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Person Recognition Using Finger Vein Biological Trait

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Abstract- Currently, one of the newest areas of study in biometric recognition is finger vein recognition. Although the Gabor filter's settings are hard to modify, it has been widely employed for vein and finger recognition. Here, an adaptive-learning Gabor filter is proposed to address this issue. Based on the goal function, the gradient of the Gabor-filter parameters is calculated, we merge convolutional neural networks with a Gabor filter. Then, we optimize its parameters by back-propagation. The Gabor filter's θ parameter can be learned at same angle as the vein texture in an image of a finger vein. There is a relationship between the Gabor filter's σ and λ parameters, and the latter can converge to ideal value. With this method, we not only select appropriate and effective Gabor filter parameters for filter bank construction, but we also consider the interrelationships between those parameters. Lastly, we conduct tests on four publicly available finger vein datasets. According to experimental results, our approach performs better in finger vein classification than the most advanced techniques.

Keywords - Gabor filters, vein recognition, convolutional nerual networks, adaptive learning

I. INTRODUCTION

One innovative biometric recognition technology is FINGER-vein recognition [1]. In order to gather finger vein images for identification, it primarily makes advantage of the near-infrared light absorption properties brought on by the hemoglobin in the veins [2].

Finger-vein information is more difficult to duplicate than fingerprint or other biometric recognition [3] [4]. Thus, compared to fingerprint recognition, finger vein recognition is comparatively safer and more reliable.

Fourier transform [6], local histogram to gram and global histogram normalization [7], and sparse representation [8] are the foundations of the traditional feature extraction techniques for finger vein detection. Nevertheless, these techniques only marginally enhance the ability to recognize low-quality images of finger vein. The extraction of vein-texture information is clearly impacted by an oriented filter. For instance, Wang et al. [9] suggested a novel technique for identifying palm veins that uses Gabor wavelet filters to extract vein features. A number of enhanced techniques as well as the traditional repeating linear-tracking algorithm [10] were suggested by other studies as picture segmentation techniques for finger veins. Texture and orientation are extracted using the Gabor filter. In addition to being a popular technique for improving finger vein images, it is also frequently used to extract textural details from finger veins. Thus, in finger vein identification technologies, the Gabor filter is crucial. A Gabor filter and a homomorphism filter were proposed by Yang et al. [11] [12]. Zhang [13] proposed a gray-level combination of the circular Gabor-filter enhancement approach for texture-feature extraction and picture improvement. A multi-channel Gabor-filter improvement technique was proposed by Yang [14]. Using an extended infrared hand dorsum image and a Gabor filter, Ferrer [15] produced a template. An enhancement technique based on symmetric Gabor-filter banks and scatter removal was presented by Shi et al. [16]. Xieetal. [17] projected a method combining symmetric Gabor filter with a steering filter to extract the finger-vein image. Lu et al. [18] projected a feature extraction method based on Gabor-corresponding histograms. Yang et al. proposed the Gabor Tri-branch structure [19] and point group method joint with a Gabor filter (PG-Gabor) [20] to employ the vein point & non-vein point. These methods solve different problems in finger-vein recognition. Nevertheless, setting up the Gabor filter's settings is challenging. In different applications & datasets, one must physically regulate the parameters to find relative optimal value. This makes parameter-setting very difficult. Furthermore, little attention has been paid to the importance of individual filters in a Gabor-filter bank. Currently, it is assumed that every filter in a filter bank is significant. However, only a small portion of the many filters in a Gabor-filter bank are important; the rest are either unnecessary or redundant. An adaptive-learning Gabor filter is suggested as a solution to these issues. This paper's primary contributions are as follows:

II. FINGER VEIN RECOGNITION METHODS

Numerous techniques for identifying veins in the fingers have been developed and used in recent years. We divide the identification techniques into two groups: the deep neural network method and the non-deep neural network approach.

