Perceived Gender Classification from Face Images

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ABSTRACT: *In this paper, a fast and efficient gender classification system based on facial features is proposed to classify the gender. Facial feature extraction is one of the most important and attempted problems in computer vision. It is a necessary step in face recognition, facial image compression. There are many methods have been proposed in the literature for the facial features and gender classification. However, all of them have still disadvantage such as not complete reflection about face structure, face texture. This technique applies to both face alignment and recognition and significantly improves three aspects. First, we introduce shape description for face model. Second, the feature extraction phase, two geometric features are evaluated as the ratios of the distances between eyes, noses, and mouths. Finally, we classified the gender based on the association of two methods: geometric feature based method and Independent Component Analysis (PCA) method for improving the efficiency of facial feature extraction stage. The algorithm has also been tested in practice with a webcam, giving (near) real-time performance and good extraction results.*

Keywords: Face Recognition, Independent Component Analysis (ICA), Facial Feature Extraction

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1. Introduction

Facial feature extraction for face recognition is a challenging problem. There are many methods for facial feature extraction. However, all of them have still disadvantage such as not complete reflection about face structure, face texture.

Accurate facial feature extraction is important for face alignment, which is an indispensable processing step between face detection and recognition. This paper is to build a feature-extraction system that can be used for face recognition in embedded and/or consumer applications. This imposes specific requirements to the algorithm in addition to extraction accuracy, such as real-time performance under varying imaging conditions and robustness with low-cost imaging hardware.

Human facial image processing has been an active and interesting research issue for years. Since human faces provide a lot of information, many topics have drawn lots of attentions and thus have been studied intensively. The most of these is face recognition [1]. Other research topics include predicting feature faces [2], reconstructing faces from some prescribed features [3].

In the last several years, support vector machine (SVM) has become one of the most promising learning machines because of its high generalization performance and wide applicability for classification as well as for regression [4]. SVM maximizes its margin of separation and obtains an optimal decision boundary determined by a set of particular training samples called support vectors. Although SVM can find an optimal boundary, it is known to us that the information of the SVM decision boundary is only contained in the support vector training samples and is not considered in non-support vector training sample [4].

Recently various learning machines for pattern classification have been proposed. For instance, Jiang et al. [8] developed a perturbation-resampling procedure to obtain the confidence interval estimates centred at k-fold cross-validated point for the prediction error and apply them to model evaluation and feature selection, Liu [9] investigated the effects of confidence transformation in combining multiple classifiers using various combination rules, where classifier outputs are transformed to confidence measures, Feng et al. [10] proposed a scaled SVM, which is to employ not only the support vectors but also the means of the classes to reduce the mean of the generalization error. Graf et al. [11] presented a method for combining human psychophysics and machine learning, in which human classification is introduced.

Gender classification is important visual tasks for human beings, such as many social interactions critically depend on the correct gender perception. As visual surveillance and human-computer interaction technologies evolve, computer vision systems for gender classification will play an increasing important role in our lives [5].

Age prediction is concerned with the use of a training set to train a model that can estimate the age of the facial images. Among the first to research age prediction were, Kwon and Vitoria Lobo who proposed a method to classify input face images into one of the following three age groups: babies, young adults and senior adults [6].

Their study was based on geometric ratios and skin wrinkle analysis. Their method was tested on a database of only 47 high resolution face images containing babies, young and middle aged adults. They reported 100% classification accuracy on these data. Hayashi focused their study on facial wrinkles for the estimation of age and gender [7].

Gender classification is arguably one of the more important visual tasks for an extremely social animal like us humans_many social interactions critically depend on the correct gender perception of the parties involved. Arguably, visual information from human faces provides one of the more important sources of information for gender classification. Not surprisingly, thus, that a very large number of psychophysical studies has investigated gender classification from face perception in humans [12].

2. The Proposed System

The proposed gender classification system is briefly outlined in this section. The process of the system is mainly composed of three phases-shape description, feature extraction, and gender classification, as illustrated in Figure 1. In shape description phase, the vertical central lines of faces. Since eyes, noses, and mouths are desirable for machine recognition of the facial expressions. And then determine the facial feature points which are representative of the boundary between these components and skin.

3. Feature model with shape description

The gender classification procedure is described in this section. Features extraction-deals with extracting features that are basic for differentiating one class of object from another. First, the fast and accurate facial features extraction algorithm is developed. The training positions of the specific face region are applied. The extracted features of each face in database can be expressed in column matrix show in figure 2.

And find the average face for same age group of face images. The mean face feature for the M face images of each age group can be described as:

$$A = \left\{ \begin{bmatrix} \cdot \\ \Psi.F_1 \\ \vdots \\ \cdot \end{bmatrix} \begin{bmatrix} \cdot \\ \Psi.F_2 \\ \vdots \\ \cdot \end{bmatrix} \cdots \begin{bmatrix} \cdot \\ \Psi.F_M \\ \vdots \\ \cdot \end{bmatrix} \right\}_{N^2 \times M}$$

The face space is computed from the Euclidean distance of feature points of two faces. The fundamental matrix A is constructed by the difference face space among the input and each face. Then, the matrix Ω can be formed by the average face features of the thirteen age groups.

