# Analysis of Emotion: An approach from Artificial Intelligence perspective

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*Abstract*: Modeling emotions can contribute to understand human emotions, to add emotional capacities to machines, and to improve appraisals on emotional state. In this work, five models, using fuzzy logic, artificial neural networks, and a hybrid of both, are presented, developed and evaluated, with the aim to infer the emotional state of children from external physiological measurements. Measurements took from a picture and compared to the canon's proportion fed the models as inputs, finding that fuzzy logic is a good tool to work with the blurry nature of emotions.

*Keywords*: Emotions, Artificial Intelligence, Emotional Expression.

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## 1. INTRODUCTION

Now at day, emotion's study has drawn the attention of several and different branches of knowledge, since emotions are not only the most unpredictable aspects of the person but also the common ones, furthermore, because emotions show the way a person perceives the world, and most important, because of the growing interest that exists on understanding how the human brain works; and emotions have been proved to be an important aspect of human intelligence. As more knowledge emerge, it became apparent that cognitive processes such as attention, memory, categorization, language comprehension, and decision-making could not be properly understood without including emotional influences on this processes (Levine, 2007).

Modelling emotions can contribute to understand human emotions and to build machines with emotional capacities making them able to interact with humans and to make decisions in dynamic and potentially dangerous environments; some theorists think that control structures with mechanisms analogous to some kind of emotions may improve environmental adaptation (Cañamero, 2005). Also, developing interfaces capable to evaluate emotional state might represent an advantage in psychological and neuro-psychological studies, in virtual relationships and in some commercial scopes (Fragopanagos and Taylor, 2005)

Facial expressions in children are informative because they are social signals, show the intellectual capacities and the personality of the child and allow regulating emotion. Parents reading and interpreting infant's expressive cues are keys to the social development and emotional regulation of the child. Although, some adults have natural skills to "read" emotional expressions, others need some help to recognize facial signs (Lewis and Sullivan, 2003). It is important to develop models capable of inferring children emotion because they can be used to several applications oriented to improve the welfare of the children in different scenarios.

The idea for the present paper is not to define a theory of emotion, but to create a model which infer infant's emotion, so, following psychologists postulates about the emotion's fuzzy nature, which seems to be the only point where exists a consensus between theorists, it was chosen the AV-Space (Arousal/Valence) designed by Russell (1980, figure 1), taking into account this feature of emotions and the way that emotions are correlated between them.

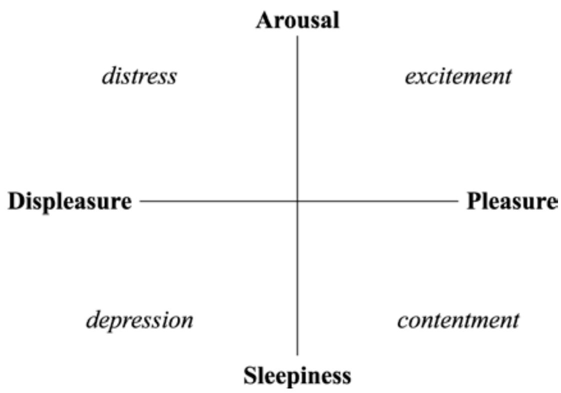


*Figure 1. Russell's AV-Space* (Russell, 1980)

The present paper looks for develop a model to infer the emotional state of a children, using Artificial Intelligence tools. As modelling emotions imply a structure, theories of emotion focusing on how emotions can be categorized are going to be used to create the models, in particular, the main model of the dimensional approach: the AV-Space or circumplex model proposed by Russell (1980). Section 2 presents the theoretical framework and section 3 the models and methodology, section 4 shows the main results, in section 5 a briefly discussion will be performed by explaining why the AV-Space was chosen over other models of emotion, then, it will be explained the importance of the investigation and finally, results are going to be discussed. Finally, a conclusion section is presented.

## 2. THEORETICAL FRAMEWORK

### *2.1 Emotion and emotional development*

"The word 'emotion' is used to designated at least three or four different kind of things" (Ryle, 1949), there is few information about what emotions are. The boundaries to the domain of what experts called emotion are so blurry and it is not clear what is an emotion and what is not. (Russell and Feldman Barret, 1999).

Recently, it was shown that emotions are an important aspect in human intelligence which plays an important role in the human decision-making process (El-Nasr et al, 2000) concluding that emotions are not just feeling, but *processes of establishing, maintaining or disrupting the relation between the organism and the environment* (Campos et al, 1989) i.e. are responses to an internal or external occurrence or event. Rolls (2006) defined emotions as states elicited by rewarding and punishing stimuli. A reward is anything for which a person will work and a punishment is anything for which a person will work to avoid. According to functionalist theory, every emotion must have a function (Redorta et al, 2006).

Responses to an event are related to, at least, one of the following aspects of the person: the subjective, the biological, the functional or the social aspect. Also, four elements allow the conceptualization of emotion: the event, that could be internal, like a previous emotional state or a change in reality's perception; or external, that is an abnormal occurrence perceived by the senses. The appraisement, when the subject measures the relevance and utility of the event and the resources to face it. The answer which is divided into the physiological component which corresponds to involuntary biological answers, the behavioural component, associated to the memory of similar previous events and the human learning process and the cognitive component that is the feeling itself. Finally, the action that appears after the entire process is complete. Fig. 2 shows the concept of emotion.

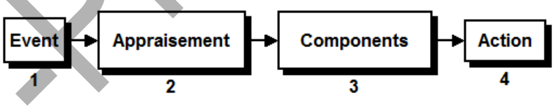


*Fig. 2 Concept of emotion (Redorta et al, 2006)*

As study of emotions has not reached a consensus between investigators, it should be pretty unreal to think about a unique theory of emotions, indeed, theory of emotion is another field in the emotions study that still being controversial.

Current theories of emotion cover a large body of ideas that can be grouped into theories focusing on how emotions arise and are perceived, and theories focusing on the emotion structure (Peter and Herbon, 2006). This emotion's structure has two main approaches: the discrete approach, which is based on the existence of universal or prototypical basic emotions, and the dimensional approach, that is based on the idea that emotions are not independent but correlated in some specific way, however, some authors considerate that these approaches are actually complementary instead of opposite and explain different aspects of the same phenomenon (Russell and Feldman Barret, 1999).

### *2.2 Emotions expression in interaction.*

The crucial feature in human interaction is the ability to infer other's emotional states based on signals (Fragopanagos and Taylor, 2005) from speech, poses and gestures among others. Social Psychology investigations have proved that transmitted messages in significant conversations are dominated by facial expressions and not by spoken words (Ioannou et al, 2005). Now at day, there are diverse sciences that study the human-human interaction (HHI) features to create facial coding systems and to describe facial action patterns,

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for example, Whisell (1989) develop the “dictionary of affect in language” which comprises at least 9000 words that have emotional importance, Ekman’s facial pattern (1993), or Izard and Abe (2004) facial expression set; and the human-computer interaction (HCI) to develop the research area of affective computing which looks for design emotion-based controlled architectures to improve machines’ adaptive capacities (Cañamero, 2005).

It is already recognized that mostof the facial components of the human expression repertoire can be observed shortly after birth (Camras et al, 1993; Izard and Malatesta,1987). Though, facial coding systems applied to kids are barely starting to move out of the laboratory. This is unfortunate because of the practical importance that has the information about facial expression for people working with kids and concerned with their proper emotional development (Lewis and Sullivan, 2003)

Facial expressions are informative because they measure the social development, give cues about intellectual characteristics and personality of the child (Haviland, 1983) and help parents to teach their kids “display rules” and how to regulate emotion (Malatesta and Haviland, 1982); also have clinical significance, because of the emotional development explain the maturation of the brain. So it could measure how much of the brain is affected in neurologically damaged children according to the developmental changes shown in expression (Lewis and Sullivan, 2003).

But the practical importance of studying facial expressions is that correct lecture and interpretation of children’s expressions are key to the child’s social development, emotion regulation and early language learning (Mundy and Willoughby, 1996 cited by Lewis and Sullivan, 2003).

