Multi-algorithm based Palmprint Indexing

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ABSTRACT
The aim of this paper is to study the multi-algorithm based palmprint indexing at feature extraction level. The proposed approach is based on the fusion of Haar wavelets and Zernike moments. Experiments are conducted on PolyU palmprint database to assess the actual advantage of the fusion of the multiple representations, in comparison to the single representation. Experimental results reveal that multi-algorithmic based approach gives good identification accuracy than identification accuracy using Haar wavelets or Zernike moments alone and indexing prior to identification is faster than conventional identification method in terms of time.

General Terms
Pattern Recognition, Security, Algorithms, Biometrics.

Keywords
Palmprints, Haar wavelets, Zernike moments, Feature level fusion, Multi-algorithm, Indexing, Kd-tree, Person Identification.

1. INTRODUCTION
Biometrics based personal identification plays an important role for automatic identification with high confidence [1, 15]. Palmprint is one of the emerging physiological characteristic for personal identification that has drawn substantial attention because it is user-friendly, inexpensive and of comparable recognition ability.

Palmprint is the unique inner surface pattern of human hand, including a number of discriminating features, such as principal lines, wrinkles, ridges, minutiae points, singular points, texture, etc. Compared with other biometric traits, the advantages of palmprint are the availability of large palm area for feature extraction, easy to capture and high user acceptability. Although the study of palmprint recognition has a shorter history than fingerprint and face recognition, more attention has been directed towards this promising field in recent years [8, 9, 11, 14, 16, 18, 20, 21, 23, and 31]. Various palmprint representations have been proposed for recognition, such as Line features [14], Feature points [23], Fourier spectrum [31], Eigenpalms features [18], Sobel's and morphological features [11], Texture energy [20], Wavelet signatures [21], Gabor phase [16], Fusion code [9], Competitive code [8], etc.

Depending on context of an application, a palmprint biometric system can be used for either person identification or for person verification. Apparently, the palmprint identification problem looks more complex than the palmprint verification problem because any identification system suffers from an overhead of more number of comparisons in the large database. As the size of database increases the time required to declare an individual's identity increases significantly.

A biometric system using a single biometric trait either for identification or for verification is called uni-modal biometric systems. A uni-modal biometric system sometimes fails to be accurate enough for the identification of a large user population due to problems such as noisy data, intra-class variations, restricted degrees of freedom, non-universality, spoof attacks, and unacceptable error rates [10]. So the problems associated with uni-modal biometric systems can be overcome by multi-biometric systems. Multi-biometric systems recognize a person based on information obtained from multiple biometric sources. Multiple biometric sources include multiple sensors, multiple instances, multiple samples, multiple algorithms, or multiple biometric traits. The problem of noisy data can be overcome by the use of multiple sensors for the same biometric trait, but other potential problems associated with uni-modal biometric systems will remain. The problem of spoofing can be reduced by multiple instances. It ensures the presence of user by asking an user to provide a random subset of biometric measurements. But this leads inconvenience to users. Even though multi-sample biometric systems improve the overall performance of the biometric system, the problems of uni-modal biometric systems still remain. Moreover in multi-sample biometric system, for a given set of biometric samples, the system should be able to automatically select the optimal subset that would best represent the individual's variability. Although multimodal biometric systems that use different biometric traits can be expected to be more effective, the cost of deploying multimodal biometric systems is substantially more due to the requirement of new sensors. As a remedy, usage of multi-algorithmic approach is recommended by researchers. In multi-algorithmic systems, the same biometric data is processed using multiple algorithms. These systems do not necessitate the deployment of new sensors and hence are cost effective compared to other types of multi-biometric systems. Furthermore, the user is not required to interact with multiple sensors thereby enhancing user convenience.

