

ADAPTIVE RULE-BASED FACIAL EXPRESSION RECOGNITION

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Abstract: This paper addresses the problem of emotion recognition in faces through an intelligent neuro-fuzzy system, which is capable of analysing facial features extracted following the MPEG-4 standard and classifying facial images according to the underlying emotional states, following rules derived from expression profiles. Results are presented which illustrate the capability of the developed system to analyse and recognise facial expressions in man-machine interaction applications.

1. Introduction

Current information processing and visualization systems are capable of offering advanced and intuitive means of receiving input and communicating output to their users. As a result, Man-Machine Interaction (MMI) systems that utilize multimodal information about their users' current emotional state are presently at the forefront of interest of the computer vision and artificial intelligence communities. Such interfaces give the opportunity to less technology-aware individuals, as well as handicapped people, to use computers more efficiently and thus overcome related fears and preconceptions. Besides this, most emotion-related facial gestures are considered to be universal, in the sense that they are recognized along different cultures. Therefore, the introduction of an "emotional dictionary" that includes descriptions and perceived meanings of facial expressions, so as to help infer the likely emotional state of a specific user, can enhance the affective nature of MMI applications.

Automatic emotion recognition in faces is a hard problem, requiring a number of pre-processing steps which attempt to detect or track the face, to locate characteristic facial regions such as eyes, mouth and nose on it, to extract and follow the movement of facial features, e.g., characteristic points in these regions, or model facial gestures using anatomic information about the face.

Most of the above techniques are based on a well-known system for describing "all visually distinguishable facial movements", called the Facial Action Coding System (FACS) [4], [6]. FACS is an anatomically oriented coding system, based on the definition of "action units" that cause facial movements. The FACS model has

inspired the derivation of facial animation and definition parameters in the framework of the ISO MPEG-4 standard [7]. In particular, the Facial Definition Parameter (FDP) set and the Facial Animation Parameter (FAP) set were designed in the MPEG-4 framework to allow the definition of a facial shape and texture, as well as the animation of faces reproducing expressions, emotions and speech pronunciation. By monitoring facial gestures corresponding to FDP feature points (FP) and/or FAP movements over time, it is possible to derive cues about user's expressions/emotions [1], [3].

In this work we present a methodology for analysing expressions. This is performed through a neuro-fuzzy system which first translates FP movements into FAPs and reasons on the latter to recognize the underlying emotion in facial video sequences.

2. Representation of emotion

The obvious goal for emotion analysis applications is to assign category labels that identify emotional states. However, labels as such are very poor descriptions, especially since humans use a daunting number of labels to describe emotion. Therefore we need to incorporate a more transparent, as well as continuous representation, that matches closely our conception of what emotions are or, at least, how they are expressed and perceived.

Activation-emotion space [3] is a representation that is both simple and capable of capturing a wide range of significant issues in emotion. It rests on a simplified treatment of two key themes:

- *Valence*: The clearest common element of emotional states is that the person is materially influenced by feelings that are “valenced”, i.e. they are centrally concerned with positive or negative evaluations of people or things or events; the link between emotion and valencing is widely agreed.
- *Activation level*: Research has recognized that emotional states involve dispositions to act in certain ways. A basic way of reflecting that theme turns out to be surprisingly useful. States are simply rated in terms of the associated activation level, i.e. the strength of the person's disposition to take some action rather than none.

The axes of the activation-evaluation space reflect those themes. The vertical axis shows activation level, the horizontal axis evaluation. A basic attraction of that arrangement is that it provides a way of describing emotional states which is more tractable than using words, but which can be translated into and out of verbal descriptions. Translation is possible because emotion-related words can be understood, at least to a first approximation, as referring to positions in activation-emotion space. Various techniques lead to that conclusion, including factor analysis, direct scaling, and others [16].

A surprising amount of emotional discourse can be captured in terms of activation-emotion space. Perceived full-blown emotions are not evenly distributed in activation-emotion space; instead they tend to form a roughly circular pattern. In this framework, identifying the center as a natural origin has several implications. Emotional strength can be measured as the distance from the origin to a given point in activation-

evaluation space. The concept of a full-blown emotion can then be translated roughly as a state where emotional strength has passed a certain limit. An interesting implication is that strong emotions are more sharply distinct from each other than weaker emotions with the same emotional orientation. A related extension is to think of primary or basic emotions as cardinal points on the periphery of an emotion circle (see Figure 1).

