



Palmprint recognition by combining left and right palmprint images for person authentication using Radon transform

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Abstract— Multibiometric systems use multiple sensors or biometrics to overcome the limitations of single biometric systems. Palm print is preferred compared to other methods such as fingerprint or iris because it is distinctive, easily captured by low resolution devices. The palmprint contains not only principle curves and wrinkles but also rich texture and miniscule points, so the palmprint identification is able to achieve a high accuracy because of available rich information in palmprint. In this paper, we perform multibiometrics by comprehensively combining the left and right palmprint images at matching score level fusion. This method integrates three kinds of scores generated from the left and right palmprint images. The scores of the left and right palmprint images and can be obtained by any palmprint identification method, whereas the third kind of score was obtained by considering the nature of both the palmprint images. For palmprint recognition, Radon transform is used for edge detection and to extract the feature vectors. Radon transform computes the line integral along parallel paths in a certain direction and used in places where accuracy is more critical. Finally features of input image and database images are compared to recognize the palmprint.

IndexTerms—Palmprint recognition, Multibiometrics, Radon Transform.

I. INTRODUCTION

A. MULTIBIOMETRICS

Biometrics has been an emerging field of research in the recent years and is devoted to identification of individuals using physical traits, such as those based on iris or retinal scanning, face recognition, fingerprints, or voices. As unauthorized users are not able to display the same unique physical properties to have a positive authentication, reliability will be ensured. This is much better than the current

methods of using passwords, tokens or personal identification number (PINs) at the same time provides a cost effective convenience way of having nothing to carry or remember. Although there are numerous distinguishing traits used for personal identification, this research will focus on using palm prints to more correctly and efficiently identify different personnel through classification at a low cost.

Palm print is preferred compared to other methods such as fingerprint or iris because it is distinctive, easily captured by low resolution devices as well as contains additional features such as principal line [9]. With the help of palm geometry, a highly accurate biometric system can be designed. Iris input devices are expensive and the method is intrusive as people might fear of adverse effects on their eyes. Fingerprint identification requires high resolution capturing devices and may not be suitable for all as some may be finger deficient.

Multimodal biometric systems use multiple sensors or biometrics to overcome the limitations of unimodal biometric systems. For instance iris recognition systems can be compromised by aging irides and finger scanning systems by worn-out or cut fingerprints [1]. While unimodal biometric systems are limited by the integrity of their identifier, it is unlikely that several unimodal systems will suffer from identical limitations. Multimodal biometric systems can obtain sets of information from the same marker (i.e., multiple images of an iris, or scans of the same finger) or information from different biometrics (requiring fingerprint scans and, using voice recognition, a spoken pass-code).

B. PALMPRINT TECHNOLOGY



The palmprint contains not only principle curves and wrinkles but also rich texture and miniscule points, so the palmprint identification is able to achieve a high accuracy because of available rich information in palmprint. Various palmprint identification methods, such as coding based methods [8] and principle curve methods [5], have been proposed in past decades. In addition to these methods, subspace based methods [2] can also perform well for palmprint identification. For example, Eigenpalm and Fisherpalm [11] are two well-known subspace based palmprint identification methods. In recent years, 2D appearance based methods such as 2D Linear Discriminant Analysis (2DLDA) [2] have also been used for palmprint recognition.

Further, the Representation Based Classification (RBC) method also shows good performance in palmprint identification. Additionally, the Scale Invariant Feature Transform (SIFT) [13], which transforms image data into scale-invariant coordinates, are successfully introduced for the contactless palmprint identification. No single biometric technique can meet all requirements in circumstances. Christo Ananth et al. [14] proposed a method in which the minimization is performed in a sequential manner by the fusion move algorithm that uses the QPBO min-cut algorithm. Multi-shape GCs are proven to be more beneficial than single-shape GCs. Hence, the segmentation methods are validated by calculating statistical measures. The false positive (FP) is reduced and sensitivity and specificity improved by multiple MTANN.

