FACIAL EXPRESSION RECOGNITION WITH ROBUST FEATURE SELECTION

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Abstract: Facial expressions are an important part of human-machine interaction as well as playing a substantial role in human communication. Since facial expressions are significant parameters in decision making on such important issues as criminal detection, monitoring the attention of the driver and patient follow-up, automatic detection of facial expressions via systems has become a popular subject. In this study, the detection of facial expressions is aimed by selecting the robust features affecting the detection of emotions in facial images. Face++ SDK is used for locating the facial keypoints. All probable distance data between the points and ratio data between the lines have been calculated, then the robust distance, ratio and distance + ratio features affecting the expression detection has been selected by Sequential Forward Selection (SFS) method. Following this step, each robust feature vectors has been classified and their success rates have been compared. For classification, Support Vector Machines (SVM) and k-Nearest Neighbors (KNN) are used. As a result, 91% success rate has been achieved with 4 robust ratio features on SVM. In our study, in which neutral, surprised, sadness, angry, happy facial expressions have been analysed, surprised has been predicted right by 100%, happy and angry by 95%.

Keywords: facial expression recognition, robust feature selection, image analysis, machine learning

Introduction

Human behavior is the basic principle behind communication among people and is also used in human-machine interaction (Shin, 2009). As one of the keystones of inter-human communication, facial expressions reveal different combinations of facial muscles and constitute one of the variations of nonverbal communication (De et al., 2015). Mehrabian underlined that facial expression is more effective in communicating a message than words in face-to-face communication (Mehrabian, 1968). In his study, he revealed that words are 7% effective, voice tone is 38% effective, and body language is 55% effective in communicating a message.

As a noted scientist in psychology, Paul Ekman determined six innate facial expressions as universal. In their study, Ekman and Friesen sought answers to the question of which facial expressions are universal. The results of the study revealed that the emotions of anger, disgust, fear, happiness, sadness, and surprise are observed in the same way among all people (Ekman & Friesen, 1971).

Automatic detection of facial expressions via systems is among the most popular subjects studied today. Facial expression can be used in areas such as the detection of criminals via computers (Stanković et al., 2015), monitoring driver attention (Zhang & Hua, 2015), human-machine interaction (Luo et al., 2015)(Mistry et al., 2014) image understanding (Sonmez & Albayrak, 2016), artificial face animation (Thalmann et al., 1998)(Tu et al., 2004), health (Lo Presti & La Cascia, 2015), computer games (Osone et al., 2010)(Liang et al., 2004)(Zhan et al., 2008), and media (An & Chung, 2009). However, while noise occurring in facial images transferred to digital media (e.g., full or partial concealment of the face by various objects, shade formation, or low resolution) increase the difficulty of this process, ensuring real-time performance further restricts the general process.

Facial expression recognition is generally carried out under three categories (Hsu et al., 2013)(Lin Zhong et al., 2012), namely geometric-based, appearance-based, and action unit- (AU) based analysis. In the geometric-based method, shape information about the face is used. The active shape model (ASM) is an example of the geometric-based approach (Oktay, 2011). For the appearance-based approach, features of the facial tissue come into prominence. Local binary pattern (LBP) (Hung et al., 2006) is an example of this approach. The active appearance model (AAM) (Cootes et al., 1998) method uses both the geometric- and appearance-based approaches. For the AU-based approach, the movements of facial muscles are identified by a system called the Facial Action Coding

System (FACS) (Ekman & Friesen, 1978).

The detection of facial expressions comprises four stages, namely detection of the facial area, preprocessing step, extraction of facial features, and classification of facial expressions. For facial feature extraction, principal component analysis (PCA) (De et al., 2015), (Sonmez & Albayrak, 2016), steerable pyramid decomposition (Mahersia & Hamrouni, 2015), histogram of gradients (HOG) (Ouyang et al., 2015), linear discriminant analysis (LDA) (Sonmez & Albayrak, 2016), LBP (Sonmez & Albayrak, 2016), Gabor filters (Bashyal & Venayagamoorthy, 2008)(Lajevardi & Hussain, 2009), and learning vector quantization (LVQ) (Bashyal & Venayagamoorthy, 2008) have provided successful results. For facial expression classifications, a support vector machine (SVM) is frequently used because of its successful results (Liao et al., 2013)(Sümer, 2014)(Zavaschi et al., 2011)(Valstar et al., 2011)(Bartlett et al., 2005)(Martin et al., 2008)(Littlewort et al., 2011)(Yurtkan & Demirel, 2014)(Zhang et al., 2012)(Zhang et al., 2016)(Ji & Idrissi, 2012).

