Minutiae Extraction for Fingerprint and Palm Print Images Using Convolutional Neural Networks

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Abstract: *With the growing use of biometric authentication systems in the recent years, spoof fingerprint detection has become increasingly important. To make it more secure palm print detection is used in addition. In this study, we use Convolutional Neural Networks (CNN) for fingerprint and palm print liveness detection. The proposed method consists of two stages. In the first stage, Local Binary Pattern (LBP) is used to change the pixel intensity in the original image. In the second stage, the minutiae extraction and Region of Interest (ROI) are applied to get minute authentication. Experimental results show that the proposed algorithm gives high security compared to existing methods such as Weber Local Descriptor (WLD) and Local Binary Pattern (LBP).*
Keywords: *Convolutional Neural Networks, Local Binary Pattern, Minutiae extraction, Region of interest, Weber Local Descriptor.*

I. Introduction

The basic aim of biometrics is to automatically discriminate subjects in a reliable manner for a target application based on one or more signals derived from physical or behavioral traits, such as fingerprint, face, iris, voice, palm, or handwritten signature. Biometric technology presents several advantages over classical security methods based on either some information (PIN, Password, etc.) or physical devices (key, card, etc.). However, providing to the sensor a fake physical biometric can be an easy way to overtake the systems security. Fingerprints, in particular, can be easily spoofed from common materials, such as gelatin, silicone, and wood glue. Therefore, a safe fingerprint system must correctly distinguish a spoof from an authentic finger. Different fingerprint liveness detection algorithms have been proposed, and they can be broadly divided into two approaches: hardware and software. In the hardware approach, a specific device is added to the sensor in order to detect particular properties of a living trait such as blood pressure, skin distortion, or odour. In the software approach, which is used in this study, fake traits are detected once the sample has been acquired with a standard sensor.

The features used to distinguish between real and fake fingers are extracted from the image of the fingerprint. There are techniques such as those in and, in which the features used in the classifier are based on specific fingerprint Measurements, such as ridge strength, continuity, and clarity.

In contrast, some works use general feature extractors such as Weber Local Descriptor (WLD), which is a texture descriptor composed of differential excitation and orientation components. A new local descriptor that uses local amplitude contrast (spatial domain) and phase (frequency domain) to form a bi-dimensional contrast-phase histogram was proposed in. In two general feature extractors are compared: Convolutional Neural Networks (CNN) with random (i.e., not learned) weights (also explored in), and Local Binary Patterns (LBP), whose multi-scale variant reported in achieves good results in fingerprint liveness detection benchmarks. In contrast to more sophisticated techniques that use texture descriptors as features vectors, such as Local Phase Quantization (LPQ), LBP with wavelets, and BSIF , their LBP implementation uses the original and uniform LBP coding schemes.

Important personal identification technique is palm print identification. It the palm print identification has capacity to achieve a high accuracy, since technique contains not only principle curves, wrinkles, rich texture and minuscule points, and also due to availability of rich information in palm print. Various palm print identification methods, such as coding based methods and principle curve method have been proposed in past years. Along with those methods one more method called subspace based methods in this method also Palm is defined as the inner surface of human hand from human wrist to the root of their fingers. Many other techniques are deployed for palm printing in that Representation Based Classification (RBC) method also shows good performance in this regard .which transforms image data into scale-invariant coordinates, are successfully introduced for the contactless palm print identification. A print is an impression made in or on a surface by pressure. A palm print is defined as the skin pattern of a palm, composed of the physical characteristics of skin