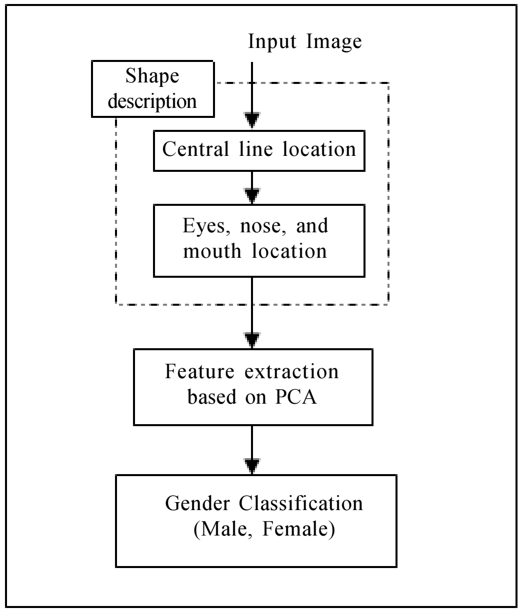


Figure 1. The Flow Chart of Gender Classification

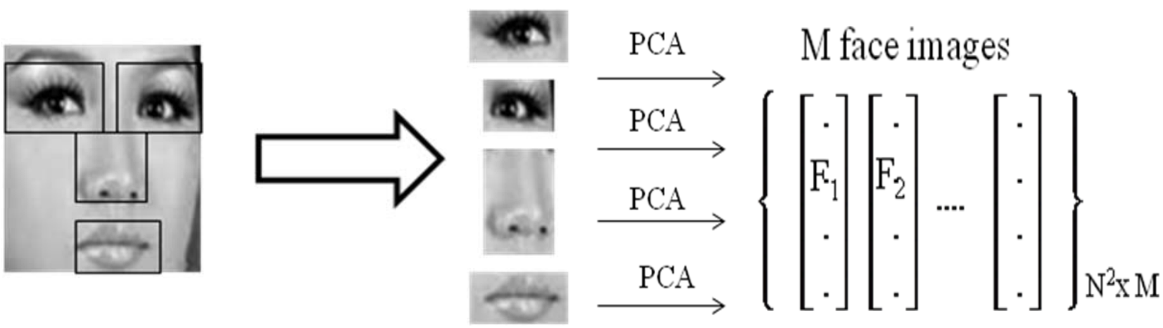


Figure 2. Feature Extraction

$$A = \left\{ \begin{bmatrix} \cdot \\ A_1 \\ \cdot \\ \cdot \\ \cdot \end{bmatrix} \begin{bmatrix} \cdot \\ A_2 \\ \cdot \\ \cdot \\ \cdot \end{bmatrix} \cdots \begin{bmatrix} \cdot \\ A_M \\ \cdot \\ \cdot \\ \cdot \end{bmatrix} \right\}_{N^2 \times M}$$

Calculate the Covariance Matrix $Cov = \Omega\Omega^T$. And then built Matrix $L = \Omega\Omega^T$ to reduce dimension. Find the eigenvector of Cov. Eigenvector represent the variation in faces. Finally, age is determined through the minimize face space.

4. PCA Method for Feature Extraction

The Principal Component Analysis (PCA) can do prediction, redundancy removal, feature extraction, data compression, etc. Because PCA is a classical technique which can do something in the linear domain, applications having linear models are suitable. Let us consider the PCA procedure in a training set of M face images.

Let a face image be represented as a two dimensional N by N array of intensity values, or a vector of dimension N^2. Then PCA tends to find a M-dimensional subspace whose basis vectors correspond to the maximum variance direction in the original image space. This new subspace is normally lower dimensional ($M << M << N2$) [4].

New basis vectors define a subspace of face images called face space. All images of known faces are projected onto the face space to find sets of weights that describe the contribution of each vector. By comparing a set of weights for the unknown face to sets of weights of known faces, the face can be identified. PCA basis vectors are defined as eigenvectors of the scatter matrix S defined as:

$$S = \sum_{i=1}^{M} (xi - \mu)(xi - \mu)' \quad (1)$$

where μ is the mean of all images in the training set and x_i is the i^{th} face image represented as a vector i. The eigenvector associated with the largest eigenvalue is one that reflects the greatest variance in the image. That is, the smallest eigenvalue is associated with the eigenvector that finds the least variance.

A facial image can be projected onto M' ($<< M$) dimensions by computing

$$\Omega = [v_1, v_2, ... v_{M'}]^T \quad (2)$$

The vectors are also images, so called, eigenimages, or eigenfaces . They can be viewed as images and indeed look like faces. Face space forms a cluster in image space and PCA gives suitable representation.

