A novel Fingervein Recognition System based on Monogenic Local Binary Pattern Features

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Abstract

As a new approach to human identification, fingervein recognition is becoming an active biometric recognition mode. This paper focuses on fingervein recognition system. First, a preprocessing algorithm is used to enhance each fingervein image. Then, an improvement technique of feature extraction based on Monogenic Local Binary Pattern (MLBP) is presented. This novel metric integrates the conventional LBP (Local Binary Pattern) with the other two rotation invariant measures (local phase and local surface type) to lower the computational complexity while slightly increasing the matching accuracy. Experimental results show that the proposed algorithm offres best performances in fingervein recognition. In fact, the area under curve of proposed approach has very close to unity (0.91)

Index Terms keyword- Fingervein, texture, classification, feature extraction, local phase, local surface type, MLBP.

I. INTRODUCTION

Over the last two decades, human recognition based on biometric features has been on a rapid development. Traditional biometric approaches using features such as the palmprint, fingerprints, iris, hand shape, ect..., to identify persons provide effective methods for many real time applications. Though, no biometric technology has been proved to be absolutely reliable. Fingerprint and palmprint, for example, are vulnerable to forgery since they are exposed outside the human body. Face identification may easily be affected by inspiration and occlusion and iris identification is also measured as unfriendly for its unpleasant image acquisition processing [1].

In recent times, a novel biometric technique using fingervein patterns has attracted the attentions of research community[2]. Compared with other biometric, fingervein identification has the following advantages[3]:

- Immunity to forgery.
- Friendliness, where a near-infrared light is used for contact, non-invasive image that ensures both convenience and cleanliness for the user.
- Polymorphism, which has been proved that each human finger from the same individual has inimitable vein pattern.

Over the last decades, human authentication based on fingervein images has received development. Fingervein extraction techniques using repeated line tracking[4] and curvelet information of the image profile with a locally interconnected Artificial Neural Network (ANN)[5], was proposed by Miura et al. and Zhang et al. respectively. Wu et al. [6] have also used the Principal Component Analysis and the ANN approach for fingervein pattern recognition.

In this paper, we propose a novel fingervein recognition system using Monogenic Local Binary Pattern (MLBP) features to lower the computational complexity while to slightly increase the matching accuracy. The flow chart of the proposed approach is shown in Figure 1.

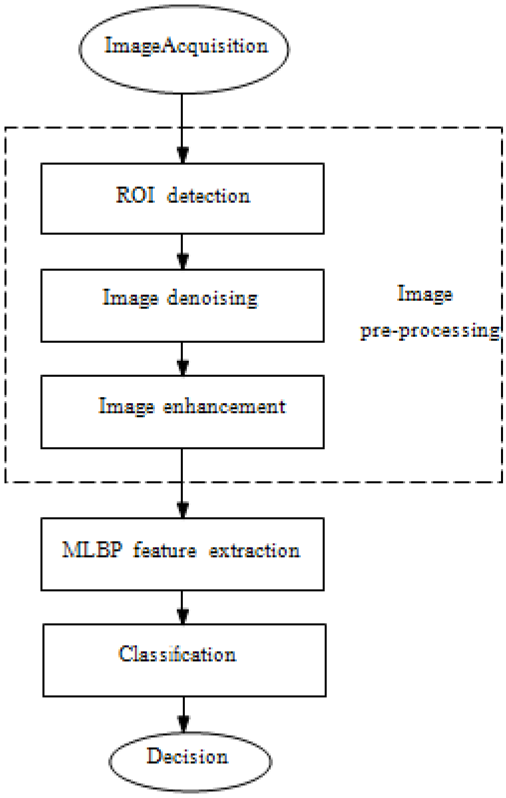

Fig. 1. Basic steps of the proposed method.

The ROI (Region Of Interest) is detected first. After that, AWS (Adaptive Wavelet Shrinkage) and CLAHE (Contrast-Limited Adaptive Histogram Equalization) are used respectively for denoising and enhancement of fingervein image. Next, the MLBP vectors are extracted to obtain the features extraction of images. Finally, based on ANN, classification is performed.

II. IMAGE PREPROCESSING

Due to various types of noise or strong reflections produced from the skin's surface and shallow infiltration of light under the skin, The original fingervein contrast is poor which makes it not distinct enough for recognition. This section contains the following three processes: ROI detection, denoising and enhancement of fingervein image. In Figure 2, the procedure of these three processes is illustrated.

