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Person Authentication Using Face And Palm Vein : A Survey Of Recognition And Fusion Techniques

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ABSTRACT: Biometric modalities are being used for person recognition for over 40 years. Face has been extensively analyzed as a biometric modality. Palm vein is a permanent and difficult to spoof, modality. For person authentication, palm vein performs better than face. Fusion of both the modalities yield recognition rates that are higher than those obtained individually. This paper presents a survey of various techniques used for authentication of a person, based on face, palm vein and fusion techniques involving both modalities. It discusses some iconic techniques, their limitations and how those were overcome in different ways in new techniques. It concludes with major problems to be analyzed in future and open areas of research.

Keywords: Multimodal Biometrics, Face Recognition, Palm Vein, Fusion techniques

1 Introduction

Security has become an integral part of our lives today with people having numerous accounts and carrying out high value transactions. The advent of technology has helped the criminal to become more intelligent. For example the internet has provided him with easy access to data. Biometrics is increasingly being preferred for security, owing to its uniqueness and being difficult to replicate. Face is used for recognition by humans and was also one of the first modalities to be used for recognition. In automated person identification systems, face is often favored due to the fact that it is a non-intrusive system where very little cooperation is required from the user. Another modality which is comparatively new is the palm vein. The vascular pattern of the palm has a wealth of information and features, compared to the finger or the dorsal side of the hand. Palm veins, being inside the body, are difficult to duplicate. Palm vein pattern recognition requires just a scan of vein of palm, thus making it easier to use. A multimodal authentication system is more reliable and has increased accuracy compared to a single modality system. In multimodal biometric systems, fusion of physically uncorrelated traits are expected to result in better improvement in performance than correlated traits 0. Fusing the palm vein features with the face features to augment it, provides a highly accurate, difficult to breach and advanced personal recognition system. In addition to enhanced security, palm vein authentication used in conjunction with face recognition systems would also keep a log of facial information should it be necessary to be used as evidence 0. In this paper, we survey various techniques used for person recognition based on face and palm vein modalities. We also present recognition techniques used in multimodal systems having either face or palm vein or both as modalities. The paper is organized as follows. In section 1, the survey of face detection and recognition techniques is presented. Section 2 discusses the palm vein recognition techniques. In section 3, various fusion techniques for multimodal systems (using palm vein or face or both) are discussed. In section 4, conclusions are presented, where major problems and limitations of the techniques discussed are presented along with scope for future work in these areas.

2 Face Detection and Recognition Techniques

Face detection systems have come into existence in the early 1970s but due to lack of technological and computational development, growth of these systems was limited. Face recognition requires specific object recognition. The most prominent difficulty in face recognition is that the frontal view of the different faces appears to be approximately similar and the differences are quite subtle. As a result, a dense cluster is formed in the image space for the frontal face images, making the pattern recognition techniques unsuccessful in distinguishing between them [1]. There are a number of factors that cause variations in the appearance of faces and they can be intrinsic or extrinsic 00. Based on research conducted through various evaluations like Face Recognition Vendor Tests (FRVT) 2000 0, Face Recognition Technology (FERET) evaluations 0, FRVT 2002 0 and the Face Authentication Test (FAT) 2004 0for several years, it is found that age, illumination and pose variations are three major problems for the face recognition systems 0. Although under constrained conditions (in which some of the factors causing variability are controlled while acquiring face images) the performance of most of the face recognition systems is quite good, it degrades rapidly when they are tested under conditions where none of these factors are regulated 0.The face based person authentication can be divided into two important steps: face detection and face recognition. Face detection serves the purpose of localizing and extracting the face region from the background 0. Face recognition is basically extracting the face features and comparing them with those in database. It can be used in identification or verification mode.

