Face emotion recognition system based on fuzzy logic using algorithm improved Particle Swarm

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Abstract
Recognition of facial emotions has important role in HCI. One of the components of the system for facial emotion Recognition is classification. For classification with the fuzzy logic system, setting parameters of membership functions has significant importance. In this research, first for extraction of feature, two extractions of feature linear subspace projection and nonlinear subspace projection toolboxes named pretty helpful development toolboxes were used. For classification of the resultant data from feature extraction, the fuzzy inference system was used. For setting the parameters of membership functions, the improved PSO algorithm was taken advantage of to be able to increase the precision of classification. Precision of system classification was calculated with each of the PSO, ACOR, Genetic and SA algorithms. Next, the precision of classification resulting from combination of PSO with each of these algorithms was calculated. Results show that combination of PSO with Genetic algorithm yields a more advantageous result compared to the other algorithms. In this research, also the precision of recognition of the emotion of contemptuousness was calculated with the proposed system which up to now has not been evaluated in any article on set of emotions. Experimental results report a mean precision of measurement of the system for Recognition of seven emotions to be 98.32 percent. Additionally, using the proposed system, the rate of Recognition of the feeling of contemptuousness was reported at 99.25 percent, where in reports obtained from fuzzy deduction system, classification with Genetic algorithm, has reported classification precisions of 100 percent as well.
Keywords:
Emotion face recognition system, Fuzzy inference system, Particle swarm optimization (PSO), Ant colony optimization real (ACOR), Genetic Algorithm (GA), Simulated annealing (SA).

1. Introduction

For creation of more effective interaction between humans and the computer, a system that can recognize a person's behavior has gained attention [21]. Facial emotion Recognition systems are made up of several main constituents. These constituents are: image preprocessing, facial recognition, extraction of facial features, classification.
Image preprocessing includes transformations on the image to make it more effective for the stage of feature extraction and classification. Up to now, many algorithms have been presented for facial recognition. In this article, we assume that the stage of facial recognition involves a front view image and part of the image which includes the face is forwarded to the next stage. The next stage after facial recognition (in many systems of emotion recognition) is extraction of facial features. Extraction of facial features is one of the most complex and time consuming stages in systems of emotion recognition. The final precision of the emotion recognition system is to a great extent dependent on the precision of this stage. As a result, selection of precise and efficient algorithms is very important for this stage. Here, the method of feature extraction tool box named pretty helpful development toolbox (PHD toolbox) was used. This toolbox is a specialized toolbox for facial processing which has been introduced by Struck in 2012 in the Mat Lab environment. This toolbox uses some facial processing techniques such as Principal Component Analysis (PCA) and Kernel Principal Component Analysis (KPCA) for recognition of face and its features. The section of this tool for extraction of feature has multiple functions, where each can be used based on need. The function of Filter Image with Gabor Bank puts the input image through Gabor Filtering to calculate the response amount. The minimum sample of each amount of the responses is calculated and finally, the amounts of responses are combined with each other in a feature vector. Linear subspace projection is calculated under the space presented by the samples or the matrix of samples. Therefore, the model created uses PCA for creation of new data in the calculated subspace in that recognition. Nonlinear subspace projection function, presented subspace of the samples or samples matrix is calculated. Therefore, the produced model uses KPCA to create new data in the calculated subspace in that recognition [1]. After extraction of face features, we attempt to classify facial emotions. Seven primary emotions suggested by Ekman (1993) were selected for system recognition. These emotions are: anger, disgust, fear, happiness, sadness, surprise and contemptuousness. Next, the mentioned emotions were classified using the fuzzy inference system (FIS). The most important part of the fuzzy inference system is membership function and regulation of its parameters. For regulation of parameters of the membership function, we can use Met heuristics

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algorithms [2]. In this line, we intend to use the PSO algorithm to evaluate the performance of the emotion recognition system with this algorithm. This algorithm with use of some strategies at high level and taking advantage of memory is able to increase speed of convergence. Additionally, it can be useful in discovery of efficient search space [3]. It should be noted that if the algorithm becomes tangled in local best, its convergence slows down which leads to lack of useful result from the algorithm [4]. Therefore, it has been considered to combine this algorithm with GA [5], SA [22] and ACOR [6] algorithms and to evaluate which combination leads to increased precision in classification with the PSO algorithm.

2. Related Work

In Table (1) some of the previous works done in the context of recognition of facial emotions have been evaluated. In methods based on fuzzy logic, precision of classification is higher. For example, Chakraborty and colleagues (2009) [8]. One of the main problems of the mentioned article is that only three separate fuzzy sets: low, high and moderate have been used for fuzzy making. In addition, only three facial features (opening the eyes, opening the mouth and length of eyebrow contraction) have been considered, and clustering FCM algorithms used for recognition of the lips area are very time consuming. Maglogiannis and colleagues (2009) have presented a cohesive system for provision of emotional recognition in which they have only used the expressions of the eye and mouth for recognition of four emotions (happiness, sadness, surprise and anger) and the normal facial expression [9]. The main part of their algorithm uses a technique of edge recognition for determination of eyes and mouth line, curve and slope. It should be noted that they do not use fuzzy inference system for recognition of emotions. Shah Hosseini and Ilbeygi (2012) have proposed a method for emotion recognition from complete and semi complete images based on fuzzy logic, where for extraction of face features two classifications of primary features (eye opening, mouth opening, eyebrow shortness, displacement of corner of mouth) and secondary features (mouth length, wrinkle over the nose, presence of teeth, eyebrow slant and lip thickness) have been used. For their fuzzy inference system, they have used 5 fuzzy sets (very low, low, moderate, high, and very high). For ordering membership functions, they have used the Genetic algorithm. Other algorithms such as the PSO which have more rapid convergence compared to the Genetic algorithm can be used for regulation of membership function parameters

