Finger vein recognition based on DSST decomposition

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***Abstract*—Among the many biometric recognition techniques, finger vein recognition has many advantages, such as in-vivo recognition, high anti-counterfeiting, high acceptability, and high stability, etc., but the structure of finger vein is simple and the available information is less. The traditional feature extraction method is not fully used to extract finger vein structure information. In this paper, discrete separable shearlet transformation (DSST) are used to extract finger vein features. DSST is used to decompose the image of finger vein, and the decomposition coefficient is obtained and analyzed. The experimental results show that this method can provide an effective and sparse feature description of the original finger vein image, and also obtain a good recognition effect when the quality of some images is poor.**

Keywords- finger vein recognition; DSST; shearlet

I. INTRODUCTION

As a biological feature, finger veins have many advantages: stable, unique, high recognition rate, living, anti-theft, easy to accept. A mainstream method of finger vein feature extraction is based on picture pixel value, such as MHD distance [1], MHD relative distance [1], template feature [2], etc. This type of method is useful, but it doesn't make full use of the information of finger vein structure , Additional, in the process of collecting the finger vein, there is often the disturbance of unstable illumination, which leads to the change of the pixel value of the vein image, which indirectly affects the recognition performance of the algorithm.

The other is based on transforming domain coefficients, the method of feature extraction based on transform domain can capture the frequency, direction and position information of vein image from different decomposition scales, and the most representative of which is wavelet transformation [3] [4]. However, the wavelet transform can only capture the singularity effectively, the direction expression ability is limited, and the ability to capture the singular information of the curve in the image is insufficient. It is necessary to find a feature description method which can best and sparsely express the finger vein image, and the multi-scale geometric analysis (MGA)method can meet this requirement. There are many kinds of MGA method: ridgelet [5][6], curvelet [7], contourlet [8], and shearlet [9], papers on feature extraction based on ridgelet and curvelet refer to [10].

Compared with other MGA methods, shearlet is the latest MGA method [11]. Shearlet have a series of excellent properties, which makes shearlet have a natural advantage in feature extraction.

The specific shearlet method used in this paper is DSST [12] (Discrete Separable Shearlet Transform),which is a discretization method consistent with continuous shearlet proposed by Kittipoom, DSST construction is simple, its discrete implementation is consistent with the theoretical framework of continuous space, and the operation speed is fast, which can meet the general requirements of feature extraction application.

In this paper, we will analyze the composition and characteristics of DSST coefficients and extract the characteristics of finger veins based on DSST.

II. SHEARLET TRANSFORMATION

Wherever Times is specified, Times Roman or Times New Roman may be used. If neither is available on your word processor, please use the font closest in appearance to Times. Avoid using bit-mapped fonts if possible. True-Type 1 or Open Type fonts are preferred. Please embed symbol fonts, as well, for math, etc.

Shearlet transform is based on composite Wavelet theory, for 2-dimentional signal, the affine systems with composite dilations are the collections as follows:

$$M_{AB}(\psi)=\left\{\psi_{i,j,k}\left(x\right)=\left|\det A\right|^{i/2}\psi\left(B^{j}A^{i}x-k\right):i,j\in Z,k\in Z^{2}\right\} \tag{1}$$

Where A , B are the 2*2 invertible matrix, A is anisotropic expansion matrix, B is shearlet transform matrix. ψ is generation function, and $\psi\in L^{2}\left(R^{2}\right)$, for any $\xi=(\xi_1,\xi_2)\in \mathrm{R}^2$, $\xi_1\neq 0$, the Fourier transform of ψ is as follows:

$$\hat{\psi}(\xi)=\hat{\psi}_1(\xi_1)\hat{\psi}_2\left(\frac{\xi_1}{\xi_2}\right) \tag{2}$$

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Where ψ_1 is continuous wavelet which meet the standard wavelet admission condition, and $\hat{\psi}_1 \in C^{\infty}(\mathrm{R})$. ψ_2 is continuous wavelet and meet the condition： $\|\psi_2\|_2 = 1$, $\hat{\psi}_2 \in C^{\infty}(\mathrm{R})$, $\mathrm{supp}\,\hat{\psi}_2 \subset [-1,1]$.If $M_{AB}(\psi)$ is a tight frame, elements in $M_{AB}(\psi)$ can be called synthesized wavelet.