2.1 Face Detection

A face first needs to be detected before it is recognized. By definition, face detection is a technology that determines locations and sizes of human faces in input image. Face detection is a two-step procedure where the first step involves roughly finding all the faces in large, complex images, which may have many faces and a lot of clutter and the second step is localization which emphasizes on spatial accuracy by accurate detection of facial features 0. The different face detection algorithm categories are:

I. Knowledge-based methods which use knowledge of the typical human face geometry and facial features arrangement. These methods find rules to describe the shape, size, texture and other characteristics of facial features (such as eyes, nose, chin, eyebrows) and relationships between them. The main problem encountered in these techniques is converting human knowledge about face geometry into meaningful and well-defined rules. Their performance also deteriorates under

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varying pose or head orientations 0. In 0, Kang-Seo Park, Rae-Hong Park, and Young-Gon Kim, proposed a face detection algorithm using the 3×3 block rank patterns of gradient magnitude images and a geometrical face model. The 3×3 block rank patterns are used to roughly classify whether the detected face candidate region contains a face or not. Finally, the face, if any, is detected by using a geometrical face model.

II. Feature invariant approaches find structural features that exist even when the viewpoint or lighting conditions vary and then use these to locate faces. Usually, they use features such as texture, shape and skin color to find face candidates and then use local facial features such as eyes, nose and mouth to verify the existence of a face. Feature invariant approaches can be problematic if image features are severely corrupted or deformed due to illumination, background and noise 0.

III. Template-based methods make use of filters, edge detectors, or silhouettes to detect a face, extracting the contours of local facial features and then the correlation with predefined stored templates of features. However these methods are sensitive to scale, shape and pose variations. Deformable template methods have been proposed to ovecome the problem of translation, scaling and rotation by modeling face geometry using elastic models 0. However sensitivity to shape and pose is still an open problem.

IV. Appearance-based methods use large number of test face images with different variations (face shape, skin color, eye color, open\closed mouth, etc). Pattern classification having two classes: “face” and “non-face” is used for face detection. Eigen faces, Support Vector Machines (SVM), Linear Discriminant Analysis (LDA), neural networks and Hidden Markov Models (HMM) are examples of appearance based models 000.The major limitation of appearance based face detection methods is the requirement to have a large database of training images.These methods are also computationally complex.

2.2 Face Recognition

A face recognition system consists of a sensor which captures the face images, face detection and feature extraction module, classification module and system database. The application for which face recognition is to be used, helps to decide the sensor to be used for capturing the face images 00.Based upon the image capture technique, images can be classified as intensity, 3D range images.

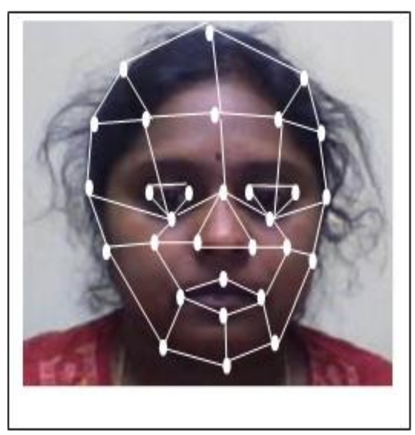
2.2.1 Intensity Image based RecognitionTechniques:

Techniques based on the intensity images can be either feature based or holistic 0000.

