A Fuzzy Reasoning Model for Recognition of Facial Expressions

Oleg Starostenko[1], Renan Contreras[1], Vicente Alarcón Aquino[1], Leticia Flores Pulido[1], Jorge Rodríguez Asomoza[1], Oleg Sergiyenko[2], and Vira Tyrsa[3]

[1] Research Center CENTIA, Department of Computing, Electronics and Mechatronics, Universidad de las Américas, 72820, Puebla, Mexico
{oleg.starostenko; renan.contrerasgz; vicente.alarcon; leticia.florespo; jorge.rodriguez}@udlap.mx
[2] Engineering Institute, Autonomous University of Baja California, Blvd. Benito Juárez, Insurgentes Este, 21280, Mexicali, Baja California, Mexico
srgnk@iing.mxl.uabc.mx
[3] Universidad Politécnica de Baja California, Mexicali, Baja California, Mexico
vera-tyrsa@yandex.ru

Abstract. In this paper we present a fuzzy reasoning model and a designed system for Recognition of Facial Expressions, which can measure and recognize the intensity of basic or non-prototypical emotions. The proposed model operates with encoded facial deformations described in terms of either Ekman´s Action Units (AUs) or Facial Animation Parameters (FAPs) of MPEG-4 standard and provides recognition of facial expression using a knowledge base implemented on knowledge acquisition and ontology editor Protégé. It allows modeling of facial features obtained from geometric parameters coded by AUs - FAPs and from a set of rules required for classification of measured expressions. This paper also presents a designed framework for fuzzyfication of input variables of a fuzzy classifier based on statistical analysis of emotions expressed in video records of standard Cohn-Kanade's and Pantic´s MMI face databases. The proposed system designed according to developed model has been tested in order to evaluate its capability for detection, indexing, classifying, and interpretation of facial expressions.

Keywords. Facial expression recognition, emotion interpretation, knowledge-based framework, rules-based fuzzy classifier.

Un modelo de razonamiento difuso para reconocimiento de expresiones faciales

Resumen. En este artículo presentamos un sistema de razonamiento difuso capaz de reconocer y medir la intensidad de cualquier expresión facial prototípica o no prototípica. El modelo propuesto utiliza como entrada las deformaciones faciales codificadas ya sea en términos de AUs (Ekman FACS) o FAPs (MPEG-4) y provee reconocimiento de expresiones faciales utilizando una base de conocimiento la cual fue implementada utilizando el sistema de adquisición de conocimiento y editor de ontologías Protégé. Esta base de conocimiento permite, además de la creación de modelos de características faciales obtenidos a partir de parámetros geométricos y codificados en términos de AUs y FAPs, también la definición de las reglas requeridas para la clasificación de las expresiones. En este artículo también se presenta un framework diseñado para codificación de las variables de entrada al clasificador difuso basado en los resultados obtenidos del análisis estadístico de las emociones expresadas en grabaciones de video en base estándar de caras creada por Cohn-Kanade y Pantic. El sistema propuesto fue evaluado con el propósito de analizar su capacidad de detección, indexado, clasificación e interpretación de expresiones faciales.

Palabras clave. Reconocimiento de expresiones faciales, la interpretación de la emoción, conocimiento marco, clasificador difuso basado en reglas.

1 Introduction

Fuzzy Logic may be considered as a field of artificial intelligence. It proposes a type of reasoning, where logical statements are not only *true* or *false* but can also range from *almost* *certain* to *very unlikely*. Software systems based on fuzzy-logic allow computers to mimic human reasoning more precisely, so that decisions can be taken with incomplete or uncertain data.

The fuzzy approach and its combination with neural networks have been successfully used for pattern recognition and for image indexing and interpretation [25], [15]. In the area of facial expression recognition the application of a fuzzy reasoning remains marginal despite that some researchers have successfully used classifying systems, which emulate the way humans identify prototypical expression [2], [9], [18]. The emotion recognition system proposed by Chakraborty uses Fuzzy C-Mean clustering with three levels of fuzzyfication (high, medium, and low) processing only three facial features, namely, eyebrow length, eye and mouth opening. That does not allow obtaining precise recognition of emotions because some of them have similar facial features (for example, sadness and fear or surprise and fear have similar eye and mouth opening) [2].

An interesting hybrid classifier was proposed in [9], where a combination of fuzzy-and case-based reasoning is used for recognition of facial expressions. The average precision of recognition for basic emotions is about 70-80%.

Recognition of 32 facial action units (AUs) representing muscular facial activity is provided by the emotion recognition system proposed in [18]. The system uses rule-based reasoning for recognition of facial gestures in frontal images. However, this system shows about 86% precision of recognition processing only AUs and the fuzzy classifier does not measure the intensity of recognized basic emotions.

Some well-known systems use other types of classifier based on the multiple adaptive neuro-fuzzy inference approach [6], support vector machine [10], hidden Markov model [28], evolutionary algorithm [17], genetic algorithm [22], etc. Even though these approaches may extract and interpret facial features, there are no reports concerning how they may link standard facial actions with particular formal models or rules for automatic emotion interpretation. Additionally, the precision of recognition is low (about 70-85%) and only basic emotions without a quantitative measurement of intensity of facial expression are interpreted [23].

Usually the systems for emotion interpretation are based on two parts: a module for generation of feature vector corresponding to the facial expression in the analyzed image (described by pixel position, colors, shapes, regions, etc.) and a classification module that recognizes the facial expression and describes its intensity.

Some facial feature extraction techniques used in well-known systems are based on Gabor Wavelets, Active Appearance and Geometric Models [26], Principal Components Analysis and Hierarchical Radial Basis Function Network [12], Optical Flow and Deformable Templates [13], Discrete Cosine Transform and Neural Networks [1], Multilevel Hidden Markov Models [11], Dynamic Bayesian networks [24], and others. The common disadvantages of these systems are the presence of errors during spatial sampling, restrictions for input visual queries, which must have small number of well-defined and separated faces without occlusion, sensitivity to scaling or rotation of analyzed regions, low precision of recognition if objects in image have week borders or complex background. The analysis of factors like tolerance to deformation, robustness against noise, feasibility of indexing of facial expression, significant amount of required memory are other factors that must be taken into account during development of models for emotion interpretation.

In this paper, we present a model for fuzzy reasoning applied to recognition of facial expressions and measurement of their intensity using standard Ekman´s AUs (Action Units), FAPs (Facial Animation Parameter) and FDPs (Facial Definition Parameter) of MPEG-4 standard. Intuitively, we expect that this approach allows creating novel systems for automatic facial feature detection as well as recognition and interpretation of basic and non-prototypical emotions.

Action units (AUs) represent muscular activity that corresponds to basic and unique facial changes, which may be classified and used for description of complex facial expression. FAPs (Facial Animation Parameters) are sets of parameters used in animating MPEG-4 model that defines reproduction of emotions from facial expressions. Each parameter set is closely related to muscle actions. The definition of FAPs is based on fiducial points defined by a manual or automatic tool for extraction of face features, which are called FDPs (Facial Definition Parameters). The readers interested in this subject, may review [4] or [7].

