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Finger Vein Recognition Based on a Histogram of Competitive Gabor Directional Binary Statistics

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ABSTRACT

Traditional methods of extracting finger vein texture changes and orientation features are susceptible to illumination, translation, noise, and rotation, and the process has difficulty directly extracting structural features through the original image. In this paper, the histogram of competitive Gabor directional binary statistics (HCGDBS) is proposed to extract discriminative structural features. First, the index of the largest filter value is obtained based on the multidirectional Gabor filter as the dominant direction, thereby obtaining the rotation-invariance feature. Second, according to the filter response size of each pixel in different directions, the order difference relationship between the adjacent three directions is compared, and a highly discriminative competitive Gabor direction binary pattern (CGDBP) is constructed. Finally, the CGDBP features are extracted in blocks, and the HCGDBS is constructed to overcome image translation. Experimental results show that it improves the recognition performance and overcomes illumination, translation, noise, and rotation.

KEYWORDS

Finger Vein Recognition, Gabor Filter, Histogram, Illumination, Noise, Rotation, Structural Feature, Translation

INTRODUCTION

Finger veins are a body feature that is difficult to forge and is highly secure (Lu et al.,2018). Referencing other biometric features, such as fingerprints (Yang et al.,2022), palm prints (Jia et al.,2013), and faces (Lei et al.,2010), vein features are used for living body recognition and are not easily damaged, so finger vein identification has gradually become a research hotspot.

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The finger vein recognition process usually consists of three stages: (1) preprocessing, including extracting a region of interest and image enhancement (Qu et al.,2022), (2) extracting features (Zhai et al.,2022), and (3) matching and identification, feature vectors are matched between test samples and training samples and then features are efficiently classified and recognized. The most important step is feature extraction, which has a great effect on recognition performance.

Recently, many studies have been performed on feature extraction methods for finger veins. Lu et al. (2014) proposed the competitive histogram representation, called HCGR, which makes full use of the Gabor filter with the ability to acquire image structural features from different directions, generates CGM and CGO images, and constructs feature histograms, which help to accurately represent finger vein orientation and texture characteristics. Yang et al. (2017) proposed adaptive vector field estimation, which is a feature representation method. By designing a spatial curve filter with variable curvature and direction, the vein curve is fitted to obtain the curve characteristics. Wang et al. (2019) proposed the DCGWLD and constructed a new variable curvature Gabor filter to replace the gradient descriptor in the original WLD. The extracted features not only have vein orientation characteristics but also reflect the degree of vein curvature. Tao et al. (2020) proposed the discriminative local descriptor AWASTP, which constructs an anisotropic Laplacian Gaussian operator, and proposed an anisotropic Weber local descriptor, which can obtain richer light-insensitive features and detailed information to enhance identification. These methods can extract local discriminative structural information through the texture variation and orientation features in finger vein images, but the images captured through the device are susceptible to illumination, translation, noise, and rotation. How to extract more discriminative structural features from finger vein images will be explored in-depth in the next work.

Inspired by HCGR and LBP, to solve the problems faced by the Gabor filter and LBP, the existing method based on the Gabor filter cannot distinguish finger vein images well; that is, the extracted features are not discriminative enough to reflect their rich structural information. Moreover, LBP and its various improvements cannot effectively solve image noise and rotation problems. This paper proposes an efficient image discriminative representation called the histogram of competitive Gabor directional binary statistics (HCGDBS). It filters the finger vein image through a Gabor filter and obtains the maximum response value as its dominant direction to overcome image noise and rotation. According to the dominant direction, the filter value of each direction is cyclically shifted, the LBP is improved by considering the intensity sequence difference relationship between the adjacent three directions of each pixel point, and the highly discriminative feature of the image is constructed. The experimental results of this paper fully reveal that this method outperforms Gabor, LBP, and various improved methods based on them.

These contributions are as follows:

1. The authors proposed extracting the dominant direction of the pixel point on the image based on the filtering response value of the multidirectional Gabor filter. According to the dominant direction, the local intensity order difference relationship between the adjacent three directions of each pixel is encoded in a rotation-invariance and robustness manner to construct the highly discriminative competitive Gabor direction binary pattern (CGDBP).
2. Based on the competitive Gabor direction binary pattern, a local feature statistical histogram HCGDBS is proposed. The HCGDBS requires no training and is designed to overcome illumination, translation, noise, and rotation.
3. Extensive experiments are conducted on four human-collected finger vein databases and compared with other related feature extraction methods for finger veins, revealing the discriminative nature of HCGDBS.

RELATED WORK

With the continuous in-depth study of finger vein feature extraction, its methods are roughly divided into three categories: (1) spatial domain, (2) frequency domain, and (3) deep learning.

The spatial domain feature extraction method extracts the rich texture variation and orientation features of finger veins through global features, local features, vein patterns, and feature learning and constructs discriminative feature descriptors. Ma et al. (2014) proposed a new global feature extraction method, namely, 2DPCA, which retains finger vein structural information and effectively reduces the feature dimension. Sikarwar et al. (2016) proposed encoding edge responses in eight directions to obtain different types of local direction patterns (LDPs) to extract features. Yang et al. (2017) proposed an innovative identification framework using a new analysis algorithm to further refine the vein pattern to obtain the vein network and trunk. Then, the similarity of the two networks and trunks is judged based on an ensemble matching strategy. Li et al. (2021) proposed a new fusion framework that combines FV and FKP. By the Gabor filter direction vector and image convolution, multimodal features are learned to maximize the distance and correlation within the interclass and minimize the intraclass distance for fusion recognition.

The frequency-domain feature extraction method uses some linear transformation or filters to convert finger vein images to the transform domain and applies some energy criterion to extract features. Ma et al. (2021), based on the encoding of discriminative information such as the orientation and scale of images in the frequency domain, proposed introducing directional gradients and local phase quantization to construct a discriminative pyramid histogram for finger vein recognition. Du et al. (2018) introduced the real-valued discrete Gabor transform to transform the extracted features into the frequency domain and then extracted the texture features of finger veins in the view of space-frequency analysis.