Lewis and Sullivan (2003) described the facial features of children for 12 discrete emotions proposed by them (Open interest, regulated interest, surprise, joy, social interaction, happiness, satisfaction, pain, frustration, anger, sadness, and fear). They based their descriptions on Izard’s Affective Expression Scoring System - AFFEX (1982) for children, Izard’s Maximally discriminative facial coding – MAX (1983/1995-unpublished), Ekman and Friesen’s Facial Coding System – FACS (1978) for adults and Oster’s Baby FACS (1978). In Table 1 appears a summary of the main features for each emotion, and the AV-coordinates according to the model blending prototypical emotions and core affect proposed by Russell and Feldman Barret (1999), for example, when children experiment surprise, it shows in their face with prominently raised eye-brows, widened eyes, and slackened jaw.

**Table 1. Summary of facial features in prototypical emotions**

| Emotion | Features | AV-Coords | |
|---|---|---|---|
| | | **V** | **A** |
| Open interest: Relaxed / Serene | Brows are raised slightly, eyes wide open and mouth is relaxed. | 4.1 | -3.1 |
| Regulated interest: Tense | Thinning and rolling inward of one or both lips, head lowering and gaze aversion. Brows pulled together. | -2.5 | 4.5 |
| Surprise | Brows are prominently raised, eyes are widened and mouth gapes with jaw slackened. | 0 | 4.9 |
| Joy in social play: Glad / Content | Closed mouth, simple smile. | 4.9 | -1.4 |
| Social Interaction: Delighted | Narrowed eyes, “Duchenne” smile (Cheek raise / Eye crinkle) | 4.1 | 3 |
| Happiness | Wide-open mouth, narrowed eyes and emergence of crow’s feet near the eyes. | 4.7 | 1.9 |
| Satisfaction | Crinkled eyes, widened mouth and dimpled cheeks. | 4.9 | -1.7 |
| Pain: Distressed | Midbrow bulge, low brows drawing together, deepened nasolabial furrow and tight squeezing of the eye orbit | -4.5 | 2.6 |

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| | | | |
|---|---|---|---|
| | muscles | | |
| Disgust: Frustration / Upset | Narrowed eyes and lip pursing (down or retracted lips) | -4.3 | 2.9 |
| Anger | Brows drawn together and lowered, narrowed eyes, mouth in form of square or sad “pout” and deepened nasolabial furrow | -2.9 | 4.5 |
| Sadness | Angular brows, narrowed eyes, mouth corners are down-turned and appearance of nasolabial furrow | -4.5 | -2.5 |
| Fear | Raised and straightened brows, widened eyes with tense lower eyelids and horizontally retracted lips. | -2.7 | 4.3 |

*2.3 Proportion canon.*

The ideal set of human figure proportions is called “the canon” and it is a set of rules fixed principally by artists to create their paintings and their sculptures according to the precepts of beauty for each epoch and place. There was designed a lot of canons, but it was not until Leonardo Da Vinci, and his studies of body’s proportions, that consensus was reached and most of the artists took it as the base for their paintings. In Fig. 3 is presented the proportion canon for infants and represents children neutral emotional state.

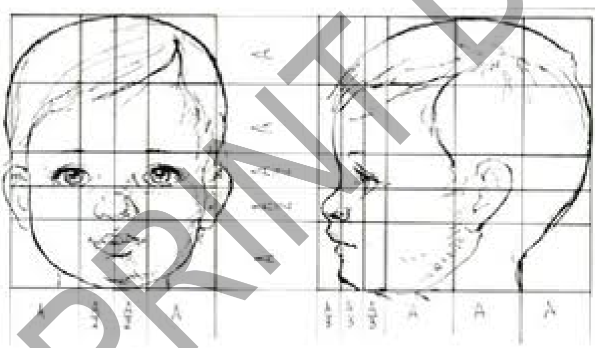

*Fig. 3 Infant’s canon of proportions (Took from: http://graffitigraffiti.com/pics/dibujo-del-canon-del-rostro-humano)*

*2.4 Antecedents*

*2.4.1 Modeling emotions in Artificial Intelligence*

Through the history of Artificial Intelligence research, a lot of models have been proposed to describe human mind (El-Nasr et al, 2000), because of the fuzzy nature of emotions, fuzzy logic (Zadeh, 1965) was one of the first tools exploited to develop computational models of emotion. Yanaru (1997) used fuzzy inference to define emotion while a person read a poem using the previous emotional state to infer the new emotion. El-Nasr et al (2000) proposed a fuzzy model to generate emotion in a virtual pet focusing on the behavioural and cognitive components of emotion so the pet could make its own decisions and learn from previous experiences using reinforcement. Mandryk and Atkins (2007) provides a method to quantify emotional states during interaction with play technologies using the physiological component of the emotion, mapping from physiological measures to Arousal and Valence values, and from Arousal and Valence to five emotions. Ioannou et al (2005) suggested a neuro-fuzzy model to recognized emotional state from images extracting the proper facial features.

Neural networks have been used to understand emotional influences in cognitive processes, mainly on those approaches which seen emotions as an information guide and a behaviour motivator (Levine, 2007). Most of the neural networks models that has been developed, used positive and negative emotions instead specific emotions, however, the research seems to go to models mapping to specific emotions, for example, Fragopanagos and Taylor (2005) develop a neural network able to recognized emotions from speech and facial information.

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*2.4.2 ANFIS inferring emotion from the cognitive component of emotion*

On a previous research[1](Mejía et al, Unpublished Results), the authors developed an Adaptive Neuro Fuzzy Inference System –ANFIS which estimates emotion, as a polar coordinate in the AV-Space, from values of Arousal and Valence. These values, taken after asking people how they feel about an event, correspond to the cognitive component of the emotion. See section 2.6.4 for further information about ANFIS tool.

This ANFIS used a fuzzy clustering technique (Mejía et al, Unpublished Results) (subtractive clustering with an acceptance ratio of 0.4) and a hybrid-learning algorithm combining least squares and back-propagation gradient descent methods to identify the optimal membership function parameters.

*2.5 The System*

The Artificial Intelligence models presented below were designed to infer measures of Arousal and Valence (Figure 1) from nine physiological inputs variables which are measures of percentage and relative changes in facial expressions taking infant's proportion canon as the neutral emotion or the (0,0) point in the AV-Space.

As canon's proportions are calculated in terms of a constant $A$ (see Fig. 2), that divide the horizontal and the vertical axis of the image in three and four portions respectively, all the measurements are calculated in terms of $A$. In Table 2 appear the proportions that have the infant canon for the different facial features. Appendix A resume in a picture, the content in Table 2.

**Table 2. Canon's proportion in terms of the constant A**

| **Facial Feature** | **Proportion** |
|---|---|
| Separation between eyebrows | A |
| Brows angle over the horizontal axis | 0 |
| Eye-Brow distance | 0.1A |
| Eye's height | 0.3A |
| Eye's length | 0.5A |
| Mouth's length | 0.8A |
| Mouth's height | 0.36A |
| Corners[2] | 2 |

The inputs, numbered in Table 3, are: percentage of difference of picture from canon's proportion in separation between eyebrows, brow-eye distance, and eye and mouth's height; difference between canon and children's mouth's length; relative change in upper and lower corners (to see if children is smiling or pouting), angle between horizontal axis and brows, and intensity measures of nasolabial furrow and midbrow bulge.

**Table 3. Inputs for the models presented**

| | Input |
|---|---|
| I1 | % Separation between eyes and brows |
| I2 | % Separation between eyebrows |
| I3 | % Eye's height |
| I4 | Relative change in corners |
| I5 | Difference in length of mouth |
| I6 | % Mouth's height |
| I7 | Intensity of midbrow bulge |
| I8 | Intensity of nasolabial furrow |
| I9 | Angle between horizontal axis and eyebrows |

To infer the emotion that bear the children, Arousal and Valence outputs of the models reported in this paper will be used as inputs to the ANFIS models described on section 2.4.2. In Fig. 3 appears the diagram of the complete model.

