



# Fuzzy cognitive maps for artificial emotions forecasting

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## ABSTRACT

At the present, emotion is considered as a critical point of human behaviour, and thus it should be embedded within the reasoning module when an intelligent system or a autonomous robot aims to emulate or anticipate human reactions. Therefore, current research in Artificial Intelligence shows an increasing interest in artificial emotion research for developing human-like systems. Based on Thayer's emotion model and Fuzzy Cognitive Maps, this paper presents a proposal for forecasting artificial emotions. It provides an innovative method for forecasting artificial emotions and designing an affective decision system. This work includes an experiment with three simulated artificial scenarios for testing the proposal. Each scenario generate different emotions according to the artificial experimental model.

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## 1. Introduction

The complexity of software systems and uncertainty within its application domains is increasing day by day. At the present, the capability to adapt its own behaviour in response to the environment in the form of self-adaptation has become one of the most promising research directions within Artificial Intelligence and systems design.

Autonomous systems should decide autonomously without or with scarce human interference how to respond to changes in their contexts and environments [9]. While some self-adaptive systems may be able to run without any external intervention, others do it with high level goals [38]. Due to self-adaptive systems are complex systems with a high degree of autonomy, it is harder to ensure that it behaves as desired and avoids wrong behaviour [16].

For autonomous systems to make highly specialized tasks, sometimes it is needed to embed affective behaviour that have not been associated traditionally with intelligence [21]. Emotions play a critical role in human's way of reasoning and its decision-making activities. In other words, emotions have a critical impact over intelligence.

According to this, that human will not make decision effectively if human's subsystem of emotions is not working well. For that reason, how to apply the intelligent function of emotions into systems and how to make systems include intelligence are strongly

interrelated. Artificial emotion is an emerging research subject and will make machine have artificial emotions [34].

According to [15], affective forecasting studies have shown that people are biased in making both random and systematic errors when anticipating their own future emotional states. Given this level of divergence between anticipated and experienced reactions, it is worth examining computational methods to avoid those issues.

This paper proposes Fuzzy Cognitive Maps (FCMs) as a worthy tool for forecasting artificial emotions in autonomous systems immersed in complex environments with high uncertainty. The Thayer's emotion model is used to map FCM outputs within an emotional space. That model defines the emotion categories in a 2-dimensional cartesian coordinate according to their valence and arousal.

The rest of the paper is structured as follows. Section 2 presents the emotional theoretical background and soft computing in emotion-aware systems. Next section introduces Fuzzy Cognitive Maps. Section 4, shows the FCM-based emotion forecasting model. In Section 5, an illustrative application is given, and conclusions are finally made.

## 2. Theoretical background

Affective computing pretends to narrow the space between computers and affective humans. Affective computing try to assign systems the human-like capabilities of emotions' observation, interpretation and generation [36].

Emotions have a critical impact on humans physical states, actions, beliefs, motivations, decisions and desires. Appropriate

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balance of emotion makes human beings having flexibility and creativity in solving problem [14]. In the same sense, if we want the systems to have real intelligence, to adapt the environment in which humans living and to communicate with human beings naturally, then systems need to understand and express emotions in a certain degree.

Affective computing is an emerging, but promising, research field dealing with the issues regarding emotions and computers. Over the last years emotions' research has become a multi-disciplinary research field with a growing interest [4]. Indeed, it plays a critical role in human–machine interaction. Automatic recognition of emotional states aims to improve the interaction between humans and machines. Furthermore, it could be used to make the systems act according to the current human emotions.

It could be worthy in a lot of real life applications as a fear-type emotion recognition for audio-based surveillance systems [11], real-life emotion detection within a medical emergency call centre [12], semi-automatic diagnosis of psychiatric diseases [35] detection of children's emotional states in a conversational computer games [42], and so on.

On the other hand, relevant advances were made in speech synthesis as well [23]. Biosignals (e.g.: ECG, EEG, and so on), face and body images are options to detect emotional states [17,32,39]. However, those kind of methods are more invasive, and so complex for applying in a lot of real applications [4]. Therefore, forecasting emotions becomes a worthy requirement. This work proposes a soft computing-based method for forecasting emotions in real life applications.

This proposal trust on Thayer's emotion model for defining the affective space. Next, an overview is shown.