The contributions of our research are the proposed fuzzy reasoning model, a knowledge database, and the designed fuzzy inference system for emotion recognition. The focus of this research does not consist in extraction of facial features. The input of fuzzy inference system is a set of images, which previously have been processed and facial features (fiducial points) expressed in AU or FDP standards already have been defined manually or using well-known automatic detection approaches reported in [9], (Chakraborty, 2009), (Maglogiannis, 2009), etc.

2 Knowledge-Based Framework

The proposed fuzzy system for emotion recognition consists of two principal modules. The first one is a knowledge-based (KDB) framework for modeling and indexing facial deformations by FAP and AU action units developed by authors according to well-known standards [4], [7]. The second module is used for recognizing facial expressions by fuzzy classifier providing interpretation of emotion intensity. In the proposed framework each basic emotion may be divided into some levels depending on the intensity of that emotion. The quantification of emotion intensity is handled empirically by measuring the range of geometrical displacement of fiducial points. There is a well-known approach for discriminating the qualitative levels of emotion intensity based on verbal descriptions of facial activities such as Trace, Slight, Pronounced, Severe, and Maximum but the perception of emotion is different for each person [19]. To reduce relative subjectivity and a lack of psychological meaning of emotional intensity levels, the statistical analysis of facial actions in Cohn-Kanade´s and Pantic´s image databases has been implemented [8], [19]. The proposed approach has not been widely used in well-known emotion classifiers, but we believe that this technique allows developing knowledge-based frameworks for emotion interpretation because the analysis of semantics of facial actions may be achieved by using rule-based descriptors and fuzzy reasoning.

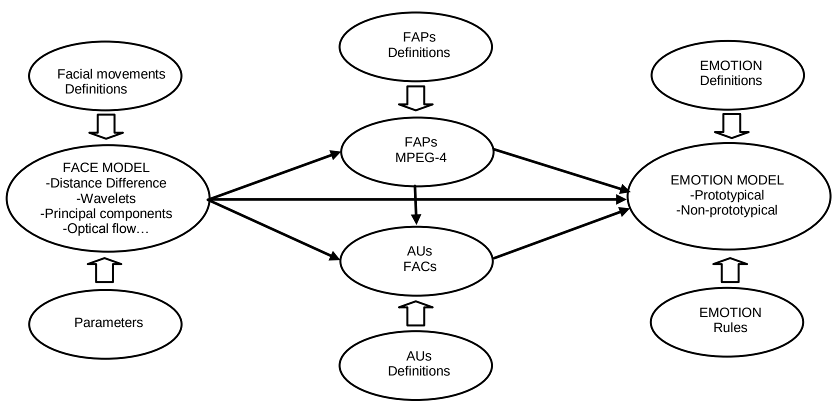


Fig. 1. Structure of a facial expression KDB based on FAPs and AUs

The proposed KDB framework allows measuring facial deformations in terms of distances between fiducial points modeled by FAPs and AUs and represented by rule-based descriptors used later in the process of fuzzyfication and interpretation of emotion intensity. The fiducial points represented by FDPs of MPEG-4 standard provides the automatic normalization of measured facial deformations making them invariant to the scale of input images. The framework also provides modeling facial deformations defining a set of rules for indexing and quantification of expressions. Fig. 1 shows the structure of a KDB framework that supports design of a fuzzy reasoning system.

The proposed approach is able to detect and measure any type of facial expression; however, it has been tested using six basic expressions (happiness, sadness, disgust, surprise, anger, and fear) and some combinations of them generating in this way non-prototypical expressions. We exploit relationships between the measured facial deformations and their mathematical description, by the corresponding AUs and FAPs and rules required for identification of expressions. This KDB framework has been implemented using the ontology editor Protégé that provides extensible, flexible, and plug-and-play environment that allows fast prototyping and application development [21].

For the KDB framework, four classes based on AUs, FAPs, and FDPs have been created. The *Emotion_Model* class provides creation of the rule-based models for emotion indexing using classes of the *Face_Model*. The *Face_Model* class defines different approaches for representation of face features. In particular, the instances of *Face_Model* class contain the basic facial actions (AUs, FAPs) that include the action number, its name, description, the direction of motion, involved facial muscles, the part of a face, where an action occurred, etc.

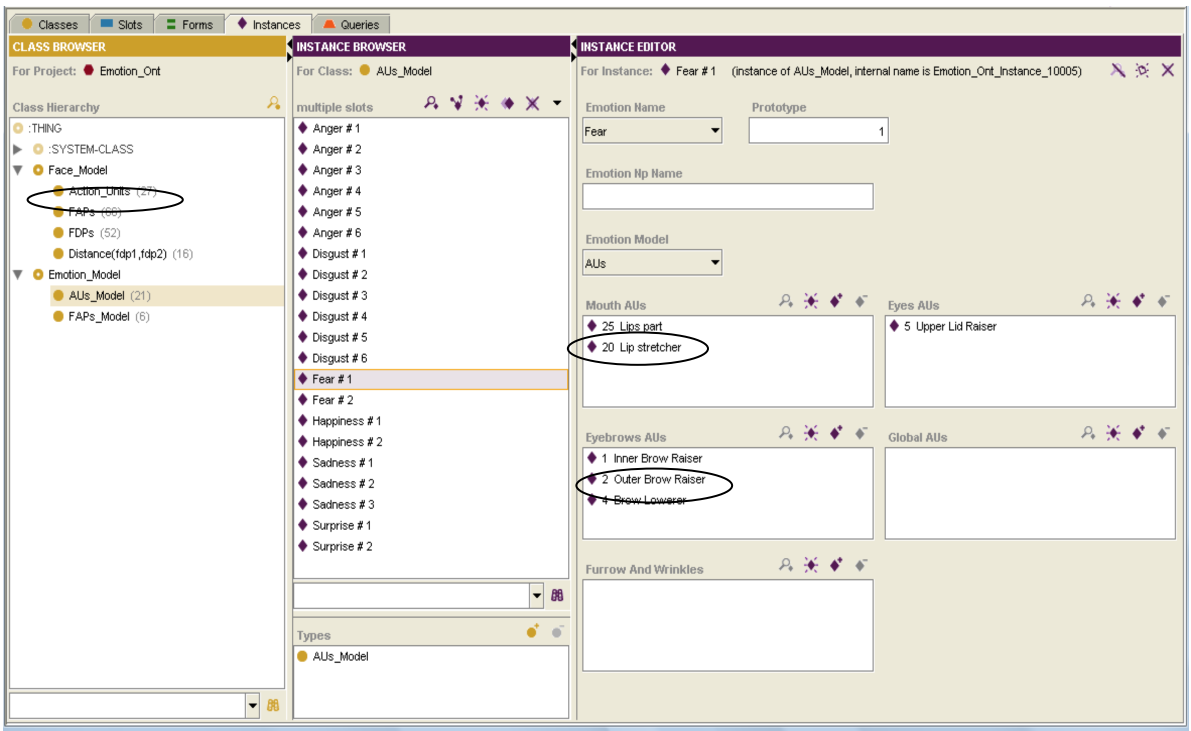


Fig. 2. The interface of the KDB framework for description of model classes and their instances

We propose indexing facial expressions based on measuring standard spatial variations of FDP positions described in the framework as *Distance(fdp1, fdp2)* implemented by our *Distance_Model* class discussed in the next section. The proposal to use the variation of positions in progress and not only the fixed length parameters of AUs and FAPs has been suggested by Zhang and Ji (2005). Fig. 2 shows the designed interface for description of classes with their corresponding attributes. The instances of the particular *Face_Model* class (see second column *Instance Browser*) contain the basic facial actions (AUs, FAPs) that serve for generation of a model for emotion description. The attributes of AUs, FAPs, and their representation by FDPs are defined in the third column *Instance Editor*. An instance is related to the mathematical description of facial motion by AUs or FAPs linking them to basic emotions.