A. ROI Detection

Generally, mathematical morphology makes full use of mathematics and geometry theory[7]. In this manuscript we use the ”open operation” of the mathematical morphology. This method [8] makes the object contour smoother. It disconnects the narrow gap and eliminates fine prominence (figure 2(b)).

After that, Hough transform is used to identify two finger edges in the contour, which is unaffected by image noise. Two boundaries of this finger are well shown in figure 2 (c) with white color.

B. Image Denoising

The wavelet shrinkage denoising approach is able to maintain local regularity of a signal while suppressing noise. In this work, an AWS denoising method is used in the fingervein denoising process. It makes use of wavelet transform to extract information on sharp variation in imagery multiresolution and applies shrinkage function which adapts fingervein features. It has the advantages of low complexity and superior performance.A fingervein after image denoising based on the adaptive wavelet shrinkage is illustrated in figure 2 (e).

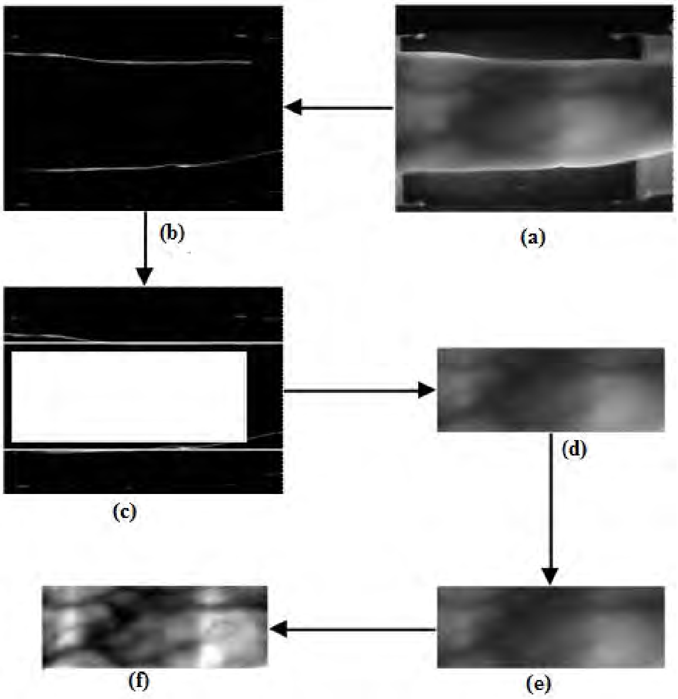

Fig. 2. Preprocessing steps: (a) Original image, (b) Fingervein contour image, (c) ROI region determination based the fingervein contour, (d) ROI image, (e) Image after denoising, (f) Enhanced image.

C. Image Enhancement

Generally, fingervein images are not forever with high quality due to the changeable tissues and frame, and still illuminations, efficient enhancement technique is essential to develop the image quality. For enhancement, we make use of the Contrast-limited Adaptive Histogram Equalization (CLAHE). It is different from the usual histogram equalization in the respect that it calculates several histograms, each related to a different section of a fingervein image, and utilize them to reorganize the lightness values of the image. So, it is suitable for developing local contrast of an image and bringing out more in detail (figure 2 (f)).

III. MONOGENIC LOCAL BINARY PATTERN TEXTURE ANALYSIS

Texture analysis is an energetic area in the fields of pattern recognition, and has various possible applications. For texture classification, Ojala et al. ([9]) proposed to use the LBP (Local Binary Pattern) histogram. As one of the efficient rotation invariant texture classification approach, LBP is generally used ever since it is easy powerful. Though, LBP tends to simplify the image structures. Therefore, we want to get other rotation invariant structures to complement LBP so as to get better the classification accuracy whereas safeguarding its simplicity. In concordance with [10], the local phase keeps up a correspondence to a qualitative measure of a local feature and it is a robust structure with respect to illumination changes and noise. We take on the monogenic signal hypothesis, which is an isotropic 2-D indicator extension of the 1D analytic signal, to get the local phase information of fingervein image in a rotation invariant mode. Moreover, we use the monogenic curvature tensor to obtain the local surface information, which is an additional rotation invariant mode. Next, we join the uniform LBP, the local phase and the local surface information as an approach of texture feature extraction, namely monogenic local binary pattern (MLBP).