However, an effective fusion strategy is necessary to combine the information presented by multiple sources of biometric information. Based on the type of information available, fusion can occur at the sensor level, feature level, match score-level, and decision level. Sensor level fusion entails the consolidation of evidence presented by multiple sources of raw data before they are subjected to feature extraction. Feature level fusion involves consolidating the information presented by two or more biometric feature sets of the same user. The scores generated by multiple classifiers pertaining to different modalities are combined in match-score level fusion. The final decisions of multiple classifiers are consolidated in decision level fusion. Along these levels the biometric information is gradually extracted and reduced. Biometric systems that integrate information at an early stage of processing are believed to be more effective than those systems which perform integration at a later stage [7]. Compared to match score level fusion or decision level fusion, the feature level fusion exhibits rich set of information. Hence, in this work we present a feature level fusion of multi-algorithm based palmprint indexing.

From the literature survey, the fusion of palmprints with other biometric traits could be traced out. Fusion is a promising approach that may increase the accuracy of systems. [7]. Many biometric traits including fingerprint [25], palm vein [19], finger surface [24, 27, 30], face [28, 4, 17, 34], iris [33] and hand shape [24, 26, 2, 5, 3] have been combined with palmprints at score level or at feature level. Researchers have examined various fusion rules including sum, maximum, average, minimum, support vector machines and neural networks. Researchers also fuse features including appearance based, line and texture features from palmprints using match score level [6, 12]. However, only a few works have been reported on multi-algorithmic based approaches. To the best of our knowledge, there is no work on feature level fusion of multi-algorithm based palmprint identification.

As we know, any identification system suffers from an overhead of more number of comparisons in the large database. As the size of database increases the time required to declare an individual's identity increases significantly. In addition to this, the number of false positives also increases with the increase in the database size [13]. Thus there are two ways to improve the performance of a biometric system. First one is by reducing the number of false positives and other is by reducing the search space. Even traditional database binning approaches does not yield satisfactory results. The reason behind is that biometrics does not possess any natural or alphabetical order. As a result, any traditional indexing scheme cannot be applied to reduce the search time. Thus the query feature vector is compared sequentially with the all templates in the database. The retrieval efficiency in sequential search depends upon indexing scheme that reduces the search space in the large biometric database. The general idea of indexing is to store closely related feature vectors together in the database at the time of enrollment. During identification, the part of the database that has close correspondence with query feature vector is searched to find a probable match. Hence, in this work, we design an indexing model as a supplementary tool for multi-algorithm biometric system based person identification.

Hence, in this work, we propose a multi-algorithm based palmprint indexing model using feature level fusion for person identification. Overall the following are the contributions of this work.

- Exploitation of the applicability of Zernike moments and Haar wavelets for identification of palmprints.
- Exploitation of the feature level fusion of multiple representations of palmprints for person identification.
- Proposed a multi-algorithm based palmprint indexing for person identification.

The remaining part of the paper is organized as follows. Section 2 describes the proposed biometric system based on the feature level fusion of multiple representations of palmprints for person identification. The detailed experimental results are shown in section 3. The overall conclusion is drawn in section 4.

2. PROPOSED MODEL

In this section, we study the suitability of Haar wavelets and Zernike moments for palmprint identification. Initially, we extract Haar wavelets and Zernike moments based features from palmprint of a person and study the identification accuracy separately. In later stage, we propose an indexing model using a feature level fusion of Haar wavelets and Zernike moments of palmprints for person identification.

2.1 Identification of palmprints based on Haar wavelets

In order to enroll the user into the database, we extracted Haar wavelets [32] of level l for k palmprint samples of each person. Let $S^{i,j}$ be the j^{th} palmprint sample of i^{th} person in the database. The coefficients of Haar wavelet $H^l{}_{E_h,E_v,E_d}$ are extracted where E_h, E_v, E_d are respectively horizontal, vertical and diagonal energies at level l. Similarly Haar wavelets $H^l_{E,K}$ are extracted for all k samples of all users. The obtained feature vectors of palmprints from each user are stored in the knowledge base.

During palmprint identification, given a palmprint of an unknown user the system has to identify the corresponding user. In this identification stage, the Haar wavelets of level l are extracted for the test image $H^l_{E,test}$ and are compared with the feature vectors present in the database. Subsequently, the Euclidean based nearest neighbor classifier is recommended to be applied for revealing the identity. Figure. 1 shows the block diagram of the palmprint identification system using Haar wavelets.