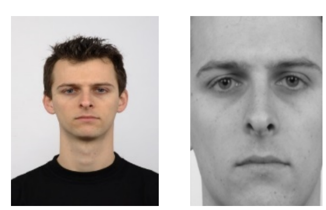
Table 1. Brief view of works performed in the context of facial emotion recognition

Average recognition rate	Number of recognized emotions	Principal characteristics	Used methods and algorithms	Authors
86.3%	32 individual facial muscle actions (AUs)	Recognition of facial emotions in the static state was performed from side profile and full profile face. With the help of the eye, eyebrow and mouth, for side profiles 19 characteristic face points and full profile 10 characteristic face points were extruded.	Reasoning based on law	Pantic & Rothkrantz(2004)[10]
94.29%	6 basic emotions and Neutral	Various techniques of extruding features such as discrete cosine transform, rapid Fourier transform, and singular value decomposition were used for extraction of face features.	Supporting vector machine	Kharat & Dudal (2008) [11]
94.4%	4 basic emotions and Neutral	Feature extraction is via eye and lips. Bezier curves with access to extruded features and with consideration of characteristics of each emotion and their changes have been estimated.	Three stage Bezier curve	Khan & Bhuiyan (2008) [12]
93%	6 basic emotions and Neutral	Face emotion Recognition is performed on fixed images based on face features and using Mamdani fuzzy system.	Mamdani fuzzy system	Khanam & etal. (2008) [13]
Average recognition rate for adult males, adult females and children in age group 8–12 years are 89.11%, 92.4%, and 96.28%, respectively.	6 basic emotions	Three distinct fuzzy sets: high, low and moderate for fuzzy were used. Additionally, only three face features (eye opening, mouth opening and length of eyebrow contraction) were considered.	Mamdani fuzzy inference system	Chakraborty & etal.(2009)
82.14%	4 basic emotions and Neutral	Only two face features (eye and mouth expression) were considered.	Use of edge recognition and measurement of the slope of eye and mouth area	Maglogiannis & etal.(2009)
83.57%	6 basic emotions and Neutral	Lip and eye features were extruded for classification of emotions by way of a set of ellipsoid equations and have been used with application of the Genetic algorithm. For prevention of overlap, neural network has also been used in continuation of the Genetic algorithm.	Genetic algorithm and neural network	Rizon & etal.(2009) [14]
94.29%	6 basic emotions and Neutral	Initially, facial image was divided into three regions, where local uniformly distributed binary pattern has been extruded from those distributed tissue features and as a representative of a describer histogram is presented.	Multiple fuzzy neural comparative inference system	Gomathi & etal.(2009) [15]

72%	4 basic emotions and Neutral	Emotions recognition system based on WISBER fuzzy video has been proposed which permits analysis of face emotions to be performed in video sequence.	Fuzzy classification	Esau & etal.(2009) [16]
Other than the emotion of fear and anger, it recognizes other emotions with a precision of 100%	6 basic emotions and Neutral	With the purpose of improvement of automatic selection of best parameters, least squares support vector machine proposes the improved PSO.	Least squares support vector machine and improved PSO	Liu & etal.(2010) [17]
With Genetic selection of feature and JAFFE data base, it is 98%	6 basic emotions and Neutral	Various methods of feature extraction and selection of feature for facial expression Recognition system are studied. Additionally, the efficiency of the method of highest level of equal local correlation of features for extraction of features is evaluated.	Highest level of equal local correlation	Lajevardi & Hussain(2010) [18]
93.96%	6 basic emotions and Neutral	For extraction of facial features, features are transformed into two groups primary and secondary for increased precision. For some primary features fuzzy classification of very low, low, moderate, high, very high has been used and for some others 3 divisions of low, moderate and high and for secondary features two classifications low and high have been used.	Fuzzy system and Genetic algorithm	Ilbeygi & Shah-Hosseini (2012)
96.42%	6 basic emotions and Neutral	For determination of effective facial regions, inseparable design curves have been used. Next, fuzzy logic has been used for classification of facial emotions.	Inseparable design curves and fuzzy logic	Ghasemi & Ahmady (2014) [19]
With radial base function neural network 93.4% and with fuzzy inference system 95.6%	3 basic emotions and Neutral	Teaching feature vectors have been implemented on a radial base function neural network and after the teaching stage, network efficiency is evaluated with other feature vectors not implemented in the teaching stage. This was also performed with the fuzzy inference system.	Radial base function neural system and fuzzy inference system	Khanmohammadi [24](2002) et al
Only in calculation of the emotion of happiness, the system has had an appropriate performance compared to other emotions	5 basic emotions and Neutral	Using fuzzy logic theory and 21 important points of human facial image, emotions were identified with the help of calculation of eye width, height of eyebrows, mouth width, level of mouth opening, distance between nose tip with lip corner and distance between pupils to cheek is identified.	Fuzzy logic	Golzadeh et al [25](2010)
It has been desirable in the out of line situation and has maximum precision of 84.62%	6 basic emotions and Neutral	Using calculation of changes in points of facial features in sequential frames of the image, Recognition of human facial expression in a form not sensitive to transfer and scale in two states of on line an off line is made. In this method, for face Recognition and its emotions algorithms and facial software development kit and for classification the simple Bayes method have been used.	Haar algorithm and software development kit and simple Bayse	Mahsouli and (2013) Safabakhsh [26]