The deep learning feature extraction method uses many images as training samples, adapts to sample images captured by different devices, and achieves accurate recognition in a less constrained environment. Xie et al. (2019) proposed an improved CNN and supervised discrete hashing for finger vein authentication. CNN-supervised discrete hashing based on the triplet loss function not only optimizes the CNN model but also significantly reduces the template size. Yang et al. (2020) proposed a Lightweight CNN and antispoofing network (FVRAS-Net). The idea of multi-intensity lighting is applied to the finger vein recognition system, and the image with the largest amount of information is automatically selected for recognition, which effectively improves the identification performance. Hou et al. (2019) proposed combining a convolutional autoencoder and a support vector machine for verification. The convolutional autoencoder can improve recognition efficiency, mainly by reducing redundant information and efficiently learning the main information of finger veins to obtain discriminative features. SVM is used for the efficient classification and recognition process.

The frequency-domain feature extraction method of the finger vein has a low feature dimension and high computational efficiency. However, the frequency-domain features are easily affected by noise, and the finger vein recognition effect is worse than that based on spatial domain methods. Deep learning feature extraction methods do not require the manual design of feature descriptors but require many samples for training. Compared with the spatial domain method, the number of calculations is large, and it is not suitable for applying biometric identification technology. In summary, the spatial domain feature extraction method of finger veins is not easily affected by noise and does not require many samples for training. The histogram of competitive Gabor directional binary statistics proposed in this paper extracts features by airspace to construct a highly discriminative feature representation.

HISTOGRAM OF COMPETITIVE GABOR DIRECTIONAL BINARY STATISTICS

This method explicitly encodes finger vein structure information to extract highly discriminative features for image classification. A multidirectional Gabor filter is proposed to obtain the dominant direction of each pixel of the finger veins. Regarding the dominant direction sequence encoding, the relationship between the order intensity difference between the adjacent three directions of each pixel is used to construct a competitive Gabor direction binary pattern (CGDBP). Next, the feature image was separated into several blocks to calculate the subhistogram of each block and then combined into a histogram, which constitutes the histogram of competitive Gabor directional binary statistics (HCGDBS). For the test samples, the normalized correlation coefficient is introduced according to the one-dimensional characteristics of finger veins, and then the distance between them and the training samples is calculated by NCC for classification and recognition. Figure 1 reveals the process of HCGDBS.

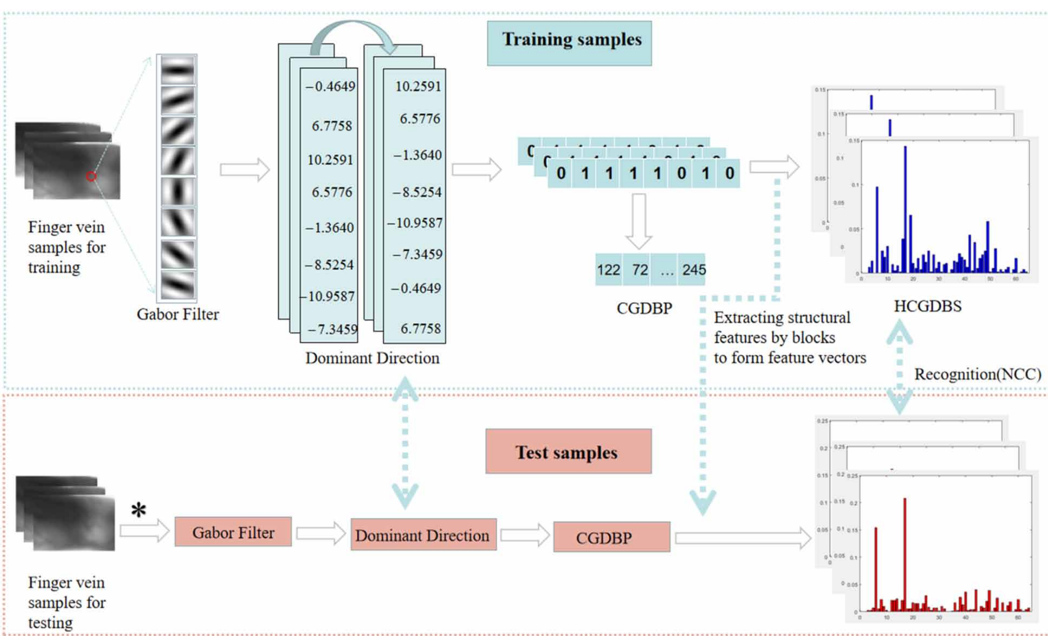
Gabor Filter

As a linear filter with adjustable direction, the Gabor filter has a similar frequency and direct expression to the human visual system and can approximate the receptive field function of a single cell well (Zhao & Zhang, 2020). In addition, the Gabor filter has good two-dimensional spectral characteristics of texture and the change characteristics of texture with two-dimensional spatial position. Due to these excellent characteristics, the Gabor filter can well describe the characteristics of the image, so it is widely applied to finger vein feature recognition. A typical two-dimensional Gabor filter has a general form:

$$G(x,y,\theta,\mu,\sigma,\beta)=\frac{1}{2\pi\sigma^2}\times\exp(-(\frac{x^2+y^2}{2\sigma^2}))\times\exp(2\pi i\mu(x\cos\theta+y\sin\theta)) \tag{1}$$

where μ represents the radial frequency, θ represents the direction of the Gabor filter, σ represents the standard deviation of the Gaussian function, and $i=\sqrt{-1}$. Referring to the introduction of competitive coding in the related literature, this paper also uses the real value of the Gabor filter to obtain structural features. To extract features more accurately, the Gabor filter is converted to an "upside-down" form (Zhang et al.,2017). Therefore, the largest filter response corresponds to the smallest convolution value. The transformed Gabor filter is defined as follows:

Figure 1.
The feature extraction process of the proposed HCGDBS



$$G(x,y,\theta,\mu,\sigma)=\frac{1}{2\pi\sigma^2}\times(1-\exp(-\frac{x^2+y^2}{2\sigma^2})\times\exp(2\pi i\mu(x\cos\theta+y\sin\theta))) \quad (2)$$

where $\theta_j=\frac{\pi\left(j-1\right)}{N_\theta},(j=1,2,.....,N_\theta)$, $N_\theta=8$.