For each AU or FAPs, an instance includes the action number, its name, description, the direction of motion, involved facial muscles, etc. For example, the instances of Face_Model class that includes particular AUs represent the encoding of Fear#1 (low intensity) emotion by Mouth and Eyebrows as it is emphasized in Fig. 2. In the same way, the instances of the Emotion_Model based on the FAPs_Model class may be modeled as well as the framework may be extended with new non-standard classes.The advantage of the proposed framework is that the classes and instances with attributes represent knowledge about facial expressions, and parameters of any model may be automatically converted to parameters of each other. For example, if input feature vector corresponding to a particular emotion is created on the basis of the non-standard *Distance(fdp1,fdp2)* model, its parameters may be immediately represented by the standard AUs or FAPs attributes and vice versa.

3 The Proposed Facial Model

The proposed facial model based on the analysis of nineteen FDPs and fifteen distances between fiducial reference points has been adopted. It describes all necessary facial actions defining either basic or non-prototypical emotions. Fig. 3 shows the selected FDPs with corresponding number of associated FAPs. Some FDPs are reference points which are remained static during facial deformation. The FDPs used define the *Distance_Class* that represent distances *Distance(fdp1,fdp2)* between fiducial reference points and particular FDPs (see Fig. 3). FAP represents facial changes of emotional expression with respect to the neutral expression. The difference *Distance(fdp1,fdp2)* quantifies facial changes in terms of units defined by MPEG-4 standard. Table 1 shows the fifteen instances (column Dd) of the *Distance_Class* chosen for our model, the geometric definitions of these distances (FDPs Differences), the measurement units (ENS - Eye-Nose Separation, ES - Eye Separation, IRISD - Iris Diameter, *MW* - Mouth Width , *MNS* - Mouth-Nose Separation), the relations with FAPs, and the actions, which those FAPs describe.

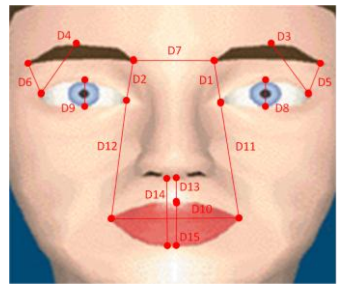


Fig. 3. FDPs used for recognizing facial expressions and definition of *Distance_Class* instances

Table 1. Description of instances in the *DistanceClass*

Dd	FDPs Differ.	Units	FDP	Action Description
D1	d{3.11,4.1}	ENS	31	raise l i eyebrow
D2	d{3.8, 4.2}	ENS	32	raise r i eyebrow
D3	d{3.7, 4.3}	ENS	33	raise l m eyebrow
D4	d{3.12, 4.4}	ENS	34	raise r m eyebrow
D5	d{3.7, 4.5}	ENS	35	raise l o eyebrow
D6	d{3.12, 4.6}	ENS	36	raise r o eyebrow
D7	d{4.1, 4.2}	ES		squeeze l/r eyebrow
D8	d{3.3, 3.1}	IRISD	21-19	close t/b l eyelid
D9	d{3.4, 3.2}	IRISD	22-20	close t/b r eyelid
D10	d{8.3, 8.4}	MW	53-54	stretch l/r cornerlip
D11	d{3.11, 8.3}	ENS	59	raise l cornerlip o
D12	d{3.8, 8.4}	ENS	60	raise r cornerlip o
D13	d{9.15, 8.1}	MNS		lower t midlip
D14	d{9.15, 8.2}	MNS		raise b midlip
D15	d{8.1, 8.2}	MNS	51-52	raise b/t midlip

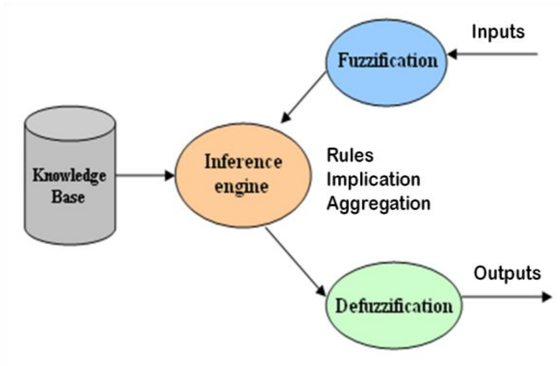


Fig. 4. Fuzzyfication-defuzzyfication processes for facial expression recognition

Table 2. AUs parameters determined for Kanade´s database

FACs	Dist.	Max	Min	Mean	Deviation
AU1	D1	339.02	0	120.55	84.52
	D2	383.92	0	123.44	88.42
AU2	D5	190.23	0	72.16	60.02
	D6	172.25	0	35.08	67.66
AU4	D1	0	-264.2	-42.54	90.92
	D2	0	-243.63	-38.47	92.88
	D3	0	-176.41	-31.23	68.42
	D4	0	-125.68	-6.2	61.99
	D5	0	-120.53	-35.26	43.4
	D6	0	-137.58	-29.92	53.46
	D7	0	-216.24	-67.69	65.2
AU5	D8	429.14	0	129.51	221.11
	D9	474.65	0	136.61	243.04
AU7	D8	0	-677.76	-288.97	171.72
	D9	0	-511.21	-318.66	148.63
AU10	D13	0	-294.11	-171.46	85.75
AU12	D10	517.28	0	273.19	147.06
	D11	0	-267.11	-129.71	103.15
	D12	0	-268.58	-140.29	122.95
AU15	D11	438.04	0	116.17	125.59
	D12	526.43	0	118.1	152.28
AU16	D14	668.44	0	306.39	247.81
AU20	D10	345.04	0	208.07	116.2
	D15	528.24	0	282.48	144.23
AU25	D15	2248.76	0	676.64	577.28
AU27	D10	0	-230.91	-108.4	62.52
	D15	2248.76	0	1440.71	401.93

Some reports such as Plutchik (2001), Pantic, (2005), and Esau (2007) suggest a geometrical model of face, which includes not only distances but also angles between the lines connecting the standard FDPs. However, this approach does not contribute significant precision and makes the processing too complex [23].

4 Fuzzyfication of Distance Instances

The fundamental process of fuzzy reasoning is fuzzyficacion of input variables and definition of the corresponding membership functions used for indexing facial deformations. The input variables between fiducial points are FAPs representing variation of distances that compose standard database of indexed facial expressions particularly, from Kanade´s and Pantic´s databases [8], [19]. The proposed fuzzyfication-defuzzyfication processes by the applied Inference engine are shown in Fig.4Each database consists of approximately 500 records with expression of different emotions by 100 subjects in the frontal position. Accompanying meta-data include annotation of FAC action units and emotion specified expressions. Recorded videos show a series of 23 facial muscle motions described by a combination of action units (e.g., AU1+AU2 means the inner and outer brows raised).