### 2.1. Thayer's emotion model

Thayers model [37] is based on mood analysis as a biopsychological concept [1]. More in detail, Thayer contemplates mood as an affective state strongly related with psychophysiological and biochemical components. In addition, personal cognitive activities and casual events play a critical role in its sudden understanding.

The Thayer's emotion model is frequently used to avoid the ambiguity of adjectives [41]. That model defines the emotion categories in a dimensional way according to their valence (how positive vs. negative) and arousal (how exciting vs. calming). The emotion classes are divided into the four quadrants of a two-dimensional cartesian coordinate system, valence ( $x$ ), arousal ( $y$ ), as shown in Fig. 1. The origin means the lack of emotions.

Each model's quadrant includes three emotions. The first one with positive valence and arousal is composed of the emotions: pleased, happy and excited. The second one with negative valence and positive arousal comprises annoying, angry and nervous. The third one with negative valence and arousal consists of sad, bored and sleepy. Finally, the last one with positive valence and negative arousal covers calm, peaceful and relaxed. As a result, the Thayer's emotion space is composed of twelve emotions.

Closer points to the origin means less intense emotions, and points far-away from the origin represents more intense emotions.

### 2.2. Soft computing within emotion-aware systems

Several previous efforts have been done to develop emotional systems in several environments, as Ambient Intelligence, emotions in music and so on.

Zhou et al. [44] propose a framework of Emotion-Aware Ambient Intelligence (AmE). It integrates Ambient Intelligence, affective computing, emotion-aware services, emotion ontology, service-oriented computing, and service ontology. It provides an open environment for developing and delivering applications that

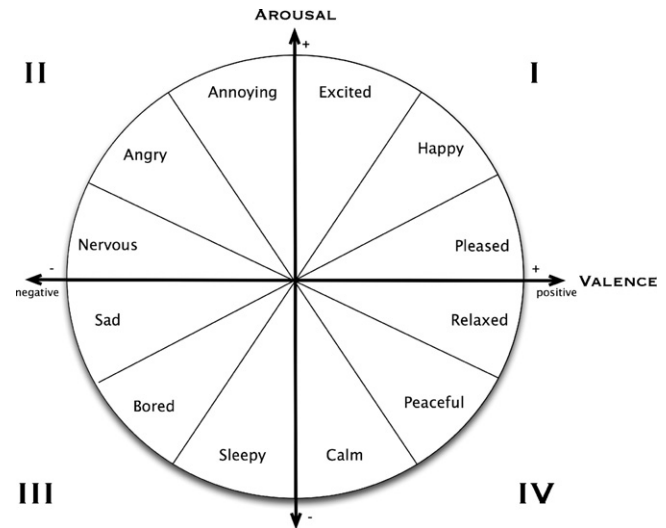


Fig. 1. Thayer's emotion model.

include emotion-aware services. In addition, they illustrate their preliminary work on AmE, the framework for emotion-aware ambient intelligence and present the overall structure of emotion in English conversation.

Marreiros et al. [22] proposes an architecture for an ubiquitous Group Decision Support System (u-GDSS) able to hold up asynchronous and distributed computational services. The proposed system will support group decision making, being available in any location, in different devices and at any time. One of the critical components of this framework is an emotional multiagent-based group decision making processes simulator.

Sharada and Ramanaiah [33] develop an emotional intelligent agent architecture based on a Neuro-Fuzzy system as event processor and a Hopfield network as emotional state calculator. The output layer of the event processor generates a numeric pattern according to the input event. This pattern is taken up by the Hopfield network for emotional state calculation.

A model called Fuzzy Logic Adaptive Model of Emotions (FLAME) was designed to generate emotions and to simulate emotional intelligence processes by [13]. FLAME applies fuzzy rules to research fuzzy logic applications emotional process modelling.

Acampora and Loia [2] present a FCM extension, Timed Automata-based Fuzzy Cognitive Map (TAFCM), by using a theory from formal languages, namely, the timed automata, for troubleshooting FCM drawbacks. A TAFCM is an ordered pair composed by an initial cognitive configuration together with a timed cognitive transition table which represents the mathematical entity acting as joining point between cognitivism and dynamism in system modelling. In this proposal, TAFCMs make use of expert knowledge to design a collection of cognitive eras and configurations modelling the temporal behaviour of the system.

