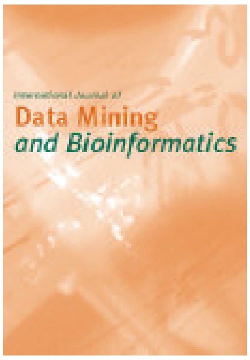

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A high precision recognition method for small area fingerprints based on machine vision

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Abstract: Aiming at the problem that the traditional small-area fingerprint recognition method is insufficient to recognise the feature points in the boundary region and the recognition accuracy is low, a high-precision small-area fingerprint recognition method based on machine vision is proposed. Firstly, by analysing the estimated values of key fingerprint parameters, Tico descriptor is introduced to obtain detailed feature points and determine the frequency field. Then, the fingerprint image of small area is enhanced based on direction and frequency to make the image features clearer. Then, based on the enhanced fingerprint image, the fingerprint model is demodulated by a suitable two-dimensional signal, the detailed features of the small-area fingerprint image are extracted, and the direction vector Angle is doubled to achieve direction smoothing, so as to achieve a better feature representation. Finally, high-precision identification of small area fingerprints is realised by matching the fingerprint point set. The experimental results show that the method proposed in this paper can extract the detailed features of small-area fingerprint images more accurately, the recognition results are more accurate, and the average recognition time is 32.6 s, which can improve the recognition efficiency, and has certain advantages.

Keywords: small area; fingerprints; high-precision; distinguish; machine vision; direction; frequency.

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1 Introduction

Fingerprints remain unchanged throughout everyone's lifetime, and this feature has been applied as a reliable means of identity recognition since ancient times. With the development of the times, various information scenarios are widely used, especially during the current epidemic period, the importance of fingerprints for identity authentication is self-evident. In the rapidly developing era of network information, people have various identification passwords, such as smart door locks, digital unlocking of mobile phones and computers, fingerprint unlocking, etc. (Qin et al., 2021a; Lamoureux and Chelouah, 2021), and each type of authentication requires a corresponding key. With the improvement of people's quality of life, security and privacy have gradually become issues of concern. In recent years, people have begun to pay attention to the security of biometric technology, without the need to worry about memorising various digital passwords. Compared to traditional identity verification methods, utilising unique features of the human body such as face, fingerprint (Liu et al., 2020), DNA, gait, and infrared thermogram for identity recognition has advantages such as good convenience and security. Fingerprint recognition not only has convenient and reliable advantages for every individual of us, but also has immeasurable value for national information security.

Liu et al. (2022) proposed a method of RF fingerprint recognition based on convolutional neural networks. The method firstly collects RF signal sample data, and then pre-processes the collected data to extract relevant features and reduce the influence of noise. Finally, convolutional neural network is used to identify, calculate the loss function and optimise the weight of the model to minimise the prediction error. In summary, RF fingerprint recognition under dynamic SNR is realised. This method improves the recognition accuracy under low SNR, but its recognition efficiency is poor. In Xie and Deng (2022), an RF fingerprint recognition method based on a signal bispectrum and improved residual neural network (ResNet) was proposed. First of all, the collected signals of different devices were transformed by bispectral transformation to obtain bispectral contour maps and marked with device labels. Then, the established improved ResNet model was used to train the bispectral contour maps, and the network weights were updated through back propagation (BP) and gradient descent to obtain the optimal model and realise the RF fingerprint classification and recognition. However, the feature extraction effect of this method is poor, resulting in low accuracy of fingerprint recognition. Liang and Xu (2022) proposes a fingerprint recognition method based on two-dimensional code and chaotic encryption technology. The method combines two-dimensional code technology, chaotic encryption technology and fingerprint recognition technology, and uses improved feature extraction algorithm and image encryption algorithm to extract fingerprint features after fingerprint pre-processing by using a 4 × 4 template search extraction method. Then the image encryption algorithm based on Logistic mapping and Sine-sine mapping is used to encrypt the image and generate the two-dimensional code. First scan the QR code, then decrypt the image, and finally compare the fingerprint to complete the fingerprint recognition. Although this method can effectively improve the accuracy of recognition, the calculation complexity of this method leads to poor recognition efficiency.

However, due to the need for high-quality fingerprints and artificial feature Settings, the above fingerprint recognition methods are not enough in the current big data society, and are limited by feature factors, and there are problems such as incomplete identification of feature points and poor identification efficiency. Therefore, a high-precision fingerprint recognition method based on machine vision is proposed. The machine vision can extract and match the fingerprint image with high precision, and accurately identify and compare the fine features of the fingerprint, so as to achieve high-precision fingerprint recognition. Firstly, by analysing the estimates of key fingerprint parameters, Tico descriptor is introduced to obtain detailed feature points and determine frequency fields, so as to better distinguish and identify the differences between different fingerprints and improve the accuracy of fingerprint recognition. And help to determine the region of interest, reduce the time of processing the entire image, thus reducing the computational complexity, improve the speed of subsequent recognition; Then, based on the enhanced fingerprint image, a suitable two-dimensional signal is used to demodulate the fingerprint model, extract the detailed features of the small-area fingerprint image, and the direction vector Angle doubling method is used to achieve direction smoothing, so as to achieve a better feature representation, breaking the limitation of feature factors. Finally, high-precision identification of small area fingerprints is realised by matching the fingerprint point set. The feasibility of small area fingerprint recognition is explored, which provides an important scientific basis for the further development of fingerprint recognition technology.

