Palmprint Recognition Using Different Level of Information Fusion

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***Abstract*—The aim of this paper is to investigate a fusion approach suitable for palmprint recognition. Several number of fusion stageis analyse such as feature, matching and decision level. Fusion at feature level is able to increase discrimination power in the feature space by producing high dimensional fuse feature vector. Fusion at matching score level utilizes the matching output from different classifier to form a single value for decision process. Fusion at decision level on the other hand utilizes minimal information from a different matching process and the integration at this stage is less complex compare to other approach. The analysis shows integration at feature level produce the best recognition rates compare to the other method**

***Index Terms*—Biometric System; Palmprint Recognition.**

I. INTRODUCTION

Humans can be individualized by the evidence presented in their biometric traits either behavioural or physical in addition to several contextual details associated with the environment.

A biometric system is a modern and powerful tool used to recognize a person by using biological and behavioral characteristics. The biometric recognition framework consists of several parts that implement subsequent steps, which leads to recognition of the person. Amongst many biometric recognition approaches, palmprint recognition is considered to be one of the most trustworthy approach because a palmprint contains many features that can be used in palmprint recognition, such as principal lines, minutiae points, ridges, texture, and singular points, which are expected to be more distinguishable than a fingerprint. Both palmprint and fingerprint share most of the discriminative features but palmprint possess much larger skin area and other discriminative features. Figure 1 shows there are three principal lines caused by flexing hand and wrist in the palm, which are named as heart line, head line and life line, respectively. It is noted that all of these features are concerned with the attributes based on points or line segments. Principle line and datum points are regarded as useful palmprint features and have been successfully used for verification. Therefore, this feature lines are regarded as reliable and stable features to distinguish a person from the others. Palmprint is one of the important biometric features with distinctiveness, constancy and high distinguishability, and its study has caught the attention of researchers in the past decades. For access control usages, scanning the palmprint is highly acceptable for the public because it is fast. Palmprint recognition refers to the process of determining whether the two palmprints are from the same person based on line patterns of the palm. Usually, palmprint recognition has made use of either high or low resolution 2-D palmprint images. High-resolution images are suitable for forensic applications, while low-resolution images are suitable for civil and commercial applications.

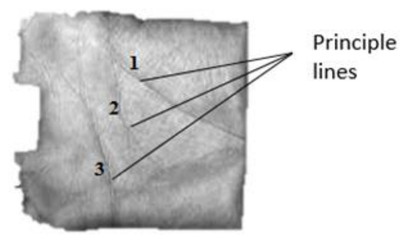

Figure 1: Principle lines of palmprint

Palmprint recognition modules include acquisition, pre-processing, feature extraction, and matching. This paper focus on feature extraction algorithm which is the most crucial and yet difficult module.

The rest of this paper is categorized as follows. Section 2 reviews a survey of palmprint features extraction algorithm. Section 3 summarizes the various fusion approaches for enhancing verification accuracy and Section 4 highlights some conclusion and offers further directions.

II. PALMPRINT FEATURE EXTRACTION ALGORITHM

Feature extractions are very important approach in biometric identification and verification. There are many features exhibited in a palmprint. Once the vital part is segmented, features can be extracted for matching. A decent feature can set apart the palmprint from different human being and at the same time be similar to each other from the same person's palmprints. This subdivision concentrate on palmprint feature extraction algorithm to reduce dimensions that consists of subspace-based approaches, statistic-based approaches, structure-based approaches and some other approaches that can support a certain scale of identification.

A. *Subspace-based approaches*

Subspace-based approaches similarly known as appearance-based approaches are proposed to regard a palmprint image as a high-dimensional vector and map to a lower-dimensional vector. Different distance measures and classifier are used to contrast the features. They used principal Component analysis (PCA), linear discriminant analysis (LDA), and independent component analysis (ICA). The main thought of principal component analysis (PCA) is to reduce the dimensionality of a data set consisting of large number of interrelated variables, while keeping maximum variation present in the data set. In vector space, PCA identifies the major directions by computing the eigenvectors and eigenvalues of the covariance matrix of the data. Zuoet. al. [1] proposed a directional PCA (BD-PCA) method that perform directly on the image matrix. The feature dimension of BD-PCA is much less than 2DPCA. Pan et. al. [2] attempted to use a Gabor feature-based (2D) 2PCA (GB (2D) 2PCA) for palmprint recognition. This novel approach can reduce augmented Gabor feature vector in two directions and then used Euclidean distance and nearest neighbor classifier for classification. While Lu et. al. [3] developed eigenpalm method by using the K-L transform algorithm. The features are extracted by projecting palmprint images into an eigenpalm subspace. In [27], the authors implement two-directional projections combining 2DPCA and 2DLPP to lower down the computation complexity and the feature dimension. The 2DPCA projection is implemented onto the training space in the row direction.