II. EXISTING SYSTEM

A. SIFT based Palmprint Recognition Method

In SIFT based algorithm, image is first preprocessed using Gabor filter [13]. After preprocessing the image is then for SIFT feature extraction where Scale space construction is performed followed by Key point localization. Orientation assignment is done which is then followed by Descriptor computing. After feature extraction proper alignment is to be done using the Homographic matrix. Given any point in one image, in the homogeneous coordinate system $[x, y, 1]^T$, the corresponding point in the second image is given by

$$[x', y', c] = H [x, y, 1]^T \quad (1)$$

If the number of correspondences is less than 4 the homograph cannot be solved. After image alignment, the query image and the gallery are better aligned.

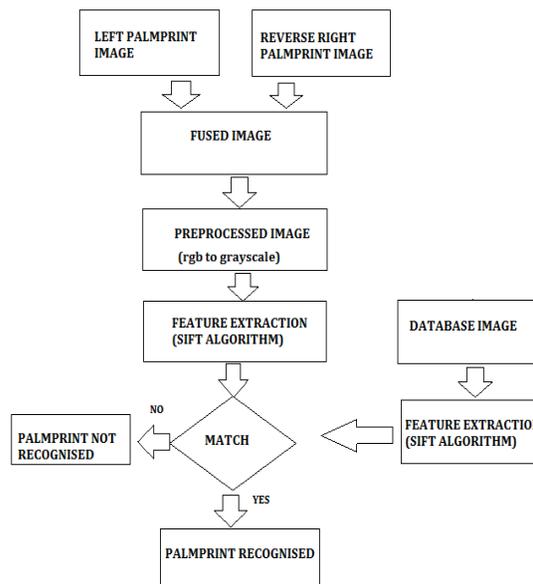


Fig 1 Block diagram of existing method

B. Working principle

Input image

Left palm image is acquired and then reverse right palm image is acquired. Finally the Input image is obtained by fusing left and reversed right palm images which is given as input to the security systems.

Preprocessing

Preprocessing is the process of converting an RGB image into Gray scale image. In addition to that Blurring of the images and noise will be removed using median filter.

Feature Extraction

In this module, features of palm print images are extracted. SIFT and Radon transformation algorithm is used to extract the features.

Matching



Finally the features obtained for Database images and input image is compared. If the features of input image and database image are equal, palm is recognized otherwise not recognized.

SIFT algorithm description

Scale-invariant feature transform (or SIFT) is an algorithm in computer vision to detect and describe local features in images. It is an image descriptor for image-based matching and recognition. This descriptor as well as related image descriptors are used for a large number of purposes in computer vision related to point matching between different views of a 3-D scene and view-based object recognition. The SIFT descriptor is invariant to translations, rotations and scaling transformations in the image domain and robust to moderate perspective transformations and illumination variations. Experimentally, the SIFT descriptor has been proven to be very useful in practice for image matching and object recognition under real-world conditions.

SIFT keypoints of objects are first extracted from a set of reference images and stored in a database. An object is recognized in a new image by individually comparing each feature from the new image to this database and finding candidate matching features based on Euclidean distance of their feature vectors. From the full set of matches, subsets of keypoints that agree on the object and its location, scale, and orientation in the new image are identified to filter out good matches. The determination of consistent clusters is performed rapidly by using an efficient hash table implementation of the generalized Hough transform.

Each cluster of 3 or more features that agree on an object and its pose is then subject to further detailed model verification and subsequently outliers are discarded. Finally the probability that a particular set of features indicates the presence of an object is computed, given the accuracy of fit and number of probable false matches.

III. PROPOSED SYSTEM

A. Palmprint Recognition Method using Radon transform by combining left and right palmprint at matching score level fusion

In this method once the input image is obtained, matching score level technique is adopted to get the fused image. It is then preprocessed and the feature vectors are extracted using Radon transform. The acquired image is then compared with the database image in order to recognize the pattern.

