Gender Recogni ition from Face Images Using PCA and LBP

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Abstract

Gender recognition is one of the most popular research areas in security, biometrics and human computer interaction applications [1]. In previous studies, structural and textural features of facial expressions were mostly used to identify gender. One of the biggest challenges of gender recognition is differentiating textual features of faces that decrease the accuracy of the proposed method, and there are lots of factors such as media, ambient lighting and environmental conditions. In order to overcome these disadvantages, firstly, a new database which has different expressions of face images is created. Then, some feature extraction and classification methods are used to improve recognition accuracy. Principal Component Analysis is used both for feature extraction and dimension reduction. Also, Local Binary Pattern Analysis which is frequently used in gender recognition is used at that stage. In classification stage, Euclidean and Manhattan classifiers are used. Finally, all methods' recognition performances are compared using the classification accuracy of applied methods.

1. Introduction

Face which distinguishes people from each other is a decisive factor for people. Face image contains lots of information such as identity, gender, race and facial expressions. In previous studies, this kind of information can be identified by the computer systems easily such as computer vision, pattern recognition and image processing.

The researches for gender recognition started at beginning of the 1990s. Nowadays, the analysis of human face for gender recognition is interesting and challenging research problem in human-computer interaction and control systems. Therefore there are lots of studies on gender recognition to develop faster and more convenient systems. The success rate of these systems depends on learning system accuracy. In this study, it is tried to determine gender from face images by testing similarities between test image and database.

Gender recognition approach can be divided into two models. They are named as appearance-based model and feature-based model [2].

Cottrell and Metcalfe [3] and Golomb et al. [4] reported the first introduction of gender recognition. They used a multi-layer neural network to recognize gender from face images. Golomb et al had 91.9 % accuracy rate with using 90 images database and Cottrell had 79 % accuracy rate with using 160 images database, on the other hand Gutta et al. [5] used a hybrid model. The model was consisting of radial basis function networks and inductive decision trees. Moghaddam et al. carried out trials with using support vector machine (SVMM) method [6]. The techniques, which are talked about above, are appearance based methods. Gender was identified without extracting any

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2. Database and Preprocessing

In this study, the database is created with face images which belong to 55 male and 55 female and separated by three age groups: young (30 images), adult (40 images) and senior (40 images). These images consist of face region including four different facial expressions such as smiling, eyes closed, angry and expressionless, and have no hair information. The sizes of taken images are 50x50. The sample images of the database are shown in Figure 1.

Due to the environmental factors such as illumination change, brightness, the images are normalized between (0-1). Hence the performance of proposed method is increased.

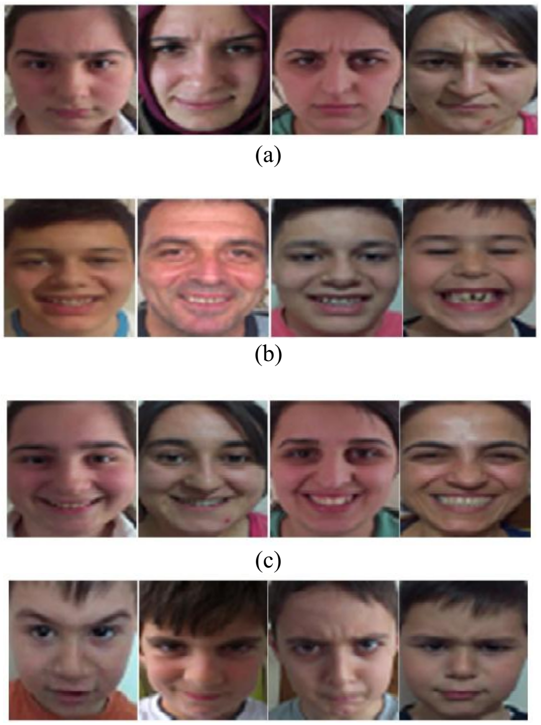


Fig. 1. (a) Images of smiling female (b) Images of smiling male (c) Images of frustrated female (d) Images of frustrated male

3. Feature Extraction

In this study, Principal Component Analysis (PCA) and Local Binary Pattern (LBP) methods are used for feature extraction. Proposed model is given below.

