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Computational Intelligence Methods for Facial Emotion Recognition: A Comparative Study

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Abstract
Emotion recognition plays a critical role in the human communications. It is one of the major ways to be in touch with others. Four parameters including eye opening size, mouth opening size, ratio of eye opening size to eye width and mouth width are used as a reduced-size feature set in this study. This paper compares the performance of facial emotion recognition classification models based on the following computational intelligence methods: fuzzy logic, chaotic gravitational search algorithm (CGSA), and artificial neural network (ANN) from eyes and mouth features tested on the FACES database. Experimental results show the superior performance of ANN-based method compared to fuzzy- and CGSA-based methods. In addition, this comparative study triggers the idea of a hybrid system based on these computational methods that outperforms the human detection system.

Keywords: Fuzzy logic, artificial neural network, chaotic GSA, face detection, eye detection, mouth detection, emotion recognition.

1. INTRODUCTION

People interact with each other with their facial emotions. By this way in each contact, large amount of cognitive information is exchanged between them. This information plays a critical role in human interactions. Early efforts in psychological research have established that the affective information in human communications is delivered at different ratio by different modalities such as the verbal expression (e.g., words and spoken text) that only accounts for 7% of the affective meaning of speakers' feeling and attitude, the vocal expression (e.g., prosody and stress) that conveys 38% of the affective message, and the facial expression that accounts for 55% of the affective information [1].

Therefore, the facial expression is considered as one of the most important aspects in analyzing and modeling natural human emotions [2] and even enhancing natural human-robot interaction [3]. Human emotion recognition ability can be modeled and used in human-machine interaction or for helping disorders which cannot distinguish the emotions [4-6].

Considering that face emotions are mostly reflected on eyes and mouth, these algorithms start with face detection to access the features of them [7]. A typical emotion recognition system includes three main subsystems [8]: face detection, feature extraction (for example the following geometric features that used in this study: eye opening size, mouth opening size, ratio of eye opening size to eye width, and width of mouth), and classification.

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Several studies have been focused on facial emotion recognition in recent years such as the following works:

- Using Gabor features and k-nearest neighbor (KNN) classifiers [9],
- Visual mismatch negative study [10],
- Extracting geometric facial features and using self-organizing map (SOM), radial-basis function (RBF), multi-layer perceptron (MLP), and support vector machine (SVM) classifiers [11],
- Using feature point tracking technique applied to the facial image regions [12],
- Employing Gabor wavelets to extract features and hybrid of artificial neural network (ANN) and hidden Markov model (HMM) classifiers [13],
- Exploring a parametric space of over 300 dimensions and testing with different machine learning techniques [14],
- Using tree structures with Gabor feature representations to present a facial emotional state and employing local experts organization (LEO) model for the processing of this tree structure representation [15],
- Selecting the best pixels of interest using MLP [16].

A reduced-size feature set including four geometric facial features is used in this study. Then, three computational intelligence methods (i.e., fuzzy logic, ANN, and chaotic gravitational search algorithm (CGSA)) are employed for automatic recognition of facial expressions on FACES database [17]. This database is gathered of the facial expressions (including neutrality, sadness, disgust, fear, anger, and happiness) in young, middle aged, and older women and men.

The rest of the paper is organized as follows: Section 2 describes the preprocessing stages before facial emotion classification including face detection and feature extraction. Section 3 introduces three computational intelligence methods used in the classification stage of this system. The comparison of experimental results is given in Section 4. Finally, Section 5 concludes the paper and gives future research directions.

2. PREPROCESSING STAGES BEFORE FACIAL EMOTION CLASSIFICATION

2.1 Face Detection

In this study, the face border is recognized using MATLAB image processing functions [18] (1-D mean filter, sobel edge detection, morphological operations (Dilation and Erosion) with linear structure element and small objects removals) on red-difference Chroma components (Cr) in YCbCr color space.

2.2 Feature Extraction

As mentioned above, four geometric facial features are used in this study as a reduced-size feature set. These features are eye opening size, mouth opening size, ratio of eye opening size to eye width, and width of mouth. The extraction details of these features are as follows:

Eye opening size: Eyes detection starts with considering only blue-difference Chroma components (Cb) while some other researches usually use a function of Cr and Cb [7, 19-22]. Applying MATLAB Software functions including edge detection, morphological operations (Dilate and Close) and binary connected component functions [18], the areas and bounding boxes for candidate eyes regions are obtained. The candidate regions are reduced based on the eyes position in the human face, then these remaining regions are chosen as eyes and cropped from S component of HSV color space for “eye opening” calculation step. In this step, the eye image is obtained using MATLAB edge detection function with threshold value set to 0.7. This procedure comprises of dilation with disk structure element functions and erosion with diamond structure element functions. At the end, the white area represents the eye and the black area shows eye border [18] (Figure 1). Eventually, to calculate the eye opening size, the pixels equal to 1 are counted along the center-line of eye.

Mouth opening size: In a×V images (a in L*a*b and V in HSV color spaces), the mouth region is seen more clear than other facial parts. So, this specification is used for mouth detection. Mouth candidate regions are found by using morphologically open binary image, close and dilate operation with disk structure element and binary connected component MATLAB functions [18]. It is noted that the true position is gained from mouth location in the face. The mouth opening size is determined by cropped mouth from Cr parameter and counted zero pixels along the center-line of mouth (Figure 1).

Eye opening/width ratio: This ratio is obtained through dividing the eye opening size by the eye width (from the width of eye region bounding box).