A common feature of common shearlet is that its parent function is band-limited function, which is unbounded in the airspace, resulting in its local properties being affected in the airspace. Ordinary discrete shearlet are not discretized from continuous shearlet in a consistent and natural way, so it is difficult to inherit the excellent mathematical properties of continuous shearlet from the complete. to solve this problem, Kittipoom et al. proposed the construction theory and discrete realization method of separable shearlet. continuous separable shearlet satisfying the multi-resolution analysis (MRA) framework were constructed by introducing the sufficient conditions of constructing shearlet given by Kutyniok et al. Compared with ordinary discrete shear wave, one disadvantage of this method is that although the whole frequency domain can be covered by shear operation and scale operation, the separation efficiency of separable shear wave is not as good as that of ordinary shear wave, and there is overlap between sections. A schematic diagram of the normal shear and DSST sections is shown in Figure 1:

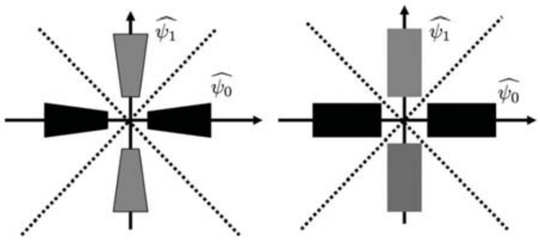


Figure 2. The tiling of General shearlet and DSST

Compared with its disadvantages, the advantages of separable shear wave are also very obvious, and its construction is simpler than that of ordinary shear wave, and it can obtain a consistent discrete realization method from continuous space to discrete space. Because of the support of the separable shear wave to the MRA frame, the discrete realization can introduce fast method and improve the calculation speed.

A special object of this paper is to preprocess the original finger vein image (denoising, region of interest (ROI) extraction, gray-scale normalization, scale normalization) and obtain a specification of 128 × 128 image of the target finger vein. Partial finger vein image is shown in Figure 2:

From the Figure 2, we can see that the image structure of some finger veins is simple, and the effective choroid information is few.

DSST decomposition coefficients of finger veins are analyzed by taking the total number of layers at decomposition scale 5 as an example, as detailed in Table 1

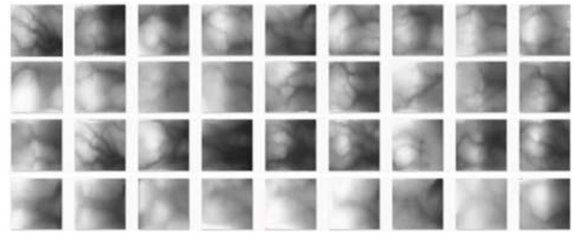


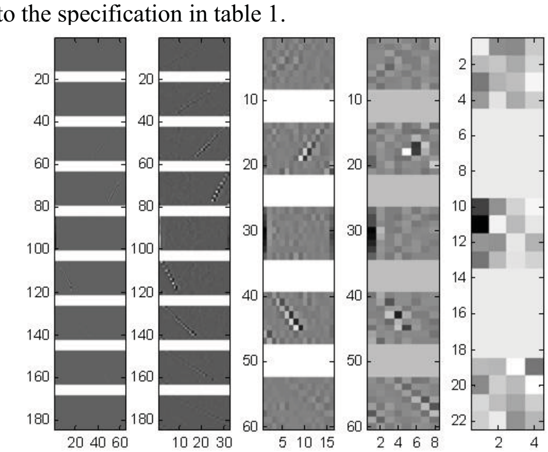
Figure 1. Finger vein image

TABLE I. THE DSST COEFFICIENTS SIZE OF N*N IMAGE

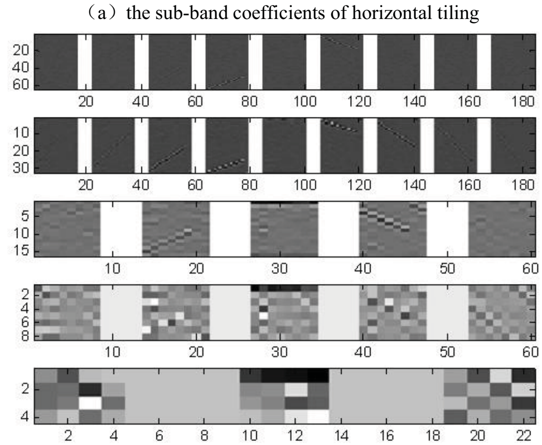
Decomposition scale	Coefficient size
1 scale	4×4×3/4×4×3
2 scal	8×8×5/8×8×5
3 scale	8×16×5/16×8×5
4 scale	16×32×9/32×16×9
5 scale	16×64×9/64×16×9

From the table, we can see that the number of coefficients of DSST decomposition has a certain increase relative to the original image, the size is 128 128 images have 29664 coefficients after 5 layers of scale decomposition, but the DSST coefficients have a strong sparsity, only a few coefficients can be very good reconstruction of the original image.

the following example of a single finger vein image in figure 4(a) gives a schematic diagram of the DSST decomposition sub-band coefficient matrix corresponding to the specification in table 1.