Furthermore, Acampora et al. [1] introduces a novel methodology for Ambient Intelligent systems through a service-oriented architecture. The functionalities are delivered by a pool of agents. These agents exploit TAFCM as well. Their proposal is based on the theory of timed automata and a formal method for modelling human moods to distribute emotional services able to increase users comfort and make simpler the human–machine interactions.

Moreover, Ayesh [6] use FCMs to model the relationships between emotions, emotional states, physical states and actions. In his proposal, sensory data is applied to estimate emotions and trigger responses. The aim is to have more reactive robots that can react almost in real time.

As a result, FCM is a proven soft computing technique within affective computing field. FCMs have similar features to other techniques, at the same time as providing other different aspects which solve the constraints of the others. Indeed, FCMs have worthy characteristics as flexibility, adaptability, fuzzy reasoning and the capacity of abstraction. FCMs have been widely used within literature as a very useful one to model and analyze complex dynamical systems. It is an easy of use cognition tool which can model the knowledge and reasoning in it efficiently. This paper proposes the link between FCMs and the Thayer's emotion model as emotional framework and an architecture for emotional systems.

### 3. Fuzzy Cognitive Maps

Classical decision support techniques assumes that decision makers can construct an accurate representation of a decision problem, that there is unlimited time for making a choice, and that the context is static, as it does not change autonomously or as a consequence of the decision maker's choices. This also assumes that decision-making is often constrained by a limitation of both external resources, such as time limitations, and human cognitive resources, such as memory capacity.

Real-world challenges are usually characterized by a number of components interrelated in many complex ways. They are often dynamic, that is, they evolve with time through a series of interactions among related concepts.

Classical modelling techniques cannot to support this kind of environments. For that reason, this paper proposes FCM as an innovative and flexible technique for modelling human knowledge in decision-making process. In addition, FCM provide excellent mechanisms to develop forecasting exercises, specially what-if analysis.

#### 3.1. FCM fundamentals

Fuzzy Cognitive Maps have emerged as alternative tools for representing and studying the behaviour of systems and people [18]. FCMs are signed fuzzy weighted digraphs, usually involving feedback, consisting of nodes indicating the most relevant factors of a decisional environment; and edges between those factors representing the relationships between them [7,29].

From an Artificial Intelligence point of view, FCMs are supervised learning fuzzy-neural systems [18,20,25,26,28,43], whereas more and more data is available to model the problem, the system improves its own adaptation and reaching a solution [27].

A FCM describes the behaviour of a system in terms of concepts; each one representing an entity, a state, a variable, or a characteristic of the system [40]. The FCM nodes would represent such concepts as events, physical components, investment, or risks, to name a few (Fig. 2). The relationships among nodes are represented by directed edges. An edge linking two nodes models the causal influence of the causal variable on the effect variable.

The causal influence of the causal variable over the effect one is modelled by an edge linking both nodes. The intensity of each edge is measured by its weight as  $w_{ji} \in \{[0, +1] \mid [-1, +1]\}$ , where  $i$  is the pre-synaptic (cause) node and  $j$  the post-synaptic (effect) one.

#### 3.2. FCM dynamics

An adjacency matrix  $\mathbf{A}$  represents the FCM nodes connectivity. FCMs measure the intensity of the causal relation between two

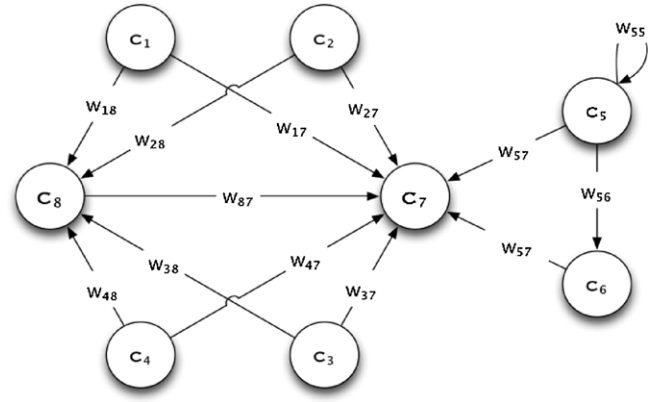


Fig. 2. Fuzzy Cognitive Map example.

factors and if no causal relation exists it is denoted by 0 in the adjacency matrix.

$$\mathbf{A} = \begin{matrix} & x_1 & \dots & x_n \\ \begin{matrix} x_1 \\ \vdots \\ x_n \end{matrix} & \begin{pmatrix} w_{11} & \dots & w_{1n} \\ \vdots & \ddots & \vdots \\ w_{n1} & \dots & w_{nn} \end{pmatrix} \end{matrix} \quad (1)$$

where  $x_i$  are the map's concepts, and  $w_{ji}$  are the edges' weights.

