Improving the Predictive Performance of SAFEL: A Situation-Aware Fear Learning Model

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Abstract— **In this paper, we optimize the predictive performance of a Situation-Aware FEar Learning model (SAFEL) by investigating the relationship between its parameters. SAFEL is a hybrid computational model based on the fear-learning system of the brain, which was developed to provide robots with the capability to predict threatening or undesirable situations based on temporal context. The main aim of this work is to improve SAFEL's emotional response. An emotional response coherent with environmental changes is essential not only for self-preservation and adaptation purposes, but also for improving the believability and interaction skills of companion robots. Experiments with a NAO humanoid robot show that adjusting the ratio between two parameters of SAFEL can significantly increase the predictive performance and reduce parameter settings.**

I. Introduction

It is a common understanding in the human-robot interaction (HRI) field that robots' social interaction becomes more believable and natural as they become more adaptable and responsive to environmental cues [1], [2], [3]. Hence, a robot capable to properly express fear responses under threatening or undesirable situations to itself could greatly increase its believability [1]. Such skill is even more important for long-term robot companions, which commonly suffer of rapid loss of interest from their users due to their poor learning and adaptation capabilities.

Under this motivation, we have proposed SAFEL (Situation-Aware FEar Learning) [4], [5], a hybrid computational model based on the fear-learning system of the brain. SAFEL tackles an persistent gap in affective models for robotics, which is the learning and memorization of sequences of events over a period of time, as well as the association of situational information with a positive or negative "emotion", analogous to fear and safety. To do so, SAFEL integrates well known classification algorithms with a symbolic and rule based platform for situation management.

SAFEL has been theoretically proposed in [4] and partially implemented in [5]. This paper focuses on studying the relationship between SAFEL's parameters in order to optimize the performance of its emotional response.

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This paper is organized as follows: Section II discusses related work. Section III summarizes the neuroscientific findings that have inspired SAFEL's design. Section IV presents SAFEL's model and implementation details. Sections V and VI present the setup and results of the performed experiment, respectively. Finally, we conclude in Section VII, where we also indicate plans for future work.

II. Related Work

One of the most influential works in artificial fear conditioning is the brain emotional learning (BEL) model, proposed by Morén and Balkenius [6] and widely used in a variety of engineering and industrial applications [7], [8], [9], [10]. Their model consists of interconnected modules of artificial neural networks (ANNs) that simulate the role of neural circuitries involved in fear learning. It receives environmental neutral stimuli and a reward signal as input, which are processed by four simulated neural regions: the thalamus, the sensory cortex, the amygdala and the orbitofrontal cortex. This model was later improved in [11], with the addition of the hippocampal module, which allows BEL to express fear responses based on contextual information.

Although SAFEL and BEL are both inspired by brain regions involved in fear learning and have similar models, BEL is purely based on ANNs, while SAFEL is a hybrid model. In addition to classification algorithms, SAFEL also uses a symbolic and rule based platform, which provides means to implement the concept of situation, as well as to compare them through temporal operations (e.g., after, during, before). This hybrid architecture allows SAFEL to create emotional associations with complex contextual information, composed of the pattern of a series of stimuli over a period of time. Unlike SAFEL, BEL can create associations only with stimuli that co-occur with the aversive stimulus.

Rudy and O'Reilly [12] have also proposed a ANN-based contextual fear-conditioning model that relies on a theoretical framework [13] 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 a unitary representation. Their unitary representation of context, however, only consider features that co-occur, ignoring the temporal relationship between them.

III. Biological Background

According to LeDoux [14], [15], fear learning relies mainly on three brain regions – the sensory system, the amygdala and the hippocampus – along with a cognitive function known as the working memory. The sensory system is responsible for providing the amygdala with information at different speeds, levels of abstraction and accuracy. The amygdala, in turn, processes the emotional significance (i.e., whether it is aversive or not) of stimuli information sent by the sensory system and notify it to higher regions of the brain, such as the hippocampus.

In the hippocampus, sensory information coming from the sensory system is combined into a 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 along with their temporal correlation.

Exposure to a stimulus that was present during a traumatic situation activates both the amygdala and hippocampal systems, which work in parallel to retrieve emotional and contextual memory about the event, respectively. These two memories are later associated in the working memory, which in future occasions will retrieve the emotional memory of the experienced trauma whenever the individual is exposed to a context similar to that of the trauma.