3- Proposed Method

As mentioned every system of facial emotion Recognition has the components of image preprocessing, facial recognition, feature extraction and classification. In the proposed method, since high quality images were used, in the preprocessing phase of the image, colored picture is transformed into grey surface image. After preprocessing of each image, the location of the face in the image is separated. Therefore, in the proposed method, the stage of facial recognition does not exist. Figure (3-2) shows an image from the Radboud face bank after preprocessing and separating the face. In the stage of feature extraction, a toolbox name PHD was used. Two feature extractions of linear subspace projection and nonlinear subspace projection were used for feature extraction from selected images.



a b

Figure 3-2 Sample image a) picture in regular state b) picture after preprocessing and separation of face from it

3-2-1- Creation of the initial fuzzy system

Based on the existing data base, initially a fuzzy inference system of the kind of Takagi-Sugeno-Kang(TSK) was defined using fuzzy clustering. Using clustering of c fuzzy means, set of fuzzy rules for modeling of the data base behavior is extruded. The number of fuzzy inputs here is equal to the number of features of the data base in use and opposed to that, the number of outputs is equal to the number of classes (clusters) of the given data base. Since we have 8 clusters (Facial emotions defined by Ekman and normal facial expression), therefore, the output is considered to be equal to 8. The membership function of the Gaussian curve is used. As shown in Figure (3-4), the proposed system includes 8 clusters which are the facial emotions used in the data base. Therefore, 8 fuzzy rules exist by which the facial emotions are recognized.

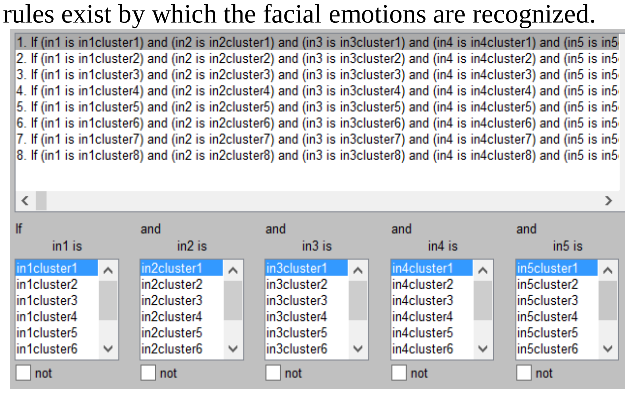


Figure 3-4. Eight fuzzy rules in the proposed method

The most fundamental part of every fuzzy clustering is regulation of membership functions parameters. In continue, for regulation of membership functions parameters, Met heuristics algorithms are used. For this task, initially fuzzy clustered membership functions parameters are separately regulated with ACOR, SA, Genetic, PSO algorithms and output of emotions classification is evaluated for each. Next, combination of the PSO algorithm with each of the three mentioned algorithms is taken advantage of for organization of membership functions parameters and the results are evaluated. The objective is reaching to the best output classification possible from PSO and other mentioned algorithms. To show that combination of PSO with each of these algorithms can yield a better result as output, combination of SA and Genetic algorithms was also used for regulation of membership functions parameters and the results were evaluated. In continue the method of implementation of each of the mentioned algorithms is described initially separately and next in combined form. In the fourth chapter, the results of implementation of each of these methods are shown.

3-2-2- PSO algorithm

The numbers of particles which are the responses are considered to be 100 and initially, this population is randomly with uniform distribution allocated to each particle. The values for these particles are the limits of membership functions for each function that have been created in the previous stage.

$$f(x;\sigma,c)=\begin{cases}\text{in1: } e^{\frac{-(x-0)^2}{2*0.169^2}} & x=[0,1]\\ \text{in2: } e^{\frac{-(x-0.5)^2}{2*0.169^2}} & x=[0,1]\end{cases} \qquad (3\text{-}1)$$

in1 and in2 are samples of two membership functions from one input (feature). In Equation (3-1), for the first membership function, the value of σ and $\boldsymbol{C}$ are 0.169 and 0 respectively and additionally for the second membership function the values for σ and C are 0.169 and 0.5 respectively. Therefore, these values of σ and C are parameters of the above equation which need to be improved using the PSO algorithm. Now, we need to determine the level of costs of each of the particles. According to Equation (3-3), minimum root mean square error (RMSE) value is used as cost function.

