Simulating Synthetic Emotions with Fuzzy Grey Cognitive Maps

Jose L. Salmeron

Computational Intelligence Lab, Km. 1 Utrera road, University Pablo de Olavide, 41013 Seville, Spain
salmeron@acm.org

Abstract . Autonomous robotic systems should decide autonomously without or with sparse human interference how to react to alterations in environment. Based on Thayer's emotion model and Fuzzy Grey Cognitive Maps, this work presents a proposal for simulating synthetic emotions. Thayer's proposal is based on mood analysis as a bio psychological concept. Recently, Fuzzy Grey Cognitive Maps have been proposed as a FCM extension. FGCM is mixing conventional Fuzzy Cognitive Maps and Grey Systems Theory that has become a worthy theory for solving problems with high uncertainty under discrete small and incomplete data sets. This proposal provides an innovative way for simulating synthetic emotions and designing an affective robotics system. This work includes an experiment with an artificial scenario for testing this proposal.

1 Introduction

Autonomous systems should decide without or with scarce human interference how to react to changes in their contexts and environments [2]. Due to the fact that self-adaptive systems are complex autonomous systems, it is hard to ensure that they behave as desired and avoid wrong behaviour [5].

For autonomous systems to make highly specialized tasks, it is sometimes needed to embed affective behavior that has not been associated traditionally with intelligence [6]. Emotions play an important role in human reasoning and its decision making.

This paper proposes Fuzzy Grey Cognitive Maps (FGCMs) 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 FGCM 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. The next section introduces Fuzzy Grey Cognitive Maps. In Section 4 an illustrative application is given and conclusions are finally shown.

2 Theoretical Background

Emotions have an important impact on human decisions, actions, beliefs, motivations, and desires [4]. In this sense, if we want the robots to have real intelligence, to adapt

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to the environment which humans are living in, and to communicate with human beings naturally, then robots need to detect, understand, and express emotions in a certain degree.

Affective computing assigns robots and systems in general a human-like potential of detection, understanding and generation of emotions. It is a new but promising research area dealing with the issues regarding emotions and systems. Nowadays, emotions research has become a multi-disciplinary and growing field [1]. Indeed, it could be used to make robots act according to the human emotions.

This proposal is inspired by Thayer's emotion model for defining the affective space. Next, a brief overview is shown.

2.1 Two-Dimensional Emotion Representation in Thayer's Model

Thayer's model [12] is based on mood analysis as a biopsychological concept. Moreover, this proposal models mood as an affective state closely related to biochemical and psycho-physiological elements.

Various emotions are divided into four quadrants of a two-dimensional Cartesian coordinate system, valence (x), arousal (y), as shown in Fig. 1. The central intersection indicates the lack of emotion.

Each model's quadrant includes three basic emotions. The first quadrant 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

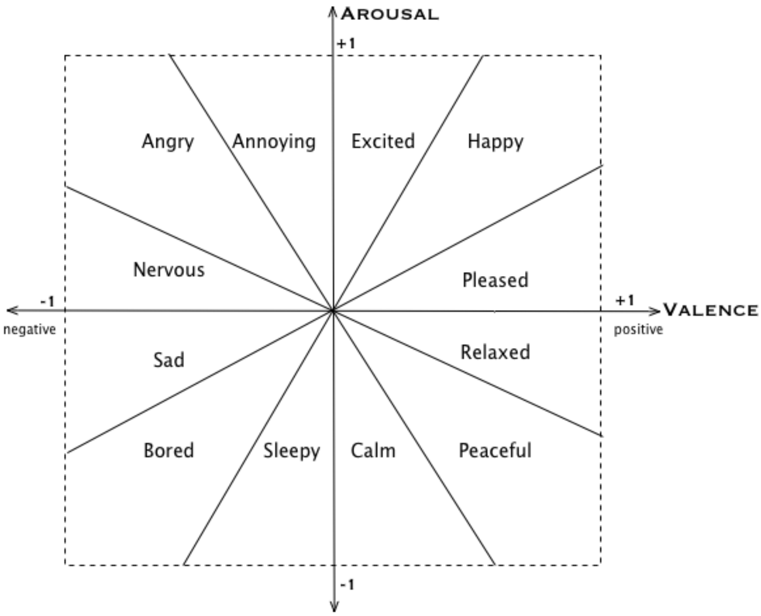

Fig. 1. Thayer's emotion graphical model [12]