Width of mouth: The width of mouth is obtained from width of mouth region bounding box. The functional block diagram of preprocessing stages before facial emotion classification is shown in Figure 2. It is noted that these preprocessing stages were performed by the authors in [23] when using GSA-based classifier. In this study, the fuzzy-based, ANN-based, and chaotic GSA-based classifiers are employed for performance comparisons and with the aim of investigating the possibility of developing a hybrid system based on these computational intelligence algorithms that outperforms the human emotion detection system.

3. INVESTIGATED CLASSIFICATION METHODS

3.1 Fuzzy-based Classifier

Real world and the human reasoning are fuzzy [24]. Fuzzy logic is the logic underlying modes of reasoning which are approximate rather than exact, thus it is closer to the human reasoning and the real world than the formal logic [24]. Fuzzy logic was introduced by Zadeh [25] and used by Mamdani to control the dynamic systems [26].

The concept of fuzzy set is a class with smooth boundaries. It provides a basis for a qualitative approach to the analysis of complex systems in

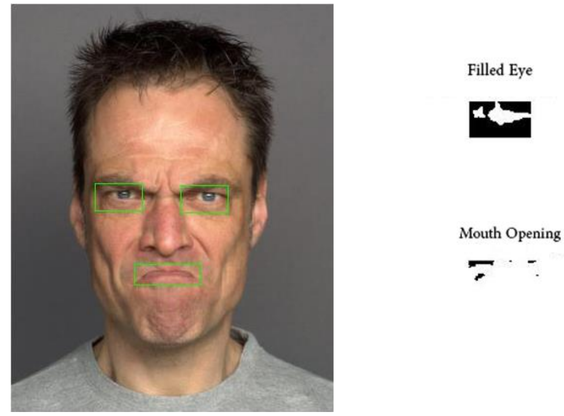

Fig. 1. Example of eye and mouth detection and preprocessing steps to determine features.

which linguistic variables rather than numerical ones are employed to describe the system behavior and performance [24]. Due to these properties, a fuzzy classifier is used in this study for mapping facial attributes to the emotion space using Mamdani-type implication relations with 94 rules and trapezoidal membership function.

To fuzzify and categorize values of features, the fuzzy sets are used as follows [27]:

- Measurement of mouth opening is categorized into LOW, MEDIUM, and HIGH (Figure 3).
- Eye opening fuzzy sets are considered as VERY LOW, LOW, MODERATE, HIGH, VERY HIGH, and EXTRA HIGH.
- Eye opening/width ratio is encoded to VERY LOW, LOW, MEDIUM, HIGH, and VERY HIGH.
- Width of mouth is categorized into LOW, MEDIUM, HIGH, and VERY HIGH.

The outputs are categorized into disgust, anger, happiness, neutrality, fear, and sadness (considering triangular membership functions) (Figure 4) Fuzzy sets and fuzzy operators are the subjects and verbs of fuzzy logic. If-then rule statements are used to formulate the conditional statements that comprise fuzzy logic [24]. Two samples of fuzzy rules in this study are as follows:

- Rule 1: if (mouth opening is LOW) and (eye opening is VERY HIGH) and (eye

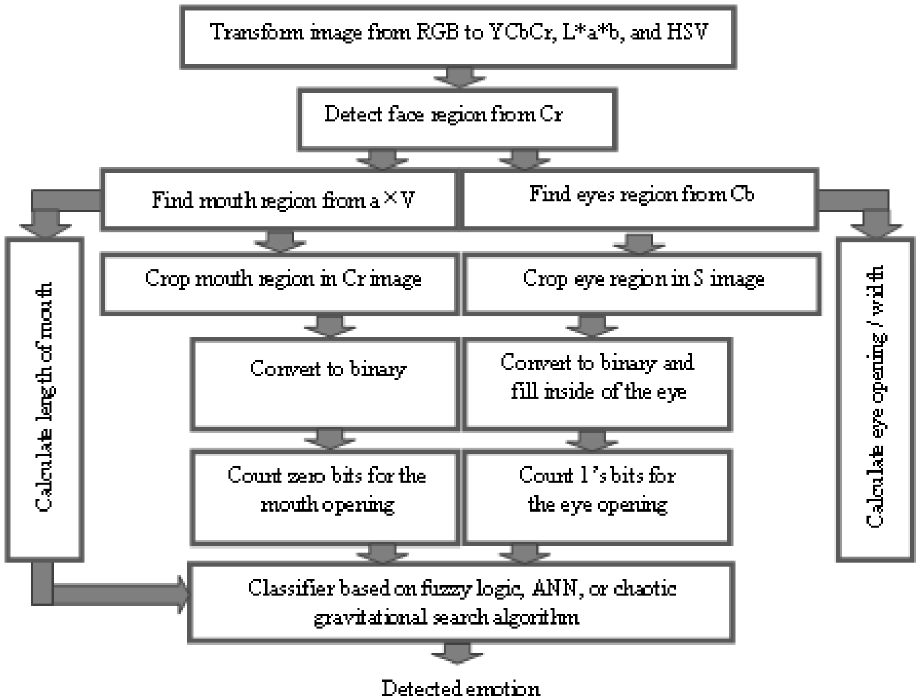

Fig. 2. Block diagram of preprocessing stages before facial emotion classification.

