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Personal Authentication Using Palm-Print Features – A SURVEY

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ABSTRACT: Palmprint recognition has been in the focus of biometric research over the last ten years. Identifying a person or authenticating a person has been most vital process and mandatory in several real time applications for security reasons. For example logging into a computer system, accessing an ATM machine, entering a room, etc. Are some of the real time applications require authentication of people. Simple and cost effective authentication systems are working based on password, pin number, etc. For authenticating people. Significant places or critical applications require biometric authentication where the authentication failure rate is very less and easy to use. Also, forging the biometric system is highly complicated. Palmprint is one of the biometric used in authenticating people. Palmprint recognition has been studied more then fifteen years. There are several palmprint authentication systems have been developed by various scientists.

KEYWORDS: Biometrics, Palmprint recognition, Pattern matching, Privacy, Security, Wavelet.

I. INTRODUCTION

In recent times, automatic biometric authentication has emerged as the backbone of the new-age solutions to our society's ever increasing demand of improved security requirements. With an increase in the world population and the advent of globalization, traditional ways of maintaining security using manual record-keeping (like signature verification, photo/identity card verification) are no longer viable. Like most other tasks, identity verification processes have also been delegated to computers. Unique digital signatures are now being provided to people by matching digitally acquired biometric templates against the pre-stored templates in large biometric databases.

The task of automatic identity management has acquired pivotal importance due to the fast expansion of these biometric databases. Biometric based applications can now be seen in use around us in our day-to-day lives. Ruling bodies in many countries across the planet have taken up the task of providing their citizens with biometric identifiers and maintain identity databases. These databases are then used at airports and other entry points to regulate public movement across borders and single out suspicious elements. USA, Brazil, Germany, United Kingdom, Iraq, Israel, Australia, New Zealand etc have already started issuing passports containing digitized biometric data like signature, photographs, iris information etc. Many other countries are leading down the same path to maintain digital records of its population and are in the process of issuing passports with embedded biometric data.

Data collected using such a flexible system working in a real world situation results in many image variations which is of significance to the recognition algorithm. The fine details of the image are lost with introduction of a variety of unwanted additional parameters like illumination variation, noise, pose transformations, contrast issues etc. All these parameters adversely affect the recognition process, reducing the system accuracy enormously. This is one of the reasons for the state of art algorithms insist on an ideal image capture modality which has uniform and constant illumination settings, fixed pose and a restricted environment with a high quality sensor. Therefore, we need to develop

recognition algorithms that can robustly handle the high degree of variability introduced due to this unconstrained and unsupervised image capture. To summarize, focus on the problems of deploying biometric authentication for

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commercial civilian applications. Camera based biometrics allows for easy to use system modality for a user by following a flexible image capturing process. This flexibility entails fluctuations in the image quality and results in loss of texture and other variations viz. illumination, noise, pose variations etc. These variations have an adverse effect on the recognition accuracy. To overcome this problem, require new algorithms designed to handle weak templates and to make use of the information available to us in the best possible way. In this chapter, we present an overview of biometrics. This includes a basic introduction to biometrics, followed by a section explaining the biometric recognition process.

II. BIOMETRICS - AN OVERVIEW

Biometrics refers to methods for uniquely recognizing humans based upon one or more physical or behavioral traits.

- Physiological characteristics are related to the physical characteristics of the body. Examples include fingerprints, face, DNA, hand and palm geometry, iris feature, which has largely replaced retina, and odor/scent. Behavioral characteristics are related to the behavior of a person. Examples include gait, and voice. Some researchers[13]
- Have coined the term behaviometrics for this class of biometrics.

In information technology, in particular, biometrics is used as a form of access control. Biometric technologies are becoming the foundation of highly secure identification and personal verification solutions. With an increase in level of security breaches and transaction frauds, the need for highly secure identification and personal verification technologies is becoming apparent.

In the current day and age of an internet savvy population, the world wide web has become an important medium to carry out social interchanges, monetary transactions and has emerged as a storehouse of personal information. According to a survey [14], an astonishing 1.7 billion users access the internet everyday as of the year 2009. While this staggering number showcases the success of the world wide web, it also subtly spells out a new genre of problems related to internet thefts and infringement of an individual's personal space. The term 'Personal security' has encompassed new dimensions in this era. In the light of increasing number of hacking attacks, passwords no longer guarantee an individual's privacy or safety of valuable information. It is possible to crack a password by using simple randomized algorithms that generate strings of different lengths with all possible combinations of the alphabet space. There are many softwares available in the market for the purpose of password cracking. Hence, there is a need for better ways to secure the financial and/or personal interchanges that we now carry out every day on the internet.