pattern such as lines, points and texture. Palm print is rich in principal lines, wrinkles, ridges, singular points and minutiae points. Palm print has a much larger area than finger tip. As the security system has very much important in several fields, it is very important to authenticate the users for any access. As many studies have been proposed but these researches did not explore the security issue in depth, so in this paper we established a framework in order to perform multibiometrics by combining left and right palm print images. The authentication system consists of enrolment and verification stages. In enrolment stage, will consider the training samples and processed by pre-processing, feature extraction and modelling modules to produce the matching templates. Where as in verification, a query sample is also processed by pre-processing and feature extraction method and then is matched with reference templates to decide whether it is sample which we considered or not. A setup system consisting of a palm print based authentication system can work with multipurpose camera in an uncontrolled circumstances like mounted on a laptop, mobile device. Unlike earlier biometric systems, it does not require equipment and have attained higher accuracy value equivalent to fingerprint. Old multibiometrics methods treat different pattern independently. However, some special kinds of biometric traits have a similarity and these methods cannot exploit the similarity of different kinds of pattern. For example, the left and right palm print traits of the same subject can be viewed as this kind of special biometric traits owing to the similarity between them, which will be demonstrated later. However, there is almost no any attempt to explore the correlation between the left and right palm print and there is no "special" fusion method for this kind of biometric identification. This specialized algorithm carefully takes the nature of the left and right palm print images into consideration, it can properly examine the similarities between the left and right palm prints of the same object/human.

The framework which we implemented here will integrate three kinds of scores; these scores are generated from the left and right palm print images to do matching score level fusion. First two kind of scores can be obtained from any other conventional methods easily but the third kind of score has to obtain using specialized algorithm, which takes the nature of the left and right palm print images into consideration, it can properly exploit the similarity of the left and right palm prints of the same subject. Moreover, the proposed weighted fusion scheme allowed perfect identification performance to be obtained in comparison with previous palm print identification methods. . Moreover, the proposed specialized fusion scheme allowed perfect identification performance to be obtained in comparison with old conventional palm print identification methods.

II. Methodology

A. Local Binary Pattern

The local binary pattern (LBP) operator was first introduced by Ojala et al. 1996.LBP is a powerful method of texture description. The original 3X3 neighborhood is thresholded by the value of the center pixel. The values of the pixels in the thresholded neighborhood are multiplied by the binomial weights given to the corresponding pixels. Finally, the values of the eight pixels are summed to obtain the LBP number for this neighborhood.

The standard version of the LBP of a pixel is formed by thresholding the 3X3 neighborhood of each pixel value with the center pixel's value. Let gc be the center pixel gray level and gp (p = 0,1,..7) be the gray level of each surrounding pixel. If gi is smaller than gc , the binary result of the pixel is set to 0 otherwise set to 1. All the results are combined to get 8 bit value. The decimal value of the binary is the LBP feature.
In this method the input image is left and right palm print is given to the registration. From the image we have to extracting the principle lines.
Let LBP p,r denote the LBP feature of a pixel „s circularly neighborhoods, where r is the radius and p is the number of neighborhood points on the circle.

$$LBP(P,R) = \sum_{p=0}^{p-1} S(g_p - g_c)2^p$$

The concept of uniform patterns is introduced to reduce the number of possible bins. Any LBP pattern is called as uniform if the binary pattern consists of at most two bitwise transitions from 0 to 1 or vice versa. For example if the bit pattern 11111111(no transition) or 00110000 (two transitions) are uniform where as 10101011 (six transition) are not uniform.

B. Minutiae extraction

Minutiae extraction using the skeleton image, the most commonly employed method that is used for minutiae extraction is the Crossing Number (CN) concept [19, 29, and 30]. In this method, a window of 3x3 pixels is used to examine the local neighbourhood of each pixel in the image and the CN value is computed as half the sum of the differences between pairs of adjacent pixels in the eight- neighbourhood. Using the

properties of the CN, the ridge pixel can then be classified as a ridge ending, bifurcation or non-minutiae point. For example, a ridge pixel with a CN of one corresponds to a ridge ending, and a CN of three corresponds to a bifurcation.

$$CN = 0.5 \sum_{i=1}^{8} |P_i - P_{i+1}|, \quad P_9 = P_1$$

Where Pi is the pixel value in the neighbourhood of P. For a pixel P, its eight neighboring pixels are scanned in an anti-clockwise direction.

The CN value for a pixel on the ridge is used to identify whether it is a ridge ending or ridge bifurcation. A CN value of 1 can corresponds to a ridge ending or termination and a value of 3 corresponds to a ridge bifurcation. If this is authenticated go to palmprint region.