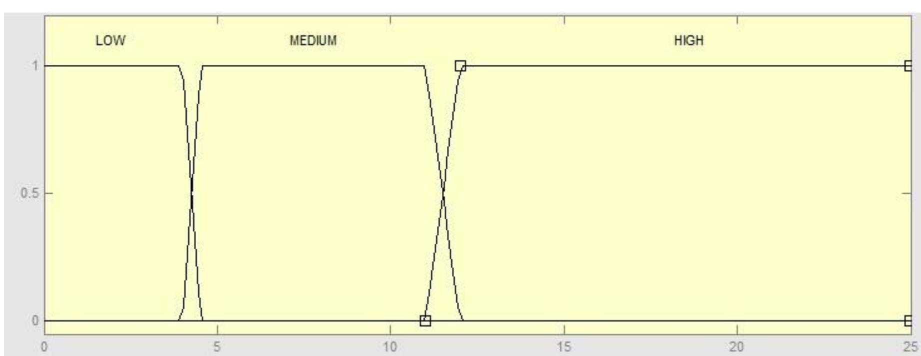

Fig. 3. Three membership functions used for fuzzification of the mouth opening.

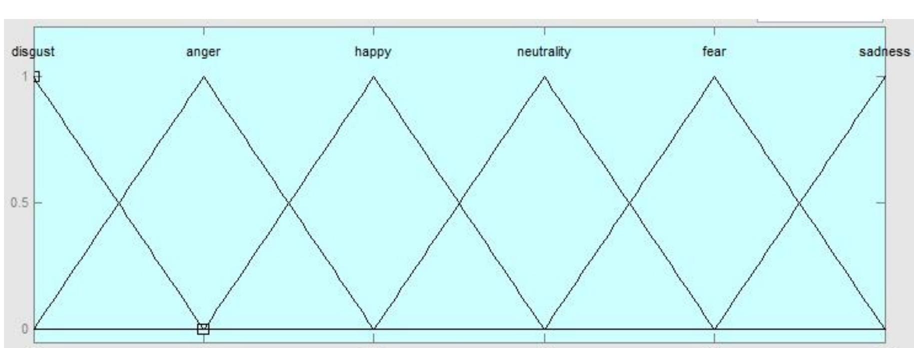

Fig. 4. Output membership functions.

opening/width ratio is LOW) and (width of mouth is HIGH), then the emotion is fear.

- Rule 2: if (mouth opening is LOW) and (eye opening is VERY LOW) and (eye opening/width ratio is VERY LOW) and (width of mouth is LOW), then the emotion is sad.

3.2 Chaotic GSA-based Classifier

Chaos is a kind of universal nonlinear phenomena in nature, whose action is complex and similar to random behavior. Owing to the randomness, regularity and special ability of avoiding being trapped in local optimal solution, the chaotic optimization algorithm has been a novel global optimization technology and has attracted considerable attention for application in various fields. Therefore, chaotic search is often incorporated into other global optimization algorithms such as neural network [28], particle swarm optimization [29], and gravitational search algorithm (GSA) [30] to enhance their search ability.

In this way, Li *et al.* [30] proposed a hybrid search algorithm by combining both chaotic and GSA [31], namely chaotic gravitational search algorithm (CGSA), for parameter identification of chaotic system. Their proposed CGSA includes two kinds of search, chaotic local search and gravitational search. Experimental results indicated that the hybrid algorithm performs better than the original GSA. So, the chaotic GSA achieves a special ability to avoid being trapped in local optimum [32, 33].

3.2.1 Brief review of GSA

GSA is a modern heuristic optimization algorithm proposed by Rashedi *et al*. [31]. According to the rules of gravity and motion, any mass understands the location and the position of the others through gravitational forces. Therefore, we can use this force as a tool for exchange of information. The GSA steps are presented in Figure 5.

This algorithm can be used to solve optimization problems where the solution can be defined as a position in the problem space. The system space is a multi-dimensional coordinate system defining the problem space and the search agents represent a set of objects; each of which is one of the problem solutions [23].

The system is supposed to be a collection of *m* masses. The position of each agent (mass), which is a candidate solution for the problem, is defined as follows:

$$X_i = \left(x^1_i, \ldots, x^2_i, \ldots, x^D_i\right) \tag{1}$$

where D is the dimension of the problem and x^d_i is the position of the ith agent in the dth dimension. The gravitational force from agent j on agent i at time t is defined as follows:

$$F^d_{ij}(t) = \frac{G(t) \times Mg_j(t)}{R_{ij}(t) + e}\left(x^d_j(t) - x^d_i(t)\right) \tag{2}$$

where Mg_j is the active gravitational mass related to agent j, e is a small constant, and $G(t)$ is the gravitational constant at time t, and $R_{ij}(t)$ is the Euclidian distance between two agents i and j that calculated as follows:

$$R_{ij}(t) = \| X_i(t), X_j(t) \|_2 \tag{3}$$

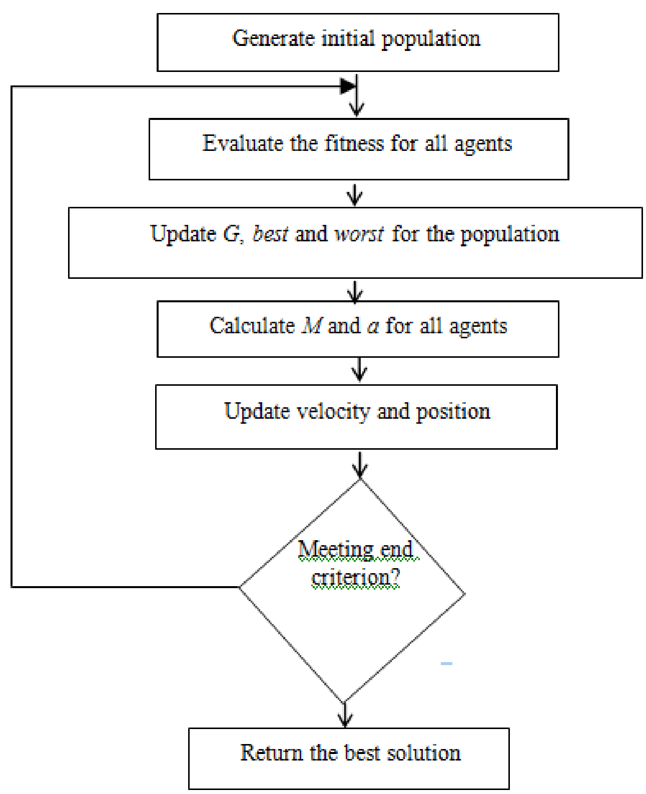

***Fig. 5. Flowchart of the gravitational search algorithm* [31].**

In a problem space with the dimension *d*, the total force that acts on agent *i* is calculated by Eq. (4):

