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MULTIMODAL PALMPRINT TECHNOLOGY: A REVIEW

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ABSTRACT

To increase security and accuracy in the systems which are based on biometrics, a multimodal system was suggested. The multimodal biometric systems, are more accurate and effective compared to the unimodal systems which are considered as a wide research field these days. Multimodal biometric system aims to improve the recognition accuracy by minimizing the limitation of the unimodal. This paper focuses on the Palmprint Multimodal system; palmprint biometrics is considered as one of the most popular biometric technologies to authenticate the identity of a human. The aim of this paper is to introduce a comprehensive investigation of a multimodal palmprint that focuses on feature level fusion. Based on the review of the multimodal palmprint system, some suggestions have been made that can be considered for future research to improve palmprint multimodal.

***Keywords**: Biometric system, Palmprint, Multimodal, Feature level fusion, Feature selection*

1. INTRODUCTION

In the last decade, the biometric system has grown as a reliable method for human authentication and the system has attracted significant attention of a number of researchers. The unimodal biometric system uses a single trait but this modal suffers from many limitations, as sensitive to noise, lack of universality as well as being vulnerable to intra-class, illumination and spoof attack [1, 2]. To overcome these limitations, a multimodal biometric system has been introduced. By multimodal we mean combining two or more traits of human physiological or behavior including, face, hand, palmprint, handwriting, signature and other features [3-7]. The review of current literature reveals that numerous researchers have studied the use of biometrics, multimodal and levels of fusion [8-15].

In our previous work [16] we presented a comprehensive review on the unimodal palmprint, while, in this paper, we focus on investigating the multimodal based on the palmprint combined with different traits. We also discussed problems pertaining to this modal, that previous works haven't discussed these problems and introduced some solutions to take into accounts. To the extent of examining a deeper degree of feature level fusion, by illustrating its scheme and investigating the palmprint database, feature extraction methods based on the different categories of the palmprint images, and briefly presenting various feature selection and classification methods. Finally, this article will make some important suggestions that will help to improve the palmprint multimodal. This study doesn't include any mathematical concepts related to multimodal palmprint.

Palmprint refers to the inner region between the wrist and fingers. It is highly rich in texture pattern (principle lines, wrinkles, and ridges) [17, 18]. A palmprint system is of high interest to both civil and forensic applications, it has some advantages over other biometric technologies, due to its large size which contains various features at different levels. These features make it difficult to forge the palmprints [19-22]. Figure 1 illustrates the palmprint features [23].

A palmprint image can divided into; the contactless images as a friendly system [24], contact-based system for high accuracy [25, 26], and latent prints for forensic application [20, 27]. Each of these categories has different features that need different algorithms to extract it. This will be discussed in the sub-section on feature extraction.

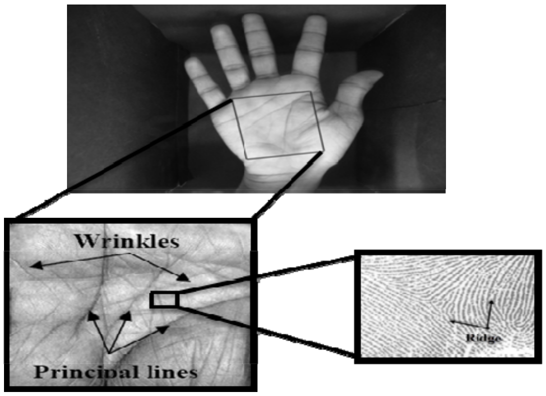

Figure 1: Features of the palmprint [23]

The rest of paper is organized as follows. Section 2 introduces a multimodal biometric system. Section 3 presents a literature review of the palmprint multimodal system, Section 4 discusses the limitations of the palmprint multimodal. Section 5 introduces the feature level fusion scheme in detail, and the paper will be concluded in Section 6.