[1] The research is currently submitted to a journal.

[2] Corners are measured using: $\frac{d(Mouth\ axis, Upper\ lip)}{d(Mouth\ axis, Lower\ lip)}$, where mouth axis is the line between both lips, upper and lower lip is the maximum and minimum points in the lips respectively and *d* is the length of the distance between the components on the parentheses.

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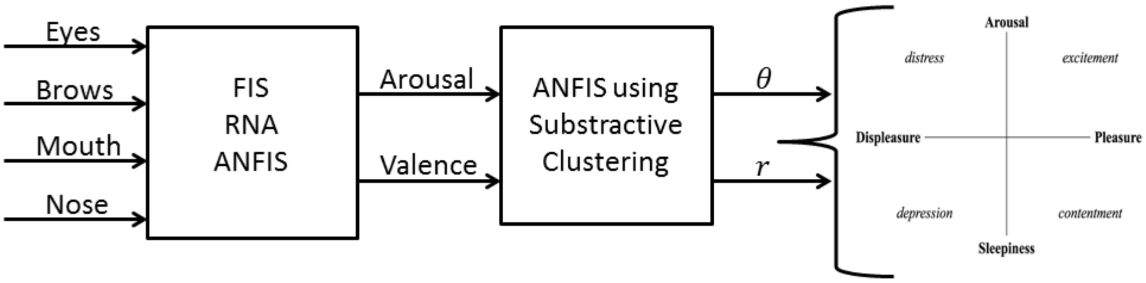


*Fig. 3 Diagram of the complete model proposed by authors.*

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### *3. MODELS AND METHODOLOGY*

#### *3.1 Mathematical Tools*

##### *3.1.1 Fuzzy Logic*

Fuzzy logic is characterized by naturally handle imprecision and conceptual simplicity, besides the use of linguistic expressions associated to numerical data. Is based on the ability of human mind to make categorizations and has been mathematically proved that it works with no linear processes. Fuzzy logic provides a solution for problems which are characterized by handling multi-valued values typical of human thought; is a method for specifying real problems without resorting to a mathematical model and with a high level of abstraction (Correa, 2004).

A Fuzzy Inference System (FIS) is built using knowledge, it is basically compound of a set of inputs, outputs and rules IF-THEN defined using the available knowledge of the system under study. Variables (inputs and outputs) are stated as a set of membership functions which are fuzzy sets; the membership degree of a value to a fuzzy set appears after the value is fuzzified. To build the inference, fuzzy logic use bi-valued logic operators (and, or, not) and inference rules (Modus ponens, Modus tollens, Hypothetical syllogism) but the definition of those operators is through a function’s family which fulfills with a norm (Babuska, 1998).

In the present paper, it was developed a rule-based Mamdani’s fuzzy inference system, which is a FIS whose consequent is linguistic, i.e. is a fuzzy proposition so the output must be defuzzified to a non-fuzzy value.

For each input, membership functions –MF were defined by the authors based on the information comprised in Table 1 and test data. In Fig. 4-11 appear the membership functions for each input. For each output, membership functions were defined using subtractive clustering using an acceptance ratio of 0.4, to a data set of emotion coordinates defined by Russell (1980). In Fig. 12 and 13, appear the membership functions for both outputs.

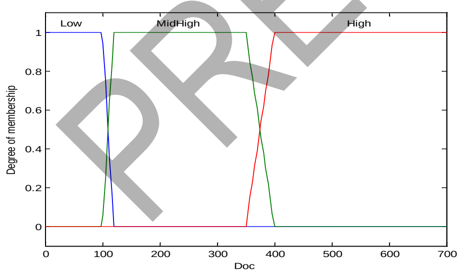


*Fig. 4 MF for separation between eyes and brows.*

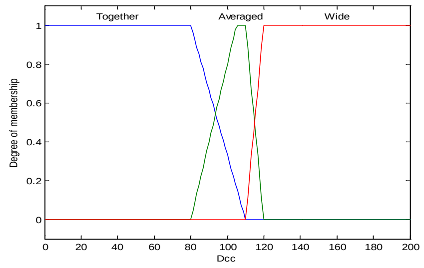


*Fig. 5 MF for separation between brows*

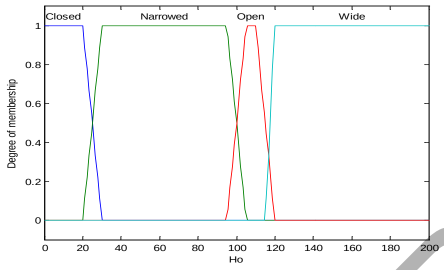


*Fig. 6 MF for eye's height.*

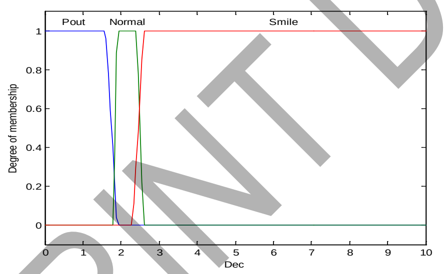


*Fig. 7 MF for changes in Mouth's axis distance from lips.*

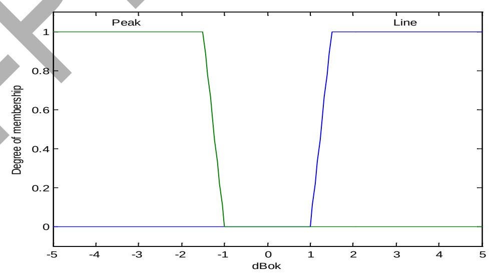


*Fig. 8 MF for mouth's length.*

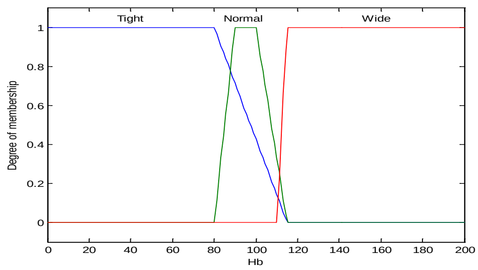


*Fig. 9 MF for mouth's height.*

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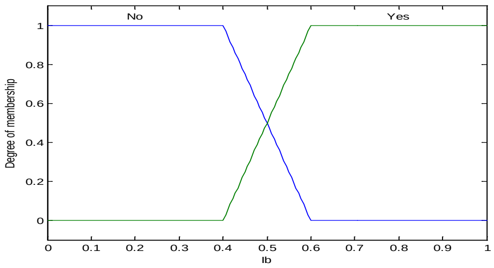


*Fig. 10 MF for nasolabial furrow - midbrow bulge intensity.*

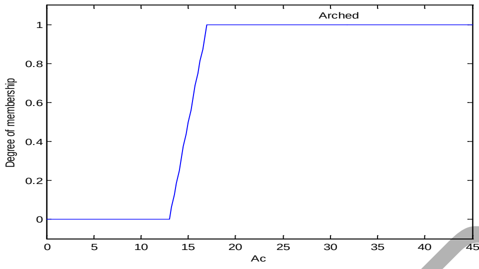


*Fig. 11 MF for brows' angle.*

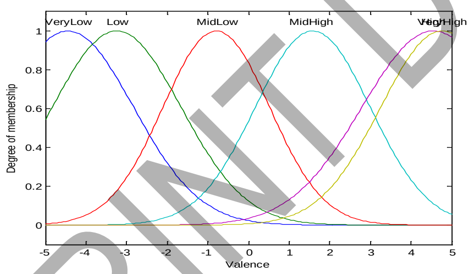


*Fig. 12 Membership functions for Valence measure.*

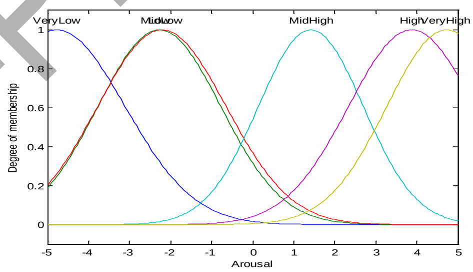


*Fig. 13 Membership functions for Arousal measure.*

Finally, to build the inference machine, 21 rules were defined based on knowledge. Rules are presented on Table 4.

