

# Fingerprint Template Matching Algorithm Based on Daubechies Wavelet

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**Abstract:** In this paper, we propose an effective algorithm of fingerprint image template matching based on Daubechies wavelet, which can preserve maximum details of the original image, reflect outline of the image objectively and decrease the FRR. New algorithm based on the multi-resolution analysis of the wavelet transforms. Choosing wavelet base for fingerprint image application must match the requirements of lossless image compression, which is, taking orthogonal wavelet base. Daubuchies wavelet base just meets the requirement. Results demonstrating significant improvements in fingerprint matching accuracy through public fingerprint databases.

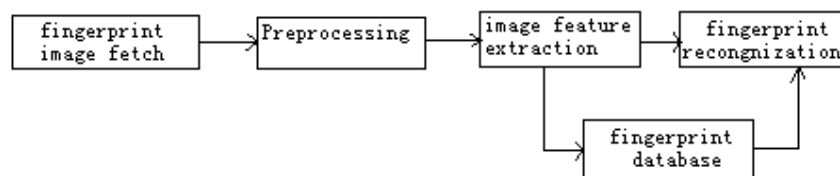
**Keywords:** *Fingerprint, template, Daubechies Wavelet*

## 1、Introduction

Fingerprints have been used for identifying individual widely, obtaining an integrated fingerprint image needs good light condition. During the process of transmission and alteration, the performance of the whole system is reduced owing to the superposition of noise and interference, thus the fingerprint image acquired

takes on many quality problems, including disconnection, drape, illegibility, uneven gray, etc. Signals are often transited through an ideal low-pass-filter (LPF) or an ideal band-pass-filter (BPF), with traditional noise deduction methods by which exists some disadvantage are flattening waveform and losing abrupt information at the same time.

The hotspot of fingerprint image recognition researching is that not only enhancing details, but reducing noise interference to details. The computer-based Automatic Fingerprint Identification System has progressed evidently during past thirty years; Fig1 is a flowchart of AFIS. After considering advantages and disadvantages of the known algorithms, we take fingerprint image matching algorithm based on wavelet decomposition, which can preserve image details in maximum, recover original information precisely, reflect image frame objectively and decrease error refusal rate (ERR).



**Fig1. AFIS Flowchart**

A fingerprint is the pattern of ridges and valleys on the surface of a fingertip. The endpoints and crossing points of ridges are called minutiae. It is a widely accepted assumption that the minutiae pattern of each

finger is unique and does not change during one's life. When human fingerprint experts determine if two fingerprints are from the same finger, the matching degree between two minutiae pattern is one of the most important

factors.

## 2、Filtering Pseudo Characteristic Points Based on Wavelet Transform

### 2、1 Selection of wavelet bases

Some design standards exist for the

selection of optimal wavelet bases due to fingerprint image multi-resolution analysis, including smoothness, approximation, precision, supporting size, filtering frequency selection, etc. All these are very important characteristics.

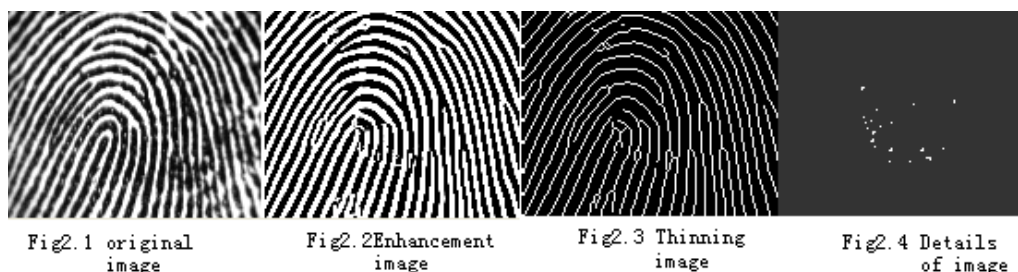


Fig2. Traditional Minutiae Extraction algorithm



Fig3. Wavelet transform based on Daubechies wavelet

Fig2 and Fig3 show traditional details distill method and distill method based on wavelet transform, Fig2.1 is original image, Fig2.2 is enhanced image, Fig2.3 is thinning image and Fig2.4 is details distribution map of the original image. Fig3 shows the decomposition of wavelet based on the Daubechies wavelet.

