WAVELETS – BASED NOVEL APPROACH FOR BIOMETRIC AUTHENTICATION USING FINGER VEIN PATTERNS

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ABSTRACT:

In any organization, providing a secured and reliable authentication system is a challenge. In this paper, we propose a reliable biometric authentication process using Finger vein patterns. Finger vein is a reliable biometric trait because of its distinctiveness and permanence properties. The proposed algorithm initially captures the finger vein image and is preprocessed using Gaussian blur and morphological operations. Then Gabor wavelet is applied on preprocessed finger vein image and histogram will be generated. The generated histogram and histogram stored in database are compared using correlation coefficient. An individual will be authenticated if the correlation coefficient is greater than the threshold value. The simulation results of the proposed algorithm have shown the FAR as 3.66%, FRR as 0.09% and the overall performance as 99.95%.

Keywords: Correlation Coefficient, Fingervein, Gabor Wavelet, Gaussian Blur, Histogram, Patterns

[1] INTRODUCTION

Biometrics is a science of identifying a person using their physiological or behavioral characteristics [1]. Biometric traits are difficult to counterfeit and hence results in higher accuracy when compared to other methods such as using passwords and ID cards. Human physiological and/or behavioral characteristic can be used as a biometric trait when it satisfies
the requirements like universality, distinctiveness, permanence and collectability [2]. However, in a practical biometric system, one needs to consider some other issues too like performance, acceptability and circumvention [3]. Keeping all these requirements in mind, biometric traits like fingerprints, hand veins [4], handwritten signatures [5], retinal patterns, ear patterns [6], electrocardiogram [7 – 9], Finger Knuckle Print [2,10,11] etc. are used extensively in areas which require security access.

Veins are the network of blood vessels underneath a person’s skin. Finger vein pattern is an accepted biometric trait because it possesses the properties mentioned in [3]. Every individual including identical twins has a unique pattern of veins. As the individual grows, the vein size increases, but the position and number of veins do not change from infancy. As the vein structure is underneath the skin, it is invisible to the naked eye and hence one cannot spoof the system easily. It is more acceptable by user because noninvasive and contactless capture of finger-vein provides convenience and hygiene. It is a natural and convincing proof that the person whose finger vein is captured is alive, since finger-vein pattern can only be taken from a live body [12].

Near-infrared light of wavelengths between 700 and 1000 nanometers is generally used to capture finger vein images [12]. Near-infrared light can be absorbed intensively by the hemoglobin in the blood, and transmits other tissues of finger easily. Hence, vein pattern in finger will be captured as shadows. There are two ways of finger vein image acquisition viz. Light Reflection method and Light Transmission method [13]. The major difference between two methods is the position of near-infrared light. In light reflection method, near-infrared light is placed in finger palm side, and finger vein pattern is captured by the reflected light from finger palm surface. Whereas, in light transmission method, the near-infrared light is placed in finger dorsal side and the light will penetrate the finger. The light transmission method is found to capture high-contrast image and hence most of the image acquisition devices employ this approach.

In general, any finger vein identification and/or authentication system involves four major steps viz. image acquisition, preprocessing, feature extraction and feature matching [14]. The feature extraction methods in finger vein recognition again can be classified into three groups viz. Vein pattern-based methods, dimensionality reduction-based methods and local binary-based methods [15]. The vein pattern-based feature extraction methods have been explored in following ways: repeated line tracking [12], maximum curvature [16], Gabor Filter [17], mean curvature [18], region growth [19], and modified repeated line tracking [20]. In these methods, initially the vein patterns are segmented. Then the geometric shape or topological structure of vein pattern is used for feature matching. Dimensionality reduction-based methods usually transform image into low-dimensional space to classify. In transformation, they keep discriminating information and remove noises. Local binary-based methods are based on local area and the extracted features are in binary format.

[2] RELATED WORK

A brief survey of the related work in the area of identification and authentication using finger vein patterns is presented in this section. Japanese medical researchers Kono et al. [21] proposed finger vein based identification, and gave an effective feature extraction method.
Yanagawa et al. [22] proved the diversity of human finger vein patterns and the usefulness of finger veins for identification on 2024 fingers of 506 people. Repeated line tracking, maximum curvature, region growth and modified repeated line tracking – all these approaches use the cross-section of image to extract vein pattern. The repeated line tracking method [12] extracts the finger-vein pattern from the unclear image by using line tracking that starts from various positions. The positions in the locus space where high values are stored are those tracked regularly in the line-tracking procedure. That is, the points with high values in the locus space have high chances of being the positions of veins. Therefore, the paths of finger veins are obtained as chains of high-value positions in the locus space. Advantage of this method is that it can be easily combined with any other hand-based biometrics. The repeated line tracking algorithm achieves good segmentation performance for low quality images of finger-vein, but it has some drawbacks such as low robustness and efficiency. This method may degrade slightly during cold weather because of reduction in the clarity of finger veins.