**Table 4. Rules of the model**

| |
|---|
| 1. If (Doc is MidHigh) then (Arousal is Low) |
| 2. If (Doc is Low) then (Valence is Low)(Arousal is High) |
| 3. If (Doc is High) then (Arousal is VeryHigh) |
| 4. If (Dcc is Wide) then (Arousal is VeryHigh) |
| 5. If (Dcc is Averaged) then (Valence is High) |

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| |
|---|
| 6. If (Dcc is Together) then (Valence is Low) |
| 7. If (Ac is Arched) then (Valence is VeryLow)(Arousal is Low) |
| 8. If (Dec is Smile) then (Valence is High) |
| 9. If (Dec is Smile) then (Valence is VeryHigh) |
| 10. If (Dec is Pout) then (Valence is VeryLow) |
| 11. If (Dec is Pout) and (Is is Yes) then (Valence is Low) |
| 12. If (Dec is Normal) then (Arousal is MidLow) |
| 13. If (Dec is Pout) and (Is is Yes) then (Valence is VeryLow) |
| 14. If (dBok is Peak) then (Arousal is VeryHigh) |
| 15. If (Hb is Tight) and (Is is Yes) then (Valence is VeryLow) |
| 16. If (dBok is not Line) and (Hb is Wide) then (Valence is High) |
| 17. If (dBok is Line) and (Hb is Wide) then (Valence is Low) |
| 18. If (Is is Yes) then (Valence is VeryLow) |
| 19. If (Ho is Closed) and (Ib is No) then (Arousal is VeryLow) |
| 20. If (Ho is Closed) and (Ib is Yes) then (Valence is VeryLow)(Arousal is MidHigh) |
| 21. If (Ho is Closed) and (Ib is Yes) then (Valence is Low)(Arousal is MidHigh) |

### *3.1.2 Clustering data techniques*

Clustering data techniques are useful in many ways: first, clustering data allows to comprises data, also can help to reduce the dimension of the problem and to understand patterns hidden in data. However, fuzzy clustering techniques allow another advantage, since membership functions can be constructed taking the results of the algorithms. The aim of clustering is to divide data into classes so the elements into a class are similar and between classes are dissimilar. Difference between fuzzy and classical clustering data techniques is that the first allows data to belong in a certain level to more than one cluster.

The main fuzzy clustering data techniques are the fuzzy c-means introduced by Jim Bezdek (1981) where data points are grouped into a given number of clusters and the subtractive algorithm, introduced by Chiu (1994), which is based on the mountain clustering technique which creates a “mountain” function that measures the closeness of the points to each possible center.

In subtractive clustering, data points are grouped on its optimal way according to an acceptance ratio which specifies the influence ratio of a center in the mountain function of the closest points. For the implementation, the acceptance ratio was selected by tuning the centers so it can take points around the entire space using least clusters, nevertheless, as dataset is compound of 11 dimensions, with different ranges, it cannot be perfectly tuned.

### *3.1.3 Artificial Neural Networks*

Artificial Neural Networks (ANN) are based on human’s biological neural network. The idea behind them is that simple linear structures well connected may describe a complete non-linear system. This idea appears while investigating the human brain it was discover that it is a highly complex system compound of a finite number of simple structures: the neurons, which are interrelated between them. (Kosko, 1992)

ANN are good finding, recognizing and classifying patterns, interpolating, coding, filtering and storing information and estimating functions, because of their capacity of learn from data. To build an Artificial Neural Network there must be define the architecture of the net, the learning mechanism and the properties of the neuron (Anh, 2008)

In the present paper, it was designed an ANN to inferred measures of Arousal and Valence from the nine inputs presented in Table 3 and described in section 2.5. The ANN outputs are connected to the ANFIS presented above, in section 2.4.2, which estimate the place of the emotion in the AV-Space.

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To define the network parameters it was created a M-file which simulate twenty-seven networks using the *newff* and the *train* commands available in Matlab and combining three values of number of neurons for layer $(10, 20, 30)$, three values for number of hidden layers $(1, 3, 5)$ and the three classical activation functions (Hiperbolic Tangent Sigmoidal function, *TanSig*; Logarithmic Sigmoidal function, *LogSig*; and linear function, *Purelin*). Training data consisted on 15 patterns taken from pictures of kids selected randomly on internet websites. The performance of each net, evaluated as mean square error (MSE), was calculated using the *sim* function of Matlab so the net selected is the combination of parameter that throws the minimum value of performance. As in an ANN initial values are essential to determine the performance and those are selected randomly, the file was iterated several times, to verify which parameter appear longer as the better one. Finally, it was programmed the back-propagation algorithm (BP) using the parameters found. The Pseudo-code for the algorithm programmed is presented below.

### *3.1.4 Adaptive Neuro-Fuzzy Inference System*

An Adaptive Neuro-Fuzzy Inference System (ANFIS) is one of the best trade-off between neural networks and fuzzy systems, integrates the best features of fuzzy systems, the representation of prior knowledge into a set of constraints, and neural networks, the adaptation, using learning algorithms to identify the parameters of the membership functions which allow the system to 'learn' from training data. Designed by Jang (1993), ANFIS is applied to models to explain past data and predict future behavior. (Bonissone, 2002).

Each layer in the net is related to a component of a Takagi-Sugeno fuzzy system, which is a FIS whose consequent is a linear function. Neurons in different layers present differences in structure. In general, an ANFIS has six layers: the first layer contains the inputs, the second, fuzzifies inputs value and determine the membership functions for each input, the third, is in charge of adjusting the rules, the fourth, normalizes the results, the fifth, adjust the parameters of the Takagi-Sugeno's function and the last layer gives a single output.

**Pseudo-code for the Back-Propagation Algorithm**

*BackPropagation ($\eta$, MaxEpoch)*
*Read data*
*Normalized data*
*Divide data in training and validating sets*
*Initialize the weights randomly*
*Minimum error = M; where M is a high number*
*While number of epoch < MaxEpoch*
    *For each pattern (d) in training set:*
    *Forward:*
    *Calculate the induce fields (v) and the outputs (y)*
    *Calculate the errors*
    *Backward*
    *Calculate the local gradients*
    *Propagate the local gradients*
    *Recalculate the Weights*
    *End*
*If Error of the epoch is lower than MinimumError*
    *Save the Weights and the Outputs*
*End*
*Calculate outputs of the validation data using the weights that throws the minimum epoch error.*

ANFIS used two learning cycles: first, in forward direction, it is used an algorithm to estimate the Takagi's function parameters (in general, it is used a least square estimation algorithm for this stage) then, in backward direction, it uses a gradient descent algorithm to back-propagate the error and estimate the inputs membership function's parameters.

To implement an ANFIS, an M-File was created to prove the performance of 36 ANFIS to inferred values of Valence, and 36 ANFIS to inferred values of Arousal, as ANFIS just works for single output problems; The 36 ANFIS vary the structure of the initial FIS, the number of epochs to train, the step size and the optimization method.

The structure of the initial Sugeno's FIS was varied using Matlab's genfis commands, genfis1 creates a FIS using a grid partition instead clustering, genfis2 generates it, using subtractive clustering and genfis3 produce it, using fuzzy C-Means clustering.

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The optimal number of clusters was given by the subclust command with an influence ratio of 1.2, and as the Fuzzy C-means start with a given cluster's number, the number of centers throw by the subtractive clustering was used to call the fuzzy C-means.

The possible number of epochs combined was 10, 20 and 30, and the step size vary between 0.01 and 0.05, finally, the optimization method could be a hybrid which uses least squares estimation and back-propagation or simply, the back-propagation algorithm.