Since the inception of world wide web in 1968 [15], its application has expanded tremendously. It is now being used as an entertainment center, a medium for exchanging information, a place for business transactions and as a new way of socializing. Web-based applications are more popular than ever. They generally work by assigning a user name and a password enabling one to access their "account". With the increase in the number of applications, people have more and more accounts to be managed. It is highly recommended to have different passwords for different accounts, so that, if the password for one account is compromised, others remain safe. Hence, there is an unnecessary task of remembering so many passwords. This can be especially tricky when carrying out financial transactions. In the face of these security threats, biometrics has emerged as a potential alternative solution to remembering passwords and carrying RFID cards. One does not need to worry about remembering different security combinations in a security model where access is granted on the basis of "Who you are?", instead of "What you remember?" (See Fig 1). This ease of use makes biometrics immensely convenient and handy. It can also help avoid fraudulent accounts where the same person is using more than one bank account by linking each account with a unique biometric id. This kind of a system is in use in the world famous amusement and theme park, Walt Disney World situated in Florida, USA. At Walt Disney, biometric measurements are taken from the fingers of guests to ensure that the person's ticket is used by the same person from day to day [16]. Biometric-based authentication applications include workstation, network, and domain access, single sign-on, application log-on, data protection, remote access to resources, transaction security and Web security. Trust in these electronic transactions is essential to the healthy growth of the global economy. Utilized alone or integrated with other

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technologies such as smart cards, encryption keys and digital signatures, biometrics are set to pervade nearly all aspects of the economy and our daily lives. Utilizing biometrics for personal authentication is becoming convenient and considerably more accurate than current methods (such as the utilization of passwords or PINs). This is because biometrics links the event to a particular individual (a password or token may be used by someone other than the authorized user), is convenient (nothing to carry or remember), accurate (it provides for positive authentication), can provide an audit trail and is becoming socially acceptable and inexpensive [17].

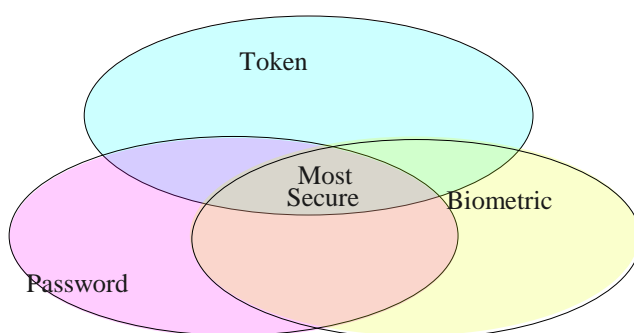


Fig 1-Ways of Authentication

In summary, biometrics is a robust authentication method since it cannot be stolen, forgotten, borrowed or hacked easily by standard password cracking software's, and forging one is practically impossible. However, one advantage of passwords over biometrics is that they can be re-issued.

III.OVERVIEW OF PALMPRINT RECOGNITION SYSTEMS

Palmprint, the inner surface of our palm normally contains three flexion creases, secondary creases and ridges. The flexion and secondary creases are also called principal lines and wrinkles, respectively. The flexion creases and the main creases are formed between the 3rd and 5th months after conception [3]and superficial lines appear after we born. Although the three major flexions are genetically dependent, most of other creases are not[23]. Even identical twins have different palmprints [23].

These nongenetically deterministic and complex patterns have rich information for personal identification. There are two types of palmprint recognition research, high resolution and low resolution approaches. High resolution approach employs high resolution images while low resolution approach employs low resolution images. High resolution approach is suitable for forensic applications such as criminal detection, while low resolution is more suitable for civil and commercial applications such as access control.

Generally speaking, high resolution refers to 400dpi or more and lower solution refers to 150dpi or less. Fig(2) illustrates a part of a high resolution palmprint image and a low resolution palmprint image. In high resolution images, researchers can extract ridges, singular points and minutia points as features while in low resolution images, they generally use principal lines, wrinkles and texture.

