Recognizing Face Using Gabor Filter with Perceptual Features

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Abstract -Face recognition and identification is a very active research area nowadays due to its importance in both human computer and social interaction. Psychological studies suggest that face recognition by human beings can be feature, configurationally, and holistic. In this paper, by incorporating spatially structured features into a histogram-based face-recognition framework, we intend to pursue consistent performance of face recognition. In proposed approach, diffusion distance is computed over a pair of human face images, the shape descriptions of these images are built using Gabor filters that consist of a number of scales and levels. It demonstrates that the use of perceptual features by Gabor filtering in combination with diffusion distance enables the system performance to be significantly improved, compared to several classical algorithms. The oriented Gabor filters lead to discriminative image representations that are then used to classify human faces in the database.

Keywords: *Configuration, diffusion distance, face recognition,holistic, perceptual features.*

I. INTRODUCTION

Face recognition (or identification) is a very active research area nowadays due to its importance in both human computer and social interaction. Recent progress in this field has witnessed some successful systems that incorporate advanced algorithms, such as principal component analysis (PCA) (Eigen face), linear discriminate analysis, elastic bunch graph matching (Fisher face), and neural networks. Psychological studies suggest that face recognition by human beings can be feature and configuration based. Feature information refers to as isolated facial components, such as hair, brow, eyes, nose, mouth, and cheeks. Configurationally information denotes the spatial relations between the features, their interaction, and to various proportions, for example, nose length to brow length. It is also widely accepted that holistic recognition plays an important role in face perception. The applications of these psychological studies have been commonly found in the community of computer vision. These are the following features that are used for face recognition,

i) Feature Based.
ii) Configuration Based.
iii) Holistic Face Recognition.

II. FEATURES FOR FACE RECOGNITION

In the proposed algorithm, the Gabor features can be obtained after we apply a Gabor-filtering function to the image. These features are extracted from a set of face images, which are then used to compute diffusion distance over pair-wise face images. Diffusion distance is a dissimilarity measure between histogram-base descriptors, which is defined in a temperature field. Histogram difference is measured by heat diffusion and is treated as the initial condition of a heat diffusion process. As a result, diffusion distance is derived as the sum of dissimilarities over scales. It has been justified that using diffusion distance is capable of handling deformations as well as quantization effects.

A. Gabor Filtering

Gabor filters include a filter bank with various scales and rotations. The filters are convolved with the image, resulting in a Gabor space. This entire process simulates the response of the 2-D receptive field profiles of the mammalian simple cortical cell.

In the spatial domain, a Gabor filter can be treated as a complex exponential modulated by a Gaussian function. Each Gabor consists of two functions in quadrature (out of phase by 90◦), located in the real and imaginary parts of a complex function as follows (see Fig. 1 for a simulation)

$$g(x,y)=K\ \exp(-\pi(a^2(x-x_0)_q{}^2+b^2(y-y_0)^2{}_r))$$
$$\exp(j(2\pi(\alpha_0 x+\beta_0 y)+Q))$$
or in polar coordinates
$$g(x,y)=K\ \exp(j(-\pi(a^2(x-x_0)^2{}_r+b^2(y-y_o)^2{}_r))$$
$$\exp(j(2\pi S_0(x\cos\omega_0+y\sin\omega_0)+Q))$$

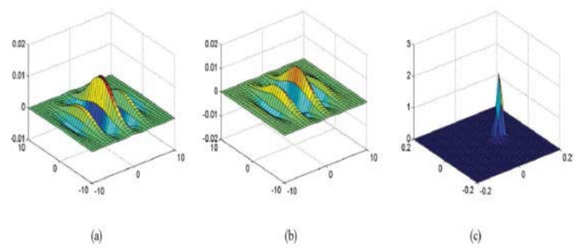

Figure. 1: Real, imaginary, and frequency components of a complex Gabor function in the spatial domain. (a) Real (b) imaginary and (c) frequency component. S = 0.2 cycles/pixel and Q = 0◦.

Where K is the magnitude of the Gaussian envelope, (a, b) are the two axis of the Gaussian envelope, (x, y) are the pixel position in the spatial domain(x0 ,y0) are the location of the peak of the Gaussian envelope, (α0,β) are the spatial frequencies of the sinusoid carrier in Cartesian coordinates (expressed as (S0, ω0) in polar coordinates), and Q is the phase of the sinusoid carrier.