As results of ANFIS are proportional to the number of train data, i.e. as long as the train dataset, the better the results are; two runs of the code were made, first, using the 15 training data used in ANN in 2.6.3 which was taken from pictures selected randomly in internet and evaluated using Table 1, and finally, it was created randomly a train set compound of sixty data, using information in Table 1 and the values in the membership functions develop in section 2.6.1.

*4.2 Validation Data*

Input data is taken from pictures of children's face. Pictures were taken randomly from diverse websites[3]; in Fig. 14, for example, appears a picture of a child whose emotional state is surprise.

*Fig. 14 Children's picture: Surprise (took from: www.bebesymas.com).*

To validate the model, eight pictures were analyzed to find the input's values. To classify each picture's emotional state, two persons, experts on identifying emotion in children, were trained on Lewis and Sullivan (2003) pattern and were asked about each face emotional state, finding a great correlation among judgments. Original training set for ANN and ANFIS was constructed in the same form as validation data.

In Appendix B appear the values for inputs and outputs for the eight faces.

4. RESULTS

To compare the models and determine which outcomes are better is used a measure of distance, the Euclidean distance, in the 2-D Arousal Valence Space.

The Euclidean distance is calculated using:

$$d(\hat{p}, p) = \sqrt{(\hat{x} - x)^2 + (\hat{y} - y)^2} \tag{1}$$

Table 5 presents the Euclidean distance between estimated points and real data for each model implemented.

**Table 5. Euclidean Distance between real and estimated data for each methodology**

| # | FIS | ANN* | ANN** | ANFIS$^{+}$ | ANFIS$^{++}$ |
|---|---|---|---|---|---|
| 1 | 2.110 | 4.493 | 2.529 | 5.083 | 5.602 |
| 2 | 1.922 | 4.560 | 2.003 | 2.975 | 4.926 |
| 3 | 0.163 | 3.656 | 3.369 | 0.545 | 0.529 |
| 4 | 0.416 | 3.021 | 1.224 | 0.587 | 0.277 |
| 5 | 0.569 | 6.594 | 4.030 | 0.608 | 0.608 |
| 6 | 1.626 | 5.580 | 8.807 | 3.869 | 3.694 |
| 7 | 1.567 | 7.319 | 7.001 | 10.166 | 10.256 |
| 8 | 1.568 | 5.361 | 5.070 | 3.037 | 3.039 |

* ANN using the Matlab newff command.
** ANN using an implementation of the BP algorithm.

[3] No copyright

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[+] ANFIS using the original training data set
[++] ANFIS using the training data set generated

*4.1 Model using Fuzzy Logic:*

In Fig. 15 are shown the real and the estimated data in the AV-Space, and in Table 6 are presented the relative percentage errors.

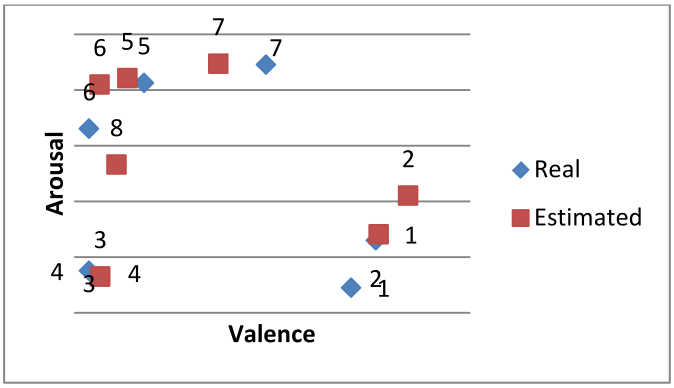


*Fig. 15 Comparison between real and estimated data in the AV-Space.*

**Table 6. Errors between real and estimated data**

| # | Real | | Estimated | | Percentage Relative errors | |
|---|---|---|---|---|---|---|
| | $\theta$ | $r$ | $\hat{\theta}$ | $\hat{r}$ | $\theta$ | $r$ |
| 1 | 324 | 5.1 | 346.6 | 5.1 | 6.9 | 0.01 |
| 2 | 342 | 5.1 | 361.9 | 5.9 | 5.82 | 17.2 |
| 3 | 212 | 5.1 | 213.2 | 4.9 | 0.55 | 2.67 |
| 4 | 209 | 5.2 | 213.2 | 4.9 | 1.99 | 4.01 |
| 5 | 122 | 5.0 | 126.3 | 5.5 | 3.54 | 8.81 |
| 6 | 149 | 5.2 | 134.8 | 5.9 | 9.55 | 13.51 |
| 7 | 75 | 5.1 | 93.1 | 4.9 | 24.1 | 2.42 |
| 8 | 149 | 5.2 | 160 | 3.8 | 7.38 | 26.2 |

*4.2 Model using Artificial Neural Networks*

Table 7 shows the percentage frequency in which each parameter appears in the net that present the minimum MSE; according to the table, the best architecture for the net is the one composed by five hidden layers with ten neurons, and using a hyperbolic tangent activation function in every layer.

**Table 7. Percentage frequency of parameters determining the minimum MSE net.**

| Number of layers | | Number of neurons | | Activation Function | |
|---|---|---|---|---|---|
| 1 | 0% | 10 | 37.5% | Tansig | 100% |
| 3 | 32.5% | 20 | 37.5% | Logsig | 0% |
| 5 | 62.5% | 30 | 25% | Purelin | 0% |

In Fig. 16 appear the performance of the net as it is calculated using the Neural Networks Toolbox. Fig. 17 shows the estimated and the real data after introducing the ANN outputs as inputs to the ANFIS. Fig. 18 presents the error's graph along 100 epochs using the back-propagation algorithm implemented; the minimum error found during the 100 epochs was 0.0945. Fig. 19 shows the estimated and the real data of the model using the outputs of the algorithm as inputs for the ANFIS. In Tables 8 and 9 are presented the outcomes for both networks with the percentage relative errors.

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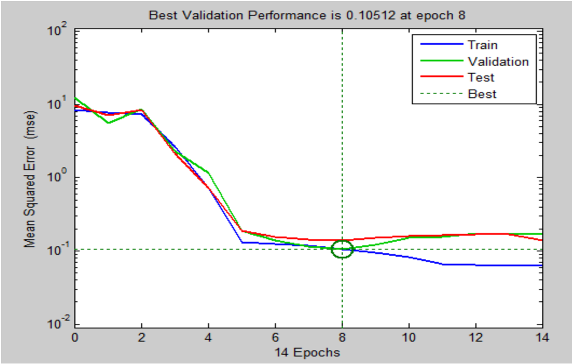


*Fig. 16 Performance of the net using Matlab' Neural Network toolbox.*

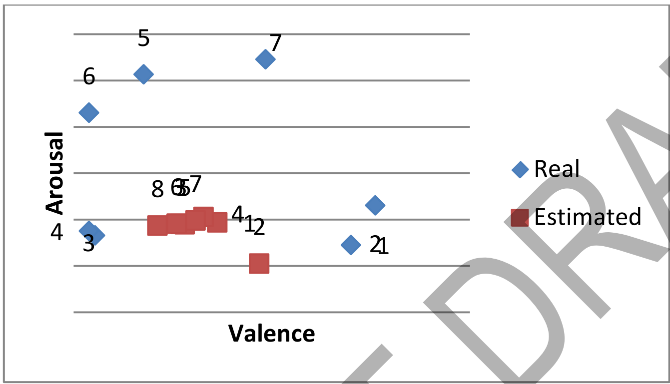


*Fig. 17 Comparison between real and estimated data in the AV-Space.*

**Table 8. Errors between real and estimated data for the ANN using the functions implemented in Matlab.**

| # | Real | | Estimated | | Percentage Relative errors | |
|---|---|---|---|---|---|---|
| | $\theta$ | $r$ | $\hat{\theta}$ | $\hat{r}$ | $\theta$ | $r$ |
| 1 | 324 | 5.1 | 262.3 | 2.2 | 19.03 | 58.17 |
| 2 | 342 | 5.1 | 285.6 | 4.1 | 16.50 | 20.53 |
| 3 | 212 | 5.1 | 248.8 | 2.0 | 17.35 | 60.02 |
| 4 | 209 | 5.2 | 235.8 | 2.7 | 12.84 | 48.33 |
| 5 | 122 | 5.0 | 238.4 | 2.6 | 95.40 | 48.56 |
| 6 | 149 | 5.2 | 233.3 | 2.7 | 56.60 | 47.66 |
| 7 | 75 | 5.1 | 243.9 | 2.3 | 225.20 | 55.03 |
| 8 | 149 | 5.2 | 225.2 | 3.2 | 51.15 | 38.62 |