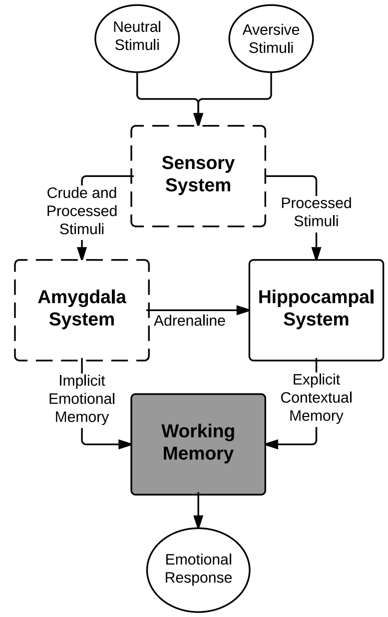

Fig. 1: The complete model of the fear-learning architecture [4], [5]. Dashed boxes represent the modules of the architecture that have not yet been implemented, which we indicate as future work. White boxes represent areas of the brain, whereas grey boxes represent cognitive functions of the brain. The model receives neutral and aversive stimuli as input, and outputs the corresponding emotional response.

IV. SAFEL Model

SAFEL is a situation-aware computational system capable to provide robots with fear-learning skills in order to predict threatening situations to their own well-being. Unlike most fear-conditioning models, which usually induce associations with a set of stimuli happening in a point in time, SAFEL allows robots to learn complex temporal patterns of stimuli over a period of time, by creating a representation of these patterns that is associated with the idea of danger or safety.

SAFEL is based on the fear-learning model of the human brain proposed by LeDoux [14], [15], described in Section III. Fig. 1 depicts SAFEL's complete architecture, which has been proposed in [4]. It is a hybrid architecture, divided into four modules, each based on a different computational approach. These modules work in an integrated and parallel manner, each inspired by a brain area or cognitive function: the sensory system, the amygdala, the hippocampal and the working memory.

The sensory system pre-processes environmental stimuli detected by the robot through either sensors or direct user input. The processed information is relayed to the amygdala and hippocampal modules. The amygdala module is responsible for detecting threats and associating them with sensed environmental stimuli. The amygdala also provides emotional feedback to the hippocampus module, which in parallel generates complex contextual representations of the environment based on the processed sensory information coming from the sensory system. Finally, emotional memories from the amygdala module and contextual memories from the hippocampus module are associated in the working memory.

From the model seem in Fig. 1, we have designed, implemented and evaluated the hippocampus and working memory modules [5]. The development of the sensory and amygdala modules is left as future work. In this paper, we propose to improve the implemented modules – hippocampus and working memory – by performing a study on their parameters. Note that this study is not affected by the absence of the sensory and amygdala modules, meaning that all results presented here will still be valid when SAFEL's implementation is complete.

In the following we summarize the main design details of these two modules of SAFEL. For further details about SAFEL's design, implementation and evaluation, we refer the reader to [5].

A. Hippocampus Module

1) Underlying Technology: The hippocampus module is responsible for SAFEL's contextual processing and is based on the concepts of situation-awareness for expert systems proposed by Dey [16]. According to Dey, a *situation* describes a collection of states of relevant entities, where each state depicts those entities' context in a given point in time. *Context*, in turn, is any information that can characterise the circumstance of an entity, which may be a person, a place, or an object relevant to the interaction between the user and the application. Thus, 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.

SAFEL's hippocampus module is based on Dey's concept of situation awareness in the sense that it is responsible for collecting, understanding and managing the states of the robot over time. To accomplish that, we have modelled and implemented the hippocampus module using SCENE [17], [18], which is a robust situation management platform based on symbolic techniques of knowledge management. SCENE extends the JBoss Drools rule engine and its CEP (Complex Event Processing) platform [19].

Drools has its own rule-based language, the DRL (Drools Rule Language), which consists 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. By using SCENE, we are able to extend the purpose of Drools' rules to incorporate the concept of *situation*.

In SCENE, general characteristics of situations are defined by their *situation type*. A situation instance is *activated* when facts whose properties satisfy the restrictions of the respective situation type (defined in Drools rules) 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 and a deactivation moment.

