Al-Nima RRO, Dlay SS, Woo WL, Chambers JA.

Human Authentication With Finger Textures Based on Image Feature Enhancement.

In: Intelligent Signal Processing Conference 2015. 2015, London, UK: The Institution of Engineering and Technology.

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This is the author's manuscript of a paper that was presented at *Intelligent Signal Processing Conference 2015*, held 1-2 December 2015, London, UK.

DOI link to article:

<http://dx.doi.org/10.1049/cp.2015.1784>

Date deposited:

09/12/2016

Human Authentication With Finger Textures Based on Image Feature Enhancement

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Abstract—The main goal of this paper is to authenticate people according to their finger textures. We propose to extract Finger Texture (FT) features of the four finger images (index, middle, ring and little) from a low resolution contactless hand image. Furthermore, we apply a new Image Feature Enhancement (IFE) method to enhance the FTs. The resulting feature image is segmented and a Probabilistic Neural Network (PNN) is employed as an intelligent classifier for recognition. Experimental results illustrate that the proposed approach has superior performance than recent published work. Moreover, the best IFE results were obtained with the Equal Error Rate (EER) equal to 4.07%.

Index Terms—biometric authentication, finger texture, image enhancement, inner knuckles, PNN

I. INTRODUCTION

BIOMETRIC technologies are currently considered as one of the most important subjects in the field of human authentication. They have been used in different approaches such as providing reliable accessing controls to security systems. Biometrics have been defined as personal authentications based on behavioural or physical features. There are different examples of biometric systems which have been used for personal authentication such as those based on the iris, retina, voice, signature, fingerprint, hand geometry and palm print [1].

One of the most popular biometrics is the human hand. It consists of rich characteristics, which can be used as reliable features to recognize people such as three-dimensional hand geometry, two-dimensional hand geometry, finger geometry, palm print [2], outer finger knuckles [3] [4], palm veins [5], finger veins [6] and fingerprint [7]. However, some of these features are challenging due to obstacles as palm veins and finger veins require a special capturing device with a specific environment. The process of acquiring hand geometry lacks high reliability. Moreover, it has been noticed that fingerprint patterns may vanish for elderly people especially those suffering from diabetes [8].

Inner finger surface texture has drawn considerable attention over the last 10 years. It has the same characteristics as in the palm. These characteristics are known as FT, and they mainly include wrinkles, visible principal lines and ridge flow patterns. It has been stated that FTs are reliable and unique between individuals or even between identical twins [1]. In addition, they have normal protection as they are located in the inner surface of the fist. Moreover, FTs are clearly visible; so, they require an inexpensive low resolution camera (or scanner) to capture their images [9]. Therefore, there are many advantages of using the inner finger surface features.

For example, they have rich information, they are generally resistant to emotional feelings, and their patterns are stable and reliable. Furthermore, employing FTs in terms of biometric security has already shown promising results [1].

This study therefore aims to contribute to this growing area of research by proposing an approach to extract more FTs from low resolution contactless hand images. This model is able to collect many features from the four fingers (index, middle, ring and little) in a short time. In addition to that this paper introduces a new method to enhance the FTs named IFE. This method is reliable and it can be used in any texture enhancement contexts.

The rest of this paper is organized as follows: Section II explains the prior and related work. Section III describes the proposed FT extraction method and the IFE method. The results and comparisons are given in Section IV. Finally, we draw our conclusions in Section V.

II. PRIOR WORK

Although extensive work has been carried out on single biometric models, no intensive study exists to concentrate on the inner finger surface textures. The idea of employing the FTs perhaps started in [10], where this study introduced a multi-biometric system by using eigenfinger and eigenpalm characteristics. Furthermore, a low cost multi-modal identification system was proposed in [11] by using FT print, palm and hand geometry. A comparison study for a fingerprint and FT surface was given in [7] based on regularized-direct linear discriminant analysis, various discriminant features and principal component analysis. A combination of knuckle print and the palm print was described in [9] as a verification system. Similarly, the same multi-modal biometric system was explained intensively in [12]. A fusion between hand geometry, palm print and FTs has been used to enhance a contactless hand images [2]. Finger veins and textures were examined and evaluated in [6] by using just two fingers (index and/or middle). A case of analysing just part of the fingers (inner knuckle print) by using an improved local binary pattern model has been described in [13]. Also, some inner knuckles (middle knuckles of the ring and middle fingers) have been fused in [14] by using a particular image acquisition system. Local feature extractions for a hand image have been applied as a multi-biometric authentication in [1].