C. Extracting principle lines

After pre-processing, to extract line features i.e. principal lines from the sub-image or ROI the canny edge detection algorithm is used .First, a Gaussian blur is applied to the image to reduce noise. Thresholding can also be used if the objects of interest are significantly contrasted from the background and detailed textures are irrelevant. Next, the edge direction and gradients at each pixel in the smoothed image are determined by applying the Sobel-operator. For that first the gradient in the x and y-direction is found respectively by applying the kernels is shown below

$$K_{Gx} = \begin{bmatrix} -1 & 0 & 1 \\ -2 & 0 & 2 \\ -1 & 0 & 1 \end{bmatrix}$$

$$K_{Gy} = \begin{bmatrix} 1 & 2 & 1 \\ 0 & 0 & 0 \\ -1 & -2 & -1 \end{bmatrix}$$

The gradient magnitudes (also known as the edge strengths) is then determined as an Euclidean distance measure by applying the law of Pythagoras as shown in Equation (1). It is sometimes simplified by applying Manhattan distance measure as shown in Equation (2) to reduce the computational complexity

$$|G| = \sqrt{G_x^2 + G_y^2} \tag{1}$$
$$|G| = |G_x| + |G_y| \tag{2}$$

Where Gx and Gy are the gradients in the x- and y-directions respectively. However, the edges are typically broad and thus do not indicate exactly where the edges are. To make it possible to determine this, the direction of the edges must be determined and stored as shown in Equation (3).

$$\theta = \arctan\left(\frac{|G_y|}{|G_x|}\right)$$

Then edges are traced using that information. And the "blurred" edges in the image of the gradient magnitudes is converted to "sharp" edges by preserving all local maxima in the gradient image, and deleting everything else. Next double thresholding is done by marking the edge pixels stronger than the high threshold as strong and edge pixels weaker than the low threshold are suppressed and edge pixels between the two thresholds as weak. Finally, in this way parallel edges (principal lines) are extracted and those with weaker gradient strengths are eliminated. The extracted principal line and strong wrinkles shown in fig.3 are corresponds two parallel edges in Canny Edge Detection algorithm. This is because that Canny Edge Detection algorithm is based on magnitude maximums of the gradient image.

The principal lines extracted images are further divided into 9×9 blocks of size 20×20. The blocks are traced to create feature vector. While generating a template the feature vector bit is set to '1'if the concerned block contain the line else the feature vector bit is set to '0'.

D. Matching left and right palm print

To understand the relative importance of various extended features, they are incrementally used for matching and the performance gains are examined. Starting with the baseline matching algorithm, which uses only minutiae, additional features (reference points, overall image characteristics and skeleton) are incrementally used. This order is roughly based on the required time in manual feature marking. The baseline

matching algorithm is not only a matcher for minutiae-only templates, but also serves as a framework to match and fuse various extended features. We provide a detailed description of the baseline matcher and then describe the approaches to using various extended features.

Baseline Matching Algorithm: The baseline matching algorithm takes only minutiae as input and consists of the following steps: 1. Local minutiae matching: Similarity between each minutia of latent fingerprint and each minutia of rolled fingerprint is computed. 2. Global minutiae matching: Using each of the five most similar minutia pairs found in Step 1 as an initial minutia pair, a greedy matching algorithm is used to find a set of matching minutia pairs. 3. Matching score computation: A matching score is computed for each set of matching minutia pairs and the maximum score is used as the matching score between the latent and rolled prints.

Local minutiae matching: In local minutiae matching, the similarity between each minutia of latent fingerprint and each minutia of rolled fingerprint is computed. Since the basic properties of a minutia, like location, direction and type, are not very distinctive features, additional features, which are collectively referred to as a descriptor, are computed for each minutia. Figure 10 show five types of features that have been used as minutiae descriptors in the literature [31, 46, 47]. In the baseline algorithm, a neighboring minutiae-based descriptor is used, since only minutiae information is available. The neighborhood of a minutia is defined to be a circular region with an 80-pixel radius. All minutiae lying in this neighborhood are called the neighboring minutiae. Let p and q be the two minutiae whose similarity needs to be computed. For each neighboring minutia pi of p, we examine if there is a neighboring minutia of q whose location and direction are similar to those of pi. If such a minutia exists, pi is deemed as a matching minutia; otherwise pi is checked against the following two criteria:
1) The minutia is unreliable,
2) It does not fall in the foreground region (the convex hull of minutiae) when mapped to the other fingerprint based on the alignment parameters between p and q.

