FACE RECOGNITION BASED ON WAVELET-CURVELET-FRACTAL TECHNIQUE[1]

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Abstract In this paper, a novel face recognition method, named as wavelet-curvelet-fractal technique, is proposed. Based on the similarities embedded in the images, we propose to utilize the wavelet-curvelet-fractal technique to extract facial features. Thus we have the wavelet's details in diagonal, vertical, and horizontal directions, and the eight curvelet details at different angles. Then we adopt the Euclidean minimum distance classifier to recognize different faces. Extensive comparison tests on different data sets are carried out, and higher recognition rate is obtained by the proposed technique.

Key words Face recognition; Wavelet decomposition; Curvelet transform; Fractal; Facial feature extraction

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I. Introduction

Face recognition has been studied for over two decades, and it is still an active subject due to extensive practical applications. Some potential applications include law enforcement, access control, security surveillance and monitoring, bank-card identification, and human-robot interaction. In all these cases, face recognition acts as a critical role. It is a difficult pattern recognition problem due to the complicated pattern distributions from large variations in facial expressions, facial details, and illumination conditions. Many approaches have been proposed in the past years[1–6]. A survey on the techniques can be found in Ref. [7].

In general, a face recognition system involves three key elements: face detection and normalization, feature extraction and discriminant analysis, identification and/or verification. The robustness of face recognition could be improved by treating the variations in these elements. Feature extraction is a very important step for face recognition. Many methods need accurate locations of key facial features such as eyes, nose, and mouth to normalize the faces[8,9]. Template-based approach was widely adopted to detect the eyes and mouth in real images. Cootes *et al.*[10] proposed a statistical shape model called Active Shape Model (ASM). It was then extended to Active Appearance Model (AAM) in Ref. [11]. In recent years, wavelet transform was successfully introduced to face recognition based on multiresolution technique[12,13].

More recently, Huang[14] proposed a new classifier, called TAF-SVM, which can deal with several problems that may occur in SVMs when applied to face recognition. Gao[15] proposed to generate a compact face feature and line edge map for face coding and recognition. Savvides[16] proposed a novel set of biometrics, which were defined in frequency domain, to represent a form of facial asymmetry. In Ref. [17], two new approaches for fractal dimension estimation are proposed for image analysis. *i.e.* wavelet energy fractal dimension and morphological fractal dimension. Zhang and Bui[18] proposed a 2D object recognition method to differentiate similar objects, detect defective objects, and recognize printed characters. Mandal[19] proposed to use curvelet transform for face recognition.

In this paper, we try to explore the similarities of facial images, and propose a novel wavelet-curvelet-fractal technique for face recognition. It is well known that wavelet technique can decom-

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pose the similarities into vertical detail, horizontal detail, and diagonal detail. Curvelet transform[19] can obtain similarities at the same directional details but at different scales. The fractal technique can make use of all these similarities. In the paper, we will take the fractal dimensions of the detailed facial images as facial features. Experiments show that these features are useful for face recognition, and can obtain higher recognition rate.

The rest of the paper is organized as follows. In Section II, we elaborate the proposed wavelet-curvelet-fractal technique. The face recognition method is presented in Section III. Some comparative test results are reported in Section IV. The paper is concluded in Section V.

II. Wavelet-curvelet-fractal Technique

The proposed wavelet-curvelet-fractal technique face recognition is outlined in Fig. 1. For a given face image, we first perform wavelet decomposition and curvelet transform to obtain the wavelet facial details and curvelet details. Then we take the corresponding fractal dimensions as facial features for recognition. The technique details are as follows.

