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Emotion Recognition Based on Interval Type-2 Fuzzy Logic from Facial Expression

[1]Mahmut Dirik, [2]Oscar Castillo, [3]A. Fatih Kocamaz

[1]Department of Computer Engineering, Sırnak University, TURKEY
[2]Tijuana Institute of Technology, Tijuana 22414, MEXICO
[3]Department of Computer Engineering, Inonu University, TURKEY

Corresponding author: Mahmut Dirik (mhmd.dirik@gmail.com).

ABSTRACT Automatic recognition of facial emotion plays an effective and important role in Human–Computer Interaction (HCI). There are various emotion recognition approaches have been proposed in the literature. The analytic face model consisted of a 26-dimensional geometric feature vector. These properties are used effectively to identify facial changes resulting from different expressions. The variation and uncertainties of these features make the emotion recognition problem more complicated. For decreasing these complications, we propose a distance-based clustering and uncertainty measures of the base new method for Emotion Recognition from Facial Expression using automatically selects 19 diagnostics of Action Units (AUs) in a 2D facial image using Type-2 Fuzzy inference system. The proposed system includes an automated generation scheme of the geometric facial feature vector. The proposed system has classified six facial expressions using the MUG Facial Expression database. The experimental results show that the proposed model is very efficient in uncertainty management policy and recognizes six basic emotions with an average precision rate of 86.175%.

KEYWORDS: Action Unit, Emotion Recognition, Facial Expression Recognition, Human–Computer Interaction, Interval Type-2 Fuzzy System

1. INTRODUCTION

In recent decades, facial expression and emotion recognition have become an important nonverbal communication step in the human-computer interface (HCI) that has attracted the attention of scientists. They are considered one of the most important ways of recognizing one's feelings, intentions or mood. Such as behavioral and neuroscience researchers there are several applications that use emotion recognition system. Identification of facial expression landmarks is an important key factor for recognition of emotion in human machine interaction. Feature extraction and classification are two significant steps in emotion recognition [1] [2]. Feature extraction refers to the acquisition of the feature vector in which features such as pixel positions, color, shape, and region of the image to be analyzed are represented. A classification module is recognized the intensity of emotional attributes into one of several emotions classes [3]. Feature selection and classifier design greatly affect the performance of a feeling-fully system. Several methods have been used to for facial feature extraction. Commonly used techniques are includes Principal Component Analysis [4], Active Contour [5], Gaussian Mixture Models [6], Neural Network [7], Deep Learning Network [8-11], Independent Component Analysis [12], Gabor Filter [13], Support Vector Machines [14] and Fuzzy logic [15-17],[21-23]. Similar characteristics of a particular emotion can be seen in facial expressions of different emotions. These are problems of uncertainty on emotion classification management. Therefore, it is difficult to have unique facial features. Although different methods have been utilized for facial expression and emotion recognition system. In this paper, Fuzzy Logic techniques have been used because of the reasoning function is understandable and also similar to human logic. The uncertainties can be handled with this method using the primary and secondary membership distributions of each measurement [26], [27]. Interval type 2 fuzzy logic (IT2FIS) methods are used to associate standard facial actions with specific uncertainties and automatic facial expression recognition rules form. The IT2FIS method provides an alternative approaches to recognize emotion from facial expression and measurement of their intensity using Ekman´s AUs (Action Units), FAPs (Facial Animation Parameter) and FDPs (Facial Definition Parameter) of MPEG-4 standard [28]– [31]. Ekman et al. conducted a meticulous study of facial expression and concluded that there are six basic expressions, these include happiness, sadness, disgust, anger, surprise and fear and also stated that facial expressions were universal and innate [32]–[34]. The Facial Action Coding System (FACS) is a human observer based system developed to detect changes in facial features or facial muscles [35]. It is an important step towards effectively recognizing facial features expression from the faces of different people. Emotion recognition system includes three stage. These are face detection, feature extraction and classification. Geometric and appearance properties-based data are common types of features used to recognize facial expression. The main purpose of this study is to present an automatic facial expression recognition and classification method using type2 fuzzy logic rules using only geometric facial features. Six emotions (Anger, Disgust, Fear, Happiness, Sadness and Surprise) proposed by Ekman were chosen for the proposed recognition system [30], [33] [36]. These emotions recognized with using IT2FIS system. Membership function parameters have a significant effect on the precision of fuzzy inference systems. In order for the membership functions to achieve a higher performance in emotion recognition system, type2 fuzzy membership functions are preferred. Thus, it is more effective than type1 in eliminating the uncertainties. The type-2 fuzzy cluster is modeled by primary and secondary membership and has the potential to handle uncertainty. Because of this feature, it has attracted our attention about using it for emotion classification. The decision-making process here aims to lead the individual emotion class to a specific fuzzy measurement group.

The main contributions and the basic philosophy of the proposed method are explained below.

- The paper provides an alternative approach for facial expression and emotion recognition using soft computing techniques.
- A robust and simple solution to recognize emotion from face images is presented.
- A fully automatic facial expression recognition method has been developed using only geometric facial features.
- The proposed system was evaluated with Interval type-2 fuzzy logic classifiers.
- Implementation of algorithms based on the different AUs (Action Units) for measuring facial emotions and their intensities are presented.

- The tune of input parameters for membership functions are used Euclidian distance calculation between all AUs contribute in a weighted linear way to the total intensity of the emotion.
- Instead of 66 feature points, to decrease the complexity and increase the robustness and simple, only 19 facial feature points are considered where most of the emotions are observable.

The rest of the paper is organized as follows: Section 2 describes the knowledge-based of a framework for facial feature extraction. Section 3 presents segmentation and key features extraction techniques of the most important geometric features measurements of Fiducial Facial Points. Section 4 describes the architecture of Facial Features Extraction methodologies involved in applying 19 data to the IT2FIS for clustering the features data into basic six emotion zones. Section 5 introduce the Preliminaries on Type-2 Fuzzy Sets and philosophies of proposed emotion classification using IT2FIS. In section 6, the measurements of facial features and Fuzzification of facial features process is introduced. In section 7, Fuzzy Inference Engine for Emotion classification is expressed. The experiments and emotion recognition are discussed in Section 8. Finally, we draw conclusions and identify future work in Section 9.

