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Full Length Research Paper

An adaptive learning model based genetic for facial expression recognition

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The genetic algorithms (GAs) are the evolutionary learning process, which are applied to complex optimization problems to find the optimum results from other results. The GAs to achieve the proper results in the iteration process selects the fitter solutions from a solution space. In this process, the parent selections, crossover and mutation operations have the important roles to find the optimum results. In this paper, the honey bees mating process has been modeled to modify the GAs learning process. For the purpose of illustration, the learning process with the proposed GA, the fuzzy membership functions were tuned with the proposed GA. In the proposed hybrid model, the core of expression recognition system is the fuzzy rule based system to classify the facial expressions recognition. Therefore, the proposed genetic algorithm called queen bee algorithm (QBA) is used with the purpose of making better performance in learning process to improve the accuracy and robustness of the system. To evaluate the system performance, images from Cohn-Kanade database were used to obtain the best functions parameters. Results showed that the membership functions under the training process have tuned properly while the accuracy of classification with optimized parameters illustrated the rate of 98% in the train process.

Key words: Queen bee algorithm, classifier, facial expression recognition, fuzzy system, genetic algorithm.

INTRODUCTION

Rule based classification technique is one of the simple approaches to facial expressions recognition (Paknikar, 2008). In recent years, fuzzy rule based system (FRBS) has been used in several studies as a more proper method than the rule based approach for classification of facial expressions (Esau et al., 2007; Chatterjee and Shi, 2010; Seyed et al., 2004). FRBS, based on the expert knowledge as well as fuzzy logic create an appropriate classification model to cover most of the expressions recognition requirements. However, the FRBS performance is closely related to its knowledge base. The knowledge base of FRBS includes two rules base and data base components (Ishibuchi, 2009). The rule base involves the fuzzy rules, while data base consists of membership functions. Usually, these two components are set based on the human expert knowledge. However, in complicated problems, such as facial expressions classification, the knowledge base is not accurately sufficient to cover the emotions recognition necessities since the estimation of the proper membership functions is a difficult work. Therefore, the main objective of this paper is to present a modified fuzzy model to provide the mentioned classification requirements.

According to Ekman and Friesen (1978), there are six basic facial expressions which are universal for all people in the world with different ages, culture and sex. These facial expressions appeared in the states of happiness, anger, sadness, surprise, fear and disgust. Facial expressions are responses to the stimulants which are produced in the human brain (Tie, 2011).These responses appear on the face with the facial muscles contraction. Therefore, with regard to the difference in facial appearances due to the different emotions, a classifier analyzes the changes of facial appearance to

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classify the facial expressions to the basic emotions. In order to classify expressions, a set of facial features are selected as the proper references of facial appearance to show the facial deformations in the emotional states. The selected features should have small bias for an emotion, while large bias between the different expressions (Tie, 2011). Therefore, a classifier with analysis of extracted features classifies the similar expressions as a similar emotion. In the rest of this paper, a classification model has been considered to develop the current facial expressions classification models with specific criteria in the challenges conditions.

LEARNING ALGORITHM

With regard to the capabilities of the FRBS to be use in problem classification, to fill the FRBS lacks, a genetic algorithm is proposed to combine with FRBS for facial expressions recognition. The genetic algorithms are the evolutionary learning process, which are applied to complex optimization problems to find the optimum results from other results (Ishibuchi and Nojima, 2009). There are several studies (Bonissone et al., 1996; Hoffmann, 2001; Alcala et al., 2005; Alcala et al., 2009) that have used the genetic algorithms to optimize the FRBS performance with generating the optimum fuzzy rules or tuning the membership functions in the classification and control problems. Therefore, two parameters of fuzzy rules and membership functions with the purpose of generating the optimum number of rules and membership parameters improvement, respectively, are determined in the learning process of genetic algorithms.

