Bayesian Face Recognition Using Gabor Features

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ABSTRACT
In this paper, we propose a new face recognition approach combining a Bayesian probabilistic model and Gabor filter responses. Since both the Bayesian algorithm and the Gabor features can reduce intrapersonal variation through different mechanisms, we integrate the two methods to take full advantage of both approaches. The efficacy of the new method is demonstrated by the experiments on 1180 face images from the XM2VTS database and 1260 face images from the AR database.

Categories and Subject Descriptors
I.5.4 **[Pattern Recognition]**: Applications-*Computer Vision; Signal Processing.*

General Terms
Algorithm, Experimentation, Performance, Theory.

Keywords
Face Recognition, Bayesian Analysis, Gabor Wavelet

1. INTRODUCTION
Face recognition is a challenging problem in pattern recognition research. Many face recognition methods have been proposed in the past few decades. A great number of methods are appearance based. Statistical techniques, such as PCA [3], LDA [6], ICA [4], and Bayes [1], etc., are used to extract low dimensional features from the intensity image directly for recognition.

A major disadvantage of the appearance based approaches is that they are sensitive to lighting variation and expression changes since they require alignment of uniform-lighted image to take advantage of the correlation among different images. An elastic graph matching (EGM) method is recently developed [2] to alleviate these problems. The EGM method utilizes an attributed relational graph to characterize a face, with facial landmarks (fiducial points) as graph nodes, Gabor wavelet around each fiducial point as node attributes and distances between nodes as edge attributes. Compared to image intensity, Gabor wavelet is less sensitive to illumination changes. However, since Gabor wavelet is a general image processing tool, which is not specifically designed for face recognition, Gabor features do not contain face specific information learned from face training data. Therefore, directly using Gabor features may not be the best approach. For example, we do not know which scale or frequency channels are more important for face recognition and how to properly weight each channel. It is reasonable to use statistical techniques for better selection of Gabor features in order to integrate the advantages of Gabor wavelet and the statistical techniques.

In this paper, we combine Gabor features with the Bayesian probabilistic model. The Bayesian algorithm [1] has achieved a superior performance in competition with other statistical approaches [5]. It casts the face recognition problem as classifying intrapersonal variation and extrapersonal variation, both of which are modeled as Gaussian distribution. In this probabilistic model, disturbing factors can be separated from the discriminating features, and thus be effectively reduced in a probabilistic measure. Our method uses the EGM Gabor features instead of the original gray scale image as the input to the Bayesian algorithm to take advantage of both methods. We test the new approach on two data sets from the XM2VTS database and the AR database. It achieves a much better performance than using the Gabor features or the Bayesian method alone, and also outperforms the traditional holistic approaches such as PCA and LDA.

2. GABOR FEATURE EXTRACTION
Gabor kernels are similar to the receptive field profiles in cortical simple cells, which are characterized as localized, orientation selective, and frequency selective. A family of Gabor kernel is the product of a Gaussian envelope and a plane wave, defined as

$$\psi_{\vec{k}}(\vec{x}) = \frac{\|\vec{k}\|}{\delta^2} \cdot e^{-\frac{\|\vec{k}\|^2 \cdot \|\vec{x}\|^2}{2\delta^2}} \cdot \left[e^{i\vec{k}\cdot\vec{x}} - e^{-\frac{\delta^2}{2}} \right]. \quad (1)$$

Here $\vec{x} = (x, y)$ is the variable in spatial domain and $\vec{k}$ is the frequency vector, which determines the scale and the orientation of Gabor kernels,

$$\vec{k} = k_s e^{i\phi_d} , \quad (2)$$

where $k_s = \frac{k_{\max}}{f^s}$, $k_{\max} = \frac{\pi}{2}$, $f = 2$, $s = 0,1,2,3,4$, and

$$\phi_d = \frac{\pi \cdot d}{8}, \text{ for } d = 0,1,2,3,4,5,6,7 .$$

We choose 5 scales and 8 orientations, totally 40 Gabor functions in our study. The number of oscillations under the Gaussian envelope function is determined by $\delta = 2\pi$. The term $\exp(-\sigma^2/2)$ is subtracted in order to make the kernel DC-free, thus become insensitive to illumination. Figure 1 shows the real part of Gabor kernels at 5 scales and 8 orientations.