Each record begins with a neutral or nearly neutral emotion (neutral face) finishing with a required target emotion. Table 2 shows the results of quantification of the distance differences (see Fig. 3) between fiducial points describing maximum and minimum values, mean, and standard deviation for each one associated with the particular AU.

Recall that the difference in distances is measured between a neutral face and a face with any action expressing an emotion. The similar results have been obtained after analysis of emotion representation by AUs using either Kanade´s or Pantic´s database. In Table 2, we already have quantitative definition of action units, which may be used for continuous interpretation of emotion.

For measuring intensity of emotional expression, the Gaussian function has been used applying the following equation

$$f(x,\sigma,c) = e^{\frac{-(x-c)^2}{2\sigma^2}} \qquad (1)$$

These parameters are determined by the statistical analysis mentioned, where *c* defines the position of the peak and *σ* controls the width of the bell shaped Gaussian curve.

The fuzzyfication process may be explained analyzing a behavior of any action unit, for example, AU12. According to the results of statistical analysis made for AU12 (see Table 2), the range of its distance variable, for example, D10, is between 0 and 517.20 MWs (Mouth Width). For each and all variables, we have defined three levels of emotion intensity (*low+, medium+,* and *high+*) dividing the range of distance variation in the corresponding proportion. Having already defined the middle section, we compute the Gaussian functions for low and high sections. Additionally, a saturation level is included taking into account the maximum possible value of a facial deformation.

Fig. 5 shows the designed GUI for visualization of fuzzyfication process for variables D10 as a part of the measurement of AU12 intensity using the Gaussian as well as the membership functions. Membership function parameters depend on input variable ranges and the number of selected distances to describe particular AU obtained from the statistical analysis of data bases with images.

In order to reduce complexity of membership function analysis, the Gaussian functions may be substituted by the triangular function. This is another option that may be selected in GUI in Fuzzy Inference System in *FIS Variables* field. Fig 6 shows the final process of fuzzyfication for variables D11.

The membership functions are obtained for each partition (*low, medium, high*) using the Gaussian or triangular functions providing measurement of intensity of action unit in continuous manner. The rule-based fuzzy model oriented for recognition of facial expressions requires expert knowledge which links the motion of fiducial points extracted by different images processing tools with the required rules that provide emotion interpretation.

There are a few well-known reports about emotion ontologies that create complete emotion recognition models based on facial expressions [14]. We proposed the following fuzzy inference system that provides six basic and some non-prototypical emotion interpretations based on the analysis of facial features.

5 Fuzzy Inference System

The proposed model for fuzzyfication of facial features has been tested on designed fuzzy inference system. The system is shown in Fig.7, it consists of two blocks: the first one measures value of AUs composing analyzed emotion; the second one recognizes and interprets the intensity of facial expressions. Fig. 8 shows the block diagram of fuzzy classifiers used for definition of action units that describe a particular expression (1st stage) and interpretation of basic or non-prototypical emotion (2nd stage). First of all, the input facial features (distances between fiducial points) are classified generating standard AUs with their corresponding level (intensity), then the emotion classifier generates complex emotion composed by detected muscular activities (AUs).

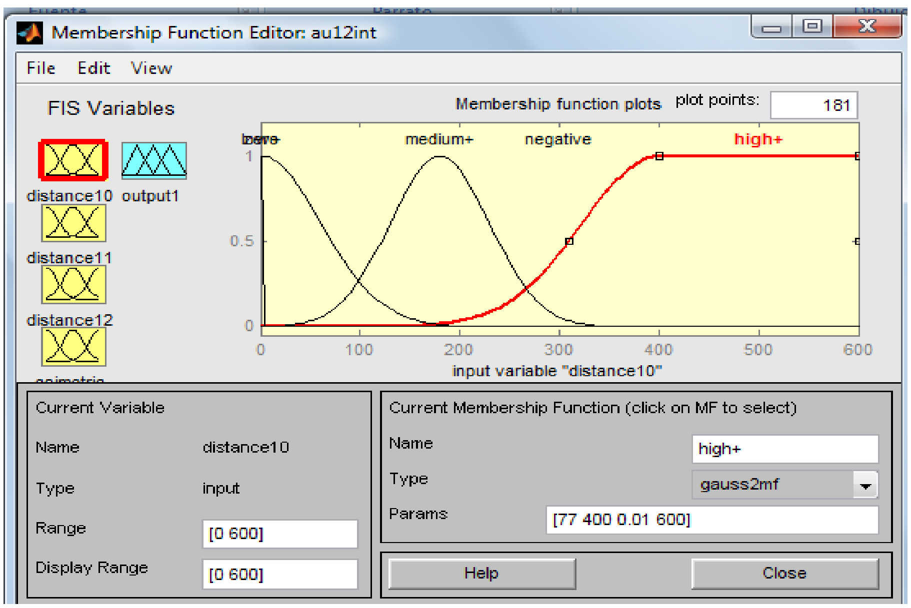


Fig. 5. GUI for visualization of Membership functions for analyzed Aus

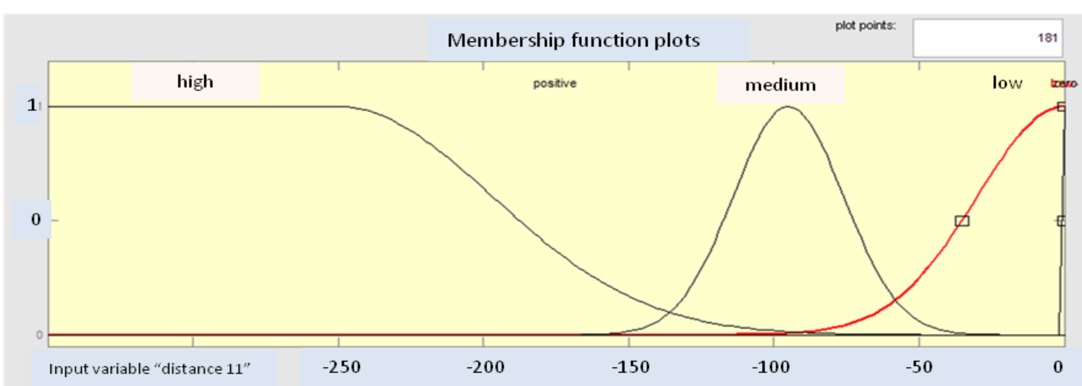


Fig. 6. Membership function plots and intensity partitions for distance variable D11

A set of rules defined for fuzzy logic that recognizes and measures intensity of AUs and corresponding emotions are shown in Tables 3 and 4. In particular, Table 3 shows the rules of AUs recognition using the distance differences proposed in our model, and Table 4 shows the rules of recognizing particular emotions using the previously identified AUs.

