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A new biometric human identification based on fusion fingerprints and fingerveins using MonoLBP descriptor

Alima DAMAK MASMOUDI, Randa BOUKHRIS TRABELSI and Dorra SELLAMI MASMOUDI

Abstract—Single biometric modality recognition is not able to meet the high performance supplies in most cases with its application become more and more broadly. Multimodal biometrics identification represents an emerging trend recently. This paper investigates a novel algorithm based on fusion of both fingerprint and fingervein biometrics. For both biometric recognition, we employ the Monogenic Local Binary Pattern (MonoLBP). This operator integrate the orginal LBP (Local Binary Pattern) with both other rotation invariant measures: local phase and local surface type. Experimental results confirm that a weighted sum based proposed fusion achieves excellent identification performances opposite unimodal biometric systems. The AUC of proposed approach based on combining the two modalities has very close to unity (0.93).

Keywords—fingerprint, fingervein, LBP, MonoLBP, fusion, biometric trait.

I. INTRODUCTION

Presently various researches are being done in single modality analysis such as fingerprint , fingervein or palmprint [1] recognition. Though, they do not offer much security. The majority of the single modality methodologies do not present satisfactorily higher identification. Unimodal algorithms have various problems such as intraclass variations, spoof attacks, non-universality, etc....

Many researchers have used fingervein and fingerprint, with some score quality when fusing results performance [11]. In this case, the biometric fusion was using data information, it outperforms single systems.

We propose, in the following work, a methoddologies of fusing the both fingerprint and fingervein images using Monogenic Local Binary Pattern (MLBP) features to lower the computational complexity while to slightly increase the matching accuracy.

The paper is organized as follows: in section II, we describe the proposed steps of fingerprint and fingervein enhancement. in section III, we describe the procedure of feature extraction based on MonoLBP. In section IV, we present the proposed system and fusion performed at score level. Then, in section V we show the comparaison of the results of combined system with these of single biometric traits. In section VI we draw the conclusion.

Alima DAMAK MASMOUDI[1], Randa BOUKHRIS TRABELSI[2] and Dorra SELLAMI MASMOUDI[3] are with Computers Imaging and Electronics Systems (CIELS) in the CEM Research laboratory, University of Sfax, Sfax Engineering School, BP W, 3038 Sfax, Tunisia, e-mail: [1]damak_alima@yahoo.fr, [2]trabelsiboukhrisranda@live.fr, [3]dorra.masmoudi@ieee.org

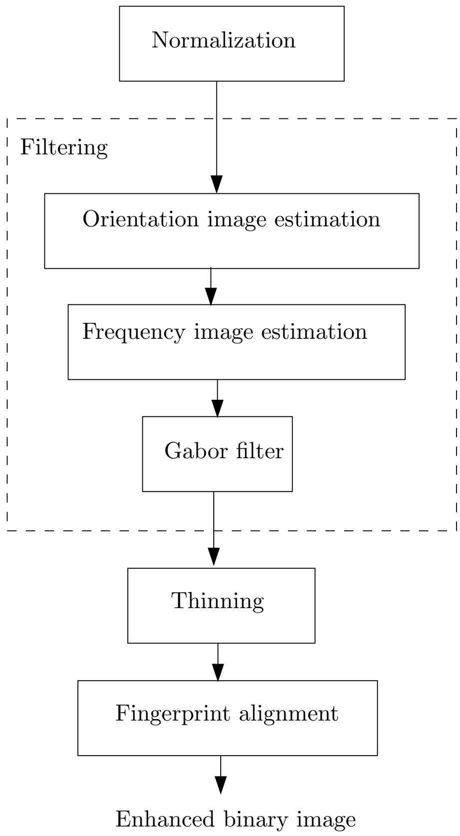

Fig. 1. Fingerprint enhancement algorithm.

II. PREPROCESSING

A. Fingerprint enhancement

Fingerprint enhancement is an essential step for higher image quality to get better matching performance. Since this process reduce the noise and improve the ridge pattern.

Enhancement technique receives an input image on which it applies a set of intermediary steps.