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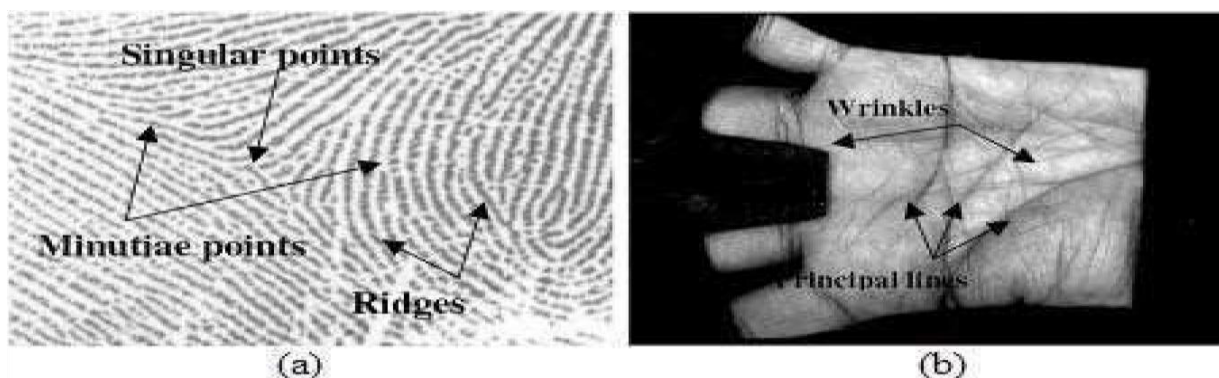


Fig 2-(a) a high resolution palmprint image and (b) a low resolution palmprint image.

A palmprint recognition system generally consists of five parts: palmprint scanner, preprocessing, feature extraction, matcher and a database illustrated in Fig3. The Palmprint scanner is to collect palmprint images. Preprocessing is to setup a coordinate system to align palmprint images and to segment a part of palmprint image for feature extraction. Feature extraction is to obtain effective features from the preprocessed palmprints. Finally, a matcher compares two palmprint features. Personal authentication using palmprint images is an emerging biometric security research area. A number of approaches have been proposed for the palmprint matching. On the basis of extracted features the Palmprint authentication can be broadly classified into three categories: namely linebased, appearance-based, and texture-based. Some other methods used "Image coding" approaches. used robust line orientation code for palmprint verification [19]. Some other coding methods are used for palmprint recognition, such as Palm Code, Fusion Code, Competitive Code, Ordinal Code [39], In the past decade, some appearance-based approaches were studied[12], and these approaches were also applied to biometrics including palmprint recognition.

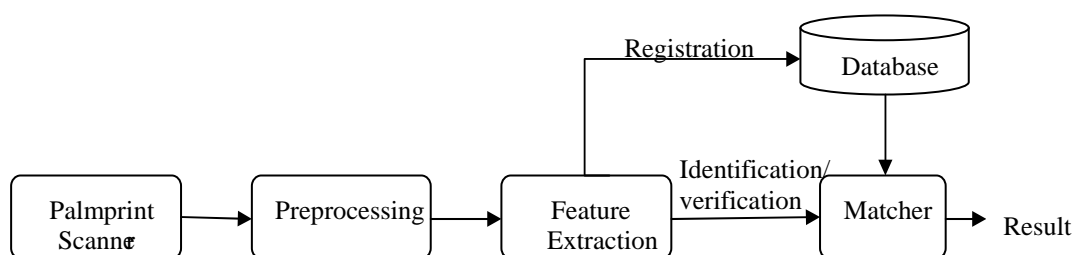


Fig 3-Matcher and a database illustrated

Comparing two palmprints requires the extraction of useful information that is ideally independent of acquisition conditions, such as hand positioning, palm ageing, illumination and dirt. This process is called feature extraction. Then, to assess one's identity, these features will be compared in a process called feature matching. Most of the research is devoted to these two phases of a biometric system. Several matching Palmprint matching techniques and Score level fusion techniques have been proposed in the literature.

IV.METHODS

- **Global Features**

These are methods that use information retrieved from the whole palmprint at once. Therefore, no spatial information is used, and extracted features are related to the whole palm. Research using global statistical features was short because it compromises performance by discarding spatial information. Such methods can discover what features a palm has, but not where those features are located in the palm.