A. Monogenic signal and monogenic curvature tensor

The monogenic signal proposed by Felsberg in [10], is an isotropic 2D extension of the conventional 1D analytic indicator. This signal is an effectual instrument to analyze intrinsic 1D and 2D signals in a rotation invariant mode. It is built upon the first order Riesz transform. The representation of the Riesz Kernel (RK), in 2D, is:

$$(RK_x(\alpha), RK_y(\alpha)) = (\frac{x}{2\pi\ |\alpha|^3}, \frac{y}{2\pi\ |\alpha|^3}) \qquad (1)$$

where $\alpha = (x,y) \in \Re^2$ and the RK transfer function is illustrated in the Fourier domain by:

$$(TF_u(\beta), TF_v(\beta)) = (-i\frac{u}{|\beta|}, -i\frac{v}{|\beta|}) \tag{2}$$

where $\beta = (u,v) \in \Re^2$

Designed for an image I(x), the monogenic signal is presented as the fusion of I and its Riesz transform

$$\begin{aligned} I(\alpha)_M &= (I(\alpha), RK_x\{I\}(\alpha), RK_y\{I\}(\alpha)) \\ &= (I, RK_x * I, RK_y * I) \end{aligned} \tag{3}$$

In [10] and [11], the local orientation can be computed as:

$$\theta = arctan\frac{RK_y\{I\}}{RK_x\{I\}}, \theta \in [0, \pi) \tag{4}$$

The intrinsic 1D signal I(x) can be defined as:

$$\begin{aligned} \sqrt{RK_x^2\{I\}(0,0), RK_y^2\{I\}(0,0)} &= |(h_1 * I\theta)(0)| \\ &= |-\frac{1}{\pi}\int_{t\in\Re}\frac{I(tcos\theta, tsin\theta)}{t}dt| \end{aligned} \tag{5}$$

where $h_1 * I$ is in fact the partial Hilbert transform of I and $h_1 = \frac{1}{\pi x}$ is the Hilbert transform kernel.

Therefore, the local phase of the intrinsic 1D signal $I(x)$ can be defined as:

$$\varphi = atan2(\sqrt{RK_x^2\{I\} + RK_y^2\{I\}, I}), \varphi \in [0, \pi) \tag{6}$$

The local phase is computed in a rotation invariant mode. Based on first order Riesz transform the monogenic curvature tensor [11] can be used to evaluate various specific intrinsic 2D signals. In this work, we make use of the even subsection of the monogenic curvature tensor, which is illustrated by:

$$CT_e = \left[RK_x\{RK_x\{I\}\}, RK_x\{RK_y\{I\}\}RK_x\{RK_y\{I\}\}, RK_y\{RK_y\{I\}\}\right] \tag{7}$$

$$determinant(CT_e) = det(CT_e) = (RK_x\{RK_x\{I\}\})(RK_y\{RK_y\{I\}\}) - (RK_x\{RK_y\{I\}\})^2 \tag{8}$$

If we embed the fingervein image $I(x,y)$ into the Monge patch $\zeta(x,y) = \{x,y,I(x,y)\}$, where $\zeta(x,y)$ is a tow dimension surface embedded in a three dimension ambient Euclidean space, after that the Gaussian curvature (GC) of ζ can partially obtain the surface type of ζ. So, surfaces with $GC > 0$ keep up a correspondence to elliptic patches while surfaces with $GC < 0$ specify hyperbolic patches. The sign of $det(CT_e)$ is identical to the sign of GC [11]. Thus, the sign of det(Te) can reflect the shape type of s embedded from the image f and it is a rotation invariant metric. Therefore, the sign of $det(CT_e)$ can reproduce the shape type of ζ, embedded from the fingervein image. In this article, we will exploit the sign of $det(CT_e)$ to illustrate the local surface type.

B. MLBP feature extraction

We present, in this subsection a novel textural image feature extraction, namely MLBP. The idea of this approach is that we want to join the conventional LBP, the local phase and the local surface type information, to improve the fingervein classification accuracy.

Particularly, we use the uniform LBP defined by Ojala et al. in [9] as:

$$LBP_{P,R}^{riu2} = \begin{cases} \sum_{p=0}^{p-1} sign(g_p - g_c), if U(LBP_{P,R}) \le 2 \\ p+1, otherwise \end{cases} \tag{9}$$

where:

Superscript $riu2$ reflects the use of rotation invariant uniform patterns

U introduces the uniformity measure

$$U(LBP_{P,R}) = |\,sign(g_{p-1} - g_c) - sign(g_0 - g_c)\,| + \sum_{P=1}^{P-1} |\,sign(g_p - g_c) - sign(g_{p-1} - g_c)\,| \qquad (10)$$

g_C is the gray level value of the central pixel

g_P is the value of its neighbors

P is the number of neighbors

R is the radius of the neighborhood

$$LBP_{P,R} = \sum_{p=0}^{P-1} Sign(g_p - g_c)2^p \qquad (11)$$

$$Sign(x) = \begin{cases} 1, x \geq 0 \\ 0, x < 0 \end{cases} \qquad (12)$$

The phase code is defined as:

$$\varphi_c = \lceil \varphi / (\pi / M) \rceil \qquad (13)$$

where $\lceil \lambda \rceil$ is the operator to go back the smallest integer not smaller than λ. Experimentally, in this work, we set M to 5 (φ_C is an integer within $1 \sim 5$)

