Bayesian Face Recognition Using Gabor Features

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Abstract

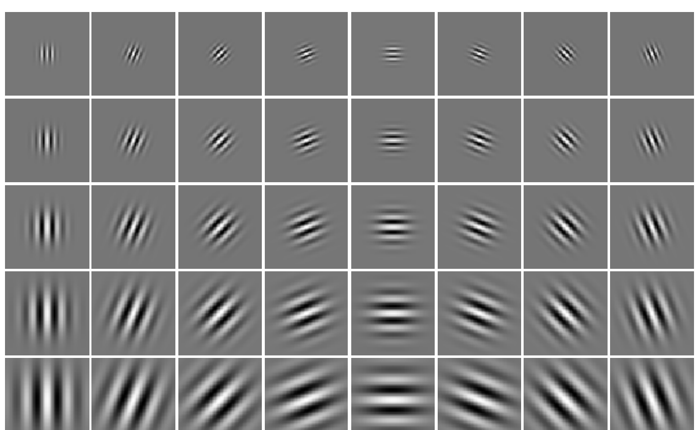
- In this paper, we propose a new face recognition approach combining a Bayesian probabilistic model and Gabor filter responses. Since both the Bayesian algorithm and the Gabor features can reduce intrapersonal variation through different mechanisms, we integrate the two methods to take full advantage 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.

Basic Idea

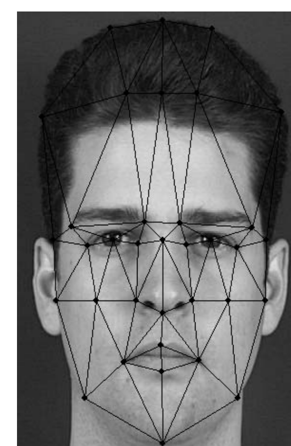
- In face recognition, it is critical to reduce the transformation difference caused by expression and lighting changes etc.
- Compared to image intensity, Gabor wavelet is less sensitive to illumination changes.
- Gabor wavelet is not specifically designed for face recognition and not learned from face training data.
- Bayesian analysis can effectively reduce the transformation difference using a probabilistic measure based on learning.
- Apply Bayesian analysis to the Gabor features can take the advantages of the two methods.

Gabor Features

- Gabor kernels are characterized as localized, orientation selective, and frequency selective. We select a set of 40 Gabor kernels in 5 scales and 8 orientations.



Real part of Gabor kernels at 5 scales and 8 orientations



Face graph model

Gabor Features

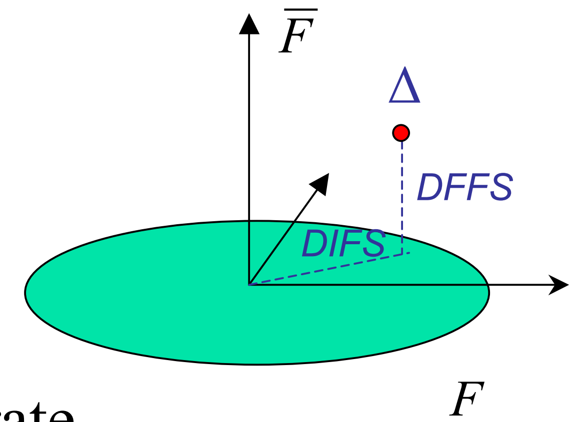
- We design a face graph with 35 fiducial points. Convolve Gabor kernels at each fiducial point and use the magnitudes of Gabor responses as features. A face image is represented by a feature vector with 40 X 35 elements.
- Gabor feature is insensitive to lighting changes since the Gabor kernels are DC-free.
- Gabor feature is insensitive to expression changes since it is based on local features and insensitive to geometrical changes

Bayesian Analysis

- Bayesian analysis classifies the face difference Δ into intrapersonal variation $P(\Delta \mid \Omega_I)$ and extra-personal variation $P(\Delta \mid \Omega_E)$.
- The similarity between tow face images is measured by $P(\Delta \mid \Omega_I)$. It is equivalent to evaluating the distance,

$$d(\Delta) = \sum_{i=1}^{K} \frac{y_i^2}{\lambda_i} + \varepsilon^2(\Delta) / \rho$$

Bayesian Analysis



- The image space is decomposed into intrapersonal principal subspace F and its complementary subspace $\overline{F}$.
- y_i is the projection weights of Δ on the intrapersonal eigenvectors, which concentrate most of the transformation difference.
- λ_i is the intrapersonal eigenvalue, representing the energy of the transformation difference. Dividing λ_i, the transformation difference is effectively reduced.
- $\varepsilon^2(\Delta)$ is the component of Δ in $\overline{F}$. $\overline{F}$ has thrown away most of the transformation difference.

Experiments

- Databases: XM2VTS and AR databases
- Methods
  - Based on holistic features:
    - Direct correlation, PCA, LDA and Bayes
  - Based on local features: geometry variation is removed
    - Direct correlation of local area image intensity, direction correlation of local Gabor features
    - Local Gabor features + Bayesian analysis

Experiments on XM2VTS Database

- 295 people with 4 face images for each person in different sessions
- Four experimental trials: one session is chosen as probe set and the remained three sessions are used for reference and training set

Examples of face images in XM2VTS database taken in four different sessions.