The maximum curvature method [16], can extract the precise details of the depicted veins, by calculating local maximum curvatures in cross-sectional profiles of a vein image. The centerlines of the veins are extracted here, without affecting the fluctuations in the width and brightness of the vein. Hence, the pattern matching will be much accurate. The vein image is viewed as a geometric shape in mean curvature method [18]. The valley-like structures with negative mean curvatures are found here. The group of pixels having negative mean curvature is seen as vein pattern. The ratio of such pixels is matched for authentication purpose. This method showed 0.25% equal error rate, which was significantly lower than the existing methods till then. In region growth method [19], vein pattern is extracted by running the region growing operator on the different seeds. The continuity and symmetry of the valleys in cross-sectional profile of vein pattern is observed here. This will help in extracting the finger vein patterns by avoiding irregular shading and noise. The finger vein is segmented to obtain binary and skeleton image in [20]. The width of finger vein is computed based on this skeleton image to revise the parameter based on this width. The locus space of finger vein is identified based on these revised parameters. The Otsu algorithm is used to do exact segmentation on this locus space and hence proved that the said procedure performs better than traditional repeated line tracking algorithm.

In finger vein recognition, Principal Component Analysis (PCA), Linear Discriminant Analysis (LDA), 2 – directional and 2 – dimensional (2D2) PCA, and manifold learning have been used for feature extraction. These methods need the training process to learn a transformation matrix. When there are new enrolled users, the transformation matrix need to learn again. So this kind of methods may be not very practical. Classifiers are used in matching for these methods. The combination of feature extraction using PCA and pattern classification using back-propagation (BP) network and adaptive neuro-fuzzy inference system (ANFIS) is used by Wu et al. [25]. The usage of PCA for feature extraction helps in reducing the computational complexity and to remove the noise. These features are then used in pattern classification and identification. The effect of ANFIS in pattern classification is verified by comparing BP network and the proposed system [23]. The experimental results indicated this system using ANFIS has better performance than the BP network for personal identification using the finger-vein patterns.
Another research work [24] used support vector machine (SVM) technique for identification using finger vein patterns. Here, PCA and LDA are used for dimensionality reduction and feature extraction. For pattern classification, SVM and ANFIS are used. The accuracy of classification using SVM is 98%. The result shows a superior performance to the artificial neural network of ANFIS in this system. Yang et al. [25] have applied 2D2 PCA to extract finger vein features and metric learning for recognition. The k – nearest neighbor (KNN) classifier is applied for every individual. Also, the synthetic minority over sampling technique (SMOTE) is used to solve class-imbalance problem. This approach resulted in 99.17% of accuracy. Generally, the variation in finger pose may cause failure in recognition system. This issue is addressed by Liu et al. [26] by combining manifold learning and point manifold distance concept. The results were found to be effective.

The Local Binary Pattern (LBP) [27, 28], the Local Line Binary Pattern (LLBP) [29], the Personalized Best Bit Maps (PBBM) [30], Personalized Weight Maps (PWM) [31] and the Local Directional Code (LDC) [32] are local binary based methods. In LBP method a 3x3 kernel used to extract the finger vein pattern, which generates an ordered set of binary values by comparing the gray values of center pixel with its eight neighboring pixels. The number of binary values generated is a product of number of kernel movements in X direction, number of kernel movements in Y direction and number of bits calculated from one position of kernel. The generated binary sequence represented in clockwise direction from top left position. Local Derivative Pattern (LDP) method extracts more elaborate discriminative features compared to LBP. The binary code extracted in LDP represents a high order derivative pattern occurred in a particular direction. First, it applies an exclusive OR operation on binary bits generated between center pixel and its eight neighboring pixels. Then the second order binary codes extracted by considering directions at particular angle. The number of bits generated is a product of number of kernel movement in X direction, number of kernel movements in Y direction, number of directions considered and extracted bits per direction. The extracted binary codes are compared against stored binary codes using Hamming distance. Compare to LBP, LDP method consumes more memory and time as it generates more binary codes.