FCMs are dynamical systems involving feedback, where the effect of change in a node may affect other nodes, which in turn can affect the node initiating the change [31]. The analysis begins with the design of the initial vector state ( $\vec{C}^0$ ), which represents the initial state (value) of each variable or concept (node). The initial vector state with  $n$  nodes is denoted as

$$\vec{C}^0 = (c_1^0 \ c_2^0 \ \dots \ c_n^0) \quad (2)$$

where  $c_1^0$  is the state value of the concept  $x_1$  at instant  $t=0$ .

The new values of the nodes are computed in an iterative vector-matrix multiplication process with an activation function, which is used to map monotonically the node value into a normalized range  $[0, 1]$ . The sigmoid function is the most used one [10] when the concept (node) value maps in the range  $[0, 1]$ , otherwise the hyperbolic tangent would be the selected activation function. The components of the vector state  $\vec{C}^{t+1} = \{c_i^{t+1}\}_{i=1}^n$  at instant  $t+1$  is computed as follows

$$c_i^{t+1} = f \left( c_i^t + \sum_{j=1}^n w_{ji} \cdot c_j^t \right) \quad (3)$$

where  $c_i^{t+1}$  is the state of the node  $i$  at the  $t$  instant,  $w_{ji}$  is the weight of the influence of  $j$  node over the  $i$  node, and  $f(\cdot)$  is the activation function. The states' value is changing along the process.

If the activation function is sigmoid, then the  $i$  component of the vector state  $\vec{C}^{t+1}$  would be

$$c_i^{t+1} = \frac{1}{1 + e^{-\lambda \cdot (c_i^t + \sum_{j=1}^n w_{ji} \cdot c_j^t)}} \quad (4)$$

where  $\lambda$  is the constant for function slope [10]. If the activation function is hyperbolic tangent then the component  $i$  of the vector state  $\vec{C}^{t+1}$  would be

$$c_i^{t+1} = \frac{e^{\lambda \cdot (c_i^t + \sum_{j=1}^n w_{ji} \cdot c_j^t)} - e^{-\lambda \cdot (c_i^t + \sum_{j=1}^n w_{ji} \cdot c_j^t)}}{e^{\lambda \cdot (c_i^t + \sum_{j=1}^n w_{ji} \cdot c_j^t)} + e^{-\lambda \cdot (c_i^t + \sum_{j=1}^n w_{ji} \cdot c_j^t)}} \quad (5)$$

After an inference process, the FCM reaches either one of two states following a number of iterations. It settles down to a fixed

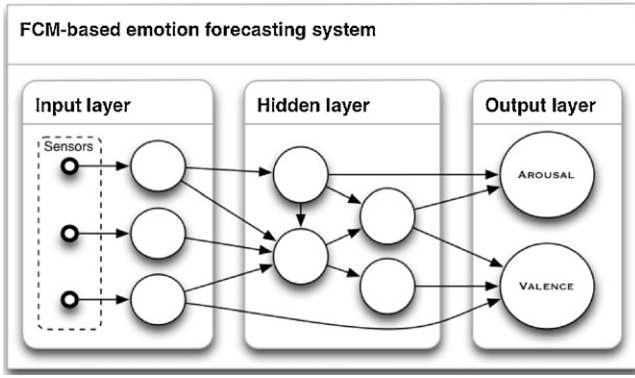


Fig. 3. FCM-based emotion forecasting system architecture.

pattern of node values, the so-called hidden pattern or fixed-point attractor. Alternatively, it keeps cycling between several fixed states, known as a limit cycle. Using a continuous transformation function, a third possibility known as a chaotic attractor exists. This occurs when, instead of stabilizing, the FCM continues to produce different results (known as state-vector values) for each cycle [30].

