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# Facial Expression Recognition Using Proposed Geometric Features

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# Facial Expression Recognition Using Proposed Geometric Features

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***Abstract*—Facial expression recognition has significant benefit due to its possible applications in computer vision. In this paper, new geometric based features are proposed for the recognition of seven facial expressions. The number of features is reduced by using feature selection methods. Obtained features are applied to SVM classifier. In the experimental studies, the extended Cohn-Kanade (CK+) dataset is used. Satisfactory results are obtained for the features selected with the sequential backward method.**

***Index Terms*—facial expression recognition, geometric based features, feature selection, support vector machine**

## I. Introduction

Facial expression is one of the most effective, natural and important tools for people to communicate their emotions and objectives [1]. Facial expressions are facial changes that show a person's inner emotional conditions, objectives, or social communications [2].Facial expressions are commonly used in behavioral understanding of emotions, cerebral science, and social collaborations [3]. There are two common methods to obtain facial features: geometric feature-based methods and appearance-based methods [1]. The geometric features introduce the shape and positions of facial components such as mouth, nose, eyes, and eyebrows that are extracted to create a feature vector representing facial geometry. In view-based methods, image filters such as Gabor wavelets are applied to the entire face or specific facial areas to remove facial appearance differences, including wrinkles, bumps and grooves

Getting an actual facial demonstration from original facial images is a crucial stage to effective facial expression recognition which is an motivating and interesting topic. Automatic facial expression recognition affects important the results in many applications. In the last decade, automatic facial expression recognition has been gaining more and more attention and has become an crucial topic in the scientific society because facial expressions are one of the most robust, natural and immediate tools for people to communicate their emotions and intentions [2]. The recognition rate of individual facial expression is usually not high, which restricts the real-time facial expression recognition. The main complexity of independent facial expression recognition is that the appearance of the human face affects the correct acquisition of expressive features [4]. In recent years, researchers have been realized many enhancements to the expression recognition system to improve the recognition rate of facial expression

By taking the median of the landmark tracking results from facial expression sequences training, the classic expression sequence is created for each facial expression class. [3]. Finally, two methods for facial expression recognition using multi-class AdaBoost with dynamic time warping or support vector machine in powered feature vectors are introduced. Bartlett et al. presented results on a user independent fully automatic system for real time recognition of basic facial expressions from video. The expression recognizer takes image pieces placed by the face detector. A Gabor representation of the piece is established and then processed by a bank of SVM classifiers. They presented an approach for further speed advantage by combining feature selection based on Adaboost with feature integration based on support vector machines [5].

Statistical local features, local binary pattern (LBP), are widely used in facial expression recognition especially with the support vector machines (SVM) [2], [6]. Appearance and geometric based features are also used with SVM in facial expression recognition [7], [8]. Li et al. proposed a recognition algorithm of person-independent facial expression based on improved LBP (Local Binary Pattern) and HOSVD (Higher-Order Singular Value Decomposition) [4]. In the phase of facial expression classification and recognition, the conventional nearest neighbor classification is modified into k- nearest neighbor pre-classification, and the local energy obtained by HOSVD is utilized to specify the resemblance of two images for secondary classification. Given the nonlinear manifold structure of the face images, a new kernel-based multilevel learning method called core discriminant isometric mapping (KDIsomap) has been proposed. [2]. KDIsomap is utilized to provide nonlinear dimensionality reduction on the obtained local binary patterns (LBP) facial features and obtain low-dimensional discriminant embedded data representations with remarkable performance enhancement on facial expression recognition stages.

The Convolutional Neural Network (CNN) is another pop-

(a) (b) (c) (d)

Fig. 1: (a) and (b) denotes feature landmark points, (c) and (d) denotes selected 28 features from SBFS.

ular method used for facial expression recognition [5], [9]. Liu et al. proposed a FER model based on improved CNN for Sobel edge detection and fused support vector machine (SVM) [10]. To solve the problem of facial recognition in face closure, Feng and Shao proposed a human eye facial expression recognition model for transfer learning. The characteristics of pre-processed data were obtained by using the Inception-v3 model, and the obtained feature information is applied into a new classifier for classification [11]. Bartlett et al. introduced a methodical comparison of machine learning methods employed to the automatic recognition problem of facial expressions. They stated results on a sequence of experiments comparing recognition methods, including AdaBoost, support vector machines, linear discriminant analysis [12].

## II. Feature Extraction

Feature extraction is the first phase of facial expression recognition that is mainly composed of three stages: face detection, facial landmark tracking, extracting features from the landmark tracking result. We used Viola-Jones face detection algorithm in face detection phase [13]. Facial landmarks are taken from the dlib's facial landmark detector [14]. 68 facial landmarks are obtained by using this detector. In literature, most of researches use both neutral state and expressions state in the feature extraction. However, in our work, first group of extracted features corresponds to the Euclidean distances between two odd numbered landmarks from 1 to 67, 3 to 67, ... etc. Second group of extracted features corresponds to the Euclidean distances between two even numbered landmarks from 2 to 68, 4 to 68, ... etc. Feature vectors are constructed by combining these two groups and taken totally 1122 extracted features.