2. MULTIMODAL BIOMETRIC SYSTEM

A multimodal-biometric system combines two or more traits. The problems with the unimodal biometric can be overcome by using the multimodal biometric system that merge indexes from multiple sources [28, 29]. A multimodal biometric system is based on various biometric data traits, such as the iris, fingerprints, hand geometry, face and other features. Non-universal problem processing, improved matching accuracy and reasonable protection against false attacks can be expected from this system [30]. These systems can also meet the stringent performance requirements of various applications. However, such a system takes more time to verify and this causes inconvenience to users. The main challenge in a multimodal system is to determine the information (biometric) sources and their combination strategies. A multimodal biometric can be applied at different levels of fusion [31, 32]:

- Sensor level Fusion: The captured templates are combined with multiple biometric sensors, and then the learning phase is implemented in these new templates;
- Feature Level Fusion: Many sequential vector features are employed to form simple and superior vectors;
- Matching level fusion: The result from multiple matchings applied to the set of features will be fused to access the final decision;
- Decision level fusion: The decision is made for each biometric identification system, and then the final decision is made by merging the previous valves.

3. MULTIMODAL PALMPRINT: LITERATURE REVIEW

The outline of the palmprint literature review has covered biometric system, unimodal palmprint, multimodal palmprint, and structure of the palmprint system. Figure 2 illustrates the literature review mapping. The highlighted items in figure 2 represent the scope of this study. This section discusses the literature review pertaining to the state-of-the-art methods developed by researchers for palmprint as a multimodal which is combined with different traits at different levels of fusion. Jazzar and Muhammad [33] proposed the fusion of the finger and palmprint. The features extraction was accomplished using the Zernike moments (ZM) invariant algorithm that works under the low-resolution scanning device for fingerprint and palmprint acquisition. In order to calculate the similarities, the Euclidean distance between the test image features and the stored features is used. Apart from that, Bellaaj et al. [34] proposed integrating the fingerprint and palm of the hand based on a possible modeling approach. A set of relevant biometric features extracted from image samples is statistically analyzed and represented by a potential distribution. The biometric templates of the palm of the hand and the fingerprint are used for decision-making by applying a score-level data fusion process.

On the other hand, a number of researchers such as Saini and Sinha [13] have been combining palmprint with the face, which used Gabor–Wigner transforms (GWT) to extract the feature vector from the face and the palmprint images for matching purposes and proposed PSO for the reduction phase, Lee and Bong [35] introduced the face and palmprint combination with the bit plane decomposition approach. Pixel level fusion is applying by using simple averaging method before bit-plane feature extraction. To reduce the feature vector dimension PCA algorithm used on the hybrid face-palm bit planes, Farmanbar and Toygar [4] introduced the face and palmprint biometric systems fusion with different level fusion, for feature extraction, Local binary patterns (LBP) are performed and these features are then fused at the

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feature level fusion. Then for the reduction phase, a backtracking search algorithm (BSA) was used to select an optimal subset of the face and palmprint extracted features. After that, a match score-level fusion is performed to show the effectiveness and accuracy of the proposed method.

Several studies have reported the combination of the palmprint with iris as conducted by Naderi et al. [36] who performed the Log Gabor, Discrete Cosine Transform (DCT). Walsh and Haar used to extract features from the images then performed the feature level fusion by concatenating the feature vectors from two modalities and used a combination of the iris and palmprint to achieve the multimodal system. They used the Intuitionistic Fuzzy c-mean (IFCM) technique to extract the features for the palmprint and Ridge energy detection (RED) algorithm for the iris feature extraction. Then they performed the matching level using a hamming distance.

Hezil and Boukrouche [37] investigated the combined ear and palmprint at the feature-level. Local texture descriptors, local binary patterns (LBP), Weber local descriptor (WLD), and binaries statistical image features (BSIF) are used for feature extraction and for the K-nearest neighbor (K-NN) are used as a classifier.

