Emotion recognition and emotional incentive model

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Abstract. Few years has passed since Rosalind W. Picard founded in 1997, the MIT Research Group Affective Computing. Since then a large number of developments aimed at improve the relationship between humans and computers has been done. Following Picard ideas, the outline of a emotional rules based model are presented in this paper, this model arises as the result of analyze theoretical emotion models, EEG pattern recognition and its possible application in computational models. The base idea are simple, develop a rule based model based on emotions, able to interact with human emotional states and take decisions based on them, in order to reduce the burden generated in the interaction between human-machine interfaces. As part of this research an emotion recognition based EEG analysis are presented, as well as the necessary rules to generate associated interpretations for the bio-signal analysis. A multidisciplinary effort of several research fields were required to create this model, such as neurology, digital signal processing, artificial intelligence, physiology, psychology and behavior analysis; Just to provide the references and the emotional interpretation to create a incentive model, capable to interpreted and execute a process modeled under the user perception.

Keywords: Affective computing, EEG analysis, Emotional ruled systems

1 Introduction

On the last decade brain computer interfaces (BCI) research has been increase dramatically, mainly due the ever-increasing development in the computational and sensors technologies [1][2]; Leading to a accelerated development in affective computing, in order to satisfy one of its principal objectives, "*create devices that allows a natural interaction between humans and machines*", to reduce the burden in the human-machine relationship. However each development in this area, involves as previously mentioned a multidisciplinary effort and the brain electrical signatures analysis, has been emerged mostly to analyze physiological disorders, such as epilepsy and sleep illness [3], however the implementation of this kind of analysis are wide diversified (i.e the analysis of cognitive processes and motor imaginary processes in humans[4][5]).

Another aspect that allows this kind of research, are the advances in technologies to analyze the brain activity; Magnetic resonance imaging (MRI), functional MRI magnetic resonance imaging (fMRI), electroencephalography (EEG) are just a some of the

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techniques developed up to date, however the portability and cost still are an important considerations to provide feasibility to a research and the viability of being applicable; The low cost of implementations and its relatively easy implementations makes the EEG, the best candidate to be implemented in the BCI's. However a drawback of this technique are the noisy information provide it by it, that requires robust techniques to process and analyze the signals. The rest of the paper are arranged as follows, in section 2, the problems related of analyze emotions and behavior over biological signals are discussed, section 3, specifies the proposed rules to create a feedback systems model, section 4, describes the proposed methodology and topology, section 5, presents the results and finally in section 6, the conclusion are presented.

2 Characterization

The EEG signals, used for this analysis were extracted from the DEAP data base [6], which is up to our best knowledge, the most complete database related to physiological signals recorded from emotional stimulus. DEAP contains the brain activity of thirty-two persons from England and Switzerland, using the 10/20 electrode placement model, [1], recording 40 different emotional states related to arousal-valence space model (AVS), provided by exposition to a audio/visual stimuli associated to single emotion over one minute for each trial, also the front video of the face for each person was recorded [2]. Each one of the stimulus, was selected by experts selection and a online ranking survey.

2.1 Wavelet analysis

Wavelets are a class of functions that are used to locate a particular function in both space and scaling. A family of wavelets can be constructed from a function $\psi(x)$, sometimes known as a *Mother wavelet* , which is confined in a finite interval. *Wavelets Daughter* $\psi^{(a,b)}(x)$ are then formed by translation (b) and contraction (a), and wavelets are especially useful for the compression of image data and capable of handling the complex behavior of the EEG signals, by their properties that are superior to some conventional Fourier transformation aspects, it has also shown good bio-signals behavior characterization, since WT allows to obtain spatial temporal information being this fundamental on the biological signals processing. For this research, the feature extraction was performed by WT[3]. One of the most convenient advantage of WT, is that the WT kernel coefficients could be used as features to perform classification.