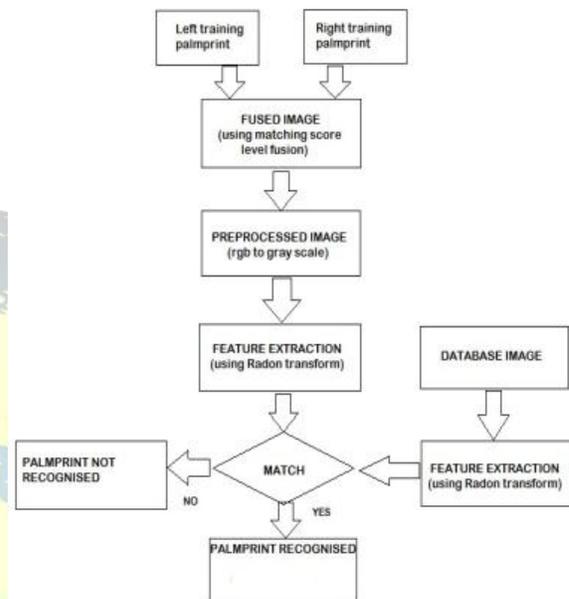


Fig 2 Block diagram of proposed method

Matching score level fusion technique

Fusion in multimodal biometric systems can be performed at four levels. In the image (sensor) level fusion, different sensors are usually required to capture the image of the same biometric. Fusion at decision level is too rigid since only abstract identity labels decided by different matchers are available, which contain very limited information about the data to be fused. Fusion at feature level involves the use of the feature set by concatenating several feature vectors to form a large 1D vector. The integration of features at the earlier stage can convey much richer information than other fusion strategies. So feature level fusion is supposed to provide better identification accuracy than fusion at other levels.

However, fusion at the feature level is quite difficult to implement because of the incompatibility between multiple kinds of data. Moreover, concatenating different feature vectors also lead to a



high computational cost. The strength of individual matchers can be highlighted by assigning a weight to each matching score. The weight-sum matching score level fusion is preferable due to the ease in combining three kinds of matching scores.

In this method the correlation between the left and reverse right palmprint has to be exploited. The principle lines of left and reverse right palmprint of the same subject is somewhat related always whereas principal lines of the left and right palmprint from different individuals have very different shape and position.

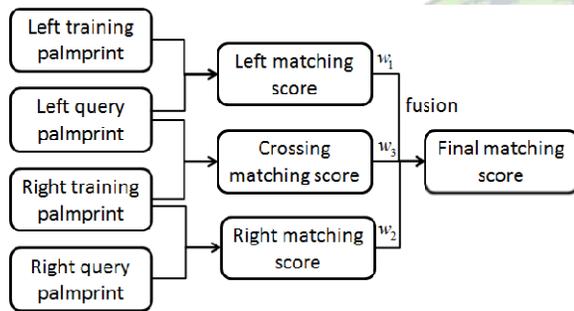


Fig 3 Matching score level fusion

The 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. Then it applies the palmprint identification method to the right palmprint images to calculate the score of the test sample with respect to each class. After the crossing matching score of the left palmprint image for testing with respect to the reverse right palmprint images of each class is obtained, the proposed framework performs matching score level fusion to integrate these three scores to obtain the identification result. The first and second matching scores are obtained from the left and right palmprint, respectively. The third kind of score is calculated based on the crossing matching between the left and right palmprint. $w_i (i = 1, 2, 3)$, which denotes the weight assigned to the i th matcher, can be adjusted and viewed as the importance of the corresponding matchers. The crossing matching score to the fusion strategy is introduced in this method.

Feature extraction using Radon transform

Radon transform is the integral transform consisting of the integral of a function over straight lines.

The Radon transform is widely applicable to tomography, the creation of an image from the projection data associated with cross-sectional scans of an object.

In Radon transform data is often called a sinogram because the Radon transform of a Dirac delta function is a distribution supported on the graph of a sine wave. Consequently the Radon transform of a number of small objects appears graphically as a number of blurred sine waves with different amplitudes and phases.



Fig 4 (a)

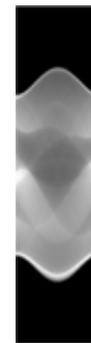


Fig 4 (b) Radon Transform

The Radon transform is useful in computed axial tomography (CAT scan), barcode scanners, electron microscopy of macromolecular assemblies like viruses and protein complexes, reflection seismology and in the solution of hyperbolic partial differential equations. It has the advantage of being more intuitive and have solid mathematical basis and used where accuracy is crucial.