Samai et al. [38] proposed using two bands (grayscale and near infrared) of palmprint images. This is in order to perform a multimodal palmprint verification system using progressive image compression through the famous Set Partitioning in Hierarchical Trees (SPIHT) coder. The images of the palmprint are compressed and decompressed at 0.5 bit per pixel (bpp). The result are three images, an image at 0.25 bpp which represents the image approximation, the other at 0.25 bpp which represents the edges or details, and the third is the global image of the both proceedings. At the stage of the final match, a level fusion is performed after analyzing the features which have been extracted from the different bands.

The combing of a palmprint with more than one trait to increase the accuracy has been studied by many researchers. Deshpande et al. [39], for an example, proposed a method which combined fingerprint, palmprint, and face recognition which are collected and stored in the database at the time of the enrollment. In the recognition phase, the query trait images will be compared to the stored templates then passed through a matching level fusion. Adjacent Orientation Vector (AOV) based minutiae algorithm was used for features extraction for the fingerprint, PCA analysis was used for both face and palmprint. For the matching phase, they used the Euclidean distance. Srikantaswamy [40] proposed three traits fusion, fingerprint, palmprint and hand geometry. For the purpose of feature extraction, they used the Histogram of Oriented Gradients (HOG) for fingerprint, for palmprint they used PCA and linear discriminant analysis (LDA) algorithms, for the hands geometry the Harris corner detection algorithm (HCDA) was utilized, and a support vector machine (SVM) was used for the matching phase. Gurunathan et al. [41] proposed fusing the palmprint and palm vein images. First, the captured traits images were enhanced with the Adaptive Histogram Equalization (AHE) for feature extraction using Speeded Up Robust Feature algorithm (SURF) for both palmprint and palm vein. The extracted features are stored in the dataset as a feature vector. To perform feature level fusion, the two features vectors were fused together using a sum rule. To calculate the similarities between the test and database, the sum of Absolute Difference (SAD) distance measure was used. Sujatha and Chilambuchelvan [42] designed a multimodal biometric system integrating four traits including the iris, palmprint, face and signature based on the coded discrete wavelet transform (DWT) for image analysis and authentication. The multi-level wavelet-based fusion approach was applied, integrated and encoded in the single composite image for the matching decision. Table 1 presents a summary of the previous work based on the palmprint combined with different traits.

4. LIMITATIONS OF MULTIMODAL PALMPRINT

Although these studies have obtained good results, they suffer from some problems such as there is no database that contains two different traits belonging to the same person, long time execution and different features form [31]. To overcome these limitations a few studies based on the combination of the left and right palmprint, Xu et al. [43] introduced a multimodal by integrating the matching level fusion which involves three kinds of matching: the first matching involves the left query palmprint with the left training palmprint, in the second matching, the right query palmprint is matched with the right training palmprint, and in the third matching the left query palmprint is

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matched with the reverse right training palmprint. The multimodal system is evaluated using different recognition approaches such that the Robust Line Orientation Code (RLOC) method, the Competitive Code method, the Binary Orientation Co-Occurrence Vector (BCOV) method, and the sparse multiscale competitive code (SMCC) method for the touch-based dataset from poly U using 3740