Moreover, FCM convergence is a critical point in FCM dynamics. Obviously, the proposal of this paper has a practical worth if it converges and therefore results in concrete outputs. In this sense, Boutalis et al. [8] have proved certain conditions for the FCM weights so that the FCM with sigmoid functions always reach an equilibrium point.

#### 4. FCM-based emotion forecasting system

This work proposes FCM as a technique for emotion forecasting. This is not an empirical research. The author proposes a FCM-based schema so that practitioners or future research can use it for forecasting emotions. It could be implemented in software tools as the proposed by [3].

The architecture of a FCM-based emotion forecasting system is composed by three layers (Fig. 3). The whole set of layers is represented by a single FCM model. The input layer collects data from environment. The data source can be sensors, other systems and so on. The input data are strongly dependent of the domain. It would include all the external data with potential (lineal or non-linear) influence over the human's emotional states. It is possible to connect nodes in the input layer with the nodes in the output layer.

The hidden layer represents the FCM subgraph for connecting inputs with the output layer. The hidden layer process the inputs and it is composed by several nodes (representing constructs) with direct influence over the arousal and the valence. A hypothetical construct is an explanatory variable which is not directly observable (e.g.: fear, nervousness, and so on).

Usually, external data have not direct impact over arousal and valence. This layer would transform the concepts within input layer in concepts with direct influence over the arousal and valence concepts. This layer would be more complex or simpler depending on the processing requirements.

The output layer is composed by a couple of nodes (arousal and valence). According to the Thayer's model, these are the needed concepts for determining the emotions.

The whole emotion forecasting system is a FCM, then it is possible to run different what-if simulations. Each simulation begins with the design of the initial vector state  $\vec{C}^0$ , which represents a

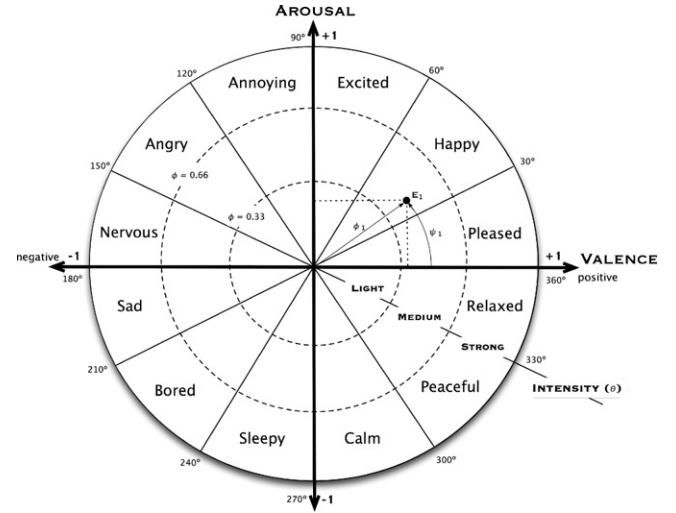


Fig. 4. FCM-based Thayer's emotion model.

proposed initial stimuli. We denote the initial vector state with  $k$  nodes in input layer and  $n$  total number of nodes as

$$\vec{C}^0 = \begin{matrix} \text{FCM layers} \\ \begin{matrix} \text{Input} & \text{Hidden} & \text{Output} \end{matrix} \\ \begin{pmatrix} c_1^0 & \dots & c_k^0 & 0 & \dots & 0 & 0 & \dots & 0 \end{pmatrix} \end{matrix} \quad (6)$$

Note that the activated nodes within the initial vector state just belongs to the input layer, because they represent the initial available data for forecasting emotions. The nodes from the remainder layers are not activated at the initial vector state and their values are zero.

The updated nodes' states are computed as detailed before. After that, each node of the output layer has a steady state [28] representing the arousal and valence final values. Those values are represented within the two-dimensional cartesian coordinate system as represented in Fig. 4.

The Thayer's emotion model establishes an emotional space, where the FCM-based proposal can mapping the valence and arousal state values to forecast emotions. After the FCM dynamics the state value of the arousal node ( $e_a$ ) and the valence one ( $e_v$ ) get their steady state.

