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Fingerprint Matching Algorithm based on Composite Gradient Vectors

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Abstract: This paper establishes a fingerprint matching algorithm based on composite gradient vectors. After pre-processing the fingerprint image, rotating it, sampling the base vectors, forming vector clusters from the base vectors, creating extreme gradient vectors, fusing composite gradient vectors and other processes, establishing the constraint relationship between local features, carrying out the principle analysis of fingerprint image retrieval and matching, and giving a complete and clear framework of image retrieval model and implementation method.

1. Introduction

In the field of biometric identification, fingerprints, as one of the most unique and persistent biometric features, are widely used for identification purposes. There is a one-to-many matching mode in the fingerprint identification problem, in which the recorded query fingerprint is matched with all registered fingerprints in the fingerprint database one by one until the registered fingerprint with the best similarity is found or the conclusion that there is no corresponding registered fingerprint is given after searching the entire fingerprint database. The identification mode is mainly used in criminal investigation fingerprint automatic identification systems, large fingerprint time and attendance systems and access control systems [1]. With the popularisation of fingerprint identification applications in society, the scale of fingerprint databases used to identify people has also risen rapidly, with the capacity of fingerprint databases for residential ID cards even reaching the level of a billion people.

The principle of fingerprint image retrieval can be visualised as follows: a number of large sieves are used to quickly and precisely screen out the majority of images in the database that do not clearly have the "same" relationship as the query fingerprint image. After the retrieval process is complete, a small number of images are left that are highly similar to the query fingerprint and need to be further identified "one by one" using fingerprint recognition algorithms [2]. How to design an efficient and accurate search algorithm is therefore a key issue in large-scale fingerprint image retrieval.

2. Acquisition of data and assumptions

The data in this paper is taken from question A of the 12th MathorCup Mathematical Modelling Challenge for Universities 2022. The following assumptions were made to facilitate model building: (a) ignore the disadvantage of a relatively small sample and consider the sample size adequate; (b) ignoring the effect of the marginal boundaries of the grain lines not being very clear; (c) considered to be sufficiently accurate when pre-processing.

3. Fingerprint matching algorithm based on compound gradient vector

3.1 Pretreatment

Because the collected fingerprint images will have different degrees of noise interference, it is necessary to do some processing on the fingerprint images to remove the noise in the images, so as to extract accurate fingerprint features in the subsequent steps. Therefore, the algorithm needs to preprocess the fingerprint images first.

(a) Fingerprint image to be identified (b) Preprocessed image

Figure 1. Schematic diagram of fingerprint image preprocessing.

Fingerprint image preprocessing is shown in Fig.1, in which Fig.1(a) is the fingerprint image to be identified; Fig.1(b) shows the fingerprint image to be identified after preprocessing, which includes the position information of the initial point $C(x, y)$ and the singular point $\sigma^{z}_{(x,y)}$.

3.2 Fingerprint image rotation

Establishing rectangular coordinate system on fingerprint image and rotating it can effectively standardize the coordinate position of singular points, and reduce the difference of coordinate position of minutiae in different images of the same fingerprint [3]. At the same time, because of the different rotation angles of different fingerprint images, it not only enhances the difference of different fingerprint features, but also effectively suppresses the interference of similar fingerprint features.

Establish a rectangular coordinate system with the detected initial point C as the origin, parallel to the right as the abscissa axis, and vertical up as the ordinate axis.

Let the original coordinates of the initial point C be (x_0, y_0) and the original coordinates of the singular point σ be (x'', y''). Since the creation of a new coordinate axis is equivalent to the translation of both the initial point and the singular point along a straight line, let the coordinates of the initial point after the translation be $(0, 0)$ and the coordinates of the singular point be (x', y'). Then

$$C_{(0,0)} = \begin{cases} 0 = x_0 - x_0 \\ 0 = y_0 - y_0 \end{cases} \tag{1}$$

$$\sigma_{(x',y')} = \begin{cases} x' = x'' - x_0 \\ y' = y'' - y_0 \end{cases} \tag{2}$$

Using the initial point C as the starting point, search for the nearest singularity σ^1 from the initial point, take this singularity as the end point, create the first basis vector and mark the first basis vector as (0), denoted as $x_{1,1} = (0)$.