and sleepy. Finally, the last one with positive valence and negative arousal covers calm, peaceful and relaxed. As a result, the Thayer's emotional space is composed of twelve emotions.

Regarding the intensity, the points closer to the intersection mean less intense emotions and points far away from the center model more intense emotions.

3 Fuzzy Grey Cognitive Maps

3.1 Fundamentals

Grey Systems Theory (GST) is an interesting set of problem solving tools within environments with high uncertainty, under discrete small and incomplete data sets [3]. GST has been designed to work with small data samples and poor information with successful applications in military science, business, agriculture, energy, transportation, meteorology, medicine, industry, geology and so on.

Fuzzy Grey Cognitive Map is based on FCMs and GST, and it has become a very worthy theory for solving problems within domains with high uncertainty [7]. FGCMs provide an intuitive yet precise way of modelling concepts and reasoning about them. By transforming decision models into causal graphs, decision-makers without technical background can understand all of the components in a given situation. Moreover, with a FGCM, it is possible to identify the most critical factor that impacts the expected target concept.

The FGCM nodes are modelling variables, representing concepts. The relationships between nodes are represented by directed edges. An edge linking two FGCM nodes is modelling the grey causal influence of the causal variable on the effect variable. The FGCM model is represented by an adjacency matrix (⊗A).

$$\otimes A = \begin{array}{c c} & \begin{array}{ccc} x_1 & \dots & x_n \end{array} \\ \begin{array}{c} x_1 \\ \vdots \\ x_n \end{array} & \begin{pmatrix} \otimes w_{11} & \cdots & \otimes w_{1n} \\ \vdots & \ddots & \vdots \\ \otimes w_{n1} & \cdots & \otimes w_{nn} \end{pmatrix} \end{array} \tag{1}$$

FGCMs are dynamical systems involving feedback where the effect of change in a variable (node) may affect other variables (nodes) which, in turn, can affect the variable initiating the change. An FGCM models unstructured knowledge through causalities through grey concepts and grey relationships between them based on FCM [7][11].

Since FGCMs are hybrid methods mixing neural networks and grey systems, each cause is measured by its grey weight as

$$\otimes w_{ij} = \left[\underline{w}_{ij}, \overline{w}_{ij}\right] | \left\{\underline{w}_{ij}, \overline{w}_{ij}\right\} \in \{[-1,+1],[0,+1]\} \tag{2}$$

where i is the pre-synaptic (cause) node and j is the post-synaptic (effect) one.

FGCM dynamics begin with an initial grey vector state ⊗C(0) which models a proposed initial imprecise stimuli. The initial grey vector state with n nodes is denoted as

$$\otimes \mathrm{C}(0) = \big(C_1(0), C_2(0), \ldots, C_n(0)\big) = \big([\underline{c}_1(0), \overline{c}_1(0)], [\underline{c}_2(0), \overline{c}_2(0)], \ldots, [\underline{c}_n(0), \overline{c}_n(0)]\big) \quad (3)$$

The updated nodes' states are computed in an iterative inference process with an activation function (usually sigmoid or hyperbolic tangent function) [7][9][10], which maps monotonically the grey node value into a normalized range [0, + 1] or [− 1, + 1], depending on the selected function. Note that grey arithmetic is detailed as [7]. Each single node would be updated as follows:

$$\otimes c_j(t+1) = f\left(\sum_{i=1}^{n} \otimes w_{ij} \cdot \otimes c_i(t)\right) = \left[\underline{c}_{\mathrm{j}}(\mathrm{t}+1), \overline{c}_{\mathrm{j}}(\mathrm{t}+1)\right] \quad (4)$$