$$MSE=\frac{1}{n}\sum_{i=1}^{n}(\widehat{Y_i}-Y_i)^2 \qquad (3\text{-}2)$$

$$RMSE=\sqrt{MSE} \qquad (3\text{-}3)$$

In Equation (3-2), $\widehat{Y_i}$ is the calculated value in the classification (classification output) for the ith data and Y_i is the original (target) value of the ith data in the data base and n is the number of samples in the data base. After calculation of the cost value of each particle, the speed value of each particle and position of the particle are up to dated using Equations (3-4) and (3-5):

$$V_i^{k+1}=\omega V_i^k+C_1rand_1()*(P_{best}^k-P_i^k)+C_2rand_2()*(P_{Gbest}-P_i^k) \qquad (3\text{-}4)$$

$$P_i^{k+1}=P_i^k+V_i^{k+1} \qquad (3\text{-}5)$$

Where in these equations, K represents period and P_i^k is the position of the ith particle in that period. ω has a value of 0.1 and learning parameters C_1 and $C2$ have the values of 1 and 3 respectively. This action is performed for each of the particles and next the cost is calculated and if conditions desired are reached, we can stop (the condition for stop is reaching 1000 repetitions). Otherwise, the operation is continued and new speeds are replaced.

3-2-3- ACOR algorithm

Every ant (membership functions parameters) leaves pheromones behind in every path it traverses and here pheromone is shown by τ_{ij} (the distance between the ith and jth ant). Initially, each ant is created randomly and

with uniform distribution, where these ants show the constants of fuzzy membership functions.
Equations (3-6), (3-7) and (3-8) shows the method of optimizing the ants using this algorithm.

$$D=D+|S_l-S_r| \quad (3-6)$$

$$Sigma=\frac{Zeta*D}{n-1} \quad (3-7)$$

$$S_i^{k+1}=S_i^k+sigma*randn() \quad (3-8)$$

In these equations, D is the distance of ants, $Zeta$ is the standard deviation rate of the distances, $Sigma$ is the variance of the data, n is the number of features, Sl is the lth ant, Sr is the rth and $randn()$ is a random number with normal distribution. The position of each ant is up to dated using Equation (3-8). After calculation of the cost (here similar to the PSO algorithm, the minimum root mean square error was used). Each ant is selected based on its level of cost and the amount of its pheromone is up to dated. Selection of each ant is performed based on the Roulette Wheel.

3-2-4- Genetic algorithm

The number of the initial population (number of chromosomes) is taken to be 100. Initially, each chromosome is created randomly with uniform distribution. The number of genes of each chromosome is equal to the number of values from the fuzzy inference system that needs to be up to dated. Selection of each chromosome is performed based on the Roulette Wheel. Here, also the method of minimum root mean square error is used for calculation of cost. For recombination and mutation, random numbers with normal distribution have been used. Rate of mutation is considered to be 0.3 and recombination rate is considered to be 0.8.

3-2-5- SA

The basis of work of this algorithm is based on local search. Therefore, design of appropriate methods of local search with consideration of the conditions and limitations of the problems simulated in this algorithm has very high importance. Parameters of this algorithm includes initial temperature ($T0$) with a value of 10 and reduce rate of 0.99.
The total number of repetitions is 1000 and number of internal repetitions is considered to be 100. The values for Δf and P here have been obtained based on Equations (3-9) and (3-10).

$$\Delta f = f(x^{new})-f(x) \quad (3-9)$$

$$P=e^{-\frac{\Delta f}{T}} \quad (3-10)$$

Where, in these equations, $f(xnew)$ is selection of new response, and $f(x)$ is selection of previous response, P is the probability of selecting a worse response and T is ambient temperature.

3-2-6- Combined algorithms

In combining two algorithms with each other, initially the population is optimized with the first algorithm and next, it is divided into two groups of good and bad and the bad group is optimized with the secondary algorithms and next populations in the two algorithms are merged and this process is repeated until conditions desired are reached [20]. In the proposed method, conditions desired is reaching the stop criteria or reaching 500 repetitions.

3-2-6-1- Combination of PSO and Genetic algorithms

Parameters of each of the algorithms in combination are similar to each algorithm on its own. Initially, the entire random population is created in the PSO algorithm. Subsequently, half of the population which does not have appropriate results is transferred to the Genetic algorithm and optimized. The optimized population is merged with the population in the PSO algorithm and the population is organized and local optimum and global optimum is determined based on the combined population. This process is continued for a set number of repeats (500 repeats).

3-2-6-2- Combination of PSO and ACOR algorithms

Initially the entire random population is created in the PSO algorithm and next half of the population which did not have desired results is transferred to the ACOR algorithm and optimization is performed on it. The optimized population is merged with the population in the PSO algorithm and the population is organized and local optimum and global optimum is determined based on the combined population and this process is continued to a set number of repeats (500 repeats).