The fingerprint image is rotated clockwise along the origin of the coordinate system until the vertical axis and the first basis vector coincide and are in the same direction, i.e. the direction of the first basis vector is the direction of the vertical axis.

The fingerprint image is rotated clockwise along the origin, which corresponds to the counterclockwise rotation of the coordinate axis along the origin, and let the angle of rotation be θ. The coordinates of the singularity point (x', y') before the rotation, and the coordinates of the singularity point *(x, y)* after the rotation.

$$\sigma_{(x,y)} = \begin{cases} x = x'\cos\theta + y'\sin\theta \\ y = y'\cos\theta - x'\sin\theta \end{cases} \tag{3}$$

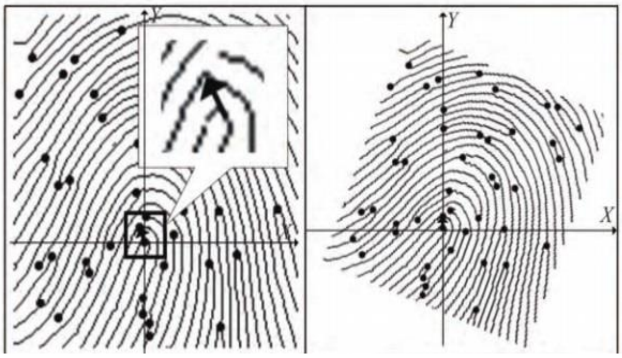

Figure 2. Rotating fingerprint image.

3.3 Feature extraction

3.3.1 Basis Vector Sampling

In this paper, in the fingerprint image, two singular points with the shortest distance in the local range are used as endpoints to establish the basis vector, which ensures that the collected basis vector is the local feature of the fingerprint image. Then, the constraint relationship between the local features is established through the processes of building vector clusters, building maximum gradient vectors and fusing compound gradient vectors, so as to form the overall distribution information of fingerprint features. Firstly, the sampling process of the basis vector is given.

In the rotated fingerprint image, taking the end point of the first basis vector as the starting point, searching for three singular points which are the nearest distance and less than the threshold E as the end points, and respectively establishing three subsequent vectors [4]. If the nearest singular point is the starting point or the end point of a basis vector, abandon this singular point and search for the next singular point; If the distance from all the singularities without the basis vector is greater than the threshold E, the establishment of the successor vector of this singularity will be abandoned. After experiments, when the threshold E is 30 pixels, the local features established by the basis vector are relatively stable and not easily affected by nonlinear deformation.

Calculate the angle between the successor vector and the abscissa axis (the range of the angle is $0 \leq \theta \leq 360$), search the successor vectors of the obtained base vectors according to the order of marking from small to large, and mark the vectors according to the magnitude of the angle. When all the singular points are the start or end points of the base vectors, stop searching, and all the base vectors of the fingerprint image have been sampled at this time. The collection of the base vectors is shown in Fig.3.

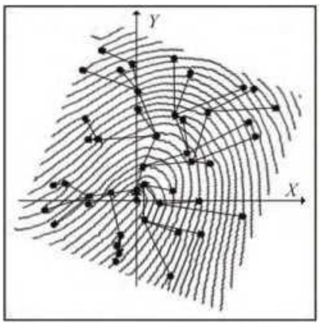

Figure 3. Calibration basis vector.

3.3.2 Vector Cluster Formation

The sampled and labeled basis vectors are formed into vector clusters VecRel {Vec, Rel}. By forming the vector clusters, the precursor and successor relationships between the basis vectors are obtained and the values, dimensional information and gradient information of the basis vectors are obtained.