2) Hippocampus Module Design: The hippocampus module receives two input types: *neutral stimuli* and *adrenaline signal*. Neutral stimuli are real values representing environmental stimuli detected by the robot's sensors that are not threatening to the robot. The adrenaline signal is a value in the range $[0, 1]$ representing the system's level of fear based on the detection of an aversive unconditioned stimulus (US). For SAFEL, an aversive US is any stimulus known to be harmful to the robot. Analogously to most animals, which are born with the knowledge of aversive US (e.g., pain, low visibility, hunger, etc.), robots should also start their lifecycle with a set of well-known aversive US (e.g., collision, low light level, low battery, etc.), which are pre-configured parameters of SAFEL.

In the full model of SAFEL (Fig. 1), the amygdala module is responsible for sending an adrenaline signal to the hippocampus. However, as previously mentioned, the amygdala module has not yet been implemented. To deal with the absence of the amygdala, we simplify the process of adrenaline management by setting it high whenever an predefined aversive US is detected, and setting it low otherwise.

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 $\mathbf{e_t} = [s_1^t, s_2^t, ..., s_n^t]$, 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 $S_j = [\mathbf{e_{a_j}}, \mathbf{e_{a_j+1}}, ..., \mathbf{e_{d_j}}]^T$, where a_j and d_j are, respectively, the times of activation and deactivation of situation j. In the case S_j is a current situation, then d_j is the current time.

There are 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 using the temporal operations provided by SCENE. Such rules are constantly matched against the current adrenaline signal and existing situations instances in Drools' memory, and can be summarized as follows:

- *Aversive situation*: An aversive situation indicates the periods of time in which the robot was (or is, if it is a current situation) exposed to aversive stimuli. It is activated when the adrenaline signal rises above a given threshold and is deactivated when the adrenaline signal returns to normal levels.
- *Predictive situation*: Predictive situations are those preceding an aversive situation. 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 chance to predict the imminent exposure to aversive stimuli. Detecting predictive situations is only possible at the activation moment of the subsequent aversive situation, i.e., after their own deactivation. In other words, they can only be detected when they are already past.
- *Safe situation*: a safe situation indicates 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. It does not co-occur with aversive or predictive situations. Like predictive situations, safe situations can only be detected when they are already past.
- *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 after their deactivation.

Unlike aversive situations, unknown situations do not have a pre-defined type of event whose occurrence can indicate their activation and deactivation moments. For this reason, the instantiation parameters of unknown situations must be fixed and pre-defined by the user. These parameters are the *situation duration* and the *situation creation delay*. Situation duration (SD) is the difference of time between the activation and deactivation moments of a situation. For example, for situation S_j, SD $= d_j - a_j$. Situation creation delay (SCD), on the other hand, is the difference of time between the activation of a given situation and the activation of its successor situation. For example, for situation S_j, SCD = $a_j - a_{j-1}$. In other works, the SCD dictates the rate at which unknown situations are instantiated.

B. 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". In this module, situation instances coming from the hippocampus firstly pass through a feature extraction process, which aims at generating compacted versions of situational information that contains the essential characteristics of each situation. This is analogous to the unitary representation of context created in the brain, discussed in Section III.

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 $S_j = [\mathbf{s_1}, \mathbf{s_2}, ..., \mathbf{s_n}]$, where $\mathbf{s_i} = [s_i^1, ..., s_i^m]^T$. Then, the new situation information S'_j generated from S_j is given by:

$$S'_j = [\overline{s}_1, ..., \overline{s}_n, \gamma_1, ..., \gamma_n, \eta_1, ..., \eta_n], \tag{1}$$

where $\overline{s}_i$, γ_i and η_i are, respectively, the mean, skewness and number of local maxima of $\mathbf{s_i}$. The mean value provides the average intensity of each sensed stimulus along the duration of S_j. The skewness provides the approximate time interval when each stimulus was more intense during S_j. Finally, the number of local maxima provides the detection frequency of each stimulus during S_j.

Besides preventing overfitting of situation patterns, this feature extraction process also reduces 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.