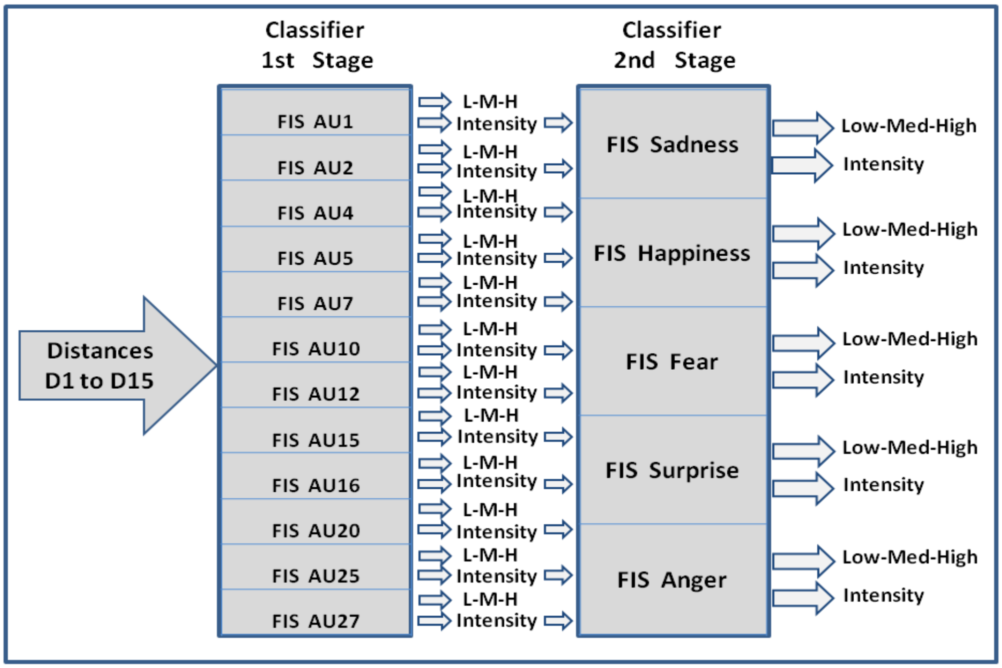


Fig. 7. Block diagram of the proposed fuzzy inference system for recognition of facial expressions

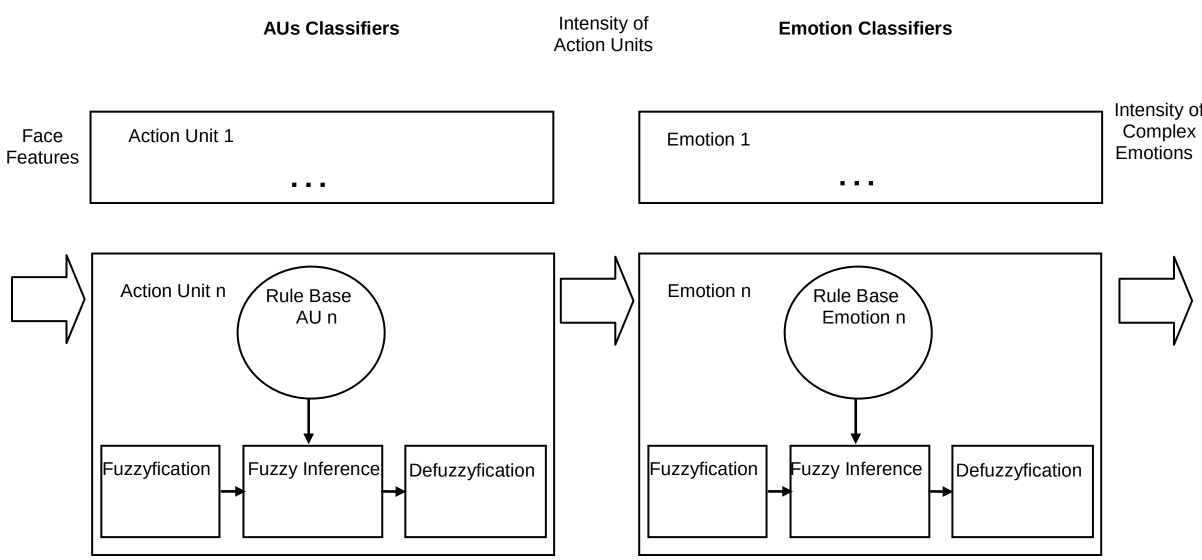


Fig. 8. Block diagram of a fuzzy classifier for interpretation of basic and non-prototypical emotions

Table 3. Description of rules and distance differences for particular AUs

Code	Description	Distance Diff.	Recognition Rules
AU1	Inner Brow Raiser	D1, D2	Both increase in same proportion
AU2	Outer Brow Raiser	D5, D6	Both increase in same proportion
AU4	Brow Lowerer	D3, D4, D7	D3&D4 increase, D7 decrease
AU5	Upper Lid Raiser	D8, D9	Both increase in same proportion
AU7	Lid Tightener	D8, D9	Both decrease in same proportion
AU10	Upper Lip Raiser	D13	D13 decrease
AU12	Lip Corner Puller	D10,D11,D12	D10 increase D11 & D12 decrease
AU15	Lip Corner Depressor	D11, D12	Both increase in same proportion
AU16	Lower Lip Depressor	D14	D14 increase
AU20	Lip stretcher	D10, D11, D12	D10, D11&D12 increase
AU25	Lips part	D15	D15 increase
AU27	Mouth Stretch	D10, D15	D10 decrease, D15 increase

Table 4. Description of rules and AUs that compose a particular facial expression

Emotion	AUs Used	Recognition Rules
Sadness	AU1, AU4, AU15	Increasing 3 actions increase expression intensity
Happiness	AU12, AU7	Presence of AU12 & AU7 but not AU7 (blinking). Increasing values increase expression intensity
Fear	AU1, AU2, AU4, AU5, AU20,AU27	Presence of the 6 actions but not AU7 (blinking). Increasing values increase expression intensity
Surprise	AU1, AU2 AU5, AU27	Presence of the 4th action but not AU5 (blinking). Increasing values increase expression intensity
Anger	AU4, AU7	Presence of AU4 & AU7 but not AU7 (blinking). Increasing values increase expression intensity

Table 5. Description of rules for facial expression recognition using FAPs

Emotion	FAPs		Emotion	FAPs	
Anger	squeeze_l_eyebrow(+)	squeeze_r_eyebrow(+)	Sadness	raise_l_i_eyebrow(+)	raise_r_i_eyebrow(+)
	lower.t.midlip(-)	raise_b_midlip(+)		close_t_l_eyelid(+)	close_t_r_eyelid(+)
	raise_l_i_eyebrow(+)	raise_r_i_eyebrow(+)		raise_l_m_eyebrow(+)	raise_r_m_eyebrow(+)
	close_t_l_eyelid(-)	close_t_r_eyelid(-)		raise_l_o_eyebrow(-)	raise_r_o_eyebrow(-)
	close_b_l_eyelid(-)	close_b_r_eyelid(-)		close_b_l_eyelid(+)	close_b_r_eyelid(+)

