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Improved differential box counting with multi-scale and multi-direction: A new palmprint recognition method

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ABSTRACT

A novel palmprint recognition called improved differential box counting (IDBC) with multi-scale and multi-directional is proposed in this paper. At present, fractal dimension as feature vectors cannot accurately reflect the characteristics of image information, and the algorithm complexity is high. Firstly we set out to improve the method of differential box counting, putting forward fractal characteristics as eigenvector. Next, for effective description of accurate orientations and scale, we combine multi-scale and multi-direction of Gabor and Curvelet with IDBC (GIDBC and CIDBC), further proving that Curvelet is more effective than Gabor for palmprint recognition. Experimental results on PolyU palmprint experiment show that the proposed method can obtain state-of-the-art recognition accuracy (99.78%), reduce algorithm complexity and meet the real-time requirements that time of feature extraction and matching is less than 300 ms.

1. Introduction

Palmprint have basic features, which are unique and unalterable, throughout one's life. It is very stable and not easy to forge. Principal lines and wrinkles also carry rich information for personal authentication and have strong discrimination abilities and anti-interference ability, which can be acquired online with low resolution scanner (about 100 dpi). As a kind of identification method with development potential, it is attracting more and more researchers into the area and gradually becoming the most extensive recognition method after fingerprinting [1–3].

Low-resolution palmprint recognition, which is more suitable for civil and commercial applications, has gradually become the focus of recent research interests. In low-resolution biometric recognition, the information of palm direction is unique and effective. In order to extract good scale and direction information of palmprint. Using the methods of transform frequency domain for image decomposition, such as wavelets, hyper wavelets and so on. Although wavelet transform can get information of different scales and different direction, it is isotropic. After further survey, we introduced new nisotropy multi-resolution systems such Gabor, Contourlet, Curvelet transform, etc. It adds a direction parameter with higher sensitivity, which can effectively express the discontinuity edge and become a new tool of palm efficient expression. Al-Amin Bhuiyan [4] addresses a novel algorithm for face recognition using neural networks trained by Gabor features. Two contributions of this paper are: scaling of rms contrast and introduction of fuzzily skewed filter. The neural network employed for face recognition is based on the multilayer perception (MLP) architecture with backpropagation algorithm and incorporates the convolution filter response of Gabor jet. But with high algorithm complexity, the improvement of recognition rate is limited. Muhammad SHARIF [5] proposed an Elastic Bunch Graph Map (EBGM) algorithm which successfully implements face recognition using Gabor filters. The system used for 5 scale and 8 direction of image filtering, selecting maximum intensity point as reference point to match. However the algorithm of point to point matching speed is slow and not suitable for real-time requirements. Kong et al. [6] and Zhang et al. [7] introduced 2D Gabor filters to extract different time-spatial local texture of palmprint image. Nevertheless, the parameters of Gabor filters are mostly determined by experience, which limits the utility and the outputs of Gabor filters are sensitive to the non-linear distortions and rotations. ZHOU et al. [8] proposed Face Recognition with adaptive local-Gabor features which are based on energy. This approach tries to build local Gabor filter bank according to three factors: different directions, different scales and global energy. The algorithm reduces dimensions of feature vectors but can only improve limited recognition accuracy for it is not sensitive to light and cannot overcome the effects of translation. WANG et al. [9] combine Contourlet Transform with SVM.

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They take advantage of direction choosing in Contourlet, which inherited the multi-resolution and local area of wavelet transform and provided more direction to choose from. Extracting the first-order statistics of high frequency sub-band (mean, value, variance) as image characteristics will lead to palmprint information loss and make it run slower. XU et al. [10] introduced Curvelet and combine it with support vector machine. They treat low frequency coefficient as feature vectors, and take it into the support vector machine. As a result, they not only lose part of palmprint information but also affect the recognition rate.

Although the above multi-resolution and nisotropy can effectively extract the feature information and make correct classification, they cannot avoid large illumination change, a certain position shift and rotation changes. The disadvantage is that it cannot describe the image texture fluctuation in the surface. Because the scale invariance features of fractal dimension [11–13] could better describe the palmprint texture, Feng Xiaohui [14] used the fractal dimension as feature vectors extracted texture features, while comparing local fractal and global fractal algorithms which has proved that local fractal algorithms can easily find the picture of complex area, but local fractal dimension has higher complexity of the algorithm. Zhao Ying [15] presented a method called multi-scale orientation texture feature extraction based on fractal theory. It is a kind of multi-level description of the texture image by adding a scale and direction information to make up for the shortcomings of the fractal dimension. Pan Xin [16] presented a novel efficient palmprint recognition method called contourlets-based local fractal dimensions (CLFD). Although this method is initiated to solve the problem of scale and direction, it really describe the image texture roughness effectively with fractal dimension to obtain an objective recognition rate, the algorithm complexity so high that it cannot meet the real-time requirements.