Non-deep neural network techniques: There were numerous traditional handcrafted feature extraction techniques prior to the deep neural network approach. In order to address the issue of ambiguous finger vein images brought on by variations in finger position and illumination, Naoto Miura et al. suggested the iterative tracking of local lines [21] & maximum curvature points [22] techniques for extracting the global vascular veins. In order to enhance recognition performance, Eui Chul Lee et al. [23] suggested representing veins by tiny nodes of finger veins & coding finger veins using local binary pattern (LBP). Researchers developed LLBP (local line binary pattern) [24] and ELBP (efficient local binary pattern) [25] to address some of the issues with LBP. A novel discriminative binary codes (DBC) [26] learning approach is suggested and shown to be successful based on the relationships among vein topics. A discriminative binary descriptor (DBD) [27] approach is proposed to learn a feature mapping relationship to improve the identification capacity of local features. Some traditional techniques for encoding and feature extraction have been developed recently, including the iterative quantization-based method (ITQM) [29], the k-means hashing-based method (KMHM) [28], weighted vein code indexing [30], anatomy structure analysis-based vein extraction (ASVAE) [31].

III. GABOR FUNCTION

A wavelet is the Gabor filter [37]. The British physicist Gabor was the first to propose the one-dimensional (1D) variant of the Gabor function in 1946. A two-dimensional (2D) Gabor function was then proposed by Daug man [38] in 1980. Both the time-domain & frequency-domain transform properties of the Gabor filter are good. Filters with varying scaling directions due to various parameters (e.g., spatial position, frequency, phase & direction) are constructed using gabor functions. Additionally, Marcel Ja [39] demonstrated that basic cellular receptive fields might be accurately described by 1D Gabor functions. The study of [40] demonstrated this association, and Daugman [38] performed a 2D spectral analysis of the distribution of cortical receptive fields. According to neurophysiological research, simple cells of various sizes have the same spatial arrangement in their receptive fields. It was demonstrated by Daug Man [41] and Porat [42] that a set of 2D Gabor wavelets sampled logarithmically in the frequency domain may best represent all simple cells.

Images can be separated into spatial and frequency-domain components for visual cortex perception, according to numerous experimental studies. Moreover, locally symmetric and anti-symmetric base functions can be used to represent an image. The Gabor function shares similarities with the human cerebral cortex's 2D reflex zone of simple cells.

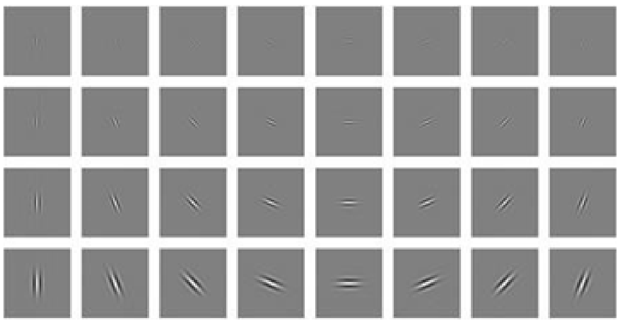


FIGURE 1. Gabor filter's frequency diagram.

Deep neural network techniques: Wu et al. [1] suggested extracting finger vein characteristics using the Radon transform, followed by classification using neural networks. Using a four-layer CNN, Radzi et al. [32] extracted features and compared the features' Euclidean distances. Additionally, light convolutional neural networks [33], two-stream convolutional neural networks [34] & completely convolution neural networks [35] are the most recent deep neural network techniques. A feature extraction technique based on deep representation was presented by Qin et al. [36]. The foreground segmentation image was first created by segmenting the finger image's foreground and background. Next, CNN is used to forecast whether each pixel in the foreground segmentation image is a vein point or a non-vein point. Ultimately, a fully convolution neural network was able to restore the segmented image's missing vein pattern.

Information about local structure that corresponds to spatial frequency (scale), spatial position, and direction selectivity can be captured by the Gabor function. The received field model of mammalian retinal nerve cells is thus compatible with the 2D Gabor filter. Orthogonal directions are represented by the real and imaginary components of the Gabor function. A complex number could be created by combining the two elements. The expression for a 2D Gabor function is (1).