2. KNOWLEDGE-BASED FRAMEWORK

The Knowledge-based framework used in the interpretation of emotional intensity uses reference points such as FAPs and AUs. Evaluating and interpreting the distances between these points according to fuzzy rules allows modeling facial expression definition and indexing in the emotional classification. Figure 1 shows the structure of a knowledge-based framework used to design the type 2 fuzzy logic system. It is utilized relationships between the measured facial AUs, FAPs and their corresponding mathematical description. These are important parameters to recognize facial expressions with fuzzy classifier which provides interpretation of emotional intensity. The measurement of the emotion intensity, the geometric displacement of these reference points and the distance between points generated are taken into account. With the implementation of the proposed method, semantic analysis of facial actions can be developed with an expert system and fuzzy logic systems. Six basic facial expressions (happiness, sadness, disgust, surprise, anger and fear) were tested using the proposed approach. The proposed system includes two classes. These are *Face Model* and *Emotion Model*. The *Face Model* class represents a variety of approaches that allow the definition of facial features. *Emotion* Model is obtained with rule-based modeling for emotion recognition and indexing and also represents the class in which basic facial actions (AUs, FAPs) or actions of facial muscles occur. The advantage of the proposed method is that it allows parameter transformations based on interrelated and interactive work of knowledge classes representing emotions.

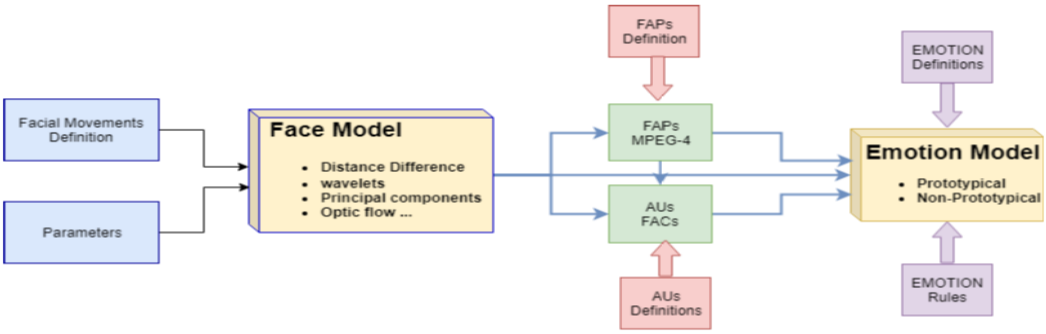


Figure 1. FAPs and AUs based emotion knowledge database structure.

3. GEOMETRIC MEASUREMENTS OF FIDUCIAL FACIAL POINTS

Facial features may provide sufficient information to recognize various facial expressions. The extracted features (from eyes area, eyebrows, lips, etc.) play an important role in providing the necessary information to recognize emotions. The contraction of facial muscles is represented and encoded by AUs of facial features that can be removed on the skin surface. In the proposed system, the face model based on the analysis of nineteen FDPs was used to determine the input parameters in the fuzzy logic system. The set of feature points selected FDPs with the suitable number of associated FAPs used in the proposed method is visualized in figure 2. The facial fiducial reference points are represented the Distance-Class of FDPs. The distance between two feature points (two red points) is combined with a blue line. These two points were calculated by Euclidean calculation method. For example, D1 represents the distance between points 1(Eyebrow left Outer) and 7 (eye Left Outer). Table 1 represents the measurement distances of the proposed model.

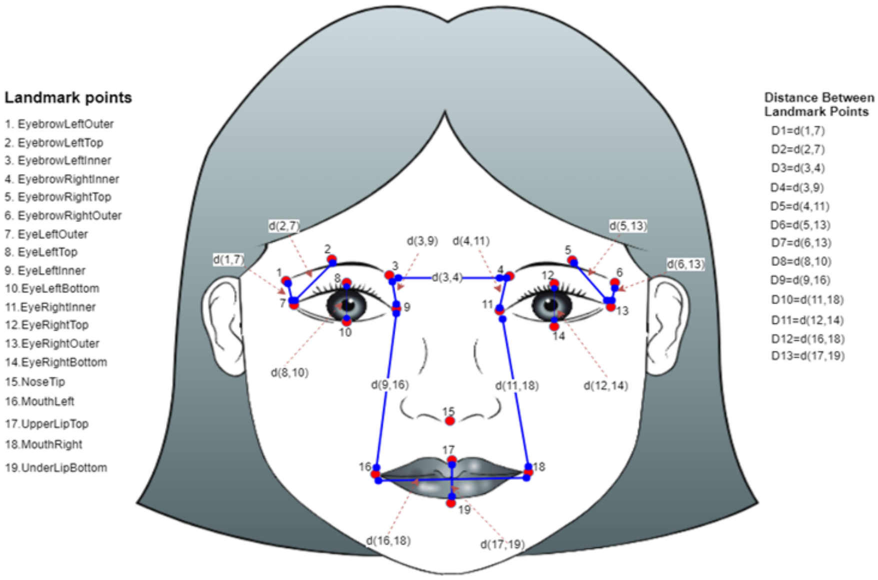


Figure 2. Visualization of feature points with specific emotions and distance vector.

The proposed facial model includes nineteen FDPs and thirteen distances between the fiducial reference points that modeled by the MPEG-4 standard and are represented by the equation D (x, y).

The thirteen-distance information selected for this model and the geometric definitions of these distances and their relations with FAPs are shown in Table 1.

Table 1. The definition of Geometric Measurements using Fiducial Facial Points.

