Controller (BELBIC) and PI Controller for Continually Stirred Tank Heater (CSTH), in: K. Maharatna, K. G. Dalapati, K. P. Banerjee, K. A. Mallick, M. Mukherjee (Eds.), *Computational Advancement in Communication Circuits and Systems: Proceedings of IC-CACCS 2014*, Springer India, New Delhi, 2015, pp. 293–301. doi:10.1007/978-81-322-2274-3_32.
- [19] M. Azizur Rahman, R. Milasi, C. Lucas, B. Araabi, T. Radwan, Implementation of Emotional Controller for Interior Permanent-Magnet Synchronous Motor Drive, *IEEE Transactions on Industry Applications* 44 (5) (2008) 1466–1476. doi:10.1109/TIA.2008.2002206.
- [20] G. Markadeh, E. Daryabeigi, C. Lucas, M. Azizur Rahman, Speed and Flux Control of Induction Motors Using Emotional Intelligent Controller, *IEEE Transactions on Industry Applications* 47 (3) (2011) 1126–1135. doi:10.1109/TIA.2011.2125710.
- [21] E. Daryabeigi, N. Abjadi, G. Arab Markadeh, Automatic speed control of an asymmetrical six-phase induction motor using emotional controller (BELBIC), *Journal of Intelligent and Fuzzy Systems* 26 (4) (2014) 1879–1892. doi:10.3233/IFS-130867.
- [22] E. Lotfi, M.-R. Akbarzadeh-T., Adaptive brain emotional decayed learning for online prediction of geomagnetic activity indices, *Neurocomputing* 126 (2014) 188–196. doi:10.1016/j.neucom.2013.02.040.
- [23] A. M. El-Garhy, M. E. El-Shimy, BELBIC for MRAS with highly non-linear process, *Alexandria Engineering Journal* 54 (1) (2015) 7–16. doi:10.1016/j.aej.2014.12.001.
- [24] A. R. Mehrabian, C. Lucas, J. Roshanian, Aerospace launch vehicle control: an intelligent adaptive approach, *Aerospace Science and Technology* 10 (2) (2006) 149–155. doi:10.1016/j.ast.2005.11.002.
- [25] M. Jafari, A. Shahri, S. Shouraki, Attitude Control of a Quadrotor Using Brain Emotional Learning Based Intelligent Controller, in: *2013 13th Iranian Conference on Fuzzy Systems (IFSC)*, 2013, pp. 1–5. doi:10.1109/IFSC.2013.6675672.
- [26] C. Kim, R. Langari, Target Tracking Control of a Mobile Robot Using a Brain Limbic System Based Control Strategy, in: *IEEE/RSJ International Conference on Intelligent Robots and Systems*, 2009. IROS 2009, 2009, pp. 5059–5064. doi:10.1109/IROS.2009.5354280.
- [27] S. Jafarzadeh, R. Mirheidari, M. Motlagh, M. Barkhordari, Designing PID and BELBIC Controllers in Path Tracking and Collision Problem in Automated Highway Systems, in: *10th International Conference on Control, Automation, Robotics and Vision*, 2008. ICARCV 2008, 2008, pp. 1562–1566. doi:10.1109/ICARCV.2008.4795757.
- [28] M. Sharbafi, C. Lucas, R. Daneshvar, Motion Control of Omni-Directional Three-Wheel Robots by Brain-Emotional-Learning-Based Intelligent Controller, *IEEE Transactions on Systems, Man, and Cybernetics, Part C: Applications and Reviews* 40 (6)