Applying the Radon transform on an image $f(x, y)$ for a given set of angles can be thought of as computing the projection of the image along the given angles. The resulting projection is the sum of the intensities of the pixels in each direction, i.e. a line integral. The result is a new image $R(\rho, \theta)$. This can be written mathematically by defining

$$\rho = x \cos\theta + y \sin\theta \quad (2)$$

After which the Radon transform can be written as

$$R(\rho, \theta) = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} f(x, y) \delta(\rho - x \cos\theta - y \sin\theta) dx dy \quad (3)$$

$$F(x, y) = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} R(\rho, \theta) \delta(\rho - x \cos\theta - y \sin\theta) d\rho d\theta \quad (4)$$

where $\delta(\cdot)$ is the Dirac delta function. There are two distinct Radon transforms. The source can either be a single point (not shown) or it can be a array of sources. The method discussed in this report uses an array of sources. The Radon transform is a mapping from the Cartesian rectangular coordinates (x, y) to a distance and an angle (ρ, θ) , also known as polar coordinates.

$$R(\rho, \tau) = \int f(x, \rho x + \tau) dx \quad (5)$$

where ρ and τ are the slopes and intercepts of the line

The transform can be defined using Delta function

$$R(r, \theta) = \int \int f(x, y) \delta(x \cos\theta + y \sin\theta - r) dx dy \quad (6)$$

where θ is the angle of the line, and r is the perpendicular offset of the line.

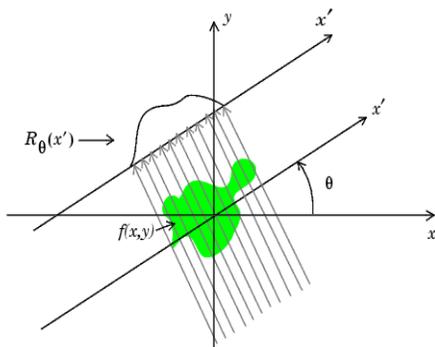


Fig5 Graphical representation of Radon transform

The steps involved in Radon transform based palmprint feature extraction are as follows:

Step 1: Acquire the fused palmprint image

Step 2: To extract ROI from the palmprint image

Step 3: Compute the Radon Transform of ROI to generate feature vector

Features of palmprint are extracted in this step. The local features from the ROI of a palmprint represent the texture information

The Radon transform of a square integrable function $f(x_1, x_2)$ is defined as

$$RA(t, \theta) = \int f(x_1, x_2) \delta(x_1 \cos \theta + x_2 \sin \theta - t) dx_1 dx_2 \quad (7)$$

where, δ is the Dirac distribution.

After extracting the feature vectors, the acquired image is compared with the image stored in the database and the palmprint identification is done.

IV. RESULTS AND DISCUSSION

Palmprint recognition system is implemented using MATLAB R2013a.

A. Input image

The Left and Right palmprint image of the person is captured as input image. The size of the input image is 256 x 256.



Fig 5 Left palmprint Image

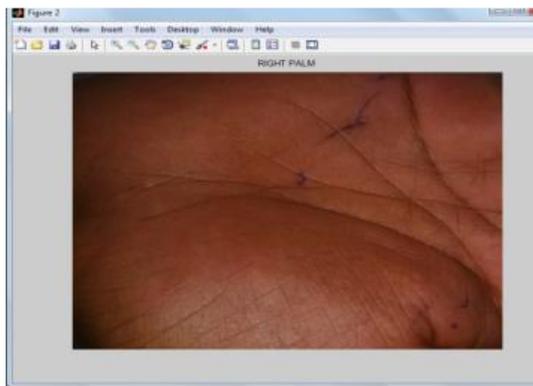


Fig 6 Right palmprint Image

Since we are considering reverse right palmprint image, the right palmprint image is reversed using suitable function.