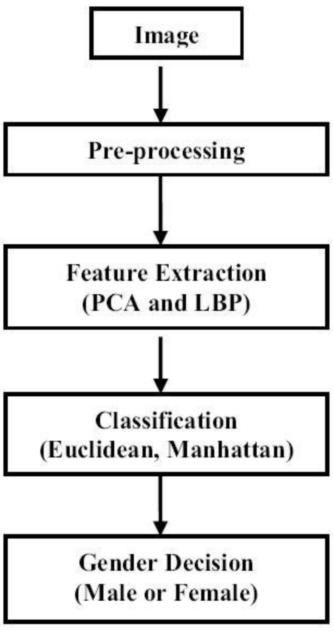


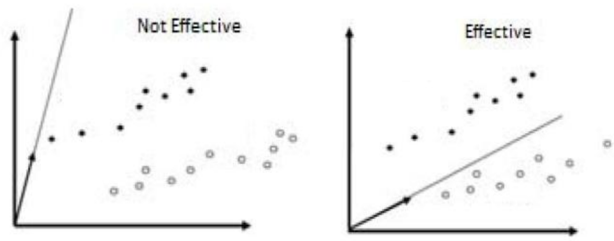
Fig. 2. Flow Chart for feature extraction.

3.1. Principal Component Analysis

Principal Component Analysis (PCA) is an effective feature extraction technique and data representation method. It is used in pattern recognition, image processing and computer vision, etc. PCA produces linear combinations of the original data and aims to find the best vector space which represents the distribution of face images and reduce wide dataset to a lower dimension to get effective results [8]. Thanks to using the reduced subspace, computations becomes more efficient. But, in case of nonlinear dependence of data, PCA cannot yield desired results.

PCA is used first by Sirovich and Kirby to represent images of human faces efficiently. They advocate that any face image could be reconstructed as a minor collection of images [9]. Then, PCA has been surveyed too much and has become one of the most successful approaches in gender recognition. The dimensionality problem of face images is considered by Penev and Sirovich when frontal face images are used in gender recognition [9], on the other hand the arbitrary effects of PCA were tried to calculate by Zhao and Yang in vision systems. They did it by using an analytically closed form formula of the covariance matrix as in this study [9].

(a) PCA uses correlation or covariance matrix for monitoring the change in variable. In this study Covariance matrix is used.



(a) (b)

Fig. 3. Distribution of the sample space (a) before PCA (b) after PCA.

(b) Eigenvalue and eigenvector are computed as follows:

$$Ax = \lambda x \tag{2}$$

$$(\lambda I - A)\, x = 0 \tag{3}$$

In (2) and (3), A is a nxn matrix, λ is the eigenvalue of matrix A and the nontrivial vector x is eigenvector of the A matrix.

In this study, QR method is used for computing eigenvalue and eigenvector. Eigenvalues and eigenvectors are orthogonal in QR method. Therefore, the images, which are represented by them, are also orthogonal. Consequently, there is no similarity between images. The other methods except QR cause increased rounding error in eigenvalues so the results are not effective.

QR method is described in the expressions below, where Q is the orthogonal matrix and R is the upper triangular matrix:

$$A=QR \quad (4)$$
$$P_{n-1}P_{n-2}P_{n-3}\ldots P_2P_1A=R \quad (5)$$
$$Q^T= P_{n-1}P_{n-2}P_{n-3}\ldots P_2P_1$$
$$Q^TA=R$$
$$QQ^TA=QR$$
$$IA=QR$$

A square matrix does not necessarily have eigenvalues and eigenvectors, but eigenvalues and eigenvectors of the covariance matrix always exist. Thus covariance matrix is used in the study.
(c) In order to find the best projection in PCA, the eigen values and eigen vectors must be sorted. Then the best projection is gained. The biggest eigenvector represents the data in data space best.

3.2. Local Binary Pattern

Local Binary Pattern (LBP) is a method which it is used to describe the texture and structure of an image. Because LBP is suitable for feature extraction, it is usually preferred in computer vision, image processing, pattern recognition, etc.

When LBP is using in application; face image is divided into small regions. Then histograms are extracted from the small regions which tell something about the local neighborhood of pixels. Consequently the histograms are combined into feature vector. The feature vector represents the face image efficiently in any recognition approach.

LBP is used to find the similarities between images by using feature vectors. The texture and shape of an image can be described easily by using LBP operator which is a binary code for an image-pixel.

The original LBP operator, which works with eight neighbours of a pixel, was introduced first by Ojala et al. [10]. The center pixel of the original LBP opperator is used as a threshold. Unless a neighbour pixel has a llower value than the center pixel, one is assigned to that pixel, annd otherwise it gets a zero. Then the LBP code for the center ppixel is generated by concatenating neighbour pixels (the eight ones or zeros) to a binary code. The original LBP operator whicch is reporting above is shown in Fig. 4.