An individual wavelet can be defined by

$$\psi^{(a,b)}(x) = |a|^{(-1/2)}\psi((x-b)/a). \tag{1}$$

[1] Also contains the respiration rate, electrocardiogram, temperature, galvanic and myoelectric information as well as a relation of relevant information for each user

[2] Each user completes a survey to verify the relationship between each real test results and expected

[3] Many authors reported good performance of WT in EEG signals analysis [7][8][9][10][11][12]

In other way

$$W_{\psi}(f)(a,b) = 1/(\sqrt{(}a)) \int_{\infty}^{\infty} f(t)\psi((t-b)/a)dt, \tag{2}$$

Unfortunately the selection of the best wavelet to implement, still are an exhaustive search process, to select the appropriate for this research a comprehensive search and trials has been performed, and the Daubechies 6, was selected as the best candidate for this analysis due to the orthogonality and asymmetry properties of this family of wavelets.

Rhythms In neurology the EEG bands of frequencies are known as rhythms [4], shown in table 1, the analysis of behavior of this rhythms are fundamental for the emotional process analysis, due that previous analysis denotes that each rhythm are associated to a natural behavior or specific task [5][14][13].

Table 1. Brain Rhythms

Brain Rhythms	
Delta	0.1 to 4 Hz
Theta	4 to 8 Hz
Alpha	8 to 12 Hz
Mu	8 to 13 Hz
Beta	12 to 30 Hz
Gamma	25 to 100 Hz

A four level WT decomposition were performed to obtain individual rhythms analysis.

Filter and domain reduction The wavelet analysis could be generalized as a band-pass filter, perform a wavelet decomposition of the signal on the desired coefficient of contraction and this feature can also be used as domain reduction, and the complementary filters could be suited for the rhythms previously defined.

2.2 Brain bounded areas

In order to reduce the computational burden, a boundary model based on the Broadmann areas was created, considering that each of these areas are related to a specific task, and discrete regions are provided by the 10/20 model, a delimited area could be generated, [6] following the considerations shown as follow [13][14][15]:

[4] This term are more associated to music than engineering

[5] I.e., the mu rhythms are recently related to the motor process and the theta are related to hippocampal process.

[6] With the intervention of an expert in neurology Dr. Carlos Francisco Romero Gaitán, emeritus member of the Mexican Society of Neurology

- Vision[7] Primary areas : 18,19 ; Secondary areas: 20, 21 and 37.
- Audition[8] Primary areas : 41 ; Secondary areas: 22, 42.
- Body sensations: Primary areas : 1,2,3 ; Secondary areas: 5,7 ; Tertiary areas: 22,37,39 y 40.
- Motor system: Primary areas : 4,6,8,44 ; Secondary areas: 9,10,11,45,46,47.

Also most of the literature refers to the limbic system as one the main brain regions related to the emotional process, taking all of this in considerations the occipital, temporal and parietal regions electrodes are associated to create a bounded model as shown in figure 1.

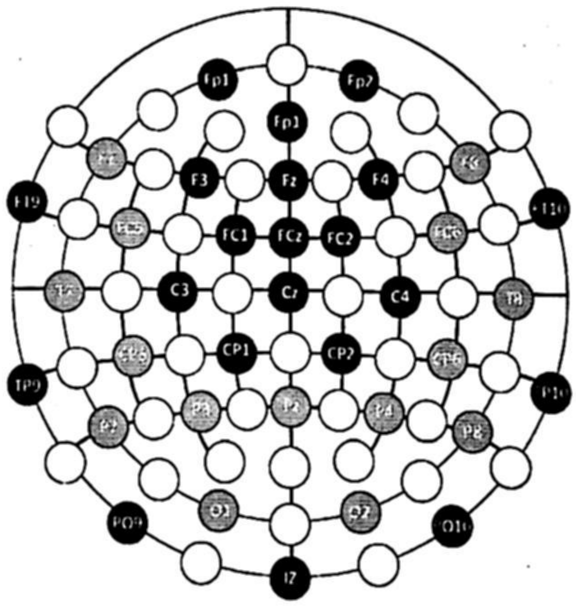

Fig. 1. Emotion regions bounded as an arc model for the 10/20 model.