The first basis vector is used as the root vector of the vector cluster VecRel {Vec, Rel}, and the successor vector of the root vector $\boldsymbol{x}_{1,1}$ is positioned in row 2 of the vector cluster, and is in columns 1, 2 and 3 of row 2, respectively, according to the markers (1), (2) and (3) at the time of sampling, and is denoted as worker $\boldsymbol{x}_{2,1}$, $\boldsymbol{x}_{2,2}$ and $\boldsymbol{x}_{2,3}$, respectively.

$$\boldsymbol{x}_{2,1} = \boldsymbol{x}_{1,1}\Theta(1) = (0,1),\ \varphi(\boldsymbol{x}_{2,1}) = 1,\ \psi(\boldsymbol{x}_{2,1}) = \left|\boldsymbol{x}_{2,1}\right| \tag{4}$$

$$\boldsymbol{x}_{2,2} = \boldsymbol{x}_{1,1}\Theta(2) = (0,2),\ \varphi(\boldsymbol{x}_{2,2}) = 1,\ \psi(\boldsymbol{x}_{2,2}) = \left|\boldsymbol{x}_{2,2}\right| \tag{5}$$

$$\boldsymbol{x}_{2,3} = \boldsymbol{x}_{1,1}\Theta(3) = (0,3),\ \varphi(\boldsymbol{x}_{2,3}) = 1,\ \psi(\boldsymbol{x}_{2,3}) = \left|\boldsymbol{x}_{2,3}\right| \tag{6}$$

If a base vector has less than three successors, the successor vectors of the next base vector in the same row will be followed by the marker, and the value of all base vectors will be the value of their precursor vectors Θ their marker value [5]. For a vector cluster, the vector cluster is divided into subvector clusters according to the rules for labeling base vectors and dividing subvector clusters, and when all root vectors in a subvector cluster have no successor vectors, the vector cluster is formed.

The formed vector cluster is represented in matrix form, where the structure matrix $\mathbf{STR}_{m\times n}$ represents the position and labeling information of the base vectors in the vector cluster, the dimension matrix $\mathbf{DIM}_{m\times n}$ and the gradient matrix $\mathbf{GRA}_{m\times n}$ correspondingly represent the dimension and gradient information of the base vectors, and the constraint matrix $\mathbf{RES}_{(m-1)\times n}$ represents the predecessor and successor relationships of the base vectors in the vector cluster.

$$
\mathbf{STR}_{m\times n}=\begin{bmatrix} \boldsymbol{x}_{1,1} & & & \\ \boldsymbol{x}_{2,1} & \boldsymbol{x}_{2,2} & \boldsymbol{x}_{2,3} & \\ \vdots & \vdots & \ddots & \\ \boldsymbol{x}_{m,1} & \boldsymbol{x}_{m,2} & \cdots & \boldsymbol{x}_{m,p} \end{bmatrix} = \begin{bmatrix} (0) & & & \\ (0,1) & (0,2) & (0,3) & \\ \vdots & \vdots & \ddots & \\ (0,\underbrace{a,\cdots,a}_{m-2},1) & (0,\underbrace{a,\cdots,a}_{m-2},2) & \cdots & (0,\underbrace{a,\cdots,a}_{m-1}) \end{bmatrix} \tag{7}
$$

The structure matrix $\mathbf{STR}_{m\times n}$ row 1 has only one element base vector $\boldsymbol{x}_{1,1}$, which is the root vector of the vector cluster VecRel {Vec, Rel}; the base vectors in row 2 are all successors of the base vector $\boldsymbol{x}_{1,1}$ in row 1 and are the root vectors of the subvector clusters {Vec_1, Rel_1}、{Vec_2, Rel_2}、{Vec_3, Rel_3} of the vector cluster VecRel {Vec, Rel} respectively; the base vectors in row 3 are all successors of the base vectors in row 2 and are the root vectors of {Vec_1, Rel_1}、{Vec_2, Rel_2}、{Vec_3, Rel_3} respectively. The relationship between the base vectors and the vector clusters and so on; the values of the structural matrix $\mathbf{STR}_{m\times n}$ quantities are the values of their precursor vectors Θ as their labeled values.