Dominant Direction

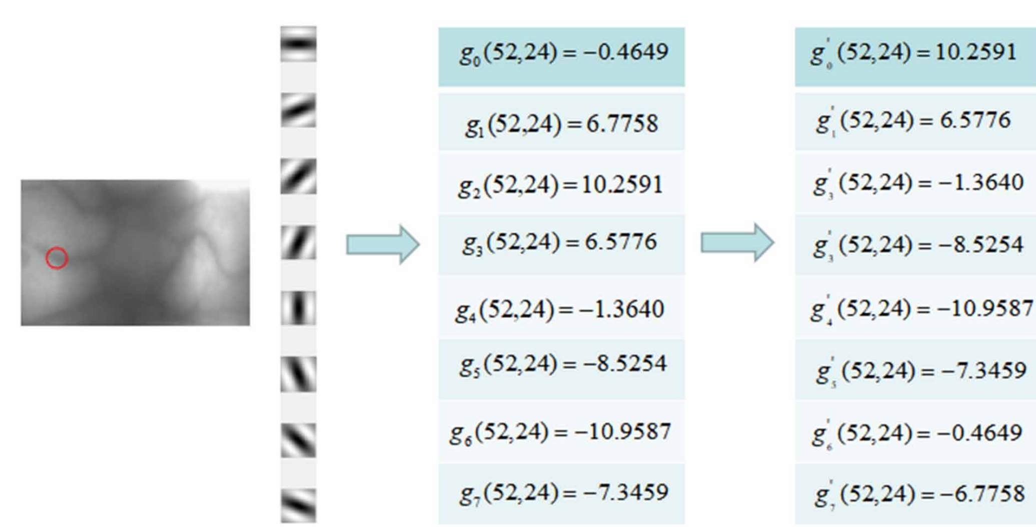
Due to the effect of the acquisition environment, light changes, finger posture, and other factors, there is irrelevant information such as rotation, translation, and noise in the captured image, which affects the finger vein recognition performance. Here, a Gabor filter is applied to filter the vein image to obtain the dominant direction of the pixel to overcome the rotation of the image. First, the Gabor filter bank with the orientation of $j\pi/8(j=0,1,...,7)$ is used to filter the preprocessed image finger vein image. Let G_j be the real part of G with direction of $j\pi/8(j=0,1,...,7)$. The convolution of the image with the filter is:

$$g_j(x,y)=G_j*I(x,y) \quad (3)$$

where "$*$" is the convolution operation, I refers to the finger vein image, $g_j(x,y)$ is the filter value of $I(x,y)$ with G_j in the direction of $j\pi/8$, and (x,y) represents the location of I.

Determining the main direction of the finger vein is extremely critical to coding. The Gabor filter is less likely to produce a larger filter response, and it is more discriminative to extract the index of its maximum filter value as the main direction (Fei et al., 2019). According to the convolution of the filter and the image, the filter response values in eight directions are obtained, and the direction with the largest filter response value is extracted as the main direction. The maximum filter response is used to overcome the effects of noise and rotation and improve the discriminative power of structural features (Wu et al., 2021).

Figure 2.
Calculation process of the dominant direction of the finger vein



$$C(x,y) = \arg\max_{j} g_j(x,y), (j = 0,1,...,7) \tag{4}$$

where $C(x,y)$ is the dominant direction at a certain pixel point (x,y) and represents the index value of the maximum filter response.

Loop filter the sequence of values according to the dominant direction until the point indexed by $C(x,y)$ is located at the first position:

$$g_0^{`}(x,y), g_1^{`}(x,y), ..., g_t^{`}(x,y), ..., g_7^{`}(x,y) := g_C(x,y), ..., g_7(x,y), g_0(x,y), ..., g_{C-1}(x,y) \tag{5}$$

where ":=" refers to the elementwise redistribution. Figure 2 is the process of extracting the dominant direction of a pixel on the finger vein.

CGDBP

Local binary patterns and their many variants are discriminative in extracting vein features (Luo et al.,2016). However, most local descriptors are encoded by comparing the local differences between the central pixel and its neighbours, which do not fully consider the local intensity order relationship between the adjacent directions of the pixel. For this problem, the researchers further propose to obtain the dominant direction referring to Gabor filtering and then encode the intensity sequence difference relationship between the adjacent three directions of each pixel point on the vein image to improve the discrimination of extracted features.

According to the filtered response values of the eight directions of the Gabor filter, the researchers evenly distributed the points in the cyclic sequence on the circle (Figure 3). According to the above mentioned dominant direction, the sequence is sorted (Formula (5)). Eight directions are used in this paper, so there are eight groups, namely:

$$\bar{g}_j = \begin{cases} (g_7^{`}, g_0^{`}, g_1^{`}), j = 0 \\ (g_0^{`}, g_1^{`}, g_2^{`}), j = 1 \\ \cdots \\ (g_6^{`}, g_7^{`}, g_0^{`}), j = 7 \end{cases} \tag{6}$$

$$\phi(j) = \mathrm{mod}(\mathrm{mod}(j-2, N_\theta) + 1, N_\theta) \tag{7}$$

$$\varphi(j) = \mathrm{mod}(\mathrm{mod}(j, N_\theta) + 1, N_\theta) \tag{8}$$

where $\bar{g}_j (j = 0,1,...,7)$ is a vector whose elements are the filtered value of the certain pixel in the direction of j.