If pi satisfies either one of these two criteria, it will not be penalized; otherwise, it will be penalized. The above process is also applied to the neighboring minutiae of q. The similarity between two neighboring minutiae-based descriptors is computed as

$$s_m = \frac{m_p + 1}{m_p + u_p + 3} \cdot \frac{m_q + 1}{m_q + u_q + 3},$$

where mp and mq denote the number of neighboring minutiae of p and q that match, up and uq denote the number of penalized unmatched neighboring minutiae of p and q, the value 1 in the numerator is used to deal with the case where no neighboring minutiae are available, and the value 3 in the denominator is empirically chosen to favor the case where there are more neighboring minutiae that match. Note that mp may be different from mq since we do not establish a one-to-one correspondence between minutiae.

E. Convolution Neural Networks

A classical convolutional network is composed of alternating layers of convolution and local pooling (i.e., sub sampling). The aim of a convolutional layer is to extract patterns found within local regions of the inputted images that are common throughout the dataset by convolving a template over the inputted image pixels and outputting this as a feature map c, for each filter in the layer.

The motivation behind pooling is that the activations in the pooled map s are less sensitive to the precise locations of structures within the image than the original feature map c.

In a multi-layer model, the convolutional layers, which take the pooled maps as input, can thus extract features that are increasingly invariant to local transformations of the input image. This is important for classification tasks, since these transformations obfuscate the object identity. Achieving invariance to changes in position or lighting conditions, robustness to clutter, and compactness of representation, are all common goals of pooling. The feed-forward pass of a single layer convolutional network. The input sample is convoluted with three random filters of size 5x5 (enlarged to make visualization easier), generating 3 convoluted images, which are then subject to non-linear function max(x; 0), followed by a max-pooling operation, and sub sampled by a factor of 2.
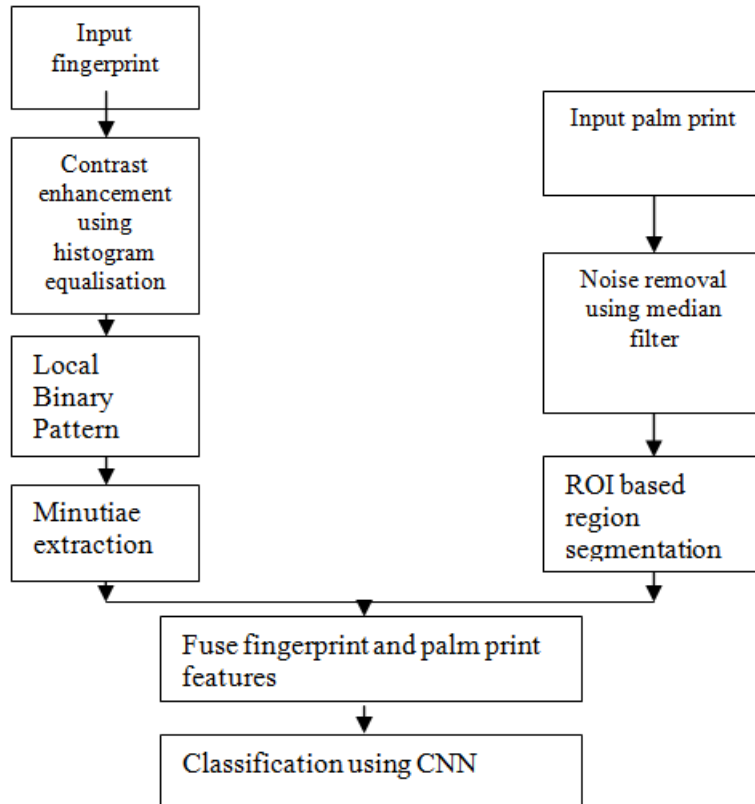
Fig.1. Block diagram

III. Simulation Verification

The proposed method was simulated using MATLAB tool for different fingerprint and palm print images, they are taken to authenticate the right person. The simulation result for fingerprint and palm print image is shown in fig.2. and fig.8. The input image is a plain image to be enhanced. The enhanced image is processed in local binary pattern and minutiae extraction, in input palm print image noise is removed using median filter and ROI segmentation is done. Where the resulted fingerprint and palm print is fused for matching and classification is done using convolution neural networks.