Given an image $I(\vec{x})$, its Gabor transformation at a particular position $\vec{x}_0$ is computed by a convolution with the Gabor kernels

$$(\psi_{\vec{k}} * I)(\vec{x}_0) = \int \psi_{\vec{k}}(\vec{x}_0 - \vec{x}) I(\vec{x}) d^2(\vec{x}). \tag{3}$$

We design a face graph model with 35 nodes on critical fiducial points as shown in Figure 2. A set of 40 Gabor features can be obtained for each fiducial point. Since phase changes drastically with translation, only 40 magnitude features are used in a local feature vector f_{p_i}.

The face image is finally represented by a large Gabor feature vector combining 35 local vectors,

$$V_{Gabor}^T = \left[f_{p_1}^T, f_{p_2}^T, \ldots f_{p_{35}}^T \right]. \tag{4}$$

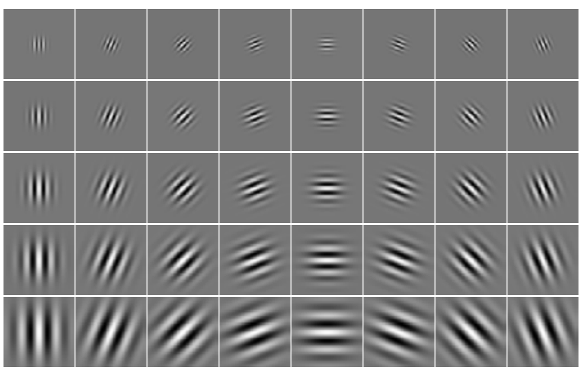

Figure 1. Real part of Gabor kernels at 5 scales and 8 orientations.

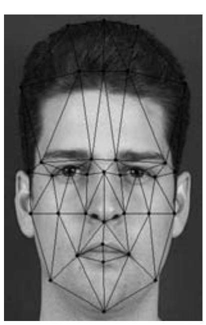

Figure 2. Face graph model.

3. Bayesian classification on Gabor features

Face recognition can be essentially considered as determining whether two face feature vectors are from the same individual (intrapersonal variation Ω_I) or different individuals (extrapersonal variation Ω_E). We can decompose the difference (Δ) between two face vectors into three components: intrinsic difference (*I*), which differentiates different individuals; transformation difference (*T*), caused by all kinds of transformations such as varying expressions, illuminations, and views; noise (*N*), which is randomly distributed in face images. *T* and *N* are two components deteriorating the recognition performance. Normally, *N* is of small energy. The main difficulty for face recognition comes from transformation *T*, which can change the face appearance substantially.

To some extent, Gabor features are insensitive to such transformations as illumination and expression. However, since Gabor transform is not specifically designed for face recognition application, its ability to decouple *T* from *I* is limited. Especially, the Gabor transformation formula is predefined instead of learned from the face training data. On the other hand, we can show that the Bayesian algorithm can also help to reduce transformation *T* in the face difference by employing a probabilistic model learned from the face training set. So we can use the Bayesian algorithm to further separate the transformation factor *T* from the discriminating feature *I* in the Gabor features.

In the Bayesian algorithm, the similarity between two images is a posterior probability given by the Bayesian rule,

$$S(I_1, I_2) = P(\Omega_I \mid \Delta) = \frac{P(\Delta \mid \Omega_I) P(\Omega_I)}{P(\Delta \mid \Omega_I) P(\Omega_I) + P(\Delta \mid \Omega_E) P(\Omega_E)}. \tag{5}$$