Activation-evaluation space is a surprisingly powerful device, and it has been increasingly used in computationally oriented research. However, it has to be emphasized that representations of that kind depend on collapsing the structured, high-dimensional space of possible emotional states into a homogeneous space of two dimensions. There is inevitably loss of information; and worse still, different ways of making the collapse lead to substantially different results. Extreme care is, thus, needed to ensure that collapsed representations are used consistently.

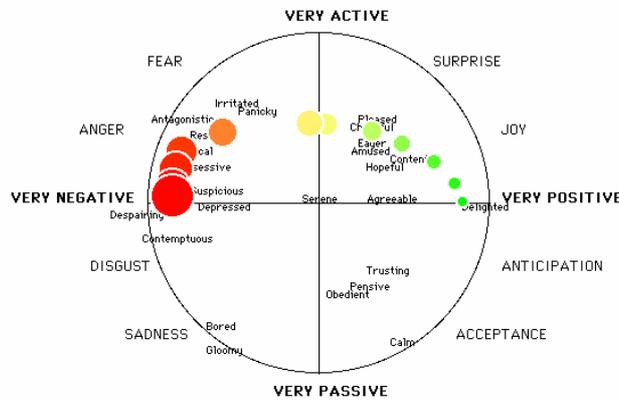


Fig. 1: The Activation-emotion space

3. Modelling Facial Expressions Using FAPs

Two basic issues should be addressed when modelling archetypal expression:

- (i) estimation of FAPs that are involved in their formation,
- (ii) definition of the FAP intensities.

Table 1 illustrates the description of “anger” and “fear”, using MPEG-4 FAPs. Descriptions for all archetypal expressions can be found in [1].

Table 1: FAP vocabulary for description of “anger” and “fear”

| | |
|-------|---|
| Anger | <i>lower_t_midlip (F₄), raise_b_midlip (F₅), push_b_lip (F₁₆), depress_chin (F₁₈), close_t_l_eyelid (F₁₉), close_t_r_eyelid (F₂₀), close_b_l_eyelid (F₂₁), close_b_r_eyelid (F₂₂), raise_l_i_eyebrow (F₃₁), raise_r_i_eyebrow (F₃₂), raise_l_m_eyebrow (F₃₃), raise_r_m_eyebrow (F₃₄), raise_l_o_eyebrow (F₃₅), raise_r_o_eyebrow (F₃₆), squeeze_l_eyebrow (F₃₇), squeeze_r_eyebrow (F₃₈)</i> |
|-------|---|

| | |
|------|---|
| Fear | <i>open_jaw (F₃), lower_t_midlip (F₄), raise_b_midlip (F₅), lower_t_lip_lm (F₈), lower_t_lip_rm (F₉), raise_b_lip_lm (F₁₀), raise_b_lip_rm (F₁₁), close_t_l_eyelid (F₁₉), close_t_r_eyelid (F₂₀), close_b_l_eyelid (F₂₁), close_b_r_eyelid (F₂₂), raise_l_i_eyebrow (F₃₁), raise_r_i_eyebrow (F₃₂), raise_l_m_eyebrow (F₃₃), raise_r_m_eyebrow (F₃₄), raise_l_o_eyebrow (F₃₅), raise_r_o_eyebrow (F₃₆), squeeze_l_eyebrow (F₃₇), squeeze_r_eyebrow (F₃₈)</i> |
|------|---|

Although FAPs are practical and very useful for animation purposes, they are inadequate for analysing facial expressions from video scenes or still images. In order to measure FAPs in real images and video sequences, it is necessary to define a way of describing them through the movement of points that lie in the facial area and that can be automatically detected. Such a description could gain advantage from the extended research on automatic facial point detection [10].

Quantitative modelling of FAPs can be implemented using the features labelled as f_i ($i=1..15$) in the third column of Table 2 [11]. The feature set employs FDP feature points that lie in the facial area. It consists of distances (noted as $s(x,y)$, where x and y correspond to FDP feature points ranked in terms of their belonging to specific facial areas [13]), some of which are constant during expressions and are used as reference points. It should be noted that not all FAPs can be modelled by distances between facial protuberant points (e.g. *raise_b_lip_lm_o*, *lower_t_lip_lm_o*). In such cases, the corresponding FAPs are retained in the vocabulary and their ranges of variation are experimentally defined based on facial animations. Moreover, some features serve for the estimation of the range of variation of more than one FAP (e.g. features f_{12} - f_{15}).

