Volume 8, No. 3, March – April 2017
International Journal of Advanced Research in Computer Science
RESEARCH PAPER
Available Online at www.ijarcs.info
ISSN No. 0976-5697

Comparative Analysis of Palmprint Matching Techniques for Person Identification

V.Subha
Department of Computer Science and Engineering
Manonmaniam Sundaranar University
Tirunelveli, India

Mariammal.G
Department of Computer Science and Engineering
Manonmaniam Sundaranar University
Tirunelveli, India

Abstract: Biometrics has been an arising field of research in the recent years and was concerned by using physical traits, such as those based on iris or retinal scanning, face recognition, fingerprints, or voices of individuals to be identified. Applying low resolution devices palmprint is easily captured also it is distinctive, compared to other methods such as fingerprint or iris palm print has preferred as well as it includes additional features such as principal lines. In past decades, various palmprint identification methods have been proposed such as coding based methods and principle curve methods. Yet, some special kinds of biometric traits have a similarity and these methods cannot exploit the similarity of different kinds of traits. This work designs a framework at the matching score level by combining the left with right palmprint. In this framework, using the left palmprint matching, right palmprint matching and crossing matching between the left query and right training palmprint three types of matching scores were calculated and these were fused to make the final decision. This framework not only combines the left and right palmprint images for identification, but also correctly exploits the similarity between the left and right palmprints of the same subject. The fusion is done by using three methods such as line based method, Scale Invariant Feature Transform (SIFT) method and Local Binary Pattern (LBP). The experimental result shows that the LBP method provides better performance in terms of recognition, false positive and negative rate compared to other two methods.

Keywords: Biometrics; Multimodal biometrics; Palmprint recognition, Line based method; SIFT method; LBP method

I. INTRODUCTION

Biometrics refers to metrics related to human traits. It is the measurement and statistical analysis of person's physical and behavioral characteristics. Multimodal biometric system is used to overcome the restraints of unimodal biometric system. Multimodal biometric system provides more accurate, reliable and larger security than unimodal biometric system. There are several biometric recognitions such as DNA, iris, fingerprint, voice and palmprint. These are the mainly used physiological biometrics. Palm print recognition inherently implements many of the same matching traits that have allowed fingerprint recognition to be one of the most well-known and best publicized biometrics. Using the information presented in a friction ridge impression both palm and finger biometrics were represented. This information combines ridge flow, ridge traits, and ridge structure of the raised portion of the epidermis. The data represented by these friction ridge impressions allows an assurance that corresponding areas of friction ridge impressions either begun from the same source or could not have been made by the same source. Because both fingerprints and palms have uniqueness and permanence, they have been used over a century as a trusted form of identification. Since the palm area is much larger, it has more distinctive features than fingerprints. This makes palmprint more suitable for identification than fingerprints.

II. LITERATURE REVIEW

A number of related works have been reported in literature review.

P.N. Belhumeur et.al [1] was developed by a face recognition algorithm that is insensitive to large variation in lighting direction and facial expression. The images of a particular face, under varying illumination, lie in 3D linear subspace was the advantages of that observation. It linearly projects the images into a subspace than explicitly modeling this deviation. Another method projects image linearly space to a low dimensional space called Eigen face, but it has similar computational requirements.

A.K.Jain et.al. [2], proposed a variety of systems that requires reliable personal recognition schemes to confirm or identify the person. By using this method only valid users can accessed these services. Using their physiological or behavioral characteristics, the persons are automatically recognized called biometric recognition. In this method, the individual information is not necessary such as ID card or password.

A new multimodal biometric system was proposed by S.Ribaric et.al [3], to identify the person using Eigen finger and palm feature. To extract the feature K-L transform method is used. Fusion is applied at matching score level. And then decision is taken by using K-L NN classifier.

In Biometric Authentication (BA), one of the major difficulties is single sample biometric recognition. To over that problem, feature level biometric fusion was implemented by Y.F.Yao et.al. [4]. It takes two types of characteristics and combines it. One is the face feature and another is the palmprint feature. The approach improves the recognition effect by using large face and palmprint database as the test data.

A single biometric feature sometimes fails, to identify the person exactly. To overcome this problem, combining multiple modalities is used and hence performance reliability was achieved. R.Chu et.al. [5], proposed a method that can easily acquire face and palmprint images by using two touchless sensors. Effective classifiers are constructed for face and palmprint based on ordinal features.