Feature-based approaches

Feature-based approaches are based on the geometric relationships between the extracted facial features like the nose, eyes etc. which gives a vector of geometric features for the input image. Faces are then matched using statistical pattern recognition techniques. In 1973 Kanade 0extracted a vector of 16 facial parameters like ratios of distances and areas to overcome variations in image size and achieved 75% recognition on a database of 20 different people using 2 images per person. Based on Kanade’s work Brunelli and Poggio0 computed a vector of 35 geometric features from a database of 47 people (4 images per person) and reported a 90% recognition rate. However, it was observed later that even simple template-matching approaches achieve higher recognition accuracies than those obtained using geometric feature vectors. Feature extraction techniques such as deformable templates ([20]00), Hough transform methods 0, Reisfeld's symmetry operator0 and Graf's filtering and morphological operations0 rely on heuristics such as restricting the search subspace with geometrical constraints 0 and they can perfectly fit the structures in the image. Using large tolerance value reduces the precision required to recognize an individual’s best-fit parameters making these techniques tolerant to the minute variations 0. However the current algorithms for automatic feature extraction using some of the techniques mentioned, have low accuracy and suffer from the problem of high computational capacity requirement [28]. Elastic bunch graph matching method was proposed by Wiskott et al. 0. This technique is based on dynamic link structures which uses Gabor filters’ responses 0. A graph for an individual face is generated as follows: a set of fiducial points on the face are chosen. Each fiducial point is considered as a node of a full connected graph, and is labeled with the Gabor filters’ responses applied to a window around the fiducial point. Each arch is labeled with the distance between the corresponding fiducial points. A representative set of such graphs is combined into a stack-like structure, called a face bunch graph as shown in Fig.1.Once the system has a face bunch graph, graphs for new face images can be generated automatically by Elastic Bunch Graph Matching. Recognition of a new face image is performed by comparing its image graph to those of all the known face images and picking the one with the highest similarity value. A recognition rate of 98% for the first rank and 99% for the first 10 ranks using a gallery of 250 individuals can be achieved. It suffers from graph placement for the first 70 faces to be done manually before the elastic graph matching becomes adequately dependable 0which was overcome by Campadelli and Lanzarotti 0.The enhanced system deals with different poses but the recognition performance on faces of the same orientation remains the same.

Fig. 1. *Face bunch graph*



Face profiles are also used for face recognition. Kaufman and Breeding 0 reported a recognition rate of 90% using face profiles for 10 individuals. Harmon et al. 0 obtained recognition accuracies of 96% on database of 112 individuals, using a 17-dimensional feature vector to describe face profiles. Liposcak and Loncaric 0 reported a 90% accuracy rate on a database of 30 individuals, using subspace filtering to derive a 21-

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dimensional feature vector to describe the face profiles and using a Euclidean distance for matching. The major disadvantage of feature based techniques for face recognition is the difficulty of automatic feature detection 0. Selecting the optimum feature set is another important concern because if the feature set lacks the ability to discriminate, no amount of subsequent processing can compensate for that intrinsic deficiency [37].

Holistic approaches

Holistic approaches use global representation to identify faces. These approaches do not use local features of the face rather they use the entire image description. The approach can be categorized into two groups: Statistical and Artificial Intelligence (AI) based approaches 0.

A) Statistical Approaches

Sirovich and Kirby 0 employed Principal Components Analysis (PCA) [38]0for the first time to economically represent face images. Turk and Pentland 00made use of eigen faces, shown in Fig.2, as features for face recognition. Eigen faces find the minimum mean squared error linear subspace that maps from the original N-dimensional data space into an M-dimensional feature space 0. Mathematically, Eigen faces are the principal components that actually divide the face into feature vectors0. The feature vector information is obtained from covariance matrix. These Eigen vectors are used to quantify the variation among multiple faces. The faces are characterized by the linear combination of highest Eigenvalues. Recognition rates of 96%, 85% and 64% were reported for database of 2,500 images of 16 people under lighting, orientation and scale variation but its performance degrades with scale changes. In [42] this was further extended and “multiple observer” methods have been suggested to deal with large changes in pose 0.Performance of PCA deteriorates when multiple images per person are used, but Belhumeur et al. [44] argued that PCA retains variations due to lighting and facial expression. “The variations between the images of the same face due to illumination and lighting rection are almost always larger than image variations due to a change in the authentic identity of the person”, was stated by Moses et al. [45].