An input fingerprint image is normalized by:

$$N(x,y) = \begin{cases} M_0 + \sqrt{g(x,y)} & if I(x,y) > M \\ g(x,y) & otherwise \end{cases} \tag{1}$$

Where:

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• $g(x,y) = \dfrac{V_0(I(x,y) - M)^2}{\sigma^2}$
• $I(x,y)$ is an image
• M and σ^2 are the gray level, mean and variance of the pixels in the original fingerprint image respectively.
• M_0 and V_0 are the gray level, mean and variance of the pixels in the normalized fingerprint image.

In spatial or frequency domain, Gabor filters are a powerful tool for analysis [2]. Thus, it's could largely enhance the fingerprint image. A complex Gabor filter given by:

$$G(x,y,\theta,f) = \exp(\frac{1}{2}(\frac{x_\theta^2}{\sigma_x^2} + \frac{y_\theta^2}{\sigma_y^2})\exp(j2\Pi f x_\theta) \quad (2)$$

$$x_\theta = x\cos\theta + y\sin\theta \quad (3)$$

$$y_\theta = -x\sin\theta + y\cos\theta \quad (4)$$

where:
• θ is the filter direction
•f is the spacial frequency of the cosine function
• σ_x and σ_y represent the gaussian standard deviations in the x and y directions
• x_θ and y_θ are the horizontal and vertical base vectors in the coordinate system of the filter.

The orientation fingerprint is estimated from the normalized input image. In[3], [4], the local orientation is estimated using:

$$V_x(i,j) = \sum_{u=i-\frac{w}{2}}^{i+\frac{w}{2}} \sum_{v=j-\frac{w}{2}}^{j+\frac{w}{2}} 2H_x(u,v)H_y(u,v) \quad (5)$$

$$V_y(i,j) = \sum_{u=i-\frac{w}{2}}^{i+\frac{w}{2}} \sum_{v=j-\frac{w}{2}}^{j+\frac{w}{2}} H_x^2(u,v)H_y^2(u,v) \quad (6)$$

$$\theta(i,j) = \frac{1}{2}\tan^{-1}(\frac{V_y(i,j)}{V_x(i,j)}) \quad (7)$$

where :
• H_y and H_x are the gradient vector elements in the x and y directions respectively.
• $\theta(i,j)$ is the least square estimate of the local ridge orientation at the block centered at pixel (i,j).

The frequency of fingerprint image is computed from the normalized input and the estimated orientation image [5].

Thinning and alignment are an important steps in fingerprint recognition, affecting greatly the speed and accuracy of matching. Figure 2 shown the Original fingerprint and his enhanced image.

Generally, the alignment parameters finally come from all aligned ridge pairs. The dissimilarity of the reference points coordinates and orientations (Δx, Δy, $\Delta\alpha$) between the template and input image are calculated by estimating the rotation matrix given by:

$$R = \left\{ \begin{array}{cc} cos(\Delta\alpha) & -sin(\Delta\alpha) \\ sin(\Delta\alpha) & cos(\Delta\alpha) \end{array} \right. \quad (8)$$

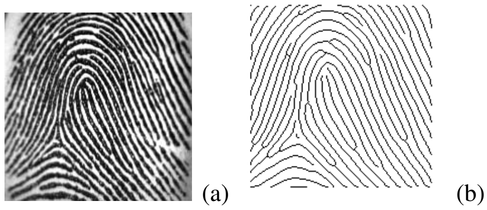


Fig. 2. Original fingerprint and his enhanced image

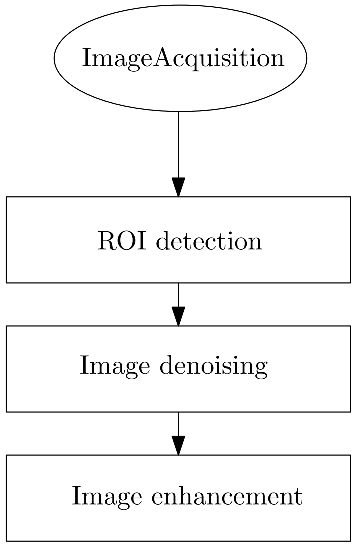


Fig. 3. Flow chart of the preprocessing.

Where:
• R is used to align both images in the orientation • $T = [\Delta x, \Delta y]^T$ is the translation vector using to align the relative distance of minutiae in both images.