Figure: 1. Architectural Diagram
[3] PROPOSED WORK

In an organization if it maintains a database of finger vein images for authentication of its employees, then each time during the authentication process the features from finger vein image in database for respective employee must be extracted for matching. Feature extraction from database finger vein image becomes repetitive and time consuming. So, we suggest storing the histogram of Gabor wavelet generated for finger vein images instead of the images themselves. Every employee of the organization is assigned a unique ID. The histogram of Gabor wavelet transformed finger vein image is stored against the ID of every individual. This will be the initial setup of the database. During authentication, finger-vein image of a person is captured and the histogram extracted. This histogram is compared with corresponding histogram in the database for a respective ID. If there is a match, the person can be authenticated. The architectural diagram for the entire authentication process is as shown in Figure-1. The various steps involved are explained hereunder.

[3.1] Image Acquisition

To capture the finger-vein image, an infrared imaging device is used. The captured image is a gray scale image. Index finger images viz. I1 and I2 of two individuals are shown as sample images in Figure-2.

![Figure 2. Original Images](image1)

(a) I1  
(b) I2

[3.2] ROI detection and Smoothing

The region of interest (ROI) which contains the finger vein pattern is extracted from captured image. Then image is resized to get a better clarity. The ROI is as shown in [Figure-3].

![Figure 3. ROI extracted from Original Images](image2)

(a) I1  
(b) I2

The resized image is smoothened by using Gaussian Blur. Gaussian blurring is highly effective in removing Gaussian noise from the image. The Gaussian blur uses Gaussian function for calculating the transformation to apply to each pixel in the image. The equation of a Gaussian function in two dimensions is –
Here, $x$ is the distance from the origin in the horizontal axis, $y$ is the distance from the origin in the vertical axis, and $\sigma$ is the standard deviation of the Gaussian distribution.

The Gaussian blur is applied on two different kernels of an image. There will be two resulting images, whose difference is computed. This is known as Difference of Gaussian (DoG). Figure-4 shows the computed DoG for the sample images I1 and I2.

![Images after computing Difference of Gaussian](image)

**Figure 4.** Images after computing Difference of Gaussian

### [3.3] Preprocessing

Preprocessing involves series of morphological operations. Morphological transformations are some simple operations based on the image shape. It is normally performed on binary images. Any morphological operation requires two inputs viz. the input image and a structuring element deciding the nature of operation. Morphological opening is performed to remove possible noise in the image. Opening generally smoothens the contour of an object, breaks narrow isthmuses, and eliminates thin protrusions. Opening is done using the equation –

$$A \circ B = (A \ominus B) \oplus B$$ (2)

Here, $A$ is an input image and $B$ is the structuring element.

When morphological erosion is applied on an image, the boundaries of the object are eroded. It is useful in removing the noise. Erosion is done using the equation –

$$A \ominus B = \{ze \in E \mid B_z \subseteq A\}$$ (3)

Dilation is used for joining the broken parts on an object in the image. Dilation is done using the equation –

$$A \oplus B = \bigcup_{b \in B} A_b$$ (4)

Preprocessed images are the required patterns in the images. These are shown in Figure 5.

![Images after preprocessing and Pattern Extraction](image)

**Figure 5.** Images after preprocessing and Pattern Extraction
[3.4] Feature Extraction

The feature extracted must not vary for an individual over period of time. We apply Gabor Wavelet transform on the image obtained after pre-processing. A Gabor wavelet is a complex planar wave restricted by a two dimensional Gaussian envelope [33]. Gabor wavelet contains two components viz. real and imaginary. Aside from scale and orientation, the only thing that can make two Gabor wavelets differ is the ratio between wavelength and the width of the Gaussian envelope. Every Gabor wavelet has a certain wavelength and orientation, and can be convolved with an image to estimate the magnitude of local frequencies of that approximate wavelength and orientation in the image.

The 2D Gabor wavelet kernel is separable, that is, it can be represented as a convolution of two orthogonal 1D components. These components are: a Gaussian \( g(x) \), and a wavelet \( w(x) \) (a complex wave enveloped by a Gaussian), defined respectively by

\[
g(x) = \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left(-\frac{x^2}{2\sigma^2}\right) \quad (5)
\]

and

\[
w(x) = g(x)e^{j\omega x} \quad (6)
\]

Where \( j = \sqrt{-1} \) and \( \omega \) is the frequency of the wavelet. These functions describe the separable components of a Gabor filter kernel. It follows that convolution of a Gabor kernel with an image can be calculated separately. For example, a horizontally aligned \( n \times n \) Gabor kernel \( K \) can be written as

\[
K = g \ast w \quad (7)
\]

where \( g \) and \( w \), are \( n \times 1 \) vectors whose elements are defined by regularly sampling \( g(x) \) and \( w(x) \) across intervals centered at \( x = 0 \). The convolution of \( K \) with an image \( I \) is then

\[
I \ast K = I \ast (g \ast w^T) = (I \ast g) \ast w^T \quad (8)
\]

By applying Gabor wavelet on a preprocessed finger vein image, we will get Gabor image as shown in Figure 6.