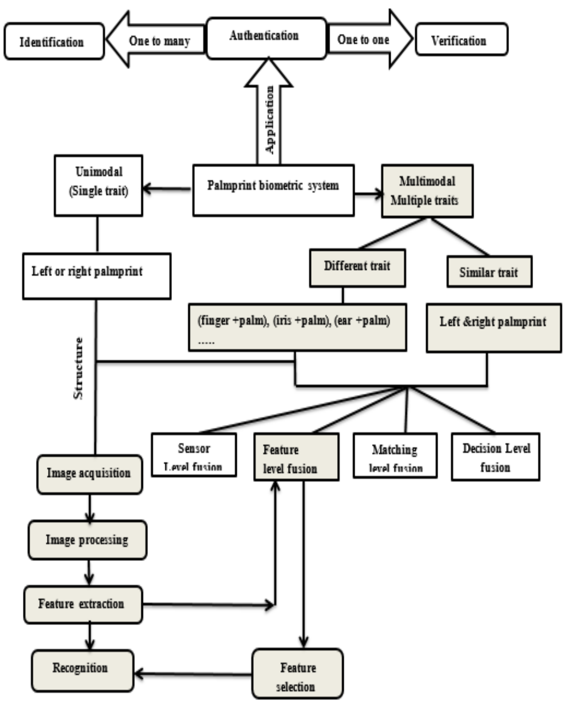

Figure 2: Literature review mapping

images from 187 individual with 10 samples for the left palm and 10 samples for the right palm, and method such as SIFT methods and the orthogonal line ordinal feature OLOF + SIFT method for the contact-less method from IITD using 3290 from 235 with 7 images from each individual. They asserted that using the score level corresponding to the sum-weight needs more time, approximately 1.5 times compared to the conventional method. They were the first researchers who identified the similarities between the left palm and right palm.

Leng et al. [44], on the other hand, introduced a multimodal biometric system based on a multi-instance palmprint combination. Two-dimensional discrete cosine transform (2DDCT) for feature extraction from left and right palmprint, dual discriminant power analysis (DDPA) for normalization and the nearest neighbor for recognition phase in this multimodal system. The experiments were performed in the contactless palmprint database of Multimedia University Malaysia, 202 images were selected from 101 users with 10 samples from each person. 5 samples were used for testing and the rest were used for training. The split training and testing dataset were randomly selected and they were run for 20 times. Both Leng et al. and Xu et al. mentioned the following advantages of the combination of the left and right palmprints.

- The palmprint images of the right and left hand of each user are relatively similar;
- These similarities were employed to improve the palmprint identification performance;
- High accuracy.

On the other hand, the feature level offers a better identification at other levels. It includes the use of a set of the feature through various vector sequence features to the large 1D vector form which, have more information for feature traits [31, 32, 45]. Therefore, we propose to develop the multimodal palmprint scheme by combining the left and right palmprint at feature level fusion. In the following section, we will illustrate the feature level fusion scheme.

5. FEATURE LEVEL FUSION SCHEME

The feature level fusion scheme is illustrated in Figure 3. This scheme consists of five basic steps namely the image capture, feature extraction, feature fusion, recognition and decision. At the feature fusion phase, the features which are extracted from the previous step from the two traits images are fused. This will lead to the high dimension of the feature vector [46]. In this scenario, it is essential to perform feature selection (FS) in order to accomplish the classification task. After proceeding to the recognition phase, and by applying a threshold, the final decision will be accomplished.

5.1 Palmprint image capture

This is the first step in any biometric system. The palmprint images can be classified into four categories [47] which are contact based, contactless, high resolutions and 3D-palmprint. The following databases belong to these categories that are available to the public are summarized in Table 2. For a multimodal palmprint, a low-resolution databases, contact based and contactless are widely used.

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Table 1: Summary of the multimodal palmprint previous work

Ref.	Recognition Approach	Fusion traits	Level fusion	Parameter	database
[33]	ZM and Euclidean distance & F-ratio	Finger and palmprint	Feature level	ACC= 100%	Unpublic database of 50 people databases of 50 people
[39]	PCA, AOV	Finger, palmprint, and face	Matching level	ACC= 98%.	Unknown database
[13]	GWT+ PSO	Face, palmprint,	Feature level and Matching score level	ACC= 98.34%	ORL, Yale-B, and Essex face database. IIT Delhi palmprint
[35]	PCA and BPNN	Face and palmprint	Feature level	ACC> 89%	Yale and ORL face database and PolyU palmprint database
[4]	LBP and BSA	Face and palmprint	feature-level and match score-level fusion	ACC= 99.17%	FERET face and PolyU palmprint databases
[40]	HOG +LDA+PCA+SVM	Finger ,palmprint and hand geometry	feature level	ACC= 93%	Unknown
[41]	SURF SAD	palm vein and palmprint	feature level	FAR = 0 % FRR= 1.91%	put.poznan.pl/vein-dataset. PolyU palmprint
[38]	SPIHT	Two band palmprint (grey and infrared)	Score level fusion	EER =0.0027	PolyU
[34]	possibilistic modelling approach	fingerprint and palmprint	Score level fusion	AUC = 0,9997	FVC fingerprint and CASIA palmprint
[42]	DWT	Iris palmprint, face, and signature	Image fusion	FAR=1 FRR=2	CASIA
[37]	LBP, WLD and BSIF and K-nearest neighbor (K-NN)	Ear and palmprint	Feature level fusion	ACC= 100%	IIT Delhi-2 ear and IIT Delhi palmprint
[36]	log Gabor and Laplacian Eigen maps based on random forest classifier	palmprint and iris	Feature level fusion	ACC= 99.80%	CASIA for both palmprint and iris
[48]	COEP &RED and sum rule	palmprint and iris	Matching level	--------	IIT Delhi for both palmprint and iris

