WRIST VEIN RECOGNITION BY ORDINARY CAMERA USING PHASE-BASED CORRESPONDENCE MATCHING

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ABSTRACT
With rapid advances in technology, biometric control systems have become part of the contemporary world. Wrist pattern is a biometric that is unique to the individual and can be seen on the skin of most individuals. This study focuses on the left wrist vein images of 20 people, in a visible light band, using a simple smartphone 5 MP camera. Selecting a reference line on wrist wrinkle, the wrist vein regions are cropped as square. The red layer of the RGB vein image has been filtered with Gaussian Low Pass Filter to eliminate any high frequency noise. Sharpening and contrast stretching operations have been used on the filtered images. Sub-pixel correspondence matching, using phase-only correlation method, can yield efficient results for biometric image matching. In this paper, phase-based correspondence matching pattern recognition method is used in order to perform person recognition from wrist vein patterns, which have been captured by a smartphone camera. It is argued that, the experiments this study has conducted demonstrates that phase-based correspondence matching provides an effective means for wrist vein recognition.

KEY WORDS
Identification, pattern recognition, image processing, image recognition, biometrics, wrist vein, phase-only correlation, touchless biometrics.

1. Introduction

Compared to the recent past, biometric identification applications are a big part of our daily life. Owing to rapidly evolving technology, smartphones - which almost everybody has - are beginning to be used for authentication applications rather than special biometric sensors. Smartphones that do not have a fingerprint sensor and sufficiently high resolution on the front camera for iris recognition can be used for biometric applications using wrist vein images.

Since the vein pattern is beneath the human body, it is difficult to replicate it. Researchers have showed that the vein pattern of the human body is unique to an individual, even for identical twins; and it remains unchanged during a person’s life. Compared to a fingerprint, users need to touch the sensor device as part of the authentication process. Iris authentication requires the direct exposure of light into a person’s eyes, which can be uncomfortable for some people [1]. In the literature, wrist vein recognition studies are performed under infrared lighting conditions [2-6]. It can be noted, however, that they require special lighting and sensors to perform person recognition from the wrist vein.

In our preliminary study, the possibility of wrist vein recognition with an ordinary camera has been explored. The relevant wrist vein dataset has been classified with artificial neural networks without proposing any pattern recognition method [7]. In this paper, phase-based correspondence matching pattern recognition method is proposed in order to perform person recognition from the wrist vein patterns which have captured under daylight by a smartphone camera.

2. Methods

In this research Phase-Only Correlation Function and Sub-pixel Correspondence Matching used for wrist vein recognition.

2.1. Phase-Only Correlation Function

Phase-Only Correlation (POC) function or Phase Correlation Function [8] has been defined as the inverse Discrete Fourier Transform (DFT) of normalized cross power spectrum in recent studies [9]. Considering two \( N_1 \times N_2 \) images, \( f(n_1, n_2) \) and \( g(n_1, n_2) \), by assuming that the index ranges are \( n_1=-M_1\ldots M_1 \) \((M_1>0)\) and \( n_2=-M_2\ldots M_2 \) \((M_2>0)\) for mathematical simplicity, and \( N_1=2M_1+1 \) and \( N_2=2M_2+1 \). Let \( F(k_1, k_2) \) and \( G(k_1, k_2) \) denote the 2D DFTs of the two images. \( F(k_1, k_2) \) is given by Equation 1 [10].

\[
F(k_1, k_2) = \sum_{n_1,n_2} f(n_1,n_2) W_{N_1}^{k_1 n_1} W_{N_2}^{k_2 n_2}
\]

\[
F(k_1, k_2) = A_F(k_1,k_2)e^{j\Phi_F(k_1,k_2)} \quad (1)
\]
Where \( k_1 = -M_1...M_1, k_2 = -M_2...M_2, W_{n1} = e^{-j2\pi n1}, W_{n2} = e^{-j2\pi n2} \) and \( \sum_{n1=1}^{N1} \sum_{n2=1}^{N2} \) denotes \( \sum_{n1=-M_1}^{M_1} \sum_{n2=-M_2}^{M_2} \). \( A_r(k_1, k_2) \) is amplitude and \( \theta_r(k_1, k_2) \) is phase. \( G(k_1, k_2) \) is defined following the same way. The cross-phase spectrum \( R_{FG}(k_1, k_2) \) is given by Equation 2 [10].

\[
R_{FG}(k_1, k_2) = \frac{F(k_1,k_2)G(k_1,k_2)}{|F(k_1,k_2)G(k_1,k_2)|} = e^{j\theta(k_1,k_2)}
\] (2)

Where \( G(k_1,k_2) \) is the complex conjugate of \( G(k_1, k_2) \) and \( \theta(k_1, k_2) \) denotes the phase difference \( \theta_r(k_1, k_2) - \theta_r(k_1, k_2) \).