Experiments on XM2VTS Database

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%

Experiments on XM2VTS Database

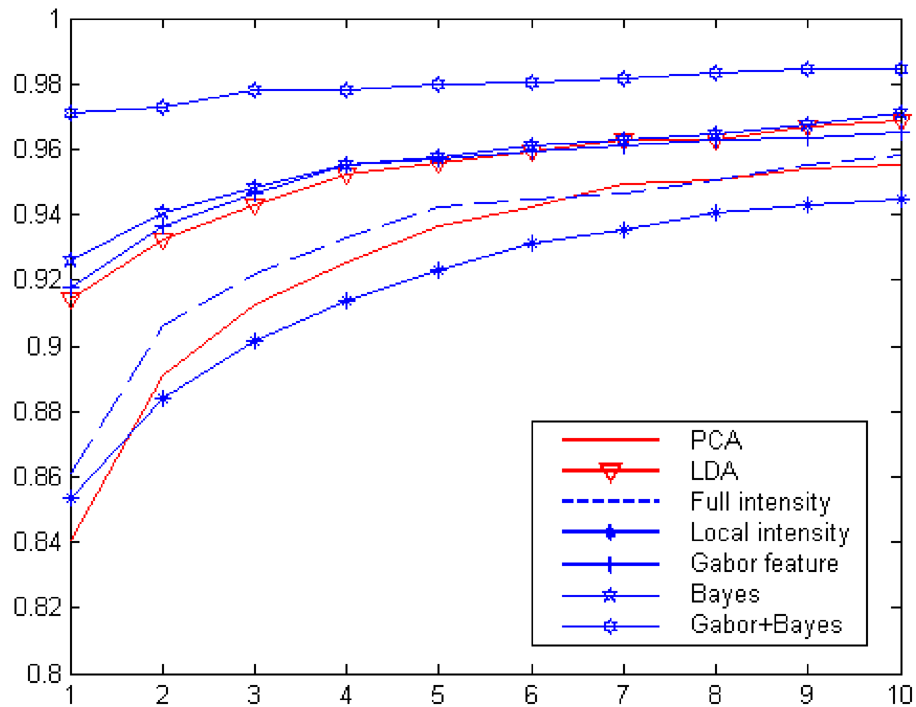


Figure 3. Average accumulative accuracy on the XM2VTS face database.

Experiments on XM2VTS Database

- Discussion:
  - Both Gabor features and Bayesian analysis improve the recognition accuracy over direct correlation of face intensity.
  - The improvement of Gabor features over the local intensity shows the advantage of Gabor transform, since neither is affected by the geometrical changes.
  - The new method integrating Gabor features and Bayesian analysis achieves the best performance. It also outperform PCA and LDA.

Experiments on AR Database

- Choose 90 people with 14 face images taken in two sessions for each person. There are 7 face images under 7 transformations for each session.
- 90 neutral face images in the first session are used as the reference gallery.
- For the Bayesian analysis, the 630 face images in the first session are used as training set.
- For testing, the 630 face images in the second session are partitioned into 3 subsets according to different types of transformations.

Experiments on AR Database

- Testing set (I): 90 neural face images;
- Testing set (II): 270 face images with expression changes;
- Testing set (III): 270 face images with lighting changes;

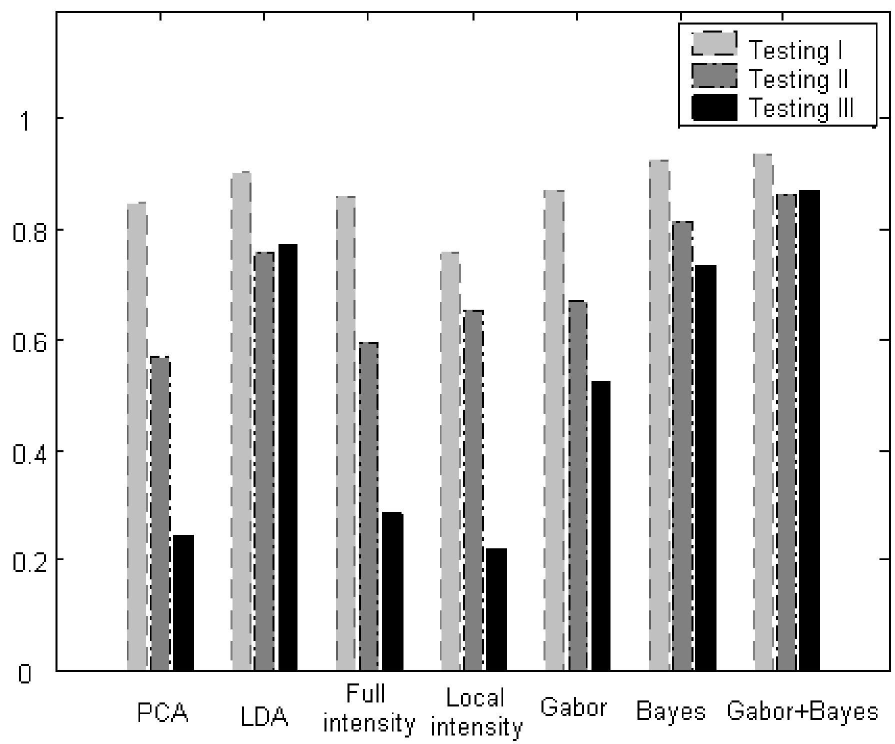
Samples of the seven transformations for the data set from the AR database.

Experiments on AR Database

Table 2. 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)	86.4%	92.5%	89.2%	87.5%	91.9%	92.9%	98.0%
II (Expression)	84.4%	91.2%	85.1%	89.2%	93.2%	91.9%	97.6%
III (Lighting)	82.0%	90.5%	86.1%	84.4%	92.9%	92.9%	97.3%

Experiments on AR Database



Results on the three testing sets from the AR database

Experiments on AR Database

- Discussion
  - The Bayesian analysis effectively reduces the lighting and expressions changes
  - Gabor features are robust to lighting changes
  - The improvement of Gabor features on expression changes comes from the graph alignment. Its result is identical to that of the local intensity features.