(ACC=accuracy, FAR=false acceptance rate, FRR, false rejection rate, EER= equal error rate)

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In addition, the captured images need to process. Image processing is a set of process used to enhance the image that is needed for biometric data after collection it to remove noise and extract the only region of interest (ROI) that has significant information. These ROIs are used in the sequential steps of the recognition system .A number of researchers were included the image processing within their works. The table 3 introduced a summary of previous work based on palmprint image processing.

5.2 Palmprint feature extraction

Feature extraction can be defined as the process to extract the higher level information of an image and to transform it into a feature vector (called descriptor), which will be used instead of the original image[49]. The feature extraction is considered as a crucial step in any biometric system, the accuracy of the system depends on how much the features are accurate. Generally, the feature extraction approaches are divided into three approaches: holistic (global), structure (local) and hybrid. Holistic approaches are divided into subspace and representation. A subspace transforms the original data image from the high space onto the lower space. These algorithms are used when there is a need to reduce the dimension which is useful when feature fusion needs to be achieved.

TABLE 2: PALMPRINT DATABASES.

Reference	Database	Image categories
[50]	Poly U	Contact-based
[51]	IITD	Contactless
[52]	GPDS	Contact less
[53]	CASIA	Contactless
[54]	THU	High resolution
[55]	Poly U-3D	3D-palmprint

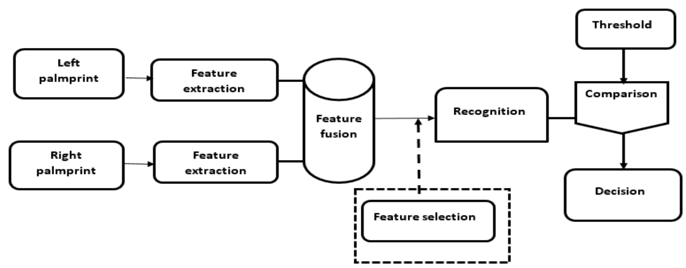

Figure 3: Feature fusion scheme

TABLE 3: PALMPRINT IMAGE PROCESSING PREVIOUS WORKS

Ref	Method description	Data base description	ROI pixel	Parameter
[56]	• Median filter to remove noise; • Moore neighbor to tracing boundary; • Using Otsu's to adopted threshold to binaries the image.	**Poly U touch based;** 7752 image; Size: 640*480 pixel.	166 *166	Method Acc rate = 98%
[57]	• Active appearance model AAM to segmented palm; • Using least square support vector regression to extract ROI.	**KTU contact less;** 1752 Image; Size: 768*576. **IITD contact less;** 1393- left hand 1376- right hand ; Size: 800*600 pixel.	128*128 128*128	RR= 99.48%; EER=0.277% RR=99.421; EER= 0.03 RR=99.409; ERR=0.149