Table 2: Quantitative FAP modelling: (1) $s(x,y)$ is the Euclidean distance between FPs x and y , (2) $D_{i-NEUTRAL}$ refers to distance D_i with the face in neutral position

| FAP name | Main Feature for description | Utilized Main Feature |
|--|------------------------------|-----------------------------------|
| squeeze_l_eyebrow (F ₃₇) | $D_1=s(4.6,3.8)$ | $f_1= D_{1-NEUTRAL} - D_1$ |
| squeeze_r_eyebrow (F ₃₈) | $D_2=s(4.5,3.11)$ | $f_2= D_{2-NEUTRAL} - D_2$ |
| lower_t_midlip (F ₄) | $D_3=s(9.3,8.1)$ | $f_3= D_3 - D_{3-NEUTRAL}$ |
| raise_b_midlip (F ₅) | $D_4=s(9.3,8.2)$ | $f_4= D_{4-NEUTRAL} - D_4$ |
| raise_l_i_eyebrow (F ₃₁) | $D_5=s(4.2,3.8)$ | $f_5= D_5 - D_{5-NEUTRAL}$ |
| raise_r_i_eyebrow (F ₃₂) | $D_6=s(4.1,3.11)$ | $f_6= D_6 - D_{6-NEUTRAL}$ |
| raise_l_o_eyebrow (F ₃₅) | $D_7=s(4.6,3.12)$ | $f_7= D_7 - D_{7-NEUTRAL}$ |
| raise_r_o_eyebrow (F ₃₆) | $D_8=s(4.5,3.7)$ | $f_8= D_8 - D_{8-NEUTRAL}$ |
| raise_l_m_eyebrow (F ₃₃) | $D_9=s(4.4,3.12)$ | $f_9= D_9 - D_{9-NEUTRAL}$ |
| raise_r_m_eyebrow (F ₃₄) | $D_{10}=s(4.3,3.7)$ | $f_{10}= D_{10} - D_{10-NEUTRAL}$ |
| open_jaw (F ₃) | $D_{11}=s(8.1,8.2)$ | $f_{11}= D_{11} - D_{11-NEUTRAL}$ |
| close_t_l_eyelid (F ₁₉) –close_b_l_eyelid (F ₂₁) | $D_{12}=s(3.2,3.4)$ | $f_{12}= D_{12} - D_{12-NEUTRAL}$ |
| close_t_r_eyelid (F ₂₀) –close_b_r_eyelid (F ₂₂) | $D_{13}=s(3.1,3.3)$ | $f_{13}= D_{13} - D_{13-NEUTRAL}$ |
| stretch_l_cornerlip (F ₆) (stretch_l_cornerlip_o)(F ₅₃) – stretch_r_cornerlip (F ₇) (stretch_r_cornerlip_o) (F ₅₄) | $D_{14}=s(8.4,8.3)$ | $f_{14}= D_{14} - D_{14-NEUTRAL}$ |
| squeeze_l_eyebrow (F ₃₇) AND squeeze_r_eyebrow (F ₃₈) | $D_{15}=s(4.6,4.5)$ | $f_{15}= D_{15-NEUTRAL} - D_{15}$ |

3.1 Profiles Creation

An archetypal *expression profile* is a set of FAPs accompanied by the corresponding range of variation, which, if animated, produces a visual representation of the corresponding emotion. Typically, a profile of an archetypal expression consists of a subset of the corresponding FAPs' vocabulary coupled with the appropriate ranges of variation. Table 3 and Figure 2 illustrate different profiles of "fear". Detailed description of profiles creation can be found in [13].

Table 3: Profiles of the expression "fear"