2.2 Identification of palmprints based on Zernike moments

In order to enroll the user into the database, we extracted Zernike moments [22, 29] of order $p,q,$ for k samples of each person. Let $S^{i,j}$ be the j^{th} palmprint sample of i^{th} person in the database. Extract p,q^{th} order of Zernike moments $S^{i,j}_{p,q}$ of sample $S^{i,j}$. Similarly p,q^{th} order of Zernike moments for all k samples of all users is extracted. The obtained feature vectors of palmprint from each person are stored in the knowledge base.

During palmprint identification, given a palmprint of an unknown user the system has to identify the corresponding user. In this identification stage, the Zernike moments of order p,q are extracted for the test image $S^{test}_{p,q}$ and are compared with the feature vectors present in the database. Subsequently, the Euclidean based nearest neighbor classifier is recommended to be applied for revealing the identity.

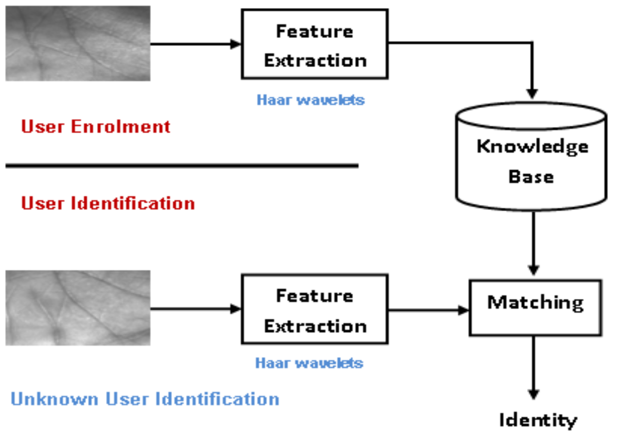

Fig 1: Palmprint identification model using Haar wavelets

2.3 Multi-algorithmic based palmprint identification

We know that, multi-algorithm based multi-biometric systems do not require the deployment of new sensors, and hence are cost effective. Users are not required to interact with multiple sensors thereby enhancing user convenience. Fusion of multi-algorithms of palmprints is expected to have a better recognition accuracy. Hence, we present a feature level fusion of Haar wavelets and Zernike moments of palmprints for person identification.

The feature vectors of Haar wavelets say $P_{HW} = \{P_{H_1}, P_{H_2}, ..., P_{H_m}\}$ and feature vectors of Zernike moments say $P_{ZM} = \{P_{Z_1}, P_{Z_2}, ..., P_{Z_n}\}$ are obtained from palmprints. The obtained feature vectors are fused using concatenation rule serially. Fusion of feature vectors obtained from Haar wavelets and Zernike moments results in a new feature vector as $F = \{P_{H_1}, P_{H_2}, ..., P_{H_m}, P_{Z_1}, P_{Z_2}, ..., P_{Z_n}\}$. This new feature vector is subsequently used for person identification and the corresponding module is shown in Figure 2.

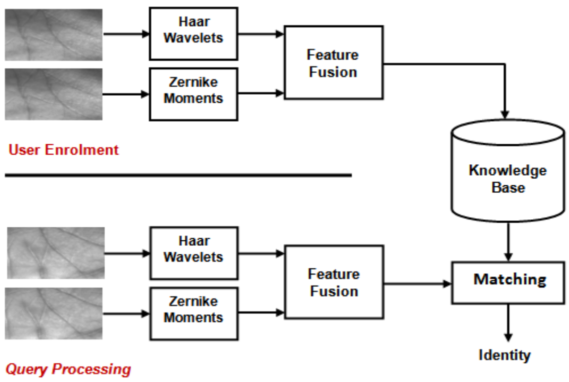

Fig 2: Feature level fusion of Haar wavelets and Zernike moments for person identification

2.4 Multi-algorithm based indexing model for palmprint identification

Once we get the fused feature vector, we store it in the database. However storing in the database in an efficient manner is required such that the possible candidate list is selected for the matching process should be very much less. Hence, there is a need of backend tool called indexing mechanism which stores the data in some predefined manner so that during matching only a few potential candidates are selected. Hence, in this paper we study the suitability of Kd-tree based indexing approach for the multi-algorithm based palmprint identification.