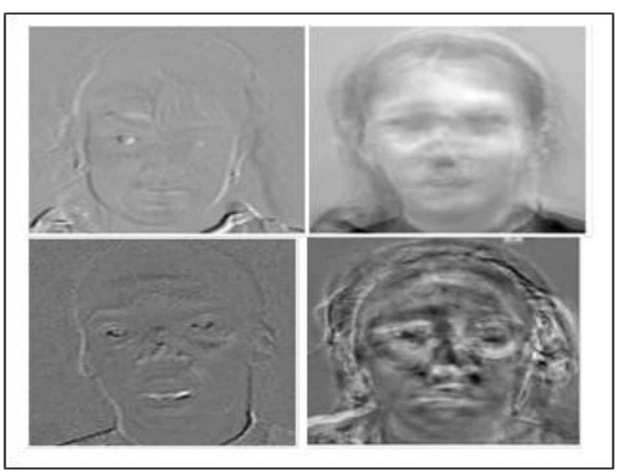

Fig.2 *Eigen Faces*

In 0 Fisher’s Linear Discriminant Analysis (FLDA) is proposed which is better at handling the variations caused by lighting and facial expression. LDA is more suited for finding projections that best discriminate different classes. It does this by seeking the optimal projection vectors which maximize the ratio of the between-class scatter and within-class scatter (i.e. maximizing class separation in the projected space) 0.Thus LDA performs dimensionality reduction while preserving as much of the class discriminatory information as possible. However it is found that with small training data PCA performs better that LDA [46]. Several extensions and variations to the eigen faces and fisher faces have been implemented. Some recent advances in PCA-based algorithms include multi-linear subspace analysis 0, symmetrical PCA 0, two-dimensional PCA 00, eigenbands 0, adaptively weighted subpattern PCA 0, weighted modular PCA [53], Kernel PCA 00 and diagonal PCA 0. Examples of recent LDA-based algorithms include Direct LDA 00, Direct-weighted LDA 0, Nullspace LDA 00.Dual-space LDA 0, Pair-wise LDA [64], Regularized Discriminant Analysis [65], Generalized Singular Value Decomposition 00, Direct Fractional-Step LDA [68], Boosting LDA 0, Discriminant Local Feature Analysis [70], Kernel PCA/LDA 00, Kernel Scatter-Difference-based Discriminant Analysis 0, 2DLDA 00, Fourier-LDA [76], Gabor-LDA 0, Block LDA 0, Enhanced FLD 0, Component-based Cascade LDA 0, and incremental LDA 0. The main drawback of the PCA and LDA methods is that these techniques assume that the face images lie on a linear space which may not be true always. Independent Component Analysis (ICA), a generalization of PCA, is a method that finds basis vectors that depend on higher-order relationships among the pixels. It aims to find an independent, image decomposition and representation. ICA is known to outperform PCA for recognizing faces across days and changes in expression. A study and comparison of four subspace representations for face recognition, i.e., PCA, ICA, Fisher Discriminant Analysis (FDA), and probabilistic eigen faces and their ‘kernalized’ versions, is presented in 0.The major limitation of statistical methods is that they are dependent on the variability and distribution of data. Changes in lighting conditions and facial expressions can severely affect the data and hence the performance of these methods.