2 Fingerprint key parameter estimation

Due to the drastic changes in the direction of singular areas in small area fingerprint images captured by machine vision, there is a discontinuity in the direction between the middle part of the fingerprint and adjacent blocks (Almajmaie et al., 2019), resulting in the inability to obtain rectangular windows and unreliable ridge frequency in this area. Therefore, in order to improve the processing effect of subsequent fingerprint images, this problem needs to be solved next. To effectively address this problem, the direction and frequency of the sub blocks are first obtained in the frequency domain, and then the direction and frequency fields are obtained, without considering the degree of dependency between them.

Step 1 Calculation of block direction and block frequency

Perform short time Fourier transform on small area fingerprint image sub blocks to convert them into frequency domain space. For convenience, convert the frequency domain coordinate $F(u, v)$ to the unit table area $F(r, \theta)$ using the following formula:

$$r = \sqrt{u^2 + v^2} \tag{1}$$

$$\theta = \arctan\left(\frac{u}{v}\right) \tag{2}$$

Among them, r and θ are the distance and direction relative to the centre of the circle in the frequency domain, respectively. Due to the local similarity of small area fingerprint images to normal waves, the distance between highlights in the frequency domain image represents the ridge frequency of the fingerprint, while the direction perpendicular to the connecting point line is the direction of the ridge.

In an ideal scenario, it is assumed that the dominant frequency component of the highlight in the frequency domain image is the signal component where the fingerprint is located. However, in reality, only the local parts of a small area fingerprint image can be regarded as periodic signals (Sui, 2019), and the overall signal is not a periodic signal. There is a certain error between it and the true periodic signal, especially for small area fingerprint images, which are affected by factors such as wrinkles, scars, and stains on the finger skin of the fingerprint collector and can generate significant noise (Qin et al., 2021b). This will disperse the energy that forms bright spots and even cause other interference components. To solve this problem, a method based on probability analysis is proposed to obtain the principal components in the frequency domain graph. The specific calculation is as follows:

$$O(x, y) = \frac{1}{2}\tan^{-1}\left\{\frac{\int_\theta |F(r,\theta)|^2 \sin(2\theta)d\theta}{\int_\theta |F(r,\theta)|^2 \, cos(2\theta)d\theta}\right\} \tag{3}$$

$$F(x, y) = \int_\theta |F(x, y)|^2 \, rdr \Big/ \int_\theta |F(x, y)|^2 \, dr \tag{4}$$

Among them, $O(x, y)$ is the size of the block direction field, $F(x, \mathrm{y})$ is the size of the block frequency field, and $F(r, \theta)$ is the size of the frequency domain value of point (r, θ) on polar coordinates.

The second step is to calculate the directional and frequency fields.

It is inaccurate to directly use the obtained block direction and block frequency as the direction and frequency fields of small area fingerprint images. Moreover, the process of obtaining block direction and block frequency is based on estimating the local area of the fingerprint as a periodic sine wave, which inherently has certain errors. The reason is that there is a lot of noise and the possibility of information loss in the small scale fingerprint image, which will lead to certain errors (Chen et al., 2019). Due to the regularity of the ridge distribution of fingerprints and the consistency of the direction and frequency of surrounding blocks, a method for optimising the direction length and frequency field of small area fingerprint images using neighbourhood feature information is proposed based on the characteristics of the ridge and the problems with the block direction and frequency mentioned above.

According to the continuity between adjacent block directions, the direction field of small area fingerprint is calculated and smoothed by Gaussian filter. The specific steps are as follows:

1 The block direction is expressed in the form of a double angle:

$$h(x, y) = \sin\left(2O(x, y)\right) \tag{5}$$

$$k(x, y) = \cos\left(2O(x, y)\right) \tag{6}$$

2 Use low-pass Gaussian operator to smooth filter the direction of each small block, and the specific calculation is as follows:

$$O'(x, y) = \frac{1}{2}\left\{\arctan\frac{\sum_{u}^{y} h(u, v) * G(u, v)}{\sum_{u}^{y} k(u, v) * G(u, v)}\right\} \tag{7}$$

Among them, $O'(x, y)$ represents the block direction after smooth filtering, and $G(u, v)$ represents the low-pass Gaussian operator. The local direction continuity in the smooth fingerprint direction field is relatively strong, which is closer to the true direction of the fingerprint ridge line.