Given a gray-level image I(x, y), the convolution of I(x, y) and g(x, y) is given as follows:

$$G(x,y)=I(x,y)*g(x,y)$$

where * denotes the convolution operator. The convolution can be computed efficiently by applying the fast Fourier transform (FFT), followed by point-by-point multiplications, and finally, the inverse FFT (IFFT). Utilization of the magnitude of Gabor representations, which provide a measure of the local properties of an image and is less sensitive to the illumination changes. The Gabor representations, denoted as $\Phi i,j$, form a feature vector for face recognition as follows:

$$\Phi=[\varphi_{1,1}, \varphi_{1,,2},\ldots, \varphi_{m,n}]^{T}$$

Where m and n are numbers of scales and orientations used in the Gabor filter. Fig. 2 illustrates examples of applying four directions' Gabor filtering to a profile face image. Fig. 2(a)–(e) reveals that different image representations correspond to the oriented filters. Note that only one phase is utilized here in this example for simplicity.

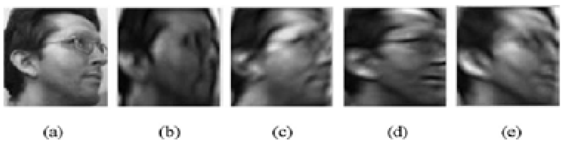

Figure 2: Examples of applying four directions' Gabor filtering to a profile face image. (a) Original (b) 0 (c) π/4 (d) π/2 and (e) 3π/4. S = 0.2 cycles/pixel and Q = 0◦.

B. Diffusion Distance

Histogram-based local descriptors (HBLDs) have been widely used in computer vision for shape matching, image retrieval, and categorization. Currently, most of the available approaches can only deal with the case where the corresponding histograms in different images have been aligned. As a consequence, these methods are very sensitive to distortions and quantization effects in the extracted local descriptor.

Consider two l-dimensional histograms h1 (**s**) and h2 (**s**), where **s** ∈ Rl is a vector.The distance between them is defined as ˆD (h1,h2). Using a temperature field, we treat the distance to be the evolution of a temperature field T(**s**, t) at time t = 0. According to the heat diffusion equation

$$\frac{\partial T}{\partial t} = \nabla^2 T$$

which has a unique solution as

$$T(s,t)= T_o(s)*f(s,t)$$

with an initial condition

$$T_o(s) = \hat{}D$$

$$\text{where } f(s,t) = \frac{1}{(2\pi)^{1/2t}} \exp\left(-\frac{s^T s}{2t^2}\right)$$

To efficiently compute the histogram distance, a distance function based on the Gaussian pyramid is adopted. This is due to the fact that the Gaussian pyramid is an efficient discretization of the diffusion process T(**s**, t). Therefore, the diffusion distance to be computed is as follows:

$$D(h_1, h_2) = \sum_{m=0}^{M} D(|d_m(s)|)$$

$$\text{where } d_m(s) = [d_{m-1}(s) * f(s,\sigma)]\_\downarrow_2$$

where m = 1, . . . , M. Equation (12), different layers of the pyramid, has an initial condition as d0 (**s**) = h1 (**s**) − h2 (**s**). The notation ↓2 is half-size down sampling. M is the number of the pyramid levels and σ is the standard deviation of the Gaussian filter f. The computational complexity of D(h1, h2) is O(L), where L is the number of histogram bins. The simplified equation is as follows:

$$D(h_1, h_2) = \sum_{m=0}^{M} (|d_m(s)|)$$

Fig. 3 denotes example of the computational results of diffusion distance over three pairs of images. It is observed that the diffusion distance is anti proportional to the similarity between the images.

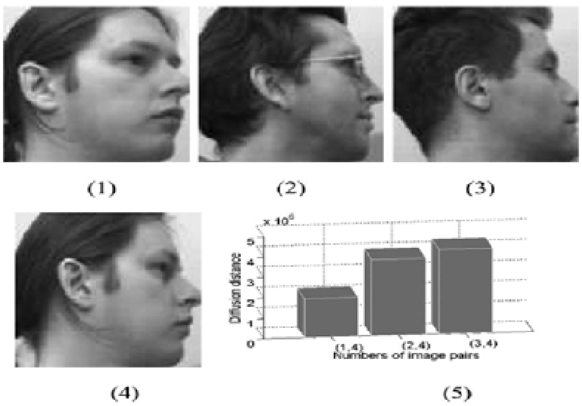

Figure 3: Image examples and computational results of diffusion distance. (1) Image 1. (2) Image 2. (3) Image 3. (4) Image 4. (5) Diffusion distance over two images. For example, (1,4) indicates image pairs 1 and 4.