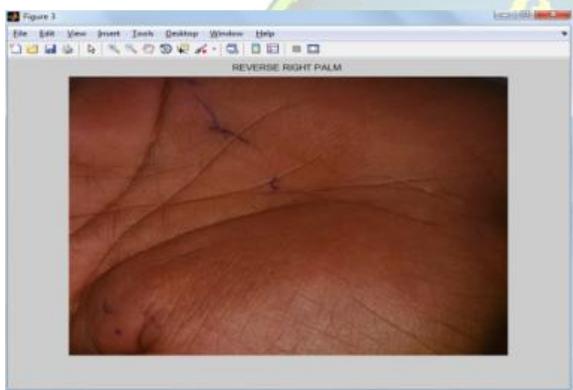


Fig 7 Reverse Right palmprint image

B. Fused image

The left and the reverse right images which was acquired as the input to the system is fused using standard fusion technique.

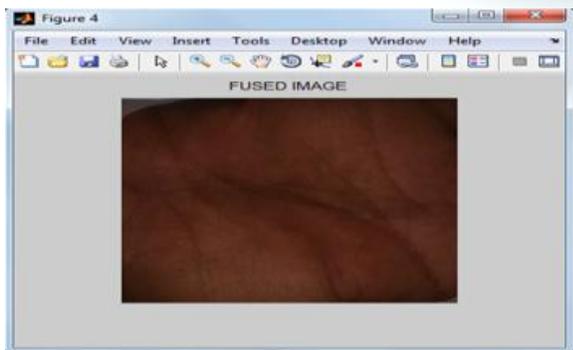


Fig 8 Fused Image

C. Preprocessed image

RGB image converted to Grayscale image and noise removed using median filter. Median filter is commonly used in preprocessing stage because it preserves the edges while removing the noise.

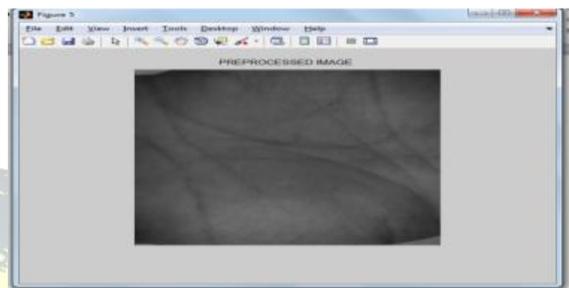


Fig 9 Preprocessed Image

D. Edge detection

Palm line detection is done using Radon transform which is commonly used in case of edge detection because it is more intuitive and used in the places where accuracy is more critical.

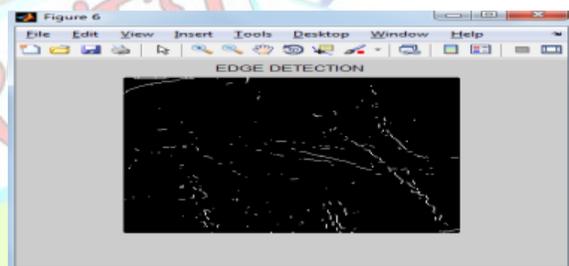


Fig 10 Image for Edge detection

E. Palm recognition

If the features extracted from the acquired image matches with that of the database image the palm is recognized. For the input data given the result is palm recognized.



Fig 11 Image for Palm been Recognised

V. CONCLUSION AND FUTURE SCOPE

Multibiometric system used in this work gives better identification accuracy with high standard security. The matching score level fusion technique adopted is more efficient. The palmprint feature extraction done here using Radon transform helped in increasing the performance and accuracy of the system. Radon transformation is rotation and translation invariant. Radon transformation has better noise resistivity i.e noise is transformed by Radon transform as pixel "offset" and it is more intuitive and have solid mathematical basis and used where accuracy is crucial. Also Radon transform is more tolerable to damaged shapes.

Compared to Scale Invariant Feature Transform performance, accuracy and efficiency are better when using Radon transform. Further work has to be done by comparing the different palmprint algorithms so that the performance parameters can be computed. However this method is an effective method for security purpose.

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