RESEARCH ARTICLE

Modified Approaches on Face Recognition By using Multisensory Image

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Abstract— A feature selection technique along with an information fusion procedure for improving the recognition accuracy of a visual and thermal image-based facial recognition system is presented in this study. A novel modular Kernel Eigen spaces approach is developed and implemented on the phase congruency feature maps extracted from the visual and thermal images individually. This study proposes a novel face recognition method which exploits both global and local discriminative features. In this method, global features are extracted from the whole face images by keeping the low-frequency coefficients of fourier transform, which we believe encodes the holistic facial Information, such as facial contour. For local feature extraction, Gabor wavelets are exploited considering their biological relevance. After that, to the global fourier features and each local patch of Gabor features.

Key Terms: - Ensemble classifier; face recognition; feature extraction; Fisher's Linear Discriminant (FLD); image fusion; kernel methods; phase congruency

I. INTRODUCTION

FACE recognition from still images and video sequence has been an active research area due to both its scientific challenges and wide range of potential applications such as Biometric identity authentication, human computer interaction (Bartlett *et al*., 2002) and video surveillance. Within the past two decades, numerous Face recognition algorithms have been proposed as reviewed in the literature survey. Even though we human beings can detect and identify faces in a cluttered scene with little effort, Building an automated system that accomplishes such objective is very challenging. The challenges mainly come from the large variations in the visual stimulus due to illumination conditions, (Lai *et al*., 2001) viewing directions, facial expressions, aging and disguises such as facial hair, glasses, or cosmetics.

As in any pattern classification task, feature extraction plays a key role in face recognition process. In feature extraction stage, a proper face representation is chosen to make the subsequent face processing not only computationally feasible but also robust to possible intrinsic and extrinsic facial variations. Existing face representations fall into two categories: Global-based and local-based. In the global -based face representation, each dimension of the feature vector contains the information embodied in every part (even each pixel) of the face image, thus corresponds to some holistic characteristic of the face. In contrast, for the local-based face representation, each dimension of the feature vector corresponds to merely certain local region in the face, thus only encodes the detailed traits within this specific area.

II. PHASE CONGRUENCY FEATURES

Image features such as step edges and lines give rise to points where the Fourier components of the image are maximally in phase. According to Oppenheim and Lim (year) the phase component is more important than the

magnitude component in the reconstruction process of an image from its Fourier domain. There is also physiological evidence indicating that the human visual system responds strongly to the points in an image where the phase information is highly ordered. Application of PCA-based recognition technique on the phase spectrum of the images resulted in better performance than on the application of intensity images and the magnitude spectrum according to Fig. 1 illustrates the concept of importance of Phase. It shows the images of two people.

The image shown in Fig. 1g is the inverse Fourier transforms of the phase spectrum from image A combined with the magnitude Spectrum of image B. The image shown in Fig. 1h is the inverse Fourier transform of the phase spectrum of image B combined with the magnitude spectrum of image A. It can be noticed that the processed images resemble the image to which their phase spectrums belong. For the face recognition techniques to be robust to illumination, the features extracted should be illumination invariant. Edge detection schemes that uses a differential approach suffers from the problem of false positives.
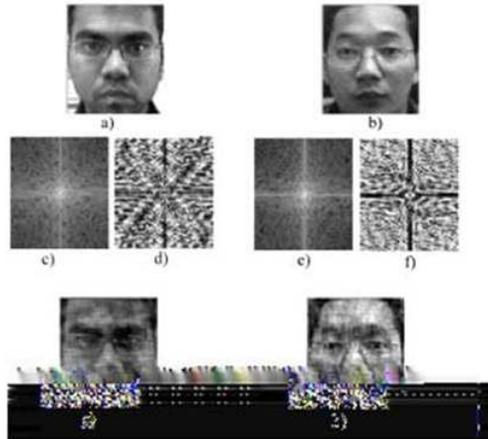

Fig. 1: Illustration of the importance of phase information in frequency domain. (a) Image A; (b) image B; (c) magnitude spectrum of A; (d) phase spectrum of A; (e) magnitude spectrum of B; (f) phase spectrum of B; (g) reconstructed with (d) and (e); (h) reconstructed with (c) and (f)
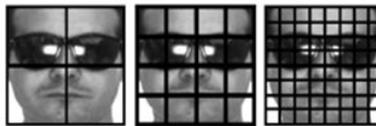

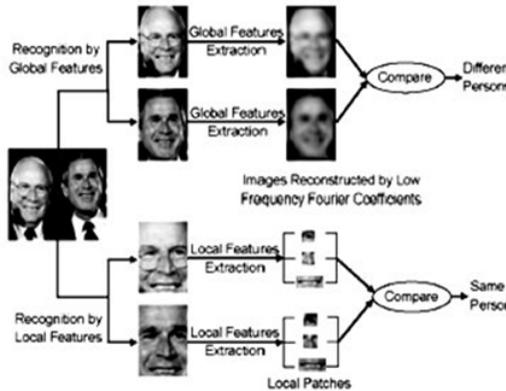Fig. 2: Illustration of the concept of localization of variations and pixel dependencies

Fig. 3: Reconstruction of the face images by using only low-frequency fourier coefficients (30% energy reserved)

That is, some points of maximum gradient will be marked as edges when humans might not perceive them as such. For example, no edge is perceived in a sine wave grating at the point, where the luminance crosses its mean value that is the point at which the gradient is maximum or the second derivative is zero.
Step and sinusoidal functions are perceived quite differently by the human visual system (Fig. 2 and 3).

Figure 2 shows the sine wave as a smooth gradual luminance change with no obvious features. In the second case we can see a sharp edge. The step edge is typical of the sharp changes in luminance at the boundary between two objects.