Linear discriminant Analysis (LDA) are manipulated to reduce palmprints from high-dimensional original palmprint space to an extensively lower dimensional feature space [4]. The bases generated using LDA are also known as fisherpalms. The palmprint from different palms can be differentiated much more efficiently. Connie et. al. [4] employ transform that feed the reduced images into PCA, FDA and ICA computation. Saviet. al. [5] extract features from a single high resolution gray-scale image of palmar surface of the hand by using LDA appearance based feature extraction approach. Xuet. al. [28] proposed a method of Gabor plus improved two dimensional linear discriminant (Gabor+I2DLDA) which is an improved 2DLDA method by integrating the Gabor wavelet representation of palm images. While Zenget. al. [6] used (2D)2LDA for dimensionality reduction of Gabor feature space. The augmented Gabor feature vector is used as an input to (2D)2LDA instead of raw palmprint images. Meanwhile Yao et. al. [7] used Gabor-based image preprocessing and PCA to extract the discriminant features of a palmprint. Imtiazet. al. [29] extract dominant wavelet coefficients based on multi-resolution feature extraction algorithm for palmprintdiscrete wavelet transform (2D-DWT). Then PCA is applied for further reduction of the feature dimension.

Apart from that, Xuet. al. [8] proposed matrix-based complex PCA (MCPCA) to denote bimodal biometric traits which two biometric traits are used as the real and imaginary part of the complex matrix. MCPCA applies a novel and mathematically tractable algorithm which directly extract features from complex matrices. Wang et. al. [9] used locality preserving projections (LPP) to extract features of the fused palmprint and palm vein images. This features technique is known as “Laplacianpalm” features. Wu et. al. [10] employ Fisher’s linear discriminant (FLD) to extract the algebraic features that have strong discriminability. Different palmprint can be differentiated much more efficiently via a linear projection based on FLD to lower the high-dimensional feature space to a significantly low-dimensional feature space.

The main principal of ICA is to decompose an observed signal or known as mixed signal into a set of linearly independent signals. The palmprint images are registered to be the mixture of an unknown set of statistically independent source images by an unknown mixing matrix when it is applied in palmprint recognition. Both PCA and ICA technique has major advantage because they only depend on the statistic properties of image data. But, the PCA technique is mostly suitable for the second order accumulation variant whereas the ICA approach can be used for multi-dimensional data. However, PCA is considered as the simplest approach, which can be used for dimension reduction by removing redundant and noise information and operates at a faster rate. Table 1 summarizes the subspace-based approaches from previous work.

B. Statistics-based approaches

Statistical approaches can be divided into two which are local statictical approaches and global statistical approaches. Local statistical approaches convert images into a new domain and then the transformed images are split into several small region. Means and variances of each small region are calculated as features for local statistics. Global statistical approaches compute global statistical features directly from the whole transformed images. Global statistics features are moments,centers of gravity and density.

Arivazhagan [11] found the texture features by calculating the mean and variance of the Gabor filtered image. While Kong et. al. [12] employ 2-D Gabor filter to obtain texture information on palmprints and two palmprint images are compared in terms of their hamming distance. Han et. al.[30] performed the feature extraction process by using simple Sobel operators and morphological operators to extract the feature points of palmprint. Sobel operators are performed to select the maximal value as resultant value of ROI. Kong et. al. [13] proposed a feature-level fusion approach with the used of multiple elliptical Gabor filter with different orientation to extract the phase information on a palmprint image.

Lee [14] apply texture-based feature extraction technique to palm vein authentication. 2-D Gabor filter was used on the palm vein pattern to extract features and normalized hamming distance was applied for the matching measurement. Sainiet. al. [15] apply Gabor-Wigner transform to extract features form biometric images which is face and palmprint multimodal system. The GWT is an operational combination of Gabor transform and Wigner distribution function. The technique of Particle swarm optimization (PSO) is used to select the significant features and to reduce the dimension of feature vector by selecting the best possible features coming from different fusion schemes. With the reduced of dimension of the feature space, performance of proposed hybrid biometric system shows that PSO is able to significantly improve the recognition rate of the system. You et. al. [16] used the concept of texture feature and interesting points to define palmprint features. The advantages of statistics-based approaches are to carry out some kinds of transform of palmprint images, which make the feature extraction easier to extract and represent and not sensitive to noise. However, this method hardly contains structural information and is probably to lose some discriminated information. Table 2 summarizes the statistics-based approaches.

