Modeling Cooperative and Competitive Emotions Using Parallel SOM for Artificially Intelligent Agents

Atifa Athar†, Khalil Ahmed††, Sagheer Abbas†††, Yousaf Saeed††††

CIIT, Lahore, Pakistan, Konsortium, Pakistan, NCBA&E, Pakistan, UOH, Pakistan

Summary

As an interactive structure in human mind the emotions contribute to the adaptive learning, rational decision making and communication proficiency. According to the psychological scheme of human mind, emotions have temporal dynamics and activate concurrently due to the variance of environmental stimuli. The affective exposition of mind can express and communicate the shared or diverse effects of simultaneous emotions to the environment. The role of emotions in the nature of agency has been identified and partially addressed. However, in multi-agent scenarios (MAS) it is required to facilitate agents with the mechanism of interactive emotional dynamics to resolve conflicts and respond quickly. Inspired from neuropsychology, and by considering the function of emotions in the establishment of agency this paper attempts to analyze and design the synergy of emotional dynamics that addresses the cooperation and competition in emotions due to the change in their determining parameters to achieve autonomy.

Key words:

Learning. Emotion affect space. SOM.

1. Introduction

The researchers have considered emotions as a secondary feature of human mind functionality earlier; however, these are not so peripheral and have a special importance as a unit of constitution in human mind. According to psychological viewpoint, awareness provides the base for segregation between an intelligent and non-intelligent mind. Awareness is an outcome of inference and emotions are well thought-out as inferential shortcuts. Emotions are necessary for having an adequate understanding [1] and emotional consciousness provides the basis for rationality [2]. To identify and comprehend the process of emotions and their causal mechanism in human mind the theory of emotional consciousness provides a broad range of different emotions, their varying intensity, their valenced character, and an account of emotional experience from initiation to the end.[3] Theory of emotional Consciousness also provides a description of emotional integration, differentiation, and change.

An Emotion is not an isolated arrangement of mind because each emotion represents a neural transaction with the environment [4]. Each of such transactions causes the generation of a different emotion with the traces of previously activated emotion. Due to these variant transactions, a human mind may experiences multiple emotions concurrently [5]. These emotions compete or cooperate with each other and their combined or diverse results are expressed and passed on to the environment. The emotional experience provides the base for the concept of temporal dynamics of emotions that includes the self-growth and decay factors of each emotion. An emotion can grow due to frequent encounters with the identical stimuli [6]. The decay rate of an emotion also depends upon the persistence of the internal/external stimuli that causes its activation.

To incorporate the growth and decay factors and effect of change due to the internal or external stimuli there is a continuous updating required in the activation level of each emotion. Since the moment an emotion generates, its intensity attenuated with time in order to reflect the emotional dynamics [7]. When the intensity of any activated emotion decreases and reaches below the defined threshold level it become deactivating and does not remain a part of an agent's overall emotional state.

Emotion terms are discrete, but emotional states form a continuum [8]. The basic emotions provide the ground for the existence of other more complex emotions. Paul Ekman identified six basic emotions i.e. fear, anger, surprise, disgust, happiness and sadness. A basic emotion consists of one emotional state while a complex emotion can have multiple and concurrent emotional states [9][10]. Breazeal considered an emotion as a specific set of computational processes that are active in the neural network system. Each emotion has an associated vector [I, V, S] [11]. The researchers have discussed a neurologically inspired dynamical systems approach on the interaction of emotions [12]

According to Wiens emotions have a strong relationship with the feedback from the other affective phenomenon as well [13]. Moods and well-being provides potential for the activation of emotions. To avoid haphazard fluctuations and chaos it is required to provide the historical context to emotions. To make this context available mood plays an important role. Based on biased evaluations which are

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relevant according to the temporal aspects moods provide the context of emotions.

The dynamic mechanism of human mind can have a variety of emotional states simultaneously and can convey their combined or diverse effect [5]. Reilly has stepped forward and presented emotion combination functions to compute the overall emotional intensity resulting from a number of distinct emotions [14]. He proposed three schemes to combine intensities that are Winner take all, additive, and logarithmic combination [15]. However, these schemes have some advantages as well as limitations.