## III. Feature Selection

The purpose of feature selection is to find better representative features from the feature vector. The reduction of dimension of feature vector provides faster classification. Three feature selection approaches are used to reduce the dimension of the feature vectors. These methods are briefly explained in the following subsections.

### A. Sequential Forward Feature Selection

In the Sequential Forward Feature Selection (SFFS), first, the best single feature is selected, then two pair of features are formed using one of the remaining features and this best feature, and the best feature pair is selected. The third step, triplets of features are taken using one of the remaining features and these two best features, and the best triplet is selected. These steps continue until best representative subset of features are selected. After the application of SFFS, we have best 60 features.

### B. Sequential Backward Feature Selection

Second feature selection method is Sequential Backward Feature Selection (SBFS). In this method, firstly, the classification function is computed for all features. Then, each feature is deleted once at a time, the classification function is computed for all subsets with all minus deleted one, and one feature having worst classification rate is discarded. These steps continue until best subset of features is selected. After the application of SBFS, we have best 28 features

### C. Feature Selection with Principal Component Analysis

Principal Component Analysis (PCA) is a technique for especially dimension reduction. The main purpose of PCA is to keep the data set with the highest variance in high dimensional data, but to provide dimension reduction while doing this. It provides lower dimension by finding general properties of the given dimension. Certain features will be lost with size reduction; but intended, these disappearing have little informational characteristics about the classification. In this study, we applied PCA as a feature selection method. In CK+ dataset, the number of eigenvalues tuned from 2 features to all features. Best recognition results are obtained by selection of 268 features.

## IV. SVM CLASSIFIER

Support vector machines (SVM) are a couple of supervised learning methods used for classification, regression, and outliers detection [15]. In this classifier, a data item is indicated as a point into the n-dimensional space along with the value of each feature corresponding to a specific coordinate. Also classification is realized by finding the hyperplane that discriminates the classes. In the SVM, if there is no linear hyperplane between two or more classes, method called kernel-trick is applied. In this study, RBF kernel is applied and classified 7 facial expression classes.

## V. EXPERIMENTAL STUDY

In the experimental study, the dataset used and test results are mentioned in following subsections.

### *A. Database*

In the Facial Expression Recognition study, the Extended Cohn-Kanade (CK+) dataset was used [16]. The dataset contains facial images from 123 subject with 7 emotions (i.e., anger, contempt, disgust, fear, happiness, sadness, and surprise). In our usage, the first frame of each sequence is taken as a neutral frame. In addition, the last two or three emotional frames has been taken in order to increase the number of samples on the dataset. This leads to a total of 989 images of 8 classes. For fair comparison with other researchers, we use 7 facial expression classes without neutral class in the recognition process. Finally, we have 866 images whose distributions according to the classes are given in the Table-I.

| Anger | Contempt | Disgust | Fear | Happiness | Sadness | Suprise | **Total** |
|---|---|---|---|---|---|---|---|
| 90 | 82 | 158 | 121 | 138 | 111 | 166 | **866** |

TABLE I: The number of classes and the sample numbers of classes in CK+ dataset

### *B. Results*

During the classification process, SVM is used together with RBF kernel. 10-fold cross validation is used to obtain average accuracy result. In this method, the dataset is divided into 3 parts as training, testing and verification. 88,2% recognition rate is obtained from RBF kernel of SVM using features without selection. Confusion matrix for this case is given in Figure 2. 89,5% and 93,5% recognition rates are obtained using RBF kernel of SVM for the features selected by SFFS (60 features) and SBFS (28 features) respectively. The confusion matrices with these cases are given in Figures 3 and 4 respectively. When the 268 features selected by PCA are

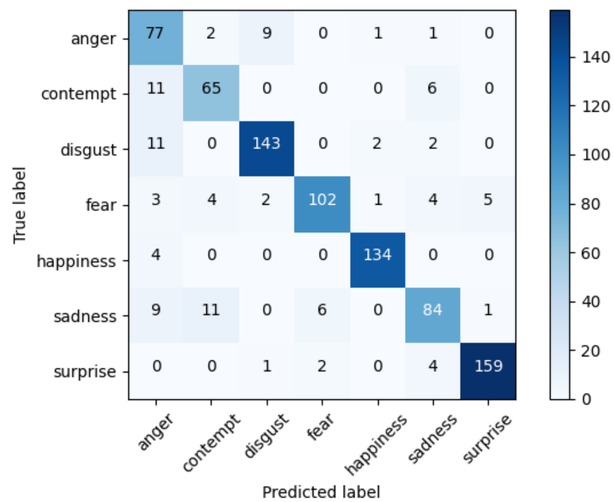


Fig. 2: Confusion matrix obtained for the features without selection.