In summary, the estimation of fingerprint key parameters provides key information for the subsequent fingerprint image processing, so as to effectively improve the processing effect.

3 Small area fingerprint image processing

Next, in order to improve the efficiency and accuracy of subsequent fingerprint recognition, after the above estimation of fingerprint key parameters, it is necessary to further study the extraction of small-area fingerprint direction field descriptor and the estimation of frequency field. Its purpose is to extract the characteristic information such as the direction and frequency of the fingerprint lines to better distinguish and identify the differences between different fingerprints and improve the accuracy of fingerprint recognition. And help to determine the area of interest, reduce the time of processing the entire image, thus reducing the computational complexity, improve the speed of subsequent recognition.

3.1 Extraction of small area fingerprint direction field descriptors

At present, there are many methods for extracting fingerprint direction fields, mainly using Tico direction field descriptors based on a certain fine node combined with surrounding detail information. In this study, Tico descriptors were used to obtain small area fingerprint directional fields (Xu et al., 2019), and the construction steps of their directional field descriptors were introduced based on the detail feature point a:

1 The Tico descriptor for obtaining small area fingerprint detail feature points is:

$$f = \left\{\lambda\left(\theta_{k,l}\right), \theta_{k-1}^{K_l}\right\}_{l-1}^{L} \tag{8}$$

In the formula, $\theta_{k,l}$ represents the direction angle of sampling point $P_{k,l}$, $\lambda(\theta_{k,l}, \theta)$ represents the angle of direction angle $\theta_{k,l}$ relative to $\theta_{k,l}$, and is the minimum direction field difference between the counterclockwise rotation of the sampling point direction field and the direction field parallel to the detail feature point direction field.

2 Find the relationship between the directional fields of detail feature points: The following is an example of calculating the relationship between the directional fields based on two detail points a, b, and the corresponding directional fields $f(a) = \{\alpha, k, l\}$ and $f(b) = \{\beta, k, l\}$ as detail points. The calculation formula is:

$$\wedge(\alpha,\beta) = \frac{2}{\pi}\min\{\lambda(\alpha,\beta), \lambda(\beta,\alpha)\} \tag{9}$$

In the equation, $\wedge(\alpha, \beta)$ represents the angle between angle α and angle β, with a range of [0, 1]. When the value is 0, it indicates that the two directions are parallel to each other, and when the value is 1, it indicates that the two directions are perpendicular to each other.

3 Calculate the similarity of the angles of detail feature points: Use a and b to represent any two detail feature points in two different small area fingerprint images, and calculate the similarity of the angles between the two detail points according to the following equation:

$$S(a,b) = \frac{1}{K}\sum_{l=1}^{L}\sum_{k=1}^{K} s\left(x_{k,l}\right) \tag{10}$$

$$K = \sum_{l=1}^{L} K_l \tag{11}$$

$$s(x) = e^{-16x} \tag{12}$$

In the formula, $S(a, b)$ is the similarity value between two detail points a, b, and a larger $s(x)$ indicates a greater degree of similarity in angles.

4 Calculate the probability function and obtain the similarity probability values between two detail points a and b according to the following equation:

$$P(a,b) = \frac{S(a,b)^2}{\sum_{i=1}^{N} S(a,b_j) + \sum_{j=1}^{M} S(a,b_j) - S(a,b)} \tag{13}$$

In the equation, L = 4, M = [27, 45, 63, 81].

3.2 Estimation of frequency field

Because the ridge of a small area fingerprint is generally hierarchical (Kaur and Pannu, 2019), and the gray value of the pixel points of the ridge and valley line can be roughly regarded as a sine wave function when viewed along the trend of the ridge. Assuming that the frequency of the ridge is equal to the frequency of the wave function (Kaur et al., 2019), the steps of calculating the frequency field of the fingerprint are as follows:

Firstly, calculate the direction angle $\theta(a, b)$ of the centre pixel position in a sub block, take the ridge direction where the pixel is located as the width, and draw A × B's rectangular window.