The unipolar sigmoid function is the most used one in FGCM when the nodes' value maps in the range of [0, 1]. If f(·) is a sigmoid, then the i component of the grey vector state at t+1 iteration ($\otimes\mathbf{C}(t+1)$) after the inference would be

$$\otimes c_i(t+1) \in \left[\left(1 + e^{-\lambda \cdot \underline{c}_i^*(t)}\right)^{-1}, \left(1 + e^{-\lambda \cdot \overline{c}_i^*(t)}\right)^{-1}\right] \quad (5)$$

On the other hand, when the concepts' states map in the range [-1, +1], the function used would be the hyperbolic tangent.

The nodes' states evolve along the FGCM dynamics. The FGCM inference process stops when the stability is reached. The steady grey vector state represents the final impact of the initial grey vector state on the final state of each FGCM grey node.

After its inference process, the FGCM reaches one steady state following a number of iterations. It settles down to a fixed pattern of node states, the so-called grey hidden pattern or grey fixed-point attractor.

Moreover, the state could keep cycling between several fixed states, known as a limit grey cycle. Using a continuous activation function, a third state would be a grey chaotic attractor. It happens when instead of stabilizing, the FGCM continues to produce different grey vector states for each iteration.

FGCM includes greyness as an uncertainty measurement. Higher values of greyness mean that the results have a higher uncertainty degree. It is computed as follows:

$$\phi(\otimes c_i) = \frac{|\ell(\otimes c_i)|}{\ell(\otimes \psi)} \quad (6)$$

where $|\ell(\otimes c_i)| = |\overline{c}_i - \underline{c_i}|$ is the absolute value of the length of grey node $\otimes c_i$ state value and $\ell(\otimes\psi)$ is the absolute value of the range in the information space, denoted by $\otimes\psi$. It is computed as follows:

$$\ell(\otimes\psi) = \begin{cases} 1 \; if \; \{\otimes c_i, \otimes w_i\} \subseteq [0,1] \\ 2 \; if \; \{\otimes c_i, \otimes w_i\} \subseteq [-1,+1] \end{cases} \tag{7}$$

3.2 FGCM Advantages over FCM

FGCMs have several advantages over conventional FCM [7][9][10]. FGCMs are able to compute the desired steady states by handling uncertainty and hesitancy present within raw data (due to noise) for causal relations among concepts as well as within the initial concepts states.

The main difference between FGCMs and FCMs is within weights design. FCM applies weights with discrete numerical values associated to edges. FGCMs uses weights with grey intensity including grey uncertainty and fuzziness to better describe the impact between the nodes.

Note that, even if the FCM dynamics would get the same steady vector state than FGCM after the whitenization process, the FGCM proposal handles the inner fuzziness and grey uncertainty of human emotions.

FGCMs are a generalization and can be applied to approximate human decision making more closely. It handles the uncertainty inherent in the complex systems by assessing greyness in the nodes and edges. The reasoning process's output would incorporate a degree of greyness expressed in grey values.

In addition, FGCMs are able to model more kinds of relationships than FCM. For instance, it is possible to run models with relations where the intensity is not known at all wi ϵ [-1,+1] or just partially known.

4 Illustrative Example

With the intention of illustrating the proposal, this paper proposes an artificial experiment. The goal is the simulation of an autonomous systems emotions generated by environmental conditions. Note that the goal of the model is not to design a real-world emotional Ambient Intelligence system but to test the FGCM approach for artificial emotions forecasting for people in a queue in a hypothetic Ambient Intelligence.

The FGCM model in Fig. 3 represents an example of a FGCM-based emotional Ambient Intelligence system. Eq. 8 shows the adjacency matrix.

