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Challenging of Facial Expressions Classification Systems: Survey, Critical Considerations and Direction of Future Work

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Abstract: The main purpose of this study is analysis of the parameters and the affects of those on the performance of the facial expressions classification systems. In recent years understanding of emotions is a basic requirement in the development of Human Computer Interaction (HCI) systems. Therefore, an HCI is highly depended on accurate understanding of facial expression. Classification module is the main part of facial expressions recognition system. Numerous classification techniques were proposed in the previous researches to use in the facial expressions recognition systems. In order to evaluate the performance of the classification system we should consider the parameters which influence the classification results. Therefore, in this article, the most recent classification techniques for the purpose of facial expressions recognition as well as features extraction were surveyed and the parameters which affect the accuracy of results were considered and discussed. Based on this article, the features type, number of extracted features, database and image type are the main parameters that influence the accuracy rate of classification models. Furthermore, as the direction of the future work of this research, a Genetic-Fuzzy classification model was proposed for facial expressions recognition to fulfill the classification requirements.

Key words: Classification, facial expressions recognition, features extraction, fuzzy logic, genetic algorithm

INTRODUCTION

The importance of classification is known in variety domains of human life. Classification makes a comprehensible structure of objects to set them in the real situation. It separates area of data into different categories according to their characteristics and qualities. So that, each class includes most similar objects against the others (Ross, 1997).

Classification methods are in two groups based on the available information of specifications of classes:

- Unsupervised classification
- Supervised classification

Unsupervised classification does not use expert knowledge or in some cases, there is information lacking regarding to the pattern of classes and their output attributes. In this technique, statistical procedures are used to estimate similarity within the area of data.In comparison, in supervised classification sufficient information about the trait of predefined classes and classes label is provided. Also training data in the learning phase fit the model to classify input data to correct known outputs (Guerra *et al.*, 2011).

Classification of objects or patterns into several groups is a main purpose in pattern recognition area. There are many applications in which pattern recognition is used as an important part such as pattern recognition in machine vision systems, optical character recognition systems, diagnostic decision support systems, human computer interaction systems, speech recognition systems and so on (Theodoridis and Koutroumbas, 2006).

Pattern recognition in the domain of facial image is one of the challenging areas. In recent years, many researchers developed several classification methods to recognize various emotions based on the images of human face. Classification of facial images can be used effectively to interact human and computer systems which have various applications in digital cameras, teleconference, animation design, customer relation management systems and so on.

The well known facial expression recognition system was introduced by Ekman and Friesen (1978). Based on their studies, there are six basic facial emotions: happiness, sadness, surprise, anger, fear and disgust. They

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Fig. 1: A labeled image in training set

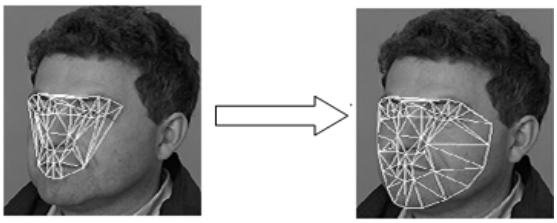


Fig. 2: Progressive AAMs fitting

showed emotions cause movement and change in the set of face muscles which are universal and have similar actions for all people in the different nations (Ekman and Friesen, 1978). Therefore, muscles movements can be used as the criterion of measurement for classification of facial expressions. Facial expression recognition systems need to have feature data of images for classification of facial expressions. Therefore, facial feature extraction is first step that prepare required data as input data for classification of facial expressions. For the purpose of facial expression recognition there are several techniques have been presented both for feature extraction and classification in recent years. In this section some of the most important of current techniques are surveyed with attention to their advantages and disadvantages.

FACIAL FEATURES EXTRACTION

Face detection: Features extraction can be performed on the static images or sequences images by using several techniques in the real time (automatic systems) or off time (non-automatic) situations. For extracting facial features, face detection is pre-requisite step to separate the face area from other parts of body such as hair and neck in the real time systems. Several methods have been proposed to face detection that are described in this part.