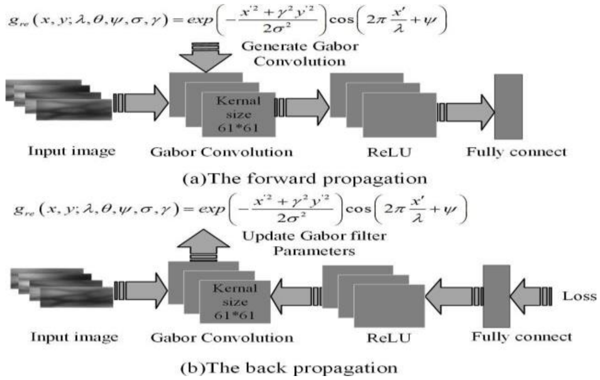
Reference		nf	no
A.K.Jain et al. [44]		5	4
S.Li et al. [45]		4-6	4-6
D.A.Clausi et al. [46]	2/4	4	4
C.Caleanu et al. [47]	0.5	7	8

TABLE 1. Gabor-filter parameter settings in the literature.

IV. OUR METHOD

Fig. 4 displays the experiment's framework. This paper's experimental technique is primarily based on CNNs, but instead of the regular convolution layer, a Gabor convolution layer is used. The Gabor-filter settings can be adaptively changed inside the network structure. Our experimental procedure is separated into two sections, as exemplified in Fig. 4 (a) & (b).

In order to lower the dimension of output features, the advancing circulation process involves sending the input picture into the fully-connected layer, the Re LU layer & the Gabor convolution layer. The



$$\theta = \theta - \alpha \nabla_{\theta} L \quad \theta; x^i; y^i \quad .$$

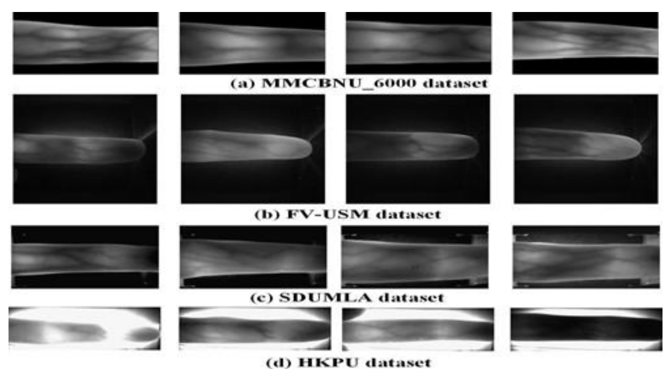
where α = step size (learning rate||)
The Gabor function's parameters need to be updated. The most popular and successful approach for training artificial neural networks is the back-propagation algorithm [50]. By determining the gradient of loss function, the gradient-descent optimization approach frequently uses back circulation to modify the Gabor filter's parameters.

Why update the Gabor function's parameters using CNNs? due to the fact that CNNs have strong feature extraction and parameter updating capabilities. In order to address the issue of the Gabor function's parameters being hard to specify using the conventional approach, CNNs can be used to automatically update the parameters. Additionally, we employ a Gabor convolution network with a Gabor convolutional layer. Based on the Gabor filter's properties, we can obtain good finger vein recognition results in smaller data sets. The Gabor filter is very good at extracting aspects of the texture of the vein. The training of the model parameters in this paper is time-consuming, but the parameters are not updated after the training process is over. Real-time processing of the finger vein image requires simply matrix multiplication and a few nonlinear operations. Real-time processing speed won't be impacted by these procedures.

V.IMPLEMENTATION AND EXPERIMENTS

DATABASE INTRODUCTION

A public database of finger vein images, MMCBNU_6000 [52], was established by 100 volunteers from 20 different nations. To get 60 finger vein photos for every volunteer, a collection is made ten times for each of the six fingers. As a result, MMCBNU_6000 has 6,000 pictures. Every image has a resolution of 480 × 640 and is saved in the.BMP format. This paper makes use of the ROI images that the database provides. Each image is 60 × 128 pixels in size. Eight images per finger, 1,200 test images, 2,800 training images, and 8 images per finger were used. University Sains Malaysia is the source of the finger vein database, FV-USM [53]. The 2, 952 BMP, 640 × 480 resolution photos that make up FV-USM were taken from 123 participants, each of whom had four fingers. Six pictures per finger were taken during two separate sessions.



Some images of different finger vein datasets in every session.

There were 984 test images, with two images per finger, and 1, 968 training images, with four images each digit. This paper makes use of the ROI images that the database provides.