Phase and instantaneous phase: A general sinusoidal signal with constant amplitude is represented as:

$$s(t) = A \cos (\mathbf{N} (t)) \qquad (1)$$

where A is the amplitude of the signal and is the instantaneous phase of the signal or the local phase of the signal. It congruency model detects points of order in the phase spectrum. Phase congruency provides a measure that is independent of the overall magnitude of the signal making it invariant to variations in image illumination and/or contrast.

The phase congruency technique used in this research is based on the one.

Developed by Kovesi (2003) this is in turn based on the local energy model developed in to calculate the phase congruency. It has been explained that the point of strong phase congruency should relate to a maximum in the energy of the waveform. Let I(x) be the input periodic signal defined in the interval:

$$T = [-\mathbf{B}, \mathbf{B}]$$

F(x) is the signal with its DC component removed and H(x) is the Hilbert transform of F(x) which is a 90º phase shift of F(x) It is proposed in that energy is equal to phase congruency scaled by the sum of the Fourier amplitudes as in:

$$E (x)\ PC (x)\ A_n \qquad (2)$$
$$n$$

This measure of phase congruency stated as the ratio of $E(X)$ to the overall path length taken by the local Fourier components in reaching the end point, makes the phase congruency independent of the overall magnitude of the signal. This provides invariance to variations in image illumination and contrast. Approximations to the components $F(x)$ and $H(x)$ are obtained by convolving the signal with a quadrature pair of filters. In order to calculate the local frequency and phase information in the signal, logarithmic Gabor functions are used instead of Gabor functions to obtain a nonzero DC component in the filtered signal. $I(x)$ If is the signal and denote the even symmetric and odd-symmetric components of the log Gabor function at a scale, the amplitude and phase in the transformed domain can be obtained a where e_n (x) and o_n(x) and are the responses of each quadrature pair of filters. Equation illustrates the response vector.
If all the fourier amplitudes at are very small then the problem of phase congruency becomes ill conditioned. To overcome the problem a small positive constant is added to the denominatorOne-dimensional analysis is carried out over several orientations and the results are combined to analyze a 2-D signal.

III. EXTRACTION OF GLOBAL AND LOCAL FEATURES FOR FACE REPRESENTATION

As mentioned previously, global and local facial features play different roles in face perception. Therefore, it is necessary to combine them together smartly. Intuitively, local information is embedded in the detailed local variations of facial appearance, while global information means the holistically structural configuration of facial organs, as well as facial contour. Thus, from the viewpoint of frequency analysis, global features should mainly correspond to the lower frequencies, while local features should be of high frequency and dependent on position and orientation in the face image. Considering that, in this study, global information is represented as the Fourier coefficients in low frequency band and local information is encoded as the responses of multi scale and multi orientation Gabor wavelets. It is known that the Gabor wavelet is a Gaussian modulated Fourier transform. Therefore, it can be tuned to extract global (usually low frequency) features by increasing the bandwidth and the radius of its Gaussian modulator. However, doing like.
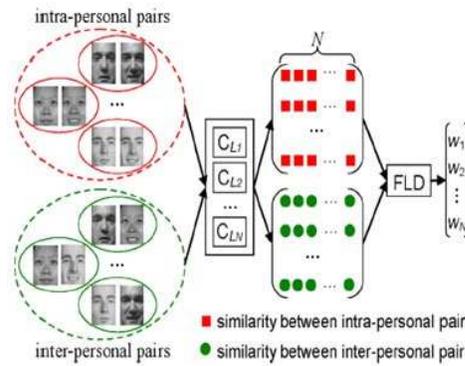
Fig. 4: Illustration of the weight learning process. C_{Li} denotes the weight of **ith** LCC; and $\mathbf{w_i}$ denotes the weight learning for component classifiers.

WEIGHT LEARNING FOR COMPONENT CLASSIFIERS

In this sub-section, we formulate weight learning as a discriminant analysis problem, In this sub-section, we formulate weight learning as a discriminant analysis problem, in which the weighted sum can be considered as linear projection from -D to 1-D and the projection coefficients can be treated as weights. The weight learning method consists of three steps. Firstly, the face images in training set are converted into image pairs, which can be divided into two classes named intrapersonal pairs and interpersonal pairs. Secondly, for each image pair, a similarity vector can be obtained. Each similarity in this vector is given by a certain LCC; therefore, the dimension of the similarity vector is. Each similarity vector can be considered as a sample in the space of dimensions.

Thus, in the last step, two classes of the -dimensional samples are fed into FLD to get an optimal linear projection from - D to 1 -D. As mentioned above, each coefficient of this linear projection can be considered as the weight of corresponding LCC. The aim of weighting LCCs is to make the similarities of image pairs from two classes (intrapersonal and interpersonal) more discriminable, which is consistent with the aim of FLD.

Thus, the projection coefficients computed by FLD is also the optimal weights for discriminating the intrapersonal Pairs and the interpersonal pairs. This weight learning process is shown in Fig. 4. The weights of GC and LEC can be similarly learned from training set by this method.

IV. CONCLUSION AND DISCUSSION

First, the combination of global and local features plays a key role. Experimental results show that they are indeed complementary for distinguishing faces. Although the local features seem significantly better than global features for face recognition, the accuracy can still be improved by carefully combining them. Second, ensemble is also a key contributor to improve generalizability. In machine learning area, ensemble learning has been widely recognized as a successful method to avoid over fitting. In the proposed method, ensemble is applied in two stages: the combination of the local classifiers and the combination of the global and local classifiers. Experimental results show that both ensemble procedures improve impressively the performance compared with the component classifiers.

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