The verification of palmprint was done by Robust Line Orientation Code (RLOC) which was implemented by W.Jia et.al. [6]. Using three strategies the performance is improved. Firstly, extraction of palmprint orientation feature is done by

Modified Finite Randon Transform (MFRAT). Secondly, due to the imperfect preprocessing the large rotation problem has occurred, to solve this problem an enlarged training set is constructed. At last stage, pixel-to-area comparison has been designed for matching algorithm that has better fault tolerance.

For forensic application Latent-to-full palmprint matching system was made by A.K.Jain et.al. [7]. At higher resolution the images are captured and used minutiae as features. Even in poor quality, the ridges and minutiae features of palmprints can be extracted by this method. The minutia matching algorithm is used for to match two palmprints. Due to the difficulty of latent-to-full palmprint matching, the recognition rate of live scan partial and latent palmprint are achieved at 78.7 and 69 percent respectively against the background database.

A.W.K. Kong et.al. [8], described capture devices, preprocessing, verification algorithm, fusion algorithm and measures for protecting palmprint system and users privacy which are used in current palmprint recognition research. And also some suggestions are offered in this paper.

A.Morales et.al. [9], provides the issues related to two of the most palmprint approaches such as Scale Invariant Feature Transform (SIFT) and Orthogonal Line Ordinal Features (OLOF) that are applied to the contactless biometric authentication. Most of the palmprint feature extraction method may not be effective in contactless framework. Different environments suggest that the SIFT performs better than OLOF. It further suggests to achieve more reliable performance that combine the matching scores of robust SIFT with OLOF.

Most of the previous palmprint recognition methods are contact based verification which limits their application. To solve that, the contactless palmprint verification based on SIFT was implanted by X.Wu et.al [10]. It contains three steps for identification. First, using an isotropic filter preprocessing process was done. Second, to extract the features of palmprint SIFT is used. Finally, matching process is carried out. For making the decision the number of final matched points is taken as the score. When the non-linear deformations exist in palmprint the proposed method is effective than other.

III. MATERIALS AND METHODS

A. *Database Description*

This work utilized IITD (Indian Institute of Technology Delhi) touchless palmprint image database which mainly includes the hand images collected from the students and staff at IIT Delhi, India. This database has been captured in the Biometrics Research Laboratory during January 2006 - July 2007 using a digital CMOS camera. The captured images were saved in bitmap format. This database contains images of left and right palmprints of more than 230 peoples, using a very simple touchless imaging setup, and made freely usable to the researchers. All the subjects in the database are in the age group 14-56 years and voluntarily contributed at least 5 hand image samples from each of the hands. In addition to the acquired whole hand images, automatically segmented and normalized palmprint regions are also made available.

B. *Pre-processing*

The aim of pre-processing here is to mitigate unwanted distortion and to improve some of the features which are important for further processing. In this work, Median filter is used for removing noise.

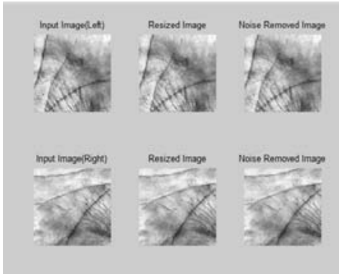

Fig. 1 preprocessing image

Fig. 1 shows the resized image and noise removed image of given input images using median filter. These images are given into further process.

C. *Methods*

- ***Line Based Methods***

The basic features of palm print are lines and in palm print verification and identification line based method plays an important role. In line based methods, the lines are extracted from the palm print using lines or edge detectors and then to perform palm print verification and identification that extracted lines are used. Using the Gobor filter, Sobel operation, or morphological operation palm print principal lines can be extracted. In Robust Line Orientation Code (RLOC) method, the pixel-to-area matching strategy was adopted for principal lines matching, which defines a principal line matching score as follows:

$$Z(X,Y) = \left(\sum_{v=1}^{r}\sum_{w=1}^{s} X(v,w) \,\&\, \overline{Y}(v,w)\right) / T_U \qquad (1)$$

Where X and Y are principal line images of two palmprint, '&' denoted as AND operation, T_U is the number of pixel points in X, then $\overline{Y}$ (v, w) denoted as a neighbor area of Y(v, w).

Edge detection using SOBEL operator:

In this work, SOBEL operator is used to extract the lines from palmprint. For each pixel position in the image, the gradient of the image was calculated. The magnitude of the vector Δp was denoted as

$$\Delta p = mag(\Delta p) = [Q_n^2 + Q_m^2]^{1/2} \qquad (2)$$

Where Q_n denoted as n direction and Q_m denoted as m direction.