In this proposed method, multi-dimensional feature vectors obtained from Haar wavelets and Zernike moments of palmprints are fused. Fusion of feature vectors obtained from Haar wavelets and Zernike moments results in a new feature vector. Then the fused feature vector is indexed using the Kd-tree. Kd-tree is an appropriate data structure for biometric identification system particularly in the analysis of execution of range search algorithm and it decreases the search time as it is supporting the range search with a good pruning. When query feature vector of multi-dimension is given, range search is invoked using Kd-tree to retrieve top matches that lie within distance 'd' from the query. These top matches are subsequently used for multi-algorithm based person identification. Figure 3 shows the block diagram of the proposed Kd-tree indexing model for multi-algorithm based biometric system for person identification.

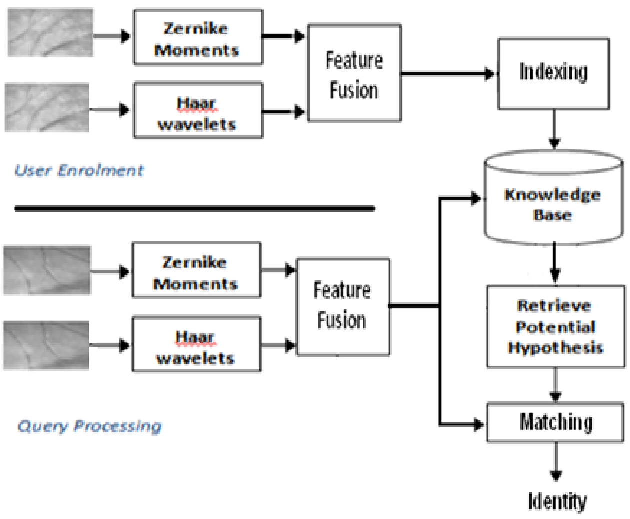

Fig 3: Block diagram of indexing model for multi-algorithm based biometric system

3. EXPERIMENTAL RESULTS

The proposed multi-algorithm based palmprint indexing is tested on Hong Kong Polytechnic University palmprint database. The PolyU 3D Palmprint Database contains 8000 samples collected from 400 different palms. Twenty samples from each of these palms were collected in two separated sessions, where 10 samples were captured in each session, respectively. The average time interval between the two sessions is one month. Each sample contains a 3D ROI (region of interest) and its corresponding 2D ROI. However, almost all the current palmprint recognition techniques use the two dimensional (2D) image of the palm surface for feature extraction and matching. Hence, in this work, we considered 4000 samples of 2D palmprint images for experimentation. Few sample palmprint images are shown in Figure 4.

In order to evaluate the performance of the proposed system, feature vectors of dimension 24 based on Haar wavelets of level 8 and feature vectors of dimension 36 based on Zernike moments of order 10 are extracted from palmprints and study the identification accuracy. Feature vectors based on Haar wavelets and Zernike moments of palmprints are fused using concatenation rule. This fused feature vector is also used for person identification. Table 1 shows the summary of the identification accuracy under varying size of the database of palmprints using Haar wavelets alone, Zernike moments alone and their fusion. From Table 1, it is clear that, fusion of Haar wavelets and Zernike moments of palmprints as representatives outperforms both Haar wavelets and Zernike moments alone. The system was trained and tested under varying the percentage of database.

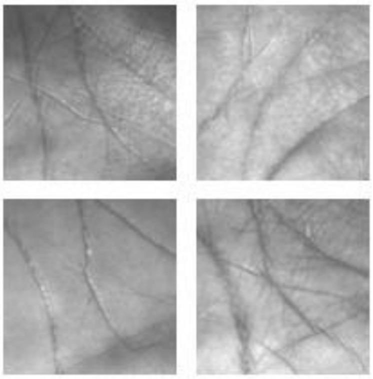

Fig 4: Few sample palmprint images

Table 1. Identification accuracy of palmprints using Haar wavelets, Zernike moments and their fusion for different training sets.