Active Appearance Models (AAMs): Cootes *et al*. (2001) proposed Active Appearance Models (AAMs) to represent the human face. The method match a face shape model and appearance parameters to the unseen face images in a searching process. At the training process, the face model may uses labels marked by points. This

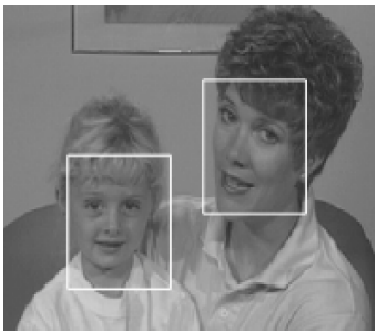


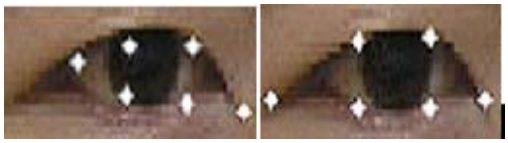
Fig. 3: Face detection using PCA

technique can be used for both gray and color images with various pose as well as illumination and different expressions (Cootes *et al*., 2001). In Fig. 1 and 2 facial feature landmarks and progress of fitting the model to face image are shown, respectively (Gao, 2008).

Principal Component Analysis (PCA): Principal Component Analysis (PCA) uses a set of training images to determine a "face space". For the purpose of face detection in an image, the projection of image selected areas onto face space is evaluated. Therefore, the region with minimum projection error is accepted as a face position. Menser and Muller (1999) performed PCA onto a set of training face images to calculate a projection matrix that determining a "face space" model. Error criterion in each region of input image by projecting a subspace of image located at that position onto "face space" is calculated (Fig. 3). Therefore, face position are regions with minimum error.

Neural networks: Several techniques (Rowley *et al*., 1998; Rhee and Lee, 2001; Seow *et al*., 2003) are proposed to face detection while used Neural Network to classify face and non-face region. Neural Network is training with a set of face and non-face training images. Then, it can detect region of face when each region of image evaluate with Neural Network. Rowley *et al*. (1998) proposed multiple hidden units in Neural Network to look at various sub-regions of image to detect main feature face such as eyes, mouth and nose. The output presented the face region.

Features extraction techniques: In pattern recognition, feature extraction is the process of indicating the relevant properties of patterns that determine certain characteristics of objects. Geometric features and appearance features are two types of facial features using in the facial expression recognition. Geometric features aim to measure the movement of extracted crucial parts of face such as eyes, eyebrows, mouth and tip of nose landmarks while a particular emotion is occurred. Another type of features



(a) (b)

Fig. 4: (a) Initial detected feature points with AAM, (b) Modified feature points extraction

(a) (b)

Fig. 5: (a) Face image region, (b) Face image divided to small size regions

called appearance features, deals with the change of face skin texture in the different emotions (Paknikar, 2008). Some of the recent methods for feature extraction are described as follow:

Morphological operators can be used onto gray regions which determine maximum or minimum area on the image, to detect the eyes corners. As the eyes regions include maximum or minimum value of luminance gradient, the information of luminance determines properly the region of eyes. Furthermore, detection of mouth key points needs to information of chrominance and luminance. As the mouth contour includes special colors when the chrominance information is presented, chrominance data is essential to detect the mouth feature points (Hammal *et al*., 2006).

Sohail and Bhattacharya (2006) presented an anthropometry based technique for facial feature extraction. They used the anthropometry model to detect regions of eyes, eyebrows, nose and mouth. Then, image processing techniques were used to search in the detected regions to extract facial feature points.

Shih and Chuang (2004) extracted the features based on face edge detection process. They used x and y projection to obtain boundary boxes of face features such as eyes, nose and mouth. Also, in order to obtain higher accuracy in the different illumination, Gabor filter is used to detect the eyes location. Then, the positions of other facial features are extracted based on the distances between eyes.

Zhou *et al*. (2011) proposed a hybrid model of Active Appearance Model (AAM) to extract facial feature points.