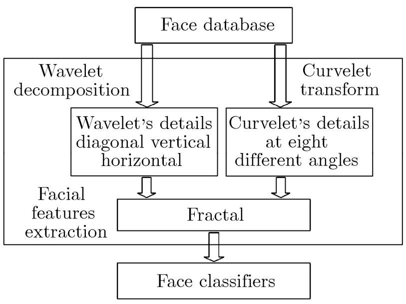

Fig. 1 Outline of the proposed curvelet-wavelet-fractal technique

1. Wavelet decomposition

Typical wavelet decomposition can be written as:

$$f_n(x,y) = f_{n-1}(x,y) + g_{n-1}(x,y) \tag{1}$$

where

$$g_{n-1}(x,y) = g_{\mathrm{LH},\,n-1}(x,y) + g_{\mathrm{HL},\,n-1}(x,y) + g_{\mathrm{HH},\,n-1}(x,y) \tag{2}$$

The above equations indicate that any image signal can be decomposed into a specific wavelet domain. Where the subscripts L and H are used to indicate low- and high-frequency components. Here we adopt a recursive algorithm to compute these low- and high-frequency components.

$$C^{(n-1)}_{\mathrm{LL},k1,k2} = \sum_{l1,l2} a_{l1-2k1} a_{l2-2k2} C^{(n)}_{\mathrm{LL},l1,l2} \tag{3}$$

$$D^{(n-1)}_{\mathrm{LH},k1,k2} = \sum_{l1,l2} a_{l1-2k1} b_{l2-2k2} C^{(n)}_{\mathrm{LL},l1,l2} \tag{4}$$

$$D^{(n-1)}_{\mathrm{HL},k1,k2} = \sum_{l1,l2} b_{l1-2k1} a_{l2-2k2} C^{(n)}_{\mathrm{LL},l1,l2} \tag{5}$$

$$D^{(n-1)}_{\mathrm{HH},k1,k2} = \sum_{l1,l2} b_{l1-2k1} b_{l2-2k2} C^{(n)}_{\mathrm{LL},l1,l2} \tag{6}$$

where $\{a_k\}$ and $\{b_k\}$ are filter decomposition sequences related to scale function $\varphi(t)$ and wavelet function $\psi(t)$, which result in various wavelet transformation, such as Daubechies, Coiflet, *etc.* At each decomposition level, the low-pass filter produces a subimage $C^{(n-1)}_{\mathrm{LL},k1,k2}$, which consists of only half wavelet coefficients of those inputted to the filter, whereas keeping most of the input information. The outputs of the high-pass filters $D^{(n-1)}_{\mathrm{LH},k1,k2}$, $D^{(n-1)}_{\mathrm{HL},k1,k2}$, and $D^{(n-1)}_{\mathrm{HH},k1,k2}$ are three sub-images with the same size as low-pass sub-image, which can present different image details in different directions.

The object image energy is distributed in different subbands, and each subband image nearly keeps a specific frequency component. In other words, each subband image contains one very noteworthy feature. The feature at different subbands can be distinguished more easily than that in the original image. In our recognition scheme, a shape matrix of 64×256 is first split into four 64×64 sub-images. For each 64×64 sub-image, the 2D wavelet transformation is applied, and four wavelet subband images are obtained, namely C_{LL}, D_{LH}, D_{HL}, D_{HH}. Fig. 2 presents the vertical facial detail image, horizontal facial detail image and diagonal detail image.

2. Curvelets via wrapping

Curvelet transform is a multiscale transform. This transform has improved directional capability, better ability to represent edges and other singularities along curves in compare with other traditional multiscale transforms, such as wavelet transform.

(1) Apply 2D FFT and obtain Fourier sam-

ples $\hat{f}[n_1, n_2]$, $-n/2 \le n_1,\ n_2 < n/2$;

(2) For each scale j and angle l, from the product $\widetilde{U}_{j,l}[n_1, n_2]\hat{f}[n_1, n_2]$;

(3) Wrap this product around the origin and obtain

$$\hat{f}_{j,l}\left[n_1, n_2\right] = W\left(\widetilde{U}_{j,l}\hat{f}\right)\left[n_1, n_2\right] \tag{7}$$

where the range n_1 and n_2 is now $0 \le n_1 < L_{1,j}$ and $0 \le n_2 < L_{2,j}$;

(4) Apply the inverse 2D Fast Founer Transform FFT to each $\hat{f}_{j,l}$, hence collecting the discrete coefficients F.