In the same way, the local surface is defined as:

$$\zeta_c = \begin{cases} 0, det(CT_e) \leq 0 \\ 1, else \end{cases} \qquad (14)$$

Finally, we obtain an improved feature vector $(\varphi_c, \zeta_c, LBP_{P,R}^{riu2})$ by By combining φ_c, ζ_c an $LBP_{P,R}^{riu2}$ namely MLBP.

IV. SYSTEM PERFORMANCES EVALUATION

Receiver Operating Characteristics (ROC) curve are usually used in various fields for judgment making we use it here to validate our proposed fingervein algorithm.

A. Database

In recent times, fingervein identification is a developed research hotspot. A SDUMLA-HMT fingervein database is the first open database in this domain. The device used to capture images is designed by Joint Lab for Intelligent Computing and Intelligent Systems of Wuhan University. Each subject, in the capturing process, was asked to provide images of his/her index fingervein, middle and ring fingervein of both hands. The collection for each of the 6 fingerveins is repeated for 6 times to obtain 6 finger images. Thus, SDUMLA-HMT fingervein database is composed of 3,816 images. Each image is stored in ”bit map” format with 320240 pixels in size. Therefore, the fingervein database takes up around 0.85G Bytes in totality.

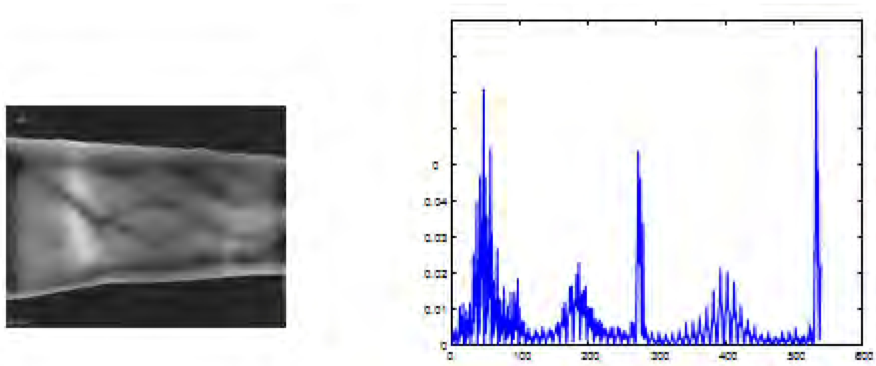

Fig. 3. Fingervein image and its corresponding histogram MLBP .

Fig. 4. Enhanced fingervein and its reconstructed MLBP image.

B. ROC curves

ROC curve is a graphical vision of the TPR (True Positive Rate) as a function of the FPR (False Positive Rate) of a fingervein recognition system.

The ROCCH (ROC convex hull) technique contained both binary and continuous ROC identification. Binary identification are symbolized by individual points in ROC curve space. Continuous identification creates numeric outputs to which, thresholds can be applied, yielding a (FPR,TPR) pairs forming a useful ROC curve. Every one point may or may not give to the ROCCH.

The AUC (Area Under the ROC Curve) is a universal metric that can be applied to compare diverse tests. The value of AUC will forever satisfies this inequalities:

$$0 \leq AUC \leq 1 \qquad (15)$$

Commonly, the AUC is close to area of unit square. This metric indicates good quality of diagnostic test, satisfied this inequalities:

$$0.5 \leq AUC \leq 1 \qquad (16)$$

C. Similarity evaluation

The system for matching a partial or full fingervein image pair is founded on the distance between both MLBP histograms. The best match corresponds to the minimum distance. To obtain the distance between two MLBP histograms, Chi-square formula can be applied [12]. So, the distance between two MLBP histograms S and M can be characterized as:

$$\chi^2(S,M) = \sum_{i=1}^{n} \frac{(S_i - M_i)^2}{S_i + M_i} \qquad (17)$$

Where : n = the number of elements in the MLBP histogram.

Chi-square formula is an efficient measurement of similiarilty between two MLBP feature histograms, thus it is appropriate for pair of nearest neighbour.

The fingervein image database used in these experiments is the SDUMLA-HMT database. The AUC of this approch has a value of 0.91 (Figure 5).

