Bimodal biometric verification based on face and lips

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\textbf{Abstract}

In this paper, we present a novel approach to person verification by fusing face and lip features. Specifically, the face is modeled by the discriminative common vector and the discrete wavelet transform. Our lip features are simple geometric features based on a lip contour, which can be interpreted as multiple spatial widths and heights from a center of mass. In order to combine these features, we consider two simple fusion strategies: data fusion before training and score fusion after training, working with two different face databases. Fusing them together boosts the performance to achieve an equal error rate as low as 0.4% and 0.28%, respectively, confirming that our approach of fusing lips and face is effective and promising.

\section{Introduction}

Over the past decade, face recognition has become one of the main biometrics showing potential for deployment in modern access control systems due to its ease of capture and the relatively low level of cooperation required. Numerous approaches to face recognition have been proposed\cite{1,2}; however, up to now, there has been very little work performed on using lips, which are a very important feature of the human face in their own right. Effective biometric verification using lip movement has been experimentally demonstrated\cite{2,3}. Recently, researchers have shown that static lips are an additional cue for person verification\cite{4}. To the best of our knowledge, little work has been done on fusing face and static lip shape features. In this paper we propose that combining face with simple lip features could outperform each of them individually, and we demonstrate the validity of this argument by experiment.

\section{Methodology}

In this section we introduce our feature extraction strategy for face and lips (see Fig. 1).

\subsection{Face detection}

Our system starts by detecting human faces from a natural image. Though many face detectors are available in the literature, we use a simple front face detector, similar to the Viola–Jones cascade detector\cite{5}, due to its simplicity, speed, and effectiveness.

\subsection{Face descriptor}

We use the discriminative common vector (DCV)\cite{6–8} and discrete wavelet feature transform (DWT) as our face descriptors, since they are widely reported in the existing literature\cite{9}. The DCV feature is a subspace method, while DWT is a function transform based approach. The DCV feature was first proposed in\cite{7} and has demonstrated superior performance over other subspace based methods, including Eigenface, Fisherface, and Direct-LDA, in terms of accuracy, speed, and storage\cite{8}. In principle, the DCV is a feature mining approach that has the capability to extract common features of each class. A common vector is computed by eliminating all feature vectors that are in the direction of eigenvectors corresponding to the non-null eigenvalues of the scatter matrix of its own class. After its computation, a DCV for each class is obtained by the product between the common vectors and a training sample of that class. The resulting DCV is then used for verification. The following gives a detailed description of the computation process.
We define a within-class scatter matrix \( S_w \) as:

\[
S_w = \sum_{i=1}^{C} \sum_{m=1}^{N_i} (x^{(i)}_m - \mu_i)(x^{(i)}_m - \mu_i)^T
\]

(1)

where \( C \) represents the total number of classes, \( i \) the \( i \)th class, \( N_i \) is the number of samples of class \( i \), \( x^{(i)}_m \) denotes the \( m \)th sample from the \( i \)th class and \( \mu_i \) is mean vector of the \( i \)th class.

Suppose that the dimension of an original sample space is \( d \), \( r \) is the rank of \( S_w \) \((V \in \mathbb{R}^r)\), and \( d-r \) is the null space rank of \( S_w \) \((V^c = \mathbb{R}^{d-r})\) where \( V \) is the range space of \( S_w \) and \( V^c \) is the null space of \( S_w \). Let \( Q = [z_1...z_r] \) be a set of eigenvectors corresponding to nonzero eigenvalues and \( Q^c = [z_{r+1}...z_d] \) be a set of eigenvectors corresponding to eigenvalues of zero. It has been proven that a unique common vector \( x_{com} \) in the same class can be obtained [7]:

\[
x^{(i)}_{com} = x^{(i)}_m - QQ^T x^{(i)}_m
\]

(2)

Now we can get the common vector \( x_{com} \) from (2) (note, \( x_{com} \) is independent of the sample index \( m \)). It shows that we can calculate \( x_{com} \) by the eigenvectors spanning the range space or those spanning the null space. By performing the above steps, we obtain \( C \) common vectors. We then find the principal components between \( C \) classes by the covariance matrix of \( x^{(i)}_{com} \):

\[
S_{com} = \sum_{i=1}^{C} (x^{(i)}_{com} - \mu_{com})(x^{(i)}_{com} - \mu_{com})^T
\]

(3)

Here \( S_{com} \) is a \( d \times d \) matrix that is the covariance matrix of the common vectors. Finally, we obtain a projection matrix \( W = [x^{(1)}_{com}...x^{(C)}_{com}] \) from \( x^{(i)}_{com} \), where \( x^{(i)}_{com} \) is the eigenvector of \( S_{com} \).