$$
\mathbf{DIM}_{m\times n}=\begin{bmatrix} \varphi(\boldsymbol{x}_{1,1}) & & & \\ \varphi(\boldsymbol{x}_{2,1}) & \varphi(\boldsymbol{x}_{2,2}) & \varphi(\boldsymbol{x}_{2,3}) & \\ \vdots & \vdots & \ddots & \\ \varphi(\boldsymbol{x}_{m,1}) & \varphi(\boldsymbol{x}_{m,2}) & \cdots & \varphi(\boldsymbol{x}_{m,p}) \end{bmatrix} \tag{8}
$$

$$
\mathbf{GRA}_{m\times n}=\begin{bmatrix} \psi(\boldsymbol{x}_{1,1}) & & & \\ \psi(\boldsymbol{x}_{2,1}) & \psi(\boldsymbol{x}_{2,2}) & \psi(\boldsymbol{x}_{2,3}) & \\ \vdots & \vdots & \ddots & \\ \psi(\boldsymbol{x}_{m,1}) & \psi(\boldsymbol{x}_{m,2}) & \cdots & \psi(\boldsymbol{x}_{m,p}) \end{bmatrix} \tag{9}
$$

The dimensional matrix $\mathbf{DIM}_{m\times n}$ and the gradient matrix $\mathbf{GRA}_{m\times n}$ correspond to the dimensional and gradient information of the basis vectors in the structure matrix $\mathbf{STR}_{m\times n}$.

$$
\mathbf{RES}_{(m-1)\times n}=\begin{bmatrix} (\boldsymbol{x}_{1,1},\boldsymbol{x}_{2,1}) & (\boldsymbol{x}_{1,1},\boldsymbol{x}_{2,2}) & (\boldsymbol{x}_{1,1},\boldsymbol{x}_{2,3}) & \\ \vdots & \vdots & \ddots & \\ (\boldsymbol{x}_{m,1,t},\boldsymbol{x}_{m,1}) & (\boldsymbol{x}_{m,1,t},\boldsymbol{x}_{m,2}) & \cdots & (\boldsymbol{x}_{m,1,p},\boldsymbol{x}_{m,q}) \end{bmatrix} \tag{10}
$$

The constraint matrix $\mathbf{RES}_{(m-1)\times n}$ represents the antecedent and successor relationships of the base vectors in the structure matrix $\mathbf{STR}_{m\times n}$. The elements in the constraint matrix are binary groups whose first element is the antecedent vector of the second element and the second element is the successor vector of the first element.

The structure matrix contains two pieces of information, the position of the base vector in the vector cluster and the value (marker) of the base vector; the dimension matrix and the gradient matrix are in the same form as the structure matrix, and their values are the dimension and gradient information of the base vector; the constraint matrix, as a complementary form of the structure matrix, expresses the predecessor and successor relationships between the base vectors.

3.4 Composite gradient vector building

The base vector is a local feature of the fingerprint image, which is less affected by non-linear deformation and can describe the fingerprint local information more stably, but the base vector cannot express the fingerprint features comprehensively, so the scattered local features need to be combined to jointly form the most obvious feature distribution constraint information in the bio-visual effect.