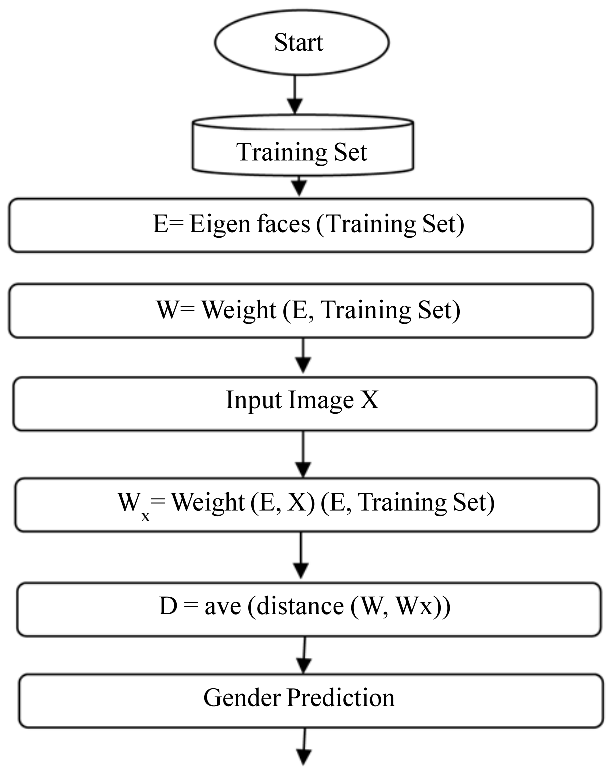


Figure 3. High-Level Functioning Principle of the Eigen face-Based Gender Classification Algorithm

These operations can also be performed occasionally to update or recalculate the Eigen faces as new faces are encountered. Having initialized the system, the following steps are then used to classify new face images:

1. Calculate a set of weights based on the input image and the M Eigen faces by projecting the input image onto each of the Eigen faces.

2. Classify the weight pattern to classify the age.

3. (Optional) Update the Eigen faces and/or weight patterns.

In the gender classification task, the age of the subject is predicted based on the minimum Euclidean distance between the face space and each face class.

5. Nearest Neighbour Classification

One of the most popular non-parametric techniques is the Nearest Neighbor classification (NNC). NNC asymptotic or infinite sample size error is less than twice of the Bayes error [13]. NNC gives a trade-off between the distributions of the training data with a priori probability of the classes involved [14]. KNN (K^{th} nearest neighbor classifier)classifier is easy to compute and very efficient. KNN is very compatible and obtain less memory storage. So it has good discriminative power. Also, KNN is very robust to image distortions (e.g. rotation, illumination). So this paper can produce good result by combining (PCA and KNN).

Euclidian distance determines whether the input face is near a known face. The problem of automatic face recognition is a composite task that involves detection and location of faces in a cluttered background, normalization, recognition and verification.

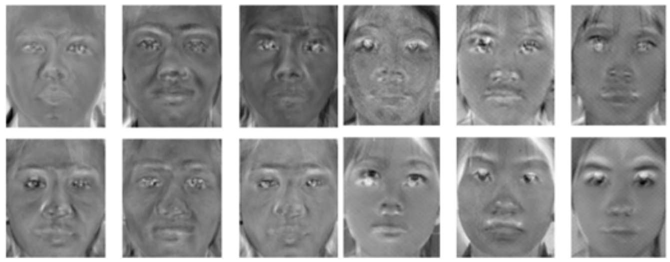


Figure 4. PCA on Average Faces

6. Experimental Results

In this paper, we present a gender classification method based on 2D facial images. We have also applied the complete algorithm into a live gender classification system using a web camera. The experimental result of gender classification can be seen in figure 5, 6 and figure 7. The proposed model has a low complexity and is suitable for real time implementations, such as real time facial animation. Because of using the frontal images, we used a 2D face model.

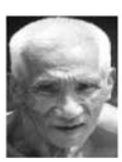
Figure 5: Some Female Group from Face Databases

Figure 6. Some Male Group from Face Databases

Gender Prediction : Female
Age Prediction : Between 20-25 years

Gender Prediction : Female
Age Prediction : Under 18 years

Gender Prediction : Male
Age Prediction : Between 25-30 years



Gender Prediction : Male
Age Prediction : Over 60 years

Figure 7. The Results of Gender Classification

7. Conclusions

In this paper, a fast and efficient gender classification system based on facial features is proposed to classify the gender. The process of the system is composed of three phases: shape description, feature extraction, and gender classification. The proposed technique has given good results when applied in a prototype real-time face recognition system for customized consumer applications. We have proposed a PCA algorithm and KNN classifier with automatic confidence and introduced a simple algorithm for calculating the label confidence value of each training sample. As future work, we would like to study the improvement on classification accuracy theoretically to other real-world pattern classification problems such as text classification, web page classification and age estimation. When a gender classifier is trained with a data set with limited demography and then tested with a data set with more general samples, the classification rate drops significantly. Dependencies between gender estimation and age [15] or ethnicity [16] have also recently been reported. New venues for research on general in particular or demographic between gender, age, and ethnicity variables in order to improve the classification across different age and ethnic groups [17].

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