B. Fingervein enhancement

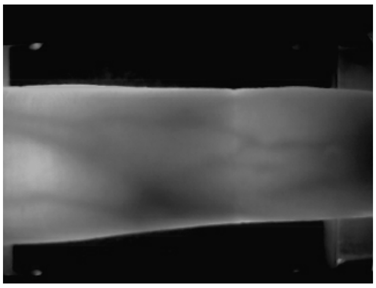
Due to various types of noise or strong reflection produced from the skin's surface and shallow infiltration of light under the skin, The original fingervein contrast is little which makes it not distinct enough for recognition.

This section contain the following three processes: ROI detection, denoising and enhancement of fingervein image. In the Figure 4 the final enhanced image of these three processes is illustrated.

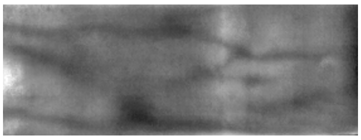
Generally, mathematical morphology makes full use of mathematics and geometry theory, in this manuscript we use the technique open operation of the mathematical morphology. This method make the object contour become smooth, it disconnects the narrow gap and eliminates fine prominence.

After that, Hough transform is used to identify two finger edges in the contour, which is unaffected by image noise. To make a decision of an ROI, a area with fixed geometrical location and size is selected to generate a normalized ROI.

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



(a)



(b)

Fig. 4. (a): Original fingervein, (b) enhanced image.

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 qualities of low complexity and superior performance.

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 makes use of the Contrast-limited Adaptive Histogram Equalization (CLAHE). It be different from the usual histogram equalization in the respect that 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.

III. Feature Extraction

Texture analysis is an energetic area in the fields of pattern recognition, and has various possible applications. For texture classification, Ojala et al. ([6]) 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 accordance with [7], the local phase keeps up a correspondence to a qualitative measure of a local feature and it is a robust structure with respect illumination changes and noise. We take on the monogenic signal hypothesis, which is an isotropic 2-D indicator extension of the 1-D analytic signal, to get the local phase information of fingerprint or fingervein image in a rotation invariant mode. Moreover, we use the monogenic

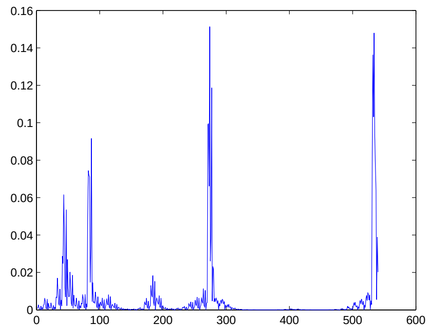


Fig. 5. Fingervein image and his corresponding histogram MonoLBP .

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 a new approach of texture feature extraction, namely monogenic local binary pattern (MonoLBP).

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 [6] as:

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

where

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

▷ U introduces the uniformity measure

$$\begin{aligned} U(LBP_{P,R}) &= |sign(g_{p-1} - g_c) - sign(g_0 - g_c)| \\ &+ \textstyle\sum_{p=1}^{p-1} |sign(g_p - g_c) - sign(g_{p-1} - g_c)| \end{aligned} \tag{10}$$

▷ g_c is the gray 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

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

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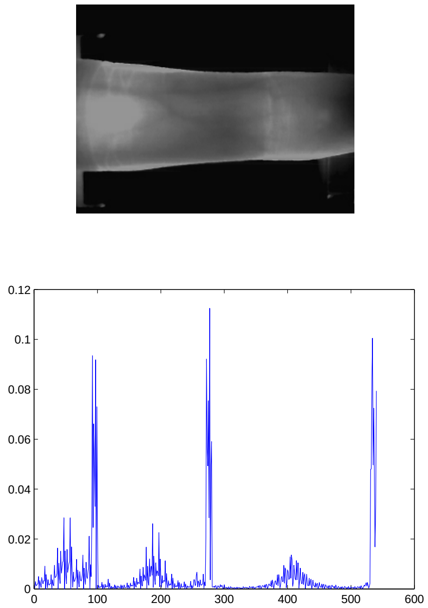

Fig. 6. Fingervein image and his corresponding histogram MonoLBP .

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

The phase code is defined as:

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

where :

• φ is the local phase of the intrinsic 1D signal of an image $I(x)$

• $\lceil X \rceil$ is the operator to go back the smallest integer not smaller than X.