In the constraint matrix $\mathbf{RES}_{(m-1)\times n}$, find all the base vectors $\boldsymbol{x}_{\alpha,\beta}$ without successor vectors and search their precursor vectors until the root vector $\boldsymbol{x}_{1,1}$ is searched; record the search path $\boldsymbol{x}_{1,1}, \boldsymbol{x}_{2,1}, \ldots, \boldsymbol{x}_{\alpha,\beta}$ and multi-dimensionally composite all the base vectors on the path to obtain the great gradient vector $\boldsymbol{X}_{\alpha,\beta}^{\max}$ of all the leaf vectors, denoted as

$$\boldsymbol{X}_{\alpha,\beta}^{\max} = \sum_{i=1,\, j=1}^{\alpha,\beta}{}^{\Theta} \boldsymbol{x}_{i,j} = \boldsymbol{x}_{1,1} \Theta \boldsymbol{x}_{2,1} \Theta \cdots \Theta \boldsymbol{x}_{\alpha,\beta} \tag{11}$$

The dimension $\varphi(\boldsymbol{X}_{\alpha,\beta}^{\max})$ and gradient $\psi(\boldsymbol{X}_{\alpha,\beta}^{\max})$ are

$$\varphi(\boldsymbol{X}_{\alpha,\beta}^{\max}) = \sum_{i=1,\, j=1}^{\alpha,\beta} \varphi(\boldsymbol{x}_{i,j}) = \varphi(x_{1,1}) + \cdots + \varphi(\boldsymbol{x}_{\alpha,\beta}) \tag{12}$$

$$\psi(\boldsymbol{X}_{\alpha,\beta}^{\max}) = \sum_{i=1,\, j=1}^{\alpha,\beta} \psi(\boldsymbol{x}_{i,j}) = \psi(x_{1,1}) + \cdots + \psi(\boldsymbol{x}_{\alpha,\beta}) \tag{13}$$

The composite gradient vector $\Delta(\boldsymbol{X}_{\alpha,\beta}^{\max})$ of the fingerprint image is obtained by fusing all the extreme gradient vectors in the vector cluster as elements, denoted as

$$\Delta(\boldsymbol{X}_{\alpha,\beta}^{\max}) = \left[\boldsymbol{X}_{\alpha_1,\beta_1}^{\max}, \boldsymbol{X}_{\alpha_2,\beta_2}^{\max}, \cdots, \boldsymbol{X}_{\alpha_3,\beta_3}^{\max} \right]^{-1} \tag{14}$$

The dimension $\varphi(\Delta(\boldsymbol{X}_{\alpha,\beta}^{\max}))$ and gradient $\psi(\Delta(\boldsymbol{X}_{\alpha,\beta}^{\max}))$ are

$$\varphi(\Delta(\boldsymbol{X}_{\alpha,\beta}^{\max})) = \sum_{i=\alpha_1,\, j=\beta_1}^{\alpha_n,\beta_n} \varphi(\boldsymbol{X}_{i,j}^{\max}) = \varphi(\boldsymbol{X}_{\alpha_1,\beta_1}^{\max}) + \cdots + \varphi(\boldsymbol{X}_{\alpha_n,\beta_n}^{\max}) \tag{15}$$

$$\psi(\Delta(\boldsymbol{X}_{\alpha,\beta}^{\max})) = \sum_{i=\alpha_1,\, j=\beta_1}^{\alpha_n,\beta_n} \psi(\boldsymbol{X}_{i,j}^{\max}) = \psi(\boldsymbol{X}_{\alpha_1,\beta_1}^{\max}) + \cdots + \psi(\boldsymbol{X}_{\alpha_n,\beta_n}^{\max}) \tag{16}$$

The dimension of a composite gradient vector is the sum of the dimensions of its elements (great gradient vectors), and from a geometric point of view, the dimension of a composite gradient vector is also the set of constraints on the singularities of its fingerprint image, i.e. the dimension of a composite gradient vector has not only numerical information, but also spatial-geometric derivatives.