Emotion modeling for agents is a key area for researchers now a day but there is a need to pay attention to the complex and multifaceted approach in which emotions manipulate the rationality and decision making of an agent. Emotion modeling has a significant role to improve the robot's intelligence and believability but only primitive emotional cues have been utilized yet [16]. The use of complex cues is still required to organize the social behavior of an agent.

From neuropsychological perspective, a human may decide in a different way even in identical situations because of emotions. Similarly, to adapt and manage social behavior in conflicting situations, an agent may require emotions because they manifest their own adaptive rationality [4].

The functionality of biological model of human mind regarding its learning ability turns out to be the motivation for the emotion modeling using ANN. It provides a high level of specificity to devise a linkage between theoretical suppositions and neural dynamics. The analysis of environmental impacts on human emotional state classification and their interactive dynamics describes that emotions are flexible and self-organized, so it is appropriate to adopt SOM architecture to analyze and integrate the dynamical emotional state transformations.

2. Proposed Model

To analyze and integrate the dynamical emotional state transformations related to complexity and to attain competence for agents, we are presenting the designing synergy of cooperative/competitive emotions here.

2.1 Emotion Affect Space

To measure the dynamics of change in an emotional state, the concept of an emotional affect space [17] will provide the context of primary emotions identified by Paul Ekman. Each emotion in the affect space influences others in cooperative/competitive mode. [18]

Before addressing the cooperation/competition between emotions, it is important to keep account of all active emotions in the affect space. While the intensity level of an emotion exceeds the defined threshold level, it become activating in the space. In comparison to the winner-take-all algorithm that allows choosing one emotion at a time, there is a possibility to have simultaneous activation for multiple emotions [5].

2.2 Cooperation and Competition

Different emotional states can affect each other as each has elements of relation with others. [19] These relationships could be observable for both the positive and negative emotions such as genuine joy, appear significantly less on the face of shocked patients as compared with the healthy women [20]. The emotional states having same valence, are cooperative in comparison to the emotional states having opposite valence that are competitive as in Fig. 1.

To measure the effect of cooperation /competition of different emotional states, it is required to assess the change in their determining parameters. All emotion parameters are computable [21], which makes it possible to calculate this change.

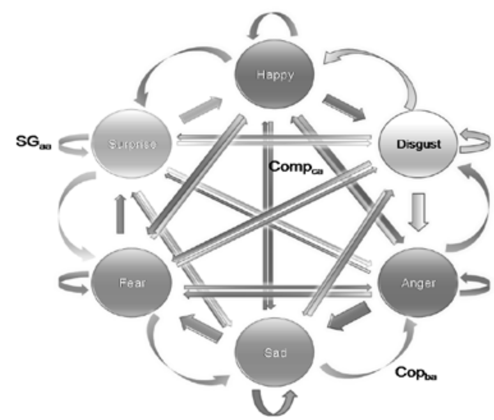

Fig. 1 Cooperation and competition among emotions

The growth rate of each individual emotion is affected by all cooperative/competitive emotional states in the affect space. The effect of all cooperative emotions will be positive and will cause an increase in the growth rate of each particular emotion while all competitive emotions will effect negatively and hence slow down its growth rate.

Let

$$E = \{HAPPY, DISGUST, ANGER, SAD, FEAR, SURPRIZE\}$$

For $a = 1 \ldots\ldots\ldots n$

To calculate the overall growth of an emotion E_a per unit time as in [22]

$$Growth\ Rate\ of\ E_a = (SG)_{aa} - (Decay)_{aa} + \sum_{b=1}^{n} (Cop)_{ba} - \sum_{c=1}^{n} (Comp)_{ca}$$

Where $(SG)_{aa}$ show the self-growth in E_a. The $(Decay)_{aa}$ factor determines that how fast the intensity of that particular emotion decreases over time and affect the growth rate of E_a.