The learning process increases the complexity of FRBS, particularly in the rules creation process (Ishibuchi and Nojima, 2009). Therefore, in this research, a genetic algorithm is presented only to tune the fuzzy membership functions, while the fuzzy rules are determined based on the expert knowledge. As a result, the fuzzy knowledge base is improved, while the computational costs are kept under control. The proposed hybrid genetic-fuzzy model is a novel scheme to fulfill the requirements of facial expressions recognition. Therefore, in this model, we believe that the genetic algorithm compensates the learning needs of FRBS to adapt with diverse conditions of facial expressions images while optimizing the membership functions (Jamshidnezhad and Nordin, 2011a). Moreover, it is expected that the hybrid genetic-fuzzy rule based system provides an appropriate model to overcome the challenges and problems related to facial expressions classification (Jamshidnezhad and Nordin, 2011b).

EXISTING CLASSIFICATION TECHNIQUES

Pardas et al. (2002) used a hidden Markov models (HMMs) with MPEG-4 parameters to model the behaviors of facial expressions from sequence images. In this research, the Cohen-Kanade database was used for training and recognizing the expressions. They modeled a four-state HMM for each emotion which was selected after testing different configurations. The system showed the overall recognition rate of 84%.

Susskind et al. (2007) and Getta et al. (2009), applied support vector machine (SVM) for facial expression recognition automatically. The results showed the corrected classification rates 79.2 and 98.5%, respectively. Cohen et al. (2003) developed a system based on Bayesian network classifier to recognize seven facial expressions by using the maximum likelihood estimation. Ma and Khorasani (2004), used neural network (NN) systems in facial expression recognition. They proposed a constructive feed forward neural network for determining a proper network size required by the complexity of a given problem. In this approach, one-hidden-layer feed forward neural network obtained with block size of 12 and a maximum of 6 hidden units and the best recognition rate of 93.75%. Seyedarabi et al. (2007) used the radial basis function (RBF) neural network as a classifier of facial expression. In this research, the best accuracy rate was reported as 91.2% for four facial expression recognition. Dubussion et al. (2002) combined principal component analysis (PCA) and decision tree for six facial expression recognition and reported the accuracy rate of 87.6%. Chen and Huang (2003) proposed a new method of linear discriminant analysis (LDA) classification which is named clustering-based discriminate analysis (CDA) and reported 93% recognition of tree emotion. Khanum et al. (2009) proposed a hybrid system of fuzzy logic and case based reasoning (CBR) which has the capability to improve the facial expression recognition. They reported the rate of 90.33% for emotion recognition. Ebin et al. (2001) used fuzzy logic for recognition of four emotions (joy, sadness, anger and surprise) and reported the rate of 86.7% for test result.

In this paper, a new learning algorithm was proposed to improve the GA results. The proposed algorithm simulates the process of bee mating to make the best genome in the offspring.

EXPRESSIONS CLASSIFICATION

Facial features extraction as well as classification are two main components of facial expressions recognition systems. In order to reduce the complexity of the feature extraction module, a simplified feature extraction scheme was used for using only twelve basic facial action points.

Facial feature extraction

The geometric method is used for the purpose of finding the facial feature points. In this method, based on the key facial component, twelve feature points included two in the inner corners of eyes, two in the upper and lower eyelids for each eye, two in the corners of eyebrows, two in the corners of mouth and two in the upper and lower points of lips were extracted manually.

Genetic-fuzzy classifier model

In this paper, fuzzy rule based system combined with a modified genetic algorithm called queen bee algorithm (QBA) has been proposed to reduce the time needed for training and to improve the robustness of the system under adverse conditions. This integration is especially useful in the classification of problems where it is hard to find crisp distinction between two classes.

Fuzzy rule based system

Rule base is made based on the empirical studies of changing the feature extracted from neutral to one emotion expression. Inference system, based on the rules classifies input feature vectors into one of the six basic emotions.

For feature extract, six linguistic variables can be defined: (a) very very small (VVS), (b) very small (VS), (c) small (S), (d) medium (M), (e) large (L) and (f) very large (VL).