The POC function \( r_{fg}(n_1, n_2) \) is the 2D Inverse DFT of \( R_{FG}(k_1, k_2) \) and is given by Equation 3 [11].

\[
r_{fg}(n_1, n_2) = \frac{1}{N_1N_2} \sum_{k1,k2} R_{FG}(k1, k2) W_{n1}^{k1n1} W_{n2}^{k2n2}
\]

\[
\sum_{k1,k2} = \sum_{k1=-M1}^{M1} \sum_{k2=-M2}^{M2}
\] (3)

If the two images are very similar, the POC function creates a distinct peak. When images are not similar, the peak drops significantly. The amplitude of the peak point provides a reliable similarity measure for image matching, and the location of the peak point marks the displacement between the two images [12].

### 2.2 Sub-Pixel Correspondence Matching

Sub-pixel correspondence matching [13] using POC is the right method to handle the nonlinear distortion and possible shifts of wrist vein images.

Sub-pixel correspondence matching employs a coarse-to-fine strategy using image blocks for robust correspondence search. This method also applies a sub-pixel window placement technique to find a pair of corresponding points with sub-pixel displacement accuracy [9].

When \( I(n_1, n_2) \) taken as reference image, \( p \) is the coordinate vector of reference pixel in \( I(n_1, n_2) \). Sub-pixel correspondence search has the aim of finding a real-number coordinate vector \( q \) in the input image \( J(n_1, n_2) \). And \( q \) corresponds to the \( p \) [9].

As the first step for \( l = 1, 2, ..., l_{max} - 1 \), it is necessary to create the \( l \)-th layer images \( I_l(n_1, n_2) \) and \( J_l(n_1, n_2) \), i.e., coarser versions of \( I_0(n_1, n_2) \) and \( J_0(n_1, n_2) \), recursively as follows [14]:

\[
I_l(n_1, n_2) = \frac{1}{4} \sum_{i1=0}^{1} \sum_{i2=0}^{1} I_{l-1}(2n_1 + i_1, 2n_2 + i_2)
\]

\[
J_l(n_1, n_2) = \frac{1}{4} \sum_{i1=0}^{1} \sum_{i2=0}^{1} J_{l-1}(2n_1 + i_1, 2n_2 + i_2)
\] (4)

In this paper, \( l_{max} \) employed as 3. For every layer \( l = 1, 2, ..., l_{max} \) calculate the coordinate \( pl = (p_{l1}, p_{l2}) \) corresponding to the original reference point \( p_0 \) recursively as follows [9]:

\[
p_l = \left[ \frac{1}{2} p_{l-1} \right] = \left[ \left[ \frac{1}{2} p_{l-1,1} \right], \left[ \frac{1}{2} p_{l-1,2} \right] \right]
\] (5)

The second step concerns \( |z| \), that is, the operation to round the element of \( z \) to the nearest integer towards minus infinity. Assuming \( q_{l_{max}} = p_{l_{max}} \) in the coarsest layer, \( l = l_{max} - 1 \), as third step [9]. From the \( l \)-th layer images \( I_l(n_1, n_2) \) and \( J_l(n_1, n_2) \), extract two image blocks \( f_l(n_1, n_2) \) and \( g_l(n_1, n_2) \) with their centers on \( p_l \) and \( 2q_l+1 \). The size of image blocks is \( W \times W \) pixels, is the forth step. Estimating the displacement between \( f_l(n_1, n_2) \) and \( g_l(n_1, n_2) \) pixel accuracy using phase correlation based image matching is step five. The estimated displacement vector is \( \delta_l \). The \( l \)-th layer correspondence \( q_l \) is determined with Equation 6 [9].

Decrement the counter by 1 as \( l = l - 1 \) and repeat from step four to current step while \( l \geq 0 \), is step six. The final step: from the original images \( I_0(n_1, n_2) \) and \( J_0(n_1, n_2) \), extract two image blocks with their centers on \( p_0 \) and \( q_0 \), respectively. Estimation of the displacement between the two blocks must be done with sub-pixel accuracy using POC-based image matching. The estimated displacement vector with sub-pixel accuracy is denoted by \( \delta = (\delta_1, \delta_2) \). Updating of the corresponding point must be done with Equation 7 [9].

\[
q_l = 2q_l+1 + \delta_l
\] (6)

\[
q = q_0 + \delta
\] (7)

### 3. Wrist Vein Dataset

Wrist vein images were captured with the help of 5 MP smartphone camera at approximately 20 cm in distance from the top of the volunteers’ left wrists in daylight - using the autofocus option of the smartphone. The dataset contains 20 volunteer’s wrist images and 3 samples captured from each one at different times. Samples from the dataset can be seen in the Figure 1. The wrist vein dataset has nonlinear distortion due to the low resolution of the smartphone camera; the possibility of related vein areas being slipped and the irregularity of daylight.