Let there exist extreme gradient vectors $\boldsymbol{X}_{\alpha,\beta}^{\max}$ and $\boldsymbol{X}_{\alpha',\beta'}^{\max}, \alpha, \alpha' \in [\alpha_1, \alpha_2, \cdots, \alpha_n]$, $\beta, \beta' \in [\beta_1, \beta_2, \cdots, \beta_n]$, whose dimensions are denoted as $\varphi(\boldsymbol{X}_{\alpha,\beta}^{\max})$ and $\varphi(\boldsymbol{X}_{\alpha',\beta'}^{\max})$ respectively, then the extreme gradient vectors $\boldsymbol{X}_{\alpha,\beta}^{\max}$ and $\boldsymbol{X}_{\alpha',\beta'}^{\max}$ dimensions are related as follows:

$$\varphi(\boldsymbol{X}_{\alpha,\beta}^{\max}) + \varphi(\boldsymbol{X}_{\alpha',\beta'}^{\max}) = \varphi(\boldsymbol{X}_{\alpha,\beta}^{\max} + \boldsymbol{X}_{\alpha',\beta'}^{\max}) + \varphi(\boldsymbol{X}_{\alpha,\beta}^{\max} \cap \boldsymbol{X}_{\alpha',\beta'}^{\max}) \tag{17}$$

3.5 Fingerprint image retrieval and matching

To address the problems of the current fingerprint classification algorithm, a new layered marking rule is designed according to the characteristics of the composite gradient vector extracted by the method in this paper, and the composite gradient vector information of the fingerprint is layered and marked to speed up the fingerprint retrieval by the fingerprint matching algorithm.

The composite gradient vector, as the main information of the fingerprint image, is firstly subjected to matching calculation to identify the fingerprint identity information; then, the dimensional information with spatial geometric derivation relationship is used as the second layer of matching information, which has certain anti-interference ability to the non-linear deformation fingerprint image; the gradient information, as the mode of the vector, is vulnerable to the non-linear deformation, and it is used as the last feature for matching calculation.

Let the composite gradient vector of the fingerprint image to be recognized be $\Delta\left(X_{\alpha,\beta}^{\max}\right)$, the dimension and gradient be $\varphi\left(\Delta\left(X_{\alpha,\beta}^{\max}\right)\right)$ and $\psi\left(\Delta\left(X_{\alpha,\beta}^{\max}\right)\right)$ respectively, and the number of fingerprint images in the fingerprint database that are successfully matched with the composite gradient vector $\Delta\left(X_{\alpha,\beta}^{\max}\right)$ of the fingerprint image to be recognized be Δ_1, whose composite gradient vectors are recorded as $\Delta_1,\cdots,\Delta_n$, the dimension as $\varphi_1,\cdots,\varphi_n$ and the gradient as $\psi_1,\cdots,\psi_n$ respectively.

First, compare $\Delta\left(\boldsymbol{X}_{\alpha,\beta}^{\max}\right)$ and $\Delta_1,\cdots,\Delta_n$ separately for Euclidian distance, calculate $e_i=\left\|\Delta\left(\boldsymbol{X}_{\alpha,\beta}^{\max}\right)-\Delta_i\right\|$ $(i=1,\cdots,n)$, and calculate $E=\arg\left(\min\limits_{1,2,\cdots,n}\left(e_i\right)\right)$.

Let the $\varphi\left(\Delta\left(X_{\alpha,\beta}^{\max}\right)\right)$ and $\varphi_1,\cdots,\varphi_n$ are calculated separately, $u_j=\left\|\varphi\left(\Delta\left(\boldsymbol{X}_{\alpha,\beta}^{\max}\right)\right)-\varphi_j\right\|$ $(j=1,2,\cdots,m)$, $U=\arg\left(\min\limits_{1,2,\cdots,n}\left(u_i\right)\right)$, and when $j=J(J=1,\cdots,m)$, there exists a unique u_j corresponding to the U value, then the fingerprint image to be recognized is the *Jth* fingerprint information.If there are $\lambda(1\le\lambda\le m)$ u_j values corresponding to U values, then the next step in the calculation is to be determined.