In this paper, bell shape membership function is used to map inputs to membership values. Bell shape membership function is one of the fuzzy membership functions that are often used to represent the natural problems:

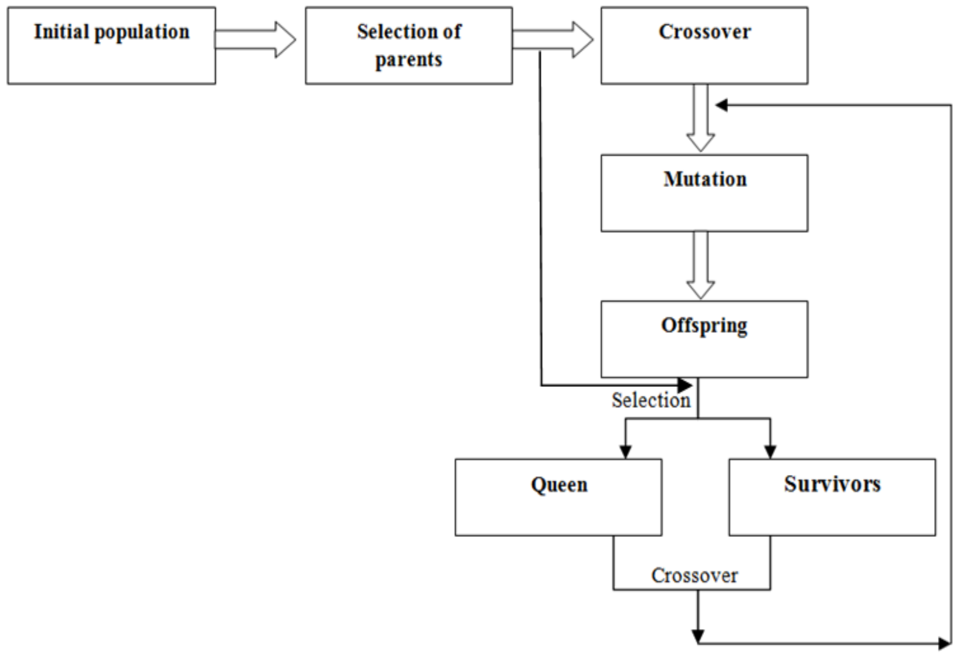

Figure 1. Queen bee genetic algorithm.

$$\mu(x) = \frac{1}{1 + \left|\frac{x-c}{a}\right|^{2b}} \qquad (1)$$

where the parameter *b* is usually positive which changes the shape. The parameters *c* and *a* locate the center and width of the curve, respectively.

Queen bee algorithm

Nowadays, scientists try to model mathematically the natural behavior of animals to solve the human real life problems in the variety of domains, particularly, in the optimization problems.

In this paper, the process of bees mating behavior has been modeled as a modified genetic algorithm which is titled QBA (Figure 1). In the proposed algorithm, best chromosome in each process plays the role of queen. In this phase, recombination between queen as one parent and every member of the selected population as another parent in each generation makes the new offsprings. However, in the classic genetic algorithm, recombination between pairs of parents which are selected from new population makes the offsprings in every generation.

In the proposed system, a QBA for the adjustment of membership functions of antecedent fuzzy sets in fuzzy rules for classification problems was developed. The modification of the restriction on the shapes of membership functions improved the performance of the classification system. The parameters of QBA are defined as follows:

1. ***Define the chromosome length****:* There are seven extracted features (f1 to f7), and each of them have six linguistic variables (VVS, VS, S, M, L and VL) and also each bell shape membership function has three parameters, so we have 126 (7 × 6 × 3) genes in each chromosome Ci = (G1, G2, ..., Gn).

2**. *Fitness function:*** Fitness functions is derived from the following objective function:

$$\text{Min } f(x) = 1 - \sum_{k=1}^{c} \left(\frac{mk}{nk}\right) \qquad (2)$$

where mk which is the numbers of correct classification for selected training data include four classes and, is the total of training data.

Table 1 shows the proposed QBA parameters in details which were used for training the fuzzy rule based system in the classification of facial expressions.

RESULTS

The proposed model was evaluated on the 80 images from Cohn-Kanade database which were selected rando-mally from four expressions including surprise, sadness, happyness and anger. In the training process, when the termination conditions were obtained, the improved model illustrated the average accuracy rate of 98% which is significantly more than the accuracy rate of fuzzy rule based classification model, while the membership functions were set by the expert knowledge. Table 2 and Figure 2 show the overall experimental results and the process of accuracy improvement with the training algo-rithm, respectively. According to Figure 2, the proposed QBA as the learning algorithm improves the membership parameters to reach the optimum solutions. This process was implemented 3 times to evaluate the reliability of the model.