$$F_i^d(t) = \sum_{j=1, j\neq i}^{m} r_j \, F_{ij}^d(t) \tag{4}$$

where r_j is a random number in the interval [0,1]. According to the law of motion, the acceleration of an agent is proportional to the resultant force and inverse of its mass, so the accelerations of all agents are calculated as follows:

$$a_i^d(t) = \frac{F_i^d(t)}{M_{ii}(t)} \tag{5}$$

where *d* is the dimension of the problem, *t* is a specific time, and Mi_i is the inertial mass of object *i*. The velocity and position of agents are calculated as follows:

$$V_i^d(t+1) = r_i * V_i^d(t) + a_i^d(t) \tag{6}$$

$$x_i^d(t+1) = x_i^d(t) + V_i^d(t+1) \tag{7}$$

As can be inferred from (6) and (7), the current velocity is defined as a fraction of its previous velocity added to its acceleration. Furthermore, the current position of an agent is equal to its previous position added to its current velocity. Agents' masses are defined using fitness evaluation; the masses of all agents are updated using Eq. (8):

$$Mg_i = \frac{fit_i(t) - worst(t)}{best(t) - worst(t)} \tag{8}$$

where $fit_i(t)$ is the fitness value of the agent *i* at time *t*; *best*(*t*) is the strongest agent at time *t*, and *worst*(*t*) is the weakest agent at time *t*. In this way, *best*(*t*) and *worst*(*t*) for a minimization problem are calculated as follows:

$$best(t) = \min_{j\in\{1,\ldots,m\}} fit_j(t) \tag{9}$$

$$worst(t) = \max_{j\in\{1,\ldots,m\}} fit_j(t) \tag{10}$$

3.2.2 Chaotic GSA

The basic idea of searching optimum using chaos variables is producing chaos variables with a kind of chaotic map, projecting chaos variables to optimize variables interval and then searching optimal solution with chaos variable. Randomness and ergodicity of chaos variables make chaos optimization possible to achieve global optimum quickly [30].

In order to improve the performance of GSA in terms of convergence speed and solution quality, the local search procedure is carried out for the current global best agent *Xg*, while the range around *Xg* could be the most promising area to find the optimal solution [30].

In CGSA, the procedure of chaotic local search (CLS) is applied to search the optimal solution around the current best solution *Xg* found by gravitational search. The chaotic optimization based on the Logistic map will affect the global search capacity and computational efficiency. The logistic map is described by following equation:

$$x_{i+1} = ax_i(1 - x_i) \tag{11}$$

where x_i (*t*) is the chaotic value in the interval [0, 1] of the agent *i* and *a* is set to 4 in simulations. The flowchart of CGSA is shown in Figure 6.

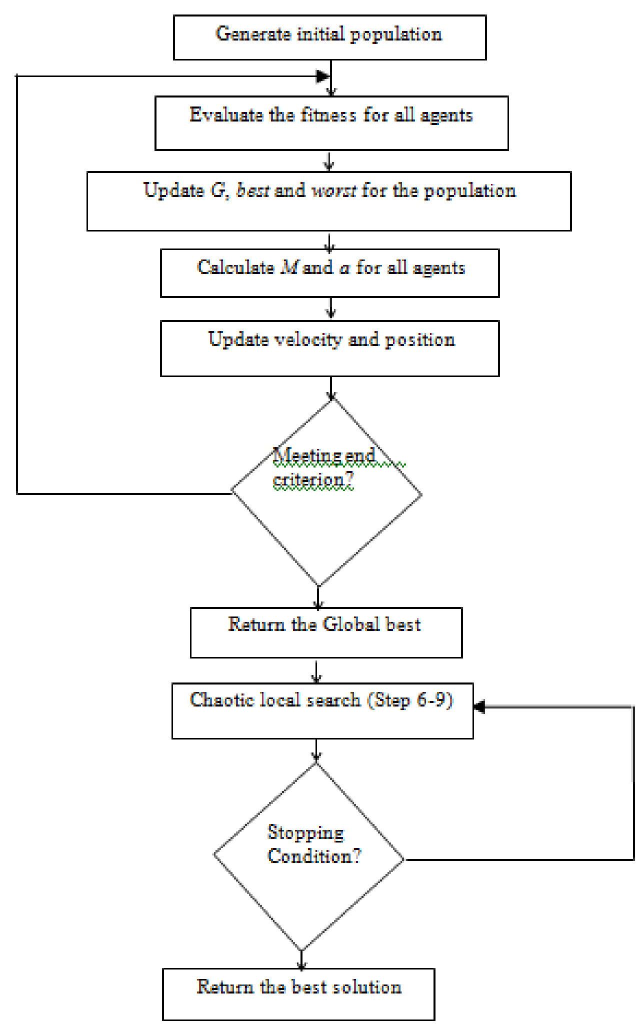

Fig. 6. Flowchart of the chaotic gravitational search algorithm.