3 Incentive rule based system

An emotional rule based model, denominated Emotional Incentive Model (EIM) is a proposal of this paper, the implementation of this model to interact with systems that recognize and classify an emotional process in a humans are the main goal of it. Also as a model capable of interfacing BCI and systems, providing feedback through a set of rules interacting with the extracted emotional status at real time [9].

Six rules have been generated to this model shown in table 2, this rules are based on the six basic emotions associated to the human survival process[18][19] [16] [17]

[7] As a Audio -visual characterization the visual area activated have to be considered.

[8] As a Audio -visual characterization the audition areas activated have to be considered.

[9] I.e A prosthesis capable to explore new configurations to avoid or reduce the stress and frustration from it user by increasing or decreasing torque or tracing new trajectories, based on the information provided by the emotion recognition system, will take into account the comfort level of the person beyond the interaction models previously created with a general purpose

[20][21]. The fundamentals from this EIM are taken from traditional notions of emotions and most accepted theories, where emotions are discretized in several ways by different authors as the six basic emotions proposed by Ekman and Friesen [22] and tree structure of emotions proposed by Parrot [23], however hard tags as such are not adequate to define the strength of an emotion considering that emotions are a continuous phenomena rather than discrete, so a dimensional emotion scales models most be considered, such as Plutchiks emotion wheel[18] and the valence-arousal scale by Russell [24] .

Table 2. Emotion based rules

Emotions	
Joy	As incentive to continue a process.
Fear	As incentive to prioritize a process.
Surprise	As incentive for good results performing a new process.
Sadness	As incentive to explore new ways to perform a process.
Disgust	As incentive to stop actual process and explore new process.
Anger	Force to stop a process.

As previous mentioned one of the main goals of affective computing systems, are focused on reducing the burden that is generated in the interaction between humans and machines; And this model aims to increase the efficiency of a system, based on the mental states considerations directly from the user [10] perception, see figure 2. [25][26][27].

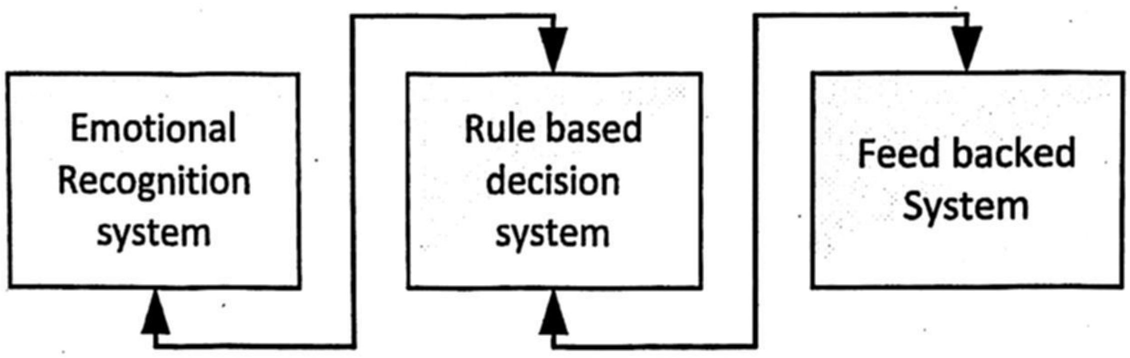

Fig. 2. Emotion Incentive Model applied to feed backed models.

In figure 2, the basic steps of the proposed model are illustrated:

EIM Basic procedures

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Step 0: Standby, waiting for Actuator System (AS) start up.
Step 1: AS process start.
step 2: Rule based decision system start.
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[10] The perception of the performance by the user, independently of the optimal model that could be determined

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Step 3: Emotional status monitor start.
Step 4: Consistent emotion detected.
Step 4: Incentive updated.
Step 5: Feedback AS.
Step 6: Process updated.
Step 7: Go to Step 0.
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Also the implementation of all the elements to sensing and acting [11], are as substantiated as affective wearables.