- (2010) 630–638. doi:10.1109/TSMCC.2010.2049104.
- [29] N. Garmsiri, F. Najafi, M. Saadat, A New Intelligent Approach to Patient-Cooperative Control of Rehabilitation Robots, *International Journal of Engineering* 27 (3) (2013) 467. doi:10.5829/idosi.ije.2014.27.03c.15.
- [30] L. Harrison, A. Duggins, K. Friston, Encoding uncertainty in the hippocampus, *Neural Networks* 19 (5) (2006) 535–546. doi:10.1016/j.neunet.2005.11.002.
- [31] C. Rizzi Raymundo, C. G. Johnson, P. A. Vargas, An architecture for emotional and context-aware associative learning for robot companions, in: 2015 24th IEEE International Symposium on Robot and Human Interactive Communication (RO-MAN), IEEE, 2015, pp. 31–36. doi:10.1109/ROMAN.2015.7333699.
- [32] R. W. Picard, *Affective Computing*, Tech. Rep. 321, Massachusetts Institute of Technology, Cambridge (1995).
- [33] R. W. Picard, *Affective Computing*, MIT Press, Cambridge, 2000.
- [34] C. Breazeal, R. Brooks, Robot emotion: A functional perspective, in: J.-M. Fellous, M. A. Arbib (Eds.), *Who needs emotions? The Brain Meets the Robot*, Affective Science, Oxford University Press, 2005, pp. 271–310.
- [35] G. Hollinger, Y. Georgiev, A. Manfredi, B. A. Maxwell, Z. Pezzementi, B. Mitchell, et al., Design of a Social Mobile Robot Using Emotion-Based Decision Mechanisms, in: 2006 IEEE/RSJ International Conference on Intelligent Robots and Systems, IEEE, Beijing, 2006, pp. 3093–3098. doi:10.1109/IROS.2006.282327.
- [36] J. W. Rudy, R. C. O'Reilly, Conjunctive representations, the hippocampus, and contextual fear conditioning, *Cognitive, Affective, & Behavioral Neuroscience* 1 (1) (2001) 66–82. doi:10.3758/CABN.1.1.66.
- [37] B. Subagdja, A.-H. Tan, Neural modeling of sequential inferences and learning over episodic memory, *Neurocomputing* 161 (C) (2015) 229–242. doi:10.1016/j.neucom.2015.02.038.
- [38] B. Kiumarsi, F. L. Lewis, D. S. Levine, Optimal control of nonlinear discrete time-varying systems using a new neural network approximation structure, *Neurocomputing* 156 (2015) 157–165. doi:10.1016/j.neucom.2014.12.067.
- [39] J. Timmis, M. Neal, J. Thorniley, An Adaptive Neuro-Endocrine System for Robotic Systems, in: *IEEE Workshop on Robotic Intelligence in Informationally Structured Space*, Nashville, 2009, pp. 129–136. doi:10.1109/RIISS.2009.4937917.
- [40] M. Neal, J. Timmis, Timidity: A Useful Emotional Mechanism for Robot Control?, *Informatica* 27 (2) (2003) 197–204.
- [41] P. Vargas, R. Moioli, L. N. Castro, J. Timmis, M. Neal, F. J. V. Zuben, Artificial Homeostatic System: A Novel Approach, in: M. S. Caparrère, A. A. Freitas, P. J. Bentley, C. G. Johnson, J. Timmis (Eds.), *Advances in Artificial Life*, no. 3630 in *Lecture Notes in Computer Science*, Springer Berlin Heidelberg, Berlin, 2005, pp. 754–764. doi:10.1007/11553090_76.
- [42] R. Valverde Ibanez, M. Keysermann, P. Vargas, Emotional Memories in Autonomous Robots, in: 2014 RO-MAN: The 23rd IEEE International Symposium on Robot and Human Interactive Communication, IEEE, Edinburgh, 2014, pp. 405–410. doi:10.1109/ROMAN.2014.6926286.
- [43] R. Ventura, C. Pinto-Ferreira, Responding efficiently to relevant stimuli using an emotion-based agent architecture, *Neurocomputing* 72 (1315) (2009) 2923–2930. doi:10.1016/j.neucom.2008.09.019.
- [44] D. Ren, P. Wang, H. Qiao, S. Zheng, A biologically inspired model of emotion eliciting from visual stimuli, *Neurocomputing* 121 (2013) 328–336. doi:10.1016/j.neucom.2013.05.026.
- [45] L. Cañamero, Emotion understanding from the perspective of autonomous robots research, *Neural Networks* 18 (4) (2005) 445–455. doi:10.1016/j.neunet.2005.03.003.