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- **Wavelet Domains**

Palmprint images are converted to three wavelet domains, which are sensitive to different orientations, therefore including information about line orientation. Then, features of wavelet sub-bands such as sparseness and energy are used to describe a palmprint. Verification is performed by calculating the difference between features from two palms. A weighted distance scheme was developed for this task [26].

- **Invariant Zernike Moments**

They compare vectors with moments of different orders using euclidean and Norm 1 distances. Higher order moments have more information for personal recognition because they relate to finer details [40].

- **Modular Neural**

Modular Neural Network as a classifier for the same features, instead of simple Norm 1 or euclidean distances [20].

- **Subregions on a ROI**

A common approach is to use finger valleys as reference points. Typically the used valleys used are between index finger and mid-finger and between ring finger and last finger. There are numerous approaches to detect such points [5;33;44].

Subregions on a ROI, and elements in the feature vector are associated to the subregions. The ROI position depends on reference points, which are the three finger valleys between all fingers but the thumb and index fingers. These subregions are based on ellipses (fig 4 and 5).

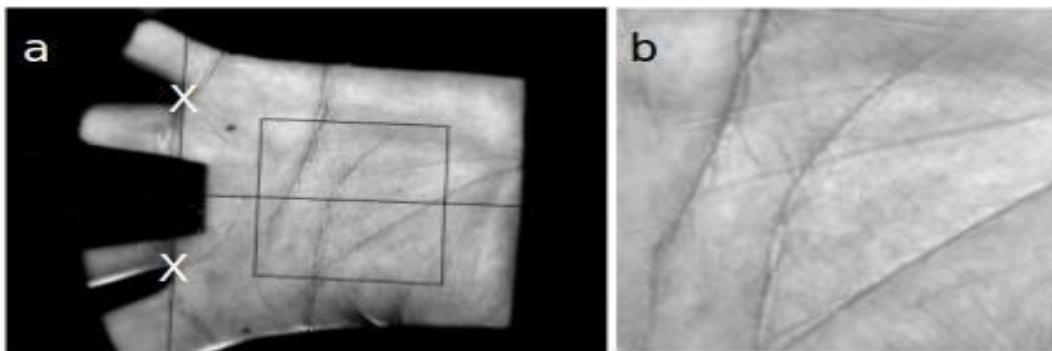


Fig 4- Coordinate system based in reference points in finger valleys. In (a), finger valleys are used as reference points (white X marks), on which a coordinate system is established. The resulting region of interest is depicted in (b).
Adapted from ref

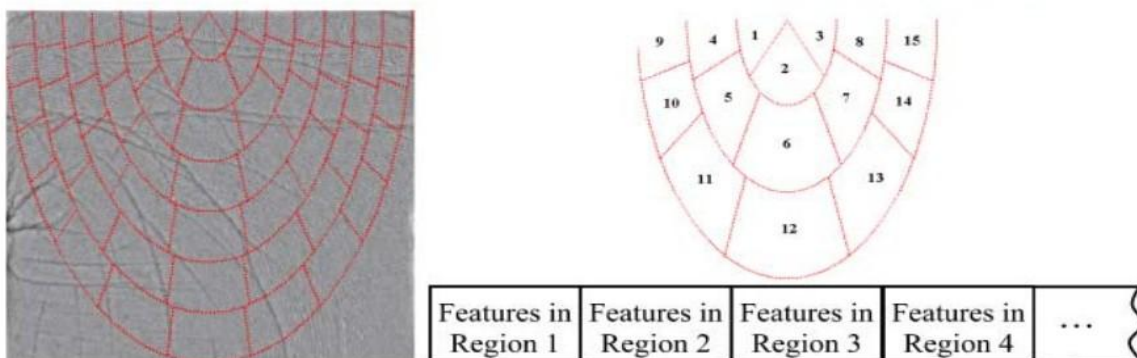


Fig 5- Elliptical coordinate system. In (a), an elliptical coordinate system is defined inside a region of interest. Values in the feature vector depicted in (b) correspond to the subregions defined in (a). Adapted from ref.