Shandong University of China is the source of the finger vein database known as the SDUMLA database [54]. The 3, 816 BMP, 320 × 240 resolution photos that make up SDUMLA were acquired from 106 participants, each of whom had six fingers. There were 2, 544 training images, four images for each finger, 1, 272 test images & two photographs for each finger. Processing in the literature yields the ROI image [55].

156 participants are included in the Hong Kong Polytechnic University finger vein database (HKPU) [56].

We use the same test regimen as that found in the literature in order to compare with the current finger vein recognition techniques objectively [20]. In the many templates test technique, all of the photographs per finger of the training dataset are used as enrolled templates, while one image per finger of the test dataset is selected as probe. After repeating this procedure, the average performance is reported. One image per finger is chosen as the probe in the second session of the HKPU database, while the remaining images are utilized as enrolled templates. This process is repeated, and the average performance is recorded. Four photos per finger of the training dataset are chosen as enrolled templates, for example, from the SDUMLA database.

VI. LEARNING OF MAIN ORIENTATION OF THE GABOR FILTER

The vein-image texture direction information can be effectively captured by the Gabor filter with parameter θ for finger vein detection. There are two categories for this experiment. First, the original ROI images from the MMCBNU_6000 dataset serve as the experimental data. This experiment demonstrates that the Gabor function's θ parameter is adaptively learned. Second, the experimental data consists of the MMCBNU_6000 dataset's original ROI image that has been rotated π/6, π/4, and π/3 after being initially enlarged by a mirror. Finger vein images with varying rotation angles and mirror fill are displayed in Fig. 7.

0 π/6 π/4 π/3

Pictures with varying mirror fill and rotation angles.

All of the evidence from original ROI image is preserved in the rotated image, preventing the introduction of the boundary problem brought on by rotation and the loss of the original ROI image information. This experiment demonstrates that the Gabor function's θ parameter may self-adapt to various rotation angle data.

$\lambda = 16$, $\theta \in [0, \pi]$, $\sigma = 5$, $\psi = 0$, $\gamma = 1$, 16 Gabor convolutions, with a convolution size of 61 × 61, are the initialization settings for the Gabor function's parameters. Learning rate of the Gabor function's θ parameter is set to 0.1 in this experiment, while the learning rates of the other parameters are set to 0. Therefore, experiment merely modifies the Gabor function's parameter θ. First, the original ROI photos serve as the experimental data. Fig. 8(a) displays the experiment's findings.

The finger-vein image, as seen in Fig. 6, expands along the finger's horizontal direction and contains distinct directional information. The Gabor function's parameter θ converges primarily at the angles of 0, π/2, and π, as seen in Fig. 8(a). The majority of θ converges close to 0 & π. To π/2, a few theta converge. Additionally, the finger's vein texture is primarily vertical and horizontal, which is compatible with the adaptively learnt Gabor function's parameter θ. Through adaptive learning, experiments demonstrate that the Gabor function's parameter θ can converge to its ideal value.

We repeat the aforementioned tests by rotating the original ROI image to further demonstrate that the Gabor function's parameter θ can be self-adaptive. The original ROI image, first enlarged by a mirror, & then rotated π/3, π/4 & π/6, constitutes the experimental data.

Fig. 8(b)–(d) displays the experiment's findings.
By rotating the image at different angles, the parameter θ can eventually learn the texture variations of image, as shown in Fig. 8(b)-(d). In the end, the Gabor function's θ parameter converges to the spinning image's texture direction. This experiment also demonstrates the adaptive adjustment of the Gabor function's θ parameter.

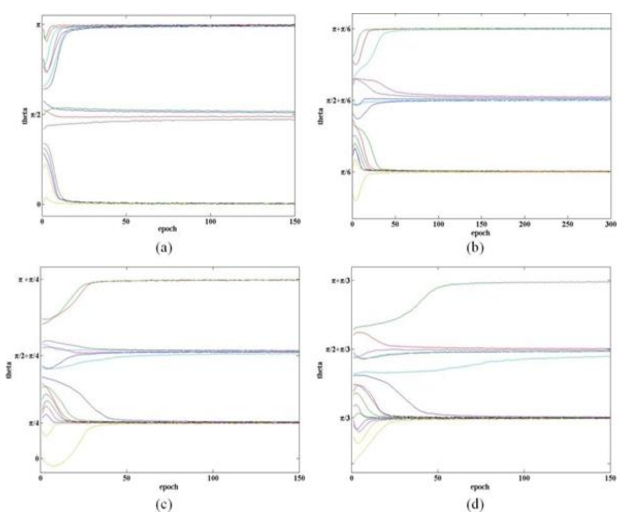
VII. LEARNING PARAMETERS AND OF GABOR FILTER