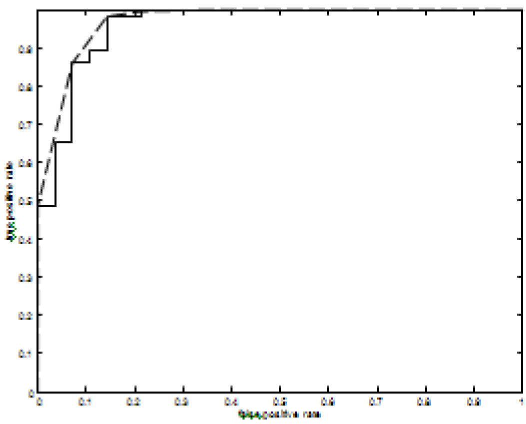

Fig. 5. ROC curve and its convex hull.

D. Fingervein classification with ANN

Typically, ANN (Artificial Neural Networks) can be considered as algorithm which is composed of interconnected elements constituting a network. It is successfully applicable in biometric imaging. Inspired by the biological nervous structure, ANN regulate weight stuck between neurons.

Let $x = (x_1, x_2, ..., x_d)^T$ be an input vector and $w = (w_1, w_2, ..., w_d)^T$ the weight respective vector, the output is defined as:

$$y = g(w^T x_b) = g(\sum_{i=1}^{d} w_i x_i - b) \qquad (18)$$

where $g(.)$ is namely a sigmoidal activation function determined by:

$$g(x) = (1 + e^{-x})^{-1} \qquad (19)$$

For each fingervein samples, MLBP vectors are computed. The description based on these features is used in the identification step as neural network inputs. The applied network architecture is illustred in Figure 6.

The relative error is defined as follows:

$$E = \frac{\sum_{i=1}^{n} (I_N - I_T)}{Numberofsamples} \qquad (20)$$

where I_N is the image resulting from ANN output and I_T is the target.

After training steps, generalization error was evaluated for different features and network conditions.

Figure 7 shows the evolution of training and generalization errors by incrementing the number of hidden layers.

For validation and test, a series of fingervein images was used. Each set is separated into two classes, one is for the ANN learning, and the other is for test of ANN generalization. Each fingervein of database has a training error ont exceeding 2.32% and a generalization error reaching a maximum with 4.71%.

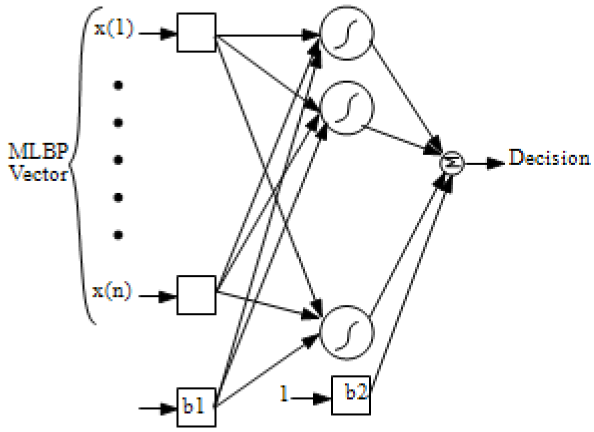

Fig. 6. The applied network architecture.

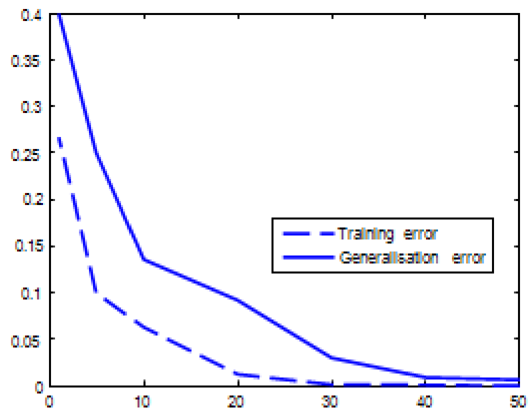

Fig. 7. Evolution of training and generalization errors by increasing the number of hidden layers

V. CONCLUSION

A robust fingervein recognition system is proposed. A novel kind of feature extraction based on Monogenic Local Binary Patterns (MLBP) descriptor is applied. The corresponding output can be appropriately standard by fixing the radius and angle parameters, giving better matching performance. SDUMLA-HMT fingervein databases is used for validation purposes.

In this paper, we consider an artificial neural network based classifier, which is an important step in fingervein recognition system.

As performance metric, we get for an AUC a value of 0.91.

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