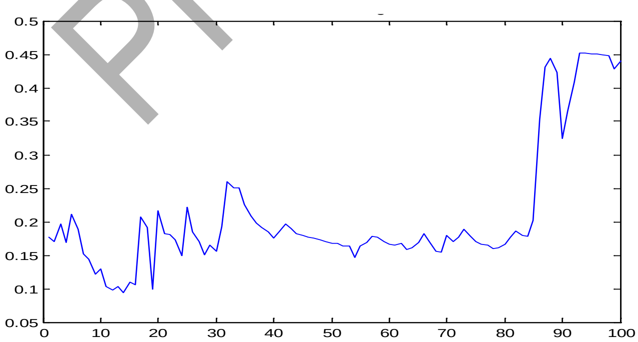

*Fig. 18. Performance of the net using the BP algorithm implemented.*

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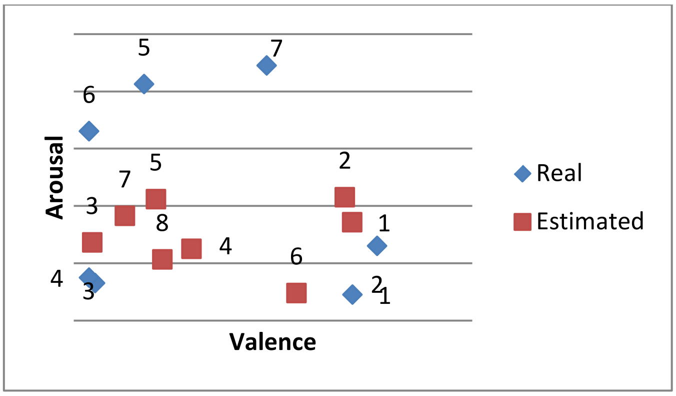


*Fig. 19. Comparison between real and estimated data in the AV-Space.*

**Table 9. Errors between real and estimated data for the ANN using the BP algorithm implemented.**

| # | Real | | Estimated | | Percentage Relative errors | |
|---|---|---|---|---|---|---|
| | $\theta$ | $r$ | $\hat{\theta}$ | $\hat{r}$ | $\theta$ | $r$ |
| 1 | 324 | 5.1 | 352.03 | 4.12 | 8.65 | 19.84 |
| 2 | 342 | 5.1 | 364.52 | 3.86 | 6.58 | 24.26 |
| 3 | 212 | 5.1 | 232.43 | 1.89 | 9.64 | 62.78 |
| 4 | 209 | 5.2 | 196.23 | 4.58 | 6.11 | 11.03 |
| 5 | 122 | 5.0 | 174.13 | 2.33 | 42.73 | 53.73 |
| 6 | 149 | 5.2 | 306.68 | 3.79 | 105.83 | 27.07 |
| 7 | 75 | 5.1 | 185.99 | 3.35 | 147.99 | 33.92 |
| 8 | 149 | 5.2 | 221.57 | 2.82 | 48.70 | 45.74 |

*4.3 Model using ANFIS*

The subtractive clustering was defined using an influence ratio of 1.2. However, for this influence ratio, using the 15 data set, appear eight clusters, and using the generated data set, appears six clusters Fig. 20 shows the centers for both data sets in the output variables, i.e. in the AV-Space.

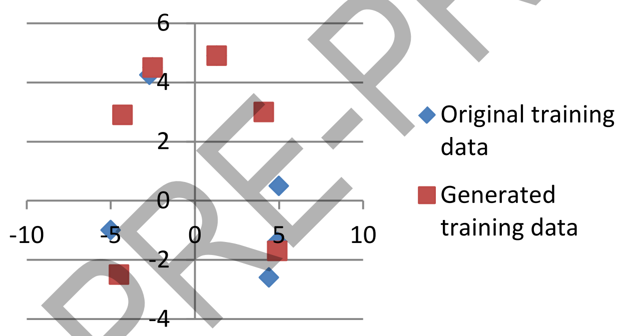


*Fig. 20. Centers using subtractive clustering.*

In Appendix C appears the averaged error for each combination of ANFIS with both training data set, i.e. using the original 15 data and the produced data which was generated as it was explain above.

As it can be seen, for the first experiment, using the original 15 training data, the best combination for both ANFIS was the one which makes a grid partition, using 10 epochs, a step size of 0.01 and the hybrid of backpropagation and least squares. Fig. 21 shows the estimated and the real data of the model using the inferred values of valence and arousal of this ANFIS structure as inputs for the ANFIS which inferred emotion in the AV-Space. Table 10 presents the outcomes with the percentage relative errors.

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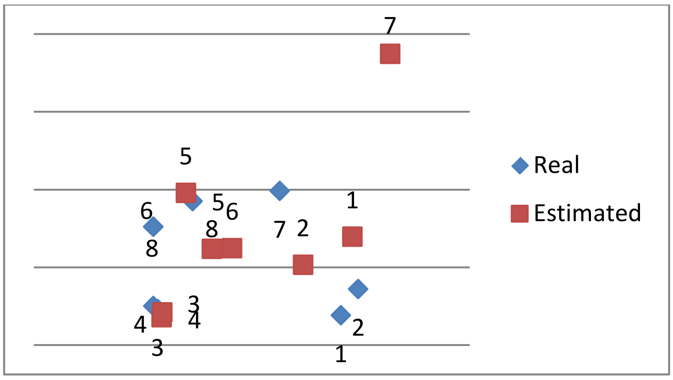


*Fig. 21. Comparison between data in the AV-Space.*

**Table 10. Errors between real and estimated data for the ANFIS using the original training data set.**

| # | Real | | Estimated | | Percentage Relative errors | |
|---|---|---|---|---|---|---|
| | $\theta$ | $r$ | $\hat{\theta}$ | $\hat{r}$ | $\theta$ | $r$ |
| 1 | 324 | 5.1 | 382.91 | 5.02 | 18.18 | 2.28 |
| 2 | 342 | 5.1 | 3.90 | 2.37 | 6.40 | 53.43 |
| 3 | 212 | 5.1 | 217.99 | 5.22 | 2.82 | 2.80 |
| 4 | 209 | 5.2 | 215.51 | 5.02 | 3.11 | 2.55 |
| 5 | 122 | 5.0 | 122.12 | 5.64 | 0.09 | 12.06 |
| 6 | 149 | 5.2 | 125.75 | 1.51 | 15.60 | 70.93 |
| 7 | 75 | 5.1 | 425.11 | 15.12 | 13.19 | 198.24 |
| 8 | 149 | 5.2 | 146.86 | 2.17 | 1.44 | 58.33 |

*Using the data set generated, the best combination for the ANFIS which inferred values of Valence is the one which makes a grid partition and train in 30 epochs, with a step size of 0.01 and uses the hybrid method. For the ANFIS which inferred values of Arousal, the best ANFIS is the one which makes grid partition using 10 epochs, a step size of 0.01 and the hybrid optimization method. Fig. 22 shows the estimated and the real data of the model using the inferred values of valence and arousal from the ANFIS and connecting it to the ANFIS which inferred emotion in the AV-Space. Table 11 presents the outcomes with the percentage relative errors.*