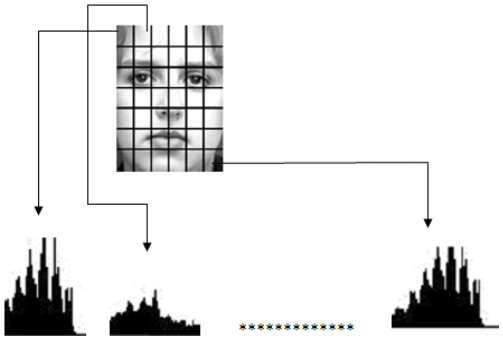


Fig. 6: LBP feature histograms extracted from small regions

To improve the AAM results, they presented a classification algorithm to classify Gabor features which are extracted from the AAM initial feature points to find the precise position of facial feature points. Figure 4 shows the initial detected feature points and tuned feature points around the eye from left to right.

Principal Component Analysis (PCA) is also used to extract the facial features base on the "face space" as it is applied to face detection. In this technique extracting the facial features require to train with a set of training data. Training data set led to create independent "feature space" for each relative facial features. Minimizing of projection error of face image regions onto the feature spaces determine the position of features on the face (Pentland *et al*., 1994).

Local Binary Patterns (LBP) method is also used for facial feature extraction with texture consideration. In this method the face region divides into a grid with small scale pieces as it has been shown in Fig. 5. Then, the LBP histograms belong to grid cells are extracted as facial features set for a particular emotion (Shan *et al*., 2009). Figure 6 shows the LBP histogram extracted from image grid cells.

SeyedArabi *et al*. (2007) used optical flow method to extract the facial features from the facial feature points which were manually marked in the first frame. In the proposed method, facial feature points in the next frames were tracked with cross correlation computation method. For the purpose of facial expression classification, facial features were extracted from feature points movements in the first and last frames in the sequence image.

FACIAL EXPRESSION CLASSIFICATION

Classification of facial expressions is the main part of facial expression recognition systems. Due to complexity of natural characteristics of human facial expressions, classification of emotions need to comprehensive analysis of semantic relations of facial features as a feature set. It means the position and relation of features toward the

AU - Description	Example image
2- Outer brow raise	
5- Upper eyelid raise	
27- Mouth stretch	

Fig. 7: Some AUs example of facial expressions in the FACS

each others should be considered as a together form. Facial Action Coding System (FACS) is known facial expression measurement system introduced by Ekman and Friesen (1978) to describe facial behavior according to the face muscles activities. Based on the FACS, Action Units (AUs) are associated with the smallest change of muscles which are appearing with the facial behavior (Cohn *et al*., 2005). Most of the AUs are related to the movements of eyes, mouth and nose. Therefore, the information of those is popular for facial expression classification systems (Seyedarabi *et al*., 2007). Facial emotion is specified when a set of AUs appear with together. For example inner brow raiser, outer brow raiser, upper lid raiser, mouth stretch related to the action units number: 1, 2, 5 and 26, respectively indicate surprise emotion. Figure 7 shows some of the AUs in the facial expressions. Many of researches for classification of facial expressions are based on the Ekman and Friesen (1978) studies to categorize the facial expressions to the universal emotions include happiness, sadness, disgust, anger, fear, surprise.

A wide range of classification techniques are used in pattern recognition which have also proposed in the facial expressions classification from static and sequence images such as Neural Networks, Radial Basis Function (RBF) Networks, Fuzzy Logic, Bayesian Networks, *k*-nearest neighbor, Support Vector Machine and so on. Some of the most important techniques are discussed in the following part.

Seyedarabi *et al*. (2007) proposed a Neural Network classifier model to recognize the facial expressions from the sequence images. They used fourteen manually extracted feature points in the first frame around the eye, eyebrow, nose and mouth, respectively. They used cross-correlation method to track the position of feature points in the next frames which were calculated based on the maximum value of cross-correlation between two frames. They proposed Neural Networks to classify the emotions while extracted seven features from feature points in the neutral image (first frame) and emotional image (last frame). To make improvement in the training process Radial Basis Function Neural Network (RBFNN) was proposed in the classification of facial expressions. The proposed model was evaluated into fifty subject images from Cohn-Kanade database. Average accuracy rate for five times running was reported around 91%.

Multilayer Perceptron model of Neural Networks was proposed by Zhang *et al*. (1998) for classification of facial expressions. They selected manually thirty four points onto face images to represent geometric locations of facial feature points. The proposed model of facial expression classifier was included multilayer Perceptron with number of hidden units that was vary from 1 to 20 to reach the best configuration for classification. Experimental results showed the best accuracy rate of 73.3% with using seven hidden units for facial expressions classification. In this study, Japanese female database was used to evaluate the classification performance of six basic emotions except fear.