3-2-6-3- Combination of PSO and SA algorithms

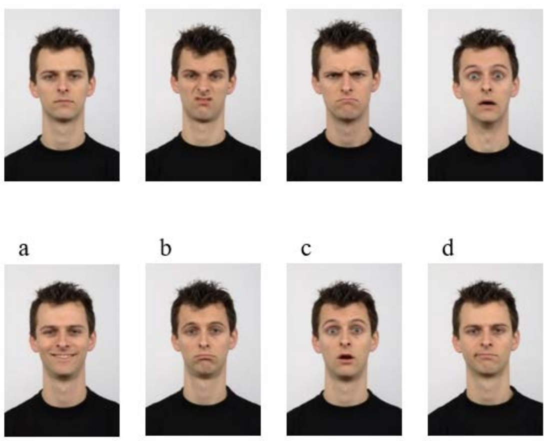
Initially the entire population is created in the PSO algorithm and next half of the population which did not have desired results is transferred to the SA algorithm and optimization is performed on it. The optimized population is merged with the population in the PSO algorithm and the population is organized and local optimum and global optimum is determined based on the combined population and this process is continued to a set number of repeats (500 repeats).

3-2-6-4- Combination of Genetic and SA algorithms

Initially the entire random population is created in the Genetic algorithm and next one fourth of the worst chromosomes is given to the SA algorithm and are optimized. The optimized population is merged with the population in the PSO algorithm and the population is organized and local and global optimums are determined based on the combined population and this process is continued to a set number of repeats (500 repeats).

3-1-3- The Radboud face bank

The Radboud face bank is a set of pictures with high quality from 67 models (including men, women and children from Caucasia, boys and men from Morocco and Netherlands) with seven emotions Anger, Disgust, Fear, Happiness, Sad, Surprise, Contemptuous and natural facial expression (in total it includes 536 images). Each emotion has been taken from three positions (looking left, looking forward and looking to the right) with five various camera angles using the Facial Action Coding System (FACS). In Figure (3-1), an example of frontal images of various emotions has been shown in an individual.



a b c d

e f g h

Figure 3-1. Example of Radboud face bank model a) Natural b) Disgust c) Anger d) Fear e) Happiness f)Sad g) Surprise h) Contemptuous

4- Evaluation and Analysis

For performing this research computer with Intel Pentium (R) CPU 2.60 GHz،RAM= 4.00 GB was used. For modeling and simulation of the proposed system Mat Lab software version R2014a (8.3.0) 32-bit was used.

4-1- Mean square error changes

Table (4-1) shows mean square error changes, its root, mean error and standard deviation for all of the methods. As shown, the value for the error in all emotions for the method of feature extraction was better for linear projection compared to nonlinear projection. The value for mean square error for linear projection feature extraction and teaching data has been shown in the following for all the methods respectively.

Combination PSO & GA < Combination PSO & ACOR = Combination GA & SA < Combination PSO & SA < Genetic < PSO < ACOR < SA

Similarly, for experimental data, we have:

Combination PSO & GA < Genetic < ACOR < PSO < Combination PSO & ACOR < Combinatio n PSO & SA < Combination GA & SA < SA

As noted, the value for mean square error in the combined PSO and Genetic algorithm in teaching data and also experimental data is better than the other methods.

Table 4-1. Changes in mean square error and other parameters in the various methods

Feature Extraction	Data	Fitness	ACOR	Genetic	PSO	SA	Combination PSO & ACOR	Combination PSO & GA	Combination PSO & SA	Combination GA & SA
Linear Projection	Train	MSE	0.106	0.066	0.072	5.071	0.059	0.056	0.063	0.059
		RMSE	0.325	0.257	0.269	2.252	0.243	0.237	0.252	0.228
		Mean	0	-0.054	-0.001	0.113	-0.043	-0.002	-0.027	-0.039
		Std	0.325	0.251	0.27	2.252	0.239	0.237	0.25	0.225
	Test	MSE	0.167	0.152	0.171	5.666	0.184	0.131	0.221	0.203
		RMSE	0.409	0.39	0.413	2.38	0.429	0.361	0.47	0.45
		Mean	0.028	-0.016	-0.003	-0.264	-0.096	0.046	-0.023	-0.053
		Std	0.409	0.391	0.414	2.373	0.42	0.359	0.471	0.448
Nonlinear Projection	Train	MSE	1.509	1.281	1.17	299.51	1.117	1.157	0.996	1.152
		RMSE	12285	1.132	1.082	17.307	1.057	1.076	0.998	1.073
		Mean	0.007	0.019	-0.122	-5.154	-0.009	0.045	0.03	-0.018
		Std	1.23	1.133	1.076	16.543	1.059	1.076	0.999	1.075
	Test	MSE	3.179	3.745	3.351	254.05	3.102	2.932	3.113	2.382
		RMSE	1.783	1.935	1.831	15.939	1.761	1.712	1.764	1.544
		Mean	0.167	0.214	0.031	-5.248	0.198	0.059	-0.069	-0.177
		Std	1.781	1.929	1.836	15.097	1.756	1.717	1.768	1.538

In some methods, the level of mean squares error is less in teaching data compared to the experimental data which shows their location in local optimum. Therefore, this combination Genetic and PSO algorithm has searched the problem space better compared to each of them.