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- **Characteristic Points**

Datum points in principal lines to define a coordinate system and align images. The concept of using lines as a reference for coordinate systems was proposed for on-line palmprint images. Which are inked and printed on paper, and it's out of date. However, the concept of using lines as a reference for coordinate systems was proposed for on-line palmprint images. This method uses points located on palm lines as reference, which is more suited to account for skin stretching. Methods that use finger valleys as reference are more subject to skin-stretching associated errors. However, there is not enough research yet using this method to support its theory [44].

- **Hidden Markov Models**

Lines are the most evident characteristic of palmprints. If one is asked whether two palmprints belong to the same individual, the most natural comparison is made through the position and aspect of lines. Some examples of this methodologies are detailed below. Sobel operators are used to detect lines. Summation of sobel response over columns and rows originates two histograms, which are used for classification by Hidden Markov Models [40].

- **Principal Lines**

A filter based approach based on Radon transform is implemented to detect lines. Superposition is used to match palmprints [44].

- **Point Invariance and Line Feature Matching**

Line segments are detected by convolution with 3X3 operators that approximate the shape of a straight line. Because the detected segments are considered to be straight, it is possible to represent them by their end-points. Matching between two images is performed by comparing coordinates of the segment end-points from the two different images [26].

In [26], lines are detected with canny filter. The extracted ROI is divided in subregions and in each subregion properties associated with canny response and line orientation are kept. Euclidean distance is used for matching.

- **Gabor Filters**

Images are convolved with one Gabor filter. For each location in the region of interest (there are 32x32 locations), Gabor response is converted to a binary format. This can be considered a feature reduction method, as Gabor response will be 1 or 0. Afterwards, hamming distance is used as a classifier. This approach was classified as texture based because Gabor filters are often used as texture discriminators. Because these filters can model lines adequately, subsequent methods used them to detect line orientation[1; 40]

- **Fast Nearest-Neighbor Algorithm**

The recognition proceeds by matching individual features to a database of features from known objects using a fast nearest neighbor algorithm, The Hough transform is used to identify all clusters with at least 3 entries in a bin. Each such cluster is then subject to a geometric verification procedure in which a least-squares solution is performed for the best affine projection parameters relating the training image to the new image [20].

- **Scale Invariant Feature Transform**

Scale Invariant Feature Transform (SIFT), as it transforms image data into scale-invariant coordinates relative to local features. For image matching and recognition, SIFT features are first extracted from a set of reference images and stored in a database. A new image is matched by individually comparing each feature from the new image to this previous database and finding candidate matching features based on Euclidean distance of their feature vectors.

- **ARotation Invariant Texture Descriptor**

Palmprint identification approach using boosted local binary pattern based classifiers. The palmprint area is scanned with a scalable sub-window from which local binary pattern histograms are extracted to represent the local features of a palmprint image. The multi-class problem is transformed into a two-class one of intra- and extra-class by classifying every pair of palmprint images as intra-class or extra-class [42].

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- **Local Binary Pattern (LBP)**

Local binary patterns is a simple yet very efficient texture operator which labels the pixels of an image by thresholding the neighborhood of each pixel and considers the result as a binary number. Due to its discriminative power and computational simplicity, LBP texture operator has become a popular approach in various applications. It can be seen as a unifying approach to the traditionally divergent statistical and structural models of texture analysis. Perhaps the most important property of the LBP operator in real-world applications is its robustness to monotonic gray-scale changes caused, for example, by illumination variations. Another important property is its computational simplicity, which makes it possible to analyze images in challenging real-time settings.

Wavelets are a mean of extracting useful information from images. There are some examples of articles using wavelets for feature extraction.

Low- and high-pass images are originated through Haar wavelets and regarded as features.

- **Wavelet**

Dimensionality reduction is performed on sub images using Independent Component Analysis(ICA)[6; 24].

- **M-bBand Wavelets**

M-band wavelets are used to decompose the image. L1-norm and variance of sub bands compose the feature vector[2; 9].

- **Image Subspace**

Approaches to determine statistically relevant subspaces, such as ICA, Principal Component Analysis (PCA) or Linear Discriminant Analysis (LDA) can be directly applied to images. The result is a feature vector by itself. Although it is not an intuitive approach to identify personal characteristics in palmprints, the purely statistical information is useful (2; 9).

