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Improving Face Verification using Symmetric Transformation

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IMPROVING FACE VERIFICATION USING SYMMETRIC TRANSFORMATION

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Abstract. One of the major problem in face verification is to deal with a few number of images per person to train the system. A solution to that problem is to generate virtual samples from an unique image by doing simple geometric transformations such as translation, scale, rotation and vertical mirroring. In this paper, we propose to use a symmetric transformation to generate a new virtual sample. This symmetric virtual sample is obtained by computing the average between the original image and the vertical mirrored image. The face verification system is based on LDA feature extraction, successfully used in previous studies, and MLP for classification. Experiments were carried out on a difficult multi-modal database, namely BANCA. Results on this database show that our face verification system performs better that the state-of-the-art and also that the addition of the symmetric virtual sample improves the performance.

1 Introduction

Identity verification is a general task that has many real-life applications such as access control, transaction authentication (in telephone banking or remote credit card purchases for instance), voice mail, or secure teleworking.

The goal of an *automatic identity verification system* is to either accept or reject the identity claim made by a given person. Biometric identity verification systems are based on the characteristics of a person, such as its face, fingerprint or signature. A good introduction to identity verification can be found in [15]. Identity verification using face information is a challenging research area that was very active recently, mainly because of its natural and non-intrusive interaction with the authentication system.

The paper is structured as follows. In section 2 we introduce the reader to the problem of identity verification. Then, in section 3 we present the proposed symmetric transformation within the framework of a state-of-the-art face verification system based on a linear discriminant feature extraction technique, successfully applied to face verification [9, 10], and on a Multi-Layer Perceptron classifier. In section 4, we provide experimental results on the multi-modal benchmark database BANCA using its associated protocol. Finally, we analyze the results and conclude.

2 Face Verification

An identity verification system has to deal with two kinds of events: either the person claiming a given identity is the one who he claims to be (in which case, he is called a *client*), or he is not (in which case, he is called an *impostor*). Moreover, the system may generally take two decisions: either *accept* the *client* or *reject* him and decide he is an *impostor*.

The classical face verification process can be decomposed into several steps, namely *image acquisition* (grab the images, from a camera or a VCR, in color or gray levels), *image processing* (apply filtering algorithms in order to enhance important features and to reduce the noise), *face detection* (detect and localize an eventual face in a given image) and finally *face verification* itself, which consists in verifying if the given face corresponds to the claimed identity of the client.

One of the major problem in face verification is to deal with a few number of images per person to train the system. A solution to that problem is to generate virtual samples from an unique image by doing simple geometric transformations [13] such as translation, scale, rotation and vertical mirroring.

In this paper, we propose to use a symmetric transformation to generate a new virtual sample. It is obtained by computing the average between the original image and the vertical mirrored image. This symmetric transformation has also the effect to normalize the face by smoothing local deformations due to small out-of-plane rotations.

3 The proposed approach

In face verification, we are interested in particular objects, namely faces. The representation used to code input images in most state-of-the-art methods are often based on gray-scale face image [16, 11, 1] or its projection into principal component subspace or linear discriminant subspace [9, 10].

Principal Component Analysis (PCA) identifies the subspace defined by the eigenvectors of the covariance matrix of the training data. The projection of face images into the coordinate system of eigenvectors (Eigenfaces) associated with nonzero eigenvalues achieves information compression, decorrelation and dimensionality reduction to facilitate decision making. The linear discriminant analysis (LDA) subspace holds more discriminant features for classification [2, 6] than the PCA subspace.

A linear discriminant is a simple linear projection $\hat{y} = b + \mathbf{w} \cdot \mathbf{x}$ of the input vector onto an output dimension: where the estimated output $\hat{y}$ is a function of the input vector $\mathbf{x}$, and the parameters $\{b, \mathbf{w}\}$ are chosen according to a given criterion such as the Fisher criterion [8].

In this section, we describe our face verification system: an MLP classifier trained on a gray-scale face image projected into LDA subspace (Fig. 1) as described in [9].