Let E_b is a cooperative emotion to E_a then the link $(Cop)_{ba}$ would provide the magnitude of cooperative interaction. Moreover, let E_c is a competitive emotion to E_a then the link $(Comp)_{ca}$ would provide the magnitude of competitive influence. There could be more than one cooperative/competitive emotions for E_a so $\sum_{b=1}^{n}(Cop)_{ba}$ and $\sum_{c=1}^{n}(Comp)_{ca}$ provides the collective magnitude of all cooperative /competitive emotions.

The link between any of two primary emotions shows either the cooperation or competition. For each link which shows competition between two primary emotions there is zero cooperation and on the other hand, for each link which shows cooperation there is zero competition.

2.3 Impact of Mood and Well Being

The homeostasis regulations form the well-being of the system and influence the emotion activation by its value [23]. On the other hand, emotions are considered as an evolved director of homeostasis regulations and thus of well-being. The adaptive system reinforces the value of well-being that concatenates with the new inputs in each iterative step. This step is relied on the ANN approach adopted [24]. In each step, the current active emotion provides the context of future well-being in the next step. Based on homeostasis regulations the well-being recreates the balance in emotions.

To realize life like dynamics the identification of emotion and mood coherence is important. Emotions and moods are distinguishable from each other because of their level of dispersion and duration of activation is different.

The measurement of level of coherence between emotion, mood, and well-being in the developmental stage is as follows:

$$I(E, M, W_b,) = (A(E, W_b), V(E, M, W_b), S(E, M))$$

Moods have same contents as emotions but with low intensity and able to last for hours. Hence, only the absolute value of emotion's intensity is under consideration in addition to the well-being for overall arousal in the system by using function $A(E, W)$.

The overall valence of the system is calculated as an average of emotional valance, mood's valence, and current well-being that ranges from [1, 0] $V(E, M, W_b)$.

The reinforcement cycle starts with emotions, which are an ongoing commentary on well-being and mood, and completes with their reinforcement for the new emotion activation

2.4 Proposed Algorithm

This research presents a parallel self-organizing algorithm for simultaneous emotion activations, in reference to [25] [26]. Our proposed algorithm introduces following features to the fundamental SOM algorithm.

- Extension of single stimuli to multiple stimuli from the environment
- Parallel weight modification with an observant control of the neighborhood function
- Convergence of weight vectors by eliminating the overlaps of neighborhood functions.
- Reinforcement of internal variable that has the significant impact on emotion dynamics.

2.5 Computational Procedure for Parallel Learning SOM

With the application of parallel learning in SOM neural network, l-dimensional input space (environmental stimuli) is mapped onto m-dimensional lattice space A (emotion space).

Let $\{\boldsymbol{x_1}, \boldsymbol{x_2}, \_\_\_, \boldsymbol{x_l}\}$ be the set of l input vectors selected at step t, and let $\{\boldsymbol{w_1}, \boldsymbol{w_2}, \_\_\_, \boldsymbol{w_m}\}$ be the set of m reference vectors readied initially. The mapping is formed so that the weight w of active unit is closest to the current input vector x in the nearest neighbor rule. The selection of set of winner emotions' vectors $\{\boldsymbol{c_1}, \boldsymbol{c_2}\_\_\_\_\_ \boldsymbol{c_l}\}$ corresponding to input vectors is as follows:

$$\boldsymbol{c_i} = \underbrace{argmin} \{\| \boldsymbol{x_i} - \boldsymbol{w_j} \|\} \quad (1)$$

Using winner emotion $\boldsymbol{c_i}$, reference vector $\boldsymbol{w_i}$ at each step is as:

$$\Delta \boldsymbol{w}_i = \sum_{j=1}^{l} v_{ij} \quad (2)$$

Where updating value v_{ij} of reference vector $\boldsymbol{w}_i$ is as follows:

$$v_{ij} = \{\, \alpha(t)(x_j - w_i) \quad (i \in (N_{c_j}(t)) \quad (3)$$

Where $\alpha(t)$ is the learning rate that lies $(0 < \alpha(t) < 1)$ and $(N_{c_j}(t))$ is the set of winner emotion c_j and its topological neighborhood reference vectors, and is a decreasing function of time.