Selection of wavelet bases should depend on application. An orthogonally normalized or bi-orthogonal base is needed for lossless compression, because it can express original signal accurately and compactly; while choosing a wavelet similar to objective component, if it's detection of specific components such as image edge and reduction of noise. Literatures point out that smoothness of orthogonal bases and

vanishing moments would affect image compression effects, and the effects of smoothness are higher than vanishing moments'. Some literatures also verify bi-orthogonal base that filter length is less than 36 has influence on image compression coding. Convolution computations will increase, as well as distortions of recovering image on explanation of boundary, with increasing filter length, thus we should determine the length of filter properly. In image compression field, we usually take 7/9 bi-orthogonal filter consists of B-spline wavelet base. Choosing wavelet base for fingerprint image application must match the requirements of lossless image compression, which is, taking orthogonal wavelet base. In this paper, we take

Daubuchies wavelet base.

## 2、2 Filtering Pseudo Characteristic Points Based on Human Eye Visual Property

Considering characteristics of fingerprint image, firstly, preprocessing source image, then reducing noise in way of filtering noise point by analyzing and locating it. Distinguishing noise points and details follow such principles:

Noising point has large singularity as well as detail, thus its' energy of fractional aspects is very large;

Owing to they not have very strong directivity for solitary noise points; energy in each direction is widely divergent as well as corresponding high frequency coefficient, whose attribute can be determined by comparing mutual differences.

We may tell noise points from details just through comparing original image's wavelet coefficients, since squared wavelet coefficient equals local direction energy and sub- graph's energy determined in terms of wavelet coefficient. Noise reduction algorithm procedures:

Firstly, make a square window (5\*5) centralized among (i, j) and three sub- graphs decomposed erotically corresponding to three HF directions, then calculate maximums and define respect as  $W_{LH}(i, j)$ ,  $W_{HL}(i, j)$ ,  $W_{HH}(i, j)$ ; Second, compute ratios between coefficients which corresponding to maximums in horizontal and vertical directions of MRI and CT. The ratios must meet below conditions:

□ Small difference between  $W_{LH}(i, j)$  and  $W_{HL}(i, j)$ ,

$$j), |\ln(W_{LH}(i, j)/W_{HL}(i, j))| < 1.5;$$

□ Regarding it as noise point, if ratios between  $W_{LH}(i, j)$  and all coefficients border upon sub-graph (centralized among 3\*3 ) are more than 3.5.

Finally, conduct median filtering on all these coefficients.

## 3 Similarity Calculation of Template Match Based on Iteration Algorithm

The main information of image transformed will concentrate on low frequency components in wavelet transform domain, while noise uniformly on all wavelet coefficients. The critical procedure which directly affects the noise reduction effect is that how to select coefficient in wavelet transform domain, that is, how to limit the threshold value.

The basic principles for template matching are: seraching original image to see whether there exists a template image, and then showing the most similar point's coordinates compared with original image in wavelet-transformed template. Its fundamental is locating the position of the graph searched by correlation function computing.

Assuming template T translated on searched graph S. Subgraph  $S^{ij}$  is the covered part under template, and  $I, j$  ranged from 1 to  $N-M+1$  are the top left corner image point's coordinates in S, which named reference point.

Now comparing T and  $S^{ij}$ , and the subtraction is zero if they are equal, thus may use anyone of following measures to wheigh the similarity:

$$D(i, j) = \sum_{m=1}^M \sum_{n=1}^M [S^{i,j}(m, n) - T(m, n)]^2 \quad (1)$$

or

$$D(i, j) = \sum_{m=1}^M \sum_{n=1}^M [S^{i,j}(m, n) - T(m, n)] \quad (2)$$

Expanding the former, as:

$$D(i, j) = \sum_{m=1}^M \sum_{n=1}^M [S^{i,j}(m, n)]^2 - 2 \sum_{m=1}^M \sum_{n=1}^M S^{i,j}(m, n) \times T(m, n) + \sum_{m=1}^M \sum_{n=1}^M [T(m, n)]^2 \quad (3)$$