Distance	Measurements	Measurement Name
D1	dist(1,7)	Eyebrow left outer-Eye left outer
D2	dist(2,7)	Eyebrow left top- Eye left outer
D3	dist(3,4)	Eyebrow left inner- Eyebrow right inner
D4	dist(3,9)	Eyebrow left inner- Eye left inner
D5	dist(4,11)	Eyebrow right inner- Eye right inner
D6	dist(5,13)	Eyebrow right top- Eye right outer
D7	dist(6,13)	Eyebrow right outer- Eye right outer
D8	dist(8,10)	Eye left top- Eye left bottom
D9	dist(9,16)	Eye left inner-Mouth left
D10	dist(11,18)	Eye right inner-Mouth right
D11	dist(12,14)	Eye right top- Eye right bottom
D12	dist(16,18)	Mouth left-Mouth right
D13	dist(17,19)	Upper lip top-Under lip bottom

4. AUTOMATIC FACIAL FEATURES EXTRACTION

In a basic sense, the system of emotion recognition consists of three main stages. These are Face Detection, Feature Extraction, and Classification stages. Facial feature extraction is one of the most complex and time-consuming stages in emotion recognition. The procedures performed at this stage have a great importance in obtaining accurate results on face recognition being robust and accurate. Many precise and effective algorithms have been recommended for this purpose. It is necessary to specify which properties are valuable for emotion recognition. We mentioned these features in the previous section. In the next steps, we'll cover the steps on how to get these features.

4.1 FACE DETECTION

The first step of the proposed method is to define the face image boundaries from the input images. One of the most notable detectors of research and algorithms focusing on facial recognition is designed by Viola and Jones [37]. Viola and Jones are known in the literature as object recognition methods. It has been found to have good performance in use as a real-time face detector. In our experiments we used these methods to extract the face region. The Viola-Jones philosophy involves two basic stages: Haar-like features extraction which is given by the summed difference of intensity (between the black and white) rectangular regions and Adaboost classifier [37], [38].

4.2 FACIAL FEATURE EXTRACTION

First of all, the exact accuracy of emotion recognition will depend on the results obtained at this stage. It is necessary to identify which features are valuable from the face region or which features are important for emotion recognition. The features used for recognition of basic emotions (Anger, Disgust, Fear, Happiness, Sadness, and Surprise) are attributes of regions of Eyes, Mouth, Eyebrows, Nose, and Lips. In this work, we used Active Shape Models (ASM) algorithm [39], [40] to extract the features of these regions. It is creating facial landmark's corresponding points and statistical of facial shape.

Nineteen facial landmarks are extracted using ASM. These are illustrated in Figure 2. To classify facial expressions, a feature vector was created using equation (1).

$$\vec{F}_{i,j} = (f_1, f_2, \dots, f_n), f = (x, y) \tag{1}$$

In (1), i and j denote the i-th landmark set for the j-th facial expression, n the number of extracted landmarks, and f = (x, y) the Cartesian coordinate for the landmark, respectively.

4.3 CLASSIFICATION

After obtained the feature vector with using eq. (1), the basic emotion proposed in [36] needs to be classified. Several classifiers have been proposed to recognize the emotions as mentioned before. In this work, we used Type 2 fuzzy inference system to evaluate and classify the facial expression and emotion recognition. The definition of membership function and fuzzy rules are the main factors that have a significant influence on emotion recognition more accurately. The graphical representation of our proposed emotion recognition system has been shown in Figure 3.

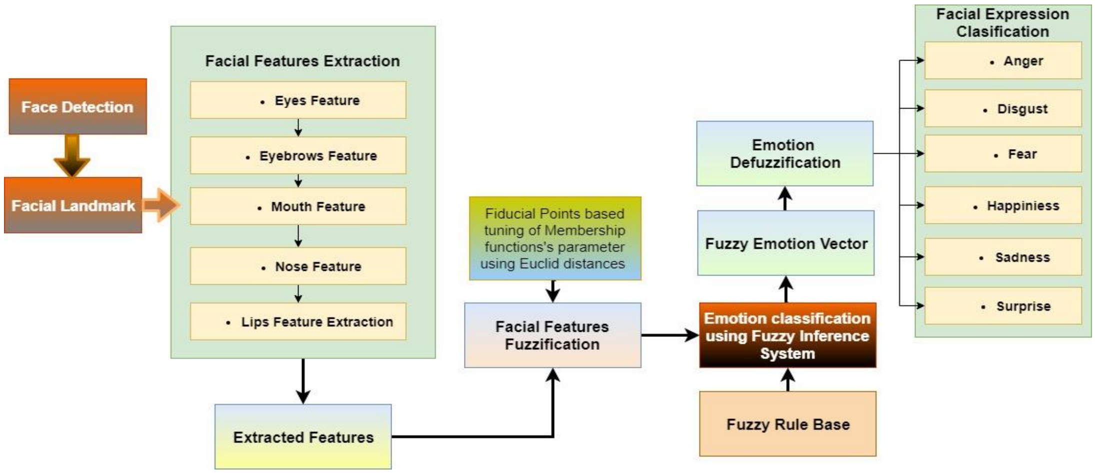


Figure 3. The graphical representation of the proposed emotion recognition system.

First of all the facial expression classification start with face detection stage. After that facial landmarks and feature of expected regions which play a vital role in the proposed system are extracted. Haar-like cascading features and Viola-Jones object detection algorithm were used for this process. The fundamental process of fuzzy reasoning is the fuzzification of inputs. In fuzzification stage, the measurements variables between fiducial points and AUs, given in Table 1, are considered as inputs. The range values of fuzzy logic membership functions were determined by considering measurements between FAUs obtained from face geometry. A fuzzy inference system was designed and a set of rules for fuzzy emotions was created. A separate set of rules was created for each basic emotion based on their own analysis of facial expressions. In the final stage, it is seen as the result of a fuzzy combination of AUs, which is the defuzzification phase of fuzzy logic, corresponding to a particular emotion classification. More details about fuzzy reasoning will be included in the next section.