4 Methodology

The implementation of this model are based on the actual performance on the emotional detection systems, which are between 70 and 85% based of our own results and several consulted literature, as shown in table 3.

Pre-processing stage A band pass filter between 0.5 and 47 Hz was applied to the raw signals and a Laplacean filter were applied to reduce the artifacts contained on the signals as on[7].

Feature extraction Daubechies 6, Discrete Wavelet transform(DWT) are applied to obtain the level 4 decomposition coefficients, that would be implemented on a neuronal network pattern recognition task.

Inputs Only 15 of the 21 electrodes where selected to perform the analysis as described on section 2, (OP3,OP4,PT8,PT7,PF7,TF8,T7,T8,FC5,FC6,Fp5,Fp6) and the relation ship of each emotions separation where made by a arousal and valence model as on figure 3, whit non negative values and uniformly distributed emotions[12] as high or low statements:

- HA/HV:High Arousal and High Valence.
- HA/LV:High Arousal and Low Valence.
- LA/HV:Low Arousal and High Valence.
- LA/LV:Low Arousal and Low Valence.

Each experiment consists of the sum of 15 electrodes model, three uncorrelated emotion from 32 users in order to avoid the trivial case, this means that independent samples are taken for training and not just the average of all users to explore the generalization of the results. Then the process are evaluated with other set of emotions, tagged to a different set of classes as in figure 3, and two architectures were tested for each of them.[13].

[11] Any sensor attached to a person could affect its normal behavior [2]

[12] Emotions selected from the Ekman model.

[13] Scaled conjugated gradient and back propagation network whit two layers and 10-fold cross validations.

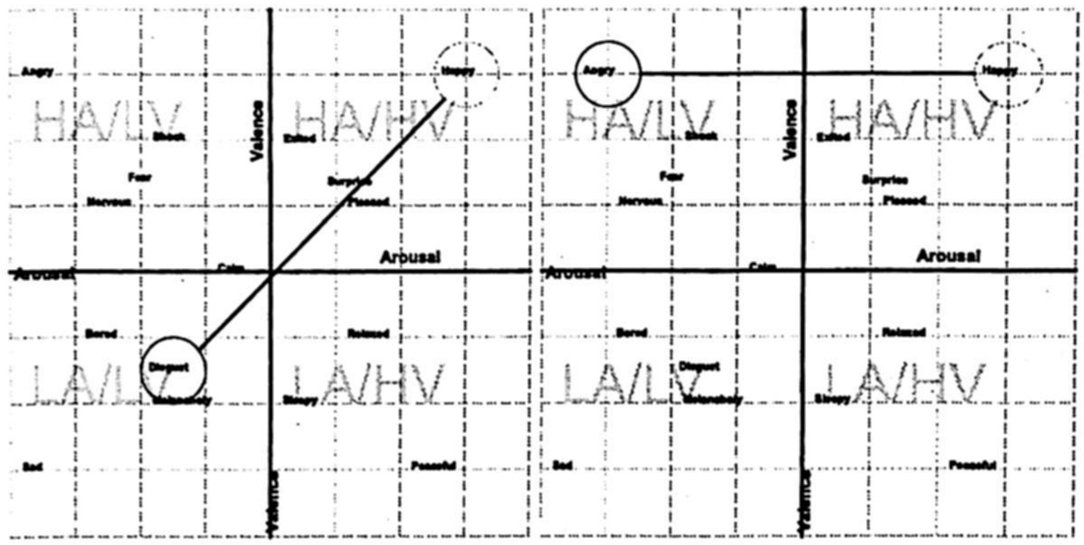

Fig. 3. Emotion selection by a AVS model and Ekman emotion distribution

10-fold cross-validation was performed to evaluate the mean performance of the analysis and identify the average behavior of classifiers test, shown in the figure 4 and in the figure 5, the average of each cross validations are presented. Other configurations were also monitored with similar results, as shown in Figure 4. A 70-30% configuration were implemented as training configurations [14]