Due to computational reasons, an emotion is represented in the emotional space [14] by a 2-tuple  $E = \{\phi, \psi\}$ , where  $\phi$  represent the emotion's intensity and it is calculated as follows

$$\phi = \sqrt{\frac{e_a^2 + e_v^2}{2}} \quad (7)$$

The position in radians from the x-axis of the emotion within the emotional space is denoted by  $\psi_{rad}$  and is computed as follows

$$\psi_{rad} = \begin{cases} \arctan \frac{e_v}{e_a} & \text{if } e_a > 0 \\ \frac{\pi}{2} & \text{if } e_a = 0 \\ \arctan \frac{e_v}{e_a} + \pi & \text{if } e_a < 0 \end{cases} \quad (8)$$

where  $\arctan$  is the arctangent function. The result of  $\psi_{rad}$  is a measure in radians. Then the calculation of  $\psi$  in degrees is done as follows

$$\psi = \psi_{rad} \cdot \frac{180}{\pi} \quad (9)$$



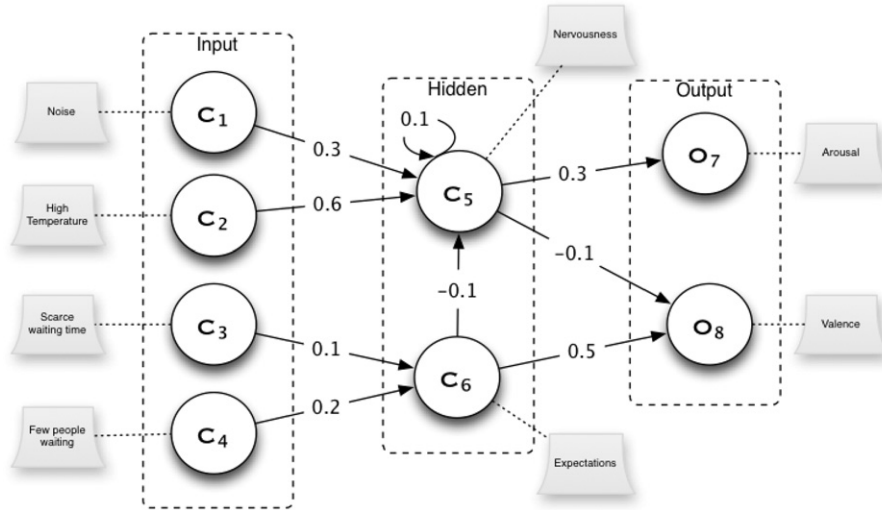


Fig. 5. FCM emotion forecasting application.

Therefore

$$\psi = \begin{cases} \frac{180}{\pi} \cdot \arctan \frac{e_v}{e_a} & \text{if } e_a > 0 \\ 90^\circ & \text{if } e_a = 0 \\ \frac{180}{\pi} \cdot \left( \arctan \frac{e_v}{e_a} + \pi \right) & \text{if } e_a < 0 \end{cases} \quad (10)$$

Fig. 4 shows an emotion  $E_1$  within the emotional space, with  $\phi_1$  and  $\psi_1$ . The emotion  $E_1$  is representing happiness, because  $30^\circ < \psi_1 < 60^\circ$ . The emotion intensity is medium because  $0.3 < \phi_1 < 0.6$ .

## 5. An illustrative experiment

According to this proposal, each problem would need to define a specific input and hidden layer related with the domain and the problem modeled.

With the intention of illustrating the proposal, this paper proposes an artificial experiment. The goal is forecasting the emotion generated by environmental conditions. Note that the goal of the model is not designing a real emotional Ambient Intelligence system, but to test the FCM approach for artificial emotions forecasting for people in a queue. The FCM model at Fig. 5 represents an example of a FCM-based emotional Ambient Intelligence system. Eq. (11) shows the adjacency matrix.

$$A = \begin{pmatrix} 0 & 0 & 0 & 0 & 0.3 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0.6 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0.1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0.2 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0.1 & 0 & 0.3 & -0.1 & 0 \\ 0 & 0 & 0 & 0 & -0.1 & 0 & 0 & 0 & 0.5 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \end{pmatrix} \quad (11)$$

Fig. 5 shows a FCM model with eight nodes and edges. The input layer includes four nodes representing external data, as noise ( $c_1$ ), high temperature ( $c_2$ ), scarce waiting time ( $c_3$ ), and few people waiting ( $c_4$ ). The input nodes have different influences over the hidden ones.