In this study, the Radboud Facial Expression Database (RaFD) was used. Facial keypoints were detected on the images of the database with Face++ SDK (Face++, 2017). Of the 26 keypoints obtained, the distance to other keypoints and the ratios of these distances were calculated. The obtained distance, ratio, and distance + ratio feature clusters were analyzed by the sequential forward selection (SFS) feature selection algorithm, and strong features affecting the facial expression response were determined. Features were entered in various classifiers, and comparative results are presented in a table. This study contributes to the literature through its analysis of the features obtained from (Zhang et al., 2016)the distances and ratios of facial keypoints and high success rates in the detection of facial expressions with only four features.

The rest of the article is structured as follows. Part 2 explains the proposed method in detail. Part 3 presents the comparative experimental results in tables. Part 4 compiles the results of the study and makes suggestions for future studies.

Proposed Method

In this study, facial keypoints were detected on human face images. The distance between these keypoints and the ratios of these distances were calculated. Based on this distance and ratio data, strong features were obtained using the SFS algorithm. The obtained data were classified by means of the KNN and SVM methods, and facial expressions were detected. A block diagram of the application is shown in Figure 1.

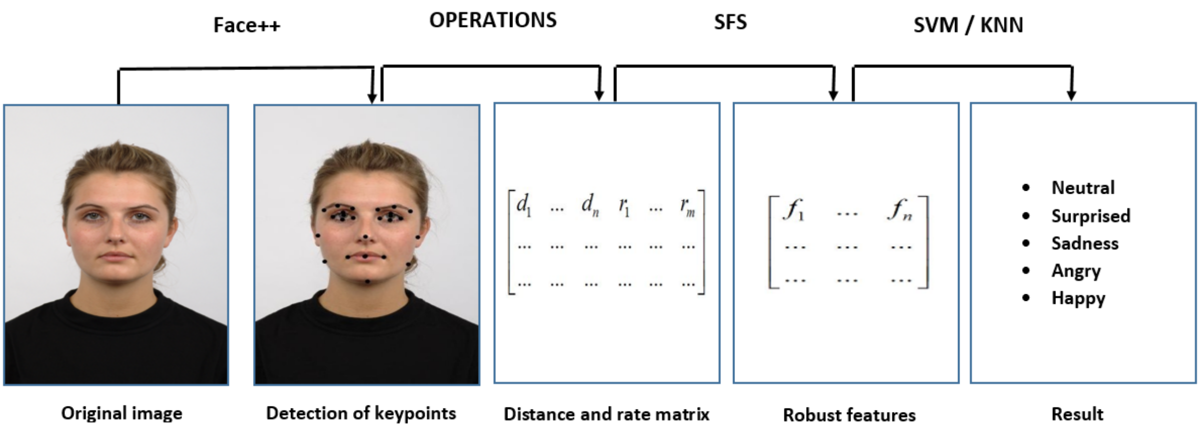


Figure 1. Proposed Method

A. Feature extraction using facial keypoints

According to psychology studies, facial expressions are formed by changes around the mouth, eyes, and nose (Lin Zhong et al., 2012). In this study, 26 points were determined and these are shown in Table 1.

The Euclidean distance of each point was calculated. The number of distance between each set of two points is calculated according to Equation 1:

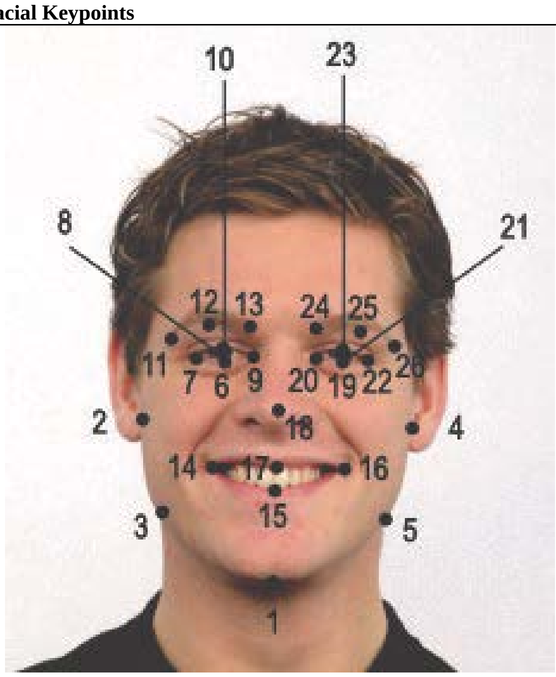
$$C(n,r) = \binom{n}{r} = \frac{n!}{r!(n-r)!} \quad (1)$$

n in Equation 1 is the total number of points (*n*=26), and the *r* value is 2 since the distance between each set of two points was calculated. Based on 325 distance data records, ratios of each distance to other distances were calculated. The number of ratio data was calculated as 52650 according to Equation 1. Information on two distances is required for ratio data. For this calculation, *n*=325 and *r*=2. Thus, 325 distance records, 52650 ratio data records, and, as the unified form, 52975 distance + ratio data records were created for each face image in the database. Since this huge number of features would create a processing load in the classification stage, features should be chosen for better detection.