In this experiment, step size is 1 and the Gabor filter's parameter σ is fixed between [4, 10]. We investigate the Gabor filter's λ parameter, tracking its variation and the correlation between it and σ. The convolution size is 61 × 61, and the loading parameters of Gabor filter are λ ∈ [30, 35], γ = 1, ψ = 0, θ = 0, & 16 Gabor convolutions. The learning rate of all other strictures in this experiment is set to zero, whereas the learning rate of Gabor function's λ parameter is set to 0.01. Therefore, the experiment merely modifies the Gabor function's λ parameter. The ROI picture from the MMCBNU_6000 dataset serves as the experimental data. In Fig. 4, the experimental flow is displayed. Fig. 9 displays the outcomes of our trials, which chose a number of distinct sigma values.

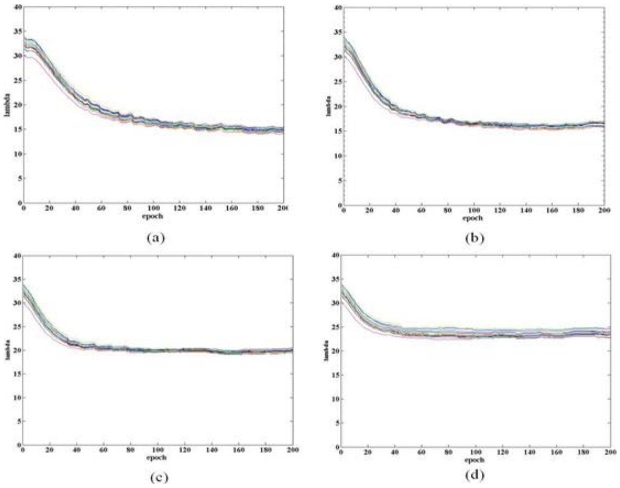
We examine the Gabor function's parameter λ, which converges in a brief interval, under a different parameter, σ. Table 2 displays the test set's accuracy as well as the correlation between parameters λ and

σ	Mean of λ	Accuracy of test set	$\frac{\sigma}{\lambda}$
4	**14.56**	**98.92%**	**0.275**
5	16.04	99.16%	0.312
6	18.03	99.08%	0.333
7	20.07	98.92%	0.349
8	22.11	98.92%	0.362
9	23.80	98.75%	0.378
10	25.76	98.50%	0.388

λ.



The 16 Gabor function's θ change curve in ROI pictures. Original ROI pictures (a), π/6 (b), π/4 (c) & π/3 (d) rotations are shown.



the λ change curve of Gabor function. σ = 4 (a); σ = 5 (b); σ = 7 (c);σ = 9 (d).

COMPARISON WITH THE STATE-OF-THE-ART ALGORITHMS

The Gabor function's 5 parameters can be modified and learned in this section. Additionally, Tables 3-6 show the effectiveness of our approach in comparison to the most advanced finger vein detection algorithms on four publicly available finger vein databases.

TABLE 3. Comparison using the MMCBNU_6000 database using the most advanced techniques.

Method	Year	EER%
Gabor filters [56]		2.42
Repeated line tracking [20]		5.74
Maximum curvature [20]		2.69
KMHM [28]	2017	2.08
ITQM [29]	2017	1.33
Gabor+Tri-branch structure [19]	2017	1.14
Combining primary and soft biometric traits [57]	2019	0.82
PG-Gabor [20]	2019	0.71
Weighted Vein code indexing [30]	2019	0.42
Our method	2019	0.11

TABLE 4. Comparison with the FV-USM database's cutting-edge techniques.