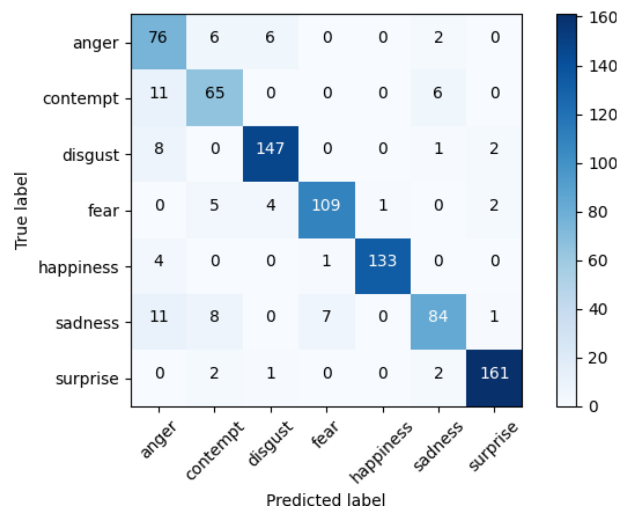


Fig. 3: Confusion matrix obtained for the features selected by SFFS.

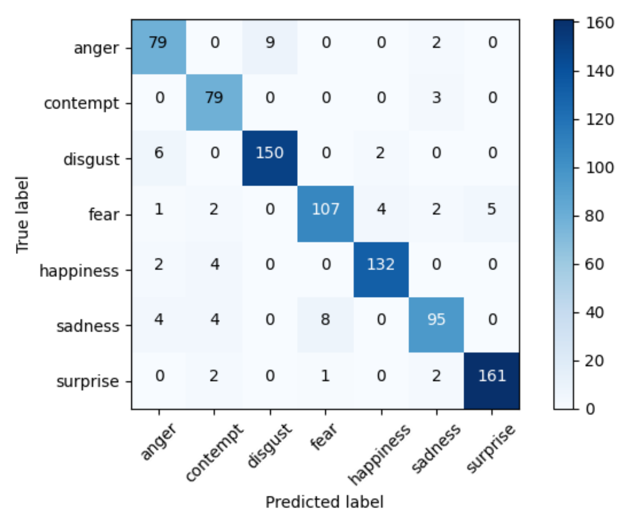


Fig. 4: Confusion matrix obtained for the features selected by SBFS.

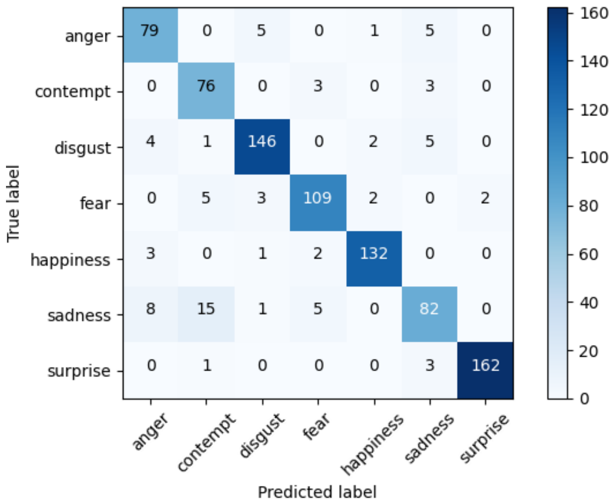


Fig. 5: Confusion matrix obtained for the features selected by PCA.

used RBF Kernel of SVM gives 90,8% recognition rate. The confusion matrix of RBF kernel SVM classifier for feature selection with PCA is given in Figure 5.

## VI. Conclusion

In this study, different geometric properties of landmarks points are used in facial expression recognition instead of usual landmarks. The Euclidean distances between two of the landmarks points by skipping one landmark point are used when obtaining geometric features. Three different feature selection methods are applied during the facial expression classification stages due to the negative impact of some features. The results of feature selection methods are given in Table-II. The feature vectors which are obtained by Euclidean distances are classified by 10-fold cross-validation with RBF kernel SVM. Highest accurate results (93,5%) are obtained with 28 features obtained from SBFS. This result is also higher than the results given in the references [7] and [17] when the RBF kernel SVM is used as a classifier.

In feature studies, it is aimed to achieve facial expression recognition with a higher success by applying geometric and appearance-based features together. In addition, it is planned to expand the work with deep learning methods to increase the classification performance.

| | | *Accuracy (%)* *RBF Kernel of SVM* |
|---|---|---|
| Selection Method | Without Feature Selection | 88.2 |
| | Feature Selection with SFFS | 89.5 |
| | Feature Selection with SBFS | **93.5** |
| | Feature Selection with PCA | 90.8 |

TABLE II: The Accuracy table of Results


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