The steps of this algorithm are given below [33]:

Step 1: Initialize a defined population of agent (mass) with random positions and velocities; that each agent contains *n* variables.

Step 2: Compute the objective values of all agents; let the current best position of each agent and its objective value be equal to its initial position and objective value.

Step 3: Update the velocity and position for each agent.

Step 4: Compare the objective value; for each agent, compare its current objective value with global best. If the current value is better; then, update the best position and its objective value with the current position and objective value.

Step 5: Check termination condition; if the maximum iteration is reached, then the best position and its global best would be determined; otherwise go back to step 2.

Step 6: Chaotic local search (CLS); set j=0 and employ Eq. (12) to map the parameters in the interval (x_{mini},x_{maxi}) into chaotic variable cx_i located in the interval [0,1]:

$$cx_i{}^j = \frac{x_i{}^j - x_{mini}}{x_{maxi} - x_{mini}} \ ; \ i = 1,2,\dots,N \tag{12}$$

Step 7: Compute the chaotic variable in the next iteration; use the famous logistic function, defined by May [34] (Eq. 11), to compute the next iteration chaotic variable, cx_i^{j+1} where cx_i is the ith chaotic variable in the range [0, 1] and j represents the iteration number.

Step 8: Transform the chaotic variable; transform cx_i to obtain parameters for the next iteration, X_i^{j+1}, using Eq. (13):

$$X_i{}^{j+1} = x_{mini} + CX_i{}^{j+1}(x_{maxi} - x_{mini}) \tag{13}$$

Step 9: Compute the new objective value for X_i^{j+1}.

Step 10: Stopping criteria; if the new objective value with smaller error or maximum iteration of CLS is reached, then the new chaotic variable X_i^{j+1} and its corresponding objective value is the final solution; otherwise, let j =j +1 and go back to Step 6.

With CGSA-based classifier, the average output of each emotion is used as a reference to find the best solution using the Euclidean distance-based fitness function. In this case, the outputs of all facial images in the same emotion are given as initial agents with 4 dimensions to the CGSA algorithm, and then it starts optimization procedure using these agents. This optimal solution has the minimum distance with the mean of each emotion [23].

3.3 ANN-based Classifier

Neural network is a massively parallel system made up of simple units which is called neuron and has a natural property for storing experimental knowledge and for making it available to use [35]. Because of dealing with uncertain, fuzzy, or insufficient data; neural networks have become a very important method for image classification. One of popular neural networks is multi-layer perceptron (MLP) that consists of an input layer, one or more hidden layers, and an output layer. Each layer consists of multiple neurons. In this type of network, the input is presented to the network and moves through the weights and nonlinear activation functions towards the output layer, and the error is corrected in a backward direction using the well-known error back propagation (EBP) algorithm.

In order to train a multi-layer feed-forward neural network [36], the nprtool GUI (Neural Network Pattern Recognition tool Graphical User Interface) of Matlab® 2010b was used in this study. The network is a two layer feed-forward type with the default tangent-sigmoid transfer functions in both the hidden and output layers.

4. EXPERIMENTAL RESULTS AND PERFORMANCE COMPARISONS

4.1 Fuzzy-based Classifier Experimental Results

The setting of the proposed fuzzy system is shown in Table 1. The confusion matrix of fuzzy-based classifier is given in Table 2. As seen in Table 2, the fuzzy-based classifier system shows 77.76% accuracy rate on the FACES database. The best results were achieved for Happy and Fear emotions and the worst results were achieved for Neutral and Disgust emotions.

Table 1. *Fuzzy system settings.*

System type	Mamdani
Number of inputs	4
Number of rules	94
And method	Min
Or method	Max
Imp. method	Min
Agg. method	Sum
Defuzz. method	Lom
Inputs membership function	Trapmf
Outputs membership function	Trimf

Table 2. *Confusion matrix of fuzzy-based classification method.*

Actual emotion	Recognized emotion from facial expression					
	Happy	Neutral	Angry	Fear	Sad	Disgust
Happy	**100**	0.0	0.0	0.0	0.0	0.0
Neutral	0.0	**50**	0.0	0.0	50	0.0
Angry	0.0	0.0	**91.6**	0.0	0.0	8.4
Fear	0.0	0.0	0.0	**100**	0.0	0.0
Sad	16.6	0.0	8.4	0.0	**75**	0.0
Disgust	0.0	0.0	41.6	0.0	8.4	**50**

4.2 Chaotic GSA-based Classifier Experimental Results

The parameters setting for the CGSA optimization method is given in Table 3. The achieved results when running CGSA for six emotions are listed in Table 4.

By performing CGSA-based optimum detection, an optimal value is assigned to each emotion (Table 4). These optimal values are used in classification based on the values of features; the output of feature extraction part is compared with these values using Euclidean distance function [37]. The Euclidean distance between two vectors is calculated as Eq. (14):

$$d(x,y)=\sqrt[2]{\sum_{i}^{n}((x_i-y_i)^2)} \tag{14}$$

here n is the dimension of solution, x_i and y_i are the elements of optimized matrix and input facial features matrix, respectively. By comparing the Euclidean distance, the minimum is selected as the output emotion.

The results on FACES database [17] show 75.06% accuracy rate (Table 5). As shown in Table 5 the best results are observed for two cases of Happy and Disgust emotions and the worst result occurs for the Fear emotion.