Fig. 2. Input fingerprint image
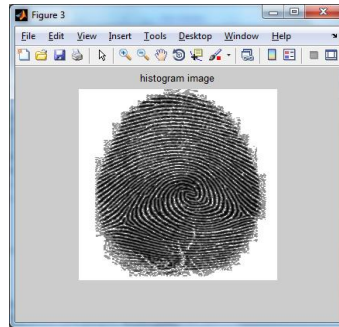
Fig.3. Histogram image
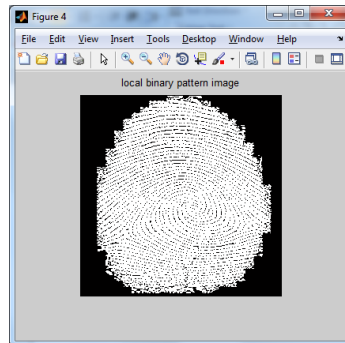
Fig 4. Local binary pattern image

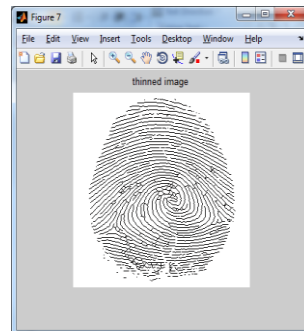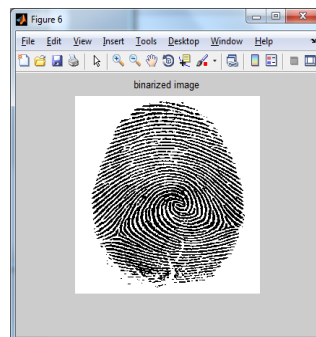The simulation results for fingerprint image shown in fig 7.

Fig.5. Thinned image

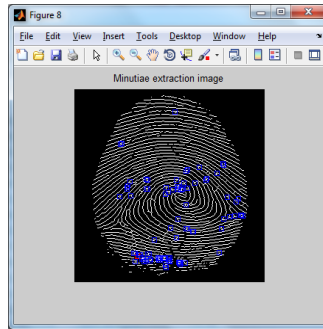**Fig.6.** Binarized image

Fig.7. Minutiae extraction image

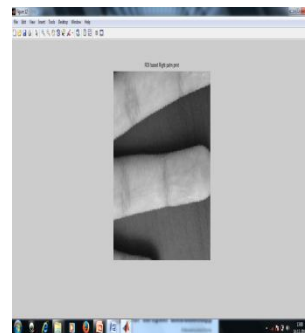**Fig.8.** Input palm image

Fig.9. ROI based right palm print

The simulation results of palm print image shown in fig.9. and fig.10.

Fig.10. ROI based left palm print

IV. Results

The performance of the proposed algorithm shown that the authentication is done with both fingerprint and palm print. Authentication is undergone by analysing the database of fingerprints, if it is authenticated then it goes to the database of the palm prints of left and right palm and if both fingerprint and palm print matches then it displays the result as authenticated.