4-2- Results of Implementation

Results of implementation of the proposed methods have been shown in the following Figures. As noted, the horizontal axis shows facial emotions and normal expression and the vertical axis shows the rate of recognition of each emotion. The blue circle diagram shows changes in recognition rate for each emotion in the method of linear feature extraction and the red square diagram shows the nonlinear feature extraction method. As also shown in Table (4-1), extraction by the linear method yields better results compared to the nonlinear method.

In the PSO algorithm, emotions of disgust, anger and contemptuousness have been recognized with higher precision compared to the other emotions.

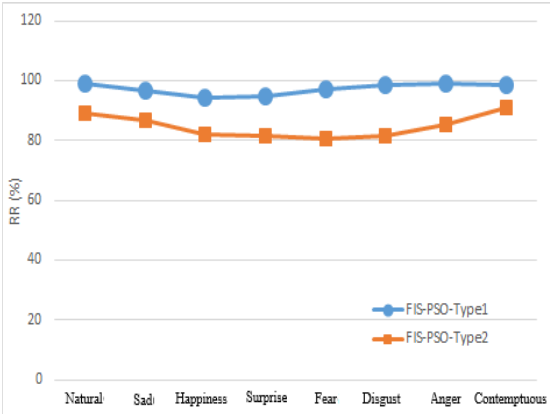


Figure 4-1. Recognition rate in the PSO algorithm

In the Genetic algorithm, facial emotions of fear, disgust, anger and contemptuousness have been recognized with higher precision compared to the other emotions.

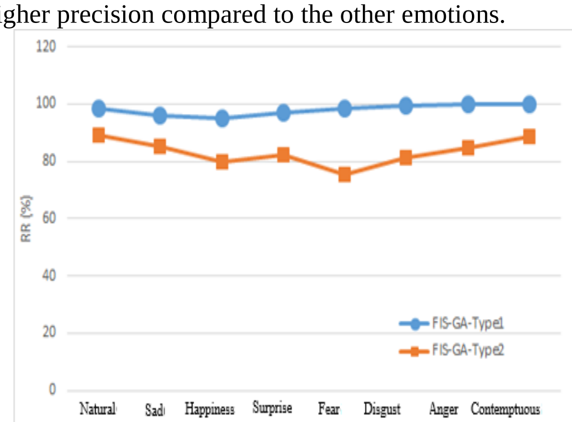


Figure 4-2. Recognition rate in the Genetic algorithm

In the ACOR algorithm, facial emotions of disgust, anger and contemptuousness have been recognized with higher precision compared to other emotions.

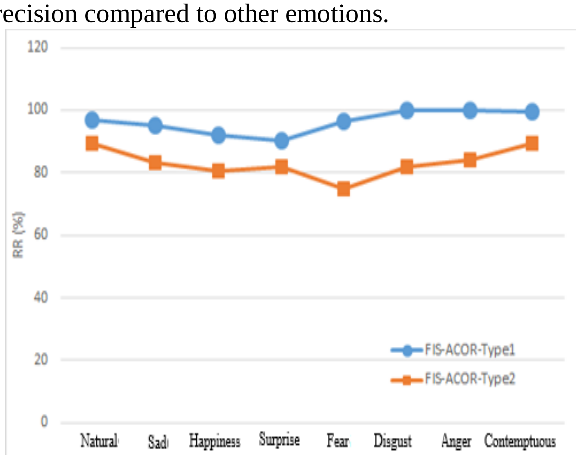


Figure 4-3. Recognition rate in the ACOR algorithm

In the SA algorithm, extraction by the linear and nonlinear methods had relatively similar results and facial emotions except for fear yielded relatively similar precision. It is evident that this method has less precision compared to the other methods.

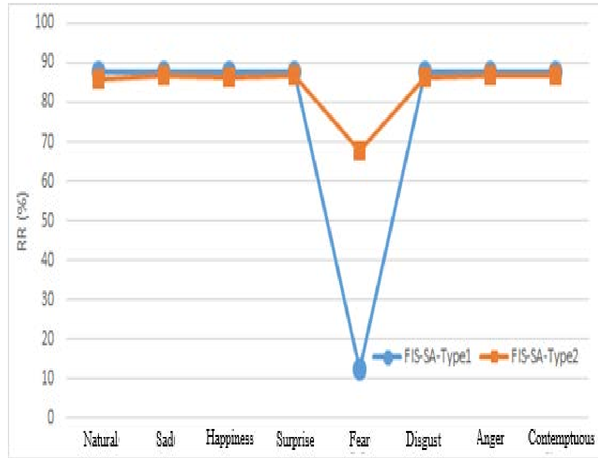


Figure 4-4. Recognition rate in the SA algorithm

In combining the PSO and GA algorithms, emotions of sadness, fear, disgust, anger and contemptuousness were recognized with higher precision compared to the other emotions.