Table 3. *CGSA parameters setting.*

CGSA parameter	Description
Notation of agents	(x_1,x_2,x_3,x_4)
Number of agents	200
Dimension of agents	4
Range of agents	[0-100]
Maximum number of iterations	20
Kind of problem	Minimization
Chaotic map	logistic

Table 4. *Mean and CGSA best agents for six emotions.*

Emotion	Mean of outputs	CGSA best
Sad	[1.125,11.58,2.72,84.95]	[0.3,13.7,1.771,84.7]
Happy	[9.79,10.45,3.07,86.2]	[8.3,11.3,3.209,84.3]
Anger	[0.7,9.16,4.16,71.7]	[0.3,7.3,4.014,71.3]
Disgust	[1.16,6.58,4.84,64.7]	[0.3,6.3,4.966,65.3]
Fear	[4.5,18.91,1.72,70.7]	[6.7,18.7,1.331,70.7]
Neutral	[0.3,14.5,2.36,75.83]	[0.3,14.3,2.728,75.3]

Table 5. ***Confusion matrix of CGSA-based classification method*.**

Actual emotion	Recognized emotion from facial expression					
	Happy	Neutral	Angry	Fear	Sad	Disgust
Happy	**100**	0.0	0.0	0.0	0.0	0.0
Neutral	0.0	**66.8**	0.0	16.6	0.0	16.6
Angry	8.3	8.3	**66.8**	0.0	8.3	8.3
Fear	0.0	8.3	0.0	**50**	8.3	33.4
Sad	0.0	16.6	0.0	8.3	**66.8**	8.3
Disgust	0.0	0.0	0.0	0.0	0.0	**100**

4.3 ANN-based Classifier Experimental Results

Parameters setting of the MLP classifier are shown in Table 6. The representation of different emotions using binary codes of target data is also given in Table 7.

It is noted that the input data are geometric facial features (eye opening, mouth opening, eye opening/width ratio, and mouth width) from 24 images of FACES database in each emotion ($24\times6=144$).

The values of mean squared error (MSE) for training, validation, and test of the MLP network are shown in Table 8. By using this network as a classifier on the FACES database, the confusion matrix is shown in Table 9. As seen, the best results are achieved for Happy, Fear, and Sad emotions with 100% accuracy rate. The performance of the system is similar for the Neutral and Disgust emotions with 83.4% accuracy rate and the worst result belongs to Angry emotion with accuracy rate of 66.8%. The average recognition accuracy of MLP-based classifier is 88.93%.

Table 6. ***Settings of nprtool for MLP-based classifier*.**

Input data size	144×4
Target data size	144×4
Number of training data	100
Number of validation data	22
Number of testing data	22
Number of hidden neurons	8

Table 7. ***Representation of emotions using binary codes as target data.***

Emotion	Binary Code
Angry	0000
Disgust	0001
Fear	0010
Happy	0011
Neutral	0100
Sad	0101

The present paper results (using fuzzy logic, chaotic GSA, and neural network) are compared to Shan *et al*. [38] work which was based on Local Binary Pattern (LBP), SVM, AdaBoost, and Boosted-LBP. Moreover, the human detection [39], SVM, and AdaBoost [40] methods' results with the same database (FACES database [17]) are used for comparison. All these comparisons are included in Table 10. Considering Table 10, based on the best recognition rate, the results are error-free for detecting Happy emotion using Fuzzy-, CGSA- and ANN-based methods. The Fear emotion detection using fuzzy- and ANN-based methods, Sad emotion detection using ANN-based method, and Disgust emotion detection using CGSA-based method are also error-free.

The worst results belong to Neutral and Disgust emotions detection when using fuzzy-based method and Fear emotion detection using CGSA-based in the FACES dataset.

In comparisons based on each emotion using the FACES dataset, Table 10 presents that in Happy emotion, all the proposed methods have quite correct detection, while the human identification is 99.6%. For Neutral emotion, fuzzy-based method has the worst recognition result and the neural network-based classifier works better whereas human detection is the best. For Anger emotion, the fuzzy-based system has the

Table 8. ***MSE for training, validation, and test data of the MLP network*.**

Dataset	Number of samples	MSE
Training	100	5.77×10^{-2}
Validation	22	6.59×10^{-2}
Test	22	1.09×10^{-1}

Table 9. ***Confusion matrix of ANN-based classification method.***

Actual emotion	Recognized emotion from facial expression					
	Happy	Neutral	Angry	Fear	Sad	Disgust
Happy	**100**	0	0	0	0	0
Neutral	0	**83.4**	0	8.3	8.3	0
Angry	0	8.3	**66.8**	0	16.6	8.3
Fear	0	0	0	**100**	0	0
Sad	0	0	0	0	**100**	0
Disgust	0	0	8.3	0	8.3	**83.4**

Table 10. ***Comparison of the investigated systems with some other systems in literature*.**

Actual emotion	Recognized emotion from facial expression								
	Tested on a database other than FACES				Tested on the FACES database				
	LBP	*SVM*	*AdaBoost*	*Boosted LBP*	*SVM and AdaBoost*	*Human detection*	*Fuzzy method*	*Neural Network method*	*Chaotic GSA method*
Happy	90.4	94.7	90.1	97.5	87.5	99.6	100	100	100
Neutral	70.3	90	95.2	92	NR	94.8	50	83.4	66.8
Angry	58.7	85	66.6	85.1	NR	77.9	91.6	66.8	66.8
Fear	61.7	68	70	79.9	91	90.4	100	100	50
Sad	72.4	69.5	61.2	74.7	NR	78.6	75	100	66.8
Disgust	85	97.5	92.5	97.5	80	76.3	50	83.4	100

NR: Not Reported

best recognition result even better than human detection. For Fear emotion, the fuzzy-based and ANN-based methods offer the best recognition results even better than human detection. The best recognition result is achieved by ANN-based classifier in Sad emotion even better than human detection. For Disgust emotion, CGSA-based performs perfect and ANN-based method is placed in the second rank. The performance of these methods is even better than human detection for this emotion.