The associative learning of the working memory module is implemented using MATLAB's *binary classification tree* [20]. The classification tree is used to classify the patterns of unknown situations into safe or predictive. Correctly classifying an unknown situation as predictive is equivalent to predicting the occurrence of an aversive situation in the near future. SAFEL outputs emotional responses according to the type of situation that the tree classifies, i.e., it outputs high fear response whenever the tree classifies an unknown situation as predictive.

The dataset used to train the classification tree starts empty, with no knowledge about the environment. As the robot explores the environment and experiences new aversive situations, the dataset grows and the tree is retrained. Thus, the robot's capability to predict imminent aversive events improves with experience, as it explores the environment.

Every non-aversive situation generated in the hippocampus is used for both training and prediction. For this reason, every situation instance that is not aversive is sent by the hippocampus to the working memory in two time-steps: first when it is still unknown and later when it is certain to be either safe or predictive. For example, at time d_j (i.e., when situation j has just been deactivated), situation S_j is sent as an unknown situation to the working memory, where it is transformed into S'_j and submitted to the binary tree for prediction. The tree will classify that situation into safe or predictive based its current training dataset. Then, at time t_n, where $t_n > d_j$, situation information S_j is sent to the working memory once again, but this time confirmed as either safe of predictive. The generated situation pattern S'_j and its type (safe or predictive) is now used for retraining the classification tree, thus increasing the training dataset.

V. Experiment with a Humanoid Robot

A. Experiment Goal

The value SAFEL's parameters (SD and SCD) can highly influence the performance of the classification tree in the working memory module. For example, suppose two subsequent situations S_1 and S_2. If $SCD > SD$, which implies that $d_1 < a_2$, then the information in between the time stamps d_1 and a_2 will not be collected by the hippocampus module and, consequently, will not be sent to the working memory module for learning and prediction. Learning this piece of information could be important for the robot to accomplish its task, and thus should not be ignored.

Now, suppose we have $SCD = SD$, which implies that $d_1 = a_2$. Even in this case, there is still some information being ignored. The working memory will be able to learn the pattern of situations S_1 and S_2, but any pattern of events starting after a_1 and finishing before d_2 will not be learned. Patterns of events in between these two time stamps could be forming the pattern of a predictive situation. Therefore ignoring this information could undermine the robot's ability to predict aversive situations.

Hence, it is important that $SCD < SD$, so that no potentially essential information is lost. However, defining how small the SCD should be in relation to the SD is still an open issue. If the SCD is too large, then essential information could be lost. If it is too small, then unnecessary redundancy could be introduced to the system, possibly reducing its response time.

Both SD and SCD are currently pre-defined parameters of SAFEL. While defining the SD value is fairly intuitive and can be easily induced from the problem the robot has to solve (e.g., the SD could be the total period of time of the sequence of events that we want the robot to learn), finding an ideal SCD value is a complex task.

The goal of this experiment is to turn the SCD into an internal parameter of SAFEL, which shall be calculated based on the value of the SD. This calculus shall take into consideration the result from a empirical study to find the best quantitative relation between SD and SCD in order to achieve the highest predictive performance possible from SAFEL. By doing so, we aim at reducing the complexity of SAFEL's pre-configuration while increasing its predictive performance.

B. Experiment Setup

The experiment has been conducted using a NAO humanoid robot, of model T14, in the Robotics Laboratory of the School of Mathematical and Computer Sciences (MACS) of the Heriot-Watt University. 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,

- 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 darkness represents an aversive stimulus. Hence, we configured SAFEL to increase adrenaline levels whenever NAO detected low light levels. The remaining stimuli (human faces, NAOmarks and sound detection) were initially neutral. Using the above-listed stimuli, we induced six situation patterns in this experiment, which are:

- Presentation of the NAOmark, followed by presentation of a human face, followed by darkness (this is the pattern of a predictive situation)
- Presentation of a human face, followed by the presentation of the NAOmark (safe situation)
- Simultaneous presentation of a human face and a NAOmark (safe situation)
- Presentation of a human face only (safe situation)
- Presentation of a NAOmark only (safe situation)
- No stimulus presented (safe situation)

Observe that the sound input (stimulus s_4) is not present in the pattern of the situations listed above. This is because the sound input in this experiment is analogous to environmental noise, i.e., it is a stimulus that is captured by the robot's sensors, but is neither aversive nor relevant for predicting aversive situations. We have introduced this kind of stimulus to the experiment in order to ensure SAFEL's capability to ignore irrelevant stimuli.