5. PRELIMINARIES ON TYPE-2 FUZZY

In this section, a general overview of some terminologies related to type-1 (T1FS) and type-2 fuzzy sets (T2FS) and a scheme for emotion recognition using interval type-2 fuzzy inference system (IT2FIS) have been presented. These terminologies will be used throughout the paper. The concept of T2FS, which is presented as an extension of T1FS, enables us to deal with numerical and linguistic uncertainties. The concept of the T2FS was introduced by Zadeh [41], [42]. In its robustness for controlling nonlinear systems with variation and uncertainties, the fuzzy type-2 method has proven to be a strong tool for controlling complex systems [43]. The presence of uncertainties in a nonlinear system control uses the highest and lowest values of the parameters, extending the type-1 fuzzy method. Uncertainty is a characteristic of information, which may be incomplete, inaccurate, undefined, inconsistent, and so on. The uncertainty is represented by a region called the footprint of uncertainty (FOU). This is a bounded region that uses an upper and lower type-1 membership function. Here we would like to emphasize the Interval type-2 fuzzy inference system.

An interval type-2 fuzzy set denoted by $\tilde{A}$ is expressed in Equation (2) or (3).

$$\tilde{A} = \{(x,y),\mu_{\tilde{A}}(x,y) | \;\forall_x \epsilon\, X, \forall_u \epsilon\, J_x \;\subseteq [0\;1]\} \tag{2}$$

Hence, $\mu_{\tilde{A}}(x,u) = 1, \forall_u \epsilon\, J_x \subseteq [0\;1]$ is considered as an interval type-2 membership function.

$$\tilde{A} = \int_{x\epsilon \mathrm{X}} \int_{u \epsilon \mathrm{J}_x} 1/(x,u)\, J_x \;\subseteq [0\;1] \tag{3}$$

where $\int\int$ donate the union of all acceptable x, u and J_x is just the interval of $[\bar{\mu}_{\tilde{A}}\,(x), \underline{\mu}_{\tilde{A}}(x)]$. $\bar{\mu}_{\tilde{A}}\,(x)$ and $\underline{\mu}_{\tilde{A}}(x)$ are denoted upper and lower membership functions.

6. FUZZIFICATION OF FACIAL FEATURES

In this case, the inputs of the fuzzy set convert into suitable linguistic variables. The membership functions consist of one or several types-2 fuzzy sets. A numerical vector x of the fuzzifier maps converts into a type-2 set $\tilde{A}$. The outputs of the type-2 fuzzy sets are considered a singleton. In a singleton fuzzification, the inputs are crisp values on nonzero membership. Input variables, in particular, FAPs of indexed facial expressions taken from MUG databases [44], accept the difference in the distances between standard reference points. It should be noted that the difference in distance is the difference between a neutral face and AUs on the face of the person performing any action that expresses any emotion. In this work we consider thirteen inputs. These are distances between fiducial facial AUs. The high number of fuzzy logic inputs can affect the number of rules to be created and can lead to complexity of the process. If we examine the face in two classes, the change between some points on the face to be right and left will yield similar mathematical results. One of these similar points or the average of these similar points may be considered. This reduces the number of inputs of fuzzy logic and reduces complexity. Therefore, search area decreases to find better parameters and it can fully adjust the parameters of the MFs. In the last step, in this study, we reduced these inputs to seven and considered the average calculation method. These are listed in the following table 2.

Table 2. Input parameter of feature points with specific emotions and average vector from figure 2 and table 1.

Average Distances	Face fiducial points	
	Left side of face	**Left side of face**
D1-7	d(6,13)	d(6,13)
D2-6	d(2,7)	d(5,13)
D4-5	d(3,9)	d(4,11)
D8-11	d(8,10)	d(12,14)
D9-10	d(9,16)	d(11,18)

In order to achieve the desired purpose, the measurements we calculated for Mouth Opening, Eye Opening and Eyebrow constriction are coded to SMALL, MEDIUM and LARGE fuzzy cluster. Gaussian, Z-Shape and S-Shape membership functions are selected for SMALL, MEDIUM and LARGE Fuzzy sets, respectively. The functions of Gaussian, Z-Shape and S-Shape membership functions are shown in the Equations. (4) - (6) respectively.

$$\mathrm{Gausian}(\mathrm{x}, \sigma, \mu) = \mathrm{e}^{-\frac{(\mathrm{x}-\mu)^2}{2\sigma^2}} \tag{4}$$

$$Z\_Shape(x,a,b) = \begin{cases} 1, & x \leq \boldsymbol{a} \\ 1-2\left[\dfrac{x-a}{b-a}\right]^2, & a < x \leq \dfrac{a+b}{2} \\ 2\left[b-\dfrac{x}{b-a}\right]^2, & \dfrac{a+b}{2} \leq \boldsymbol{x} < \boldsymbol{b} \\ 0, & x \geq \boldsymbol{b} \end{cases} \tag{5}$$

$$S\_Shape(x,a,b) = \begin{cases} 0, & x \leq \boldsymbol{a} \\ 2\left[\dfrac{x-a}{b-a}\right]^2, & a < x \leq \dfrac{a+b}{2} \\ 1-2\left[\dfrac{x-b}{b-a}\right]^2, & \dfrac{a+b}{2} \leq x < b \\ 1, & x \geq \boldsymbol{b} \end{cases} \tag{6}$$

The parameters given herein; x is any continuous feature; in addition, a, σ, μ and b are membership function parameters. These parameters have a significant effect on the obtained performance. S / Z memberships are functions that are suitable for the selection of emotion classes in cases where the reference range of the parameters used as input for emotion recognition is lower or higher. For intermediate functions and normally distributed data, we select the Gauss membership function. It is known that the basic blocks used for type-2 FIS are the same as those used with type-1. A type-2 FLS includes a fuzzifier, a rule base, a fuzzy inference engine, and an output processor. The output processor includes a type-reducer and defuzzifier. The type-reducer is the main distinctive point between type-1 and type-2 fuzzy systems. A type-1 fuzzy set output is generated from the type-reducer or a crisp number is generated from the defuzzifier [43] [45]. The type reducer is added because of its association with the nature of the membership grades of the elements [46]. Figure 4 illustrates the block diagram of proposed fuzzy system structure using the mentioned input.