Secondly, the amplitude value of the directional angle can be calculated using the following equation.

$$M(k) = \frac{1}{S}\sum_{d=0}^{S-1} N(u,v), k = 0,1,...,N-1 \tag{14}$$

$$u = a + \left(d - \frac{S}{2}\right)\cos\theta(a,b) + \left(k - \frac{N}{2}\right)\sin\theta(a,b) \tag{15}$$

$$v = a + \left(d - \frac{S}{2}\right)\sin\theta(a,b) - \left(k - \frac{N}{2}\right)\cos\theta(a,b) \tag{16}$$

Then, according to the above equation, $M(k)$ is a discrete sine wave. Assuming there are continuous peaks in this sine wave, it can be proven that the fingerprint information contained in this window is valid. The distance between adjacent peaks is h_a, and the average distance between ridges is L, then the frequency is:

$$L_a = \frac{h_a}{i-1}, i = 2,3,...,k \tag{17}$$

$$L = \frac{1}{m}\sum_{a=2}^{k} L_a \tag{18}$$

4 High precision identification methods for small area fingerprints

4.1 Small area fingerprint image enhancement based on direction and frequency

After the above processing, in order to improve the quality, clarity and readability of fingerprint images, make subsequent feature extraction more comprehensive, and improve the performance of fingerprint recognition, small area fingerprint image enhancement based on direction and frequency is carried out. Directional filters can achieve good resolution in both the time and frequency domains, and have good enhancement effects on small area fingerprint images. The function expression is as follows:

$$h(x,y,\varphi,f) = \exp\left\{-\frac{1}{2}\left[\frac{x_\Psi^2}{\sigma_x^2}\frac{y_\Psi^2}{\sigma_y^2}\right]\right\}\cos(2\pi fx\varphi) \tag{19}$$

$$x_\varphi = x\cos\varphi + y\sin\varphi \tag{20}$$

$$y_\varphi = -x\sin\varphi + y\cos\varphi \tag{21}$$

In the formula, φ is the direction, f is the centre frequency, and σ_x^2 and σ_y^2 are the standard deviations of the envelope of the directional filter function in the x and y directions, which are generally set as fixed values.

From the above formula, it can be seen that the main components of the directional filter function are:

$$g(x,y,\varphi,f) = \exp-\frac{1}{2}\left[\frac{x_\psi^2}{\sigma_x^2} + \frac{y_\psi^2}{\sigma_y^2}\right] \tag{22}$$

This formula is the expression of the two-dimensional Gaussian filter function, so the directional filter function is essentially the modulation function of the two-dimensional Gaussian filter function.

The frequency domain characteristics of the directional filter function can be determined by its modulation transfer function, and the enhanced frequency domain expression is:

$$H(u,v,\varphi,f) = 2\pi\delta_x\delta_y \exp\left\{-\frac{1}{2}\left[\frac{(u_{?}-u_0)^2}{\delta_u^2} + \frac{(v_\varphi - v_0)^2}{\delta_v^2}\right]\right\} \tag{23}$$

It can be seen from the above formula that the small area fingerprint image can be directionally filtered by moving the frequency response of the two-dimensional Gaussian filter function on the spectrum using the two norms of direction and frequency of the small area fingerprint image obtained by the short-time Fourier transform.

4.2 Minutiae feature extraction of small area fingerprint images

Then, based on the enhanced fingerprint image, detailed feature extraction is expanded to provide more comprehensive information support for subsequent matching recognition, so as to improve the accuracy of recognition. The specific extraction process is as follows: Firstly, a suitable two-dimensional signal is used to demodulate the fingerprint model; secondly, in order to improve the effectiveness of feature extraction and avoid the influence of translation and rotation in the collection process, the small-area fingerprint signal is analysed and processed in the frequency domain to obtain the direction and phase information of the small-area fingerprint signal. The initial characteristics of small area fingerprint signal are obtained. Finally, in order to avoid direction vector elimination caused by Angle average, the method of direction vector Angle doubling is used to set the smoothing window to achieve direction smoothing, so as to better feature representation and improve subsequent matching performance, so as to improve the accuracy of recognition. Thus, the detail feature extraction of small area fingerprint image is realised.

Due to the fact that the small area fingerprint signal is two-dimensional, the Ritz transform suitable for two-dimensional signal demodulation is used to demodulate it. It can be represented as $r(x, y) = [r_1(x, y), r_2(x, y)]$ in two-dimensional space, and the corresponding conversion function is $h(x, y) = [h_1(x, y), h_2(x, y)]$.

$$h_1(x,y) = \frac{x}{2\pi(x^2+y^2)^{\frac{3}{2}}} \tag{24}$$

$$h_2(x,y) \frac{y}{2\pi(x^2+y^2)^{\frac{3}{2}}} \tag{25}$$

In the equation, x and y represent the horizontal and vertical coordinates in two-dimensional space, respectively. The expression of the constructed two-dimensional Analytic signal is:

$$f_g(x,y) = g(x,y) + (i,j)\left[r_1(x,y), r_2(x,y)\right] \tag{26}$$

Small area fingerprint images are inevitably affected by translation and rotation during the collection process, leading to deformation and the introduction of pseudo fine nodes. Therefore, analysing and processing small area fingerprint signals in the frequency domain can improve the effectiveness of feature extraction. The specific methods are as follows:

1 Convert the small area fingerprint signal $g(x, y)$ and conversion functions $h_1(x, y)$ and $h_2(x, y)$ in the time domain into the frequency domain, and after conversion, they can be represented as $G(u, v)$, $H_1(u, v)$, and $H_2(u, v)$ respectively:

$$H_1(u,v) = \frac{ui}{\sqrt{u^2 + v^2}} \tag{27}$$

$$H_2(u,v) = \frac{vi}{\sqrt{u^2 + v^2}} \tag{28}$$

In the formula, u and v respectively represent the horizontal and vertical coordinates in the frequency domain.