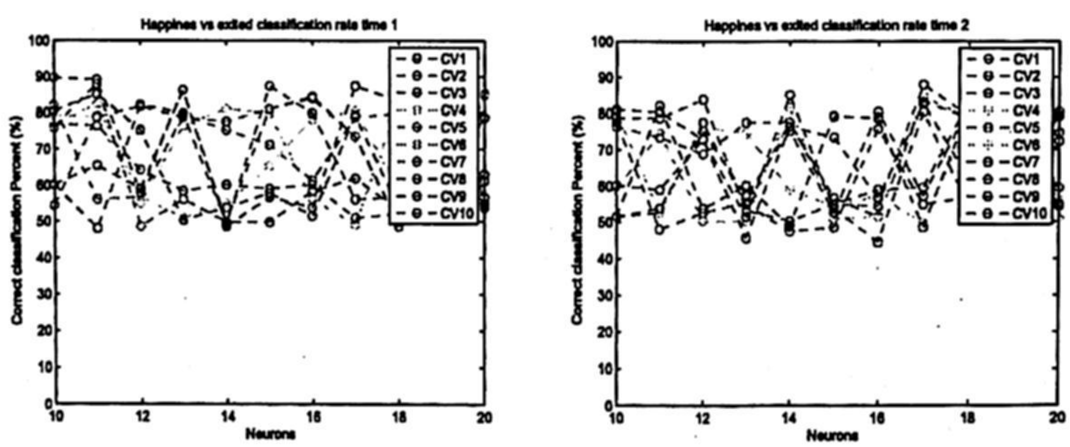

Fig. 4. 10 fold cross validations performance

The results of the recognition task provided by the EIM, are then carry out to the process described in section 3, and improve the user experience while they are interacting with an external system.

[14] Also the exploration of different configurations as 60-30 and 50-50 were made if, however 70/30 shows the better performance.

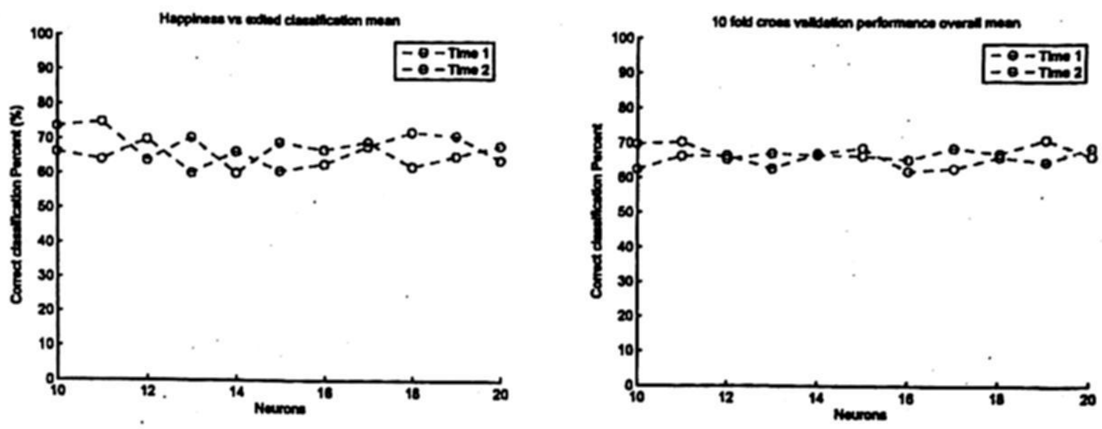

Fig. 5. Mean 10 fold cross validations performance for two temporal analysis (2 of 6).