The offside third term free from to  $(i,j)$  is a constant, which represents the template's total energy; the first term differing from  $(i,j)$  slowly represents the sub-graph  $(S^{i,j})$ 's energy; the second term varying as  $(i,j)$  is correlation function of sub-graph and template, which gets maximum when  $T$  matches with  $S^{i,j}$ , so we can use following relation function for measuring similarity:

$$R(i,j) = \frac{\sum_{m=1}^M \sum_{n=1}^M S^{i,j}(m,n) \times T(m,n)}{\sum_{m=1}^M \sum_{n=1}^M [S^{i,j}(m,n)]^2} \quad (4)$$

Or normalized to be:

$$R(i,j) = \frac{\sum_{m=1}^M \sum_{n=1}^M S^{i,j}(m,n) \times T(m,n)}{\sqrt{(\sum_{m=1}^M \sum_{n=1}^M [S^{i,j}(m,n)]^2)} \sqrt{(\sum_{m=1}^M \sum_{n=1}^M [T(m,n)]^2)}} \quad (5)$$

Knowing from Schwarz Inequation, the  $R(i,j)$  in Eq.(5) extends from 0 to 1 and gets maximum (equals 1) only when the ratio of  $\frac{S^{i,j}(m,n)}{T(m,n)}$  is a constant. Eq.(5) may be replaced by a more concise partten, Inner-Product. Assuming  $S_1(i,j)$  represents subgraph and  $t$  for modul, instead of Eq.(5),

$$R(i,j) = \frac{t^T S_1(i,j)}{\sqrt{(t^T t)} \sqrt{(S_1^T(i,j) S_1(i,j))}} \quad (6)$$

When the angle between  $t$  and  $S_1$  is zero degree, that is,  $S_1(i,j)=kt$ ,  $R(i,j)=1$ ; otherwise,  $R(i,j)<1$ . As correlation calculation must be operated on as many as  $N-M+1$  reference points, computation of using correlation method of matching may be strong and all the work conducted on non-matching points is vain except for one. We take sequential similarity detection algorithm (SSDA) in the text. Its main points are as following:

(1) Defining absolute error as:

$$\mathcal{E}(i,j,m_k,n_k) = S^{ij}(m_k,n_k) - \hat{S}(i,j) - T(m_k,n_k) + \hat{T} \quad (7)$$

Where,

$$\hat{S}(i,j) = \frac{1}{M^2} \sum_{m=1}^M \sum_{n=1}^M S^{i,j}(m,n) \quad (8)$$

$$\hat{T}(i,j) = \frac{1}{M^2} \sum_{m=1}^M \sum_{n=1}^M T(m,n) \quad (9)$$

(2) Discarding some non-matching points, for it up to the threshold value after less calculation with a monotone increasing threshold sequence, while it will meet the threshold value after many times error accumulation at real matching points.

(3) Choosing image points randomly in subimage. Calculating the error  $\mathcal{E}$  corresponding to the point in  $T$ , then accumulating all the error value and stopping if the total error exceeds  $T_k$  after  $r$  times accumulation, writing down the times  $r$ . Defining the detected curved surface as:

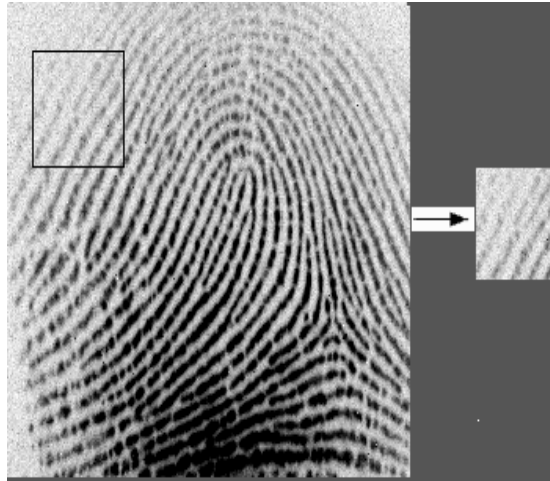
$$I(i,j) = \{r \mid \min_{1 \leq r \leq m^2} [\sum_{k=1}^r \mathcal{E}(i,j,m_k,n_k)] \geq T_k\} \quad (10)$$

(4) Considering relatively maxier  $I(i,j)$  as matching point  $(i,j)$ , because the total error  $\sum \mathcal{E}$  of this point will exceed  $T_k$  only after many times accumulation. There is no need to choosing priority of all the  $N-M+1$  reference points point-by-point, that is, it doesn't have to consider each point. Taking Coarse and Fine uniformly Searching Method for example, in other word, detecting matching degree per 5 points, and then matching the reference points inside the partial scope where the point gets extreme maximum value. Whether this method will not lose real matching points or not, it partly depends on the smoothness and the unimodality of the surface  $I(i,j)$ .