A. Fingerprint authentication result

A fingerprint authentication by minutiae extraction shows ridge point, where it is divided into branches called bifurcation. The ridge and bifurcation pattern reveals the authentication, where each person's identity is shown.
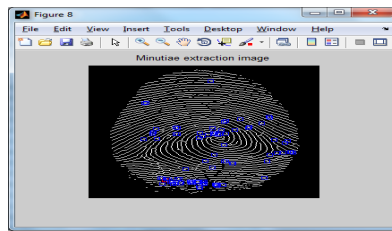

Fig.11. fingerprint minutiae extraction result

B. Palm print authentication result

A palm print authentication by minutiae extraction shows ridge point, where it is divided into branches called bifurcation. The ridge and bifurcation pattern reveals the authentication, where each person's identity is shown.
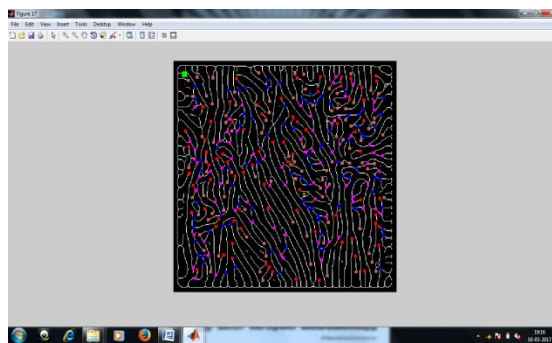

Fig.12. palm print minutiae extraction result

V. Conclusion

Combining fingerprint, Left and Right Palm print images for person identification receiving increasing attention from law enforcement community. A few palm print matching systems have been proposed recently. However, the efficiency of these systems is far from satisfactory. In this paper, multi feature based fingerprint, palm print identification gives double security of person identification. The proposed algorithm contains three types of query images and minutiae extraction. Multiple features were extracted from this palm print containing enhanced information. The discriminative powers of different feature combinations were analyzed and we find that density is very useful for palm print recognition. The future work of this paper is adding multiple features more than this paper for identification of person and we have to get high security of person identification using palm print.

References

[1]. Antonelli. A, Capelli. R, Maio. D and Maltoni. D (2006), 'Fake finger detection by skin distortion analysis', Information forensics and security, IEEE transactions on, Vol. 1, No. 3, pp. 360-373.

[2]. Baldisserra. D, Franco. A, Maio. D and Maltoni. D (2005), 'Fake fingerprint detection by odour analysis', in Advances in Biometrics. Springer, 2005, pp.265-272.

[3]. Menotti. D, Chiachia. G, Pinto. A, Robson Schwartz. W, Pedrini. A, Xavier Falcao, and Rocha. A (2015), ' Deep representations for iris, face and fingerprint spoofing detection' ,Information Forensics and Security, IEEE Transactions on, Vol. 10, No. 4, pp. 864-879.

[4]. Graganiello. D, Poggi. G, Sansone. C and Verdoliva. L (2013), 'Fingerprint liveness detection based on weber local image descriptor', in Biometric Measurements and Systems for Security and Medical Applications (BIOMS), IEEE Workshop on. IEEE, 2013, pp. 46- 50.

[5]. Rodrigo Frassetto Nogueira, Roberto.A.Lotufo, Rubens campos machado, 'Livdet (2016) fingerprint liveness detection using convolutional neural networks'.

[6]. Ahonen. T, Hadid. A and Pietikainen. M (2004), ' Face recognition with local binary patterns', in computer vision-ECCV. Springer, 2004, pp. 469-481.

[7]. Coli. P, Marcialis. G. L and Roli. F (2008), 'Fingerprint silicon replicas: static and dynamic features for vitality detection using an optical capture device', International Journal of Image and Graphics, Vol. 8, No. 04, pp. 495- 512.

[8]. Frasetto Noguiera. R, De Alancar Lotufo. R and Campos Machado. R (2014), 'Evauating software based fingerprint liveness detection using convolutional networks and local binary patterns', in Biometric Measurements and Systems for Security and Medical Applications (BIOMS) Proceedings, IEEE Workshop on. IEEE, 2014, pp. 22- 29.

[9]. Galbally. J, Alonso- Fernandez. F, Fierrez. J and Ortega- Garcia. J (2012), 'A high performance fingerprint liveness detection method based on quality related features', Future Generation Computer Systems, Vol. 28, No. 01, pp. 311-321.

[10]. Ciresan. D, Meier. U and Schmidhuber. J (2012), 'Multi-column deep neural networks for image classification', in computer vision and pattern recognition (CVPR), IEEE 2012, pp. 3642- 3649.