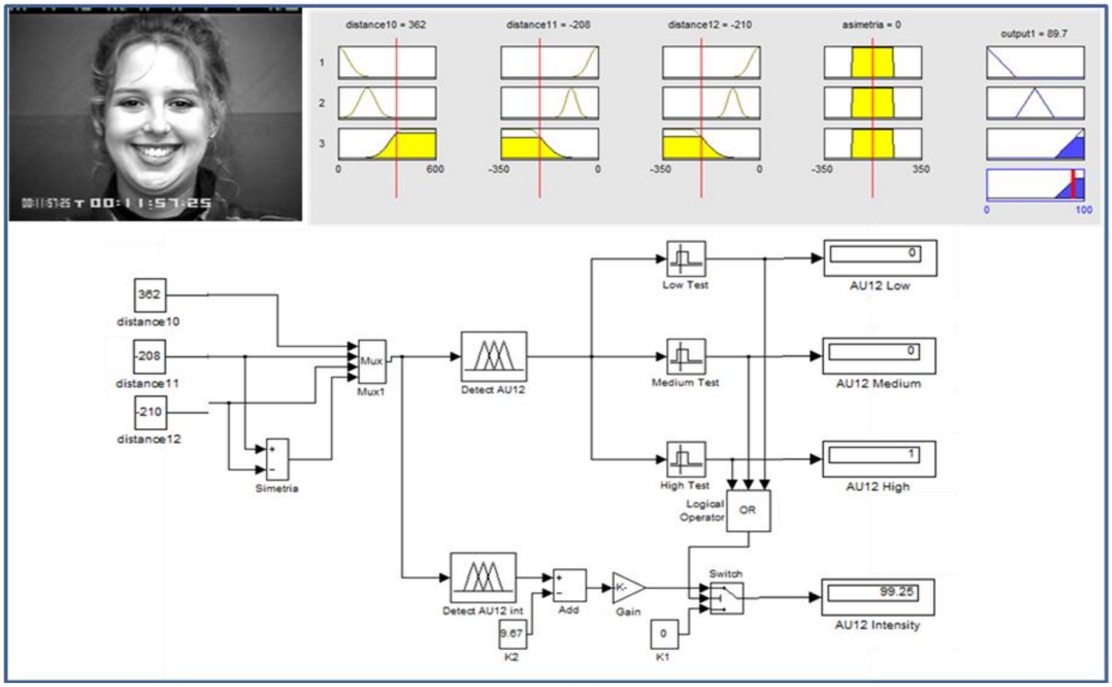


Fig. 9. Measurement of AU12 *Lip Corner Puller* representing happiness of high intensity

Table 5 shows the rules established for recognition of *anger* and *sadness* facial expressions using facial actions FAPs. For example, squeeze_l_eyebrow (+) means the increment of squeeze of left eyebrow.

Formally, the fuzzy rule-based classifiers, as a family of fuzzy systems, may be described as *FRBS=(μ, R, T, S, DEF),* where μ is membership functions, *R* is fuzzy-based rule, T - norm for fuzzy aggregation (i.e. operations with one rule), the *S* – norm for fuzzy composition (i.e. operations under some rules), and DEF defines the defuzzyfication method.

In Fig. 9, the user interface of designed fuzzy inference system is shown. In the right upper corner, the reasoning process is visualized with intensity of analyzed action unit, in this case for AU12. The intensity of input values is tested by the classifier applying three discrimination levels described by the Gaussian functions: 1-st row in Fig. 9 presents low intensity for all input distances, 2-nd row presents medium and 3-rd - high intensity. The shaded areas correspond to the magnitude of the membership functions that describe the contribution of each distance difference to particular expression.

In some cases the displacement of symmetrical points on a face is different. Thus, it is also measured and shown in 4-th column. The intensity of output variables for the particular action unit presented in 5-th column is modeled by three levels described by the triangular functions instead of the Gaussian functions. This approach is easy to implement, it provides fast facial expression recognition without additional errors during interpretation. The proposed model of reasoning is flexible enough to allow its extension incorporating new features for recognition of non-prototypical facial expressions.

6 Obtained Results and Discussion

The tests of system performance and efficiency of the fuzzyfication model have been done using Kanade´s and Pantic's databases. Tables 6 and 7 show the confusion matrices obtained for five basic prototypical emotions in case of medium and high intensity.

Table 6. Confusion matrix with expression of medium intensity

Emotion	Sadness	Surprise	Happiness	Anger	Fear
Sadness	81%	9.50%	0	0	9.50%
Surprise	0.30%	96%	0	0	3.70%
Happiness	0	0.20%	96%	1.90%	1.90%
Anger	0	4.50%	0.10%	92%	3.40%
Fear	6%	5.80%	0	0	88.20%

Table 7. Confusion matrix for expressions of high intensity

Emotion	Sadness	Surprise	Happiness	Anger	Fear
Sadness	84%	8%	0	0	8%
Surprise	0.20%	96.40%	0	0	3.40%
Happiness	0	0	97.60%	1.20%	1.20%
Anger	0	1.70%	0	96.70%	1.60%
Fear	4.70%	5.70%	0	0	89.60%

a)

b)

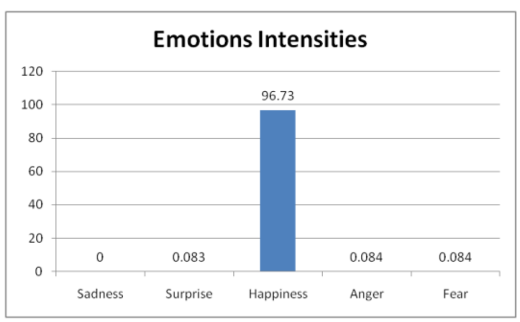


Fig.10 a) Facial expressions of happiness and b) its intensity degree reported by the system

In Fig 10a) and Fig. 11a), the images with facial expressions of happiness and sadness are presented. The recognition degree reported by the proposed system for corresponding facial expressions are sown in Fig 10b) and Fig. 11b), respectively. For correct evaluation of the expression reported by the system, Table 8 shows comparison between intensity of expression *Surprise* given by the classifier and reported by evaluation committee of ten persons participated in usability tests usually reported in similar researches [5]. Additionally, in Table 9, a comparison of reports about the performance of the proposed and well-known systems for recognition of facial expression is presented.

a) 

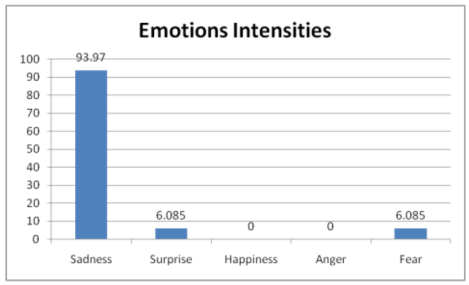
b) 

Fig.11. a) Facial expressions of sadness and b) its intensity degree reported by the system

Table 8. Usability test results for *Surprise* emotion

	Output	Evaluation	Status		Output	Evaluat.	Status
1	6.814	Low	OK	11	51.03	Medium	OK
2	50.33	Medium	OK	12	47.7	Medium-	OK
3	51.04	Low	FAIL	13	6.678	Low	OK
4	48.59	Medium	OK	14	50.2	Medium	OK
5	49.85	Medium	OK	15	17.95	Medium	FAIL
6	94.08	High	OK	16	95.12	High	OK
7	69.97	High	OK	17	94.05	High	OK
8	51.46	Medium	OK	18	49.29	Medium	OK
9	93.93	High	OK	19	93.21	High	OK
10	94.94	High	OK	20	93.41	High	OK
Correct assessment :				90%			

Table 9. Performance comparison of the proposed and similar prototypes for facial expression recognition

Approach	Author	Feature extracted	Expression identification	Intensity measure	Recognition of facial. actions	Facial action measure	Complex emotions	Required training	Recognition degree
Expert system	Pantic, 2006	Multi-detector	not	not	yes	not	not	not	86% only AUs
Fuzzy Classifier	Esau, 2007	Angles	yes	yes, 3-levels	not	not	yes	yes	72%
Fuzzy & Case Reasoning	Khanum, 2009	Edge detection	yes	not	yes	not	not	not	70.83%
Fuzzy Classifier	Proposed system	Distance difference	yes	yes, 3-levels	yes	yes, 3-levels	yes	not	81.40%

The main quantitative characteristic of the analyzed systems is recognition degree or precision of recognition that also is shown in the Table 9 for each system.