![Real part of Gabor image](image)

(a) I1
(b) I2

Figure 6. Real part of Gabor image

[3.5] Authentication

This step contains the computation of parameters required for decision making towards authentication. The histogram \( H_1 \) is generated for the real part of the Gabor wavelet image obtained as shown in Fig. 7. The correlation coefficient is computed between every pair of histograms. If \( H_1 \) and \( H_2 \) are histograms of two images, then the correlation coefficient between them is calculated using –
The obtained histogram H1 will be compared with histogram H2 is retrieved from database for given ID using correlation coefficient. If the resultant correlation coefficient is greater than the threshold value, the person is authenticated, otherwise rejected.

Figure 7. Histograms of Gabor Images

Table 1. Algorithm for authentication

<table>
<thead>
<tr>
<th>Inputs:</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>I :</td>
<td>Finger vein image</td>
</tr>
<tr>
<td>N :</td>
<td>ID number</td>
</tr>
<tr>
<td>T :</td>
<td>Threshold value</td>
</tr>
<tr>
<td>Output:</td>
<td>Authentication result</td>
</tr>
</tbody>
</table>

Procedure Authentication

Begin

<table>
<thead>
<tr>
<th>Step</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>R := ExtractROI(I)</td>
</tr>
<tr>
<td>2</td>
<td>I1 := GaussianBlur(R, k1)</td>
</tr>
<tr>
<td>3</td>
<td>I2 := GaussianBlur(R, k2)</td>
</tr>
<tr>
<td>4</td>
<td>I3 := I2 – I1</td>
</tr>
<tr>
<td></td>
<td>// Difference of Gaussian</td>
</tr>
<tr>
<td>5</td>
<td>Apply morphological operations on I3</td>
</tr>
<tr>
<td>6</td>
<td>I4 := Gabor waveletTransform(I3)</td>
</tr>
<tr>
<td>7</td>
<td>Plot histogram H1 for I4</td>
</tr>
<tr>
<td>8</td>
<td>Fetch histogram H2 for given N from database</td>
</tr>
<tr>
<td>9</td>
<td>Find Correlation coefficient C between H1 and H2</td>
</tr>
<tr>
<td></td>
<td>If (C &gt; T)</td>
</tr>
</tbody>
</table>

End
return True  //Authenticated
Else
return False  //Rejected
End

[4] IMPLEMENTATION AND PERFORMANCE ANALYSIS

The proposed algorithm given in Table 1 is implemented using OpenCV in Python 2.7.8, and it is tested on Finger Vein images taken from Finger vein database SDUMLA-FV built by Shandong University [34]. They used light transmission method to acquire the finger vein image. The SDUMLA database contains 3816 finger vein images of 106 individuals, which includes six images of ring, middle and index finger of both left and right hand of each individual. Images are stored in .bmp format with 320×240 pixels in size. For the experimental purpose, only the index finger images of 106 individuals are considered in this paper. The confusion matrix is generated based on simulation results of these 106 images, and is shown in Table 2.

<table>
<thead>
<tr>
<th>Actual</th>
<th>Tested</th>
<th>Accept</th>
<th>Reject</th>
</tr>
</thead>
<tbody>
<tr>
<td>Accept</td>
<td>105</td>
<td>4</td>
<td></td>
</tr>
<tr>
<td>Reject</td>
<td>1</td>
<td>11126</td>
<td></td>
</tr>
</tbody>
</table>

The false accept ratio (FAR) of the proposed algorithm is found to be 3.66% and the false reject ratio (FRR) is 0.09%. And the overall efficiency of the system is found to be 99.95%.

[5] CONCLUSION

In this paper, we propose an efficient way of finger vein authentication using Gabor wavelets. In the proposed technique, we have applied Gabor wavelet on preprocessed finger vein image, then histogram is plotted for real part of Gabor wavelet generated. The histograms are stored in database along with the unique Identification number assigned to every individual.

To authenticate a person, we compare the histogram generated for captured image and that in the database for given ID using correlation coefficient. If the correlation coefficient between the two histograms is greater than the threshold value, then authenticate the person, otherwise reject.
REFERENCES