B) AI Approaches

Machine learning techniques and neural networks are used in AI based face recognition. Some prominent AI approaches that have resulted in good performance have been included in 0000 and those based on boosting in 00. HMMs have also been employed for the face recognition task. Samaria and Harter 0, used a one-dimensional HMM to obtain a peak recognition accuracy of 87% on the ORL database. Zhang et al. 0proposed an approach in which a similarity function is learnt, describing the level of confidence that two images belong to the same person. The facial features are selected by obtaining Local Binary Pattern (LBP) histograms of the sub-regions of the face image and the Chi-square distances between the corresponding LBP histograms are chosen as the discriminative features. The AdaBoost learning algorithm, introduced by Freund and Schapire , is then applied to select the most efficient LBP features as well as to obtain the similarity function in the form of a linear combination of LBP feature-based weak learners. In Statistical relation (SR)-based methods it is assumed that each class in the gallery has sufficient samples and the query lies on the subspace spanned by the gallery of the same class. But such an assumption is easily violated in verification, where the task is to determine if two faces belong to the same person. This is overcome when SR encoding is performed on local image patches rather than the entire face. Thorough experiments on exYaleB, BANCA, AR, FERET, and ChokePoint datasets indicate that the local SR approach obtains considerably better and more robust performance than several previous state-of-the-art holistic SR methods. The l 1-minimisation-based encoding has higher recognition rates but suffers from considerably higher computational cost when compared with STATISTICA Automated Neural Networks (SANN)-based and probabilistic encoding 0. Face recognition of newborn babies with a recognition rate of 87.04% has been proposed in 0. The partial occlusion problem has been overcome to a certain extent in 0 where a novel face recognition framework based on the grammatical face models has been proposed. The experimental results confirm the promising ability and robustness of the proposed method against partial occlusion and out performs the various state of the art methods. The vulnerability of face biometric systems to spoofing attack has been addressed in 0 which proposes an approach based on analyzing facial image using texture and gradient structures of the facial images using a set of low-level feature descriptors, fast linear classification scheme and score level fusion for detecting whether there is a live person in front of the camera or a face print. AI based approaches are proven to perform better than the statistical approaches. However, these methods very often require large training data sets with good correlation and are computationally expensive. Holistic approaches an advantage, over other approaches, that they do not concentrate on only limited regions or points of interest 0. This same property however is also a drawback as these approaches assume that all the pixels in the image are equally important 0. Some techniques require a high degree of correlation between the test and training images, and do not perform effectively under large variations in pose, scale and illumination along with being computationally expensive 0.

2.2.2 3D Range Image based RecognitionTechniques:
Face recognition using 3D shape is believed to offer advantages over the use of intensity images 000. Current 2D face recognition systems encounter difficulties in recognizing faces with large pose variations and lighting conditions. Utilizing the pose-invariant features of 3D face data has the potential to handle multi view face matching 0.The problem of occlusion in 2D face recognition systems can also be overcome to a large extent using 3D face recognition techniques. Range image based 3D face recognition has been demonstrated to be effective in enhancing the face recognition accuracy. A ‘‘range image,’’ also sometimes called a ‘‘depth image,’’ is an image in which the pixel value reflects the distance from the sensor to the imaged surface 0. Techniques for 3D face recognition in the literature use a broad range of face descriptors in the matching step. Some descriptors amount to a complete representation, in that the original face shape can be recovered (perhaps approximately) from the representation (e.g., a principal components representation). Others are incomplete since they cannot yield such a reconstruction, but these can offer other benefits (e.g., robustness to occlusion)0. One of the earliest approaches of 3D range image based face recognition can be seen in 0, where the principle curvatures of the face surface are calculated from range data, after which this data supplemented by a priori information about the structure of the face is used to locate the various facial features (i.e., the nose eyes, forehead, neck, chin, etc.). The faces are then normalized to a standard position and interpolated onto a regular cylindrical grid. The volume of space between two normalized surfaces is used as a similarity measure. The system was tested using the face images of 8 people (3 images per person). Castellani et al. 0 approximate the range images of faces obtained by stereoscopic analysis using Multi-level B-Splines and SVMs are then used to classify the resulting approximation coefficients. Several approaches have also been proposed that integrate 2D texture and 3D shape information0. Wang et al. 0,extracted 3D shape templates from range images and texture templates from gray scale images of faces, applied PCA separately to both kinds of templates to reduce them to lower-dimensional vectors, then concatenated the shape and texture vectors and, finally, applied SVMs to the resulting vectors for classification. In 0, authors have proposed a feature extractor based on the directional maximum to estimate the nose tip location and the pose angle simultaneously. A nose profile model represented by subspaces is used to select the best candidates for the nose tip. Assisted by a statistical feature location model, a multimodal scheme is presented to extract eye and mouth corners. Using the automatic feature extractor, a fully automatic 3Dface recognition system is developed whose block diagram is shown in Fig.3.