Therefore, our study is attempting to work more intensively with the FT patterns and fully exploit their features in the task of human authentication.

Fig. 1: The general block diagram of the proposed finger authentication scheme; the switches are used to change between training and testing operation

III. PROPOSED METHODOLOGY

In this study we utilize a series of logical processing. We start from the hand images, and then apply preprocessing operations including binarization and multiplication; we then determine the finger locations and perform separations; we then acquire the Region of Interest (ROI) adaptively to the finger size. We then collect full features, and enhance the finger surface textures by applying multiple image processing operation; we segment the ROI images and calculate the Co-efficient of Variance (CV) for each segment; we then arrange these values in to vectors and train the PNN with labeled data. The general block diagram of our proposed methodology is given in Fig. 1. We next describe the important steps in more detail.

A. Finger Extractions/ROI

The key idea of this section is to extract full FTs from the finger image. We propose a modified algorithm to acquire full finger width and three inner knuckles from the four fingers, namely the index, middle, ring and little fingers. These inner knuckles refer to the horizontal lines distributed on the finger areas. Due to regular finger bending, these dominant wrinkle lines are very clear compared to their surrounding skin areas. They usually appear on three locations denoted as upper knuckle, middle knuckle and lower knuckle. See Fig. 2. From these three wrinkles locations, richer textures contribute to the FT patterns [12].

Fig. 2: Full Finger Texture Region

In this paper, low resolution contact free 2D hand images from the Hong Kong Polytechnic University database version 1.0 have been used [15]. All the hand images are in colour. Thus, the first step required is to convert the colour hand images to grayscale. Then, a number of morphological operations are adopted to reduce the noise and maintain the hand borders. Assume that the 8-bit grayscale hand image is denoted as

$H(x, y) : Z^2[0, 255]$. To convert this image from the 8-bit grayscale to a binary image a threshold θ was executed according to equation (1):

$$B(x, y) = \begin{cases} 1 & \text{if } H(x, y) > \theta \\ 0 & \text{if } H(x, y) \leq \theta \end{cases} \quad (1)$$

where $B(x, y)$ is the binary image and θ is the suitable threshold. A suitable value of θ was found empirically to be about 0.135 in this type of the database. This maintains the hand borders rather than the finger surfaces from undesirable erosions. A multiplication operation has been used to combine the original grayscale hand image with the binary image. Fig. 3 shows an example hand image with the main preprocessing stages.

Fig. 3: (a) The original image, (b) The grayscale image, (c) The binary image, (d) The hand image with the black background

Eight connected contour tracing, which described in [7], was applied to draw the boundaries. The main finger points (tips and valleys) can be specified from the local minima and local maxima points. Other points can be determined from the contour boundaries, such as the reference point before the index finger and the reference point after the little finger. The contour image with the essential points is demonstrated in Fig. 4. In this figure $\{T_1, T_2, T_3 \text{ and } T_4\}$ represent the tips for the index, middle, ring and little fingers respectively. Whereas, the points $\{V_1, V_2 \text{ and } V_3\}$ are given for the valleys between the fingers as follows: V_1 is the valley point between the index and middle, V_2 is the valley point between the middle and ring, and V_3 is the valley point between the ring and little. The reference point before the index finger is marked as R_1 and the reference point after the little finger is marked as R_2 .

The set points $\{R_1 \text{ and } R_2\}$ are specified in such way that the length of the straight line T_1-V_1 is equal to the length of the straight line T_1-R_1 . Similarly, the length of the straight line T_4-V_3 equals the length of the straight line T_4-R_2 .

Fig. 4: The contour image with the essential points: tips, valleys and references

Additional points have been determined in the finger base to specify the finger direction. The finger base is defined as the line between the two valley points around the finger, and take the form:

$$p_n(x) = \frac{p_1(x) + p_2(x)}{2} \quad (2)$$

$$p_n(y) = \frac{p_1(y) + p_2(y)}{2} \quad (3)$$

where p_n is the new assigned point, p_1 and p_2 could be two valley points or a valley and a reference point, and x and y are for the x_axis or y_axis coordinate respectively. These equations could be repeated between each two valley points, or even between a valley and a reference point to specify the new points in each finger. Consequently, the finger direction angle in degrees can be calculated according to the following equation:

$$angle = \tan^{-1} \left| \frac{T(y) - p_n(y)}{T(x) - p_n(x)} \right| \times 180/\pi; \quad (4)$$

Each finger image is extracted separately according to its tip point, and two valley points before and after the finger or a valley and a reference point before and after the finger. Furthermore, more pixels have been collected after the valley and reference points, empirically around 20 pixels, there by ensuring that the lower knuckle has been completely included in the FT region.