To create a controlled test environment, where we can compare the performance of SAFEL with different values of SCD under the same time line of events, we have separated the experiment in three phases. First we collected data, by presenting the above-listed situation patterns to NAO several times and then storing NAO's sensor readings. In the second phase, we assembled the collected data in a specific time line under three different values of *inter-stimulus interval* (ISI), which is the time interval between the offset of the predictive situation and the onset of the aversive situation. We created different versions of dataset by varying the ISI between 5, 10 and 15 seconds. 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.

VI. Results

The habit of overestimating danger is ubiquitous and essential in nature, as the cost of underestimating a danger is usually much higher than that of overestimating it [15]. The same rule may apply to robots, as they inhabit our physical world and may face similar threats. Thus, it is of our interest that SAFEL be capable to mimic nature's tendency to overestimate danger. For this reason, we use the *F2-score* as performance metric to evaluate SAFEL's efficacy for classifying unknown situations into safe or predictive.

The F2-score is a modified version of the *F1-score* (also known as *F-measure*), which gives more importance to recall (i.e., the fraction of aversive events that were predicted) than precision (i.e., the fraction of correctly predicted aversive events). While the F1-score is defined as the harmonic mean between precision and recall, the F2-score gives twice the weight to recall in comparison to precision.

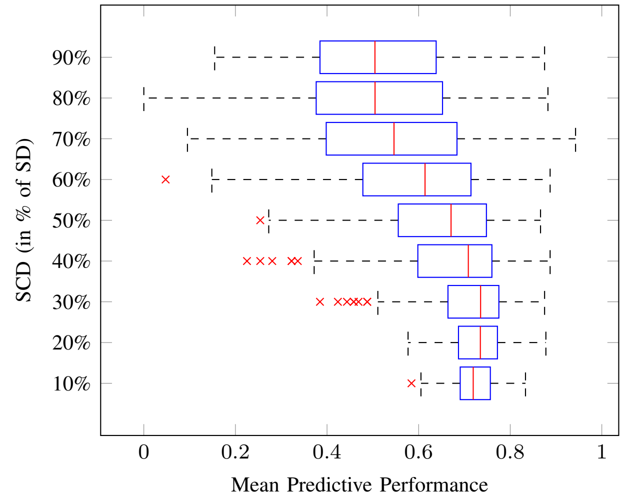

Fig. 2: Boxplot of the predictive performance of SAFEL by SCD. On each box, the central red mark is the median, the edges of the box are the 25^{th} and 75^{th} percentiles, the whiskers extend to the most extreme data points not considered outliers, and outliers are plotted as red marks.

Every dataset has been tested with three different values of SD: 20, 30 and 40 seconds. For each dataset, predictive performance started to be measured after SAFEL had processed the initial 20% of its instances, which we assume to be the minimum amount of samples necessary for the classification tree to create a distinction between each situation type (safe and predictive).

We have tested nine SCD values, which were defined as a percentage of the corresponding SD. For each combination of dataset configuration (3 ISIs and 3 SDs), we tested a SCD equals to 10% of the SD, a SCD equals 20% of the SD, and so on, until 90% of the SD. Fig. 2, shows the median and percentiles of predictive performance for each SCD tested. It is clear from Fig. 2 that a higher performance is obtained when the SCD is in between 10% and 30% of the SD.

We used the *factorial analysis of variance* (ANOVA) to study the effects of different SCDs in SAFEL's predictive performance, where the null hypothesis states that there is no statistically significant difference in the predictive performance among different SCDs, and is rejected when $p \leq 0.05$. The ANOVA test found statistically significant difference in performance ($p \approx 0$) when comparing SCDs smaller and bigger than 30%. This result can be observed in Fig. 3, which compares the means of predictive performance by SCD. Fig. 3 shows that better predictive performance is obtained when the SCD is 20% of the SD, and the difference in performance is statistically significant when compared with SCDs ranging from 40% to 90% of the respective SD. However, the difference is not statistically significant when