Experimentally, in this work, we set M as 5 (φ_c is an integer within $1 \sim 5$)

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

$$\zeta_c = \begin{cases} 0, & det(T_e) \leq 0 \\ 1, & else \end{cases} \quad (14)$$

where :

• T_e is the monogenic curvature tensor

• $det(T_e)$ is determinant of T_e

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

IV. Biometric Fusion

A. Framework of the proposed system

Figure refbloc illustrated the block-diagram of the proposed multimodal biometric system recognition integrating fingerprint and fingervein. Fingerprint identification or fingervein identification all involve image enhancement, feature extraction, matching score and final decision. In an operational phase, the two biometric sensors are processed by the MonoLBP feature extraction modules to produce a fingerprint or fingervein matching.

Fig. 7. Fingerprint and his reconstructed MonoLBP image.

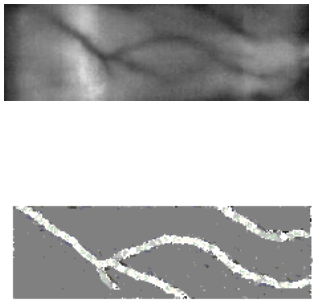

Fig. 8. Fingervein and his reconstructed MonoLBP image.

B. Fusion

Generally, scores generated from unimodal biometric traits are jointly by matching score level [8]. A various techniques such as simple or weighted sum, min/max rules was obtained for achieving the matching score level [9]. In our algorithm we will use simple sum. m_{print} and m_{vein} correspond to the matching scores obtained by the system of recognition of fingerprint and fingrvein respectively. The first step involved in fusion of both approach is the normalization score. Normal-

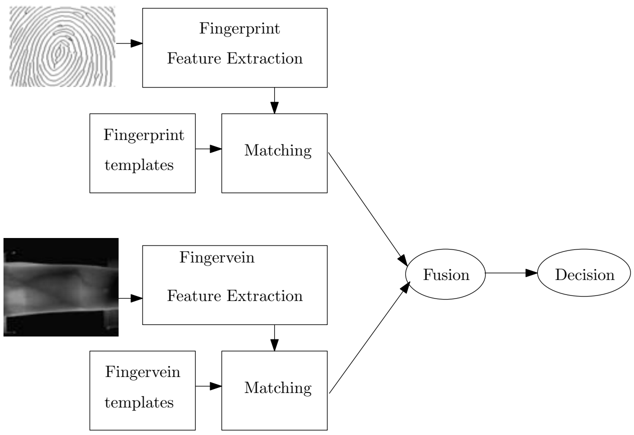

Fig. 9. Blockdiagram

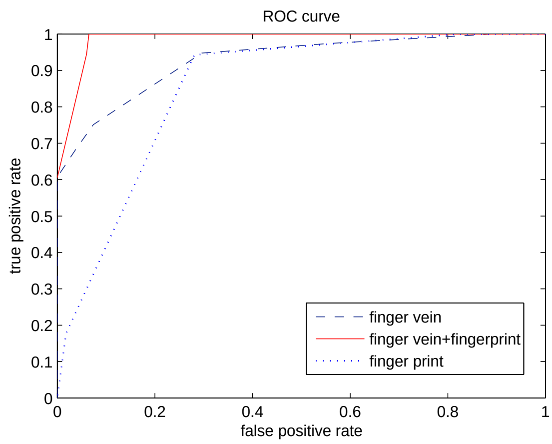

Fig. 10. Receiver Operating Characteristic (ROC) curve showing the performance when sum rule is used to combine the matching scores of fingerprint and fingervein.

ization transforms the scores into a common range included between 0 and 1 is illustred by the following rule:

$$s_{print} = \frac{m_{print} - min_{print}}{max_{print} - min_{print}} \quad (15)$$

$$s_{vein} = \frac{m_{vein} - min_{vein}}{max_{vein} - min_{vein}} \quad (16)$$

where $[min_{print}, max_{print}]$ and $[min_{vein}, max_{vein}]$ correspond to the minimum and maximum scores for fingerprint recognition and fingervein recognition respectively, s_{vein} and s_{vein} correspond to the normalized matching scores of fingerprint and fingervein. To finish, the two normalized similarity matching scores from the individual recognizers s_{print} and s_{vein} are then passed to fusion using sum rule [10] to generate a final matching score as follows:

$$M_S = s_{print} + s_{vein} \quad (17)$$

Matching score M_S is passed to the decision step to define if the person as genuine or as imposter.