Henceforth, the ROI region is extracted using the largest rectangle inside the finger image, similar to the one proposed in [2]. However, we further modified this approach, to achieve an effective method to extract the largest rectangular region to include more features. That is performed by cropping the region around the finger tips and the black areas around the finger widths. Empirically, the around tip region has been reduced to 30 pixels; then the lines handling black pixels before and after the finger width have been eliminated. The ROI rectangle length is spread to the area after the valley and reference points, as mentioned. According to this method the ROI is adaptive to the size of a finger and the maximum characteristics will be collected.

Finally, image resizing is performed to each ROI in order to

provide the same normalization and later processing. In this paper the size of each ROI is equal to 40×170 . Fig. 5 shows four finger image extractions with their ROIs.

Fig. 5: Four finger image extractions with their ROIs: Each column represents a finger; from the left: little, ring, middle and index respectively, whereas the first row is assigned for finger images, the second row for ROIs according to the adaptive rectangle and the last row for resizing of ROIs

B. IFE

We propose an IFE method to enhance the characteristics of the ROI finger image. The variation of illumination of each finger image is a challenge even for the same subject. This problem can lead to failure in the recognition process. In order to solve the illumination issue, Contrast Limited Adaptive Histogram Equalization (CLAHE) has been applied to the ROI finger images. Furthermore, three CLAHE histograms have been investigated here: flat, exponential and bell-shaped histograms. The key idea of CLAHE is that the image is segmented into small areas called tiles, then a histogram equalization is performed upon each tile according to the histogram type mentioned before. The histogram transformation is calculated for the centre pixels of each tile. Whilst, bilinear interpolations are used to combine the neighbouring pixels [16].

As each finger image has specific features, enhancements and feature fusions are important to collect as many characteristic values as possible. Obtaining the top-hat and bottom-hat values, then fusing all features appeared to yield a high-quality enhancement [17]. For analysis, a structuring element is created as a kernel of a disk shape of ones [18]:

$$h = R^2 \times \pi \quad (5)$$

where R is the radius of pixels. Secondly, the top-hat and the bottom-hat details are extracted from the image, respectively [19]:

$$Im_{out1} = I_{in} - (I_{in} \circ h) \quad (6)$$

$$Im_{out2} = I_{in} - (I_{in} \bullet h) \quad (7)$$

where $\circ$ refers to the open morphological operation and $\bullet$ refers to the close morphological operation, and they are denoted as [20]:

$$(I_{in} \circ h) = (I_{in} \ominus h) \oplus h \quad (8)$$

$$(I_{in} \bullet h) = (I_{in} \oplus h) \ominus h \quad (9)$$

For a grayscale image $I_{in}(a_{I_{in}}, b_{I_{in}})$ and a structure element $h(a_h, b_h)$, the erosion $\ominus$ and dilation $\oplus$ operations are denoted as [21]

$$(I_{in} \ominus h)(a_{I_{in}}, b_{I_{in}}) = \min \{I_{in}(a_{I_{in}} + a_h, b_{I_{in}} + b_h) - h(a_h, b_h)\} \quad (10)$$

$$(I_{in} \oplus h)(a_{I_{in}}, b_{I_{in}}) = \max\{I_{in}(a_{I_{in}} - a_h, b_{I_{in}} - b_h) + h(a_h, b_h)\} \quad (11)$$

Thirdly, we add the top-hat details to the original image followed by subtracting the bottom-hat details from the original image [18]

$$Im_{out3} = [I_{in} + (I_{in} - (I_{in} \circ h))] - (I_{in} - (I_{in} \bullet h)) \quad (12)$$

In other words, we extract the highest values and add them to the original image and extract the lowest values then subtract them from the original image. These will increase the contrast between the top details and the bottom details of the original image [17].

C. Image Segmentation

To reduce the FT vector size, non-overlapped segmentation is then used. Thus, Im_{out3} is segmented into fixed sized matrices of 5×5 pixels. The CV is calculated for each segment as [22]:

$$CV_S = \frac{SD_S}{AV_S} \quad (13)$$

where S is the matrix of 5×5 pixels, AV is the average, SD is the standard deviation and CV is the coefficient of variance. The CV values have been arranged for each image into a one dimensional vector. Fig. 6 shows examples of the four finger images features before and after the enhancements.