- **Linear Discriminant Analysis:**

An example of image subspace as features is the work presented by Wu *et al.*, [2003]. Images are treated as a point in a multidimensional vector and LDA is used to reduce its dimensionality.

- **Principal Component Analysis**

Good characteristics for palmprint recognition. Based on the Karhunen–Loeve (K–L) transform, the original palmprint images used in training are transformed into a small set of characteristic feature images, called “eigenpalms”, which are the eigenvectors of the training set. Then, feature extraction is performed by projecting a new palmprint image into the subspace spanned by the “eigenpalms”. And applied to palmprint recognition with a Euclidean distance classifier [7].

- **Fractals**

The central projection transformation (CPT) to describe the shape, the wavelet transformation to aid in the boundary identification, and the fractal features to enhance image discrimination. It reduces the dimensionality of a two-dimensional pattern by way of a central projection approach, and thereafter, performs Daubechies' wavelet transform on the derived one-dimensional pattern to generate a set of wavelet transform sub-patterns, namely, curves that are non-self-intersecting [11].

- **Fourier Transform**

The use of phase components in 2D (two-dimensional) discrete Fourier transforms of palmprint images makes possible to achieve highly robust palmprint recognition [18].

Which efficiently exploits the local spatial variations in a palmprint image. The entire image is segmented into several narrowwidth spatial bands and a palm-print recognition scheme is developed based on extracting dominant spectral features from each of these bands using two-dimensional discrete cosine transform (2D-DCT). The proposed dominant spectral feature selection algorithm offers an advantage of very low feature dimension and it is capable of capturing

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precisely the detail variations within the palm-print image, which results in a very high within-class compactness and between-class separability of the extracted features. A high-resolution palmprint recognition system based on minutiae is introduced in [31]. Each step has been specifically designed and optimized to process large palmprint images with a good tradeoff between accuracy and speed. A sequence of robust feature extraction steps allows to reliably detect minutiae; moreover, the matching algorithm is very efficient and robust to skin distortion, being based on a local matching strategy and an efficient and compact representation of the minutiae.

In PalmCode approach [46], images are convolved with one Gabor filter.

- **Subspace Approaches**

A good example of using subspace approaches is described in [32]. Magnitude from Gabor filters is useful to take information from images. 40 different filters combining eight different directions and five scales were used. As the images are 128 x 128, the total number of features is $128 \times 128 \times 40 = 655360$. AdaBoost, an adaptive machine learning algorithm, and LDA, are used to reduce the number of features. This is done by training the algorithm towards separation of self classes and external classes. The resulting number of features is less than 200. There is no discrimination between which gabor filter are being used, or from where in the palm are features being taken, because they do it all at once.

- **Clustering Algorithm**

An example of clustering algorithms is a subsequent work to Competitive Code [24]. In this approach Gabor filters with six different orientations are used to extract line orientation. An improvement to this approach using a clustering algorithm was related in [32] where filters with 180 orientations were used to extract features. Through clustering with Fuzzy C-Means algorithm the 180 orientations are clustered into six centroids. Implementing Competitive Code with Gabor filters oriented as the detected centroids results in improved performance while using the same amount of information.

- **Support Vector Machines**

2-dimensional 2_band (Discrete Wavelet Transform) and 3_band wavelet decomposition to get the low subband images, and then use them as identification feature vectors. We. Choose support vector machines as classifier [38].

- **Statistical Properties and Neural Network.**

Should be performed to obtain a square region in a palm table which is called region of interest(ROI). Then, the feature extraction process to obtain the feature vectors by the Sobel and morphological operations. The reference templates for a specific user are generated in the modeling module [5].

- **Latent Palmprint Matching**

Scale-Invariant Feature Transform (SIFT) and minutiae extraction techniques were applied for full to full and partial to full palmprint matching. The block diagram of the proposed full-to-full palmprint matching system is shown in Fig 6. The system consists of three major components: (1) pre-processing, (2) feature extraction, and (3) minutiae matching [22].

- **Modified Phase Only Correlation (MPOC) Technique**

Recognition Systems using SIFT and minutiae features. Minutiae extraction is difficult in poor quality images. high recognition performance thus demonstrating its ability to tackle the problem of identifying low quality partial palmprint images giving an equal error rate (EER) less than 0.4% [27].