Table 1. The proposed QBA parameters.

Genetic algorithm parameter	Queen bee genetic algorithm
Size of primary population	50
Parent selection	Roulette wheel
Size of parents	10
Crossover	2 points per each parameter
Mutation	Random mutation
Mutation rate	10%
Number of offspring in the first generation	10
Number of offspring in the second and further generations	20
Survivor selection	Elitism based on offspring and primary population
Number of survivors	10
New population	Selected survivors

Table 2. Overall experiment results.

Experiment parameter	The proposed model	FRBS model
Total number of subjects	20	20
Number of training images in each running	80	80
Classifier Method	QBA	FRBS
Number of Emotions	4	4
Number of facial points	12	12
Times of running the learning process	3	1
Average accuracy rate at the end of training phase using QBA	98%	85
Max accuracy rate at the end of training process	98.75	85
Min accuracy rate at the beginning of the training process	87.5	85
Best Accuracy result using fuzzy system without training algorithm	85%	85

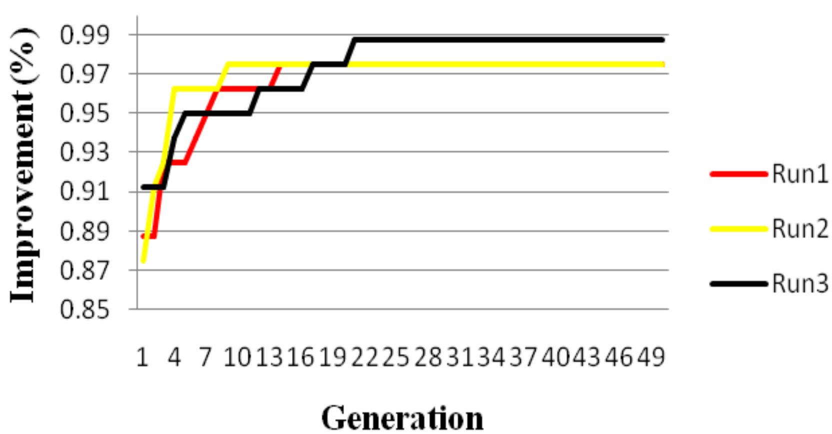

Figure 2. Tuning evolution with training algorithm.

Table 3 shows the classification results of the proposed model, while the training algorithm improved the fuzzy membership functions in comparison with the existing works. The existing works which are mentioned in Table 3 using FRBS while the membership functions of those have been set with human expert knowledge. Moreover, these studies used the number of four emotions for classification except in the study of Kanade et al. (2000) in which six emotions were used in the classification. According to Table 3, the proposed model achieved the higher accuracy rate for facial expressions classification with the tuned membership functions.

Table 3. Comparison of the proposed classification technique with existing works.

Classifier	FRBS	FRBS	FRBS	FRBS	Proposed model
Reference	Esau et al. (2007)	Tsapatsoulis et al. (2000)	Seyed et al. (2007)	This study	This study
Accuracy rate (%)	72	81	89.1	85	98

CONCLUSION

In recent years, interaction between human and computer devices is growing in various aspects. Classification is a method by which the capability of computer to overcome to the human requirements can be enhanced. FRBS is known to be used in problems with the uncertainty solutions. Although, FRBS has been used in a wide range of studies as a classification technique; however, lack of learning process in the FRBS causes the performance of classification with FRBS to be reduced, particularly in the complicated domains, such as facial expressions recognition.

Therefore, our aim in this research is to develop the training process in a FRBS for facial expressions classification. Therefore, a modified genetic algorithm was used as a learning algorithm to adjust the FRBS. Experimental results showed that the learning algorithm adapts the membership functions with the feature vectors as inputs to achieve the best classification results. The outcomes of this paper were obtained with the selected facial images from the Cohn-Kanade database as the training set; therefore, for the future work, we propose to evaluate the generalization of the trained model with the unseen images.

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