5. CONCLUSION AND FUTURE WORK

This paper investigated the feature representation and three classification schemes to recognize six different facial expressions on the FACES database [17]. In this way, an algorithm was introduced to extract reduced-size geometric facial features (including four eye- and mouth-related features). The performance of three classification methods based on the computational intelligence algorithms (i.e., fuzzy logic, chaotic GSA, and ANN) was also evaluated in this task. Experimental results showed that the ranking of recognition results among investigated methods is as follows: ANN-based (88.93%), fuzzy-based (77.76%), and chaotic GSA-based (75.06%).

Based on achieved experimental results and as future works, the following activities are recommended to improve the performance of emotion recognition:

- Developing a hybrid system based on the investigated computational intelligence methods that can achieve average recognition accuracy up to 95.83% (based on the best results reported in Table 10 for these systems). It is noted that the average recognition accuracy of human detection is 86.26%.
- Using more facial features such as eyebrow and nose features. It is noted that more geometric facial features are used in recent works, for example 26 geometric facial features (including eyebrow, eyes, nose, and lip) used in [11].

However, the proposed system in this study has the potential to achieve the average recognition rate of 95.83% using only four facial features. On the other hand, the recent reported research in [11] achieves the following average recognition rates over six basic emotions using the MMI database [41]: SOM classifier: 93.5%, RBF classifier: 66.6%, MLP classifier: 72.2%, and SVM classifier: 92.5%. It is noted that one of emotions in the MMI database is different from the FACES database (Surprise emotion instead of Neutral state).

REFERENCES

[1] Mehrabian, "Communication without words," Psychology Today, vol. 2, no. 9, pp. 52-55, 1968.

[2] R. W. Picard, Affective computing, MIT Press, Cambridge, 1997.

[3] L. Zhang, M. Jiang, D. Farid, and M. A. Hossain, "Intelligent facial emotion recognition and semantic-based topic detection for a humanoid robot," Expert Systems with Applications, vol. 40, no. 13, pp. 5160-5168, 2013.

[4] M. S. George, T. Huggins, W. McDermott, P. I. Parekh, D. Rubinow, and R. M. Post, "Abnormal facial emotion recognition in depression: Serial testing in an ultra-rapid-cycling patient," Behavior Modification, vol. 22, no. 2, pp. 192-204, 1998.

[5] M. B. Harms, A. Martin, and G. L. Wallace, "Facial emotion recognition in autism spectrum disorders: A review of behavioral and neuroimaging studies," Neuropsychology Review, vol. 20, no. 3, pp. 290-322, 2010.

[6] B. T. Lau, "Portable real time emotion detection system for the disabled," Expert Systems with Applications, vol. 37, no. 9, pp. 6561-6566, 2010.

[7] I. Maglogiannis, D. Vouyioukas, and C. Aggelopoulos, "Face detection and recognition of natural human emotion using Markov random fields," Personal and Ubiquitous Computing, vol. 13, no.1, pp. 95-101, 2009.

[8] M. Ilbeygi, and H. Shah-Hosseini, "A novel fuzzy facial expression recognition system based on facial feature extraction from colour-faces images," Engineering Applications of Artificial Intelligence, vol. 25, no.1, pp. 130-146, 2012.

[9] M. Tkalčič, A. Odić, and A. Košir, "The impact of weak ground truth and facial expressiveness on affect detection accuracy from time-continuous videos of facial expressions," Information Sciences, vol. 249, no. November, pp. 13-23, 2013.

[10] G. Stefanics, G. Csukly, S. Komlósi, P. Czobor, and I. Czigler, "Processing of unattended facial emotions: A visual mismatch negativity study," NeuroImage, vol. 59, no. 3, pp. 3042-3049, 2012.

[11] A. Majumder, L. Behera, and V. K. Subramanian, "Emotion recognition from geometric facial features using self-organizing map," Pattern Recognition, vol. 47, no. 3, pp. 1282-1293, 2014.

[12] A. Besinger, T. Sztynda, S. Lal, C. Duthoit, J. Agbinya, B. Jap, D. Eager, and G. Dissanayake, "Optical flow based analyses to detect emotion from human facial image data,"

Expert Systems with Applications, vol. 37, no. 12, pp. 8897-8902, 2010.

[13] T. Hu, L. C. De Silva, and K. Sengupta, “A hybrid approach of NN and HMM for facial emotion classification,” Pattern Recognition Letters, vol. 23, no. 11, pp. 1303-1310, 2002.

[14] H. Fang, N. Mac Parthaláin, A. J. Aubrey, G. K. L. Tam, R. Borgo, P. L. Rosin, P. W. Grant, D. Marshall, and M. Chen, “Facial expression recognition in dynamic sequences: An integrated approach,” Pattern Recognition, vol. 47, no. 3, pp. 1271-1281, 2014.

[15] J.-J. Wong, and S.-Y. Cho, “A local experts organization model with application to face emotion recognition,” Expert Systems with Applications, vol. 36, no. 1, pp. 804-819, 2009.

[16] T. Danisman, I. M. Bilasco, J. Martinet, and C. Djeraba, “Intelligent pixels of interest selection with application to facial expression recognition using multilayer perceptron,” Signal Processing, vol. 93, no. 6, pp. 1547-1556, 2013.