Let the $\psi\left(\Delta\left(X_{\alpha,\beta}^{\max}\right)\right)$ and $\psi_1,\cdots,\psi_\lambda$ are calculated separately, $u_k=\left\|\psi\left(\Delta\left(\boldsymbol{X}_{\alpha,\beta}^{\max}\right)\right)-\psi_k\right\|$ $(k=1,2,\cdots,\lambda)$, $V=\arg\left(\min\limits_{1,2,\cdots,\lambda}\left(v_k\right)\right)$, and when $k=K(K=1,\cdots,\lambda)$, there exists a unique v_k corresponding to the V value, then the fingerprint image to be recognized is the *Kth* fingerprint information. If there is more than one v_k corresponding to a V value, the fingerprint image does not exist in the fingerprint library.

In order to test the time complexity and space complexity of the composite gradient vector fingerprint matching method, this paper uses the attached data to test the composite gradient vector method of this paper according to the standards of the fourth International Fingerprint Recognition Competition, and the test results are compared and analyzed with the fingerprint matching methods of the participating countries, and the test results are shown in Tab.1.

Table 1. FVC2006 algorithm test results.

Algorithm	Avg FMRI	Avg FMRI	Avg	Avg	Avg Enroll	Avg Match
CGV	3. 70%	5. 92%	9. 52%	89. 02%	0. 35	0. 23
P066	3. 21%	4. 76%	7. 33%	100. 00%	0. 61	0. 80
P045	3. 43%	7. 42%	15. 02%	100. 00%	0. 16	0. 24
P009	3. 17%	4. 22%	6. 29%	70. 28%	0. 55	0. 61
P017	3. 75%	5. 94%	9. 55%	100. 00%	0. 08	0. 08
P015	3. 39%	4. 48%	6. 62%	75. 31%	1. 19	1. 21
P074	3. 76%	5. 51%	9. 05%	76. 13%	0. 20	0. 21
P058	3. 41%	4. 38%	5. 74%	81. 80%	0. 32	0. 32
P131	3. 26%	7. 47%	16. 80%	100. 00%	0. 21	0. 34
P067	4. 58%	6. 66%	9. 38%	100. 00%	0. 24	0. 27
P101	4. 25%	15. 70%	16. 27%	100. 00%	0. 51	0. 57

From the test data in Tab.1, we can see that the average equal error rate EER of the CGV method in this paper is 2. 52%, which is 0. 36% higher than that of the top algorithm P066, ranking sixth; the average registration time is 0. 35s, which is 0. 23s less than that of P066; the average matching time is 0. 25s, which is 0. 55s less than that of P066, and among the top ten algorithms, the average registration time and average matching time of this method rank third. The sum of registration time and average matching time of this paper's method ranks third among the top ten algorithms, only higher than algorithms P045, P017 and P074.

In the results, the CGV method in this paper has similar recognition accuracy as the top ten algorithms in the competition, while the registration time and matching time of the algorithm are reduced. This is mainly due to the fact that the CGV method combines discrete features in the fingerprint image as the basis for target matching, which maintains a high recognition accuracy, and uses a hierarchical tagging rule to tag the collected CGVs, which reduces the fingerprint retrieval time, and the CGVs themselves have less information and a shorter matching time [6]. It can be seen that the composite gradient vector method can be used for fingerprint recognition to ensure high recognition accuracy while achieving fast computational speed.

4. Conclusion

In this paper, the composite gradient vector of fingerprint images is tagged by CGV method, so that the coverage of fingerprint tags in the fingerprint database is 100%, and the number of fingerprints in each layer can be controlled by up to n+1 layers, which speeds up the fingerprint retrieval. In the process of retrieving fingerprints, if a match is not successful in the next layer, the result of the previous layer will prevail, so that no fingerprints are missed and the accuracy of fingerprint retrieval is improved. The use of this method not only increases the speed of fingerprint retrieval, but also has a positive effect on the accuracy of fingerprint matching.

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