

# Application of Neuro Fuzzy Network for The Analyzing The Pain Through Facial Expression

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**Abstract-** In the present paper we define the different type of pain with the extraction of appropriate facial features and consequent recognition that can be robust to facial expression variations among different samples. The automatic recognition of facial expressions of pain has potential medical significance: some patients are unable or unwilling to ask for analgesia, but it has been rather little studied. This paper deals with knowledge based expert systems which have been developed for the diagnosis of diseases based on the symptoms obtained from the interaction and observation by the facial expressions. A novel Neuro fuzzy system is then created, based on rules that have been defined through analysis of FAP variations. The Neuro fuzzy system allows for further learning and adaptation to specific users' facial expression characteristics, measured through FAP estimation in real life application of the system, using analysis by clustering of the obtained FAP values.

**Index Terms-**Facial expression analysis, MPEG-4 facial animation parameters; Activation evaluation emotion representation, Neuro fuzzy network; Rule extraction; Adaptation, Back Propagation Algorithm, fuzzy relational mappings.

## I. INTRODUCTION

Human face tells about the human being and so many communication and prediction can be done through the face facial features such as lip reading and various expressions come on to the face of human being. Interpersonal communication is for the most part of disease diagnosis predicted by Physicians by the face expression. Facial expressions are generated by contractions of facial muscles. Facial expression representation is an important parameter of this approach is the effectiveness of the image processing procedures. In actual situations, such as processing of visual data from personal interaction feature extraction. The easiest (and safest) way for expression recognizers to get around would be to provide a label for the given sequence. However, the lack of evidence for a particular feature being deformed, when this feature is used in the representation of an expression, should not always be considered as absence of this feature it may be attributed to a mistake of the image processing algorithms. In this paper, we describe the uncertainty generated during the image processing for feature extraction phase through validation of the results against a set of anthropometric criteria and propose a methodology based on which fuzzy

rules containing knowledge on expression analysis and estimation can be evaluated in an uncertain environment. The evaluation of the fuzzy rules representing the mapping between measure features and estimated expression, given the uncertainty contained in the input provided by the image processing.

### A. Facial Expression Recognition:

Ekman and Friesen find six universal facial expressions that are expressed and interpreted in the same way by humans of any origin all over the world. Figure shows one example of each facial expression. The Facial Action Coding System (FACS) precisely describes the muscle activity within a human face .So-called Action Units denote the motion of particular facial parts and state the involved facial muscles. Combinations of AUs assemble facial expressions. Extended systems such as the Emotional FACS specify the relation between facial expressions and emotions.



No Pain      Severe      Chronic      Mild

The Cohn-Kanade Facial Expression Database (CKDB) contains a number of 488 short image sequences of 97 different persons showing the six universal facial expressions. Each sequence shows a neutral face at the beginning and then no pain severe chronic and mild.

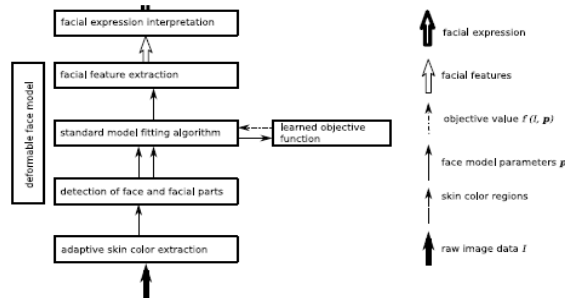
Fig. Procedure for recognizing facial expressions according to Pantic develops into the peak expression. Furthermore, a set of AUs has been manually specified by licensed FACS experts for each sequence.

### B .Model-based Interpretation of Facial Expressions for Diagnosis:

Our approach makes use of model-based techniques, which exploit a priori knowledge about objects, such as their shape or texture. Reducing the large amount of image data to a small set of model parameters facilitates

and accelerates the subsequent facial expression interpretation, which mitigates the computational.

Fig. 3. Model-based image interpretation splits the challenge of image interpretation into computationally independent modules.



Our model-based approach consist of seven components, which are illustrated in Fig. This approach fits well into the three-phase procedure of Pantic where pre-processing step, mentioned by Chibelushi. Phase 1 is contains by the core of model-based techniques: the model, localization, the fitting algorithm, and the objective function. Phase 2 consists of the facial feature extraction, and Phase 3 is the final step of facial expression classification.