[58]	• Using conventional neural network CNN	**CASIA contact less;** 5239 images; Size: 640*480 pixel.	196*147	RR=99.3493%
[59]	• Using conventional neural network CNN	**HKPU contact-based;** 7752 images; Size: 384*284 pixel; **2DHKPU;** contact- less; 3540 images; **IITD contact-less;** 2601 images; Size: 800*600 pixel.	224*224 224*224 224*224	EER= 0.0125 ACC=0.983 EER= 0.0276
[60]	• Blob analysis; • Morphological and geometrical	**Sfax- Mircal contact less;** 1080 image; 1024*768 pixel. **IITD contact less;** 2601 image; 800*600 pixel; **Poly U 3D/2D;** 1770 images; 640*480 pixel.	------------	Extraction error= 0%;0.27%;0.26%
[61]	• Image thresholding; • Boundary tracing ; • Combination of fingers and valleys from square region; • ROI determined by multiplying the largest and width of segmentation	Data baes acquiring smart phone used image = 5 image	196%	---------------------
[62]	• Otsu's threshold; • Boundary extraction ; • Smoothing to remove noise ; • Euclidean distance to extract key point	**CASIA contact less;** 5502 images; Size: 640*480.	150*150	ACC rate of automatic position = 98%
[63]	• Median filter to remove noise ; • Apply Otsu's threshold ; • Euclidean distance to track boundary;	**Poly U contact based;** 2000 image; 640*480 pixel	-------------	Acc rate of automatic position 97.8%
[64]	• Apply Otsu's threshold; • Canny edge detection; • Morphological operation	**CASIA V.1.0;** multispectral; 7200 images; 200*200 pixel.	181*181	----------
[65]	• Determine three key point in a local area; • Align palmprint image depends on these points; • Extract square sub image of palmprint.	**Unknown data base touch base;** 1600 images; 292*413 pixels.	154*154	--------------------

The representation approach is based on classification. The local approaches are considered more accurate than the global approaches which in turn are divided into line, coding and texture. The line based and coding approaches are appropriate for contact-based images, the texture-based approach is appropriate of contact less and high resolution.

Hybrid approaches are combine both local and global approaches [66, 67].

A considerable number of the feature extraction methods extracted various palmprint features according to palmprint image category. Contact-based feature extraction methods can be divided into line based and orientation based such as in the principle lines[68], competitive code [69], palm code [70], fusion code [71], ordinal code [72], double orientation code (DOC) [73], binary orientation code vector (BOCV) [74], E-BOCV [75], robust line orientation code (RLOC) [76] and orthogonal line ordinal feature (OLOF) [72]. On the other hand, the most significant features for contactless feature extraction method are scale invariant feature transform (SIFT) [77], local binary pattern (LBP) [78], local line directional pattern (LLDP) [79] and OLOF [72]. For the high-resolution feature, the minutiae points are considered as a significant feature [80], local ridge direction (LRD) [81] and modified finite radon transform (MFRAT) is often used to detect principal lines [82]. On the other hand, the Mean curvature image (MCI), Gaussian curvature image (GCI) [83] and surface type (ST) vector [84] are needed for 3-D palmprint image.

Depending on the category of palmprint, the relevant feature vector will be extracted. This vector (descriptor) will be fused with other vectors at the feature level fusion.

5.3 Feature fusion

In this step, two or more trait features will be fused together as one feature vector. The

concatenate rule is to consider the simple rule which is used to combine different feature vectors [46]. *F* fused feature will be calculated as the following [46]:

If: First feature set = $f1k \times m$, Second feature set= $f2k \times n$

Then:

F fused = $fK \times (m+n)$

Where m, n are size variable, K= 1.

5.4 Feature Selection

After the fusion of the features have been conducted at the feature level, the feature vector dimension becomes long, which make the feature selection urgent need for feature reduction. Many researchers study the feature reduction methods because of its importance in many fields [85-87] [88] [89] [71-74]. In general, the feature reduction dimension can be divided into feature extraction and feature selection as illustrated in Figure 4. The feature extraction methods include the subspace algorithms such as the principal component analysis (PCA), independent component analysis (ICA) [89]which transforms the dimension into low dimension. For the palmprint recognition, a number of researchers are using a well-known approach of PCA for the feature reduction phase in these works [35, 40, 90, 91]. PCA suffers from the a number of limitations; the search for the samples have bigger variant features when compared with each other and it does not work well with a classifier [92]. To overcome the PCA limitations, it is imperative to shift to the feature selection methods. The goal of the features selection is to reduce the size of the data by looking for a small set of important features that can provide a good classification [93]. The feature selection methods will eliminate the smallest feature discriminator, leaving a part of the original characteristics that retain enough information to distinguish between the categories.