Next, the researchers sorted the three filtered values in each group:

$$\bar{d}_j = \begin{cases} (d_{j,1}, d_{j,2}, d_{j,3}), j = 0 \\ (d_{j,1}, d_{j,2}, d_{j,3}), j = 1 \\ \cdots \\ (d_{j,1}, d_{j,2}, d_{j,3}), j = 7 \end{cases} \tag{9}$$

where $\bar{d}_j (j = 0,1,...,7)$ is a vector whose elements are the filtered value in descending order.

Finally, based on Formula (10), the researchers encode according to the intensity order difference relationship between the filtered values in the three directions in each group. The formation process of CGDBP is displayed in Figure 3.

$$CGDBP = \sum_{j=0}^{7} s((d_{j,1} - d_{j,2}) - (d_{j,2} - d_{j,3}))2^j \tag{10}$$

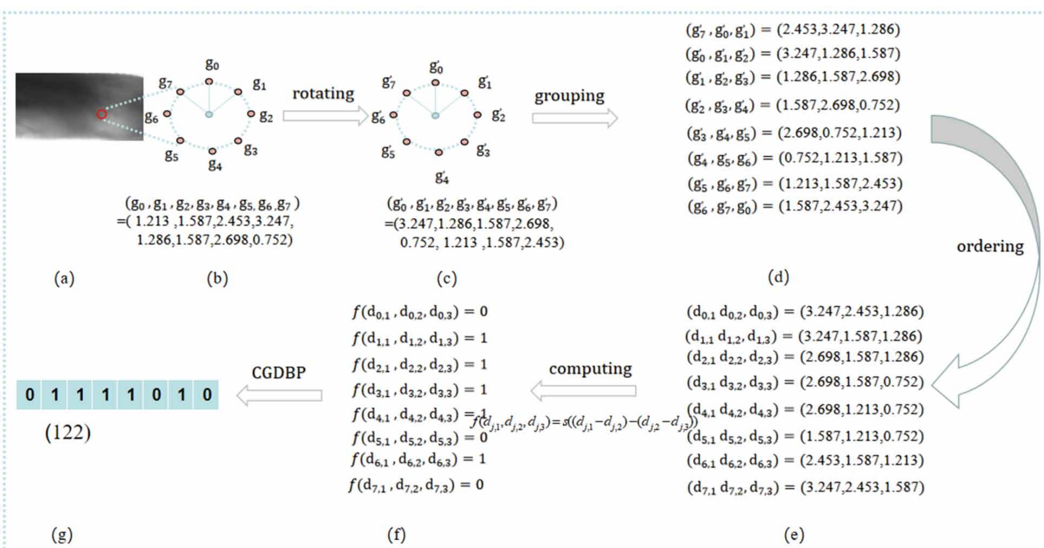
$$s(g) = \begin{cases} 1, g > 0 \\ 0, g \le 0 \end{cases} \tag{11}$$

In Figure 3 (a) The ROI image of the preprocessed finger vein, (b) eight filter response values of a pixel on the finger vein image convolved with the Gabor filter, (c) the filter results in eight directions are cyclically shifted according to the maximum value of the filter response, (d) grouping, dividing each direction and adjacent two-direction filter values into a group, (e) ordering filtered values within each group, (f) calculating the sequential intensity difference relationship between each direction of each pixel and adjacent directions, (g) calculating the CGDBP value corresponding to a certain pixel of the image according to Formula (10).

HCGDBS

To improve the identification effect, the local description extraction method based on histograms can overcome image translation to obtain discriminative features. The feature map is divided into blocks, local block features are extracted, and then a joint feature histogram is formed by concatenation. First, the feature map is divided into small cells ($M \times N$). Then, several cells are formed into a block ($K \times L$), the CGDBP of all cells in a block is calculated, and the size of the cell is used as the moving step. According to Formula (10), the value range of the CGDBP is [0, 255], and 4 is used as the moving step in [0, 255], which can make the extracted feature dimension from 255 to 64. The HCGDBS feature dimension of a finger vein image ($H \times W$) is

Figure 3.
Formation process of the CGDBP



$$Length(\mathrm{HCGDBS}) = ((H - K) / M + 1) * ((W - L) / N + 1) * 64 \quad (12)$$

This paper proposes a feature representation called HCGDBS, which has the following properties. First, it is robust to finger vein image rotation by referring to the main direction, and the discriminative feature obtained by computing the CGDBP using the local sequential difference relation is robust to illumination. Second, the HCGDBS extracts image features by blocks, which not only obtains rich local detail information but also overcomes image translation and improves the recognition performance. Third, HCGDBS enriches local features, including local dominant directions, local adjacent three directions, and their sequential difference relationships. None of these are explored in Gabor and LBP.

Matching and Identification

In recognition experiments, the researchers use NCC to evaluate the similarity between two finger vein images. $A = (a_1, a_2, \ldots, a_n)$ and $B = (b_1, b_2, \ldots, b_n)$ are the feature vectors of the training set and test set, respectively.

$$NCC = \frac{\left|\sum_{i=1}^{n}(a_i - \mu_A)(b_i - \mu_B)\right|}{l \times \sigma_A \times \sigma_B} \quad (13)$$

where $\mu_A(\mu_B)$ refers to the mean of $A(B)$, $\sigma_A(\sigma_B)$ represents the standard deviation of $A(B)$, and l is the length of A or B. Judging by the NCC value, if its value is equal to 1, it means that the two samples are likely to be the same; otherwise, they are considered different.

In the authentication experiments, the class labels of the finger vein images are known. The researchers evaluated the experimental performance by conducting a genuine-imposter matching analysis on four different finger vein databases.

EXPERIMENTAL ANALYSIS

In this section, the researchers performed extensive experiments on four finger vein databases, including PolyU (Kumar & Zhou, 2011), SDUMLA-FV (Liu et al.,2014), FV-USM (Asaari et al.,2014), and FV-TJ (Hu et al.,2018).