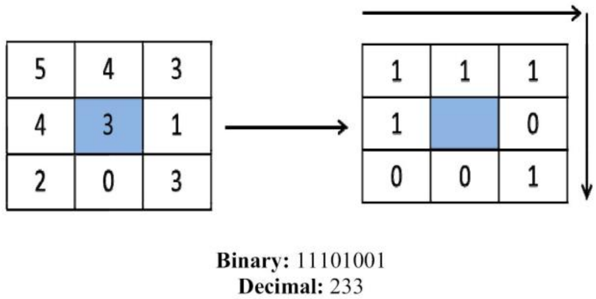


Fig. 4. Original LBP Operator.

The mathematical formulation of LBP operator is given by:

$$LBP(x) = \sum_{i=1}^{8} s(G(X_i) - G(X))2^{i-1} \quad (6)$$

$$s(t) = \begin{cases} 1, & t \geq 0 \\ 0, & t < 0 \end{cases} \quad (7)$$

The LBP operator can be expanded for aapplying in a circular neighbourhood (for different radius size)) [11]. A circle is described with radius R and sampling points P, which are used for comparing the center pixel (X_c, Y_c), on the edge of the circle. The coordinates of the neighbour pixels (X_p, Y_p) can be calculated as in Equation 8 and 9. In this sstudy, only 3x3 LBP operator is used.

$$X_P = X_C + R\cos\frac{2\pi p}{P} \quad (8)$$

$$Y_P = Y_C + R\sin\frac{2\pi p}{P} \quad (9)$$

The results are shown in Fig. 5 after applying LBP.

In previous studies LBP method is usually used in gender recognition, so the LBP method is addeed to the study for comparing the results with PCA on the same database.

Fig. 5. LBP applied male image.

4. Classification

Euclidean and Manhattan distance classifiers, used to evaluate the performance of the proposed method, are defined in Equation 10 and 11, respectively.

$$d_E = \sqrt{\sum_{i=0}^{N} (Xi - Yi)^2} \quad (10)$$

$$d_E = \sqrt{\sum_{i=0}^{N} (Xi - Yi)^2} \quad (11)$$

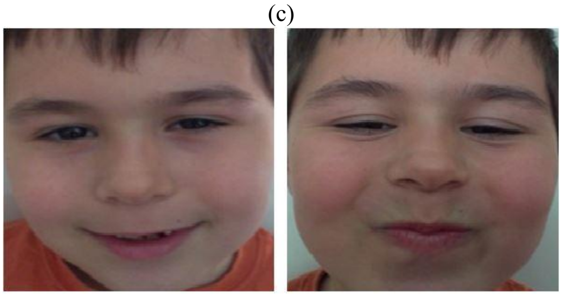
4. Experimental Results

In Fig. 6, the images, which are on left side, are test images applied to the system and the images, which are on the right side, are detected images after test. As cas be seen from Fig. 6, even if the facial expressions are different, gender recognition is performed successfully.

(a)

(b)

(c)



(d)

Fig. 6. Test images.

Table 1. Success rates for LBP

LBP Results		
	Classifier	
	Euclidean	**Manhattan**
Young(4-20)	%89.30	%82.17
Adult(21-50)	%90.00	%84.43
Senior(51-85)	%88.13	%80.11

Table 2. Success rates for PCA

PCA Results		
	Classifier	
	Euclidean	**Manhattan**
Young(4-20)	%93.30	%88.15
Adult(21-50)	%95.25	%89.62
Senior(51-85)	%91.15	%85.00

6. Conclusions and Future Work

In this study, PCA and LBP methods are used for gender recognition. PCA transforms high dimensional data space to low dimensional one, just as LBP has discriminative power and computational simplicity. The efficiency of proposed approach is analyzed on database and compared against PCA and LBP methods. Both of them are used for feature extraction and comparing with each other. Then, Euclidean and Manhattan classifiers are used for classification. The best results are taken from the PCA with Euclidean classifier as in Table 2.

In addition the results that give the general success rate of proposed method as in Table 3 are taken between only male and female groups.

K-Fold cross validation technique is used for accuracy estimation. When K is preferred as 5, the best results are taken from the proposed approach as in Table 2. The database is divided into 5 sections. In each iteration one section is used for test and the others are used training. (22 face images are used for testing and the others are used for training). Consequently, the results of proposed approach effective in PCA compared with LBP.

The promising results of the proposed approach in gender recognition imply its potential success over previous gender recognition approach. An effective way for improving the accuracy rate of work is expanding the database or using another method except PCA and LBP in future works.

7. References

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