III. GABOR DIFFUSION DISTANCE FOR FACE RECOGNITION

Like pyramid-matching kernel (PMK), the computation of diffusion distance involves the sum of the histogram difference over different scales of the original images. Diffusion distance- based algorithms have not considered the spatial structure information that has been proved to be valuable in face recognition. Some approaches have been developed to extract the spatial structure information of face images. In the meantime, Gabor features can be effectively extracted from the images, being shape contexts for the recognition purpose. Investigate of a new approach by incorporating the Gabor filtering into the scheme of diffusion-distance-based similarity search.

A. Perceptual Features for Image Representation

A filter bank of Gabor functions are normally used for descriptions of cell receptive fields in V1 of the primate visual cortex. This is obtained by convolving the image I with the filter bank to produce a vector of filter response

$$\hat{I}(x,y)=I(x,y)*\ f(x,y)$$

which characterizes the image patch centered at (x, y) (˜ f is a filter function). The filter bank consist of a number of scales and orientations.

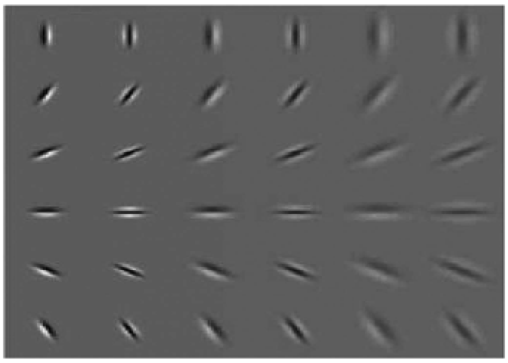

Figure 4: Filter bank of 36 filters consisting of two phases (even and odd), three scales (spaced by half-octaves), and size orientation (uniformly spaced from 0 to π).

B. Bayesian Model

We now look at the available features out of the Gabor filters and their corresponding model distribution p(β), where β is a set of model parameters of the distribution. In face recognition, a face is associated with the feature appearance A and spatial structures χ. Let Ad and χd be the appearance of the detected feature and spatial structures, respectively. The similarity between two histograms (or images) can be determined by a Bayesian decision B (**S** indicate that two faces refer to the same person and ¯**S** is the opposite)

$$B = \frac{p(S/A, A_d, X, X_d)}{p(S/A, A_d, X, X_d)}$$

C. SIMILARITY MEASURE

Similarity measure is necessary for face recognition. For histogram similarity, it is often to compute “distances” between two faces, and then, use a defined distance metric for similarity measure. On the other hand, kernel-based schemes can be used for face recognition, where an inner product is performed. Our proposed approach, alike the former, is to describe a set of Gabor features in a histogram.

Perceptual features can be extracted using the Gabor filtering; The logarithm of B directly links back to the computation of diffusion distance between two faces. In the previous section, recognition for two face images has been discussed. For face recognition of multiclass face images, we first conduct a pair-wise similarity measure, which is followed by a classification procedure (k-means) that categorizes the overall faces into corresponding classes. We could use other classifiers that may or may not end up with better recognition rates. Nevertheless, our main attention in this study is to justify the superiority of the proposed feature extraction scheme to the state of the art, rather than the classifier’s performance. Therefore, the proposed algorithm for multiclass face recognition is shown in the following tabulation (see Algorithm).

Algorithm:

1.Initialisation of Gabor phasas,scales and orientation parameters
2. For scales n_2=1:3
3. For orientations n_3= 0:$\frac{\pi}{3}$:π
Repeat
4. Gabor filtering using the equation
5. Computation of oriented diffusion distance
Repeat
6.Pyramid formation
7. Histrogram differencing
8.Summation of the difference
Until
9. Simpilarity measures
Until
10. End for
11.End for
12.Apply k mean classification

IV. CONCLUSION

In this paper, we have presented a new face-recognition algorithm by combining Gabor features within the scope of diffusion-distance calculation. This strategy starts from the Gabor filtering that consists of three scales and six orientations. It is followed by the calculation of diffusion distance based on a Bayesian model. This proposed algorithm has been compared against several state-of-the-art techniques. The experimental results show that the proposed face-recognition scheme has the best performance in accuracy.

Most classical HBLDs can only be used to deal with the aligned shapes and are sensitive to distortion and quantization of the images. To compound these problems, in this paper, Gabor features are generated to represent the local characteristics. These features are driven by the nature of human perception, being of a good capability to differentiate the face images used. To enhance the performance of face recognition, a Bayesian model was used to determine the similarity degree between two histograms. The rationale of using this Bayesian decision model is to ensure the maximization of likely estimation across different histograms. The available experimental results have justified the successful usage of the Gabor features and the Bayesian model..

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