The concept  $c_5$  in hidden layer represents the construct nervousness, and it receives influence from  $c_1$  (noise) and  $c_2$  (high temperature) nodes. In addition, nervousness is increasing by itself. The other construct is expectations ( $c_6$ ). It represents the (good) expectations of the members of the queue about when they go

ahead.  $c_6$  receives influence from  $c_3$  (scarce waiting time) and  $c_4$  (few people waiting). In addition, good expectations reduce nervousness construct.

The output layer is composed by the arousal ( $o_7$ ) and valence ( $o_8$ ) nodes. Arousal ( $o_7$ ) receives influence from  $c_5$  (nervousness) and valence ( $o_8$ ) from  $c_6$  (expectations) and negative one from nervousness  $c_5$  (nervousness).

The analysis begins with the definition of the initial vector which represents a proposed initial situation. Using FCM is possible to design initial vector states (initial scenarios) mixing activated and not activated nodes. Furthermore, it is possible to develop what-if analysis using different initial vector states.

Three initial scenarios have been designed. In each of the test scenarios, we have an initial vector  $A_0^i$ , representing the initial state values of the events at a given time of the process, and a final vector  $A_f^i$ , representing the steady state that can be arrived at. The final vector  $A_f^i$  is the last vector got in convergence region.

**1. First scenario of FCM emotion forecasting.** For the first case study, the initial vector state and the steady vector state are the following

$$\begin{aligned} A_0^1 &= (0.5 \quad 0.5 \quad 0 \quad 0 \quad 0 \quad 0 \quad 0 \quad 0) \\ A_{f=66}^1 &= (0.14 \quad 0.14 \quad 0 \quad 0 \quad 0.73 \quad 0 \quad \mathbf{0.68} \quad \mathbf{-0.56}) \end{aligned} \quad (12)$$

According with the  $A_f^1$  results,  $Arousal = 0.68$  and  $Valence = -0.56$ . The computation of the forecasted emotion in the first scenario  $E_1$  is as follows

$$\begin{aligned} \phi^1 &= \sqrt{\frac{(0.68^2) + (-0.56^2)}{2}} \\ &= 0.6224 \end{aligned} \quad (13)$$

$$\begin{aligned} \psi^1 &= \frac{180}{\pi} \cdot \left( \arctan \frac{-0.56}{0.68} + \pi \right) \\ &= -39.66^\circ \\ &= 320.34^\circ \end{aligned} \quad (14)$$

Then  $E_1 = \{0.6718, 320.34^\circ\}$  and the forecasted emotion is **medium peaceful**.

**Table 1**  
Emotion forecasting scenarios results

Scenario	Axis	Weight	$E_i = \{\phi_i, \psi_i\}$	Emotion
1	Arousal (x)	0.68	$\phi_1 = 0.6224$	Medium peaceful
	Valence (y)	−0.56	$\psi_1 = 320.34^\circ$	
2	Arousal (x)	−0.63	$\phi_2 = 0.6748$	Strongly angry
	Valence (y)	0.72	$\psi_2 = 48.89^\circ$	
3	Arousal (x)	−0.67	$\phi_3 = 0.6718$	Strongly happy
	Valence (y)	−0.68	$\psi_3 = 225.49^\circ$	

**2. Second scenario of FCM emotion forecasting.** For the second case study, the initial vector state and the steady vector state are the following

$$A_0^2 = (-0.2 \ 0 \ 1.0 \ 1.0 \ 0 \ 0 \ 0 \ 0)$$

$$A_{f=73}^2 = (-0.12 \ 0 \ 0.14 \ 0.14 \ 0.56 \ 0.48 \ -0.63 \ 0.72)$$

According with the  $A_f^2$  results,  $Arousal = -0.63$  and  $Valence = 0.72$ . The computation of the forecasted emotion in the second scenario  $E_2$  is as follows

$$\phi^2 = \sqrt{\frac{(-0.63^2) + (0.72^2)}{2}} \quad (15)$$

$$= 0.6748$$

$$\psi^2 = \frac{180}{\pi} \cdot \left( \arctan \frac{0.72}{-0.63} + \pi \right) \quad (16)$$

$$= 48.89^\circ$$

Then  $E_2 = \{0.6748, 48.89^\circ\}$  and the forecasted emotion is **strongly happy**.