| <i>Profiles</i> | <i>FAPs and Range of Variation</i> |
|-----------------|--|
| $P_F^{(0)}$ | $F_3 \in [102,480], F_5 \in [83,353], F_{19} \in [118,370], F_{20} \in [121,377], F_{21} \in [118,370], F_{22} \in [121,377], F_{31} \in [35,173], F_{32} \in [39,183], F_{33} \in [14,130], F_{34} \in [15,135]$ |
| $P_F^{(1)}$ | $F_3 \in [400,560], F_5 \in [307,399], F_{19} \in [-530,-470], F_{20} \in [-523,-463], F_{21} \in [-530,-470], F_{22} \in [-523,-463], F_{31} \in [460,540], F_{32} \in [460,540], F_{33} \in [460,540], F_{34} \in [460,540], F_{35} \in [460,540], F_{36} \in [460,540]$ |
| $P_F^{(2)}$ | $F_3 \in [400,560], F_5 \in [-240,-160], F_{19} \in [-630,-570], F_{20} \in [-630,-570], F_{21} \in [-630,-570], F_{22} \in [-630,-570], F_{31} \in [460,540], F_{32} \in [460,540], F_{37} \in [60,140], F_{38} \in [60,140]$ |
| $P_F^{(3)}$ | $F_3 \in [400,560], F_5 \in [-240,-160], F_{19} \in [-630,-570], F_{20} \in [-630,-570], F_{21} \in [-630,-570], F_{22} \in [-630,-570], F_{31} \in [460,540], F_{32} \in [460,540], F_{33} \in [360,440], F_{34} \in [360,440], F_{35} \in [260,340], F_{36} \in [260,340], F_{37} \in 0, F_{38} \in 0$ |
| $P_F^{(4)}$ | $F_3 \in [400,560], F_5 \in [-240,-160], F_8 \in [-120,-80], F_9 \in [-120,-80], F_{10} \in [-120,-80], F_{11} \in [-120,-80], F_{19} \in [-630,-570], F_{20} \in [-630,-570], F_{21} \in [-630,-570], F_{22} \in [-630,-570], F_{31} \in [460,540], F_{32} \in [460,540], F_{33} \in [360,440], F_{34} \in [360,440], F_{35} \in [260,340], F_{36} \in [260,340], F_{37} \in 0, F_{38} \in 0$ |

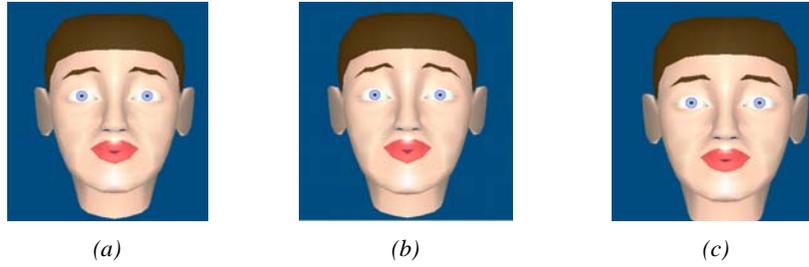


Fig. 2: MPEG-4 face model: animated profiles of "fear"

The rules used in the facial expression recognition system have derived from the created profiles.

4. The Facial Expression Recognition System

In general, six general categories are used, each one characterized by an archetypal emotion. Within each category, intermediate expressions are described by different emotional and optical intensities, as well as minor variations in expression details.

A hybrid intelligent emotion recognition system is presented next, consisting of a connectionist (subsymbolic) association part and a symbolic processing part as shown in Figure 3. In this modular architecture the *Connectionist Association Module* (CAM) provides the system with the ability to ground the symbolic predicates (associating them with the input features), while the *Adaptive Resource Allocating Neuro Fuzzy Inference System* (ARANFIS) [14] implements the semantic reasoning process.

The system takes as input a feature vector \underline{f} that corresponds to the features f_i shown in the third column of Table 2. The particular values of \underline{f} are associated to the symbolic predicates – i.e., FAP values shown in the first column of the same table – through the CAM subsystem. The CAM's outputs form the input vector \underline{G} to the fuzzy inference subsystem, with the elements of \underline{G} expressing the observed value of a corresponding FAP. The CAM consists of a neural network that dynamically forms the above association, providing the emotion analysis system with the capability to adapt to peculiarities of the specific user. In the training phase, the CAM learns to analyse the feature space and provide estimates of the FAP intensities (e.g. low, high, medium). This step requires: (a) Using an appropriate set of training inputs f , (b) Collecting a representative set T_f of pairs (f, s) to be used for network training, and (c) Estimating a parameter set \mathbf{W}_f , which maps the input space F to the symbolic predicate space S .