- [46] J. Morén, *Emotion and Learning - A Computational Model of the Amygdala*, dissertation, Lund University (2002).
- [47] Z. Beheshti, S. Z. M. Hashim, A Review of Emotional Learning and Its Utilization in Control Engineering, *International Journal of Advances in Soft Computing and Its Applications* 2 (2) (2010) 191–208.
- [48] R. C. O'Reilly, J. W. Rudy, Conjunctive Representations in Learning and Memory: Principles of Cortical and Hippocampal Function, *Psychological Review* 108 (2) (2001) 311–345. doi:10.1037/0033-295X.108.2.311.
- [49] J. LeDoux, The Emotional Brain, Fear, and the Amygdala, *Cellular and Molecular Neurobiology* 23 (4-5) (2003) 727–738. doi:10.1023/a:1025048802629.
- [50] I. P. Pavlov, *Conditioned Reflexes: An Investigation of the Physiological Activity of the Cerebral Cortex*, Oxford University Press, 1927.
- [51] R. Phillips, J. E. LeDoux, Differential Contribution of Amygdala and Hippocampus to Cued and Contextual Fear Conditioning, *Behavioral Neuroscience* 106 (2) (1992) 274–285. doi:10.1037/0735-7044.106.2.274.
- [52] C. Herry, J. P. Johansen, Encoding of fear learning and memory in distributed neuronal circuits, *Nature Neuroscience* 17 (12) (2014) 1644–1654. doi:10.1038/nn.3869.
- [53] J. W. Rudy, N. C. Huff, P. Matus-Amat, Understanding contextual fear conditioning: insights from a two-process model, *Neuroscience and Biobehavioral Reviews* 28 (7) (2004) 675–685. doi:10.1016/j.neubiorev.2004.09.004.
- [54] N. J. Fortin, K. L. Agster, H. B. Eichenbaum, Critical role of the hippocampus in memory for sequences of events, *Nature Neuroscience* 5 (5) (2002) 458. doi:10.1038/nn834.
- [55] J. W. Rudy, R. M. Barrientos, R. C. O'Reilly, Hippocampal Formation Supports Conditioning to Memory of a Context, *Behavioral Neuroscience* 116 (4) (2002) 530–538. doi:10.1037/0735-7044.116.4.530.
- [56] A. Krause-Utz, B. M. Elzinga, N. Y. L. Oei, C. Paret, I. Niedt-feld, P. Spinhoven, M. Bohus, C. Schmahl, Amygdala and dorsal anterior cingulate connectivity during an emotional working memory task in borderline personality disorder patients with interpersonal trauma history, *Frontiers in Human Neuroscience* 8 (848). doi:10.3389/fnhum.2014.00848.
- [57] T. Spellman, M. Rigotti, S. E. Ahmari, S. Fusi, J. A. Gogos, J. A. Gordon, Hippocampal-prefrontal input supports spatial encoding in working memory, *Nature* 522 (7556) (2015) 309–314. doi:10.1038/nature14445.
- [58] A. K. Dey, Understanding and Using Context, *Personal Ubiquitous Comput.* 5 (1) (2001) 4–7. doi:10.1007/s007790170019.
- [59] M. Bali, *Drools JBoss Rules 5.X Developer's Guide*, Packt Publishing, 2013.
- [60] S. C. Marsella, J. Gratch, P. Petta, Computational Models of Emotion, in: K. Scherer, T. Bänziger, E. Roesch (Eds.), *A Blueprint for Affective Computing: A Sourcebook and Manual*, Affective Science, OUP Oxford, 2010.
- [61] J. Anderson, *The Architecture of Cognition*, Cognitive Science, Lawrence Erlbaum Associates, New Jersey, 1996.
- [62] J. F. Allen, An Interval-Based Representation of Temporal Knowledge, in: *Proceedings of the 7th International Joint Conference on Artificial Intelligence, IJCAI'81*, Morgan Kaufmann Publishers Inc., San Francisco, 1981, pp. 221–226.
- [63] J. F. Allen, Maintaining Knowledge About Temporal Intervals, *Communications of the ACM* 26 (11) (1983) 832–843. doi:10.1145/182.358434.
- [64] I. Pereira, P. Costa, J. Almeida, A Rule-Based Platform for Situation Management, in: 2013 IEEE International Multi-Disciplinary Conference on Cognitive Methods in Situation