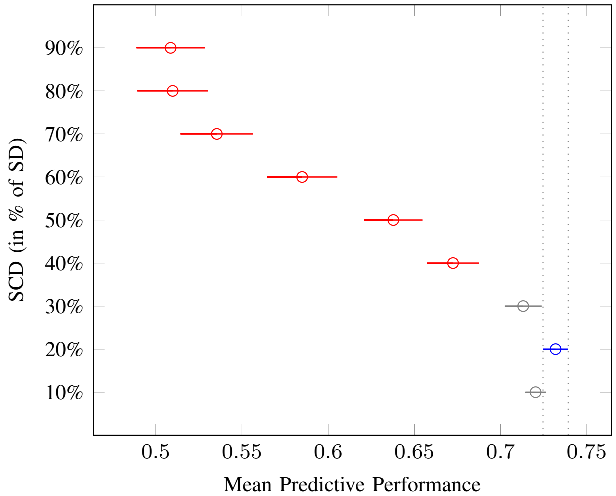

Fig. 3: Comparison of performance means by SCD. Each performance mean is represented by a mark, and their respective 95% confidence intervals are represented by error bars. Two performance means are significantly different if their intervals are disjoint. The highest performance mean is highlighted in blue. For the remaining performance means, it is represented in red if there is a statistically significant difference from the highest performance, otherwise they are represented in grey.

comparing SCDs between 10% to 30% of the SD.

When observing the interactions between the different values of SCD and ISI (Table Ia), we found an statistically significant difference indicating that, regardless of the ISI value (5, 10 or 15 seconds), best performance is still mostly obtained when SCD ranges from 10% to 30% of the respective SD. On the other hand, when analysing the interactions between the different values of SCD and SD (Table Ib), we found some influence of the SD in the performance. The ANOVA test indicates that, when SCD is between 10% and 50% of the SD, running SAFEL with SD equal to 20 seconds leads to statistically significant better performance if compared with the other tested values of SD (30 and 40 seconds). Also, the performance is consistently better when SCD is 30 seconds than when it is 40 seconds, though the difference is not statistically significant.

This result indicates that it is worth fixing the SCD value as 20% of the SD in terms of predictive performance. Interactions between the analysed variables indicate that the SD value can possibly affect SAFEL's performance, and that smaller SDs may provide better predictive performance than larger ones. However, a proper experiment must be performed in order to confirm this hypothesis, which we indicate as future work.

VII. Conclusion

In this paper, we have performed a study on SAFEL, a situation-aware fear learning model that allows robots to memorize temporal context and predict undesirable situations through a fear-conditioning-like procedure. This study aimed at optimizing SAFEL's parameters to improve its predictive performance. The goal was to find the best quantitative relation between two parameters of SAFEL: the situation duration (SD) and the situation creation delay (SCD). Experiments with a NAO humanoid robot have been performed, which demonstrated that fixing the SCD as 20% of the respective SD leads to higher predictive performance. By doing so, we have also reduced parameter settings, as the user no longer needs to pre-configure the SCD value.

As future work, we plan to implement the sensory and amygdala modules (see Fig. 1), which are the last missing modules to complete SAFEL's development. Lastly, we intend to 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.

TABLE I: Analysis of the effect of variables interaction in the predictive performance. The underlined number indicates the highest predictive performance. Bold numbers indicate values of predictive performance that have no statistically significant difference from the highest performance.

(a) Mean predictive performance by SCD and ISI.

		ISI (sec)		
		5	10	15
SCD (% of SD)	10%	**0.711**	**0.720**	**0.730**
	20%	**0.716**	**0.733**	**0.746**
	30%	0.657	**0.728**	**0.754**
	40%	0.571	0.706	**0.741**
	50%	0.521	0.665	**0.727**
	60%	0.431	0.625	0.699
	70%	0.375	0.566	0.665
	80%	0.366	0.525	0.638
	90%	0.371	0.527	0.628

(b) Mean predictive performance by SCD and SD.

		SD (sec)		
		20	30	40
SCD (% of SD)	10%	**0.753**	0.719	0.689
	20%	**0.775**	0.721	0.700
	30%	**0.773**	0.704	0.662
	40%	**0.756**	0.665	0.597
	50%	**0.728**	0.605	0.580
	60%	0.704	0.530	0.521
	70%	0.658	0.474	0.474
	80%	0.616	0.466	0.448
	90%	0.601	0.440	0.485

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