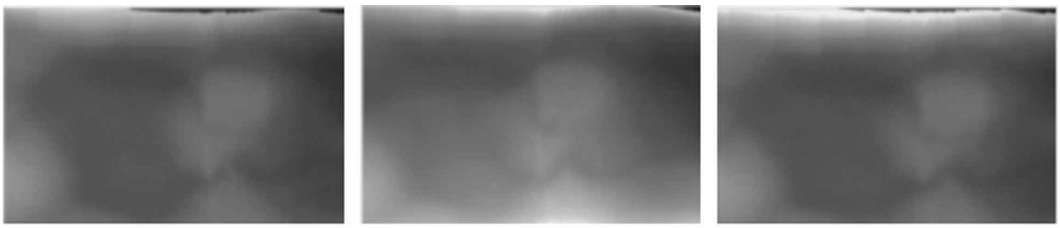
Database Introduction

On the PolyU database, finger vein images were collected two times, the shortest time interval was one month, and the longest time interval is more than six months. The first-stage database was used in the experiment. A total of 156 subjects provided vein images, each provided 2 fingers, and each finger provided 6 samples. By default, finger vein images captured by different fingers of a person are considered as different classes, namely, 312 (156 objects and 2 fingers) categories, with 6 samples in each category. The image undergoes a series of preprocessing operations, and the size of the image is 150×96. In the experiments, samples 1, 3, and 5 are selected for training, and samples 2, 4, and 6 are used for testing.

On the SDUMLA-FV database, which contains images collected from 106 individuals, each provides 6 fingers, and each finger provides 6 image samples. Similar to PolyU, by default, images captured by different fingers of the same person are considered to be of different classes, namely, 636 (106 objects and 6 fingers) classes with 6 samples per category. The image undergoes a series of preprocessing operations, and the size of the image is 150×96. In othe experiment, samples 1, 3, and 5 are selected for training, and samples 2, 4, and 6 are used for testing.

Figure 4.
The finger vein database of Hong Kong Polytechnic University (PolyU)

Figure 5.
The finger vein database of Shandong University MLA Laboratory (SDUMLA-FV)



On the FV-USM database, which contains 4 different fingers from 123 different subjects, 6 images are collected for each finger. As above, by default, the FV-USM database contains 492 (123 subjects and 4 fingers) classes with 6 samples per class. The size of the image is 300×100 . In the experiment, samples 1, 3, and 5 are selected for training, and samples 2, 4, and 6 are used for testing.

The FV-TJ database contains finger vein images obtained from 64 different individuals, and 15 images were collected for each finger, with a total of 64 categories. The sample images in the database are all preprocessed, and the image pixels are 172×76 . In the experiment, the first 5 images of each class of samples are selected for training, and the rest are selected for testing.

Figure 6.
The finger vein database of the University of Technology Malaysia (FV-USM)

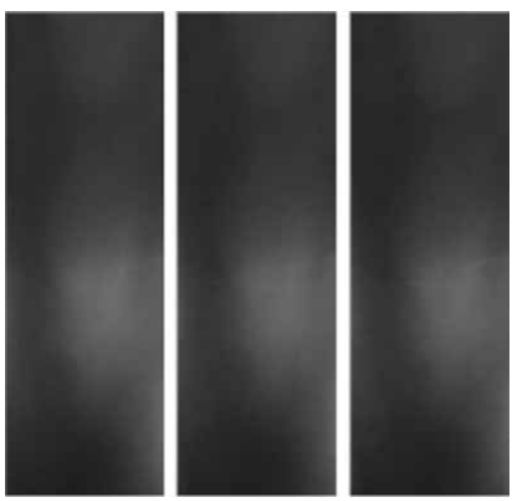
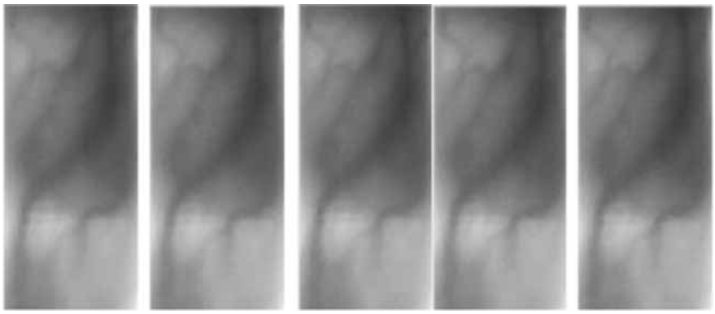


Figure 7.
The finger vein database of Tianjin Key Laboratory (FV-TJ)



Parameter Test

In this experiment, the researchers investigate the effect of the proposed method for finger vein recognition under different parameter values, including frequency u and standard deviation σ . To make the histogram of competitive Gabor directional binary statistics achieve the optimal effect in finger vein identification, the effects of different u and σ on the recognition performance are analysed in four databases. The researchers employ two metrics, RR and EER, to evaluate HCGDBS performance. RR is an abbreviation for recognition rate, and EER is an abbreviation for equal error rate. FAR denotes the false acceptance rate, FRR denotes the false rejection rate. Formula (14) and Formula (15) show how FAR and FRR are calculated.

$$\mathrm{FAR} = \frac{\text{Number of matching scores in false acceptance}}{\text{Number of matching scores}} \tag{14}$$

$$\mathrm{FRR} = \frac{\text{Number of matching scores in false rejection}}{\text{Number of matching scores}} \tag{15}$$

When the two are equal, the value is EER.

First, the researchers evaluate the effect of the frequency u in the Gabor filter on the identification effect and choose the best value for subsequent experiments. The frequency u varies from 0.0085 to 0.0435 in 0.005 intervals. It can be observed in Table 1 that when u =0.0385, the experimental effect on the databases is optimal. When the frequency u parameter is fixed, according to Table 2, the standard deviation σ has a significant impact on the recognition performance. Through the comparison of the following eight groups of experiments, when the standard deviation is σ =12.2998, the PolyU database RR reaches 99.89%, and the EER reaches 0.5342%. The SDUMLA-FV database has an RR of 99.11% and an EER of 0.8386% when u =0.0385 and σ =13.2998. Compared with PolyU, SDUMLA-FV has fewer clear finger vein (FV) images, so the RR decreases. The FV-USM database is less affected by parameters; the RR is 99.73%, and the EER is 0.2710%. The FV images in the FV-TJ database are clear, the RR can reach 100%, and the EER can reach 0%.