Because we have only \( C \) common vectors the projection matrix contains at most \( C-1 \) eigenvectors corresponding to nonzero eigenvalues, since the last eigenvector is the linear combination of the other eigenvectors. When a new test sample is given \( x_{test} \), we compute the test vector using the projection matrix \( W \) as \( x_{test} = W^T x_{test} \); after his projection, we have obtained the DCV features. Because \( W \) was obtained from \( x_{com} \), which is in the range space of \( x_{com} \), we can also project samples of the same class onto one point by the projection matrix \( W \) directly.

For the purpose of comparison, our second face descriptor is DWT [9], a well-known function transform based approach. Mathematically, it is defined as follows:

\[
C[j,k,l] = \sum_{n,m \in Z} f[n,m] \psi_{j,k,l}[n,m]
\]

(4)

The same symbol \( C \) is used for the number of classes, where \( f[n,m] \) is our image and \( \psi_{j,k,l} \) is the transform function:

\[
\psi_{j,k,l}[n,m] = 2^{-j/2} \psi[2^{-j}n - k, 2^{-j}m - l]
\]

(5)

In our experiment, we have used “bio5.5” [10]; it is a discrete biorthogonal wavelet family with three pyramid levels for our feature extraction, similar to [9], obtaining 19 \times 15 DWT coefficients.

2.3. Lip descriptor

To build the lip descriptor, we first need to extract the lip region. To do this, we use a simple transformation to convert a color image to gray scale image using \( R - (2G) + B \) to enhance the lip region. Fig. 2 shows examples of face images after this transformation, where enhanced lip regions can be clearly identified as the interior middle region from the face detection. A binarization method by Otsu [11] is further applied on the enhanced image to segment the lips. We then extract the lip shapes using morphological operators, subtracting the binary image and its dilated version (see Fig. 2—there are no images of this in Fig. 2) obtained with a mask size of \( 3 \times 3 \). We would like to clarify that the dataset we have studied does include users with beard or mustache as shown in Fig. 3. From this, we can see that our approach is still capable of extracting relatively reliable lip contour. Open lips issue does occur frequently in the research of lip reading. However, we would like to argue that it is very rare for a normal person to leave his/her mouth open when being quiet, such as not speaking, laughing, crying, etc. We would like to categorize this open issue into the research area of biometrics based on lip dynamics; see [2] for some initial work on this.

A set of geometric features are extracted based on the distances from equally sampled points along the vertical and horizontal centroid axes, to points on the lip contour. For the vertical centroid axis, we equally sample 300 points from a right initial point to the other left end of the mouth and while sampling
database, the PIE Face Database [12], which consists of 68 users.

3. Classification and fusion system

A support vector machine (SVM) with radial basis function kernel is used for our experiment as it has been demonstrated to be a good classifier for face verification [9]. Specifically, we used the SVM light implementation [9] with a RBF kernel:

\[ k(x,y) = \exp \left( -\frac{||x-y||^2}{2\sigma^2} \right) \]  

We have used two different strategies for fusion, based on data and score. For data fusion, we concatenated each feature vector (lips and face features) into one feature vector before input to the classifier. For the score fusion, we have implemented two different fusion rules, based on the likelihood function of individual verifiers as follows:

\[
\begin{align*}
\text{a) } \max & \sum_{i=1}^{2} p(X/\lambda_i) \text{ and b) } \max \prod_{i=1}^{2} p(X/\lambda_i)
\end{align*}
\]

where \(\lambda_i\) is the model per user (verification approach) from the SVM of the feature modality \(i\) (face and lips), and \(p(X/\lambda_i)\) is the likelihood function of the feature vector from a test sample \(X\) against the model \(\lambda_i\).

4. Experiments and results

We constructed a face database for our experiments, named the GPDS-ULPGC Face Database, which consists of 50 users with 10 samples per user (500 images in total) with the average detected face size of 800 \(\times\) 600 pixels, and besides, we have used a public database, the PIE Face Database [12], which consists of 68 users with 11 samples per user (748 images in total), with the average detected face size of 200 \(\times\) 200 pixels. We report our results in terms of the equal error rate (EER) based on 10 runs/splits in a similar fashion with cross validation. For each run/split, we randomly select 50% of the samples for training and the rest for testing. This test is repeated 10 times, thus constructing the 10 runs/split protocol. The mean accuracy and standard deviation of EERs of those runs among all classes are reported.