Sreenivasa Rao *et al.* (2011) proposed a feed forward Neural Networks model to classification of happy, anger, fear, sad and neutral from sequence images, respectively. After extracted the features of eyes and mouth by morphological operations the extracted feature vectors were used in three neural networks model in terms of the left eye, right eye and mouth features. As each model in this study represented four facial expressions and neutral, three recognition results were reported with using each vector, therefore, the optimum rate was obtained with respect to the combination of results. In spite of the estimating the number of layers and their units to make the Neural Networks structure is the time expensive task, the best performance of the proposed Neural Networks model was presented where it was consisted five layers with number of units for every layer. The recognition rates of 87 and 81% were reported for training and new sequence images as testing subjects, respectively.

Hammal *et al*. (2007) proposed a rule based system and compared it with the Bayesian model for classification of facial expressions. Facial feature points around the mouth, eyes and eyebrows were selected to obtain five geometric features from facial movements. Then, the extracted features consist of distances value from feature points were fed to the classifier to categorize four classes include neutral. They evaluated the proposed classifier in the different databases and obtained average accuracy rate of 61.1% for classification of Joy, Surprise, Disgust and Sadness in three classes from Cohen-Kanad and Dailey-Cottrel databases for instance. Furthermore, to improve the classification performance, the combination rate of joy and disgust as a class also surprise and fear were added to the joy, disgust and surprise classes that showed accuracy rate of 99.3%.

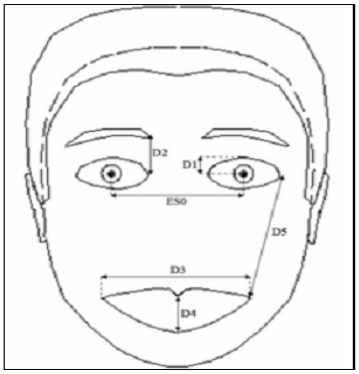


Fig. 8: Distances between points as extracted features

Support Vector Machine (SVM), Bayes classifier and Adaboost were examined in study of Guo and Dyer (2005) for facial expressions classification problem. Thirty four points were manually selected in each face image then Gabor filter were used at the selected points to extract the features. 612 extracted feature vectors were used in the SVM classifier model while using 60 and 80 feature showed the best accuracy rate of classification in the Bayes and Adaboost methods, respectively. Experiment results showed the best recognition rate of 92.4, 71 and 71.9% in SVM, Bayes and Adaboost methods, respectively for classification of all basic facial expressions in the Japanese Females database, respectively. Based on this study, small numbers of training samples make bias to estimate the classification of the test data as the general probability distribution is not covered in the learning process when bayes and Adaboost are used to classification of facial expressions with few training images.

Hupont *et al*. (2008a, b) used rule-based classifier to facial expressions recognition. In this study, 20 feature points around the mouth, eyes and eyebrows and five distances between them were extracted as facial features for evaluating the model performance in Ekman's all basic expressions. Experiment results showed 71% accuracy rate for using static images of FG-net and MMI databases. Furthermore, for the purpose of accuracy improvement, nose wrinkles and mouth shape information were added to extracted features that increased performance rate to the 85 and 91%, respectively. They showed, geometric feature method and rule based technique simplify the classification problem while keep accuracy rate enough good if the face parameters are selected correctly. Figure 8 shows five distances between points that used in the proposed rule-based classifier model. SVM and Naive Bayes, as other well known classifier methods, were also compared in the further study by Hupont *et al*. (2008a, b) in the classification of facial expressions with 14 facial distance parameters include 20 selected feature points. The recognition rate of 70 and 71.5% were reported in the classification of all basic emotions. In this study minimum rate was belong to the sadness with the value of 30 and 40% in SVM and Bayes classifier, respectively.

Samad and Sawada (2011) proposed Support Vector Machine for classification of facial expressions recognition where Gabor wavelet with a few parameters was utilized to feature extraction. The proposed model was evaluated on the FG-net (FEED) database and accuracy rate of 81.7% was obtained for classification of basic expressions except disgust emotion. The strength point in the proposed model was simplicity and lower computational cost in feature extraction process than the other studies which used Gabor wavelet as the feature extraction technique.