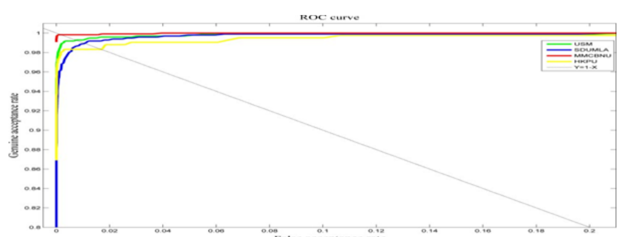
Method	Year	EER%
Gabor filters [57]		4.75
KMHM [28]	2017	5.41
ITQM [29]	2017	1.05
Deep representation-based feature extraction [36]	2017	1.69
Combining primary and soft biometric traits [57]	2019	0.22
Weighted Vein code indexing [30]	2019	0.07
Our method	2019	0.57

TABLE 5. Comparison with the SDUMLA database's cutting-edge techniques.

Method	Year	EER%
LLBP [31]		2.65
Repeated line tracking [20]		5.85
Maximum curvature [20]		3.65
Gabor filters [57]		2.58
KMHM [28]	2017	4.97
ITQM [29]	2017	2.78
Gabor+Tri-branch structure [19]	2017	4.04
PG-Gabor [20]	2019	1.35
Weighted Vein code indexing [30]	2019	0.99
Combining primary and soft biometric traits [57]	2019	0.72
Our method	2019	1.09

TABLE 6. Comparison with the most advanced techniques on the HKPU database's second session.

Method	Year	EER%
Gabor [56]		4.61
Fusion-based method [58]	2015	4.47
ELBP [25]	2016	5.59
Deep representation-based feature extraction [36]	2017	3.02
ASAVE [31]	2018	2.91
Weighted Vein code indexing [30]	2019	3.33
Our method	2019	1.67



ROC curve comparisons between the suggested approach and several finger vein databases.

Tables 3-5 show how we contrast our suggested adaptive Gabor filter approach with various Gabor techniques, including Gabor filter and Gabor Tri branch structure [19], PG- Gabor [20], Compared to other Gabor approaches, ours performs better. This demonstrates that our approach can extract primary vein information from a finger vein image & improve the Gabor function's parameters. Additionally, our approach outperforms both more recent and more traditional approaches, including the k-means hashing-based method (KMHM)[28], iterative quantization-based method (ITQM) [29], Deep representation-based feature extraction [36], Repeated line tracking, Maximum curvature, LLBP, ELBP. However, our approach performs worse on the SDUMAL and FV-USM datasets when compared to Weighted Vein code indexing [30] and Combining Primary and Soft Biometric Traits [57]. The key reason is that [30] includes a highly complicated inquiry, and [57] combines primary and soft biometric features to maximize the amount of information. However, our approach can retrieve the image's original attributes and is an end-to-end learning method. The test results in an open-world environment are displayed in Table 6. In the second session, we train and test using the HKPU dataset from the first session. Training data and test data are classified into several classes. The outcomes of the trial also show how successful the suggested approach is. The comparison of the suggested method's ROC curves on several finger vein datasets is displayed in Figure 10. Overall, our approach is more concerned with resolving the issue of the challenging tuning of Gabor parameters. Furthermore, the suggested method's performance is on par with the most recent techniques for identifying finger veins.

VIII. CONCLUSION

In order to address the issue of its parameters being hard to modify, we suggested an adaptive Gabor filter. First, we demonstrated how to combine the gradient de-scent and Gabor convolution into a single filtering and optimization architecture. Second, the directional information was represented by the Gabor filter's θ parameter, which had minimal relationship with other parameters. Experiments demonstrate that the finger vein recognition performance outperformed the generic Gabor approach and that parameter θ could be learned independently. Third, there was a link between parameter σ or parameter λ & the Gabor filter's parameter λ well-converged to ideal value. In order to create the Gabor filter bank, we might use the previous relationship of parameters and select the optimal Gabor-filter parameters. Lastly, experimental findings demonstrate that our approach performed well on four datasets of finger veins. Our approach beats the most advanced techniques in finger vein classification, and this performance was better than that of previous Gabor methods. Later on. Our goal is to create an adaptable Gabor convolution neural network with weights that incorporate spatial frequency and direction information. In order to enhance identification performance, we will also integrate the delicate characteristics of the veins in the fingers.

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