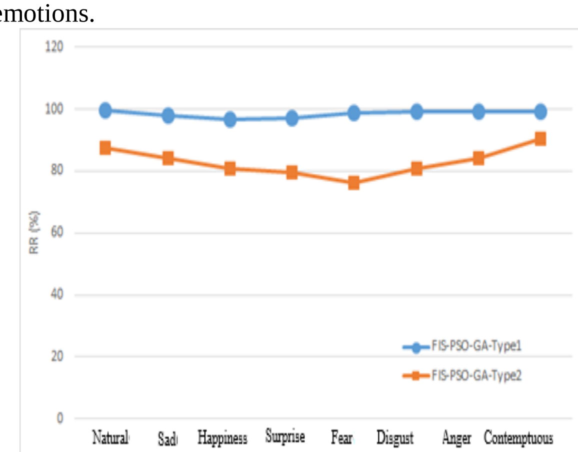


Figure 4-5. Recognition rate in the combination of PSO and Genetic algorithms

In combining the PSO and ACOR algorithms, the emotions of surprise, fear, disgust, anger and contemptuousness were recognized with higher precision compared to the other emotions. Additionally, sadness had the least level of recognition compared to other facial emotions.

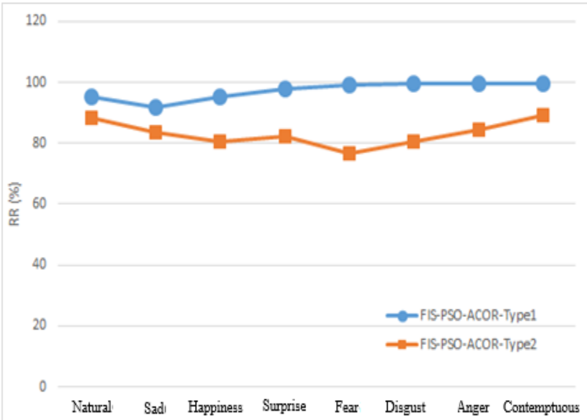


Figure 4-6. Recognition rate of the combined PSO and ACOR algorithms

In combining the PSO and SA algorithms, emotions of fear, disgust, anger and contemptuousness were recognized with higher precision compared to the other emotions. Additionally, the emotions of happiness and surprise had the least level of recognition compared to other facial emotions.

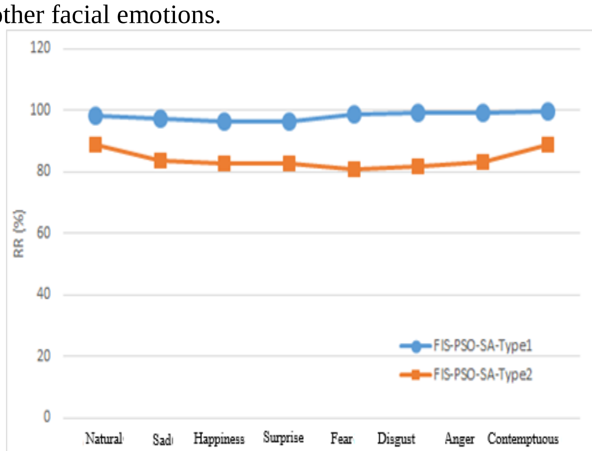


Figure 4-7. Recognition rate in the combined PSO and SA algorithms

In combining the SA and Genetic algorithms extraction by the linear method performed better than the nonlinear method and all facial emotions had similar rate of recognition.

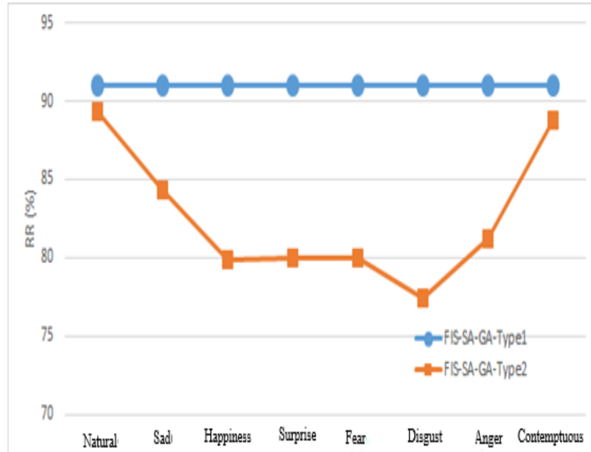


Figure 4-8. Recognition rate in the combined Genetic and SA algorithms

4-3- Mean Rate of Recognition

Figure (4-9) shows the values for mean rate of recognition for facial emotions for the algorithms. In this figure, Type1 refers to classification with linear projection feature extraction and Type2 refers to classification with nonlinear projection feature extraction. In Table (4-2), the recognition rate of the proposed method (classification of emotions using combination of PSO and Genetic algorithms) was compared with the method of Ilbeygi and Shah-Hosseini (2012). Results showed that recognition rate of the proposed method were higher for all emotions except happiness.

Table (4-3) shows the recognition rate of the emotion of contemptuousness by the algorithms under study. As noted, recognition rate for the emotion of contemptuousness in the proposed method is reported at 99.25 percent while use of fuzzy inference system based on Genetic algorithm with linear projection feature extraction has reported a recognition rate for this emotion of 100 percent.