Hidden Markov Models (HMMs) as popular statistical models are widely used to model time series data and classification problems. Recently, HMMs were used also to classification of facial expressions in the studies of Pardas *et al*. (2002), Cohen *et al*. (2003) and Shin and Chun (2008). These studies tried to model the sequence of image states in HMMs to find the highest probability of expressions in new images to fit with trained models. Pardas *et al*. (2002) obtained a reasonable classification rate for basic emotions from Cohen-kanad sequence images while facial feature points based on the MPEG-4 standard were extracted. They reported 84% accuracy rate for expressions recognition. The proposed model was four states HMMs which was configured after several examinations to find the best HMMs structure for each emotion. Therefore, defining the configuration of the HMMs is a time consuming task for classification of emotions. Moreover, the model is used usually, in the most of research, for classification of facial expressions if a sequence of images is available to make a dynamic process. Therefore, classification of facial expressions from the static images is a challenging mission. On the other hand, based on the Cohen *et al*. (2003). studies, over fitting problem maybe arise due to matching just to the set of training samples also local optimal results rather than global optimal maybe obtained in the training process for setting HMMs parameters. Whereas the HMMs has a good potential for classification in the vary conditions such as diverse display of a facial expression with different people.

Appearance feature method indicates more information of face images compare with geometric feature methods, however, not only the appearance methods need to more complicate computation but also they need to some feature points extracted with geometric feature methods as an initialization step. A combination of geometric and appearance feature methods were used in the study of Youssif and Asker (2011) to increase the information of facial features to make more accurate classification compare with using geometric methods or appearance methods alone. 19 feature points were

extracted from the eyes, nose and mouth regions also histogram of face edge map as the appearance features from the whole face with 64 feature vectors were used to radial Basis Function (RBF) neural networks classifier. Experiment results showed 93.5% accuracy with using Cohen-kanade images for classification of all basic emotions. The reported accuracy is a considerably rate for using RBF neural networks compare with other studies which used the similar classification method. Whereas, the proposed extracted features needs to an expensive time for sequence images.

k-Nearest Neighbor method also showed suitable performance for classification of emotions from sequence images. Cheon and Kim (2009) proposed k-Nearest Neighbor (k-NN) classifier method to recognize the facial expressions with using Hausdorff distance between face sequence images. The features were extracted based on a modified AAMs method to make robust results in the vary conditions such as pose and illumination for classification of Happy, Anger and Surprise. In this study, different numbers of k were tested to find the best performance of classification as k = 3 showed the optimum result of 96.09% accuracy rate for sequence images compare with 92.53% where static images were used. As the k-NN can be used for classification of static images indeed, however, to improve the recognition performance the Hausdorff distance was utilized to implement the kNN classifier on the sequence images. Nevertheless, in this study the numbers of categories were less than other classifier techniques.

Shan *et al*. (2009) examined the SVM method to classification of emotions. In this study, LBP method was used as an appearance method to features extraction. Experiment results on the images of Cohen-Kanade databse showed average of 90% accuracy rate where SVM with using LBP method showed better results compare with using Gabor wavelet both in time and memory as a features extraction technique for classification of six basic emotions.

SVM is also proposed in the work of Piątkowska (2010) with using LBP for features extraction from the image sequences. He evaluate the proposed classification method on the FG-Net and Cohen- Kanade databases for recognition all basic expressions. The recognition rate of 71% from FG-Net compare with 77% from Cohen-Kanade showed the FG-Net database includes more complicate expression images than the another one. Whereas, with regarding to the feature extraction method as a robust method and the type of images which are sequence it seems that the obtained accuracies were not competitive rates.

In recent years, fuzzy logic has been used to model the problems with the purpose of making more accurate and real results. Classification of facial expressions is one of the complicate problems that follows the natural rules as deals with human activities. Therefore, fuzzy logic was used to solve some classification limitations related to the facial expressions such as: facial features do not belong to only one specific emotion that is a set of extracted features may represent different emotions in various classes with different chances. Therefore, ambiguity is an inherent characteristic of facial expressions (Wu *et al*., 2005).