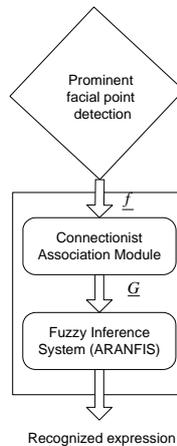


Fig. 3: The emotion analysis system

ARANFIS evaluates the symbolic predicates provided by the CAM subsystem and performs the conceptual reasoning process that finally results to the degree at which the output situations – expressions- are recognised. ARANFIS [14] is a variation of the SuPFuNIS system [5] that enables structured learning. ARANFIS embeds fuzzy rules of the form “If s_1 is LOW and s_2 is HIGH then y is [expression - e.g. anger],

where LOW, and HIGH are fuzzy sets defined, respectively, on input universes of discourse (UODs) and the output is a fuzzified expression.

Input nodes represent the domain variables-predicates and output nodes represent the target variables or classes. Each hidden node represents a rule, and input-hidden node connections represent fuzzy rules antecedents. Each hidden-output node connection represents a fuzzy-rule consequent. Fuzzy sets corresponding to linguistic labels of fuzzy *if-then* rules (such as LOW and HIGH) are defined on input and output UODs and are represented by symmetric Gaussian membership functions specified by a center and spread. Fuzzy weights w_{ij} from input nodes i to rule nodes j are thus modeled by the center w_{ij}^c and spread w_{ij}^s of a Gaussian fuzzy set and denoted by $w_{ij}=(w_{ij}^c, w_{ij}^s)$. In a similar fashion, consequent fuzzy weights from rule nodes j to output nodes k are denoted by $v_{jk}=(v_{jk}^c, v_{jk}^s)$. The spread of the i -th fuzzified input element is denoted as s_i^s while s_i^c is obtained as the crisp value of the i -th input element. Knowledge in the form of *if-then* rules can be either derived through clustering of input data or be embedded directly as a-priori knowledge.

It should be noted that in the previously described emotion analysis system, no hypothesis has been made about the type of recognizable emotions, that can be either archetypal or non-archetypal ones.

5. Application Study

Let us examine the situation where a PC camera captures its user's image. In the pre-processing stage, skin color segmentation is performed and the face is extracted. A snake is then used to smooth the face mask computed at the segmentation subsystem output. Then, the facial points are extracted, and point distances are calculated. Assuming that the above procedure is first performed for the user's neutral image, storing the corresponding facial points, the differences between them and the FPs of the current facial image of the user are estimated.

An emotion analysis system is created in [12]. In the system interface shown in Figure 4, one can observe an example of the calculated FP distances, the rules activated by the neurofuzzy system and the recognised emotion ('surprise').

To train the CAM system, we used the PHYSTA database in [2] as training set and the EKMAN database [4] as evaluation test. The coordinates of the points have been marked by hand for 300 images in the training set and 110 images in the test set. The CAM consisted of 17 neural networks, each of which associated less than 10 FP input distances (from the list of 23 distances defined as in Table 1 and mentioned in Table 4) to the states (high, medium, low, very low) of a corresponding FAP, and was trained using a variant of backpropagation learning algorithm [15]. Moreover, 41 rules were appropriately defined, half of them taken from the associated literature and half of them derived through training [13], and inserted in the ARANFIS subsystem.



Fig. 4: System Interface

Table 5 illustrates the confusion matrix of the mean degree of beliefs (*not the classification rates*), for each of the archetypal emotions *anger*, *joy*, *disgust*, *surprise* and the *neutral* condition, computed over the EKMAN dataset, which verifies the good system performance, while Table 6 shows the more often activated rule for each of the above expressions.

