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Integrating the original face images and "symmetrical faces" to perform face recognition

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ABSTRACT

Using the original and 'symmetrical face' training samples to perform representation based face recognition was first proposed in [1]. It simultaneously used the original and 'symmetrical face' training samples to perform a two-step classification and achieved an outstanding classification result. However, in [1] the "symmetrical face" is devised only for one method. In this paper, we do some improvements on the basis of [1] and combine this "symmetrical faces" transformation with several representation based methods. We exploit all original training samples, left "symmetrical face" training samples and right "symmetrical face" training samples for classification and use the score fusion for ultimate face recognition. The symmetry of the face is first used to generate new samples, which is different from original face image but can really reflect some possible appearance of the face. It effectively overcomes the problem of non-sufficient training samples. The experimental results show that the proposed scheme can be used to improve a number of traditional representation based methods including those that are not presented in the paper.

1. Introduction

Face recognition [2–8] is a computer technology which can identify the identity by analyzing and comparing the feature of the face. Face recognition is a branch of biometrics, which distinguishes individual organisms by recognizing the biometric traits [9–12]. The mankind can remember and identify thousands of different human faces, but to use the machine to perform automatic face identification is a very challenging problem now [13–16]. The huge challenge not only comes from complicated facial structure, but also comes from the non-rigid constitution of face [17]. Non-rigid object recognition is more difficult than the rigid object recognition. The face recognition system usually has the following five procedures to perform recognition: image capture, preprocessing, feature selection or feature extraction, classification and recognition [18–21]. Usually these procedures are consecutively implemented and each procedure is necessary. A large number of classifiers have been used to classify the face images [22–28]. The nearest neighbor classifier (NNC) is one of the oldest and simplest classifiers [29]. NNC first identifies the training sample that is the closest to the test sample and assumes that the test sample is from the same subject as this training sample [30].

In real-world applications, limited number of available training sample is an agonizing problem for face recognition [31–34]. The mainly reasons are that a face recognition system usually has limited storage space, and there usually has limited time to capture training samples. Non-sufficient training samples become a bottleneck of face recognition. In order to overcome the shortage of insufficient size of the training set in supervised learning process, a lot of literatures which have proposed to synthesize new samples from the true face images. For example, Niyogi et al. [35] used prior knowledge by creating virtual examples and thereby expanding the effective training-set size. Tan et al. [36] exploited "one sample per person" to identify a person from the database later in time in any different and unpredictable poses, lighting and so on. Beymer et al. [37] first developed example-based techniques for applying the rotation seen in the prototypes to essentially "rotate" the single real view which is available. Then the combined set of one real and multiple virtual views is used as example views for a view-based, pose-invariant face recognizer. Sung et al. [38] presented an example-based learning approach for locating vertical frontal views of human faces in complex scenes, and then models the distribution of human face patterns by means of a few view-based "face" and "non-face" model clusters.

Xu et al. [1] proposed a good means to generate new samples from the original training sample. They use the original and 'symmetrical face' training sample to perform representation based two-step face recognition which obtained a very high recognition rate. The proposed method first generates 'symmetrical face'

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training samples, and then uses the original and 'symmetrical face' training samples to perform two-step face recognition, respectively. Finally, the method combines the scores obtained using the second and third steps to conduct weighted score level fusion, getting the ultimate classification result. In this method, the number of the available training samples is three times of that of the original training samples. The ultimate classification result is superior to that of the original two-step classification. We do some improvements on the basis of [1], and the improved idea can perform well on a number of representation based methods.

In this paper, we exploit the symmetry of the face to generate new samples, and then devise a representation based method to perform face recognition. Our scheme can be applied to the following previously proposed methods: collaborative representation classification (CRC) [39], a simple and fast representation-based face recognition (SFRFR) [40], an improvement to the nearest neighbor classifier and face recognition (INNC) [41], and a two-phase test sample sparse representation method (TPTSR) [2]. The new samples reflect some possible appearance of the face. We first obtain the 'symmetrical face' i.e. new training samples. Then we use original samples and new training samples to perform these representation based methods. We also use original and new training samples to perform these representation based methods. Finally, we combine the result of previous steps to get the final recognition result. This method also takes advantages of the score level fusion, which has proven to be very competent and is usually better than the decision level and feature level fusion.