For the purpose of robustness improvement, Xiang *et al*. (2008) proposed a Fuzzy c-Means (FCM) model to classify the facial features derived from using Fourier transform. Therefore, FCM classify a set of attributes with different membership values into the several categories. They reported 88.8% accuracy rate for basic expressions recognition from sequence images.

As facial expressions deal with universal action units for each basic expressions based on the FACS (Ekman and Friesen, 1978), therefore, rule based classifiers were proposed in some studies such as Hammal *et al*. (2007), to model the universal facial behaviors into the rules set to indicate the emotions. Fuzzy rule based system is another proposed model which is used to facial expressions to improve the rule based systems. For example, the fuzzy model was presented by Tsapatsoulis *et al*. (2000) with the purpose of using expert knowledge in form of rules and based on the MPEG-4 facial definition parameters which consist of 84 facial feature points (Tekalp, 2000). They defined fifteen feature vectors which were computed from the Euclidian distances between feature points in neutral and emotion expressions to feed the fuzzy inference system. The recognition rate of 81% was reported to classification of six basic emotions from the static images.

Another example of fuzzy rule based system is the proposed model by Esau *et al*. (2007) to classify the emotions. In this study, a set of predefined fuzzy rules specified the belonging degree (strong or weak) of facial features vectors to each emotion. The proposed classification model used six angles based on the fourteen feature points to measure the deformation of features from neutral to emotions. The experiment results showed the accuracy rate of 72% for classification of four emotions (happiness, sadness, anger, fear and neutral, respectively) from Cohen-Kanade database.

SeyedArabi *et al*. (2007) compared a fuzzy classification system with different approaches to recognize the facial emotions. They used fuzzy rule based system with seven feature vectors as a classifier to assess difference between first frame (neutral expression) and last frame (peak of expressions) of sequence images from Cohen-kanade database. Feature vectors were obtained based on the 21 facial feature points which were selected manually on the first frame and tracked on the last frame.

For the purpose of using human knowledge, a table of fuzzy rules was generated based on the psychological studies on the facial expressions. In this work the best recognition rate of 89.1% was reported for six basic expressions.

As another example, we can illustrate Chatterjee and Shi (2010) work that used fuzzy rule based system for facial expressions recognition and tuned the fuzzy model in a learning process. In this study, Adaptive Neuro Fuzzy Inference System (ANFIS) was proposed to tune the fuzzy rule based model to track properly the given input/output data. The learning process is performed based on the feed forward neural network to generate the fuzzy rules. They reported 85-95% accuracy rate for classify five facial expressions with five ANFIS model while different LBP model were used to feature extraction from JAFFE database images. According to this study, generating the fuzzy rules in the ANFIS makes the recognition process more automatic and improves the recognition rate, whereas it decreases the human knowledge intervention in the structure. On the other hand, the system is more complicate in which neural model needs to more computational process compare with the fuzzy rule based systems to reach the results.

As we mentioned before, HMM has a good potential to classify the objects in the different domains, but is not enough robust in the facial expressions classification. In the study by Miners and Basir (2005) fuzzy logic used in the HMMs to improves the recognition process with fuzzy measures for states and observations. Experiment results showed fuzzy HMMs compare with traditional HMMs make higher recognition rate while take less training time to classify the expressions.

SUMMERY AND DISCUSSION

Following table shows the summary of current facial expression classification methods and compares them with the different criterions.

Based on the literature review there are various classifications techniques that are used in the facial expressions domain. In the Table 1 the popular classifier methods which have used for facial expressions classification in the recent years are summarized. Each technique has some advantages and disadvantages inherently that make them more appropriate or inappropriate compare with the others to use them in the different domains with various conditions. Some of the disadvantages that challenge the use of classifiers in the facial expressions are as follow:

Hidden Markov models (HMMs):

- Configuring the proper structure needs to experimentation time
- It is a robust technique if the sequence of images (not proper for static) are used as input data
- The over fitting problem is not unpredictable

Rule based methods:

- Depending to the prior knowledge completely
- They have not learning process to improve them based on the conditions
- Generalization ability is low

Bayesian classifier:

- The chance of having an accurate statistical distribution for classes is low with regarding to the data base
- Need to a large training data set

Fuzzy methods:

- Depending completely to prior knowledge of experts
- Time consuming task for setting the fuzzy parameters
- The lack of learning process to tune the models

Neural networks: Neural Networks enable to predict properly the class of unseen objects in the multiclass non linear problems. Neural Networks and SVM are the most popular methods recently as they show proper accuracy rate in the most studies compare with other methods. However, they have still some drawbacks regarding to classification.