The obtained results indicate a correct assessment of intensity about 90% for *Surprise* facial expression. For other expressions such as joy, sadness, anger, and fear, the percentage of corresponding correct recognition is about 80, 85, 77, and 75% respectively. That gives an average recognition degree of the proposed model of about 81.4%. The high degree of recognition mainly depends on the number of AUs or FAPs used for description of expression. For recognition of non-prototypical expressions, the Plutchik´s emotion model presented in Fig. 12 is used. It describes a non-prototypical expression as a combination of basic ones.

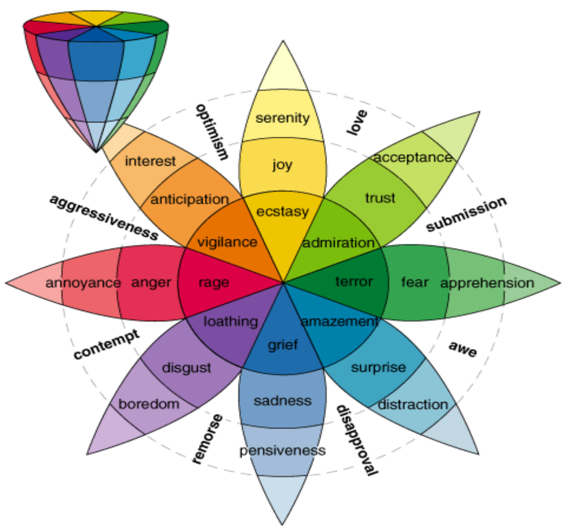


Fig.12. Plutchik´s emotion model

In the Fig. 13 a) and b), a particular non-prototypical facial expression and intensity degrees of corresponding basis expressions detected by system are presented. According to Plutchik´s model, the recognized expression is *awe* that may be described as a combination of *fear* and *surprise.* The recognition of non-prototypical emotions is in the range of about 40-60%.

Such a low level of recognition can be explained by complexity in selection of AUs for representation of non-prototypical emotion, by the simplicity of Plutchik´s emotion model, and by subjectivity of expression perception by each person.

The proposed framework opens a new possibility for designing systems aimed at facial expression detection and its intensity recognition.

5 Conclusions

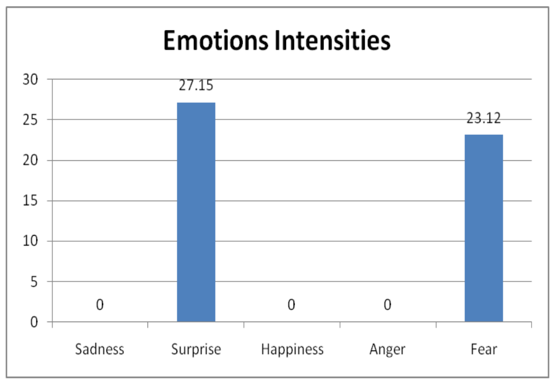
In this paper, we presented a model for fuzzyfication of facial features used for recognition of basic or non-prototypical expressions. For quantification of facial expressions and their intensities, a statistical analysis of Kanade's and Pantic's face databases has been done. Two-stage fuzzy inference using Gaussian and triangular functions is applied providing measurement and recognition of emotion intensity.

In the preliminary experiments, the recognition of basic expressions achieves up to 75-90% depending on complexity in selection of AUs for representation of a particular expression and on subjectivity of its perception by each person.

The designed knowledge-based framework is general enough to create diverse instances of facial expressions. It also provides a sufficiently exact quantitative description of measured facial actions. This allows a simple and formal definition of relationship between expressions, facial actions, and their descriptors. The proposed framework also allows postulation of rules for recognition of prototypical or non-prototypical expression using any type of classifier.

In the future, we will attempt to design systems which may operate in real time improving the precision of emotion recognition by applying the proposed fuzzy inference classifiers for facial expression interpretation. The module for automatic facial feature detection may be connected to the proposed fuzzy classifier for construction of a stand-alone or Web accessible system for emotion recognition. Finally, the system may be improved by extending recognized facial non-prototypical expressions and including mixed expressions occluded in real scenes.

a)



b)

Fig. 13. a) Facial non-prototypical expressions of awe and b) its intensity degrees reported by system

Acknowledgments

This research is sponsored by Mexican National Council of Science and Technology, CONACyT, Projects: #109115 and #109417.

References

1. **Black M., Kim, S. & Simeral, J. (2008).** Neural control of computer cursor velocity by decoding motor cortical spiking activity*, Journal of Neural Engineering, 5, 455–476.*
2. **Chakraborty, A. & Konar, A. (2009).** Emotion recognition from facial expressions and its control using fuzzy logic, *IEEE Transactions on Systems, Man, and Cybernetics-Part A: Systems and Humans, 39(4), 726–743.*
3. **Contreras R., Starostenko, O. & Alarcon-Aquino,V. (2009).** A Knowledge-based Framework for Analysis of Facial Expressions Using FACS and MPEG-4 Standards, *10th International Conference on Pattern Recognition and Information Processing*, Minsk, Belarus, 251–256.
4. **Ekman, P. & Friesen. W.V. (1978)**. *Facial Action Coding System (FACS). CA, USA: Consulting Psychologists Press.*
5. **Esau N., Wetzel, E., Kleinjohann, L. & Kleinjohann, B. (2007).** Real-Time Facial Expression Recognition Using a Fuzzy Emotion Model. *IEEE International Fuzzy Systems Conference*, London, England, 1–6.
6. **Gomathi, V. & Ramar, K. (2009).** Human Facial Expression Recognition using MANFIS Model. World *Academy of Science, Engineering and Technology, 50.*
7. *Information technology – Coding of audiovisual objects.* Part 2: Visual, ISO/IEC14496-2:2001(E), Second edition.
8. **Kanade, T., Cohn, J.F. & Yingli, T. (2000).** Comprehensive database for facial expression analysis. *4th IEEE Conference on Automatic. Face and Gesture Recognition,* Grenoble, France, 46–53.

9. **Khanum, A., Mufti, M. & Javed, M.Y. (2009).** Fuzzy case-based reasoning for facial expression recognition. *Journal of Fuzzy Sets and Systems, 160(2), 231–250.*

10. **Kharat, G.U. & Dudul, S.V. (2008a).** Human Emotion Recognition System Using Optimal SVM. WSEAS *Journal Transactions on Computers, 7 (6), 650–659*.

11. **Kharat G.U. & Dudul S.V. (2008b).** Neural Network Classifier for Human Emotion Recognition. *Conference on Emerging Trends in Engineering and Techn*ology, Iran, 1–6.

12. **Kyoung, S.C., Yong-Guk, K. & Yang-Bok, L. (2006).** Real-Time Expression Recognition System Using Active Appearance Model and EFM. *Computational Intelligence and Security Conference,* Guangzhou, China, 1–6.