C. Feature extraction

The left, right, top and bottom-most coordinates of the eye and mouth masks, the left right and top coordinates of the eyebrow masks as well as the nose coordinates, are used to define the feature points. For the nose and each of the eyebrows, a single mask is created. A feed-forward back propagation neural network trained to identify facial area.

- (1) A second neural network, with similar architecture to the first one, trained to identify mouth regions.
- (2). Luminance based masks, which identify eyelid and sclera regions.
- (3). Edge-based masks.
- (4). A region growing approach based on standard deviation.

All detected masks have to be validated against a set of criteria; For example, two criteria that can be used for the validation of the eye masks are the following:

$$M_{eye}^{1c} = 1 - \left| 1 - \frac{d_2/d_6}{0.49} \right| \tag{1}$$

$$M_{eye}^{2c} = 1 - \frac{|d_4|}{d_5} \tag{2}$$

where  $M_{eye}^{1c}$  and  $M_{eye}^{2c}$  are the confidence degrees acquired through the application of each validation criterion on an eye mask. The former of the two criteria is based on where the ration of eye width over bipupil breadth is reported as constant and equal to 0.49. In almost all cases these validation criteria, as well as the other criteria utilized in mask validation, produce confidence values in the [0,1] range. In the rare cases that the estimated value exceeds the limits, it is set to the closest extreme value, 0 for negative values and one for values exceeding one. The features measured for the

application of the two example criteria are explained in FAPs vocabulary for archetypal expression description

**No Pain** F3, F4, F5, F6, F7, F12, F13, F19, F20, F21, F22, F33, F34, F41, F42, F53, F54

**Sevier:** F4, F5, F16, F18, F19, F20, F21, F22, F31, F32, F33, F34, F35, F36, F37, F38

**Mild:** F3, F4, F5, F8, F9, F10, F11, F19, F20, F21, F22, F31, F32, F33, F34, F35, F36, F37, F38

**Chronic:** F3, F4, F5, F8, F9, F10, F11, F19, F20, F21, F22, F33, F34, F55, F56, F57, F58, F59, F60

**Eye mask features used in the process of mask validation**

- d6-** Bipupil breadth
- d2-** Eye width
- d4-** Distance of eye’s middle vertical coordinate and eyebrow’s middle vertical coordinate
- d5 -**Eyebrow width

A way to evaluate our feature extraction performance is Williams’ Index (WI), which compares the agreement of an observer with the joint agreement of other observers. An extended version of WI, which deals with multivariate data, can be found in Chalana and Kim . The modified Williams’ Index I’ divides the average number of agreements (inverse disagreements,  $D_{j,j'}$ ) between the computer (observer 0) and  $n - 1$  human observers ( $j$ ) by the average number of agreements between human observers:

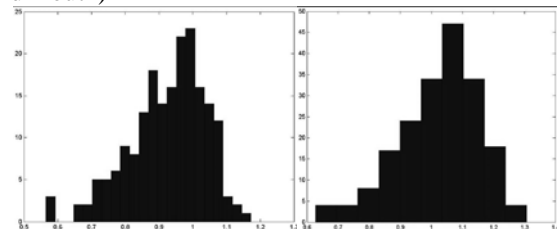
$$WI = \frac{\frac{1}{n} \sum_{j=1}^n (1/D_{0,j})}{\frac{2}{n(n-1)} \sum_j \sum_{j':j'>j} (1/D_{j,j'})} \tag{3}$$

and in our case we define the average disagreement between two observers  $j, j'$  as:

$$D_{j,j'} = \frac{1}{D_{bp}} \| M_j^x \vee M_{j'}^x \| \tag{4}$$

where  $\vee$  denotes the pixel-wise xor operator,  $\| \cdot \|_{xj}$  denotes the cardinality of feature mask  $x$  constructed by observer  $j$ , and  $D_{bp}$  (bipupil breadth) is used as a normalization factor to compensate for camera zoom on video sequences.