Fig. 6: Four finger images before and after texture enhancements: Each column represents a finger; from the left: little, ring, middle and index respectively, where the first row is the original finger images, the second row the ROI finger images after the IFE based flat histogram, the third the ROI finger images after the IFE based exponential histogram and the fourth for the ROI finger images after the IFE based bell-shaped histogram

D. PNN

In our work, we employ a PNN and supervised training. The general form of PNN is shown in Fig. 7. The main structure of the PNN consists of multiple layers. The first layer is the input layer, in this layer all the input vectors are prepared to the next layer. The second layer is the hidden or the pattern layer, in this layer a Radial Basis Function (RBF) is used according to the following equation [23][24]:

$$z_{i,j} = \exp\left[-\frac{\|\mathbf{x} - \mathbf{w}_{i,j}\|^2}{2\sigma^2}\right], \quad i = 1, 2, \dots, c, \quad j = 1, 2, \dots, p \quad (14)$$

where:

$z_{i,j}$: is the output of a hidden or pattern node.

$\mathbf{x}$: is the input vector $\mathbf{x} = [x_1, x_2, \dots, x_n]^T$.

$\mathbf{w}_{i,j}$: is a training vector $\mathbf{w} = [w_1, w_2, \dots, w_n]^T$.

σ : is the width of the RBF, and $\|\cdot\|$ denotes Euclidean normalization.

The third layer is the summation layer, where the output of the hidden nodes will be added together for each class, uniform weighting is used. The final layer is the decision layer according to (the winner take all rule), that is the winner class will be set to one and all others to zero.

The main advantages of the PNN is that it has a very short training time and it has flexible architecture where it is easy to enlarge the number of neurons if additional inputs are added [25].

Fig. 7: The general form of PNN representing the input, hidden, summation and decision layer respectively

IV. RESULTS, COMPARISONS AND DISCUSSIONS

As mentioned, the database which has been used consists of 1770 hand images, collected from people of different ages (ranged between 18-50 years) with multiple ethnic backgrounds and both genders. Each participant has contributed with 10 images taken for their right hands in two sessions. The time lapse between the two sessions ranged between one week to three months. No restrictions or pegs have been used to confine the hand location. However, the participant has asked to hold his/her hand far from the acquisition device in about 0.7 meter distance after removing jewellery. The same indoor environment has been used with a black background to collect image data [15].

To evaluate our proposed method in extracting the ROIs from the four finger images, we compared our method with [10] [7] and [2] to build up the comparisons. These publications use only a small ROI region. This means ignoring some important features from the FT patterns. In [10] the length of ROI was specified to be five-sixths of the length of the finger and the

ROI's width was assigned to have a fixed ratio with the ROI's length, this ratio was determined empirically for each finger. It can be argued that the ratio between the ROI length-width is not fixed between individuals, that is, the proportional ratio for the length-width of the person who has long and fat fingers does not equal to the proportional ratio of the person who has long and thin fingers. So, in [10] the full finger's width was not always collected, so the lower knuckles were only partially included in their ROIs. Similarly, in [7] the ROI length was determined after dividing the finger length by 1.5 and the ROI width was assigned after dividing the finger width by 2.3. The ROIs in [7] were too small, the upper knuckles and the lower knuckles were only partially included rather than the ROI's width. However, this paper used the fingerprint, located in the upper knuckle, to build up its contributions. On the other hand, in [2] an adaptive largest ROI rectangle has been suggested to fit in the finger length and width, but in this publication the lower knuckle was not included.

In our contribution, a further modified model for the adaptive ROI rectangle has been applied, where more features have been collected for each finger from the ROI areas. In addition, in our suggested algorithm the morphological opening operation is not required as in [2], because of using a suitable threshold for the image binarization. Instead, the morphological opening operation was required in [2] after using Otsu's threshold for the image binarization in order to maintain the hand surface rather than the finger borders. Moreover, in [10] [7] and [2] six extra points were assigned to determine the symmetry of each ROI, where two points in each side of the finger were assigned in the contour border and another calculated two points in the middle of the finger. This method is more likely to be used with high resolution hand images, acquired from a touch scanner as in [10] and [7]. However, using the adaptive largest ROI rectangle has covered the symmetry problem by collecting as many features as possible. Therefore, our suggested algorithm has less complexity and computations because just 4 assigned points are used for each finger, three of them are main points: tip, valley or reference. Furthermore, the proposed model is able to work with a very low resolution contactless hand images [15]. Table I provides a summary of the above mentioned comparisons.