- Configuring the optimal structure needs to experimentation time
- Need to large training data to generalize the model(Groth, 2000)
- Numerous attributes increase the over fitting problem (Seetha *et al*., 2008)
- The method does not deal with the expert knowledge

SVM:

- High complexity and computation costs for multiclass problems
- Finding its accurate parameters is difficult (Seetha *et al*., 2008)

Beside some weaknesses mentioned above, when we see closely to the Table 1 this is found out that various conditions can affect on the accuracy rate of classification methods. Some of the most important are as follow:

- **Static images versus sequence images:** Classification of static images is more difficult than sequence images as the input information of static images to the classification model is too less than the sequence images. Therefore, the accuracy rate of using static images has tangible difference compare with sequence images. But, with regard to simple computation model for classification of static images and existence of many applications that use the static

Table 1: Facial expressions classification techniques: The state of the art

Reference	Classification technique	No of emotions	Image type	Feature extraction method	No of points	Database	Accuracy rate
Hammal *et al*. (2006)	Rule based method	4 (3 Classes)	Static	Geometric	-	Cohen -Kanade & Daily-Cottrel	61.1
Hupont *et al*. (2008a,b)	SVM	6	Static	Geometric	20	FG-net & MMI	70
Hupont *et al*. (2008a,b)	Rule based method	6	Static	Geometric	20	FG-net & MMI	71
Guo and Dyer (2005)	Bayes	6	Static	Gabor wavelet	34	JAFFE	71
Piątkowska (2010)	SVM	6	Sequence	LBP	-	FG-net	71
Hupont *et al*. (2008a,b)	Naive bayes	6	Static	Geometric	20	FG-net & MMI	71.5
Guo and Dyer (2005)	Adaboost	6	Static	Gabor wavelet	34	JAFFE	71.9
Zhang *et al*. (1998)	NN (Perceptron model)	5	Static	Geometric	34	JAFFE7	3.3
Piątkowska (2010)	SVM	6	Sequence	LBP	-	Cohen-Kanade	77
Sreenivasa Rao *et al*. (2011)	NN (Feed forward)	4	Sequence	Geometric	-	Cohen-Kanade	81
Samad and Sawada(2011)	SVM	5	Sequence	Gabor wavelet	-	FG-net	81.7
Pardas *et al*. (2002)	HMMs	6	Sequence	Geometric	-	Cohen-Kanade	84
Shan *et al*. (2009)	SVM	6	Sequence	LBP	-	Cohen-Kanade	90
Seyedarabi *et al*. (2007)	NN (RBFNN)	6	Sequence	Geometric	14	Cohen-Kanade	91
Zhang *et al*. (1998)	NN (Perceptron model)	5	Static	Gabor wavelet	34	JAFFE	92.2
Guo and Dyer (2005)	SVM	6	Static	Gabor wavelet	34	JAFFE	92.4
Cheon and Kim (2009)	k-NN	3	Static	AAM	Not mentioned	Cohen-Kanade	92.53
Youssif and Asker (2011)	NN(RBFNN)	6	Sequence	Geometric & appearance	19	Cohen-Kanade	93.5
Cheon and Kim (2009)	k-NN	3	Sequence	AAM	Not mentioned	Cohen-Kanade	96
Hammal *et al*. (2006)	Rule based method	6(3Classes)	Static	Geometric	-	Cohen-Kanade	99.3
Esau *et al*. (2007)	FRBS	4	Static	Geometric	14	Cohen-Kanade	72
Tsapatsoulis *et al*.(2000)	FRBS	6	Static	Geometric	-	Cohen-Kanade	81
Chatterjee and Shi(2010)	FRBS &NN	5	Static	LBP	-J	AFFE	85-95
Xiang *et al*. (2008)	FCM	6	Sequence	Appearance	-	Cohen-Kanade	88
Seyedarabi *et al*. (2007)	FRBS	6	Sequence	Geometric	21	Cohen-Kanade	89.1
Khanum *et al*. (2009)	CBR & FRBS	6	Static	Geometric	21	FG-net	90.33

images, the classification of static images is an essential task.