Figure 2 Williams index distribution (average on eyes and mouth)



Thus, for cases in which two distinct definitions exist for an FAP, the final value and confidence for the FAP are as follows:

$$F_i = F_i^1 + F_i^2 / 2 \tag{5}$$

The amount of uncertainty contained in each one of the distinct initial FAP calculations can be estimated by :

$$E_i^1 = 1 - F_i^{1c} \tag{6}$$

The amount of uncertainty contained in each one of the distinct initial FAP calculations can be estimated by:

$$E_i^1 = 1 - F_i^{1c} \tag{7}$$

for the first FAP and similarly for the other. The uncertainty present after combining the two can be given by some t-norm operation on the two:

$$E_i^1 = t(F_i^{1c}, E_i^2) \quad (8)$$

The Yager t-norm with parameter  $w = 5$  gives reasonable results for this operation

$$E_i = 1 - \min\{1, ((1 - E_i^1)^w + (1 - E_i^2)^w)^{1/w}\} \quad (9)$$

The overall confidence value for the final estimation of the FAP is then acquired as

$$F_i^c = 1 - E_i \quad (10)$$

FAP measurements are transformed to antecedent values  $x_j$  for the fuzzy rules

using the fuzzy numbers defined for each FAP, and confidence degrees  $c_j$ ,  $x$  are inherited from the FAP:

$$x_j^c = F_i^c \quad (11)$$

where  $F_i$  is the FAP based on which antecedent  $x_j$  is defined.

#### D. Possibilistic rule evaluation

In the process of exploiting the knowledge contained in the fuzzy rule base and the information extracted from each frame in the form of FAP measurements, with the aim to analyze and classify facial expressions, a series of issues has to be tackled

(1) FAP degrees need to be considered in the estimation of the overall result

(2) The case of FAPs that cannot be estimated, or equivalently are estimated with a low degree of confidence, needs to be considered.

(3) The activation of contradicting rules needs to be considered.

A conventional approach to the evaluation of fuzzy rules of the form

IF  $x_1, x_2, \dots, x_n$  THEN  $y$

is as follows

$$y = t(x_1, x_2, \dots, x_n)$$

where  $t$  is a fuzzy t-norm, such as the minimum

$$t(x_1, x_2, \dots, x_n) = \min(x_1, x_2, \dots, x_n)$$

the algebraic product

$$t(x_1, x_2, \dots, x_n) = x_1 \cdot x_2 \cdot \dots \cdot x_n$$

the bounded sum

$$t(x_1, x_2, \dots, x_n) = x_1 + x_2 + \dots + x_n$$

and so on. Another well-known approach in rule evaluation is described in Lee and Takagi and utilises a weighted sum instead of a t-norm in order to combine information from different rule antecedents.

$$y = w_1 x_1 + w_2 x_2 + \dots + w_n x_n.$$

Both approaches are well studied and established in the field of fuzzy automatic control.

The extreme cases are:

(1)  $Bel = P_1 = 1$ , which occurs when  $y = y_c = 1$  and implies absolute confidence that the specific profile is the one perfectly matching the observed face

(2)  $Bel = P_1 = 0$ , which occurs when  $y = 0$  and implies absolute confidence that the specific profile is not one matching the observed face

(3)  $Bel = 0, P_1 = 1$  which occurs when  $y = 1, y_c = 0$  and implies absolute ignorance.

#### CONCLUSIONS:

Facial expression analysis and classification systems based fuzzy rules for the representation of the knowledge

utilized by the expert system. In the case of facial expression analysis, where fuzzy inputs are the output of the imperfect process of feature extraction via image processing, conventional fuzzy rules and conventional rule evaluation methodologies are often inadequate and lead to extremely poor performance. In this paper, we have chosen to independently apply multiple image processing methodologies and fuse their results, by minimizing the uncertainty that is inherent in this process. Thus, the resulting system outperforms its conventional predecessor in cases where the observed facial expression does not strictly comply to the specified rules by missing some optional characteristic. The expert system has been successfully developed and tested for the diagnosis of other diseases. This approach is reliable and provides wide spread of information to help the physician in reaching a more logical conclusion for a more accurate diagnosis. The system has been successfully tested for disease diagnostics for number of combinations of healthy and diseased categories. With the help of this system, it is possible to know the degree of severity as well as the type of disease. This approach is reliable and provides wide spread of information to help the physician in reaching a more logical conclusion for a more accurate diagnosis. The system has been successfully tested for disease diagnostics for number of combinations of healthy and diseased categories.

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