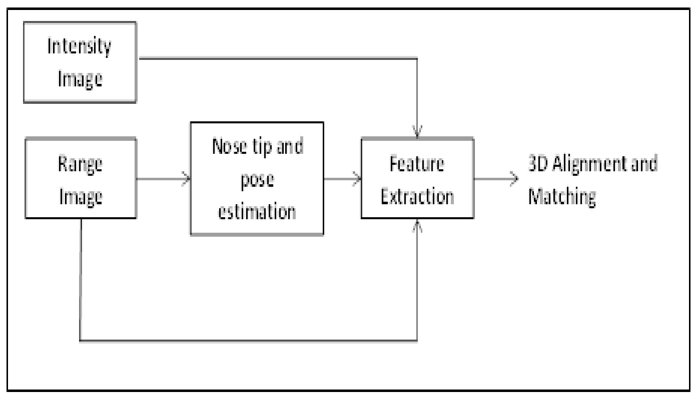

Fig.3 *Automatic 3D face recognition system*

In 0,Xin Gen et al, propose an automatic age estimation method named AGing pattern Subspace (AGES) where the basic idea is to model the aging pattern, which is defined as the sequence of a particular individual's face images sorted in time order, by constructing a representative subspace. The proper aging pattern for a previously unseen face image is determined by the projection in the subspace that can reconstruct the face image with minimum reconstruction error, while the position of the face image in that aging pattern will then indicate its age. The quality of 3D sensors has improved in recent years, but features such as being less sensitive to ambient lighting, having fewer artifacts, and requiring less explicit user cooperation are desired. Another limitation of current 3D sensor technology, especially relative to use with non-cooperative subjects, is the depth of field for sensing data. 3D face recognition needs algorithms that are more tolerant of real world variety in the pose, facial expression, eye-glasses, jewelry and other factors. At the same time, they need to be less computationally demanding. 3Dface recognition in general seems to require much more computational effort ‘‘per match’’ than does 2D face recognition

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3 Palm Vein Based Recognition Techniques

Palm vein based automated person authentication is a popular recent trend. It is a noninvasive method and since veins are internal to the body and have a large number of differentiating features, forging an identity is extremely difficult, enabling a high level of security 0. Fujitsu has developed a palm vein pattern authentication based on vascular patterns 0. Reducing the size of the palm vein sensor and shortening the authentication time are goals to be achieved 0. Image sensing and software technology is combined to form the contactless palm vein authentication technology 0. Palm vein authentication technology operates based on identifying the vein patterns in a person's palm. An infrared beam is used to penetrate the user's palm as it is held over the sensor. The vein structure, believed to be unique for each person, extracted from infrared-ray images, is represented as dark lines. To extract these lines many researcher used edge detection and morphological operators 0. It is also possible to determine palm vein pattern, using Near Infrared (NIR) imaging. The location of the veins is mapped by the Near Infrared (NIR) light when a user's hand is held over a scanner. The unique vein pattern of the palm is captured by holding the palm above the scanner, which is then registered 0. The rays are absorbed by the red blood cells in the veins and appear as black lines and the remaining white. This vein pattern is then verified against a preregistered pattern to identify the person. The palm-vein imaging typically requires infrared illumination which is one component of multispectral illumination for the multispectral palm print imaging. Therefore, the multi-spectral palm print images inherently acquire palm-vein details. However, as compared to the bi spectral approaches, multispectral methods introduce a significant amount of additional computations (which often adds to the cost of device) while achieving very little or marginal performance improvement 0. Palm vein recognition comprises of four important steps: Infrared palm images capture, Detection of Region of Interest (ROI) including pre-processing, Palm vein feature extraction and Feature matching 0. First an image is captured and a small area of the image is located as the ROI to extract the features. When features within ROI are used for recognition, computation efficiency improves significantly 0. For image-based biometric systems, various preprocessing implementations are utilized for obtaining better quality of image that will be used in the processing stage as an input image. Normally, the captured palm vein pattern is gray scale and subject to noise. To ensure the quality of the subsequent steps of feature extraction, noise reduction and contrast enhancement are crucial 0. Feature extraction plays an important role in palm vein based recognition because the performance of feature matching is greatly influenced by the extracted features 0. In feature matching, input image is compared with those existing in the database and if matched, then the person is authenticated. In the following sections we survey various ROI and feature extraction and matching techniques used for palm vein images.