**3. Third scenario of FCM emotion forecasting.** For the last case study, the initial vector state and the steady vector state are the following

$$A_0^3 = (-1.0 \ -1.0 \ -1.0 \ -1.0 \ 0 \ 0 \ 0 \ 0)$$

$$A_{f=66}^3 = (-0.14 \ 0 \ 0 \ -0.14 \ -0.69 \ -0.43 \ -0.67 \ -0.68)$$

According with the  $A_f^3$  results,  $Arousal = -0.67$  and  $Valence = -0.68$ . The computation of the forecasted emotion in the third scenario  $E_3$  is as follows

$$\phi^3 = \sqrt{\frac{(-0.67^2) + (-0.68^2)}{2}} \quad (17)$$

$$= 0.6718$$

$$\psi^3 = \frac{180}{\pi} \cdot \left( \arctan \frac{-0.68}{-0.67} + \pi \right) \quad (18)$$

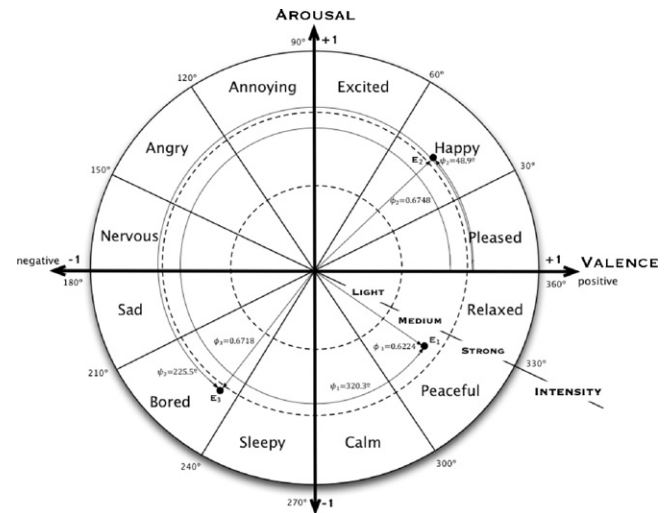
$$= 225.49^\circ$$

Then  $E_3 = \{0.6718, 225.49^\circ\}$  and the forecasted emotion is **strongly bored**.

The summary of the results of each simulation is shown at Table 1 and the graphical representation at Fig. 6.

The results of the scenarios show that the proposed approach is a worthy one. From different initial conditions, the proposal forecasts different emotions. The model tested is an artificial experiment just for validation.

Anyway, the results are consistent with the goal of the experiment. The first scenario starts with medium values of noise and temperature and with null values of waiting time and the number of people waiting. As a result, the emotion forecasted is medium peaceful. The interpretation is that the noise and the temperature have not enough values for irritating. The second scenario has low noise and so scarce time and people waiting. Obviously, it forecast a happy emotion, because the time in queue would be short. Finally,



**Fig. 6.** Emotion forecasting results.

the third scenario has the lower values in the four input nodes. As a result, it is a bored scenario.

## 6. Conclusions

Emotions have a critical impact on humans physical states, actions, beliefs, motivations, decisions and desires. Emotions forecasting and its application in intelligent and autonomous systems is an emerging and promising research field and able to improve systems interaction with humans.

Taking into account the importance of emotions in human behaviour decision, the design of an emotion forecasting module based on artificial emotion and Thayer's emotion model was proposed.

This paper shows and example illustrated of a FCM-based emotion forecasting system. FCM is fuzzy-graph structure for representing causal reasoning within complex environments with high uncertainty. This paper shows that it is possible to forecast the emotions generated from sensors' raw data with FCMs.

From a static point of view, the FCMs can indicate the relationships between the environmental variables and the emotions. From a dynamic point of view, FCMs can make what-if simulations and forecasting emotions according to a previous environmental conditions.

This is not an empirical research. A FCM-based framework based on external data, constructs and output nodes is presented. Furthermore, a mechanism is proposed for evaluating the FCM output and associated them with the Thayer's emotion model. Indeed, the goal is not to model a real world system, but it just proposes a FCM-based theoretical framework so that practitioners or future research can use to forecast or generate emotions within their own systems.

Future research will include real applications, linking new emotional models with FCMs and its extensions and FCM learning algorithms for emotion forecasting.

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