Table 4: Training the CAM module

| FAP name | Primary distance | Other distances | States (VL-VeryLow, L-Low, M-Medium, H-High) |
|--|------------------|--|--|
| Squeeze_l_eyebrow (F ₃₇) | d ₂ | d ₆ , d ₈ , d ₁₀ , d ₁₇ , d ₁₉ , d ₁₅ | L, M, H |
| Squeeze_r_eyebrow (F ₃₈) | d ₁ | d ₅ , d ₇ , d ₉ , d ₁₆ , d ₁₈ , d ₁₅ | L, M, H |
| Lower_t_midlip (F ₄) | d ₃ | d ₁₁ , d ₂₀ , d ₂₁ | L, M |
| Raise_b_midlip (F ₅) | d ₄ | d ₁₁ , d ₂₀ , d ₂₁ | VL, L, H |
| Raise_l_l_eyebrow (F ₃₁) | d ₆ | d ₂ , d ₈ , d ₁₀ , d ₁₇ , d ₁₉ , d ₁₅ | L, M, H |
| Raise_r_l_eyebrow (F ₃₂) | d ₅ | d ₁ , d ₇ , d ₉ , d ₁₆ , d ₁₈ , d ₁₅ | L, M, H |
| Raise_l_o_eyebrow (F ₃₅) | d ₈ | d ₂ , d ₆ , d ₁₀ , d ₁₇ , d ₁₉ , d ₁₅ | L, M, H |
| Raise_r_o_eyebrow (F ₃₆) | d ₇ | d ₁ , d ₅ , d ₉ , d ₁₆ , d ₁₈ , d ₁₅ | L, M, H |
| Raise_l_m_eyebrow (F ₃₃) | d ₁₀ | d ₂ , d ₆ , d ₈ , d ₁₇ , d ₁₉ , d ₁₅ | L, M, H |
| Raise_r_m_eyebrow (F ₃₄) | d ₉ | d ₁ , d ₅ , d ₇ , d ₁₆ , d ₁₈ , d ₁₅ | L, M, H |
| Open_jaw (F ₃) | d ₁₁ | d ₄ | L, M, H |
| close_left_eye (F ₁₉ , F ₂₁) | d ₁₃ | - | L, H |
| close_right_eye (F ₂₀ , F ₂₂) | d ₁₂ | - | L, H |
| Wrinkles_between_eyebrows (F ₃₇ , F ₃₈) | d ₁₅ | d ₁ , d ₂ , d ₅ , d ₆ , d ₇ , d ₈ , d ₉ , d ₁₆ , d ₁₇ , d ₁₈ , d ₁₉ | L, M, H |
| Raise_l_cornerlip_o (F ₅₃) | d ₂₃ | d ₃ , d ₄ , d ₁₁ , d ₂₀ , d ₂₁ , d ₂₂ | L, M, H |
| Raise_r_cornerlip_o (F ₅₄) | d ₂₂ | d ₃ , d ₄ , d ₁₁ , d ₂₀ , d ₂₁ , d ₂₃ | L, M, H |
| widening_mouth (F ₆ , F ₇) | d ₁₁ | d ₃ , d ₄ , d ₁₄ | L, M, H |

Table 5: Results in images of different expressions

| | Anger | Joy | Disgust | Surprise | Neutral |
|----------|-------|-------|---------|----------|---------|
| Anger | 0.611 | 0.01 | 0.068 | 0 | 0 |
| Joy | 0.006 | 0.757 | 0.009 | 0 | 0.024 |
| Disgust | 0.061 | 0.007 | 0.635 | 0 | 0 |
| Surprise | 0 | 0.004 | 0 | 0.605 | 0.001 |
| Neutral | 0 | 0.123 | 0 | 0 | 0.83 |

Table 6: Activated rules

| Expressions | Rule more often activated (% of examined photos) |
|-------------|---|
| Anger | [<i>open_jaw_low, lower_top_midlip_medium, raise_bottom_midlip_high, raise_left_inner_eyebrow_low, raise_right_inner_eyebrow_low, raise_left_medium_eyebrow_low, raise_right_medium_eyebrow_low, squeeze_left_eyebrow_high, squeeze_right_eyebrow_high, wrinkles_between_eyebrows_high, raise_left_outer_cornerlip_medium, raise_right_outer_cornerlip_medium</i>] (47%) |
| Joy | [<i>open_jaw_high, lower_top_midlip_low, raise_bottom_midlip_verylow, widening_mouth_high, close_left_eye_high, close_right_eye_high</i>] (39%) |
| Disgust | [<i>open_jaw_low, lower_top_midlip_low, raise_bottom_midlip_high, widening_mouth_low, close_left_eye_high, close_right_eye_high, raise_left_inner_eyebrow_medium, raise_right_inner_eyebrow_medium, raise_left_medium_eyebrow_medium, raise_right_medium_eyebrow_medium, wrinkles_between_eyebrows_medium</i>] (33%) |
| Surprise | [<i>open_jaw_high, raise_bottom_midlip_verylow, widening_mouth_low, close_left_eye_low, close_right_eye_low, raise_left_inner_eyebrow_high, raise_right_inner_eyebrow_high, raise_left_medium_eyebrow_high, raise_right_medium_eyebrow_high, raise_left_outer_eyebrow_high, raise_right_outer_eyebrow_high, squeeze_left_eyebrow_low, squeeze_right_eyebrow_low, wrinkles_between_eyebrows_low</i>] (71%) |
| Neutral | [<i>open_jaw_low, lower_top_midlip_medium, raise_left_inner_eyebrow_medium, raise_right_inner_eyebrow_medium, raise_left_medium_eyebrow_medium, raise_right_medium_eyebrow_medium, raise_left_outer_eyebrow_medium, raise_right_outer_eyebrow_medium, squeeze_left_eyebrow_medium, squeeze_right_eyebrow_medium, wrinkles_between_eyebrows_medium, raise_left_outer_cornerlip_medium, raise_right_outer_cornerlip_medium</i>] (70%) |