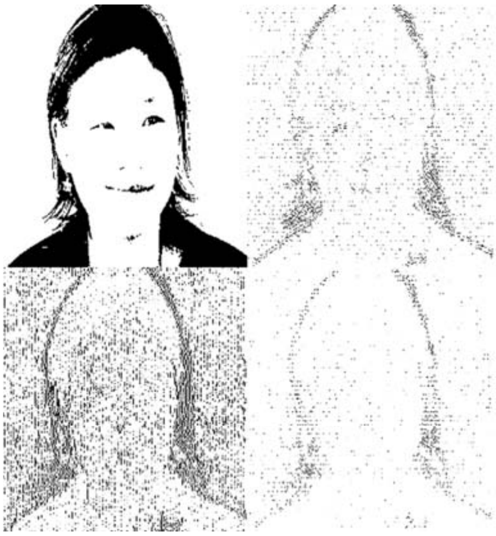

Fig. 2 The horizontal, vertical, and diagonal detail image after wavelet transformation

As shown in Fig. 3, the approximated image of curvelet coefficients at 5 different resolutions from fine to course are given from left to right.

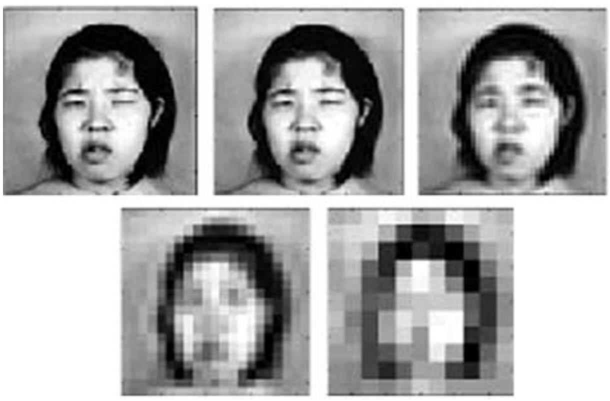

Fig. 3 Approximated curvelet coefficients at 5 different resolutions from fine to course

3. Fractal

We adopt the Differential Box-Counting (DBC) approach for fractal computation. Assume that the image of size $M \times M$ pixels has been scaled down to a size $s \times s$ where s is an integer and $M/2 > s > 1$. Then we know that $r = s/M$. Consider the image in a 3D space with (x, y) denoting 2D position and the third coordinate (z) denoting its gray-level. The (x, y) space is partitioned into grids of size $s \times s$. On each grid there is a column of boxes of size $s \times s \times s$. Let the minimum and maximum gray level of the image in the (ii, jj)-th grid fall in the kk-th and the ll-th box, respectively. Then

$$n_{r(ii,jj)} = ll - kk + 1 \tag{8}$$

is the contribution of N_r in the (ii, jj)-th grid. Then the contributions from all grids can be obtained from

$$N_r = \sum_{ii,jj} n_{r(ii,jj)} \tag{9}$$

The interest region is the union of N_r distinct (non-overlapping) copies of itself scaled up or down by the ratio r. Then the FD is given by

$$\mathrm{FD} = \frac{\log N_r}{\log(1/r)} \tag{10}$$

Therefore, the FD could be estimated as the slope of the least-squares linear regressions of the logarithmic plot of N_r versus $1/r$.

III. Face Recognition

In face recognition, a feature vector contains four components: the horizontal wavelet detail facial box-counting; the vertical wavelet detail facial box-counting, the diagonal wavelet detail facial box-counting, and the curvelet detail facial box-counting. The classifier is as follows. A testing image is identified as one image by a simple Euclidean minimum distance classifier[18].

$$D(q) = \frac{1}{j}\sum_{p=1}^{NN}\left(g_p - g_p^q\right)^2 \tag{11}$$

where g_p is the pth feature vector of the testing image, and g_p^q is the p-th feature vector in the q-th training image in the database, and j is a scale. The minimum distance classifier is simple to implement and works well when the distance between means is large.

IV. Experimental Analysis

We tested the proposed technique on several databases. We will report the experimental results on two well-known datasets. *i.e.* the Japanese Female Facial Expression (JAFFE) database and the Faces94 database. Both databases can be freely downloaded from the internet via the following links: http://www.kasrl.org/jaffe.html; http://cswww.essex.ac.uk/mv/allfaces/faces94.html.