Classification and Recognition

Finger vein recognition is a classification matching process that determines the labels of test finger vein images at this stage. Usually, the class label of the training sample is known. By comparing

Table 1.
Test results of parameter u on finger vein databases

μ	PolyU		SDUMLA-FV		FV-USM		FV-TJ	
	RR(%)	EER(%)	RR(%)	EER(%)	RR(%)	EER(%)	RR(%)	EER(%)
0.0085	93.91	4.2422	95.60	3.2219	99.53	0.4353	98.91	0.6250
0.0135	96.47	2.7095	96.91	2.2358	99.66	0.4605	99.38	0.6250
0.0185	97.76	1.9388	97.75	1.9392	99.59	0.4605	100	0.4629
0.0235	99.04	1.4473	98.32	1.6965	99.66	0.3388	100	0.1147
0.0285	99.15	1.0684	98.43	1.2935	99.73	0.2710	100	0.1353
0.0335	99.57	0.6410	98.74	1.1619	99.66	0.2710	100	0.0568
0.0385	99.89	0.5342	99.11	0.9434	99.66	0.2710	100	0
0.0435	99.79	0.8547	99.11	1.0330	99.73	0.3388	100	0

Table 2.
The test results of the parameter σ when u =0.0385 on finger vein databases

σ	PolyU		SDUMLA-FV		FV-USM		FV-TJ	
	RR(%)	EER(%)	RR(%)	EER(%)	RR(%)	EER(%)	RR(%)	EER(%)
6.2998	99.15	1.2433	98.17	1.4980	99.46	0.7389	100	0.1563
7.2998	99.36	1.0099	98.43	1.4151	99.53	0.5092	100	0.0863
8.2998	99.47	0.9615	98.32	1.2583	99.73	0.4123	100	0.0899
9.2998	99.68	0.8547	98.69	1.2871	99.66	0.3388	100	0.1563
10.2998	99.68	0.6410	98.69	1.0482	99.66	0.3388	100	0.1632
11.2998	99.68	0.6410	98.90	1.0507	99.73	0.3388	100	0
12.2998	99.89	0.5342	99.11	0.9434	99.66	0.2710	100	0
13.2998	99.89	0.6410	99.11	0.8386	99.73	0.2730	100	0

the training sample and the test sample, the class label with the greatest similarity with the training sample is used as the class label of the test sample.

Table 3 summarizes the vein recognition effects of spatial domain feature extraction methods on the PolyU, SDUMLA-FV, FV-USM, and FV-TJ databases. LBP and HOG are widely used local descriptors that are simple to calculate and robust to illumination but are susceptible to noise. Global WLD are easily affected by illumination, translation, and rotation, so their recognition performance is not as good as block WLD. DBC and DBD extract local features through feature-learning methods. Compared with LBP, WLD, and HOG, the performance has been significantly improved, but they not only include the process of feature extraction but also feature learning. Relatively speaking, the time is not as good as other traditional times. DCGWLD takes into account variable curvature, and the effect is significantly improved, but the collected vein images are easily affected by rotation, and considering that the curvature of the vein alone is not enough to reflect its discriminating information, it does not achieve the best effect. BMULBP considers the scale change in vein images and effectively extracts local texture features by introducing multiscale circular neighbourhood LBP. Compared with the above descriptors, the recently proposed SRRLR uses low-rank representation to reduce the structural feature dimension and improve extraction efficiency.

Table 3.
Comparison between the proposed method and spatial domain method on databases

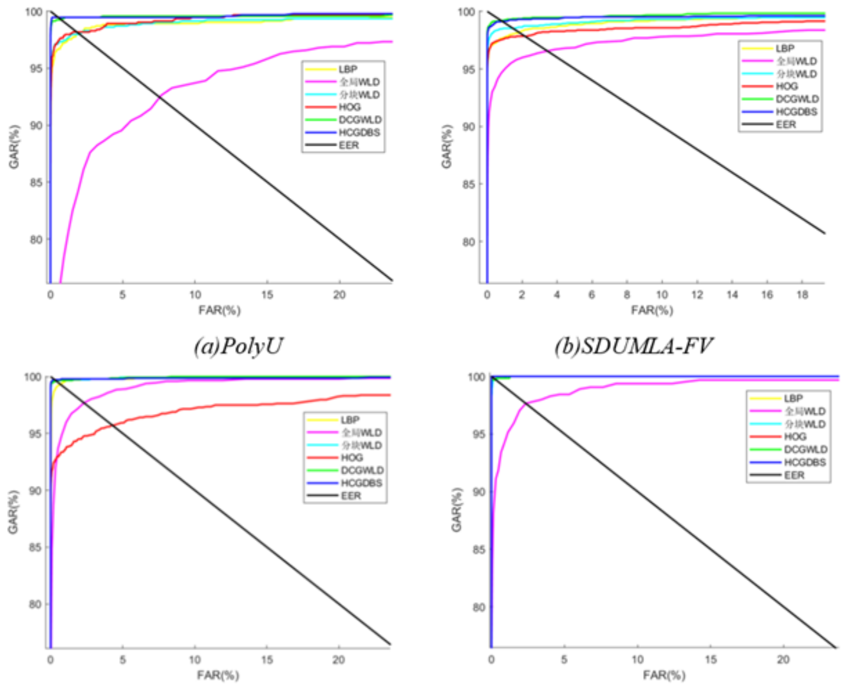
Categories	Methods	PolyU	SDUMLA-FV	FV-USM	FV-TJ
		EER(%)	EER(%)	EER(%)	EER(%)
Spatial	LBP (Ojala et al.,2002)	2.0299	1.8302	0.6775	0.1106
	HOG (Dalal & Triggs, 2005)	1.8162	2.1488	4.2683	0.0025
	global WLD (Chen et al.,2009)	7.5536	3.4379	2.3124	2.3482
	block WLD (Luo et al.,2016)	1.9627	1.4675	0.3388	0.3125
	DBC (Xi et al.,2017)	1.4400*	0.8800*	-	-
	DBD (Liu et al.,2017)	0.6900*	1.8900*	-	-
	DCGWLD (Wang et al.,2019)	0.7479	0.7862	0.3413	0.2755
	BMULBP(Hu et al.,2020)	-	-	1.8900*	0.1600*
	SRRLR(Yang et al.,2021)	2.6600*	3.7500*	-	-
Proposed method	HCGDBS	0.5342	0.8386	0.2710	0

*EER are cited from the original literature.