#### 4. Experimental results

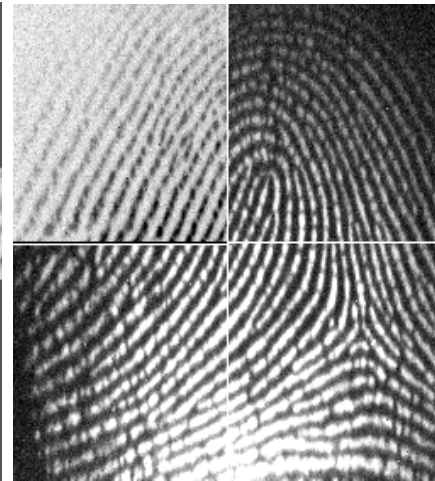
In order to confirm the effectiveness of our proposed fingerprint template matching algorithm, we carried out experiments as follows. All experiments discussed in this paper are conducted on databases from fingerprint databases used in the Fingerprint Verification

Competition FVC2000 and FVC2002, respectively. Fig4 is a schematic diagram of the proposed algorithm in this paper, Fig4.1 shows select template from an original image, size of the template is in the range of less than a quarter of the original image, aim of this step is to



**Fig4.1 Select template**

simulate a database of the fingerprint fragmentation, the followed is to separate the original image into 4 parts just as Fig4.2 and calculate the correlation between the template and 4 parts of the original image, compared with results, we will find the similarity region.



**Fig4.2 Find the region of the template**

**Fig4. Template matching**

## 5. Conclusion

The conducted testing of a novel fingerprint template matching based on Daubechies wavelet shows good correspondence to the fingerprint identification. The usefulness of this approach was confirmed in the experiments conducted here, which reveals that the identification results are encouraging and our approach is promising. We project to overcome the strong local or global deformations and to propose a distributed matching algorithm for the minutiae texture maps extraction to improve the computation times of our matching approach.

## References

- [1] Jianjiang Feng, Zhengyu Ouyang, "Fingerprint matching using ridges", *Pattern Recognition*, Volume 39, Issue 11, November 2006, Pages 2131-2140.
- [2] F. Benhamadi, M.N. Amirouche, "Fingerprint matching from minutiae texture maps", *Pattern Recognition*, Volume 40, Issue 1, January 2007, Pages 189-197.
- [3] V.J. Law, N. Macgearailt, P. Cunningham "Frequency domain reflectometry of plasma chambers", *Vacuum*, Volume 81, Issue 8, 30 March 2007, Pages 958-968.
- [4] Xuchu Wang, Jianwei Li, "Fingerprint matching using Orientation Codes and PolyLines", *Pattern Recognition*, Volume 40, Issue 11, November 2007, Pages 3164-3177.
- [5] Loris Nanni, Alessandra Lumini, "A hybrid wavelet-based fingerprint matcher", *Pattern Recognition*, Volume 40, Issue 11, November 2007, Pages 3146-3151.
- [6] You Lin, Xu Maozhi, Zheng Zhimin, "Digital signature systems based on smart card and fingerprint feature", *Journal of Systems Engineering and Electronics*, Volume 18, Issue 4, December 2007, Pages 825-834.
- [7] Jianjiang Feng, "Combining minutiae descriptors for fingerprint matching", *Pattern Recognition*, Volume 41, Issue 1, January 2008, Pages 342-352.
- [8] Xifeng Tong, Songbo Liu, Jianhua Huang, Xianglong Tang, "Local relative location error descriptor-based fingerprint minutiae matching", *Pattern Recognition Letters*, Volume 29, Issue 3, 1 February 2008, Pages 286-294.
- [9] Yuliang He, Jie Tian, Xiping Luo, Tanghui Zhang, "Image enhancement and minutiae matching in fingerprint verification", *Pattern Recognition Letters*, Volume 24, Issues 9-10, June 2003, Pages 1349-1360.