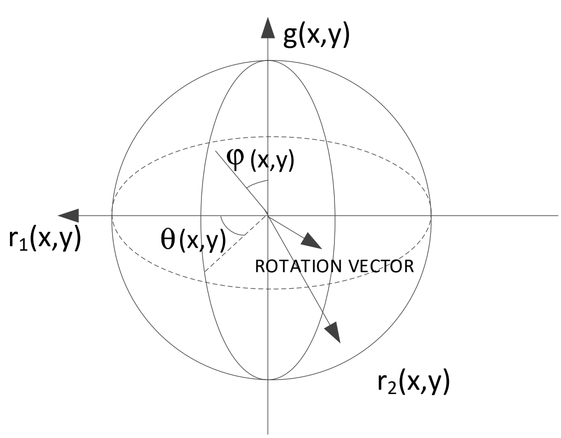
2 Multiply the above conversion function $[H_1(u, v), H_2(u, v)]$ and $G(u, v)$ to obtain the following expression:

$$R(u,v) = \left[H_1(u,v), H_2(u,v)\right]G(u,v) \tag{29}$$

3 Since the two-dimensional Analytic signal of the small area fingerprint signal is constructed in the time domain, $r(x, y) = [r_1(x, y), r_2(x, y)]$ can be obtained by inverse Fourier transform of the formula. Thus, the three components $[g(x, y), r_1(x, y), r_2(x, y)]$ of the two-dimensional Analytic signal are obtained, and their expressions in the spherical coordinate system are shown in Figure 1.

Analytic signal is a complex signal containing real function and Virtual function. Its value at any (x, y) is obtained by rotating a small area fingerprint signal in the complex space. The rotation vector can be represented by the phase vector of the fingerprint signal.

Figure 1 Spherical coordinate system



According to Figure 1, the three components obtained through analysis are:

$$g(x, y) = b(x, y)\cos[\varphi(x, y)] \tag{30}$$

$$r_1(x, y) = b(x, y)\sin[\varphi(x, y)]\cos[\varphi(x, y)] \tag{31}$$

$$r_2(x, y) = b(x, y)\sin[\varphi(x, y)]\sin[\varphi(x, y)] \tag{32}$$

Analogous to one-dimensional Analytic signal, the amplitude of small area fingerprint signal can be expressed as:

$$b(x, y) = \sqrt{g^2(x, y) + r_1(x, y) + r_2(x, y)} \tag{33}$$

Therefore, it can be concluded that the fingerprint signal containing only small area fingerprint phase features is:

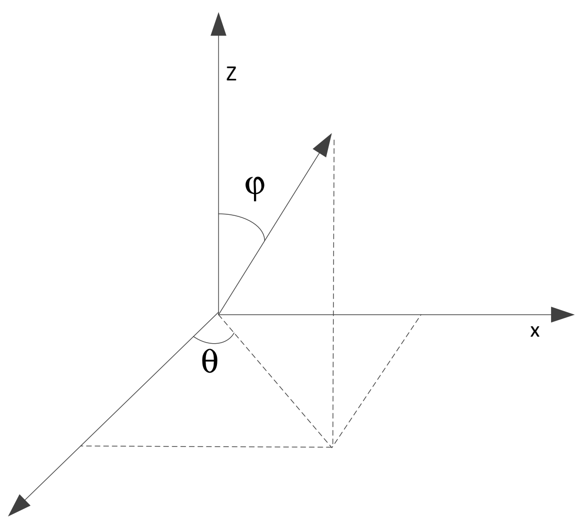
$$q(x, y) = \cos[\varphi(x, y)] \tag{34}$$

By comprehensively analysing the above equations, it can be concluded that:

$$\theta(x, y) = tan^{-1}\left(\frac{r_2(x, y)}{r_1(x, y)}\right) \tag{35}$$

In Figure 1, $\theta(x, y)$ and $\varphi(x, y)$ represent the direction information and phase information of the small area fingerprint signal, respectively. Their relationship is shown in Figure 2, so $\varphi(x, y)$ can be determined based on $\theta(x, y)$.

Figure 2 Relationship between φ and θ of small area fingerprint signals



$$\varphi(x, y) = tan^{-1}\left(\frac{q(x, y)}{\frac{r_1(x, y)}{r_2(x, y)}}\right) \tag{36}$$

At this point, the obtained $\theta(x, y)$ is the initial feature of the small area fingerprint signal.