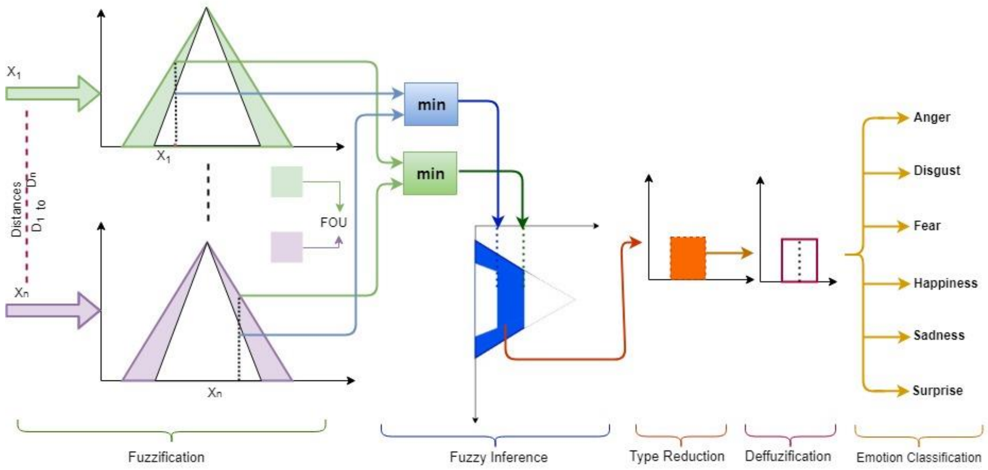


Figure 4. Structure of a type-2 fuzzy logic system.

7. FUZZY INFERENCE ENGINE FOR EMOTION CLASSIFICATION

After obtaining distance classes on natural facial image. These values are used for fuzzy emotion inference through fuzzification and membership function definition process. The inference engine is an interface that processes input values according to certain rules and produces output type-2 fuzzy sets. It is necessary to compute the intersection and union of type-2 sets and implement compositions of type-2 relations. The desired behavior is defined by a set of linguistic rules. By checking various images, we developed fuzzy rules for emotion recognition and experimented with many facial images of different emotions, testing the integrity and accuracy of these rules, and checking whether these rules would recognize real emotions. It is necessary to set the rules adequately to achieve the desired result. For instance, a type-2 fuzzy logic with p inputs ($x_1 \in X_1, \ldots x_p \in X_p$) and one output (y ∈ Y) with M rules has the following form.

$$R^{\ell}\text{: IF } x_1 \text{ is } \tilde{F}_1^{\ell} \ldots\text{and } x_p \text{ is } \tilde{F}_p^{\ell} \text{ THEN } y \text{ is } \tilde{G}^{\ell},\ \ell = 1 \ldots . M$$

The knowledge bases for each controller consist of several rules related to the emotion classifications. Two examples of fuzzy rules for emotion recognition using the fuzzy values of facial features as precursors are shown below.

- Rule 1: If (*D1-7* is LARGE) and (*D2-6* is LARGE) and (*D4-5* is LARGE) and (*D8-11* is LARGE) and (*D13* is LARGE) and (*D12* is SMALL) then (Emotion is Surprise)
- Rule 2: If (*D2-6* is MEDIUM) and (*D3* is SMALL) and (*D4-5* is SMALL) and (*D9-10* is LARGE) and (*D8-11* is SMALL) then (Emotion is Disgust)

In these experiments, Mamdani-type implication operators for fuzzy emotion recognition were selected and used minimum t-norm operation. The rule firing strength $F^i(x)$ for crisp input vector is given by the type-1 fuzzy set

$$F^l(x') = \left[\underline{f}^{\,l}(x'), \overline{f}^{\,l}(x')\right] \equiv [\underline{f}^{\,l}, \overline{f}^{\,l}] \tag{7}$$

where $\underline{f}^{\,l}$ and $\overline{f}^{\,l}$ are the lower and upper firing degrees of the $l\ th$ rule, computed using Equations (8) and (9).

$$\underline{f}^{\,l}(x') = \underline{\mu}_{\tilde{F}_1^l}(x_1') * \dots * \underline{\mu}_{\tilde{F}_p^l}(x_p') \tag{8}$$

$$\overline{f}^{\,l}(x') = \overline{\mu}_{\tilde{F}_1^l}(x_1') * \dots * \overline{\mu}_{\tilde{F}_1^l}(x_p') \tag{9}$$

The given $*$ in the equation represents the t-norm, which is the $prod$ operator. The single combined type-2 fuzzy set is processed with the type reducer and the defuzzifier. Type-1 fuzzy set output is generated with the type reducer method. These outputs are converted into the crisp output through the defuzzifier. The defuzzifier combines the output sets to obtain a single output using one of the existing type reduction methods. Many methods can be used for type reduction. Centroid type reduction, height type reduction, and center of set are the most commonly used [47]. In these experiments a center of sets (cos) type reduction method was used. This method expressed as Equation (10).

$$Y_{cos}(x) = [y_l, y_r] = \int_{y^1 \in [y_l^1, y_r^1]} \cdots \int_{y^1 \in [y_l^M, y_r^M]} \int_{f^1 \in [\underline{f}^{\,1}, \overline{f}^{\,1}]} \cdots \int_{f^M \in [\underline{f}^{\,M}, \overline{f}^{\,M}]} \Big/ \frac{\sum_{i=1}^{M} f^i y^i}{\sum_{i=1}^{M} f^i} \tag{10}$$

The values of f_i and y_i which are associated with y_l are donated to $f_l{}^i$ and $y_l{}^i$, respectively, and the values of f_i and y_i which are associated with y_r are donated to $f_r{}^i$ and $y_r{}^i$ respectively, $\underline{f}^{\,\mathrm{i}}$ and $\overline{f}^{\,\mathrm{i}}$ are the lower and upper firing degrees of the $i\ th$ rule and and M is the number of fired rules. These points are given in Equations (11) and (12).

$$y_l = \frac{\sum_{i=1}^{M} f_l{}^i y_l{}^i}{\sum_{i=1}^{M} f_l{}^i} \tag{11}$$

$$y_r = \frac{\sum_{i=1}^{M} f_r{}^i y_r{}^i}{\sum_{i=1}^{M} f_r{}^i} \tag{12}$$

The average of y_l and y_r are used to defuzzify the output of an interval singleton type-2 fuzzy logic system as given in Equations (13).