To solve the above problems, combine advantage of the new nisotropy multi-resolution systems and fractal dimension, we propose a novel palmprint recognition based on improved differential box counting with multi-scale and multi-directional. Firstly, the image is transformed by multi-scale and multi-direction. And in order to obtain better describe palm eigenvector, we improve the algorithm of differential box dimension, using the fractal characteristics of the operator as feature vector and parallel fusion as the final feature vector. Finally, we adopt the chi-square distance to match. The experiment we conducted proved that this algorithm is of high efficiency and good robustness.

The remainder of this paper is organized as following: We introduce the basic theoretical knowledge of Gabor, Curvelet, differential box dimension in part 2; then, in part 3 we propose a novel palmprint recognition based on improved differential box counting with multi-scale and multi-directional; the following part is the place to describe GIDBC and CIDBC algorithm, as well as the experimental results of Gabor, Curvelet. Part 5 shows our conclusion.

2. Related work

2.1. Gabor transform

2D Gabor wavelet [17] can extract image frequency domain information with multi-scale and multi-direction, like a microscope amplifying gray level changes and having certain robustness to light. Using Gabor transform to process palmprint image, some of the key features of it can be enhanced in order to distinguish different palmprint images [18].

2D Gabor wavelet is defined as follows:

$$\psi(k,z)=\frac{||k||^2}{\sigma^2}\exp\left[-\frac{||k||^2||z||^2}{2\sigma^2}\right]\cdot\left[\exp(ikz)-\exp\left[-\frac{\sigma^2}{2}\right]\right] \quad (1)$$

where σ is a constant related to the wavelet frequency band width defining $\sigma=2\pi$, $z=(x,y)$ is space coordinates; k is the direction and scale of the kernel, defining $k_{u,v}=k_v e^{i\varphi_\mu}$, $k_v=k_{\max}/f^v$ is sampling scale and ν is scale; $\phi_u=\pi\mu/n(n\in Z)$ is sampling direction, among μ is direction; $k_{\max}$ is maximum frequency (define $k_{\max}=\pi/2$) and f is kernel interval factor of frequency ($f=\sqrt{2}$).

In the following figure, I is input image and $\psi(k,z)$ is the resultant image of Gabor filter. When the original image with Gabor filter is multiplied, a new image is acquired which is equal to J_k, where x and y is the height and width of the image respectively [19].

$$J_k(z)=I(z)*\psi(k,z) \quad (2)$$

Similar to Fourier transform, the Gabor feature of sample image is plural, can be written as:

$$J_k(z)=Re(J_k(z))+jIm(J_k(z))=A_k e^{i\varphi_k} \quad (3)$$

$$A_k(z)=\sqrt{(Re(J_k(z)))^2+(Im(J_k(z)))^2}$$
$$\varphi_k(z)=\arctan\left(\frac{Im(J_k(z))}{Re(J_k(z))}\right) \quad (4)$$

2.2. Fast Discrete Curvelet Transforms

E.J. Candes and D.L. Donoho developed a new multiscale and multidirection transform which they called the Curvelet transform can provide optimal approaching to curve, especially for the edges with competent handling of curve singularities. At present, it has developed for two generations [20].

Because of the complexity of the digital implementation for the first generation Curvelet transform, the second generation Curvelet transform was proposed. Not only greatly increased calculation efficiency, at the same time also makes Curvelet has a better description of curve characteristic. As wavelet and ridgelet transforms, Curvelet transform also belongs to sparse theory category and continuous Curvelet can be represented as inner product of signal and base functions [21]:

$$c(j,l,k):=\left\langle f,\varphi_{j,l,k}\right\rangle$$

where $\varphi_{j,l,k}$ is Curvelet. j, l and k represent scale, direction and position respectively and Curvelet Implements stand for the frequency domain. By defining two windows called “radial window” and “angular window” at scale j, we can create a window function using parabolic scaling, with wedge support areas refined by “radial window” and “angular window”. The representation of the window function in frequency domain is just the Curvelet at scale j. Since the Curvelet at scale j is known, the Curvelet at scale 2^{-j} can be obtained through rotation and translation.

The second generation Curvelet transform has two digital implementations. One is Digital Curvelet Transform via Unequispaced FFTs, and the other is Digital Curvelet Transform via Wrapping. In this paper, we choose the second one to use.

2.3. Differential box-counting method

The concept of fractal geometry is created by French American mathematician B.B.M and elbrot first proposed in 1975. This theory is one of the most valuable findings of mathematical science in the 20th century. Its founders describe the geometric characteristics of the image and provide a new way. The most common model is ε-blanket model, fractional Brownian motion model and box number approach. Different from various estimation algorithm based on coverage, Box Counting fractal dimension algorithm is not directly measure the surface of the image, but the minimum number of boxes cover the surface of image as a measure. The algorithm since 1986 Gangepain and Roques-Carmes [22] proposed has been widely used because of its simple, but there are also many