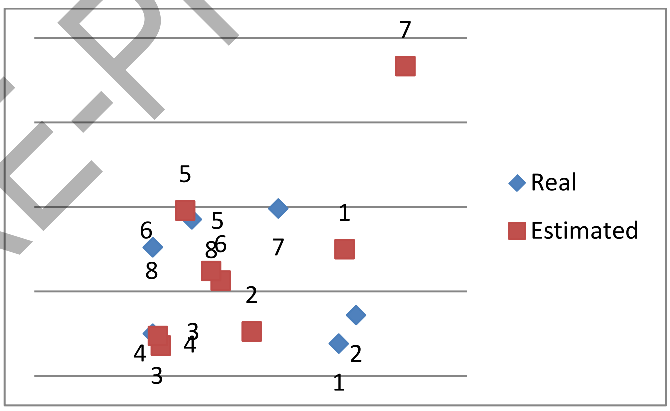


*Fig. 22. Comparison data in the AV-Space.*

**Table 11. Errors between real and estimated data for the ANFIS using the generated training data set.**

| # | Real | | Estimated | | Percentage Relative errors | |
|---|---|---|---|---|---|---|
| | $\theta$ | $r$ | $\hat{\theta}$ | $\hat{r}$ | $\theta$ | $r$ |
| 1 | 324 | 5.1 | 19.80 | 5.02 | 20.31 | 2.28 |
| 2 | 342 | 5.1 | 271.70 | 2.37 | 20.56 | 53.43 |
| 3 | 212 | 5.1 | 217.80 | 5.22 | 2.74 | 2.80 |
| 4 | 209 | 5.2 | 211.80 | 5.02 | 1.34 | 2.55 |

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| | | | | | | |
|---|---|---|---|---|---|---|
| 5 | 122 | 5.0 | 122.10 | 5.64 | 0.08 | 12.06 |
| 6 | 149 | 5.2 | 154.90 | 1.51 | 3.96 | 70.93 |
| 7 | 75 | 5.1 | 61.70 | 15.12 | 17.73 | 198.24 |
| 8 | 149 | 5.2 | 146.40 | 2.17 | 1.74 | 58.33 |

## 6. DISCUSSION

Even when there are proposed a lot of models of emotion, implementing a mathematical model requires to focus on the problem itself, and to define the boundaries of it. The idea for the present paper is not to define a theory of emotion, but to create a model which infer infant's emotion, so, following psychologists postulates about the emotion's fuzzy nature, which seems to be the only point where exists a consensus between theorists, it was chose the AV-Space which was designed by Russell (1980), taking into account this feature of emotions and the way that emotions are correlated between.

The present research focused on children emotional expression, it is because children express their emotions in a different way of adults, following limited social rules and with a highly grade of emotional "immaturity", even when there have been proved that most of the facial components of the human expression repertoire can be observed shortly after birth (Camras et al, 1993; Izard and Malatesta, 1987; cited by Lewis and Sullivan, 2003); also, despite this finding, emotional expression in children and facial coding research have barely start taking strength and there is no much information about how did children express their emotions; and finally, it is because there exists some software for training in emotional identification on adults (Ekman, 1993) but there is not for children.

Another novel approach is the use of the proportion canon as base to find changes in facial features, the main works that take facial features to infer emotions did not take relative and percentage changes from a basic pattern as inputs and as it was show on the results of the papers, it gives good approximations to the emotion felt by the infant. Some Psychologists might argue that there is not a non-emotional face but some pathological expressions, and that it cannot be possible to compare the proportion canon as a non-emotional expression, however, in the present paper, proportion canon represent, not the non-emotion face but the neutral expression, and using a pathological expression as base to compare healthy children seems to be not reasonable.

Focusing on results, fuzzy logic was the methodology that throws better results, corroborating Russell's idea (1980), who postulates that fuzzy logic allows handling the imprecision inherent in human emotions in a natural way that have not been found in any other tool.

Artificial Neural Networks implementation was not good enough, but this could be easily explained: there was few data in the training set and the number of points needed to cover the entire space should be larger enough to be significant according to problem's dimension. Another thing that must be discussed is the fact that there was generated a training data set in the implementation of the ANFIS, but this set was not used in the networks; this was because the generated set was based on the membership functions defined for the fuzzy system, and ANFIS is related to fuzzy logic, but neural networks are not.

ANFIS results were not good enough either: 50% of the times, the generated set did not improve the outcomes of the ANFIS that uses the original set, which implies that the generated set was not good enough to resume the complete space. Another thing to highlight is that in both implementations, best results were cast using a grid partition and not a clustering partition which is the usual, this can be explained because of the way the number of clusters was selected: acceptance ratio was selected as the one that takes into account all the space with few clusters, but this was only checked in the 2-dimension space formed by the outcomes, so maybe the acceptance ratio selected is not taking into account the entire 11-dimension space.

A suggestion that could improve results is not to use an ANFIS but to implement a Neuro-Fuzzy system which allow a Mamdani's Fuzzy Inference System as initial FIS, and accept two outputs, so the FIS implemented, which threw the better results, could be improved taking the advantages of the neural networks.

Finally, it must be clear that, to make a proper estimation of a person's emotion, it should be taken into account the three components of the emotion: behavioral, physiological and cognitive, however, this is not easy and requires high technology and long time, and for infants, it becomes harder because emotions are different and emotional development is just starting, so there are not clear behavioral patterns, however, results exposed in this paper, showed that it could be reached a good approximation just taking signals of the face.

## 6. CONCLUSION

Five models, using artificial intelligence tools, were developed to approximate infant's emotions in the AV-Space from a set of facial features took from a picture. This work proves that fuzzy logic could be useful to test

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infant's emotions and that artificial intelligence tools can be used to measure human emotional states using the physiological and cognitive components of emotion.

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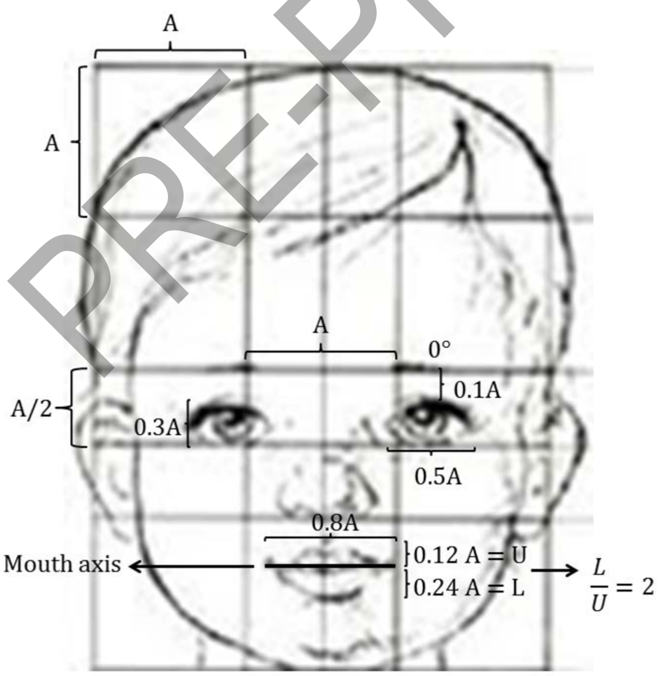
Appendix A. Canon’s proportions in terms of the constant *A*



Appendix B.Validation Data: Inputs and outputs

| Pattern | I1 | I2 | I3 | I4 | I5 | I6 | I7 | I8 | I9 | Valence | Arousal |
|---|---|---|---|---|---|---|---|---|---|---|---|
| **1** | 333 | 100 | 111 | 2.4 | 2 | 93 | 0 | 0 | 10 | 4.1 | -3.1 |
| **2** | 300 | 100 | 100 | 10 | 1 | 139 | 0 | 0 | 10 | 4.9 | -1.4 |
| **3** | 240 | 60 | 93 | 0.7 | 1 | 61 | 0.1 | 0.1 | 20 | -4.3 | -2.7 |
| **4** | 167 | 50 | 83 | 1.8 | 1 | 102 | 0.4 | 0.4 | 30 | -4.5 | -2.5 |
| **5** | 100 | 50 | 100 | 0.7 | 1 | 111 | 0.6 | 0 | 0 | -2.7 | 4.3 |
| **6** | 60 | 100 | 67 | 1.7 | 3 | 122 | 0.4 | 0.7 | 0 | -4.5 | 2.6 |
| **7** | 600 | 140 | 133 | 0.6 | 1 | 89 | 0.4 | 0 | 10 | 1.3 | 4.9 |
| **8** | 100 | 80 | 20 | 1.8 | 2 | 122 | 0.8 | 1 | 0 | -4.5 | 2.6 |