- **Invariant Local Minutiae Descriptors**

New rotation invariant technique in which the palmprint images were first enhanced by using a conventional fingerprint enhancement technique [28].

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- ### Invariant Local Minutiae Descriptor

Minutiae points and proposes a set of invariant feature descriptors referred to as Invariant Local Minutiae Descriptors (ILMDs). The structure of ILMD comes to overcome the drawback of the minutiae pairing used in fingerprint matching [25]. The proposed ILMD is capable to efficiently match a partial-to-full palmprint image under translation, rotation and illumination changes and does not require any prior alignment.

The coordinates of the minutiae points are used to locate them in the palmprint image as follows: for each minutiae a surrounding area is sampled and a feature vector is constructed using the values of all the orientation histograms sets entries within a local area of 16×16 pixels width.

- ### Principal Lines

Use of multiple features, namely, minutiae, density, orientation, and principal lines, for palmprint recognition to significantly improve the matching performance of the conventional algorithm [8].

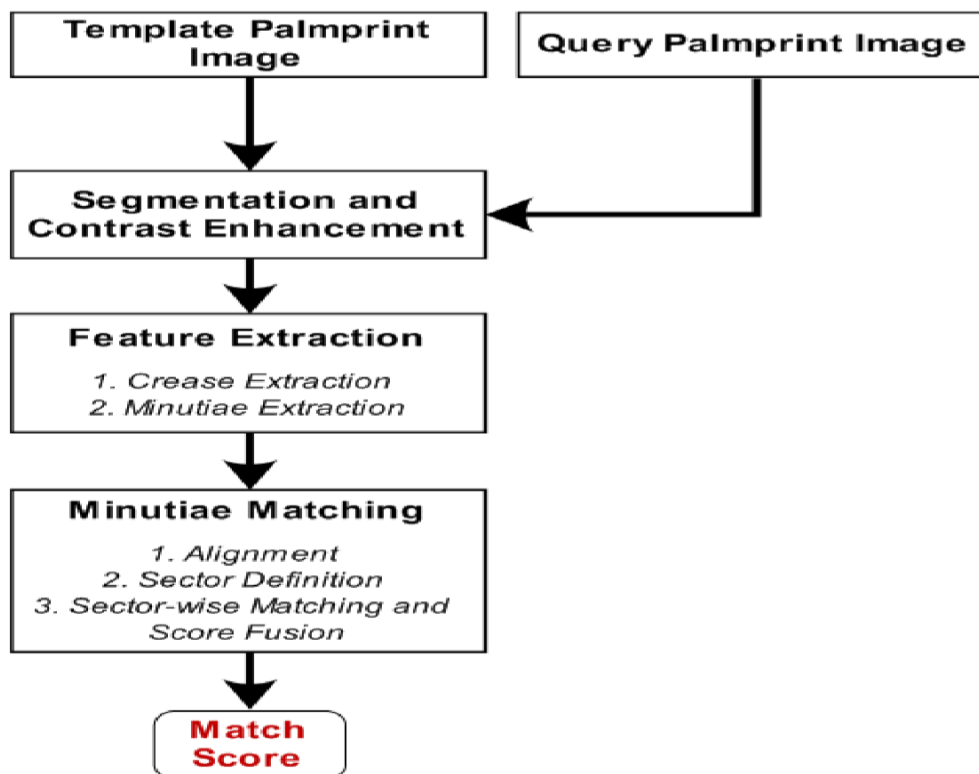


Fig6-Block diagram of the proposed full-to-full palmprint matching system.

V. CONCLUSION

In this paper, the state of the art palmprint recognition process is discussed. Palmprint features are generally described by forensic experts at three levels of detail. However, not all palmprint features that are utilized in manual Palmprint matching are employed in automatic matching systems. The availability of higher resolution palmprint sensing has made automatic extraction and matching of high level extended features feasible. This paper presented an overview of palmprint identification, in which the definition of a palmprint, the formation and structure of palmprint features, palmprint identification metrics, automated palmprint identification systems, and a number of computer vision and pattern recognition algorithms were discussed. A summary of the current palmprint research including sensors,

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preprocessing, feature extraction, matching, identification in large databases, fusion and security is also presented and the related issues including privacy and performance evaluation are discussed.

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