From Table 3, the proposed HCGDBS outperforms the listed spatial domain finger vein feature extraction methods. This method not only weakens the influence of image illumination, translation, and rotation but also considers the order difference relationship between the response values of the Gabor filter in the adjacent three directions and obtains a highly discriminative local feature histogram. Compared with several other spatial domain feature extraction methods, the HCGDBS proposed on the PolyU database has a 1.8283% EER lower than the average EER of several other methods. Because the sample images on the PolyU database have translation and rotation, the HCGDBS proposed in this paper can solve this problem well, so the experiment has a good effect. For the SDUMLA-FV database, compared with spatial domain finger vein feature extraction methods, it is improved, but the EER increases by 0.0524% compared to the DCGWLD method. Because the images in the SDUMLA-FV database are blurry and severely deformed, the variable curvature Gabor filter constructed by DCGWLD considers the degree of curvature of the vein curvature and enriches the line features of images. In later experiments, the researchers will consider the degree of curvature of the vein and the convexity and concavity of the vein curve to extract highly discriminative vein structure features. The HCGDBS proposed in this paper on the FV-USM and FV-TJ databases reduces the EER by 1.3671% and 0.5349%, respectively, compared with other listed spatial domain feature extraction methods. Among them, the vein recognition effect on the FV-TJ database is remarkable, the RR reaches 100%, and the EER is reduced to 0%. In summary, on the PolyU, SDUMLA-FV, FV-TJ, and FV-USM databases, the proposed method is not only more robust to image noise but also compared with similar spatial domain feature extraction methods. It has good robustness to images with translation and rotation and can overcome the differences between similar samples and extract highly discriminative features. Figure 8 shows the ROC curve of finger vein feature extraction in the spatial domain. Through analysing the above experimental data and the observation of the ROC curve, the results indicate that the HCGDBS proposed in this paper has a good finger vein recognition effect.

Table 4 lists three finger vein feature extraction methods based on the frequency domain, with a low feature dimension and a small number of calculations, but the recognition effect is poor compared with the feature extraction method in the airspace. It is concluded from Table 4 that the RR of the proposed method on the four finger vein databases is significantly improved compared with other frequency-domain feature extraction methods. On the PolyU database, the RR of HCGDBS is 5.87% higher than that of DCT and 3.55% higher than that of PLPQ. The quality of finger vein

Figure 8.
ROC curves of finger vein databases



(a)PolyU (b)SDUMLA-FV
(c) FV-USM (d) FV-TJ

images collected on the SDUMLA-FV database is poor, and the features extracted by RDGT are not sufficiently discriminative. The proposed method can overcome this defect well, and the RR is improved by 3.04%. The improvement effect of the recognition rate on FV-USM and FV-TJ databases is not as good as PolyU and SDUMLA-FV, but it is improved overall, with an average increase of 1.78% and 0.78%. In summary, it is improved.

Deep learning feature finger vein extraction method: Gabor & CNN adaptively learns the parameter of the Gabor filter by the CNN, which solves the problem that the Gabor filter parameter is hard to adjust. The multitask learning model improves feature discrimination by optimizing the ROI and feature extraction process. The CycleGAN-based method improves the recognition performance

Table 4.
Comparison between the proposed method and frequency-domain method on databases

Categories	Methods	PolyU	SDUMLA-FV	FV-USM	FV-TJ
		RR (%)	RR (%)	RR(%)	RR(%)
Frequency	DCT (Dale et al.,2009)	-	-	96.41	98.44
	RDGT (Du et al.,2018)	94.02	96.07	99.39	100
	PLPQ (Ma et al.,2021)	96.34*	-	98.05*	-
Proposed method	HCGDBS	99.89	99.11	99.73	100

*RR are cited from the original literature.

when using unobserved finger vein data. According to Table 5, compared with the other three deep learning feature extraction methods listed, the EER of the proposed method is significantly reduced on the PolyU, SDUMLA-FV, FV-USM and FV-TJ databases.

Ablation Experiment of HCGDBS

To further clarify the effectiveness of HCGDBS and verify that the proposed CGDBP has high discriminative power, the authors performed the following experiments. (1) The eight-direction response values after the dominant direction is determined are sequentially encoded according to the magnitude relationship between the adjacent two directions, and an eight-bit binary sequence is obtained, which is recorded as $CGDBP_1$. (2) The eight-direction response values after the dominant direction is determined are sequentially encoded according to the magnitude relationship between the adjacent three-direction differences to obtain an eight-bit binary sequence, which is recorded as $CGDBP_2$. (3) The eight-direction response values after the dominant direction is determined are sequentially encoded according to the magnitude relationship of the adjacent three-direction descending differences, and an eight-bit binary sequence is obtained, which is recorded as $CGDBP_3$ (HCGDBS). In the above representations, three local binary statistical feature histograms are formed. In this research, to better prove the effectiveness of the HCGDBS, the authors conducted a wide test on the four different databases mentioned above.