Due to the spiral shape of the pixels at the small area fingerprint detail points, the direction is $[0, 2\pi)$, but the range of the direction field is $[0, \pi)$, that is, θ and $\theta + \pi$ are in the same direction as the ridge line. To avoid directional vector cancellation caused by angle averaging, this article uses the method of doubling the directional vector angle, setting the smoothing window W to 18 * 18, and then achieving directional smoothing according to the following expression.

$$\vec{d} = [r \cdot \cos(2\theta), \sin(2\theta)] \tag{37}$$

$$\vec{k} = \left[\frac{1}{n^2}\sum_{w=0}^{M} r \cdot cos(2\theta), \frac{1}{n^2}\sum_{w=0}^{M} r \cdot sin(2\theta)\right] \tag{38}$$

Among them, r is proportional to the intensity of direction estimation, $\vec{d}$ is the direction vector, $\vec{k}$ is the average angle within the neighbourhood, and the set of average angles within the neighbourhood constitutes the direction field of small area fingerprints.

Based on other pixels within the eighth neighbourhood of the pixel where the fine node is located, the shape of the pixel in the phase field is calculated using the knight. When $\varepsilon(x, y) = 2\pi$ or -2π, it is considered that the pixel is located at the fine node, presenting a positive spiral shape and a negative spiral shape, respectively.

$$\varepsilon(x, y) = \sum_{i=0}^{l} \Gamma\left(\Phi_{(i+1)mods}, \Phi_i\right) \tag{39}$$

$$\Gamma\left(\Phi_a, \Phi_b\right) = \left(\Phi_a - \Phi_b + \pi\right) mod 2\pi - \pi \tag{40}$$

4.3 Fingerprint point set matching

By analysing the detailed features of the small-area fingerprint images extracted by the above numbers, it can be concluded that the feature types of the feature points in the boundary region of the small-area fingerprint include positive spiral shape and negative spiral shape. Next, in order to ensure the accuracy of the recognition results, fingerprint point set matching is carried out on the basis of the above characteristic point types. Set the template small area fingerprint details as $T = (m_1, m_2, ..., m_m)$, where $m_i = \{x_i, y_i, \theta_i\}$, $i = 1, ..., m$, and m represent the total number of small area fingerprint details in the template. Enter the fingerprint detail point $I = \left(m_1', m_2', ..., m_m'\right)$, where $m_j' = \left\{x_j', y_j', \theta_j'\right\}$. Form (m_i, m'_j) into a pair of detail points, calculate the difference in position information and direction information between the two, which is the detail point calibration amount, denoted as $(\Delta x^+, \Delta y^+, \Delta\theta^+)$. The specific steps are as follows:

First, first calculate the direction difference $\Delta\theta$ between the pairs of detail points, and then approximate it to the discretisation angle θ^+. At this time, two problems should be noted:

1 The error problem of direction difference: The direction range of the detail point is [0360], so that n represents the degree of discretisation. There are two methods for calculating the direction difference. One is to discretisation the direction angle first, and then calculate the difference, that is, $\theta^+ = round(\theta_i/n) - round(\theta'_i/n)$. This method discretisation θ_i and θ_j respectively, which is easy to cause two units of error, thus increasing the error between the direction angles of the detail point; The other is to calculate the angle difference between the two before discretisation, that is, $\theta^+ =$

round(θ_i–θ'_i/n). This method only conducts discretisation once, which can cause an error of one unit at most. Therefore, this article selects method 2 to calculate the error between detail point pairs.

2 Optimisation of directional angle range: The direction angle range of the detail point is [0360], so the direction angle difference range is [–360360]. To make the difference range [–180180], the direction difference in this paper is as follows, and then discretisation Δθ to get θ^+.

Step 2 Rotate each minutiae in the input small area fingerprint according to the discretisation angle, and the new input minutiae position information is expressed as (x'', y')

$$\begin{bmatrix} x'_j \\ y''_j \end{bmatrix} = \begin{bmatrix} cos\theta^+ & -sin\theta^+ \\ sin\theta^+ & cos\theta^+ \end{bmatrix} \begin{bmatrix} x''_j \\ y'_j \end{bmatrix} \tag{41}$$

Step 3 Calculate the difference (Δx, Δy) between the details of the template's small area fingerprint and the position information of the converted new input fingerprint details

$$\begin{bmatrix} \Delta x \\ \Delta y \end{bmatrix} = \begin{bmatrix} x_i \\ y_i \end{bmatrix} - \begin{bmatrix} x''_j \\ y'_j \end{bmatrix} \tag{42}$$

Step 4 Quantify the position difference obtained in step 3 to the nearest discretisation coordinate (Δx^+, Δy^+)

A three-dimensional matrix is established, and each dimension represents the difference Δx^+, Δy^+, θ^+ of the position information and direction information of the fine node pair after discretisation. Its size is determined by Δx, Δy, θ and n.