The function selection algorithms can be categorized into three groups: filtering methods, wrapping methods and embedded methods. The filtering methods focus on the general characteristics of the data to evaluate and select the subsets of the features without including the selected learning algorithm or classifier [93]. While the wrapping methods depends on the predictive performance of the selected features by considering the learning algorithms [86]. The embedded methods on the other hand, is considered as a bridge between the wrapper methods and filter methods [88]. Table 4 illustrates the comparison between these three methods.

For palmprint recognition G.A and PSO are suggested [86]. Several systems have been reported in which the particle swarm optimization (PSO) algorithm is extensively used as a feature selection for multimodal biometric systems fusion schemes based on the palmprint and face fusion at the feature level [13, 94-96]. PSO does not use previously-generation populations [4]. Genetic algorithm (GAs) belongs to a family of biologically inspired techniques that use several mechanisms to imitate natural evolution. GAs has been

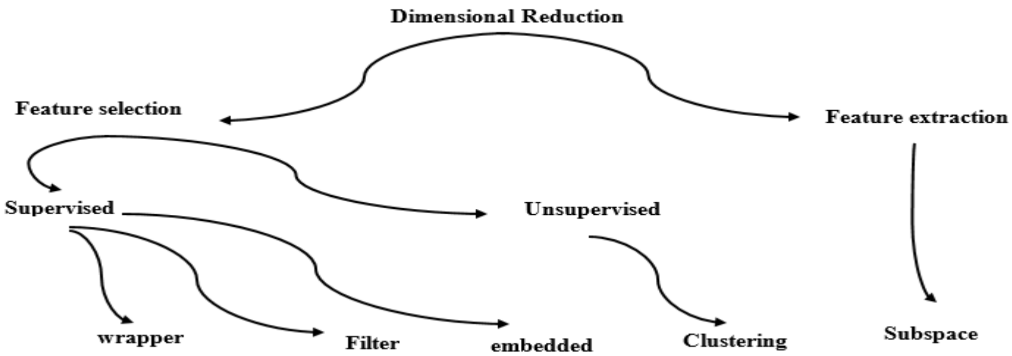

Figure 4: Dimension Reduction methods

TABLE 4: FEATURE SELECTION COMPARISON

	Wrapper methods	**Filter methods**	**Embedded methods**
Description	Depends of classifier learning; Use predictive accuracy of a classifier to evaluate feature set; Optimization algorithms.	Independent from classifier learning; Use Masseur distance information, correlation to evaluate the feature set; Statistical algorithms.	Bridge between wrapper and filter; Depends of the classifier; Achieve both wrapper accuracy and filter efficiency.
Pros	Good generation; More accurate.	Robust against over fitting; Fast.	Less computational than wrapper.
Cons	More computational; Expensive run time.	Sometimes fail to Select best feature.	Much slower than filter.
Example	GA,PSO, ASO,BSA	Relief, Fisher score , Information Gain	Lasso Regularization, Elastic Net, and Ridge regression.

successfully used in feature subset optimization problems [86]. The applications of the GA-based wrappers for feature selection include speech recognition [97], face recognition [98], image processing [99] and multimodal biometric fusion [100]. On the other hand, the Backtracking Search Optimization is applied to many numerical optimization benchmark problems [101]. GA, PSO and BSA belong to an evolutionary algorithm. After the set of features has been selected, it is put through the recognition step in order to evaluate the performance quality of these features.