The relevant wrist regions were cropped as square in the size of the width of each wrist; the wrist wrinkle line has been taken as reference line. When the dataset is examined, the vein lines in the red layer are shown in Figure 2.c are more significant than the grayscale conversion which is shown in Figure 2.b. Gaussian Low Pass Filter and Unsharp Masking Technique is applied to the images. Gaussian Low Pass Filter is applied in order to remove high frequency noise. Unsharp Masking Technique extracts the softened version of the image from the original image for sharpening. This blurs the original image, creates a mask by subtracting blurred image from original image and adds the mask to the original image [15].
Finally, Contrast Stretching has been applied to avoid the contrast difference that may occur in the changes in ambient light. Contrast stretching is a simple image enhancement technique that attempts to improve the contrast in an image by stretching the range of intensity [16]. Each image resized to 128x128 pixels. Final image is shown in Figure 2.d.

The matching method aims to find the similarity ratio between the two images of wrist vein. Wrist vein regions cannot be expected to be in the same placement for each the different image and causes nonlinear distortion. Sub-pixel correspondence matching using POC function is robust solution for distorted image matching. With the sub-pixel correspondence matching method, the similarity ratio is obtained with the local image blocks around the related points without being affected by the shifts between the two wrist images - as seen in Figure 3.

The image to be recognized is $I$ and the image which will be compared is $J$; the corresponding points on $J$ are obtained by sub-pixel correspondence matching method by placing reference points at 8 pixel intervals on $I$. Image blocks with central reference points on $I$ and center corresponding points on $J$ are extracted and the POC function is executed for each image block. If the two image blocks are very similar, the POC function creates a peak which is visible in Figure 4. To increase the Peak to Noise Ratio (PNR), the average of the POC function’s output of each image block is taken [17]. The highest peak value of the average is taken as the matching score between images of $I$ and $J$.

**4. Experiment and Results**

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The wrist vein database that was used in this work consists of 60 images (128 × 128 pixels) with 20 subjects and 3 different images of left wrists. False Non Match Rate (FNMR) is the ratio for all the possible combinations of genuine attempts. The total number of genuine attempts is calculated as a binary combination of 3 samples for 20 subjects, \( \binom{3}{2} \times 20 = 60 \).

False Match Rate (FMR) is the ratio for all the possible combinations of impostor attempts. And the number of possible impostor attempts is calculated as binary combination of all samples minus the possibility of genuine attempts, \( 60 \binom{3}{2} - \binom{3}{2} \times 20 = 1710 \).

The system makes a decision according to the threshold. If the similarity score between two images is greater than the threshold, then the system decides that they are match, if similarity score is lower than threshold decision will be non-match.

FNMR calculated as wrong decision ratio when the corresponding threshold is greater than the corresponding genuine attempt’s similarity score. And FMR calculated as a wrong decision ratio when the corresponding threshold is smaller than the corresponding impostor attempt’s similarity score. The corresponding FNMR and FMR curve spans over a range of all normalized thresholds between maximum and minimum threshold. The FNMR - FMR curve is visible in Figure 5.

Equal Error Rate (EER) can be determined at the point which FMR equals FNMR. For proposed wrist vein recognition system, EER is 13.29%. FMR against the verification rate is created as Receiver Operation Characteristics (ROC) curve which has shown in Figure 6. The verification rate is the likelihood of correctly accepting a genuine match or 100-FNMR [18]. The point of false match rate equals %13.29 or EER, and the verification rate equals %86.71 as seen in the Figure 6. The threshold range, which corresponds to the minimum equal error, is the operating range of the system. In this study, the success rate for the optimal threshold range is %86.71.

6. Conclusion

This paper proposes a wrist vein recognition method using phase-based correspondence matching. Sub-pixel correspondence matching using the Phase-Only Correlation (POC) provides a means to recognize wrist vein images which are captured by an ordinary smartphone camera.

In the literature, there aren’t any past research studies on the topic of wrist vein recognition by smartphone camera with the same or similar pattern recognition method. Therefore it is not possible to make any one-to-one comparison with the other results. But still, the error rate can be considered to be fairly high as %13.29. However, the number of people in the database is low. As the number of people in the dataset increases, the error rate will be decreased. Also, some participant’s wrist vein patterns may not be visible through the skin. Subjects that raise the error rates are those whose wrist vein patterns are less obvious on the skin. This can be avoided with a high resolution camera. Further, higher results can be achieved by improving the enrollment stage. This proposed method can be used in the enrollment phase to prevent the inconsistent samples. For the person which cannot achieve a certain similarity ratio, system can stipulate to retry the enrollment phase.

Future work could explore the ways in the wrist vein recognition system. It is possible to improve the system by refining the enrollment phase and determining whether the system is suitable for mid-secure access control applications for particular groups and multimodal applications.
References