C. Structure-based approaches

As we know, palm lines together with principal lines and wrinkles are the basic features of palmprint at a low resolution palmprint image. The principal lines can be treated as a separate feature to characterize a palm. Luoet. al. [17] propose a new feature input space from intensity and gradient spaces to line space using feature extraction in LBP-structure descriptors. The LBP-like descriptor operates in the local line geometry space hence proposed a novel image descriptor which is local line directional patterns (LLDP). The proposed LLDP descriptors are suitable for robust palmprint recognition.While Jiaet. al. [18] Proposed two palmprint identification schemes exploiting principle lines and LPP features. The two schemes are based on fusion strategy.Modified finite Radon transform (MFRT) is design to extract palmprint's feature lines. Table 3 summarizes the structure-based approaches.

D. Other approaches

Some methods are tricky to be categorized because they combine several image processing methods to extract palmprint features and occupy some standard classifiers to make the final decision.

Li et. al. [19] proposed a texture-based approach for palmprint feature representation. This new approach in contrast to the traditional method based on local line and point feature extraction. They used texture energy and develop a dynamic selection scheme to guide the search for the best matching.

Another paper, Zhang et. al. [32] perform three novel global features of 3-D palmprint by treating the features as a column vector and used orthogonal linear discriminant analysis to reduce dimensionality.

Duta et. al. [20] execute feature points method to extract a set of feature points of two palmprints. The two palmprints are categorical belong to the same hand by classifying the scores resulting from matching the features sets of the two palmprints. Jing et. al. [31] extend discriminative common vectors (DCV) algorithm to the kernel space and then present a new nonlinear discriminative feature extraction approach which is Kernel DCV (KDCV) approach.

Farmanbaret. al. [21] proposed a hybrid multimodal biometric system based on face and palmprint by using local binary pattern (LBP) feature extraction method. LBP is a nonparametric operator which describes the local spatial structure of an image to extract face and palmprint features separately.

Morales et. al. [22] proposed a new approach for different contactless palmprint identification by combining two kinds of matching scores obtained by several matchers. The author recommend the combination of robust scale invariant feature transform (SIFT) matching scores along with those from orthogonal line ordinal features (OLOF) can be applied to achieve more reliable performance improvement.

III. Fusion In Palmprint Biometric

Fusion describes the point of integration of multiple sources of information in a multibiometric system. Fusion of multiple palmprint is a promising method that may increase the accuracy of palmprint identification. It can be achieved at various levels in a biometric system which is fusion at the feature extraction level, fusion at the matching score level, and fusion at the decision level. Many biometric traits such as fingerprint, palm vein, finger shape, finger knuckle print, iris and face fuse information with palmprint at the feature level fusion. More recently researchers have begun to fuse information at the match score level.

Zhang et. al. [23] performed a fusion of 2-D and 3-D palmprint by using the support vector machine method (SVM). The fusion can be performed on any level either matching score level or feature level. Other than that, Michael et. al. [24] also used SVM method to fuse the scores output by the palmprint and knuckle print. Xuet. al. [25] combine the left and right palmprint images by employing weight fusion scheme to integrate three kinds of scores generated from the left and right palmprint. Another author fused the principle line and minutiae by using their proposed method which is heuristic rule.

Fusion at the feature extraction level concatenate two vectors into a new single vector. While fusion at matching score level combine different matching scores obtained from different biometric system. Whereas decision level fusion combine decisions taken by the different biometric system either to accept or reject the decisions. Biometric fusion has been carried widely in the high level that is in the decision level. Le-qinget. al. [26] proposed a decision level fusion multimodal system in which three biometrics are used which is finger geometry, knuckle print and palmprint features of the human hand. Table 4 summarizes some various level of fusions in a biometric system.

IV. Experimental Analysis

The effectiveness of the fusion approach is tested usingPolyUpalmprint dataset developed at Hong Kong Polytechnique University. The image represent 200 subjects are randomly choose from PolyU datasets and each subject consists of 12 images such that six samples are taken from the first session and the next six samples are taken from the second session. The average time interval between the first and second session is two months. Two images is used for training and ten images for testing. The effectiveness and the performance of the proposed methods are measured by verification and identification rate. In the first analysis, we examine the verification performance by using 1500 (150 x 10) genuine scores and 223500 (150 x 10 x 149) imposter scores. The experiment is conducted by presenting the ROC curves corresponding to the Genuine Acceptance Rate (GAR) at different False Acceptance Rate (FAR).