（a）the sub-band coefficients of horizontal tiling



（b）the sub-band coefficients of vertical tiling

Figure 3. The DSST sub-band coefficients of finger vein image

a total of 29664 coefficients of finger vein images of size 128 × 128 after DSST decomposition, only a few of them can reconstruct the original image, that is, the DSST coefficient has sparsity, the amplitude of most coefficients is close to zero, and the amplitude of a small number of coefficients is very large.

III. DSST FEATURE EXTRACTION

A total of 29664 coefficients of finger vein images of size 128 after DSST decomposition. although the number is large, only a few can reconstruct the original image, that is, the DSST coefficient is sparse, the amplitude of most coefficients is close to zero, and the amplitude of a small number of coefficients is very large. All the information of the finger vein is contained in this small part of the large value coefficient, so an intuitive idea is to directly take this small part out as a finger vein feature, but in fact this practice is not feasible, because the decomposition coefficient contains information not only in its amplitude, but also in its position in the coefficient matrix. The position of the coefficient determines which layer scale it belongs to, which sub-band in the direction, and finally the singular information size of the corresponding frequency and corresponding direction is described by its amplitude.

In this paper, the coefficients of all sub-bands are pulled into vectors and connected in series according to the sequence from horizontal cone to vertical cone, from low scale to high scale, along clockwise direction. If each finger vein image is extracted in this fixed order, the position information of the coefficients is reflected in the specific position in the feature vector.

Here is a schematic diagram of two different finger vein images pulled into vectors after DSST decomposition.

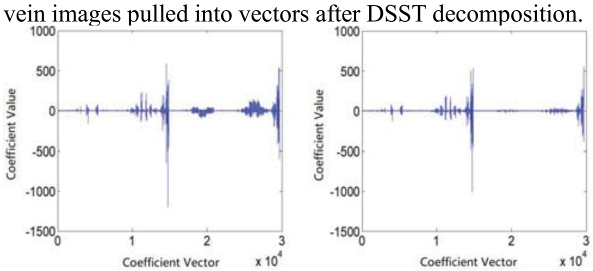


Figure 4. The coefficients vector of finger vein image

the overall structure of the coefficient vector of the two finger vein images is obviously different from that of the observed figure 4. Because of the large dimension of coefficient vector in the graph, it is difficult to distinguish some local differences, but from the recognition rate results of each scale and sub-band in each direction given in Table 2 and Table 3 below, we can see that the structure of each small segment (or each sub-band in each direction) is still very different, even with the coefficient vector of only one sub-band can effectively classify and recognize the finger vein image.

For investigating the effect of the total number of layers in the decomposition scale on the recognition rate, three different strategies for DSST decomposition of the pretreated finger vein images are performed as follows:

(1) The total number of layers in the decomposition scale is 5, and the number of sub-bands in the direction from rough scale to fine scale is 6,10,10,18 and 18, respectively, in which the horizontal cone and the vertical cone are half.

(2) The total number of layers in the decomposition scale is 4, and the number of sub-bands in the direction from rough scale to fine scale is 6,10,10 and 18, respectively, in which the horizontal cone and the vertical cone are half.

(3) The total number of sub-bands is 3, and the number of sub-bands from rough scale to fine scale is 6,10 and 10 respectively. all finger vein images were DSST decomposed according to the above three strategies. all the obtained DSST coefficients were pulled into one-dimensional vectors according to the method described above, and then PCA dimensionality reduction and classification recognition were carried out respectively.

IV. SIMULATION EXPERIMENTS AND RESULTS ANALYSIS

The recognition experiment of this section is 299 people's finger vein images ,5 each, a total of 1495.

The specific methods of the experiment in this section are as follows :3 images of each finger vein are randomly selected for training, the remaining 2 images are used for test recognition ,10 experiments are repeated, and the final report results are taken as the mean of 10 experiments. nearest neighbor classifier is used in classification.

First, the recognition rate of a single DSST coefficient sub-band is calculated to measure the content of characteristic information contained in DSST decomposition coefficients of different scales and directions. Draw the coefficients of each scale and direction sub-bands into vectors and perform PCA dimensionality reduction and classification recognition respectively. The classifier used here is still the nearest neighbor classifier.

it should be noted that there are only 16 sub-band coefficients in each direction of the decomposition scale of layer 1, which do not need PCA dimensionality reduction, and can be directly classified and identified. since the number of sub-bands after DSST decomposition is too many (a total of 62 sub-bands), it is difficult to give one by one the distribution map of recognition rate with the number of PCA retained features, so the best recognition rate results are directly given in table 1. Table 1 is the recognition rate of sub-band coefficients on horizontal cone and Table 2 is the recognition rate of sub-band coefficients on vertical cone.