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Appendix C. Results for first stage ANFIS

- Using the original training data

| # | Initial FIS | Epoch | Step Size | Method | Error | |
|---|---|---|---|---|---|---|
| | | | | | **Valence** | **Arousal** |
| 1 | Subtractive | 10 | 0.01 | Backpropagation | 0.75 | 0.63 |
| 2 | Subtractive | 10 | 0.01 | Hybrid | 0.00 | 0.00 |
| 3 | Subtractive | 10 | 0.05 | Backpropagation | 3.77 | 3.13 |
| 4 | Subtractive | 10 | 0.05 | Hybrid | 0.00 | 0.00 |
| 5 | Subtractive | 20 | 0.01 | Backpropagation | 0.69 | 0.56 |
| 6 | Subtractive | 20 | 0.01 | Hybrid | 0.00 | 0.00 |
| 7 | Subtractive | 20 | 0.05 | Backpropagation | 3.46 | 2.81 |
| 8 | Subtractive | 20 | 0.05 | Hybrid | 0.00 | 0.00 |
| 9 | Subtractive | 30 | 0.01 | Backpropagation | 0.63 | 0.50 |
| 10 | Subtractive | 30 | 0.01 | Hybrid | 0.00 | 0.00 |
| 11 | Subtractive | 30 | 0.05 | Backpropagation | 3.12 | 2.52 |
| 12 | Subtractive | 30 | 0.05 | Hybrid | 0.00 | 0.00 |
| 13 | FCM | 10 | 0.01 | Backpropagation | 1.19 | 1.09 |
| 14 | FCM | 10 | 0.01 | Hybrid | 0.00 | 0.00 |

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| | | | | | | |
|---|---|---|---|---|---|---|
| 15 | FCM | 10 | 0.05 | Backpropagation | 3.69 | 3.53 |
| 16 | FCM | 10 | 0.05 | Hybrid | 0.00 | 0.00 |
| 17 | FCM | 20 | 0.01 | Backpropagation | 1.14 | 1.04 |
| 18 | FCM | 20 | 0.01 | Hybrid | 0.00 | 0.00 |
| 19 | FCM | 20 | 0.05 | Backpropagation | 3.25 | 3.25 |
| 20 | FCM | 20 | 0.05 | Hybrid | 0.00 | 0.00 |
| 21 | FCM | 30 | 0.01 | Backpropagation | 1.09 | 1.00 |
| 22 | FCM | 30 | 0.01 | Hybrid | 0.00 | 0.00 |
| 23 | FCM | 30 | 0.05 | Backpropagation | 3.03 | 2.98 |
| 24 | FCM | 30 | 0.05 | Hybrid | 0.00 | 0.00 |
| 25 | Grid | 10 | 0.01 | Backpropagation | 3.29 | 1.86 |
| **26** | **Grid** | **10** | **0.01** | **Hybrid** | **0.00** | **0.00** |
| 27 | Grid | 10 | 0.05 | Backpropagation | 1.94 | 1.72 |
| 28 | Grid | 10 | 0.05 | Hybrid | 0.00 | 0.00 |
| 29 | Grid | 20 | 0.01 | Backpropagation | 2.34 | 1.21 |
| 30 | Grid | 20 | 0.01 | Hybrid | 0.00 | 0.00 |
| 31 | Grid | 20 | 0.05 | Backpropagation | 1.58 | 1.46 |
| 32 | Grid | 20 | 0.05 | Hybrid | 0.00 | 0.00 |
| 33 | Grid | 30 | 0.01 | Backpropagation | 1.71 | 0.94 |
| 34 | Grid | 30 | 0.01 | Hybrid | 0.00 | 0.00 |
| 35 | Grid | 30 | 0.05 | Backpropagation | 1.36 | 1.28 |
| 36 | Grid | 30 | 0.05 | Hybrid | 0.00 | 0.00 |

- Using the training data set generated.

| # | Initial FIS | Epoch | Step Size | Method | Error | |
|---|---|---|---|---|---|---|
| | | | | | Valence | Arousal |
| 1 | Subtractive | 10 | 0.001 | Backpropagation | 0.7394 | 0.8194 |
| 2 | Subtractive | 10 | 0.001 | Hybrid | 0.3341 | 0.4853 |
| 3 | Subtractive | 10 | 0.005 | Backpropagation | 3.0144 | 3.0755 |
| 4 | Subtractive | 10 | 0.005 | Hybrid | 0.2685 | 0.4449 |
| 5 | Subtractive | 20 | 0.001 | Backpropagation | 0.7362 | 0.8101 |
| 6 | Subtractive | 20 | 0.001 | Hybrid | 0.2937 | 0.4659 |
| 7 | Subtractive | 20 | 0.005 | Backpropagation | 2.9526 | 2.9978 |
| 8 | Subtractive | 20 | 0.005 | Hybrid | 0.2497 | 0.4214 |
| 9 | Subtractive | 30 | 0.001 | Backpropagation | 0.7055 | 0.7903 |
| 10 | Subtractive | 30 | 0.001 | Hybrid | 0.2722 | 0.4466 |
| 11 | Subtractive | 30 | 0.005 | Backpropagation | 2.7578 | 2.8199 |
| 12 | Subtractive | 30 | 0.005 | Hybrid | 0.2396 | 0.4052 |
| 13 | FCM | 10 | 0.001 | Backpropagation | 1.7544 | 2.2743 |
| 14 | FCM | 10 | 0.001 | Hybrid | 0.6777 | 0.594 |
| 15 | FCM | 10 | 0.005 | Backpropagation | 4.1927 | 4.6624 |

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| | | | | | | |
|---|---|---|---|---|---|---|
| 16 | FCM | 10 | 0.005 | Hybrid | 0.7166 | 0.5791 |
| 17 | FCM | 20 | 0.001 | Backpropagation | 1.7298 | 2.1978 |
| 18 | FCM | 20 | 0.001 | Hybrid | 0.6406 | 0.59 |
| 19 | FCM | 20 | 0.005 | Backpropagation | 3.957 | 4.2151 |
| 20 | FCM | 20 | 0.005 | Hybrid | 0.5276 | 0.5034 |
| 21 | FCM | 30 | 0.001 | Backpropagation | 1.6962 | 2.1284 |
| 22 | FCM | 30 | 0.001 | Hybrid | 0.6125 | 0.5859 |
| 23 | FCM | 30 | 0.005 | Backpropagation | 3.6886 | 3.8753 |
| 24 | FCM | 30 | 0.005 | Hybrid | 0.4682 | 0.4763 |
| 25 | Grid | 10 | 0.001 | Backpropagation | 3.3777 | 2.5988 |
| **26** | **Grid** | **10** | **0.001** | **Hybrid** | 0 | **0** |
| 27 | Grid | 10 | 0.005 | Backpropagation | 2.4103 | 2.2472 |
| 28 | Grid | 10 | 0.005 | Hybrid | 0 | 0 |
| 29 | Grid | 20 | 0.001 | Backpropagation | 2.7382 | 2.1458 |
| 30 | Grid | 20 | 0.001 | Hybrid | 0 | 0 |
| 31 | Grid | 20 | 0.005 | Backpropagation | 2.0114 | 1.9626 |
| 32 | Grid | 20 | 0.005 | Hybrid | 0 | 0 |
| 33 | Grid | 30 | 0.001 | Backpropagation | 2.2607 | 1.8434 |
| **34** | **Grid** | **30** | **0.001** | **Hybrid** | **0** | 0 |
| 35 | Grid | 30 | 0.005 | Backpropagation | 1.7845 | 1.7884 |
| 36 | Grid | 30 | 0.005 | Hybrid | 0 | 0 |

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