1. Test on JAFFE database

The JAFFE database contains 213 images of 7 facial expressions (6 basic facial expressions and one neutral) posed by 10 Japanese female models. Each image has been rated on 6 emotion adjectives by 60 Japanese subjects. As shown in Fig. 4, the images were taken against a homogeneous background with extreme expression variation, and the image size is of 256×256.

Fig. 4 Some sample images from JAFFE database with different facial expressions

For this database, we downsize the images to 64×64 subimages, and set the training and testing ratio as 9:13. To show statistical robustness of the proposed methods, we adopt the cross validation sampling technique where all recognition rates were determined by averaging 10 different rounds of face recognition. The recognition rate by the proposed technique is given in Tab. 1. As a comparison, we also give the results by other methods listed in Ref. [20]. Clearly, the curvelet-wavelet-fractal technique achieved the highest recognition rate in this test.

2. Test on Faces94 database

The Faces94 database contains images of 153 individuals (both male and female), 20 images per person. The subjects sit at fixed distance from the camera and are asked to speak, whilst a sequence of images is taken. Images are contained in three different folders: male (113 individuals), female (20 individuals) and male staff (20 individuals). Faces of this database show considerable expression changes but very minor variations in lighting or head position. As shown in Fig. 5, the background is plain green, and the image size is of 180×200. We converted the color images into grey-scale for the experiments.

Tab. 1 Recognition accuracy by different methods for JAFFE database

Methods	Recognition rates (%)	Recognition time (s)
Eigenface+k-NN[13]	92.0	9.51
Discriminant eigenface+k-NN[12]	93.5	9.62
Waveletface+k-NN[13]	92.5	9.61
Curveletface+k-NN[13]	94.5	9.44
Discriminant waveletface+k-NN[12]	94.5	9.54
Discriminant waveletface+MLP[12]	94.9	9.43
Curveletface+PCA+k-NN[13]	94.9	9.52
Discriminant waveletface+NFL[12]	95.1	10.30
Discriminant curveletface+k-NN[12]	95.3	9.99
Discriminant waveletface+NFP[12]	95.8	9.77
Discriminant waveletface+NFS[12]	96.1	9.78
Wavelet-curvelet-fractal	98.8	9.51

Fig. 5 Some sample images from Faces94 database with different facial expressions

For this database, we downsize the images to 50×45 subimages, and set the training and testing ratio as 8:12. We implemented the proposed technique and some related methods just as in the first test. The recognition rates by different methods are listed in Tab. 2. We can see that the proposed technique outperformed other algorithms in the test. The reason is that the curvelet-wavelet-fractal technique makes use of facial similarities that exist in the detailed images. Thus higher recognition rate can be achieved.

Tab. 2 Recognition accuracy by different methods for Faces94 database

Methods	Recognition rates (%)	Recognition time (s)
Eigenface+k-NN[13]	93.0	25.99
Discriminant eigenface+k-NN[12]	94.5	28.99
Waveletface+k-NN[13]	93.5	28.14
Curveletface+k-NN[13]	95.5	24.77
Discriminant waveletface+k-NN[12]	95.5	24.53
Discriminant waveletface+MLP[12]	93.9	28.44
Curveletface+PCA+k-NN[13]	93.9	26.57
Discriminant waveletface+NFL[12]	94.1	32.55
Discriminant curveletface +k-NN[12]	92.3	31.45
Discriminant waveletface+NFP[12]	96.9	29.45
Discriminant waveletface+NFS[12]	98.1	29.33
Wavelet-curvelet-fractal	99.0	25.87

V. Conclusions

In this paper, we have proposed a wavelet-curvelet-fractal technique to extract the facial features and applied it to face recognition. The method is based on the similarities preserved by wavelet and curvelet transform. Thus higher recognition rate is achieved compared with other methods. One drawback of the proposed method is heavy computation burden due to the high feature vector dimension. The problem may be solved by face pre-filtering technique.

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