V. Comparison With Unimodal Methods

The performance evaluation of a biometric system is done by the Receiver Operating Characteristic (ROC) curves, these curves are frequently used in such fields for the decision phase to validate the proposed algorithm.

The ROC curve keep up a correspondence to a graphical image of the true positive rate (TP) against the false positive rate (FP) of the biometric system.

Experimentally, the performance obtained from the proposed multimodal approach is higher as compared to the two other unimodal biometric approaches, as it is evident from the ROC curves in figure 10.

For performances evaluation, the easiest mean possibility is to calculate the AUC. The value of AUC which keep up a correspondence to a very excellent diagnostic test will satisfy by this inequalities:

$$0 \leq AUC \leq 1 \quad (18)$$

Trait	Area under curves
Fingerprint	0.74
Fingervein	0.81
Fusion	0.93

TABLE I
THE AREA UNDER CURVES

In table I,results shown gives the AUC of the both algorithms of identification based fingervein and fingerprints respectively and the algorithm based on our fusion approach.

In this work, our approach based on MonoLBP descriptors with the simple fusion mechanism provides better results than unimodal biometric algorithm of recognition on its own, hence confirming the robustness of our approach.

In our proposed aproch, we have fused tow traits (fingerprint +fingervein) and the result has increased performance of the biometric system.

The algorithm for matching is based on the distance between both feature histograms. The minimum distance of tow MonoLBP histograms corresponds to best match. Chi-square formula can be used to get the distance between these histograms. The chi-square formula between both histograms S and M can be defined by:

$$\chi^2(S, M) = \sum_{i=1}^{n} \frac{(S_i - M_i)^2}{S_i + M_i} \quad (19)$$

where n is the number of elements in the MonoLBP histogram.

VI. Conclusion

A multimodal biometric system based on fusion of fingerprint and fingervein unsing MonoLBP descriptor has been proposed. Fusion of these two biometric traits is agreed out at a matching score. Based on the proximity MonoLBP feature vector, each subalgorithm has its own matching score. These scores are lastly fused into a ending matching score. To evaluate our approach consisting of multimodal approach with the single biometric system, an ROC curve has been plotted. The experimental results shown that the proposed algorithm gives a high performance.

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Alima Damak Masmoudi she received her Engineering degree in Electrical Engineering since 2005 and MSc in Automatic-Computer-industrial Engineering since 2006 from the National Engineering School of Sfax, Tunisia. Subsequently, she joined the Computers Imaging and Electronics Systems (CIELS) groups in Control and Energy Management Laboratory (CEM-Lab) to work towards her thesis. She received her PhD in 2010. Her researches include image processing applications and neural network implementations. Currently, she is an associated professor in the Physical Department of the Faculty of Sciences, University of Sfax.

Randa Boukhris Trabelsi was born in Sfax, Tunisia, in 1985. She received the B.S. degree in electronic from the Faculty of Sciences of Sfax, Tunisia in 2008, and the M.Sc. in electrical engineering from the National Engineering School of Sfax (ENIS), University of Sfax, Tunisia in 2010.Now she is an assistant in the Faculty of Sciences, University of Monastir since 2010. She is currently preparing her PhD in Multimodal Fusion for Individuals Recognition in Computer Imaging and Electronic System Group (CIElS)from (CEM)laboratory at University of Sfax, Tunisia.

Dorra Sellami Masmoudi was born in Sfax, Tunisia in 1969. She received her engineer's degree from Sfax National Engineering School in 1994 and has been awarded by the president of the republic of Tunisia. Subsequently she joined IMS. Lab at Bordeaux and received her Ph.D. degree in 1998 in electronics system design and she has been assistant Professor at Sfax National Engineering School from 1999. Since 2006, she gets HdR degree. She is actually a full professor. Her researches include neural and fuzzy based systems, evolutionary and genetic algorithms, pattern recognition, image and video processing, feature extraction, classification data fusion, it covers a large spectrum of applications: neural, fuzzy and neuro-fuzzy based image processing, biometry based personal identification and medical image processing for breast cancer automatic diagnosis.