Textural feature based face recognition for single training images

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A novel face recognition algorithm using single training face image is proposed. The algorithm is based on textural features extracted using the 2D log Gabor wavelet. These features are encoded into a binary pattern to form a face template which is used for matching. Experimental results show that on the colour FERET database the accuracy of the proposed algorithm is higher than the local feature analysis (LFA) and correlation filter (CF) based face recognition algorithms even when the number of training images is reduced to one. In comparison with recent single training image based face recognition algorithms, the proposed 2D log Gabor wavelet based algorithm shows an improvement of more than 3% in accuracy.

Introduction: Face recognition is one of the most challenging problems of biometric systems. Face recognition algorithms such as local feature analysis (LFA) [1] and correlation feature (CF) [2] need a large set of training images. These algorithms learn from the training data and use the feature set for matching. However if the training set is small, the performance of these algorithms decreases. Typically, for law enforcement applications only a single face image is available for training. In [3] and [4], face recognition algorithms are proposed to solve the problem of single training images using $E(PC)^2A$ and SVD perturbation, respectively. These algorithms achieve an accuracy of around 85% on the FERET database [5].

We propose an algorithm to improve the performance of face recognition with a single training image. The proposed verification algorithm uses the 2D log Gabor wavelet [6] to extract the set of textural features from the face image. The 2D Gabor has been widely used in face recognition to extract Gabor features or form Gabor jets for matching [7]. We use Gabor wavelets to extract textural features considering the face image as a texture which is to be matched. A comparison of the proposed approach with existing algorithms is also presented.

Methodology: Gabor functions are Gaussians modulated by complex sinusoids. A useful property of these functions is that they are maximally compact in both space and frequency. In order to give the same emphasis to different frequency octaves, and because natural textures often have a linearly decreasing log power spectrum, we use the 2D log form of Gabor filters [6]. The centres of these filters in the frequency domain are equally spaced in a log polar representation of the spectrum of an image. In the frequency domain, the log Gabor filter bank is defined as:

$$G_{ij}(\omega_r, \omega_\varphi) = G(\omega_r - \omega_{r_i^\alpha}, \omega_{\varphi_i^\alpha}) \tag{1}$$

where (r, φ) are polar co-ordinates, $\omega_{r_i^\alpha}$ is the logarithm of the centre frequency at scale i, $\omega_{r_i^\alpha}$ is the jth orientation and $G(\omega_r, \omega_\varphi)$ is defined as:

$$G_{\omega_r,\omega_\varphi} = \exp\left(\frac{\omega_r^2}{2\sigma_{ri}^2}\right)\exp\left(\frac{\omega_\varphi^2}{2\sigma_{\varphi j}^2}\right) \tag{2}$$

where σ_{ri}^2 and $\sigma_{\varphi j}^2$ are the Gaussian parameters, $1 \le i \le M$ and $1 \le j \le N$. Here, M is the number of scales and N is the number of orientation bands. The N orientations are taken to be equidistant:

$$\begin{aligned} \sigma_{\varphi_j} &= \pi/2N \\ \omega_{\varphi_j} &= 2\sigma_{\varphi_j}(j-1) \quad \text{for } 1 \le j \le N \end{aligned} \tag{3}$$

The M scales are obtained by dividing the frequency range $\omega_{\max} - \omega_{\min}$ into the desired number of octaves which yields $\sigma = (\omega_{\max} - \omega_{\min})/2(2^M - 1)$ and

$$\begin{aligned} \sigma_{r_i} &= 2^{i-1}\sigma \\ \omega_{r_i} &= \omega_{\min} + \{1 + 3(2^{i-1} - 1)\}\sigma \quad \text{for } 1 \le i \le M \end{aligned} \tag{4}$$

The response of the Gabor filters on an image are computed in the frequency domain by multiplying the Fourier-transformed image with the filter responses in (1), and transforming the results back to the spatial domain. Working in the frequency domain avoids the image boundary problems which occur when convolving in the spatial domain. Only phase information is used to generate the template because the amplitude is not very discriminating. The phase information does not depend on imaging contrast, illumination, camera properties, or to some extent on the behavioural characteristics of the face image such as rotation, facial expression and occlusion.