- **Geometric features versus appearance features:** Geometric methods are deal with the place of number of points on the face and analysis their movements when an emotion is occurred. Geometric features impose less computational process than the appearance features as deal with some points on the face image rather than whole the face. On the other hand, most of the appearance methods need to have feature points as initial step to perform the feature extraction (Shan and Braspenning, 2009). Nevertheless, a classifier method should perform the classification robustly when geometric features are used. Therefore, lower accuracy rate of a classification method that uses the geometric features does not make uncertainty to its robustness. To prove this matter, we may refer to the Zhang *et al*. (1998) study. In this study, as it is showed in the Table 1, Neural Network classifier with using geometric

features showed the accuracy rate of 73.3% while it showed the rate of 92.2% when Gabor wavelet were used.

- **Number of feature points:** There is a direct relation between number of feature points with accuracy rate and computation process. Therefore, using lower number of feature points is an objective for classification systems if the level of accuracy rate is kept up.
- **Database:** With take a look at the Table 1 we find that there are different databases which are used to implementation process. Difference between databases is due to number of subjects, variety of subjects and the control conditions that subjects have tested. For example Cohen-Kanade database is one of the full control databases. However, FG-net database is semi control database which is more naturally condition. The subjects in FG-net database represent the emotions in the semi naturally conditions, therefore the face appearance is more complicate in different emotions than fully control database. Our evidence for this matter is the study of Piątkowska (2010) that is shown in the Table 1. They evaluated the proposed classifier on the Cohen-Kanade and FG-net databases and reported the accuracy rate of 77 and 71%, respectively.

As the overall results, this is difficult to say which classifier is more robust in the nonlinear problems. To evaluate the classifiers, some conditions in which implementation is performed such as feature extraction method, database, number of feature points (if exist) and type of images beside the strengths and weaknesses of those classifiers should be considered accurately.

CONCLUSION

As the overall results, this is difficult to say which classifier is more accurate and robust in the nonlinear problems. Therefore, to evaluate the classifiers, some conditions in which implementation is performed such as feature extraction method, database, number of feature points (if exist) and type of images beside the strengths and weaknesses of those classifiers should be considered. Moreover, the results from the existing studies show that using the geometric features with small size of feature points extracted from the static images which are express the emotions in a non-controlled conditions make a difficult structure for a classification model. Therefore, a classifier is robustness if shows the high accuracy rate using the above parameters.

DIRECTION OF THE FUTURE WORK

Based on the literature, Fuzzy rule based classifier has several factors that makes it as a proper method for facial expressions classification. Fuzzy rule based classifier consists of expert knowledge that is useful for a classifier with respect to this matter that human as an intelligent individual represent the ways of logic to understand the facial emotions based on the face appearance. Also, Fuzzy methods describe mathematically the uncertainty conditions of facial expressions into the simple model with low recognition complexity compare with some other methods such as SVM and Neural Networks (SeyedArabi *et al*., 2004). Therefore, with respect to the Table 1 we can see several studies used the Fuzzy methods for the facial expressions problem and obtained the reasonable results particularly where classification of the static images with low training data and Geometric features were followed. However, for the purpose of performance improvement of Fuzzy rule based classification, Genetic Algorithm is proposed to decreases some limitation of Fuzzy rule based classifier. In various studies (Bonissone *et al*., 1996) Genetic Algorithms as a learning algorithm were combined with FRBS to add the following merits to a Fuzzy systems:

- Making a learning process for Fuzzy model
- Tuning membership functions or generating the Fuzzy rules, automatically
- Reaching to optimal performance with construction adjustment of the model
- Making generalizations in the diverse conditions for the model

However, the Genetic learning algorithm combined with Fuzzy rule based system has not been used as a hybrid model in the expressions recognition domain in the existing studies. Therefore, according to this research a Genetic-Fuzzy classifier model is proposed as the future work to develop the facial expressions classification from the low level information of images to fulfil the Fuzzy classification requirements.

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