$$y(x) = \frac{y_l + y_r}{2} \tag{13}$$

8. EXPERIMENTAL RESULTS AND DISCUSSION

This section presents the results of facial features extraction and classification of facial expressions into six basic emotions showing the accuracy of the proposed methodologies. We employ the publicly available and well-known MUG database [44] for our research purpose. This database consists of numerous (86 subjects) face images performing facial expressions. MUG is a high quality face database with pictures of six emotional expressions. Some examples of the MUG image set are shown in Figure 5. The system's performance accessed using this database sample images. The performance of the proposed algorithms is evaluated in two stages. Evaluation of proposed feature extraction algorithms constitutes the first stage and evaluating the final sensitivity of the proposed fuzzy emotion recognition system constitutes the second stage. To evaluate our algorithms for feature extraction, we experimented on 175 (25x7 for each of emotion) randomly selected front-face images from the MUG facial expression databases. These 175 images have different emotions and expressions; these include natural, happy, sad, fear, angry and other facial features. As a result, we thoroughly evaluate the proposed feature extraction algorithms with these different test images. Table 3 reports the average sensitivity of selected feature extraction algorithms as an example of the test images described above. We employ the automatically selected features obtained by using the Viola-Jones philosophy to estimate the intensities of the 19 selected AUs. The differences of the extracted Euclidean distance features between the neutral and any expressive frames are used for AU intensity estimation are the parameters of system inputs. The results obtained are summarized in Table 3. Seven examples are shown in this table. The first example is a naturel face image. These data are used for a range of the membership functions. The other images represent 6 different emotion classes and are exemplary of the automatically acquired properties of the images. The distances used here are arranged according to the structure in figure 2. For example, D10 is represented the distance between the Eye right inner and Mouth right. Other distances have been obtained with this logic.

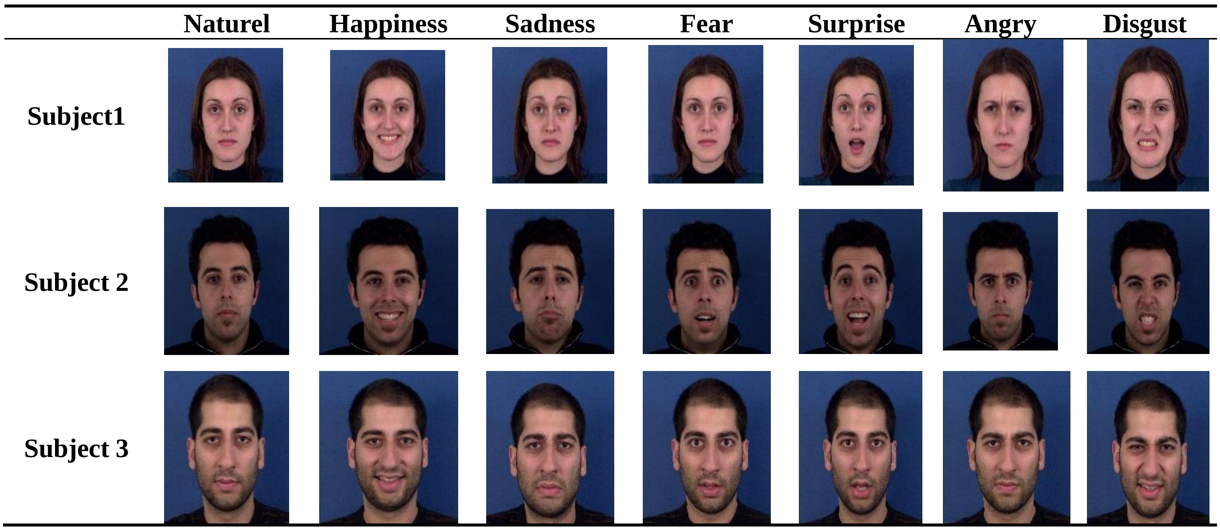
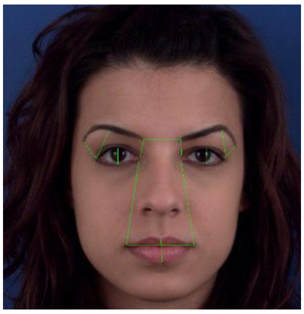
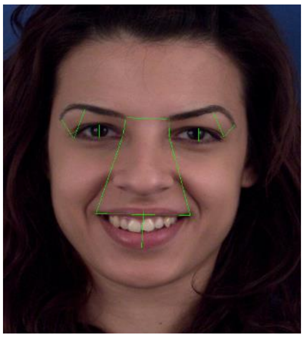
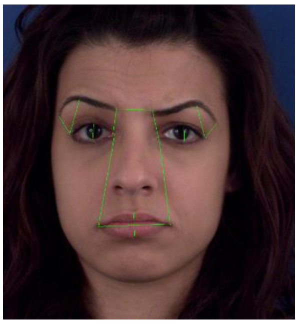


Figure 5. Examples from MUG database that show six basic emotional expressions

The second part of the experimental results focus on determining the classification accuracy obtained using the proposed IT2FIS based classification method. The result of emotion recognition and classification accuracies using the IT2FIS have been presented in table 4. The experimental results were tested using 25*7 samples and focused on determining the classification accuracy obtained by the proposed IT2FIS based classification method. The accuracy of classification provided by IT2FIS was found to be highest (90.25%) for happiness and least (80.27%) for anger, which was 86.175% with an average recognition rate. It is worth noting that the current method for emotion recognition is significantly higher in performance and accuracy.

Table 3. Examples of facial features detection results and distances between specified fiducial points using proposed methods.