Table 1
Summary of subspace-based approach

Feature extraction	Subspace	Classifier	Ref.
Nil	BD-PCA	Nearest neighbor and nearest line classifier	[1]
Gabor features	$(2D)^2$PCA	Euclidean distance	[2]
Nil	PCA and eigenpalms	Weighted Euclidean distance	[3]
Wavelets: Haar, Daubechies and Symmlet	PCA, FDA, ICA	L_1 measure L_2 measure Cosine measure Probabilistic Neural Network (PNN)	[4]
Nil	LDA	Euclidean distance	[5]
Gabor features	2D2LDA	Euclidean distance	[6]
Gabor transform	PCA	Nearest neighbor classifier	[7]
Nil	FLD	K-L transform	[10]
Gabor features	2D-PCA	Euclidean distance	[27]
Gabor wavelets	I2DLDA	Weighted Euclidean distance	[28]
2D-DWT	PCA	Euclidean distance	[29]

Table 2
Summary of statistical-based approach

Feature extraction	Classifier	Ref.
Gabor wavelet	Minimum distance criterion	[11]
2-D Gabor filter	Hamming distance	[12]
Gabor filter	Hamming distance	[13]
2-D Gabor filter	Hamming distance	[14]
Gabor-Wigner transform	Hamming distance	[15]
Nil	Hausdorff distance	[16]
Sobel, morphological features	Backpropagation neural network	[30]

Table 3
Summary of structure-based approach

Feature extraction	Classifier	Ref.
Local line directional pattern	Manhattan distance Chi-square distance	[17]
Radon transform	Nearest neighbor classifier	[18]

Table 4
Summary various level of fusion in a biometric system

Biometric traits and features	Fusion method	Ref.
Palmprint+palmvein	Score	[9]
2-D and 3-D palmprint	SVM	[23]
Palmprint+knuckle print	SVM	[24]
Left+Rightpalmprint	Weight fusion	[25]
Finger geometry+knuckleprint+palmprint	Decision	[26]

Figure 2 shows that the performance of the feature fusionoutperforms the other method with the best performance is GAR = 94% at FAR = 0.1%. Fusion at decision level produce the lowest performance which is GAR = 76% at FAR = 0.1%. In the second analysis, we examine the recognition rate of different fusion method with different number of training images as shown in Figure 3. Different number of training images produce different amount of information. Thus this analysis shows different method of fusion approach is able to produce rich information in the feature space. The results shows fusion at feature level produce the highest recognition accuracy which is 98% achieved by using 5 training images per subject.

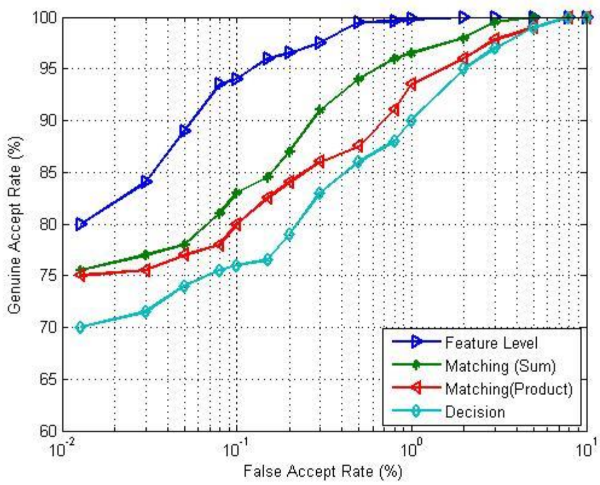

Figure 2: Verification rate analysis

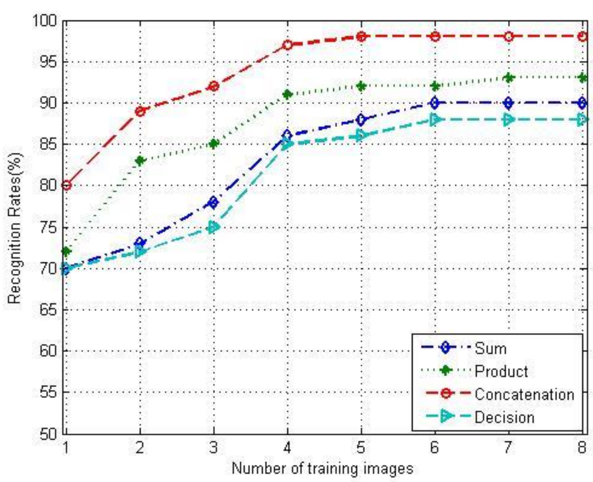

Figure 3: Recognition rates analysis

V. CONCLUSION

A pamprint biometric system using fusion approach is presented in this paper. In this research, a fusion method is used to increase the important features exist in palmprint images. Fusion at feature level by combining different features of palmprint images is able to produce the best performance for verification and recognition rates. This method is able to enhance the discrimination power in the feature space. The experimental results tested using PolyU datasets demonstrate superior performance in terms of recognition and verification rates. The best performance of the proposed method is showed as 98% recognition rates and 98% GAR at 0.1% FAR.

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