[17] N. Ebner, M. Riediger, and U. Lindenberger, “FACES - A database of facial expressions in young, middle-aged, and older women and men: Development and validation,” Behavior Research Methods, vol. 42, no. February, pp. 351-362, 2010.

[18] C. Gonzalez, E. Woods, and L. Eddins, Digital Image Processing Using MATLAB, 2nd edition, Gatesmark Publishing, 2009.

[19] S. Phung, A. Bouzerdoum, and D. Chai, “Skin segmentation using colour and edge information,” Proc. Seventh Int. Symp. Signal Processing and Its Applications, vol. 1, pp. 525-528, 2003.

[20] A. Chakraborty, A. Konar, U. K. Chakraborty, and A. Chatterjee, “Emotion recognition from facial expressions and its control using fuzzy logic,” IEEE Transactions on Systems, Man, and Cybernetics-Part A: Systems and Humans, vol. 39, no. 4, pp. 726-743, 2009.

[21] H. Kalbkhani, and M. Chehel Amirani, “An efficient algorithm for lip segmentation in colour face images based on local information,” Journal of World’s Electrical Engineering and Technology, vol. 1, no. 1, pp. 12-16, 2012.

[22] A. Nasiri, H. Sadoghi Yazdi, and M. Naghibzadeh, “A mouth detection approach based on PSO rule mining on colour images,” Proc. 5th Iranian Conf. Machine Vision and Image Processing, pp. 4-6, 2008.

[23] F. Shahrabi Farahani, M. Sheikhan, and A. Farrokhi, ”Facial emotion recognition using gravitational search algorithm for colored images,” Presented in Symposium on Artificial Intelligence and Signal Processing, Sharif University of Technology, Tehran, Iran, Dec. 2013.

[24] I. Elamvazuthi, P. Vasant, and J. Webb, “The application of Mamdani fuzzy model for auto zoom function of a digital camera,” International Journal of Computer Science and Information Security, vol. 6, no. 3, pp. 244-249, 2009.

[25] L. A. Zadeh, “Outline of a new approach to the analysis of complex systems and decision processes,” IEEE Transactions on Systems, Man, and Cybernetics, vol. 3, no. 1, pp. 28-44, 1973.

[26] E. M. Mamdani, “Applications of fuzzy algorithms for simple dynamic plants,” Proc. IEEE, vol. 21, no. 12, pp.1585-1588, 1974.

[27] F. Shahrabi Farahani, M. Sheikhan, and A. Farrokhi, “A fuzzy approach for facial emotion recognition,” Proc. 13th Iranian Conf. Fuzzy Systems, Qazvin, Iran, Aug. 2013 (IEEEXplore Digital Object Identifier: 10.1109/IFSC.2013.6675597).

[28] K. Aihara, T. Takabe, and M. Toyoda, “Chaotic neural networks,” Physics Letter A, vol. 144, no. 6-7, pp. 333-340, 1990.

[29] D. L. Jia, Y. M. Jiao, and J. D. Zhang, “Satisfactory design of IIR digital filter based on chaotic mutation particle swarm optimization,” Proc. Third Int. Conf. Genetic and Evolutionary Computing, pp. 48-51, 2009.

[30] C. Li, J. Zhou, J. Xiao, and H. Xiao, “Parameters identification of chaotic system by chaotic gravitational search algorithm,” Chaos, Soli-

tons& Fractals, vol. 45, no. 4, pp. 539-547, 2012.

[31] E. Rashedi, H. Nezamabadipour, S. Saryazdi, “GSA: A gravitational search algorithm,” Information Sciences, vol. 179, no. 13, pp. 2232-2248, 2009.

[32] L. Wang, D. Z. Zheng, and Q. S. Lin, “Survey on chaotic optimization methods,” Computing Technology and Automation, vol. 20, pp. 1-5, 2001.

[33] F. Ju, and W. Hong, “Application of seasonal SVR with chaotic gravitational search algorithm in electricity forecasting,” Applied Mathematical Modelling, vol. 37, no. 23, pp. 9643-9651, 2013.

[34] R. M. May, “Simple mathematical models with very complicated dynamics,” Nature, vol. 261, no. June, pp. 459-467, 1976.

[35] B. Dhanya, and P. Punitha, “Image classification using artificial neural networks: An experimental study on Corel database,” International Journal of Machine Intelligence, vol. 3, no. 4, pp. 225-229, 2011.

[36] D. Svozil, V. Kvasnicka, and J. Pospichal, “Introduction to multi-layer feed-forward neural networks,” Chemometrics and Intelligent Laboratory Systems, vol. 39, no. 1, pp. 43-62, 1997.

[37] Y. Taghizadegan, H. Ghassemian, and M. Moghaddasi, “3D face recognition method using 2D-PCA Euclidean distance classification,” ACEEE Int. J. on Control System and Instrumentation, vol. 3, no. 1, pp. 1-5, 2012.

[38] C. Shan, S. Gong, and P. McOwn, “Facial expression recognition based on local binary patterns: A comprehensive study,” Image and Vision Computing, vol. 27, no. 6, pp. 803-816, 2009.

[39] C. Ebner, and M. K. Johnson, “Age-group differences in interference from young and older emotional faces,” Cognition & Emotion, vol. 24, no. 7, pp. 1095-1116, 2010.

[40] H. Halawani, “Emotion recognition system based on facial expression,” M.S. Thesis, University of Sheffield, 2011.

[41] M. Pantic, M. F. Valstar, R. Rademaker, and L. Maat, “Web-based database for facial expression analysis,” Proc. IEEE Int. Conf. Multimedia and Expo, pp. 317-321, 2005.