To estimate the intrapersonal likehood $P(\Delta \mid \Omega_I)$, principle component analysis (PCA) is applied on the intrapersonal difference set $\{\Delta \mid \Delta \in \Omega_I\}$. Ω_I contains *T* and *N* only, since it comes from the same individual. Therefore the PCA analysis produce a set of principle axes dominated by *T* only. When a face difference Δ (either intrapersonal or extrapersonal) is projected onto the subspace, its *T* component is therefore compacted onto a small number of largest eigenvectors in the principle subspace *F*, while the *I* and *N* components are randomly distributed on all eigenvectors. Because the number of eigenvectors in the complementary subspace $\overline{F}$ is much larger than the eigenvectors in the principle subspace *F*, the energy of *I* and *N* are mainly concentrated in the complementary subspace $\overline{F}$. In such a way, *T* and *I* are decoupled. $P(\Delta \mid \Omega_I)$ is estimated as the product of two independent marginal Gaussian densities in principle space F and its complementary space $\overline{F}$,

$$\hat{P}(\Delta \mid \Omega_I) = \left[\frac{\exp\left(-\frac{1}{2} d_F(\Delta) \right)}{(2\pi)^{K/2} \prod_{i=1}^{K} \lambda_i^{1/2}} \right] \left[\frac{\exp\left(-\varepsilon^2(\Delta)/2\rho \right)}{(2\pi\rho)^{(N-K)/2}} \right]. \tag{6}$$

Table 1. Recognition accuracy using cross-validation on the XM2VTS face database.

Partition	PCA	LDA	Full intensity	Local intensity	Gabor	Bayes	Gabor + Bayes
1	86.4%	92.5%	89.2%	87.5%	91.9%	92.9%	98.0%
2	84.4%	91.2%	85.1%	89.2%	93.2%	91.9%	97.6%
3	82.0%	90.5%	86.1%	84.4%	92.9%	92.9%	97.3%
4	83.4%	91.5%	84.1%	80.3%	89.2%	92.9%	95.6%
Mean	84.1%	91.4%	86.1%	85.4%	91.8%	92.7%	97.1%

In (6), $d_F(\Delta)$ is a Mahalanobis distance in F, referred as "distance-in-feature-space" (DIFS),

$$d_F(\Delta) = \sum_{i=1}^{K} \frac{y_i^2}{\lambda_i}, \tag{7}$$

where y_i is the principle component and λ_i is the eigenvalue. Since λ_i explicitly describes the energy distribution of *T*, *T* can be effectively reduced by the inverse weighting of eigenvalues. $\varepsilon^2(\Delta)$ is defined as "distance-from-feature-space" (DFFS), equivalent to PCA residual error in $\overline{F}$. It could throw away the component *T* on large eigenvectors, while keeps most of *I*. So it is also a distinctive component for recognition. $P(\Delta \mid \Omega_E)$ can be estimated in a similar way, but it plays a less critical role than $P(\Delta \mid \Omega_I)$.

The above discussion shows that, both the Gabor features and the Bayesian algorithm can reduce the transformation difference. However, they use different mechanisms. By using the two methods together, we hope to combine the advantages of the two mechanisms. We first apply Gabor transformation on face image, and then use the extracted Gabor features on 35 fiducial points as the input to the Bayesian algorithm for face recognition. The method is expected to achieve a superior performance than using the Gabor features or the Bayesian algorithm alone.

4. EXPERIMENT

In this section, we evaluate the new method on two data sets from the XM2VTS face database [7] and the AR face database [8]. We compare the new method with two traditional holistic approaches: PCA and LDA, and four other approaches: direct correlation of face image intensity; the Bayesian algorithm using the face image intensity; direct correlation using Gabor features; direct correlation using local area image intensity around each of the 35 fiducial points. The later two methods are based on the graph model shown in Fig. 2, so the geometry variation is removed.