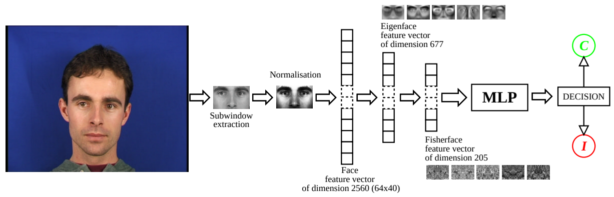

Figure 1: Face Verification using LDA and MLP

3.1 Feature Extraction

In a real application, the face bounding box will be provided by an accurate face detector [14], but here the bounding box is computed using manually located eyes coordinates, assuming a perfect face detection. In this paper, the face bounding box is determined using face/head anthropometry measures [7].

Face pre-processing: The extracted face is downsized to a 64x40 image. Then, we perform histogram normalization to modify the contrast of the image in order to enhance important features. Finally, we smooth the enhanced image by convolving a 3x3 Gaussian ($\sigma = 0.25$) in order to reduce the noise. After enhancement and smoothing (Fig. 2), the face image becomes a feature vector of dimension 2560.

Symmetric transformation: The symmetric transformation is obtained simply by computing the average between the original image and the vertical mirrored image (Fig. 2). It generates a new virtual sample to enlarge the training and testing dataset. This transformation also normalizes the face by smoothing local deformations due to small out-of-plane rotations for instance.

Figure 2: Face pre-processing and symmetric transformation. From left to right: the original 64x40 pre-processed image, the mirrored image and the symmetric image.

Face representation: It was chosen to represent the pre-processed input face into the LDA subspace, as described in [9].

The direct computation of the *LDA*-transform matrix is impractical because of the huge size of the face data in the original space (2560 dimensions). Therefore, a dimensionality reduction must be applied before solving the eigenproblem. This reduction is usually achieved by PCA.

PCA and LDA projection matrices have been computed on all images from XM2VTS database (295 identities and 8 images per identity). In the PCA space, the components accounting for $>= 4\%$ of the total variation are selected, reducing the dimensionality to 677. Then, the *LDA*-projection matrix is computed as described in [9] using all images of each identity projected into PCA subspace. In the LDA space, the components accounting for $>= 1\%$ of the total variation are selected, reducing the dimensionality to 205.

3.2 Classification

Our face verification method is based on Multi-Layer Perceptrons (MLPs). MLPs are learning machines used in many classification problems [4].

For each client, an MLP is trained to classify an input to be either the given client or not. The input of the MLP is a feature vector corresponding to the projection of the face image into the LDA subspace. The output of the MLP is either 1 (if the input corresponds to a client) or -1 (if the input corresponds to an impostor). The MLP is trained using both client images and impostor images, often taken to be the images corresponding to other available clients. In the present study, we used the 300 client images from the Spanish part of the BANCA database (see next section).

Finally, the decision to accept or reject a client access depends on the score obtained by the corresponding MLP which could be either above (accept) or under (reject) a given threshold, chosen on a separate validation set to optimize a given criterion.

4 Experimental results

4.1 The BANCA database and protocol

This section gives an overview of the BANCA database and protocol, but a detailed description can be found in [3].

4.1.1 The Database.

The BANCA database was designed in order to test multi-modal identity verification with various acquisition devices (2 cameras and 2 microphones) and under several scenarios (controlled, degraded and adverse).

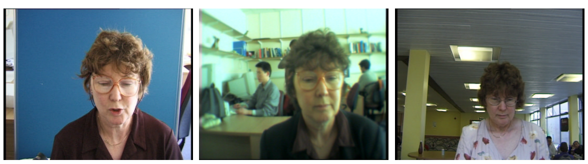

Figure 3: Examples of images from the BANCA database for each scenario. From left to right: controlled, degraded and adverse.

For 5 different languages[1], video and speech data were collected for 52 subjects (26 males and 26 females), i.e. a total of 260 subjects. Each language - and gender - specific population was itself subdivided into 2 groups of 13 subjects (denoted $g1$ and $g2$).

Each subject participated to 12 recording sessions, each of these sessions containing 2 records: 1 true *client access* (T) and 1 informed [2] *impostor attack* (I). For the image part of the database, there is 5 shots per record. The 12 sessions were separated into 3 different scenarios (Fig. 3): *controlled* (for sessions 1-4), *degraded* (for sessions 5-8), and *adverse* (for sessions 9-12).