The paper is organized as follows: Section 2 describes the proposed method; Section 3 introduces some representation based methods which we used in this paper. Section 4 shows the rationales and advantages of "symmetrical face" transformation; Section 5 presents the experimental results on different database. Section 6 offers our conclusions.

2. The proposed method

In this section we will present the main steps of the proposed method in detail. Suppose that there are c classes and each class has n training samples. We call "symmetrical face" which is generated by the left face the first virtual training sample, and call "symmetrical face" which is generated by the right face the second virtual training sample.

Fig. 1 shows some original training samples from the ORL face database and the first virtual training samples and the second virtual training samples generated from the original training samples. Fig. 2 shows some original training samples from the FERET face database and the first virtual training samples and the second virtual training samples. Fig. 3 shows some original training samples from the Yale face database and the first virtual training samples and the second virtual training samples. From these figures, we see that the 'symmetrical face' training samples are different from original training samples and they can somewhat reflect basic characteristic of the training samples.

The proposed method includes the following main steps. The first step generates 'symmetrical face' training samples. These samples reflect possible variation of the face. The second step exploits original training samples for classification. The third and fourth steps respectively exploit the first virtual training samples and second virtual training samples for classification. The fifth step uses the score fusion for ultimate face recognition. We present these steps as follows:

Step1: Use original training sample to generate two 'symmetrical face' training samples, i.e. the first and second virtual training samples. Let X_i be the i-th training sample in the form of image matrix. Let x_i^1 and x_i^2 respectively stand for the first and second

Fig. 1. Several original training samples from the ORL face database. The first row shows the original training samples. These second and third rows respectively show the first virtual training samples and the second virtual training samples generated from the original training sample.

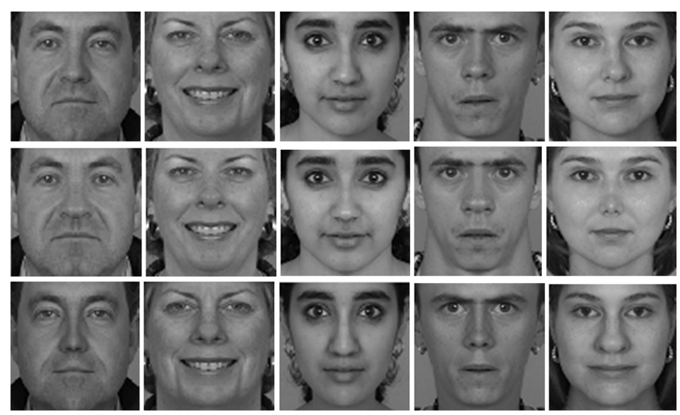

Fig. 2. Several original training samples from the FERET face database. The first row shows the original training samples. The second and third rows respectively show the first virtual training samples and the second virtual training samples generated from the original training sample.

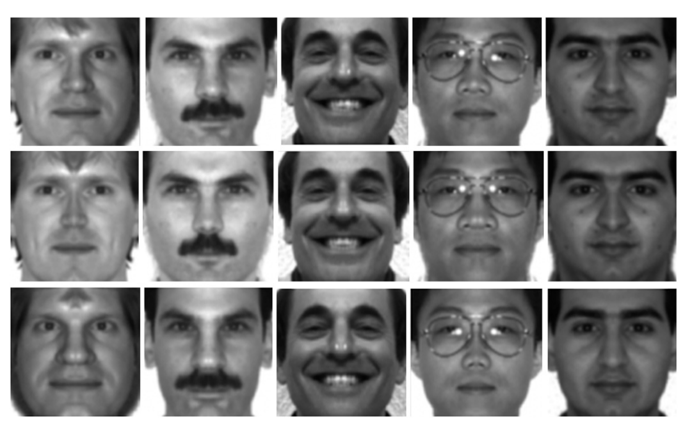

Fig. 3. Several original training samples from the Yale face database. The first row shows the original training samples. The second and third rows respectively show the first virtual training samples and the second virtual training samples generated from the original training sample.