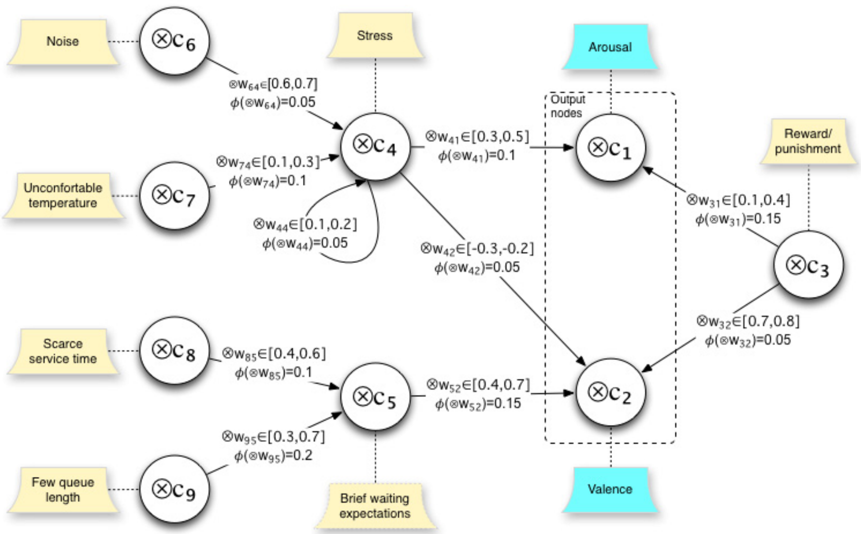

Fig. 2. FGCM-based model

$$\otimes A = \begin{pmatrix}
[.0,.0] & [.0,.0] & [.0,.0] & [.0,.0] & [.0,.0] & [.0,.0] & [.0,.0] & [.0,.0] & [.0,.0] \\
[.0,.0] & [.0,.0] & [.0,.0] & [.0,.0] & [.0,.0] & [.0,.0] & [.0,.0] & [.0,.0] & [.0,.0] \\
[.1,.4] & [.7,.8] & [.0,.0] & [.0,.0] & [.0,.0] & [.0,.0] & [.0,.0] & [.0,.0] & [.0,.0] \\
[.3,.5] & [-.3,-.2] & [.0,.0] & [.1,.2] & [.0,.0] & [.0,.0] & [.0,.0] & [.0,.0] & [.0,.0] \\
[.0,.0] & [.4,.7] & [.0,.0] & [.0,.0] & [.0,.0] & [.0,.0] & [.0,.0] & [.0,.0] & [.0,.0] \\
[.0,.0] & [.0,.0] & [.0,.0] & [.6,.7] & [.0,.0] & [.0,.0] & [.0,.0] & [.0,.0] & [.0,.0] \\
[.0,.0] & [.0,.0] & [.0,.0] & [.1,.3] & [.0,.0] & [.0,.0] & [.0,.0] & [.0,.0] & [.0,.0] \\
[.0,.0] & [.0,.0] & [.0,.0] & [.0,.0] & [.4,.6] & [.0,.0] & [.0,.0] & [.0,.0] & [.0,.0] \\
[.0,.0] & [.0,.0] & [.0,.0] & [.0,.0] & [.3,.7] & [.0,.0] & [.0,.0] & [.0,.0] & [.0,.0]
\end{pmatrix}$$

Table 1. FGCM nodes and description

Node (xi)	Label	Description
x_1	Arousal	State of being awake or reactive to stimuli
x_2	Valence	The intrinsic attractiveness (positive valence) or averseness (negative valence) of an emotion
x_3	Reward/Punishment	Reward is related to a positive queue where individuals are going to get something positive (e.g.: a lottery award). Punishment is when they are in the queue for something negative (e.g.: paying taxes)
x_4	Stress	A person's response to a stressor, such as noise or uncomfortable temperature
x_5	Waiting expectations	Waiting time considered the most likely to happen according to people before each one and time in service for each one
x_6	Noise	Environmental noise
x_7	Uncomfortable temperature	Temperature higher or lower than comfortable
x_8	Scarce service time	Waiting time for each person
x_9	Few queue length	People in the queue

In the test scenario, we have an initial vector C(0) representing the initial state values of the events at a given time of the process and a final vector C(t) representing the steady state that it can be arrived at. The final vector C(t) is the last vector in the convergence region.