Two cameras were used, a cheap one and an expensive one. The cheap camera was used in the degraded scenario, while the expensive camera was used for controlled and adverse scenarios. Two microphones, a cheap one and an expensive one, were used simultaneously in each of the three scenarios. During the recordings, the camera was placed on the top of the screen and the two microphones were placed in front of the monitor and below the subject chin.

[1] English, French, German, Italian and Spanish
[2] The actual speaker knew the text that the claimed identity speaker was supposed to utter.

Table 1: Comparative results between ORG/SVM, LDA/SVM^{-} and LDA/MLP^{+}.

ORG/SVM			**LDA/MLP^{-}**			**LDA/MLP^{+}**		
FAR	**FRR**	**HTER**	**FAR**	**FRR**	**HTER**	**FAR**	**FRR**	**HTER**
4.91	27.72	16.32	15.38	15.81	15.59	13.94	14.95	**14.44**

4.1.2 The Protocol.

In the BANCA protocol, we consider that the true client records for the first session of each condition is reserved as training material, i.e. record T from sessions 1, 5 and 9. In all our experiments, the client model training (or template learning) is done on at most these 3 records.

We consider the following protocol, namely Pooled test (P) protocol, where one controlled session is used for client training and all conditions sessions (within the same group) are used for client and impostor testing.

4.1.3 Performance Measures.

In order to visualize the performance of the system, irrespectively of its operating condition, we use the conventional DET curve [12], which plots on a log-deviate scale the *False Rejection Rate* FR as a function of the *False Acceptance Rate* FA. Traditionally, the point on the DET curve corresponding to $FR = FA$ is called EER (Equal Error Rate) and is used to measure the closeness of the DET curve to the origin.

We measure the performance of the system using the Half Total Error Rate ($HTER$) defined as:

$$HTER = (FR + FA)/2 \tag{1}$$

FR and FA (and thus $HTER$) vary with the value of the decision threshold Θ, and Θ is usually optimized so as to minimize $HTER$ on the development set D. The *a priori threshold* thus obtained is always less efficient than the *a posteriori threshold* that optimizes the $HTER$ on the evaluation set E itself.

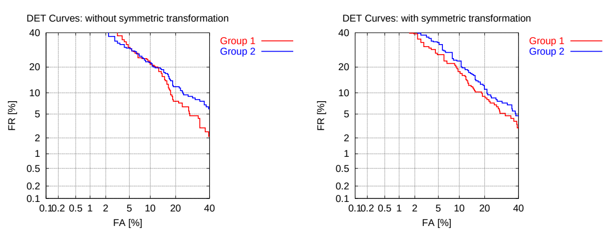

Figure 4: DET curves for experiments using LDA/MLP. From left to right: without symmetric transformation and with symmetric transformation.

4.2 Results

In this section, we provide experimental[3] results obtained by our face verification system, with (LDA/MLP^{+}) and without (LDA/MLP^{-}) the symmetric virtual sample. These results are compared to those obtained by the best method [1], namely ORG/SVM, published on the BANCA database.

ORG/SVM is using the original face image of size 61x57 as input of a Support Vector Machine (SVM) [5]. We report in Table 1 the average (on groups g1 and g2) FAR/FRR and HTER of the above methods on the test set. We provide also the corresponding DET curves (Fig. 4) of the LDA/MLP method only.

Table 1 shows that LDA/MLP^{-} performs better than ORG/SVM, and that this performance is improved by the use of symmetric virtual samples. This symmetric transformation brings more variability to the training and testing datasets, but also normalizes small out-of-plane rotations.

[3]The machine learning library used for all experiments is Torch *http://www.torch.ch*.

5 Conclusion

In this paper, we proposed to use a transformation based on symmetry that generate a new virtual sample in order to enlarge the training and testing dataset of a face verification system. The face verification system used in this study is based on LDA feature extraction and use a MLP to classify the input face as a client or an impostor.

Experiments were carried out on the BANCA benchmark multi-modal database using its experimental protocol. Results have shown that our approach performs better than the state-of-the-art on the pooled test protocol and that the proposed symmetric virtual sample improves the performance.

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