Emotion	Image	Length (pixel)		Start x	Start y	End x	End y
		D1	49.21	278	384	308	423
		D2	72.49	308	356	338	422
		D3	84	418	378	502	378
		D4	43.93	408	375	417	418
		D5	42.11	501	379	504	421
		D6	60.53	596	359	604	419
		D7	34.71	604	393	627	419
		D8	38	357	399	357	437
Natural		D9	198.13	376	427	405	623
		D10	197.29	502	429	532	624
		D11	35	561	400	561	435
		D12	154.01	378	621	532	622
		D13	54.04	456	606	458	660
		D1	46.64	281	407	305	447
		D2	67.67	307	383	329	447
		D3	80.06	411	403	491	406
		D4	35.35	404	406	409	441
		D5	43.01	495	404	496	447
		D6	60.17	582	389	604	445
		D7	32.02	606	419	626	444
Happiness		D8	28	357	419	357	447
		D9	179.98	350	445	403	617
		D10	175.85	497	450	538	621
		D11	29	554	427	554	456
		D12	190.04	349	616	539	620
		D13	87.09	441	604	445	691
		D1	45.79	293	394	317	433
		D2	80.08	315	357	337	434
		D3	76.03	418	378	494	380
		D4	56.57	409	377	417	433
		D5	60.21	495	381	507	440
		D6	71.07	590	370	607	439
		D7	39.21	609	409	633	440
		D8	36.13	365	411	368	447
Sadness		D9	203.04	378	432	413	632
		D10	193.62	508	437	533	629
		D11	39.05	562	417	564	456
		D12	155.17	377	626	532	632
		D13	51.04	454	602	456	653
		D1	47.51	250	394	274	435
		D2	87.82	276	349	288	436
		D3	79.23	382	385	461	391
		D4	49.16	376	386	380	435
		D5	51.79	461	394	470	445
		D6	79.25	563	360	577	438
		D7	42.52	577	406	605	438
		D8	39.01	327	412	328	451
Fear		D9	218.23	346	438	377	654
		D10	207.39	471	443	495	649

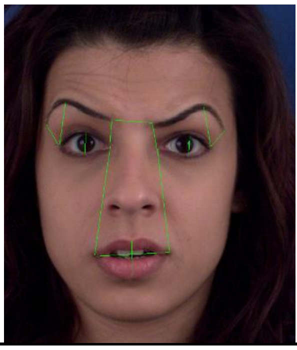
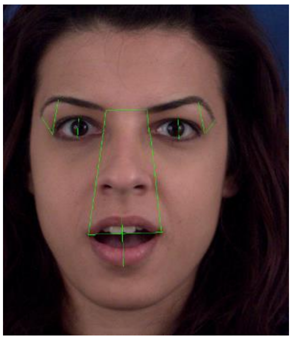
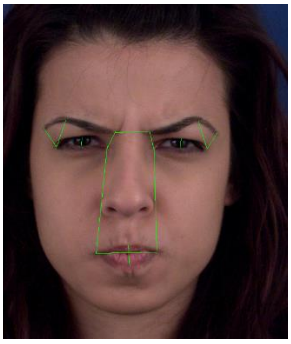
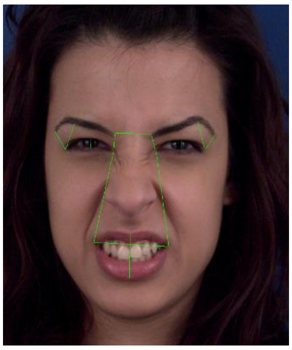
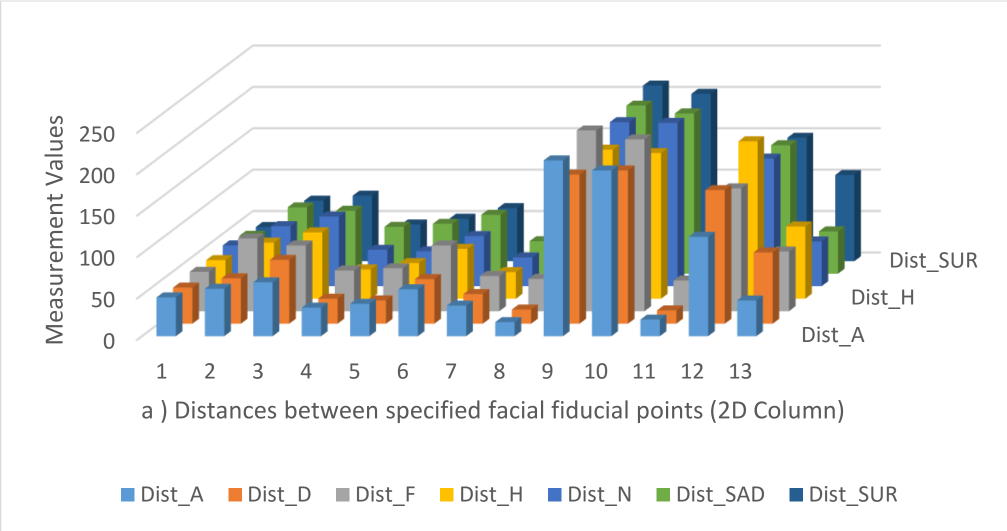
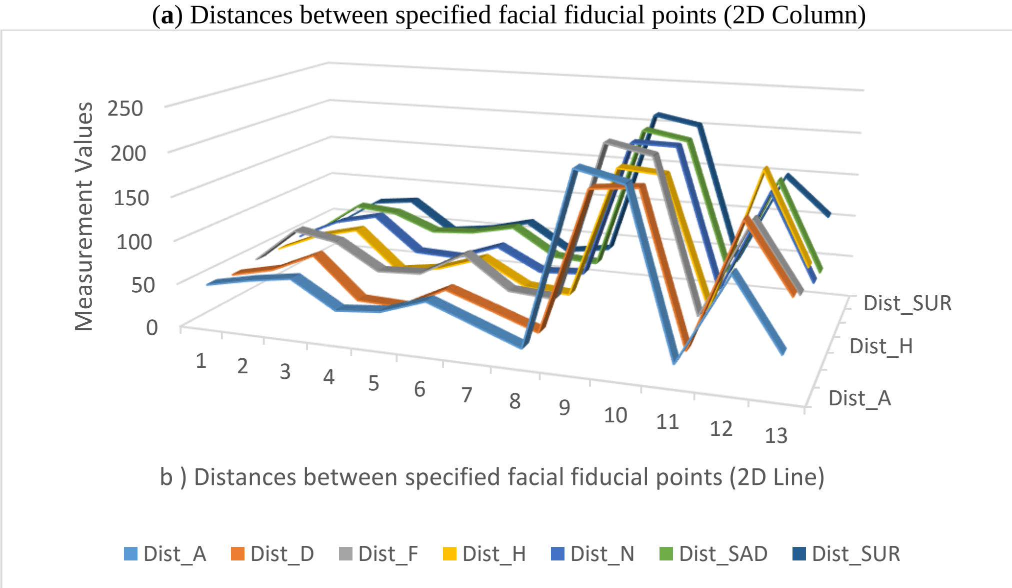
		D11	37.05	533	417	535	454
		D12	148.22	348	648	496	656
		D13	72.01	420	625	421	697
Surprise		D1	41.34	263	400	285	435
		D2	72.99	284	364	296	436
		D3	79.03	393	383	472	385
		D4	44.28	386	385	391	429
		D5	51.25	473	385	478	436
		D6	64.13	576	369	588	432
		D7	32.21	590	406	609	432
		D8	40.11	334	402	337	442
		D9	212.13	356	430	386	640
		D10	202.20	480	435	502	636
		D11	40.05	535	405	537	445
		D12	149.08	356	635	505	640
		D13	104.04	423	602	426	706
Angry		D1	46.87	263	402	289	441
		D2	57.26	288	386	307	440
		D3	65.03	403	409	468	411
		D4	34.44	389	409	404	440
		D5	39.05	471	408	480	446
		D6	56.62	567	389	584	443
		D7	36.89	584	412	604	443
		D8	17.03	337	420	338	437
		D9	212.15	366	438	388	649
		D10	200.06	480	444	485	644
		D11	20.09	531	423	533	443
		D12	120.02	366	646	486	648
		D13	43.15	429	632	432	675
Disgust		D1	43.57	278	412	301	449
		D2	54.78	301	399	321	450
		D3	77.01	407	418	484	419
		D4	30.15	403	420	406	450
		D5	28.16	483	422	491	449
		D6	53.85	581	395	595	447
		D7	35.81	597	420	618	449
		D8	17.03	354	429	355	446
		D9	179.96	361	452	403	627
		D10	184.98	493	452	520	635
		D11	16	547	432	547	448
		D12	161.21	361	626	522	634
		D13	86.01	437	609	438	695