Training	Haar wavelets	Zernike moments	Fusion of Haar wavelets and Zernike moments
10 %	58.19	85.56	88.81
20 %	73.66	92.50	94.47
30 %	81.11	95.89	96.89

Fusion of Haar wavelets and Zernike moments of palmprints results in a new feature vector. The fused feature vector of dimension 60 is indexed through Kd-tree. The output of an indexing algorithm is the set of top hypotheses [35]. If the corresponding query is in the list of top hypotheses, we take the indexing result as a correct result. Hence, the measures such as False Acceptance Rate (FAR) and False Rejection Rate (FRR) which are generally used for verification are not suitable for evaluating the results of an indexing algorithm [35].

In this work, we use Correct Index Power (CIP) as the performance evaluation measure for indexing. CIP is the ratio of the correct queries to all queries. The system is trained using 10%, 20%, and 30% samples per user and is tested with remaining 90%, 80%, and 70% samples per user respectively. When a query feature vector 'Q' of n (n = 60) dimensions is given, it retrieves top matches that lie within distance 'd' from query 'Q' and top matches are subsequently used for person identification. The graph of CIP v/s percentage of database search under varying training samples is shown in Figure 5. From Figure 5, we can infer that good CIP can be achieved by indexing the multi-algorithm based features for the purpose of person identification.

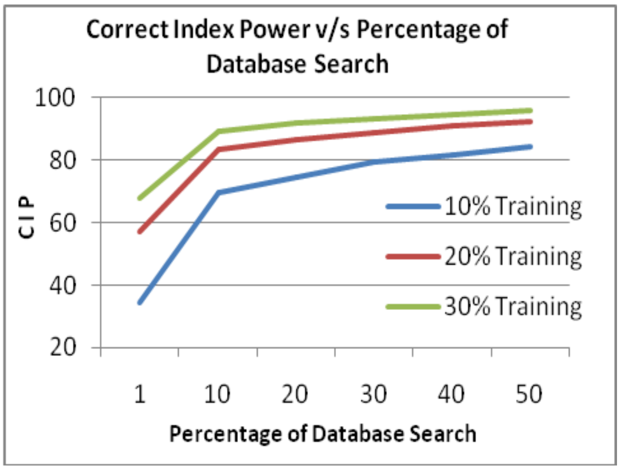

Fig 5: Correct index power v/s percentage of database search for different training sets

The beauty of our indexing scheme lies in its efficiency from the point of search time. The time analysis for indexing based and conventional identification methods for 30% training is tabulated in Table 2. From Table 2, it is clear that, the proposed indexing method reduces the search time, which supports range search with a good pruning. It is also clear that, the test sample is searched within a database using negligible amount of time when compared to conventional identification with same accuracy. Hence we claim that indexing prior to person identification is faster than conventional person identification. The percentage of time reduction for person identification using the Kd-tree based indexing model against the conventional identification method for different training sets is shown in Table 3.

Table 2. Time analysis of methods with proposed indexing and without indexing

	Percentage of Database	Time in Seconds	Accuracy in %
With Indexing	1 %	0.00065	68.00
	10 %	0.00070	89.39
	20 %	0.00074	92.04
	30 %	0.00081	93.50
	40 %	0.00091	94.46
	50 %	0.00115	95.79
	85.58 %	0.00290	96.89
Conventional identification with 100% scanning		0.17378	96.89

Table 3. The percentage of time reduction for person identification using the proposed indexing model against the conventional identification method

Training	Identification time in secs		Time reduction in %
	Conventional	Indexing	
10%	0.0778	0.0015	98.07
20%	0.1346	0.0030	97.77
30%	0.1738	0.0030	98.27

4. CONCLUSIONS

In this paper, we proposed a multi-algorithm based palmprint indexing. Feature level fusion of multiple representations of palmprints using Haar wavelets and Zernike moments is also proposed for person identification. Experiments are conducted on PolyU palmprint database. The obtained experimental results are more encouraging and we claim that feature level fusion of multiple representations of palmprints gives a good identification accuracy when compared to the identification accuracies obtained by Haar wavelets or Zernike moments alone. Also from the experimental results, we claim that indexing prior to person identification is faster than conventional person identification.

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