TABLE I: Summary of related work for extracting the ROIs from the four finger images

Comparison Subject	Proposed Method	[10]	[7]	[2]
Upper knuckle	Include	Include	Partially include	Include
Lower knuckle	Include	Partially include	Partially include	Not include
Full finger width	Include	Not always include	Partially include	Include
ROI rectangle	Adaptive rectangle	Proportional rectangle	Proportional rectangle	Adaptive rectangle
Morphological opening operation	Not required	Not required	Not required	Required
Number of assigned points	4	10	10	9
Execution time	0.049 sec.	0.067 sec.	0.055 sec.	0.08 sec.

Fig. 8: The histograms of the four finger image before and after the CLAHE: Each column represents a finger's histogram; from the left: little, ring, middle and index respectively, whereas the first row has assigned for the histograms of the original images, the second row for the histograms of CLAHE based on the flat distribution, the third row for the histograms of CLAHE based on the exponential distribution and the fourth row for the histograms of CLAHE based on the bell-shaped distribution

The execution time in Table I has been recorded for a computer with 8 GB of RAM and a 3.2GHz Intel core i5 processor. It is true that there is no significant enhancement in the execution time, but there are important improvements in collecting features from the finger region. As well the suggested algorithm has less computations and operations than the other algorithms. In the respect of the feature extraction, Fig. 8 shows samples of histograms for the three CLAHE distributions flat, exponential and bell-shaped histograms. Each one of these types has been evaluated as a part of the IFE for the authentication purposes. For the crucial comparisons, the proposed IFE method has been evaluated for the four finger images, which have similar ROIs to that described in [2]. Another comparison has been established for the IFE method but this time with our suggested ROIs model, where more features have been included. PNN has been employed as a classifier for the training and verification process. A total of 885 samples has been applied in the first stage, where 5 samples from each subject have contributed to verify the individual. The rest of the samples have been used in the second stage to evaluate the recognition process. The two mentioned comparisons are given in Table II and Table III respectively.

TABLE II: Feature extraction comparisons with limited ROIs features

Approach	Feature extraction method	EER
Proposed feature extraction	IFE based flat histogram	5.54%
	IFE based exponential histogram	5.42%
	IFE based bell-shaped histogram	12.66%
[2]	CompCode	6%

TABLE III: Feature extraction comparisons with full ROIs features

Approach	Feature extraction method	EER
Proposed feature extraction	IFE based flat histogram	4.07%
	IFE based exponential histogram	4.07%
	IFE based bell-shaped histogram	7.01%

It can be seen from Tables II and III that there are significant improvements in the Equal Error Rate (EER) when using full ROIs features, where the inner knuckle has been included. This reveals that better FT verifications can be attained after including more features or characteristics. Moreover, the results of using the IFE with the CLAHE based flat histogram is very close to that of using the IFE with the CLAHE based exponential histogram. According to Fig. 7 both histograms for the exponential and flat histograms have close distributions. On the other hand, the IFE based bell-shaped histogram achieved poorer results than the other histogram types. That is because the bell-shaped histogram has not provided a useful data distribution as shown in Fig. 7. In other words, it has provided unsatisfactory contrast between the FT features, see Fig. 6.

V. CONCLUSION

A modified approach to extract additional features from the FT surfaces based on an adaptive ROI rectangle and adding more pixels to include the lower knuckle was proposed. Secondly, a new feature extraction model has been suggested based on the IFE. This method consists of a series of image processing steps. Briefly, these processing steps are CLAHE to equalize the image illumination, followed by the feature fusion, which is that collecting the lower details of the image (such as the wrinkles of the lower, middle and upper knuckles), subtracting these information from the original image (the image after the CLAHE), collecting the upper features from the same image and adding these features to the resulted image (the subtracted image). Moreover, three CLAHE histogram distributions have been explored flat, exponential and bell-shaped histograms. The results of this study indicated that significant improvement in the FT biometric authentication can be obtained after including more FT characteristics. Furthermore, using the CLAHE histogram of type exponential or flat distributions show better results than using the bell-shaped distribution type in the case of IFE.

ACKNOWLEDGMENT

"The Hong Kong Polytechnic University Contact-free 3D/2D Hand Images Database version 1.0".

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