To generate the face template, the face is first detected from the image using the face detection algorithm described in [8]. The detected face is then converted into polar co-ordinates and convolved with the 2D log Gabor filter in frequency domain. The convolved form of the image is a complex valued matrix Z ($Z = \mathrm{Re}(Z) + j\mathrm{Im}(Z)$) containing real and imaginary parts. Phase quantisation is applied using (5) to extract the phase information of the convolved image and generate the binary face template:

$$face[r, \varphi] = \begin{cases} 1 & \text{if } \mathrm{Re}(Z)^*\mathrm{Im}(Z) \ge 0 \\ 0 & \text{if } \mathrm{Re}(Z)^*\mathrm{Im}(Z) < 0 \end{cases} \tag{5}$$

This binary face template is the textural feature representation of the face image. To match two face templates, a window based comparison method is presented. The face template generated by this algorithm is a two-dimensional array of 1's or 0's. Instead of using bit by bit comparison, window-wise threshold based comparison is performed using (1):

$$D_{i,j} = \begin{cases} 1 & (FT_1(i,j) \otimes K) - (FT_2(i,j) \otimes K) \ge thresh \\ 0 & (FT_1(i,j) \otimes K) - (FT_2(i,j) \otimes K) < thresh \end{cases} \tag{6}$$

where *thresh* is the threshold value, K is the kernel given by

$$K = \begin{bmatrix} 1 & 1 & 1 \\ 1 & 1 & 1 \\ 1 & 1 & 1 \end{bmatrix}$$

$\otimes$ stands for convolution, and FT is the face template. If P and Q are the dimensions of the face template then the matching score S is calculated as

$$S = \sum_{i=1}^{P} \sum_{j=1}^{Q} D_{i,j} \tag{7}$$

A person is correctly matched if the matching score S is less than a matching threshold. The optimal performance of the algorithm in terms of the face recognition accuracy is obtained when the matching score S is equal to 0.36.

Experimental results: The proposed algorithm is tested on the frontal face images from the coloured FERET database [5]. From this database we have chosen 3000 frontal face images from 600 individuals with variations in pose from 0 to 10 degrees. Using this database, the number of training images for each individual is varied from a maximum of four images to one image. The proposed algorithm is compared with LFA [1] and CF [2], the performances of which are known to be good when a large training set is used.

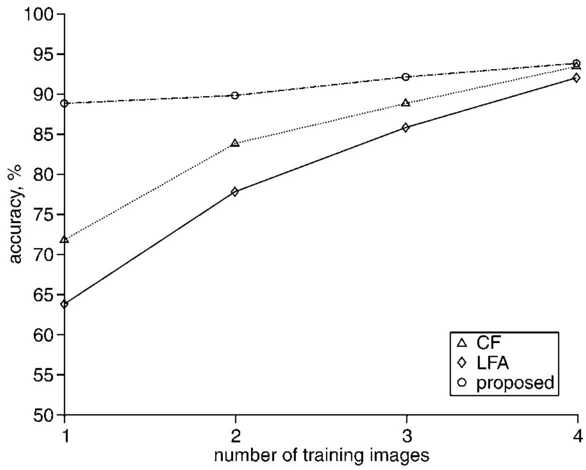

Fig. 1 *Accuracy of algorithms on varying the number of training images*

Fig. 1 shows that when the number of training images is four, the accuracy of all the algorithms is high. However, as the number of training images is gradually reduced, the accuracy of LFA and CF based algorithms drops significantly compared to the 2D log Gabor algorithm. For example, experimental results show that with only a single training image, the accuracy of the LFA algorithm is reduced to 64.21%, resulting in a drop of 27.95%, while the accuracy of the CF algorithm is reduced to 71.66%, resulting in a drop of 22.21%. Comparatively, the 2D log Gabor algorithm maintains a higher level of accuracy at 89.14%, resulting in a drop of only 5.05%.

We next compare our results with two recent face recognition algorithms, $E(PC)^2A$ [3] and SVD perturbation [4], that use single training images. The same database is used for comparison purposes. Experimental results show that the proposed algorithm has an FRR of 9.17%, an FAR of 1.69%, and an overall accuracy of 89.14%. An improvement of 5% in accuracy is achieved compared to the $E(PC)^2A$ algorithm [3] which has an accuracy of 84.55%. The 2D log Gabor also shows an improvement of 3% compared to the SVD perturbation algorithm [4] which has an accuracy of 86.24%.

The experiments performed using a common database provide a baseline for effectively comparing the performance of our proposed approach with other recent algorithms. We show that using texture features extracted with the 2D log Gabor wavelet improves face recognition accuracy even when a single image is used for training.

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