Morphological operations:

Morphology is a broad set of image processing operations that process images based on its shape, which are encoded in the structuring element. These operators often take a binary image and a structuring element as input and combine them using a set operator. The lines are represented as white and background as black color by using this method. The more sophisticated operators take 0's as well as 1's and don't cares in the structuring elements.

- ***SIFT Based Method***

SIFT is an algorithm to detect and describe the local features in images. In recent years, for contactless palmprint identification it was originally proposed for object classification applications. If the features are invariant to image scaling, rotation and partially invariant to the modification of projection and illumination then that are extracted by using SIFT method**.** Thus, the SIFT based method is insensitive to the scaling, rotation, projective and illumination aspects, and that is advisable for the contactless palmprint identification. The SIFT based method initially searches over all scales and locations of images by difference-of-Gaussian function and thereby identifies potential interest points. Then an elaborated model was used to decide finer location and scale at each candidate location and keypoints were selected based on the stability. Next one or more orientations were assigned to each keypoint location based on local image gradient directions. Certainly, the local image gradients are evaluated at the selected scale in the region around each keypoint. The Euclidean distance can be employed at the identification stage which is used to determine the identity of the query image. If the Euclidean distance is small then similarity between the query image and the training image is high.

This framework, first works for the left palmprint images and uses a palmprint identification method to calculate the scores of the test sample with respect to each class. Formerly, it applies the palmprint identification method to the right palmprint images to compute the score of the test sample with respect to each class. Afterwards the crossing matching score of the left palmprint image for testing with respect to the reverse right palmprint images of each class is obtained, this framework performs matching score level fusion to combine these three scores to obtain the identification result.

The method is presented in detail below. It supposes that there are K subjects, each of that has r available left palmprint images and m available right palmprint images for training. Let A^c_v and B^c_v denote the v^{th} left palmprint image and v^{th} right palmprint image of the c^{th} subject subsequently, where v = 1, . . . ,r and c = 1, . . , K. Let O_1 and O_2 stand for a left palmprint image and the corresponding right palmprint image of the subjects to be identified. O_1 and O_2 are the so-called test samples.

Step 1: Generate the reverse images $B^{\sim c}_v$ of the right palmprint images B^c_v. Both B^c_v and $B^{\sim c}_v$ will be used as training samples. $B^{\sim}$ c_v is obtained by: $B^{\sim c}_v$ (l, c) = B^c_v (IB –l + 1, k), (l = 1 . . . IB, k = 1 . . . KB), where IB and KB are the row number and column number of B c_v respectively.

Step 2: Use O_1, A^c_vf and a palmprint identification method, such as the method introduced in Section II, to calculate the score of O_1 with respect to each class. The score of O_1 with respect to the v^{th} class is denoted by f_v.

Step 3: Use O_2, B^c_vf and the palmprint identification method used in Step 2 to calculate the score of O_2 with respect to each class. The score of O_2 with respect to the v^{th} class is denoted by e_v.

Step 4: $B^{\sim c}_w$ (w= 1 . . . r_, r_ ≤ r), which have the property of Sim_score ($\tilde{B}^c_w$, A_c) ≥ match_threshold, are selected from $B^{\sim c}$ as additional training samples, where match_threshold is a threshold. Sim_score ($\tilde{B}^c_w$, A^c) is defined as:

$$\text{Sim\_score}(B, A^c) = \sum_{e=1}^{E}(J(\tilde{B}_t, A^c))/E \quad (3)$$

$$J(\tilde{B}_e, A^c) = \max(Score(\tilde{B}_e, A^c)),\ i = \{1 \ldots r\}, \quad (4)$$

Where B is a palmprint image. A^c is a set of palmprint images from the c^{th} subject and A^c_v is one image from A^c. $\hat{A}^c_v$ and $\hat{B}$ is the principal line images of Ac_v and B, respectively. E is the number of principal lines of the palmprint and e represent the e^{th} principal line. Score (B, A) is calculated as formula (3) and the Score (B, A) is set to 0 when it is smaller than sim_threshold, which is empirically set to 0.15.

Step 5: Treat $B^{\sim c}_w$ is obtained in Step 4 as the training samples of O_1. Use the palmprint identification method used in Step 2 to calculate the score of O_1 with respect to each class. The score of the test sample with respect to $B^{\sim c}_w$ f of the v^{th} class is denoted as h_v.

Step 6: The weighted fusion scheme di = g_1f_i+ g_2e_i+g_3h_i, where 0 ≤ g_1, g_2≤ 1 and g_3= 1 –g_1–g_2, is used to calculate the score of O_1 with respect to the v^{th} class. If l = arg min Id_w, then the test sample is recognized as the l^{th} subject.