6. Conclusions

Facial expression recognition has been investigated in this paper, based on neuro-fuzzy analysis of facial features extracted from a user's image following the MPEG-4 standard. A hybrid intelligent system has been described that performs extraction of fuzzy predicates and inference, providing an estimate of the user's emotional state. Work is currently been done, extending and validating the above developments in the framework of the IST ERMIS project [12].

References:

1. N. Tsapatsoulis, A. Raouzaïou, S. Kollias, R. Cowie and E. Douglas-Cowie, "Emotion Recognition and Synthesis based on MPEG-4 FAPs," in *MPEG-4 Facial Animation*, Igor Pandzic, R. Forchheimer (eds), John Wiley & Sons, UK, 2002.

2. EC TMR Project "PHYSTA: Principled Hybrid Systems: Theory and Applications," <http://www.image.ece.ntua.gr/physta>.
3. R. Cowie, E. Douglas-Cowie, N. Tsapatsoulis, G. Votsis, S. Kollias, W. Fellenz and J. Taylor, "Emotion Recognition in Human-Computer Interaction", *IEEE Signal Processing Magazine*, 18 (1), p. 32-80, January 2001.
4. P. Ekman and W. Friesen, *The Facial Action Coding System*, Consulting Psychologists Press, San Francisco, CA, 1978 (<http://www.paulekman.com>)
5. S. Paul and S. Kumar, "Subsethood-Product Fuzzy Neural Inference System (SuPFuNIS)," *IEEE Trans. on Neural Networks*, vol. 13, no 3, pp. 578-599, May 2002.
6. ISO/IEC JTC1/SC29/WG11 N3205, "Multi-users technology (Requirements and Applications)", December 1999, Maui
7. A.M. Tekalp, J. Ostermann, "Face and 2-D mesh animation in MPEG-4", *Signal Processing: Image Communication*, Vol. 15, No. 4-5 (Tutorial Issue on the MPEG-4 Standard), pp. 387-421, January 2000.
8. EC TMR Project PHYSTA Report, "Development of Feature Representation from Facial Signals and Speech," January 1999.
9. P. Ekman, "Facial expression and Emotion," *Am. Psychologist*, vol. 48 pp.384-392, 1993
10. P. Chellapa, C. Wilson and S. Sirohey, "Human and Machine Recognition of Faces: A Survey," *Proceedings of IEEE*, vol.83, no. 5, pp. 705-740, 1995.
11. K.Karpouzis, N. Tsapatsoulis and S. Kollias, "Moving to Continuous Facial Expression Space using the MPEG-4 Facial Definition Parameter (FDP) Set," in *Proc. of the Electronic Imaging 2000 Conference of SPIE*, San Jose, CA, USA, January 2000.
12. IST Project: Emotionally Rich Man-Machine Interaction Systems (ERMIS), 2001-2003
13. A. Raouzaïou, N. Tsapatsoulis, K. Karpouzis and S. Kollias, "Parameterized facial expression synthesis based on MPEG-4", *EURASIP Journal on Applied Signal Processing*, Vol. 2002, No. 10, pp. 1021-1038, Hindawi Publishing Corporation, October 2002.
14. M Pertselakis, N. Tsapatsoulis, S. Kollias and A. Stafylopatis, "An Adaptive Resource Allocating Neural Fuzzy Inference System," in *Proc. of "IEEE Intelligent Systems Application to Power Systems" (ISAP'03)*, Lemnos, Greece, 2003.
15. S. Haykin, "Neural Networks: a Comprehensive Foundation", Macmillan College Publishing Company, Inc., New York, 1994
16. C. M. Whissel, "The dictionary of affect in language", in R. Plutchnik & H. Kellerman (Eds), *Emotion: Theory, research and experience: vol 4, The measurement of emotions*, Academic Press, New York 1989.