5 Results

Our group [15] are currently developing the affective wearables, to implement this model [16], however the task of emotion recognition are getting some good results as shown in the table 3, where the behavior of the application model from the defined area is presented.

Our initial data generate an overall behavior of 80% recognition rate, on four emotions (anger, sadness, happiness, disgust). This rate could be increased by using more robust pre-processing technique like DTC-WT (Dual tree Complex Wavelet transform) or MNF (maximum noise fraction) techniques, however as a first approach the proposed model here provides interesting results, because even that each of the trails includes 1440 EEG signals mixed from 32 persons, the average of classification are very competitive, see table 3.

A different trial, are shown in the figure 6, a total of 32 persons where involved on a single analysis with random selected characteristics, from the same four emotions; Then were evaluated all the by a 85% training/test and 15% for validations. The two combinations of temporal analysis, showing similar performance than most of the reported recognition task table 3 .

Table 3. Reported works and models

Autor	Reported Classification rate (\%)
Sun [25]	70-76
Lin [26]	69
Murugappan [7]	81*
Narajan [8]	91*
Yaacob [9]	93*
Daimi [5]	67-83

*Trivial cases (single emotion recognition)

[15] Laborarotio de Computación Afectiva (LabCAfe)

[16] Myoelectric devices and signal acquisition systems.

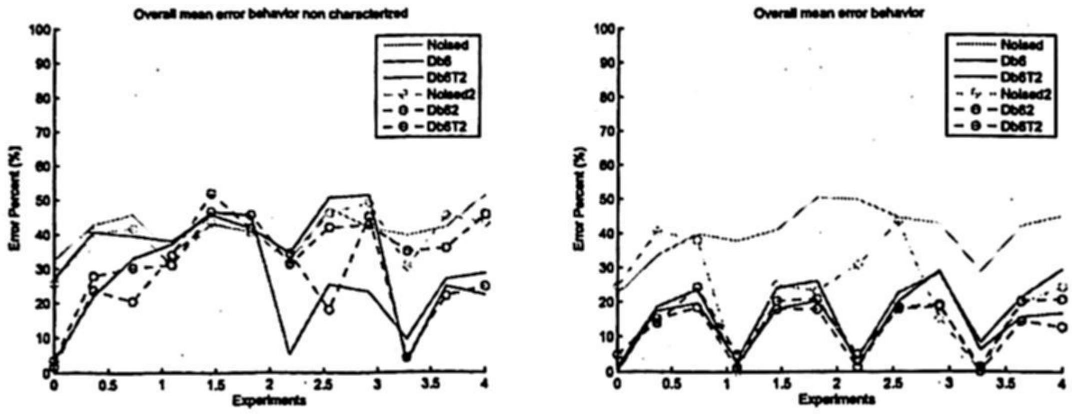

Fig. 6. Mean of 10 fold cross validations performance for two architectures

6 Conclusions

The implementation of systems that could interact with humans in a more natural way, are today a more feasible idea with technological advances, like powerful mobile devices and the reduction in the size of these, also the advances in smart computing enables to solve a complex task, in a more reliable and flexible way, this means that the need to explore new ways to apply the biological signals analysis are growing.

The emotion rule incentive introduced are a model that pretends interact with any device as translator between computer and human. Note that the main contribution lies in the EIM model, and the results that shows on its implementation versus the results provided several other models that reports emotions recognition systems [28] [29] [30] [31]. The proposed incentive rule based systems are one of the first approached models generated to be included as a computational model, not as virtual agent. Also one of the great challenges of these processes is that they lack generalizable data sources, but on the other hand research of emotion recognition are a increasing field, and the combination of disciplines generates less complex models, that can perform up to acceptable rates [17], to sustain the acquisition of rules directly from the human, to provide a natural feedback which allows to a system adapt to its user and provide a better interaction.

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To the ITT postgraduate department and Conacyt.

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