Begin [*Beginning of **Main** procedure]*

1. Iterate through all neurons.
2. Randomly initialize the weights given to the features of environmental stimuli.
   [*Initialize the reference vectors.* $\{w_1, w_2, \_\_\_, w_m\}$]
3. Choose the features of environmental stimuli to input to the First layer of the proposed SOM under the probability distribution of input vector $P(x)$.
   [*Read the Input vectors.*$\{x_1, x_2, \_\_\_, x_l\}$]
4. Initialize time step. $t = 0$.
5. **Call** First Layer Procedure.
6. Refine the state of each active emotion/s by the value of mood and wellbeing i.e. S = M +W_b.
   [***Then*** *{**If*** $(S \geq 0)$ $c_i = c_i + S$
   Else if $(S < 0)$ $c_i = c_i - S$ }]
7. Randomly initialize the weights given to the features of refined emotions. [*Initialize the reference vectors.*$\{w_1, w_2, \_\_\_, w_m\}$]
8. Input the features of processed winner emotions to the Second layer of the proposed SOM under the probability distribution of input vector $P(x)$. [*Input vectors.*$\{x_1, x_2, \_\_\_, x_l\}$]
9. Initialize time step. $t = 0$.
10. **Call** Second Layer Procedure.
11. Return all-active emotions with the final states after competition /cooperation.

End [*End of **Main** procedure.*]

Begin [*Beginning of **First layer** Computation procedure*]

1. Measure the distance between the multiple inputs and weights for$(l * m)$ SOM. [*Classify Neighbor set* N_i *based on radii for each winner emotion's reference vector* w_i, *and parallel degree l.*]
2. Determine the emotion/s that are activated simultaneously in the first layer SOM.
   [*The set of winner emotions' vectors* $= \{c_1,\ c_2\_\_\_\_\_\, c_l\}$ *corresponding to input* x_i $, (i = 1, 2, \ldots \ldots, l)$ *based on (1).vectors is determined*]
3. Update w_i based on (2) and (3) using c_i as determined.
4. Increment in time step as $t = t + 1$
5. Test for termination condition. If $(t == T_{max})$
   a. Then **Return** to main procedure.
   b. Else **Go to Step 1** and repeat the steps.

End [*End of **First Layer** Computation procedure.*]

Begin [*Beginning of **Second layer** Computation procedure*]

1. Measure the distance between the multiple inputs and weights for$(l * m)$ SOM.
   [*Classify Neighbor set* N_i *based on radii for each winner emotion's reference vector* w_i, *and parallel degree l.*]
2. Determine the emotion/s which are activated simultaneously in the in the second layer SOM.
   [*The set of winner emotions' vectors* $= \{c_1,\ c_2\_\_\_\_\_\, c_l\}$ *corresponding to input* x_i $, (i = 1, 2, \ldots \ldots, l)$ *based on (1).vectors is determined*]
3. Update w_i to measure the cooperation and competition between all active emotions based on (2) and (3) using c_i as determined.
4. Increment in time step $t = t + 1$
5. Test for termination condition. If ($(t == T_{max})$
   a) Then **Return** to main procedure.
   b) Else **Go to Step 1** and repeat the steps.

End [*End of **Second Layer** Computation procedure.*]

2.6 Structure of the Proposed Hierarchical SOM

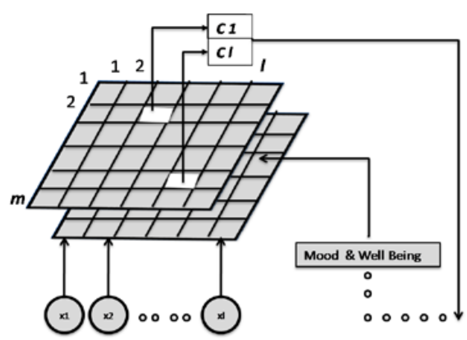

Fig. 2 Proposed Hierarchical Model

This research presents a hierarchical SOM structure in Fig. 2 to express the cooperation and competition between emotions, which consists of bottom-up hierarchy of two layers. The two layers in the proposed model use parallel and reinforcement learning rules.