Initialise the matrix space and erase Europe, then correspond the calibration amount (Δx^+, Δy^+, θ^+) between each group of detail points to the matrix, and accumulate the calibration amount for each group of detail points. The accumulation formula is:

$$A\left[\Delta x^+, \Delta y^+, \theta^+\right] = A\left[\Delta x^+, \Delta y^+, \theta^+\right] + 1 \tag{43}$$

Perform fingerprint peak point detection on the calibration amount of detail point pairs to achieve high-precision recognition of small area fingerprints, denoted as (Δx^*, Δy^*, θ^*):

$$\left(\Delta x^*, \Delta y^*, \theta^*\right) = argmax_{\Delta x^+, \Delta y^+, \theta^+} A\left[\Delta x^+, \Delta y^+, \theta^+\right] \tag{44}$$

There may be multiple calibration values corresponding to the peak points obtained by the above method, so based on this, the input fingerprint is calibrated and matched according to the obtained position calibration values and direction calibration values, achieving high-precision recognition of small area fingerprints.

5 Analysis of experimental results

5.1 Database selection

5.1.1 Self built dataset

The self-built database is composed of a PMOLED screen acquisition device built to collect fingerprint data. The fingerprint dataset is collected by 28 students, with each student collecting 10 fingers and one finger collecting 50 valid fingerprint images, totaling 14,000 images. The fingerprint dataset is numbered from 1 to 280 based on the principle of first left, then right, and then thumb, and finally, the fingerprint images are randomly divided into training registration set test sets in a 4:1 ratio. The specific information is shown in Table 1:

Table 1 Image information of self-built fingerprint dataset

Aggregate	*Collector type*	*Pixels*	*Number of images*	*Resolution ratio/dpi*
Registration set	optics	216*216	11,200	508
Test set	optics	216*216	2,800	508
Total			14,000	

Select experimental sample images from them as shown in Figure 3:

Figure 3 Sample diagram of self-built dataset

5.1.2 FVC2002DB2 dataset

The reconstructed and expanded fingerprint images from the international publicly available fingerprint dataset FVC2002D2 are used as the second dataset, which includes 100 fingers, each finger containing 6 images, with a total number of 600 images and a resolution of 500 dpi. After cropping and reconstructing the original image, a fingerprint image of the same size as the self-built database is obtained. In order to ensure the robustness of the fingerprint dataset during testing and verification, 5 images are cropped on each fingerprint image, The edge information of the original large area fingerprint image must also be included. After cropping, each finger has 40 small area fingerprint images, and the original fingerprint image is selected as shown in Figure 4.

Figure 4 EVC2002DB2 fingerprint sample image

After determining the image of the experimental sample, to ensure the reliability of the test results, the boundary range is determined by detecting features such as the direction of the line and the change of density in the image, so that it is small enough and contains enough feature information.

5.2 Experimental results

In order to verify the effectiveness of the method proposed in this paper, a comparative analysis of the fingerprint image recognition performance was conducted using the methods of Liu et al. (2020), Xie and Deng (2022), and this method. The results are as follows:

Figure 5 Comparison of feature point recognition results (a) the proposed method is identified (b) Liu et al. (2020) method Identification (c) Xie and Deng (2022) method identification (see online version for colours)

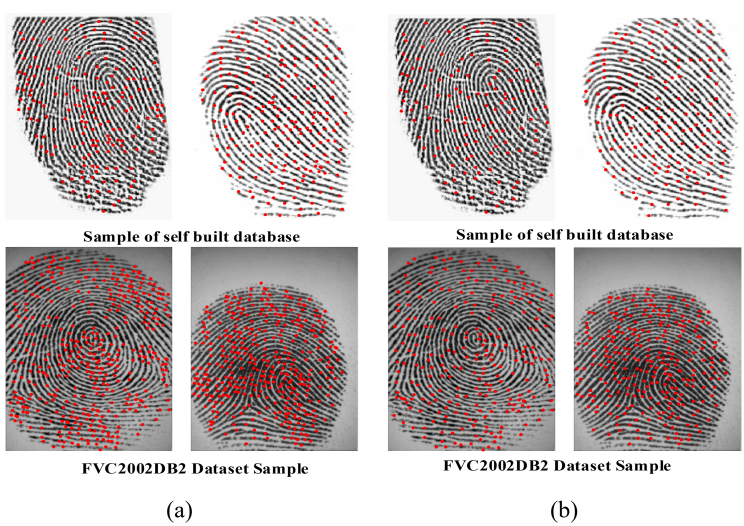


Figure 5 Comparison of feature point recognition results (a) the proposed method is identified (b) Liu et al. (2020) method Identification (c) Xie and Deng (2022) method identification (continued) (see online version for colours)