Table 4. Confusion matrix of the proposed IT2FIS classification system tested for the six basic emotions.

Emotions	IT2FIS-Based Recognized Emotion From Facial Expression					
	Happiness (%)	**Sadness (%)**	**Fear (%)**	**Surprise (%)**	**Angry (%)**	**Disgust (%)**
Happiness	**90.25**	1.3	1.5	4.60	1.30	1.05
Sadness	1.32	**87.53**	2.58	1.72	2.34	4.51
Fear	1.79	1.16	**90.14**	4.69	0.97	1.25
Surprise	5.67	1.86	3.6	**85.07**	1.67	2.13
Angry	1.62	8.61	4.92	1.85	**80.27**	2.73
Disgust	1.98	7.52	2.88	1.23	2.6	**83.79**



(**a**) Distances between specified facial fiducial points (2D Column)



(**b**) Distances between specified facial fiducial points (2D Line)

Figure 4. Examples of one subject (person) for six facial emotions' distances between specified facial fiducial points. (a) Figure demonstration of 2D Line, (b) Figure demonstration of 2D column.

Figure 4 illustrates an example of the facial features that occur in the detection of six basic facial expressions using the IT2FIS classifier, and the Euclidean distance between these features. While the horizontal axis shows 13 different distance information, the vertical axis shows the measured value of emotion recognition distance information. These graphs should be read in such a way that Euclidean distance measurements change as emotions change. This information was used to determine the input parameters of the proposed classifier. An overall assessment of the accuracy of all tests performed to recognize six basic emotions is shown in Table 4. From this table, it is concluded that the system performance is high and the proposed method is applicable.

9. CONCLUSIONS AND FUTURE WORKS

In this paper, we present a completely automated system for facial geometric features detection and facial emotion recognition classification is proposed. We introduce different techniques to detect facial geometries and facial landmark extraction based on the proposed platform. Then, 19 motion-based feature sets containing emotional information were selected using automatic feature selection methods. We used derived AUs intensity and distinctive of AUs combinations to identify six basic emotions that use specific community classifiers for each emotion category. These are density of AUs that was well estimated by high accuracy. These feature sets were subsequently employed as inputs to an array of IT2FIS to estimate the diagnostic facial emotion. We calculated the Euclidean distances between the face motion points we obtained. For achieving a higher performance for the proposed fuzzy emotion recognition system, we determined the average set of points in the right and left regions of the face showing similar distances (for example distance of D1 and D7). Then we used both the average of these distances and the distances which is not similar to each other in length for the input of the classifier. Finally, the number of inputs used is reduced from 13 distances to seven input parameters calculated in 19-point sets. The aim is to reduce complexity and to make the rules of the designed expert system more understandable. The performance and accuracy of our proposed techniques evaluated by 175 samples from MUG emotional image database in order to see the reliability of the proposed methods. The off-line evaluation results using the MUG database indicated that the proposed ensemble models consistently outperform the IT2FIS-based classification and have achieved an averaged recognition accuracy of 86.175% for the recognition of the six basic emotions. The best recognition accuracy was observed for Happiness facial expression (>90%) and lowest recognition accuracy rate was observed for angry (80.27%).

In the future, we aim to improve emotion recognition performance and sensitivity by developing robust and real-time applicable algorithms with the use of the proposed algorithm for the removal of related facial features and minimizing the effects of disturbances such as head movements or external illumination conditions changes on the 3D image. In addition, optimization techniques on 3D face image databases will be developed to improve the robustness and efficiency of the IT2FIS proposed expert system. Finally, we also aim to incorporate other optimization algorithms such as Particle Swarm Optimization, Genetic algorithm (PSO), for optimizing parameters of membership functions.

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