4.1 Experiment on the XM2VTS database

The data set from the XM2VTS database contains 295 people with 4 face images for each person. We use a cross-validation analysis for testing. The 1180 face images are

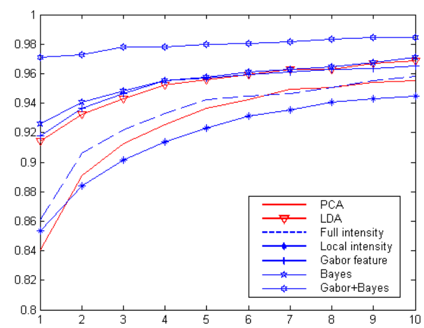

Figure 3. Average accumulative accuracy on the XM2VTS face database.

partitioned into 4 folders. Each folder contains one face image for each individual. For each experimental trial, one folder is chosen as the probe set, and the remaining three folders are used as the reference gallery and the training set. The recognition accuracies of the seven methods on the four experimental trials and their mean accuracies are reported in Table 1. Figure 3 plots their accumulative accuracies from top 1 to top 10 candidates.

The results show that both Gabor features and the Bayesian analysis improve the recognition accuracy over the direct correlation of face intensity. The improvement of Gabor features over the features of the local area intensity shows the advantage of the Gabor transformation since neither is affected by the geometrical changes. Our new method integrating the Gabor features and the Bayesian algorithm achieves the best performance. It also outperforms the holistic approaches PCA and LDA.

4.2 Experiment on the AR face database

In this experiment, we choose 90 people from the AR face database. For each individual, 14 face images taken in two sessions are selected. For each session, there are 7 face images under 7 different transformations as listed in Table 2. Examples of the 7 transformations are shown in Fig. 4. We use the 90 neutral face images in the first session as the reference gallery. For testing, the 630 face images in the second session are partitioned into 3 subsets according to different types of transformations. As shown in Table 2, testing set (I) contains 90 neutral face images; testing set

Table 2. Seven transformations for each individual in the data set from the AR database.

I	II			III		
Neutral	Expression			Lighting		
	Smile	Frown	Cry	Left	Right	Front
1	2	3	4	5	6	7

Figure 4. Samples of the seven transformations for the data set from the AR database.

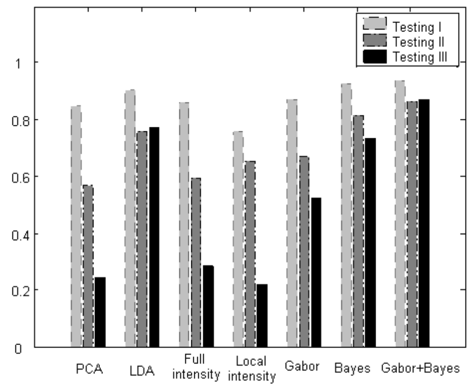

Figure 5. Results on the three testing sets from the AR

Table 3. Recognition results on the three testing sets of the data set from the AR database.

Testing	PCA	LDA	Full intensity	Local intensity	Gabor	Bayes	Gabor + Bayes
I (Neural)	84.4%	90.0%	85.6%	75.6%	86.7%	92.2%	93.3%
II (Expression)	56.7%	75.6%	59.3%	65.2%	66.7%	81.1%	86.0%
III (Lighting)	24.4%	76.7%	28.5%	22.2%	52.2%	73.0%	86.7%

(II) contains 270 face images with expression changes; testing set (III) contains 270 face images under different lighting conditions. For the Bayesian analysis, the 630 face images in the first session are used as training set.

The results are shown in Table 3 and Fig. 5. The accuracies of direct correlation of full intensity on testing sets (II) and (III) are very low, because of the great difference caused by expression and illumination changes. The Bayesian algorithm effectively reduces the two factors and achieves a significant improvement. For expression changes, the improvement of Gabor features mainly comes from the graph model because the result is nearly identical to that of the local intensity features. Gabor features are robust to illumination changes. Adding the Bayesian method to the Gabor features further improve the accuracy and give the best performance.

5. CONCLUSION

Both the Gabor features and the Bayesian algorithm have the property of reducing transformation difference. The Bayesian algorithm can learn from the training set and decouple *T* and *I* on the second order statistical dependency. Gabor analysis is insensitive to transformation variation perhaps on higher order dependency by the elastic graph model and the wavelet transformation. By integrating the two complementary approaches, our new method achieves a better performance.

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