Awareness and Decision Support (CogSIMA), 2013, pp. 83–90. doi:10.1109/CogSIMA.2013.6523827.

- [65] C. Rizzi Raymundo, P. Dockhorn Costa, J. Almeida, I. Pereira, An Infrastructure for Distributed Rule-Based Situation Management, in: 2014 IEEE International Inter-Disciplinary Conference on Cognitive Methods in Situation Awareness and Decision Support (CogSIMA), 2014, pp. 202–208. doi:10.1109/CogSIMA.2014.6816563.
- [66] MATLAB, version 8.4.0.150421 (R2014b), The MathWorks Inc., Natick, Massachusetts, 2014.
- [67] L. Breiman, J. Friedman, R. Olshen, C. Stone, Classification and Regression Trees, Wadsworth International Group, Belmont, California, U.S.A., 1984.
- [68] T.-S. Lim, W.-Y. Loh, Y.-S. Shih, A comparison of prediction accuracy, complexity, and training time of thirty-three old and new classification algorithms, *Machine Learning* 40 (3) (2000) 203–228. doi:10.1023/A:1007608224229.
- [69] A. Weiss, C. Bartneck, Meta Analysis Of The Usage Of The Godspeed Questionnaire Series, in: 2015 24th IEEE International Symposium on Robot and Human Interactive Communication (RO-MAN), IEEE, 2015, pp. 381–388. doi:10.1109/ROMAN.2015.7333568.
- [70] S. Koziel, X. Yang, Computational Optimization, Methods and Algorithms, Vol. 356, Springer Berlin Heidelberg, 2011. doi:10.1007/978-3-642-20859-1.
- [71] P. A. Vargas, E. A. Di Paolo, I. Harvey, P. Husbands, The Horizons of Evolutionary Robotics, MIT Press, 2014.



Caroline Rizzi received her Bachelor and Masters degrees in Computer Science from the Federal University of Espírito Santo (Brazil) in 2010 and 2013, respectively. During her masters, she worked with the modelling of distributed situation-aware systems. She is currently pursuing her

Ph.D. in Computer Science in the University of Kent (England, UK). Her research interests include computational neuroscience, machine learning, autonomous robotics, affective computing and situation-aware systems.



Colin G. Johnson received his PhD from the University of Kent (England, UK) in 2003. He is a Reader in the School of Computing and Associate Dean of the Faculty of Sciences at the University of Kent. His research interests include program synthesis, machine

learning and meta-heuristics, and their application to a wide variety of areas including robotics, medicine, engineering and digital humanities.



Fabio Fabris received his bachelor (2010) and masters (2013) degrees in Computer Science from the Federal University of Espírito Santo, Brazil. Before starting his Ph.D. he has worked in research projects aimed at solving real-world problems using data-mining and optimization techniques: finding fraudulent electricity consumers, classifying faults in oil-rig motor pumps and optimizing samples sizes for statistical analysis. He is currently pursuing his Ph.D. in Computer Science in the University of Kent, United Kingdom. His main interest is the application of data-mining and optimization algorithms to solve real-world problems, in particular the classification of ageing-related proteins.



Patricia A. Vargas received her PhD. on Computer Engineering from the University of Campinas, Unicamp (Brazil) in 2005. She is the Founder Director of the Robotics Laboratory and Associate Professor/Reader in Computer Science and Robotics at the School of Mathematical and Computer Science at HeriotWatt University (Edinburgh, UK). She is an executive member of the Edinburgh Centre for Robotics. She worked at the Centre for Computational Neuroscience and Robotics, University of Sussex (England, UK) for 3 years. Her research interests include Evolutionary and Bio-inspired Robotics, Computational Neuroscience, Data Mining, Machine Learning, Biologically-inspired algorithms, Human-Robot Interaction and Rehabilitation Robotics.