5.5 Classification

The success of any biometric system is measured in this step. In object recognition (classification), Machine learning considers promising performance methods. ML can learn by themselves; when they have the input data, they learn how to solve problems. ML is divided into supervised and unsupervised [102] methods. The

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supervised methods predict the value of the output variables by comparing the N sample of the inputs and the corresponding output value [103]. The most popular supervised methods used in a palmprint recognition are Artificial Neural Network (ANN), Decision Tree, Support Vector Machine (SVM) and recently deep learning [104-107].

In unsupervised methods, in this case, only a set of input vector x is known. The most unsupervised common methods is clustering, which is a process of groping data which share a level of high similarity. A similarity can be achieved by a distance function [103]. K- mean is the well-known clustering method which is widely used in palmprint recognition [108]. The most significant problems faced by any classification model are overfitting and underfitting. The overfitting occurs when the dataset is not too large, and the model is complex. While the underfitting occurs when the model is not complex which is incapable of handling a large data [109].

To measure the performance of the classification model, a dataset is typically set into a training set (70%) and testing test (30%). Another method that can be used is by dividing the data set to a K subset, using each of these subset as a testing and (K-1) as a training set [103]. If the errors on the training set are small and the errors in the testing set are high, this will be overfitting and if both the errors on the training set and testing set are high, this will be the underfitting[109] case.

To avoid the overfitting& underfitting cases, Srivastava et al. [110] introduced a solution using the regularization methods. The regularization means training a range of models, compare the performance on an independent dataset then select the best performance[110].

The machine learning is an important methods for the recognition step and performs better than the other approaches [111]. Table 5 introduced previous works based on palmprint recognition.

TABLE 5: PALMPRINT CLASSIFICATION PREVIOUS WORKS

Ref	Feature extraction	Recognition	Parameter	Data base
[112]	PCA,LDA,ICA	PNN	ACC = (95.8324%, 96.6718%, 96.5826%)	IITD
[113]	LBP	PNN	ACC= 91.91%	Private data/ 110
[114]	CNN feature	Hausdorff	EER=0.0443%,0.0803%,01113%	PolyU, CASIA, IITD
[115]	CNN feature	CNN	EER= 9.25%	Poly U
[116]	PCA	BP	ACC =93.33	Private
[35]	Bit-plane	BP	ACC= 89%	Poly U +(ORL +Yala) face database.
[117]	Deep Scattering Network	SVM	ACC= 99.9	Poly U
[118]	CNN feature	CNN	ACC= 99.979	Poly U
[119]	LBP	PNN	EER = 0.74	Private with 20 image sample
[120]	CNN-F	CNN-F	EER= 0.25	PolyU
[104]	Discrete cosine transform DCT	Radial basis probabilistic (RBPNN)	ACC= 99.75%	CASIA

6. DISCUSSION

This study is a comprehensive review based on palmprint multimodal. Multimodal can be achieved in four levels of fusion, sensor, feature, matching, and decision. We focused on feature level fusion, we explained in details the steps of this level. Based on this review, the palmprint multimodal system can be improved by combining left and right palmprint in different levels of fusion, especially that the palmprint databases were collected left and right palmprints that belong to the same person. That will increase the level of security. For the limited space, the limitations of this work are focusing on one level fusion, and lacking analysis of the different recognition system. The researchers can introduce different reviews based on different levels of fusion, they also can introduce reviews based on recognition algorithms.

7. CONCLUSION

We introduced in this paper, a multimodal system concept, palmprint multimodal literature review, and an in-depth investigation of the feature level fusion scheme. It is noted that Palmprint recognition still remains as a challenging problem and it is not completely solved. A multimodal is considered a good solution to increase the accuracy, but it still suffers from some problems, as there is yet to be a database that contains two different traits belong to the same person, long-time execution and different form features. Therefore, for the similarity between the left and right palms, future research on palmprint recognition should focus on the field of multimodal which combines pairs of palmprint that belongs to the same person. Feature extraction is considered an important step for any biometric system, for choosing an approach to be used depends on the database images which work with different features. Finally, the literature review indicates that there are no standards or specific feature selection method thus, every researcher selects a method based on their own experience. Generally, Machine learning is a promising development in the classification phase.

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