To sort out the data negatively affecting the result, the obtained distance, ratio, and distance + ratio data were subjected to the feature selection process. Instead of working with all the data, the possibility of achieving the same level of success is increased by using less and more meaningful data. With the feature selection process, the load on memory and the processor is reduced. Thus, the SFS algorithm was used in this study.

A ratio and distance matrix and its unified version were analyzed separately by the SFS algorithm. As a result of the analysis, six robust features were selected from the 325 distance data records of each image. The four robust feature data were selected from 52650 ratio data. The 52975 ratio + distance data records were reduced to five features.

Table 1: Facial Keypoints and their Explanation

Facial Keypoints	Point	Explanation
	1	Chin
	2	Left ear level
	3	Left cheek level
	4	Right ear level
	5	Right cheek level
	6	Left under eye
	7	Left eye outer corner
	8	Left pupil
	9	Left eye inner corner
	10	Left over eye
	11	Left eyebrow outer end
	12	Left eyebrow center
	13	Left eyebrow inner end
	14	Mouth left corner
	15	Mouth center bottom lip
	16	Mouth right corner
	17	Mouth center top lip
	18	Nose
	19	Right under eye
	20	Right eye inner corner
	21	Right pupil
	22	Right eye outer corner
	23	Right over eye
	24	Right eyebrow inner end
	25	Right eyebrow center
	26	Right eyebrow outer center

B. Selection of the robust feature for facial expression recognition

In this study, SFS was used for the robust feature selection. The SFS algorithm was proposed by Whitney (Whitney, 1971). Classification is used in the algorithm. Although its working speed is low, its performance is high because of its capacity to analyze different feature clusters together and evaluate the relationships between features (Kaya, 2014).

The SFS algorithm begins by working with one feature vector from the feature cluster. With the help of a classifier, it scans the features, selects the best feature affecting the result with the first feature, and creates a feature cluster with two elements. Afterwards, the algorithm continues working with the same logic for the selection of a new feature from the feature cluster. This cycle continues until there is no further improvement in the classification process and ends when it reaches the present success limit. Pseudo code of SFS is as follows:

I. Create an empty set, $F_0 = \{\}$

II. Select a feature for the best result: $Z^t = \arg\max\left[J(F_k + Z)\right] \& Z^t \notin F_k$

III. Add Z^t to the set: $F_{k+1} = F_k + Z^t \& k++$

IV. Go to II

C. Classification of the Facial Expression

After the determination of robust features affecting facial expression recognition, these features have to be classified. In this study, SVM (Sümer, 2014),(Beszedes & Culverhouse, 2007) and KNN (Lee et al., 2016)(Cheon & Kim, 2008)classifiers, which produced successful results in the literature, were used for the classification of facial expressions, and the success rates were compared. Since the resulting data will be used in another study on the analysis of attention, the present study was conducted for five emotions. These expressions are neutral, surprised, sad, angry, and happy.

SVM is a classification algorithm developed by Vapnik et al. based on statistical learning theory that calculates the longest distance between the classes to sort out different classes (Cortes & Vapnik, 1995)(Vapnik, 1999). SVM draws a hyperplane in the training set that maximizes the distance of the data from different classes and covers the possible largest part of the data from the same class.

SVM uses various core functions (Lee et al., 2008). These functions are linear, polynomial, sigmoid, and radial based functions (RBF). The RBF core function is mostly preferred in classification studies using SVM. According to the performance assessments, the most successful results are achieved with the RBF core (Ayhan & Erdoğmuş, 2014), so the RBF core function is used in this study.

KNN algorithm (Cover & Hart, 1967) developed by Cover et al. is a statistical and supervised algorithm. It is based on the principle of determining the class of the data by considering its distance to k number of neighbors. In the calculation of the distance between data, various methods, such as Chebychev distance, Manhattan distance, and Euclidean distance, can be used (Mulak & Talhar, 2015). In this study, the Euclidean distance method is used.

Experimental Results

Various databases have been used for training and testing purposes in studies on the detection of facial expressions. In this study, the RaFD (Langner et al., 2010) face database was used. RaFD provides successful results in facial expression studies (Ahmady et al., 2013)(Shokrani et al., 2014)(Kanan & Ahmady, 2012).