For the synthetic case study, the initial vector state and the steady vector state are the following:

$$A(0) = ([0,0], [0,0], [0.2,0.2], [0,0], [0,0], [0.2,0.3], [-0.2,-0.1],$$
$$[0.1,0.3], [0.3,0.4])$$
$$A(t) = ([\mathbf{0.04}, \mathbf{0.20}], [\mathbf{0.12}, \mathbf{0.42}], [0.2,0.2], [0.7,0.24], [0.13,0.43], [0.2,0.3],$$
$$[-0.2,-0.1], [0.1,0.3], [0.3,0.4\ ])$$

According to the A(t) results, Arousal = [0.04, 0.20] and Valence = [0.12, 0.42], and the simulation emotion is mixing light/medium pleased and light happy.

5 Conclusions

Emotions have a critical impact on human’s motivations, decisions, actions, beliefs and desires. Emotion simulation and its application in autonomous systems and robics is an emerging and promising research area. For those reasons, there is a sign of an emotion simulation module based on FGCMs and Thayer's emotion model was proposed.

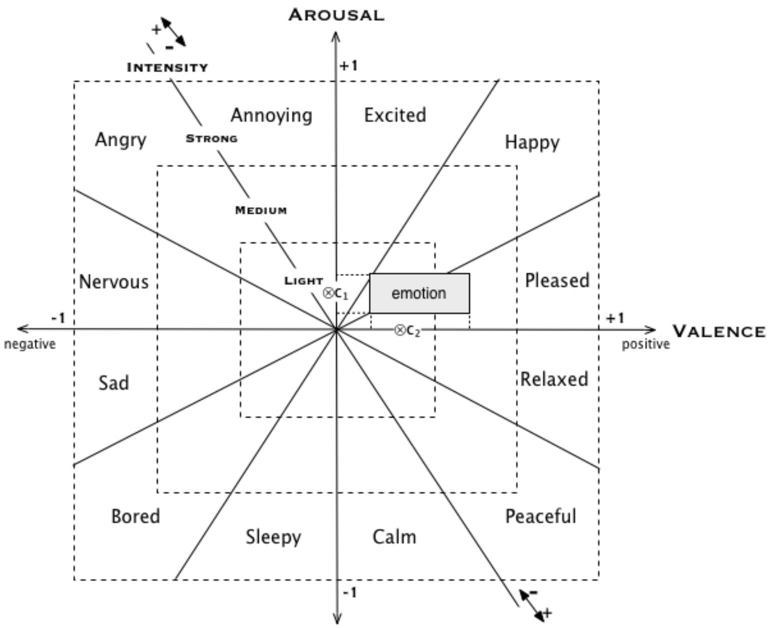

Fig. 3. Experiment results

This paper shows an artificial experiment of a FGCM-based emotion simulation system. FGCM is an FCM extension for representing causal reasoning within complex systems with high uncertainty. FGCM represents knowledge, uncertainty and relates states, variables, events, inputs and outputs in a similar way to that of human beings. This paper shows that it is possible to simulate the emotions generated from sensors raw data with FGCMs.

This is not an empirical research. An FGCM-based framework is based on external data. Constructs and output nodes are also presented. Indeed, the goal is not to model a real world system, but it just proposes an FGCM-based theoretical model, so that robotics practitioners or future research can use it to simulate or generate emotions.

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