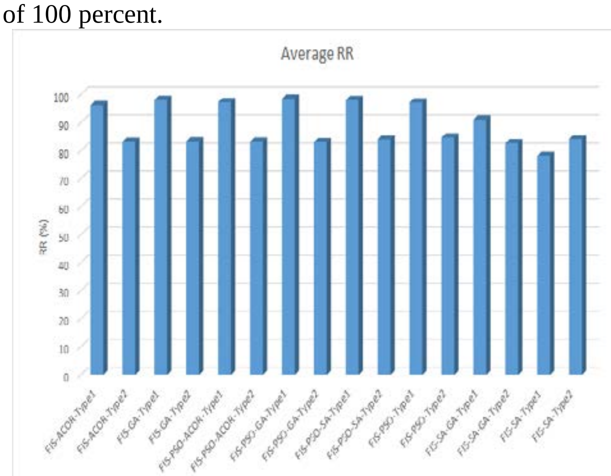


Figure 4-9. Mean recognition rate in the algorithms

Table 4-2. Comparison of results of the proposed method with Ilbeygi and Shah-Hosseini

Proposed Method	Ilbeygi & Shah-Hosseini	Emotion
97.20	94.20	Surprise
99.06	91.30	Disgust
96.82	98.55	Happiness
99.06	92.75	Anger
98.69	94.20	Fear
98.13	92.75	Sad
98.32	93.96	Average

Table 4-3. Recognition rate of the emotion of contemptuousness with the algorithms evaluated in this study

Feature Extraction	ACOR (%)	Genetic (%)	PSO (%)	SA (%)	Combination PSO & ACOR(%)	Combination PSO & GA (%)	Combination PSO & SA (%)	Combination GA & SA (%)
Linear Projection	99.44	100	98.50	87.50	99.62	99.25	99.62	91.04
Nonlinear Projection	89.17	88.61	90.85	86.94	89.63	90.29	88.61	89.88

4-4- Overall emotions recognition rate

Figure (4-10) shows the recognition rate of all emotions for all algorithms. As shown, recognition rate of all emotions by the combined PSO and Genetic algorithms similar to previous results is higher than the other methods. Therefore, this figure confirms results of the other diagrams.

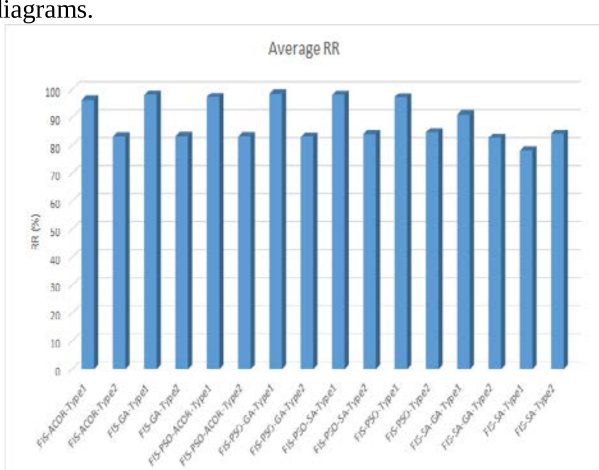


Figure 4-10. Recognition rate of all emotions by each of the algorithms

5. Conclusion

Every system of facial emotion recognition is composed of the components of image preprocessing, facial recognition, feature extraction and classification.

In this research, membership functions parameters in classification with the method of fuzzy inference system in the facial emotions recognition system has been regulated using the improved PSO algorithm so precision of emotion classification is improved. For this purpose, picture looking to the front from the Radboud face base was used and in the stage of preprocessing of images, colored pictures of the face base under study was transformed into images with grey surface and since part of the image that includes the face is separated from the rest of the image, extraction of face was not performed on the images. In the stage of feature extraction, two functions of linear and nonlinear subspace projection feature extraction toolboxes named pretty helpful development toolboxes were used. For classification, the fuzzy inference system used was the TSK with Gaussian curve membership functions, where for regulation of membership functions, to increase classification precision, the improved PSO algorithm has been used. For this purpose, Genetic, ACOR, and SA algorithms were used in this study. Fuzzy inference system membership functions were initially regulated separately for each of the 4 mentioned algorithms and results obtained for classification precision were calculated for them. Next, combination of PSO with each of the 3 algorithms was taken advantage of for regulation of membership functions. Results of these implementations show that combination of PSO with GA algorithm with the linear subspace projection feature extraction method yields better classification precision compared to the other implementations. To determine that the improved PSO yields better results, combination of SA and GA algorithms was used and its results was compared to the proposed method, where the proposed method yielded better results. Experimental results show that classification precision by the proposed method has a recognition rate for emotions of 98.32 percent which shows efficient improvement in the methods discussed in this domain. Additionally, in this research the emotion of contemptuousness was added to the set of emotions which has not been evaluated in any other article. Using the proposed method, recognition rate for the emotion of contemptuousness was reported at 99.25 percent, where in results obtained in fuzzy inference system, classification of data resulting from linear projection feature extraction with the GA algorithm, precision of classification was reported at 100 percent.

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