- ***LBP Based Method***

For texture description, LBP method is very effective. The LBP method labels the pixels of an image by thresholding the neighborhood of each pixel and thereby considers the result as a binary number. It divides the images into cells. And considers each cell as a 3X3 matrix and center pixel of this matrix is assigned as a threshold value, then center pixel value is compared with the neighborhood pixels (i.e. left top, left middle, left bottom, right top etc.). The comparison is either in clockwise or anti clockwise direction. Then the pixel values are converted into binary format such as 0 or 1. If the pixel value is greater than the threshold value (center pixel), it represented as 1 else it is represented as 0. The binary code is then converted into decimal value for convenience. The LBP computation is defined as:

$$LBP_{X,Y} = \sum_{x=0}^{X-1} R(d_x - d_t)2^x \quad (5)$$

Where X denotes neighborhood pixel value and Y denotes the LBP descriptor. To convert the binary code into decimal value, it is multiplied by the powers of two and then they are added. Consider the below example

10	40	35
12	25	15
25	30	5

→

0	1	1
0		0
1	1	0

Here the threshold value is 25 and it is compared with eight neighborhood pixels then they are turned into binary code as 0's and 1's.

IV. Performance Analysis

The process of evaluating the performance of a particular scenario in comparison of the objective which was to be obtained is called performance analysis.

A. *Performance Metrics*

Performance metrics give hard data to support such evaluations. A good performance metric yields results that measures clearly defined quantities within a range that allows for improvement.

False Acceptance Rate (FAR): The probability, that the system matches the input figure to a non-matching template inaccurately in the database**.** It scales the percent of input that are invalid inputs and which are incorrectly accepted. In case of similarity scale, if the person is a pretender in reality, but the matching score is greater than the threshold. This increases the FAR, which thus also rely upon the threshold value.

FAR = (NFA / NIP) * 100

NFA = Number of False Acceptances, NIA = Number of Pretender Attempts.

False Rejection Rate (FRR): The probability that the system fails to reveal a match between the input figure and a matching template in the database. It measures the percent of valid inputs which are falsely unaccepted.

FRR = (NFR / NEA) * 100

NFR = Number of Failed Rejections, NEA = Number of legitimate Access Attempts

Recognition Rate (RR): Recognition rate is number of images correctly matching with the training images, while false acceptance is how many images (outside the dataset) are matching with the dataset images. True rejections are the number of images (from the dataset) that are not matching with the training dataset.

RR = (TP+TR) / (Total)

TP = True Positive, TR = True Rejection

B. Result and Analysis

Parameters	***Line Based Method***	***SIFT Based Method***	***LBP Based method***
Recognition Rate	75	95.6	98.5
False Acceptance Rate	60	75	85
False Rejection Rate	20	10	5

Table.1 Parameter Table

Table 1 shows the performance analysis of various methods for palmprint recognition.

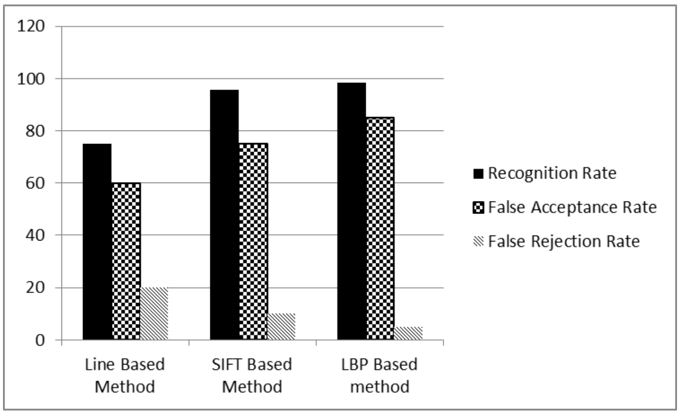

Fig. 2 Performance chart

Fig 2 shows the graphical representation of the results given in table 1. It can be inferred from the table and graph that LBP method performs better than the other methods in terms of recognition rate, false acceptance rate and false rejection rate.

V. CONCLUSION

This work presents a comparative analysis of palmprint recognition systems using Line based, SIFT and LBP methods. Line based method carefully takes the nature of the left and right palmprint images into account, and uses SOBEL operator for edge detection and morphological operation for evaluating the similarity between them. SIFT based method takes left and right palmprint images and find the similarity between them using Euclidean distance. LBP method is very effective for texture descriptor. It is used for extracting the features of palmprint images. It is based on matrix formation. The simulated results show that LBP method provides better recognition rate with minimum error rate than other two methods.

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