From the comparison results, the authors can draw observations. On four finger vein databases, $CGDBP_3$ (HCGDBS) outperformed $CGDBP_1$ and $CGDBP_2$. This result suggests that HCGDBS improves the discriminative power by encoding the order difference between adjacent three directions. The RR of $CGDBP_2$ on the PolyU, FV-USM, and FV-TJ databases is higher than that of $CGDBP_1$. For the SDUMLA-FV database, the EER of $CGDBP_2$ is 0.1612% lower than that of $CGDBP_1$, which indicates that extracting three-direction difference features is more discriminative than extracting adjacent two-direction features.

Table 5.
Comparison between the proposed method and deep learning method on databases

Categories	Methods	PolyU	SDUMLA-FV	FV-USM	FV-TJ
		EER (%)	EER (%)	EER (%)	EER (%)
Deep learning	CNN (Zhang et al.,2019)	1.6700*	1.0900*	0.5700*	-
	Multi-task(Hao et al.,2020)	-	1.1700*	0.7400*	-
	CycleGAN (Noh et al.,2021)	0.5800*	2.1700*	-	-
Proposed method	HCGDBS	0.5342	0.8386	0.2710	0

*EER are cited from the original literature.

Table 6.
Comparison of three local descriptors

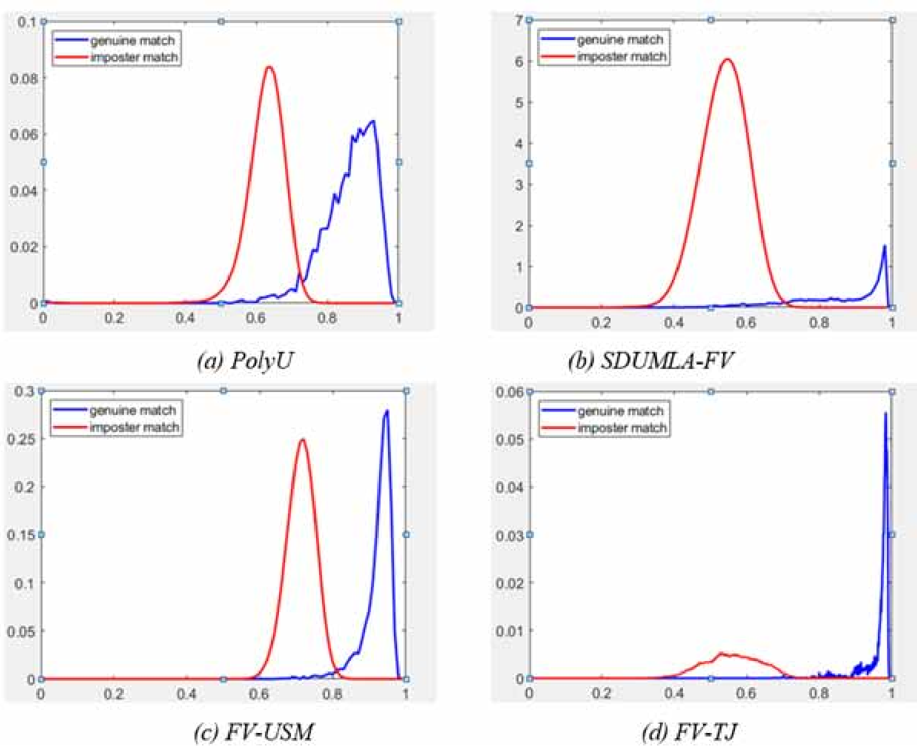
Local Descriptors	PolyU		SDUMLA-FV		FV-USM		FV-TJ	
	RR(%)	EER(%)	RR(%)	EER(%)	RR(%)	EER(%)	RR(%)	EER(%)
$CGDBP_1$	99.25	0.9071	98.85	1.2112	99.66	0.3632	100	0.1200
$CGDBP_2$	99.36	0.5342	98.74	1.0500	99.66	0.4065	100	0
$CGDBP_3$ (HCGDBS)	99.89	0.5342	99.11	0.8386	99.73	0.2710	100	0

Finger Vein Verification

In finger vein authentication, each image is matched one-to-one with other images in the same database according to the class label of the image. Then, a true-false matching analysis is employed to evaluate the experimental effect. Genuine matching is the feature matching between the same type of finger veins, and imposter matching is the feature matching between different types of finger veins.

The authors compute genuine and imposter matching scores by the HCGDBS. Referring to matching the distribution of scores, the performance of the algorithm can be qualitatively measured. Figure 9 (a)-(d). shows the distribution of matching scores about genuine and imposter on the PolyU, SDUMLA-FV, FV-USM, and FV-TJ databases, respectively. Figure 9 demonstrates that genuine matching and imposter matching have highly independent distributions from the vein database. Among them, the genuine matching scores are mainly concentrated in regions greater than 0.8, while the imposter matching scores are mainly concentrated in regions less than 0.8. This shows that the HCGDBS feature has strong discriminative power for finger vein images. On the FV-TJ database, the matching scores show a high degree of independence, while there is partial overlap on the other three databases. The images in these three databases have severe deformation, blurring and scale changes, which lead to the change in the features extracted by the Gabor filter being the main reason for this result. In the next step, the authors consider using multiscale, multiorientation, and multicurvature to enhance the robustness of HCGDBS features to fit shape and scale changes.

Figure 9.
Finger vein database genuine matching score and imposter matching score



CONCLUSION

The histogram of competitive Gabor directional binary statistics proposed in this paper is an effective image representation. It calculates the sequential filtering difference relationship between adjacent three directions under the multidirectional Gabor filter regarding the dominant direction and obtains the discriminative feature of each pixel from finger vein images. HCGDBS is based on training-free and designed to overcome illumination, translation, noise, and rotation, and the effectiveness of the HCGDBS is validated using widely used finger vein databases.

In addition, there are still some problems in this paper that need further research. (1) HCGDBS considers the rotation, translation, and illumination of the image but ignores the influence of scale change and curvature on the extracted features. In the next experiments, multiscale and multicurvature Gabor filters can be used to extract vein image features to improve the discrimination of extracted features. (2) The current research is based on finger vein recognition, but this method may also apply to other biometric recognition methods, such as palmprint and fingerprint.

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