13. **Lin, D.T. (2006).** Facial Expression Classification Using PCA and Radial Basis Function Network. *Journal of Information Science and Engineering,* 22 (5), 1033–1046.

14. **López, J.M., Gil, R. & Cearreta, R. (2008).** Towards an Ontology for Describing Emotions. *Lecture Notes in Artificial Intelligence*, 5288, 96–104.

15. **Maglogiannis, I. *et al*. (2009).** Face detection and recognition of human emotion using Markov random fields. Ubiquitous Computing *Journal, 13 (1), 95–101.*

16. **Mufti M., & Khanam, A. (2006).** Fuzzy Rule Based Facial Expression Recognition, *International conference on Computational Intelligence for Modeling, Control and Automation*, Sydney Australia, 57.

17. **Muthukaruppan, K., *et al*. (2007).** Development of a Personified Face Emotion Recognition *Technique Using Fitness Function. Japan: Springer.*

18. **Pantic, M. & Rothkrantz, L.J. (2004).** Facial Action Recognition for Facial Expression Analysis from Static Face Images. *IEEE Transaction on Systems, Man, and Cybernetics*, 34 (3), 1449–1461.

19. **Pantic M., Valstar M.F. & Rademaker R. (2005).** Web-based Database for Facial Expression Analysis, *IEEE Conference and Expo*, Netherlands, 1–6.

20. **Plutchik R. (2001).** The nature of emotions. *American Scientist,* 89 (4), 344–350.

21. **Protégé. (2009).** *Ontology editor*, Retrieved from: http://protege.stanford.edu/download/download.html

22. **Rizon, M. *et al*. (2009).** Personalized Human Emotion Classification Using Genetic Algorithm. Open International *Conference on Visualization, CA, USA, 1–6.*

23. **Starostenko O., Contreras, R. & Alarcon-Aquino, V. (2010).** Facial Feature Model for Emotion Recognition Using Fuzzy Reasoning. Advances in pattern *Recognition. Lecture Notes in Computer Science, 6256, 11–21.*

24. **Wood, F. & Black, M. J. (2008).** A non-parametric Bayesian alternative to spike sorting, *Neuroscience Methods*, 173(1) 1–12.

25. **Young-Joong K. & Myo-Taeg L. (2005).** Near-Optimal Fuzzy Systems Using Polar Clustering. *Lecture Notes in Computer Science,* 3684, 518–524.

26. **Yu, A., Elder, C., Yeh, J. & Pai, N. (2009).** Facial Recognition using Eigenfaces. Retrieved from http://cnx.org/content/m33180/latest/.

27. **Zhang, Y. & Ji, Q. (2005).** Active Information Fusion for Facial Expression Understanding. *IEEE Transactions on Pattern Analysis and Machine Intelligence,* 27 (5), 699–714.

28. **Zhou, X. & Huang, X. (2004).** Real-time facial expression recognition in the interactive game based on hidden Markov model. *Conference on Computer Graphics, Imaging and Visualization, Penang, Malaysia, 1–8.*

Oleg Starostenko received his BSc and MC degrees in Computer science from Lviv State University of Ukraine in 1982 and Ph.D. degree in Mathematics and Physics from the University Autónoma in Mexico in 1996. He is currently a full-time professor in the Department of Computing, Electronics and Mechatronics at the Universidad de las Americas Puebla, Mexico. He is the author of more than 150 research articles in several refereed journals, books, and conference proceedings. His current research fields are the access, retrieval, transmitting, and processing of multimedial information in distributed environments. He is a member of the Mexican National System of Researchers (Level I).

Renan Contreras Gómez graduated in electronic engineering from the National Polytechnic Institute, Mexico. He received his Ph.D. degree in Computer Sciences from the Universidad de las Americas Puebla in 2009. Currently, he is a professor in the School of Engineering and Applied Sciences in the Tecnologico de Monterrey in Puebla, Mexico. His research interest includes robotic vision, image processing and artificial intelligence. He is the author of several articles published in refereed research journals and proceedings of international conferences.

Vicente Alarcón Aquino received the Ph.D. and D.I.C. degrees in performance monitoring of communication networks from Imperial College London, London, U.K., in 2003. He is currently a full-time professor and a graduate coordinator at the Department of Computing, Electronics and Mechatronics of Universidad de las Americas Puebla, Mexico. He is the author of over 100 research articles in several refereed journals, books, and conference proceedings; he wrote a research monograph on MPLS networks, and has over 100 citations to his research articles. His current research interests include security in communication networks, wavelet theory applied to performance monitoring of communication networks, intrusion detection, wavelet-based image processing, and path restoration in MPLS networks. He is a member of IEEE and the Mexican National System of Researchers (Level I).

Leticia Flores Pulido received her Ph.D. degree from Universidad de las Américas Puebla, México, in 2011. She received a Master Science degree in Computer Science from the National Institute of Astrophysics, Optics, and Electronics, Puebla, Mexico, in 2001. Her research is focused on pattern recognition involving areas of artificial intelligence, particularly knowledge representation and machine learning in visual image retrieval systems. She is the author of several articles published in refereed research journals and proceedings of international conferences in the areas of visual information retrieval, wavelet transform applied to image processing, modeling visual elements, pattern recognition, and others.

Jorge Rodríguez Asomoza was born in Puebla, México in 1971. He received his B.S. degree in electronics and the M.S. degree in optoelectronics from the Benemérita Universidad Autónoma de Puebla (BUAP), México, in 1996 and 1997, respectively. In April 2001, he received his Ph.D. degree from the National Institute of Astrophysics, Optics and Electronics (INAOE), in Tonantzintla, Puebla, México. Since August 2001, he has been an Associate Professor at the Department of Computing, Electronics and Mechatronics Engineering of Universidad de las Américas, Puebla, where he works in electronics, optoelectronics for electric signal sensing systems and signal processing.

Oleg Yu. Sergiyenko received his B.S. and M.S. degrees from Kharkiv National University of Automobiles and Highways, Kharkiv, Ukraine, in 1991, 1993, respectively. He received a Ph.D. degree from Kharkiv National Polytechnic University in the specialty of Tools and Methods of Non-destructive Control in 1997. He has written 1 book (editor), 5 book chapters, 47 journal papers and holds 1 patent in Ukraine. He presented his research at several International Congresses in USA, England, Japan, Italy, Ukraine, and Mexico. He is currently the Head of Applied Physics Department of Engineering Institute of Baja California Autonomous University, Mexico. His scientific interests are automated metrology & smart sensors, control systems, robot navigation, 3D coordinates measurement.

Vira V. Tyrsa received B.S., and M.S., degrees in Kharkiv National University of Automobiles and Highways, Kharkiv, Ukraine, in 1991, 1993, respectively. She received a Ph.D. degree in Kharkiv National Polytechnic University in the specialty of Electric Machines, Systems and Networks, Elements and Devices of Computer Techniques in 1996. She wrote 3 book chapters, more than 21 papers and holds 1 patent in Ukraine. In November 2006, she was invited by the Polytechnic University of Baja California to hold a professor position at the Mechatronics Faculty. Her scientific interests are automated metrology & electric measurement theory, mechatronics, robot navigation, 3D coordinates measurement.

Article received on 11/12/2010; accepted 05/04/2011.