The second layer covers the advanced level of abstraction than the first layer. The numbers of layers are static in the hierarchy and each of these designed for parallel learning using simultaneous inputs. The process of each layer in the hierarchy is as under:

i. Configuration of First Layer

The multiple inputs given to the first layer, consists of vectors based on the properties of multiple environment stimuli, to activate primary emotions in it. This layer consists of 15 *15 neurons in a two- dimensional torus structure represented in Fig. 3a.

Each neuron has the six proportions for all six primary emotions. All primary emotions in this layer are represented by symbols either different in shape or color. Each symbol represents the activation of each neuron in the layer.

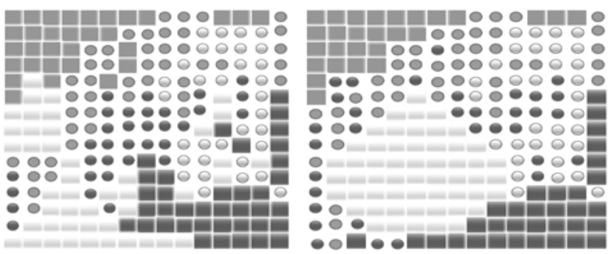

Fig. 3 a: First Layer in Random state b: First Layer after Input

The aspects of change are apparent in the state of each neuron in this layer after presenting the inputs with random weights to it as shown in fig.3b. The number of neurons for the active winner emotions becomes more than the neurons of passive emotions. There is an increase in the area taken by neurons of winner emotions while area covered by passive emotions becomes smaller.

ii. Reinforcement of Internal Variables

The set of winner emotions produced by first layer in the proposed structure are combining with the mood and well-being, which are also known as internal variables. These internal variables may have positive or negative values depending upon the previous experience of emotions by the system. Initially the contribution of these variables towards emotion activation is zero because there is no prior experience available. For further processing, the calculation of the value of these variables depends upon the emotions already produced and became a part of experience.

iii. Configuration of Second Layer

The first layer in hierarchy only explains how to calculate the effect of environmental stimuli on emotion generation but it does not evaluate the kind of influence that each active emotion have on others. To measure emotion dynamics it is required to express this influence both in cooperative and competitive manner between winner emotions. By introducing second layer, SOM that is above the first in the hierarchy the quantification of emotion dynamics is possible. The combination of the outputs of first layer and the value of mood and well-being provides the inputs to the second layer. The ordering and modification in the reference vector represents the convergence in the second layer SOM. This convergence caters the process of cooperation and competition between multiple active emotions to form complex emotions.

3. Conclusion and future work

By considering the additive property of emotions and their parallel execution in human mind, the proposed design provides the context of coherent spectrum of emotions. It also computes the bipolar conceptualization of emotional affect by providing the dual mode for emotion interactions. It also gives an account of co-active emotional states of an agent to be in while responding to the multifaceted dynamic environment. This account of emotion processing also provides an inner source of autonomy by permitting the valenced information processing of events.

With the observance of emotional states in reference to the environment, this approach establishes the reason for an agent to make adaptive inferences that afford it a role in rational decision-making.

With the development of a computational architecture in reference to the proposed design, and its integration with agent could regulate its behavior in terms of stability to achieve autonomy. In MAS, the computational scalability and flexibility of an agent’s emotional state would provide the base for judgment, evolvement, and its social conduct assessment.

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Atifa Athar is currently working with CIIT, Lahore. Pakistan as an Assistant Professor in the Department of Computer Science. Her Area of Expertise is emotion modeling for conscious machines.