TABLE II. THE RECOGNITION RATE(%) OF THE SUB-BAND COEFFICIENTS ON HORIZONTAL CONE

Scale	Recognition rate(%)								
1	74.8			82.0			75.8		
2	71.8		77.9		82.9		78.7		72.8
3	58.7		67.8		76.9		73.8		63.7
4	31.1	36.1	45.2	55.8	66.7	57.7	47.4	37.2	34.1
5	21.1	25.1	37.2	47.2	56.8	52.8	41.7	27.1	23.1

TABLE III. THE RECOGNITION RATE(%) OF THE SUB-BAND COEFFICIENTS ON HORIZONTAL CONE

Scale	Recognition rate (%)								
1	62.2			69.8			64.8		
2	61.8		65.7		71.9		66.8		63.8
3	41.2		46.2		56.8		46.9		40.9
4	22.1	29.1	36.2	44.2	47.2	45.2	37.1	30.1	21.2
5	10.0	13.1	27.1	33.1	41.4	34.2	26.1	15.1	13.0

The table 2、3shows:

(1) The sub-band coefficient recognition rate on vertical cone is generally lower than that on horizontal cone. the recognition rate of high-scale sub-band coefficients is lower than that of low-scale. The sub-band coefficient recognition rate of horizontal cone and vertical cone is lower than that of middle cone.

(2) Although the sub-band coefficients on the first scale (the roughest scale) are only 16 dimensions each, their classification recognition rate is very high and they have the characteristics of low dimension and high efficiency. the lower the sub-band coefficient scale in the corner direction, the higher the recognition rate.

Based on the above analysis, the detailed sub band coefficient screening strategies based on 5-layer decomposition and 4-layer decomposition are given:

(1) Five layers of DSST decomposition were performed. the 4th and 5th layer decomposition scales on the horizontal cone only retain the intermediate 3 sub-band coefficients, and all sub-band coefficients of the 1st ,2nd and 3rd layer decomposition scales are all retained; because of the low recognition rate of the vertical cone upper sub-band coefficients, only the intermediate 1 sub-band coefficients are retained for the 4th and 5th layer decomposition scales, and all sub-band coefficients of the 1st ,2nd and 3rd layer decomposition scales are retained.

(2) Four layers of DSST decomposition were performed. the 4th layer decomposition scale on the horizontal cone retains only the intermediate 3 sub-band coefficients, and all sub-band coefficients on the 1st ,2nd and 3rd layer decomposition scales are retained; the 4th layer decomposition scale on the vertical cone retains only the intermediate 1 sub-band coefficients, and all sub-band coefficients on the 1st ,2nd and 3rd layer decomposition scales are retained.

A comparison of the recognition rates of two filter coefficient vectors and three decomposition strategies in the previous section is given below.

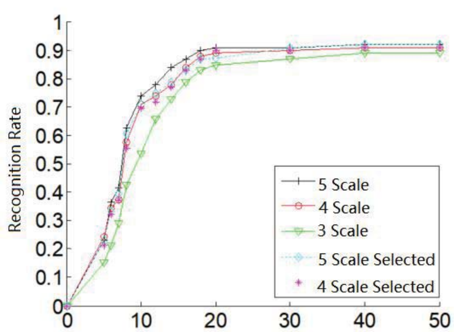


Figure 5. The recognition result comparison of different DSST decomposition strategy and selection strategy

From figure 5, we can see that the feature expression sparse performance of the filtered coefficient feature vector is slightly lower than that of the full coefficient feature vector before screening, but when the number of PCA features retained is more than 30, the recognition rate is equivalent to the coefficient feature vector before screening, and the highest recognition rate is the same as that before screening. i.e., reasonable screening of the DSST decomposition coefficients does not affect the classification recognition results, but the total dimension of the filtered coefficient eigenvectors is significantly reduced. the number of coefficients after screening according to the first strategy is 8160, and the number of coefficients after screening according to the second strategy is 4064. this is mainly because the higher the scale of DSST decomposition, the higher the dimension of sub-band coefficients on each scale, but its recognition rate is getting lower and lower (especially the sub-bands in the direction of edges), so it is reasonable and necessary to screen the coefficient sub-bands of high scale. this is different from the feature extraction method in the last two sections of this chapter, because the dimension of the feature vector based on one-dimensional distribution characteristics and invariant moments does not change with the number of sub-band coefficients.

V. Conclusion

Using the full coefficient value after DSST decomposition of the finger vein as a feature is a direct and effective method. the experimental results also show that the DSST decomposition can provide an effective and sparse feature description for the original finger vein image, but the full coefficient numerical feature vector has the problem of too large dimension. In this paper, the recognition rate of each sub-band coefficient and the information direction inclusion are analyzed one by one, and a reasonable coefficient screening scheme is given, which can effectively reduce the dimension of coefficient characteristics under the premise of ensuring recognition performance.

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