RaFD is a free face database that contains facial images of Caucasians. These facial images were obtained with five cameras with different angles (i.e., 0, 45, 90, 135, and 180 degrees). Using the content of this database, researchers can conduct studies on facial expression analysis and detect the viewing angle and head orientation. According to the studies of Ekman mentioned in the introduction, the fact that the database consists of Caucasians does not constitute an impediment for the analysis of universal emotional expressions. Moreover, the database has eight different facial expressions (i.e., neutral, angry, sad, afraid, dis-gusted, surprised, happy, and contempt) and three different viewing angles (i.e., straight, right, and left). All images were prepared based on FACS examples. The database has images of 49 people, 39 adults and 10 children; 6 of the children are girls, and 19 of the adults are women. In this study; for training process 235, for testing process 100, totally 335 images were used.

Table 2 presents the total number of data records for each feature cluster, the number of reduced features, and the locations of the selected features on the face after applying SFS. For example, lines 13-16 in Table 2 refer to the length between the 13th and 16th points.

These features were classified with the SVM and KNN algorithms. The success rates are presented in Table 3 and Table 4.

Table 2: Reduced features as a result of SFS Algorithm

Data Type	Total Data Number	Data Number after SFS	Selected Features
Distance	325	6	13-16, 6-12, 12-17, 21-26, 6-15, 9-13
Ratio	52650	4	1-8 / 2-22, 1-11 / 3-11, 6-19 / 15-25, 7-21 / 15-19
Distance + Ratio	52975	5	1-8 / 2-22, 20-24, 1-6 / 11-22, 1-2 / 2-11, 1-23 / 7-20

Table 3: Complexity matrix of the features obtained after SFS by classification with SVM

Expression	Distance Data (%)	Ratio Data (%)	Distance + Ratio (%)
Neutral	60	80	60
Happy	95	95	100
Angry	100	95	100
Sad	85	85	70
Surprised	90	100	95
Average	86	91	85

Table 4: Complexity matrix of the features obtained after SFS by classification with KNN (k=1)

Expression	Distance Data (%)	Ratio Data (%)	Distance + Ratio (%)
Neutral	50	65	40
Happy	100	100	100
Angry	95	90	100
Sad	65	80	80
Surprised	95	100	95
Average	81	87	83

In both classification algorithms, it has been observed that the most successful results are obtained as a result of entering only the ratio feature data. One of the most important results of the study is that a high level of success has been achieved with only four facial ratio feature data records. Comparative results of the proposed algorithm with other studies extracting features are shown in Table 5.

Table 5: The Comparison of the proposed method with the other methods Detecting Facial Expressions

Researchers	Database	Methods	Neutral (%)	Happy (%)	Angry (%)	Sad (%)	Surprised (%)	Average (%)
Lee et al. (Lee et al., 2016)	Mobile platforms	AAM+KNN	80	86	85	77	95	85
Ren et al. (Ren & Huang, 2015)	BU-3DFE	AAM+SIFTW+SVM	-	84.1	82.5	77.3	84.5	81.4
Mistry et al. (Mistry et al., 2014)	Cohn Kanade (CK+)	AAM+LBP+ANN	-	86.7	83.3	96.4	93.3	88.8
Cheon et al. (Cheon & Kim, 2008)	Facial Expression Database (FED06)	Dif-AAM+KNN (k=5)	92.5	93.69	82.11	-	96.29	91.52
Beszedes et al. (Beszedes & Culverhouse, 2007)	Private database	AAM+SVM	78	95	84	-	95	-
Senechal et al. (Senechal et al., 2012)	GEMEP-FERA	LGBP+AAM	-	96.8	96.3	76	-	83.5
Proposed	Radboud	KNN(k=1)	65	100	90	80	100	87
		SVM	80	95	95	85	100	91

Conclusion

This study presents an algorithm with high success where features are minimized for the detection of facial expressions. In experimental studies using the Radboud database, 26 important keypoints have been determined for face images. The Euclidean distance of these 26 keypoints to each other was calculated, and 325 distance feature data records were obtained for each image. Ratios of the 325 distance data records were calculated, and 52650 ratio data records were obtained.

In the next step, distance, ratio, and distance + ratio data were analyzed with the SFS feature selection algorithm, and six distance, four ratio, and five distance + ratio feature data records were obtained. These features were classified with SVM and KNN classifiers, and the comparative results are presented in the tables. It was observed that the highest success rate was achieved by using only ratio feature data. Thus, facial expressions were predicted correctly 92% of the time using the SVM algorithm with four ratio feature data records. With the KNN algorithm, an 87% success rate was achieved with the stated four ratio features.

For future research, the proposed system could be strengthened with different features and different classification algorithms. Angles between the lines formed by the 325 distance data records can be determined as a new feature cluster. Since the changes in the muscles that occur when facial expressions are formed also change the important facial points, angles between the lines are formed by distances. A study could be conducted on the unified effect of angle information and distance and ratio and distance + ratio data on the results. Moreover, the analysis results for the five conditions obtained in this study could be used in the various fields studying facial expressions, as stated in the introduction.

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