We tried six different cases: (1) lips only, (2) DCV face only, (3) DWT face only, (4) combining lips and face by feature fusing before training, (5) combining by score fusing (sum rule), and (6) combining by score fusing (product rule). For each case, our system contains two parameters: the EER threshold for verification (it is the decision value at the point of EER—equal error rate in the ROC curve) and the width of the RBF kernel \(\delta\) see Tables 1 and 2), which is automatically determined by the SVM using grid search on training images only. Those best parameters are selected based on a grid search. Tables 1 and 2 show the corresponding result of each case.

From Table 1, we can see that lip shape and face appearance perform well individually, with lip shape giving slightly better results for the GPDS-ULPGC Face Database. For face verification only, the DCV feature performs better than the DWT feature (3.48% vs. 3.71%). Based on these results, we select the DCV as the face descriptor when combining face and lip together (for comparison, we also include the results of fusing face DWT feature and lips shape features). Table 1 also shows that data fusing (2.32%) by feature concatenation performs worse than score fusing (0.44% and 0.43%). From Table 2, using the PIE Face Database, we have obtained similar or even better results (see Table 2). We achieved the error rate as low as 0.28% using the score fusing, for lips and faces. This observation is consistent with the experiments on our own dataset, i.e., fusing the two modalities together boosts the performance.

This is because perhaps, in the case of feature concatenation, the SVM assigns a single weight to each sample in the training process for the two types of features, whilst in the case of score fusion the two trained SVMs assign different weights to each sample, thus reflecting the different roles of lip features and face in discrimination. We further notice that the probabilistic product rule performs similar to the sum rule, which indicates that lip geometric features are likely to be independent from face DCV

<table>
<thead>
<tr>
<th>Table 1</th>
<th>EER for different approaches with lip and face data for GPDS-ULPGC Face Database.</th>
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</thead>
<tbody>
<tr>
<td>Kind of feature</td>
<td>EER</td>
</tr>
<tr>
<td>Lips</td>
<td>2.59% (\pm) 0.56</td>
</tr>
<tr>
<td>DCV faces</td>
<td>3.48% (\pm) 0.37</td>
</tr>
<tr>
<td>DWT faces</td>
<td>3.71% (\pm) 0.58</td>
</tr>
<tr>
<td>Lips + DCV faces</td>
<td>2.32% (\pm) 0.57</td>
</tr>
<tr>
<td>Lips + DWT faces</td>
<td>2.55% (\pm) 0.82</td>
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<tr>
<td>Lips + DWT faces</td>
<td>1.63% (\pm) 0.22</td>
</tr>
<tr>
<td>Lips + DWT faces</td>
<td>1.57% (\pm) 0.20</td>
</tr>
<tr>
<td>Lips + DVC faces</td>
<td>0.43% (\pm) 0.17</td>
</tr>
<tr>
<td>Lips + DVC faces</td>
<td>0.44% (\pm) 0.11</td>
</tr>
</tbody>
</table>

<table>
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<tr>
<th>Table 2</th>
<th>EER for different approaches with lip and face data for PIE Face Database.</th>
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</thead>
<tbody>
<tr>
<td>Kind of feature</td>
<td>EER</td>
</tr>
<tr>
<td>Lips</td>
<td>12.75% (\pm) 0.76</td>
</tr>
<tr>
<td>DCV faces</td>
<td>1.74% (\pm) 0.49</td>
</tr>
<tr>
<td>DWT faces</td>
<td>0.71% (\pm) 0.38</td>
</tr>
<tr>
<td>Lips + DCV faces</td>
<td>9.17% (\pm) 0.39</td>
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<tr>
<td>Lips + DWT faces</td>
<td>9.57% (\pm) 0.57</td>
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<tr>
<td>Lips + DVC faces</td>
<td>0.42% (\pm) 0.02</td>
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<tr>
<td>Lips + DVC faces</td>
<td>0.40% (\pm) 0.03</td>
</tr>
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<td>Lips + DVC faces</td>
<td>0.29% (\pm) 0.05</td>
</tr>
<tr>
<td>Lips + DVC faces</td>
<td>0.28% (\pm) 0.05</td>
</tr>
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</table>
features and that they are complementary. Fusing the lip shape features with the face DCV features performs best.

5. Conclusion

This paper presents an effective and novel personal verification approach by fusing face appearance and lip shape. The face appearance feature is described by DVC, while lip shape is represented by simple geometrical features. Our study shows that both types of features are effective and complementary. Fusing them under the probability score product strategy reduced the EER to as low as 0.44% and 0.28%, according to GPDS-ULPGC and PIE Face Databases, respectively. Our approach suggests a promising direction to improve the appearance-based face recognition performance in future human verification applications.

It is worth pointing out that we have not considered rotation in our experiments. In those scenes where faces are rotated, we could employ some rotation invariant face detector available in literature to detect and correct the rotated face. In this way the lips features could be made rotation invariant.

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References


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