(c)

From the recognition results in Figures 5, 6, and 7, it can be seen that the method proposed in this paper can recognise both the self-built dataset sample image and the EVC2002DB2 fingerprint sample image, with an average recognition feature point and the ability to recognise the features at the fuzzy fingerprint ridge line in the boundary area. When using the Liu et al. (2020) method, there are areas where the fingerprint ridge feature points are centred in the centre of the self-built database sample image, and the ridge lines are clear. There are fewer recognition feature points at the fuzzy boundary ridge lines, and the identified features cannot construct a specific ridge outline; When identifying the EVC2002DB2 fingerprint sample image, the overall ridge features are relatively average, but the amount of ridge features identified is less than the recognition results of this method, and there is a phenomenon of missing some edge ridge features. When using the Xie and Deng (2022) method, there is a phenomenon of missing external ridge feature points and chaotic recognition of central ridge feature points for self-built database samples. However, when recognising EVC2002DB2 fingerprint sample images, although the original fingerprint image is relatively comprehensive, there is a phenomenon of missing ridge feature points and uneven feature points. For significant areas of central ridge lines, more feature points are identified, but there are missing features at the boundary ridge lines, This indicates that the method has unstable factors and cannot achieve accurate recognition. From this, it can be seen that when using the method proposed in this article for small area fingerprint recognition, compared to the Liu et al. (2020) method and Xie and Deng (2022) method, it has more recognition feature points, is comprehensive, and has higher accuracy. This is because the proposed method analyses the estimates of key fingerprint parameters, introduces Tico descriptor to obtain detailed feature points, determines frequency field, and enhances small-area fingerprint images to make image features clearer before matching and identifying fingerprint point sets. Finally, combining with demodulation, the detailed features of small area fingerprint images are extracted, thus improving the effect of feature point recognition.

To further validate the effectiveness of the method proposed in this paper, the fingerprint image recognition time was compared and analysed using the Liu et al. (2020) method, Xie and Deng (2022) method, and the method proposed in this paper. The results are shown in Table 2:

Table 2 Comparison of recognition time consumption/s

Sample size	*Liu et al. (2020) Method*	*Xie and Deng (2022) Method*	*Proposed method*
200	32	23	13
400	35	32	14
600	39	34	23
800	42	36	28
1,000	46	39	30
1,200	51	42	38
1,400	53	45	41
1,600	62	56	47
1,800	74	63	49
2,000	83	70	53

As can be seen from Table 2, with the increase of the number of samples, the identification time of the three methods showed a gradual increase trend. When using the method proposed in this paper, with the increase of the sample size, the increase of the recognition time is small, the overall stability is good, and there is no sudden increase trend, while when using the other two methods, with the increase of the sample size, the recognition time will show a sudden increase trend, especially when the sample size reaches 1,400, the time of the two methods will suddenly increase. When the sample size reached 2,000, the identification time of the method in Liu et al. (2020), Xie and Deng (2022) and the method in this paper reached 83s, 70s and 53s, respectively. Compared with the obtained results, the identification time of the method in this paper was shorter. According to the average statistics of the results in the Table 2, the average time of the three methods is 51.7s, 44s and 32.6s respectively. Compared with the results obtained, the recognition time of the method proposed in this paper is shortened by 19.1s and 11.4s, respectively, compared with that of the method in Liu et al. (2020) and Xie and Deng (2022). In summary, it can be seen that the fingerprint recognition method adopted in this paper can effectively shorten the identification time, and the fluctuation is small, which can achieve the expected goal of improving the identification efficiency, and has certain advantages. This is because the proposed method enhances the small-area fingerprint image based on direction and frequency, making the image features clearer, thus speeding up the recognition speed and reducing the recognition time.

6 Conclusions

A high-precision recognition method for small area fingerprints based on machine vision is proposed to address the problems of insufficient recognition of boundary area feature points and low recognition accuracy in traditional recognition methods. The experimental results indicate that:

1. When the method proposed in this paper is used to identify the sample images of the self-built database, the number of ridge feature points is larger than that of the methods in the Liu et al. (2020) and Xie and Deng (2022), and the distribution of the identified feature points is relatively uniform
2. When the method proposed in this paper is used to identify EVC2002DB2 fingerprint sample images, compared with the methods in Liu et al. (2020)] and Xie and Deng (2022), the number of ridge features is more and more average, and the ridge features on image edges are more accurate, which can achieve the expected goal of improving the recognition accuracy
3. When the method proposed in this paper is used, the average recognition time is 32.6s, which is 19.1s and 11.4s shorter than the methods in Liu et al. (2020) and Xie and Deng (2022), respectively. Moreover, the fluctuation of recognition time is small and the recognition time is more stable, which achieves the expected goal of improving the recognition efficiency.

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