3.1 ROI Extraction

Extraction of ROI comprises of detecting and extracting a part from the original image. ROI extraction has two important advantages. Firstly, by fixing the reference frame, it helps in removing the effects of translation and rotation introduced during collection of data. Secondly, it helps in extracting the most informative area in the images. It also helps in decreasing the total amount of data without severe loss of important information. This helps in fast computation of feature extraction and matching 0. To extract the ROI, Zhou and Kumar 0 constructed a coordinate system utilizing two webs as the reference points/line, i.e., the web between the index finger and middle finger together with the web between the ring finger and little finger. Fig.4 shows the palm vein image with ROI key points. Initially, the acquired palm images from a contactless system are binarized in order to separate the background from the palm. This is followed by the estimation of the distance from center of the binarized palm to the boundary of palm. The two webs are then located by finding the corresponding local minima from the calculated distance. The location and size of the ROI is adaptively selected based on the distance between the two webs. It is then segmented and the images are scaled to generate a fixed size region. Histogram equalization is then employed to obtain the normalized and enhanced palm-vein image. This enhancement method has significantly improved the details and contrast of the ROI images. Many researchers employed this method to find the ROI; like 0.Li et al. 0 adopted a 5x5 median filter to remove the speckling noise in the ROI image. Ladoux et.al **Error! Reference source not found.**extracted the ROI and applied 5x5 box filter on the ROI in order to reduce the noise. This was followed by correcting the non-uniform brightness by applying a Gaussian low-pass 51x51 filter on the ROI to obtain the brightness image in the low frequencies. This brightness is then subtracted from the original ROI. As the contrast was still poor, normalization method was applied.

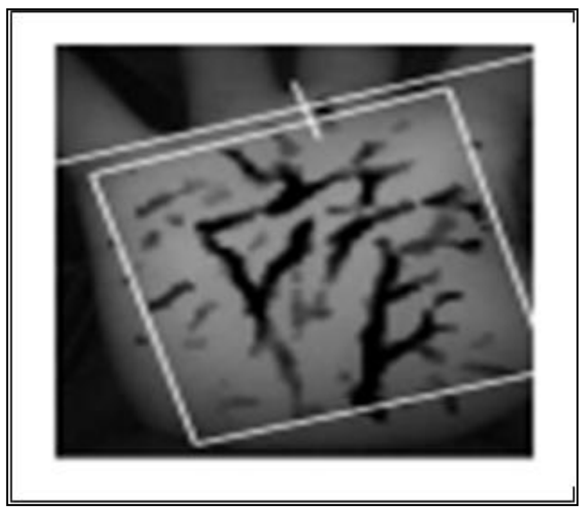

Fig.4 *Palm vein image with ROI Key points*

In 0, the authors have proposed a similar ROI extraction technique where a small area (128*128 pixels) of the captured palm image is located as the ROI. The input image is first binarized and the boundaries of the gaps, (Fixj; Fiyj) shown in Fig.5, are obtained. A tangent of the two gaps (the line connecting(x1, y1) and (x2, y2)) is computed and used as the Y axis. The line passing through the midpoint of the two points (x1, y1) and (x2, y2), which is also perpendicular to the Y-axis, is used as the X axis. The ROI is located as a square of fixed size whose center has a fixed distance to the palm coordinate origin. After that, noise reduction and contrast enhancement are carried out to produce a better quality of image.

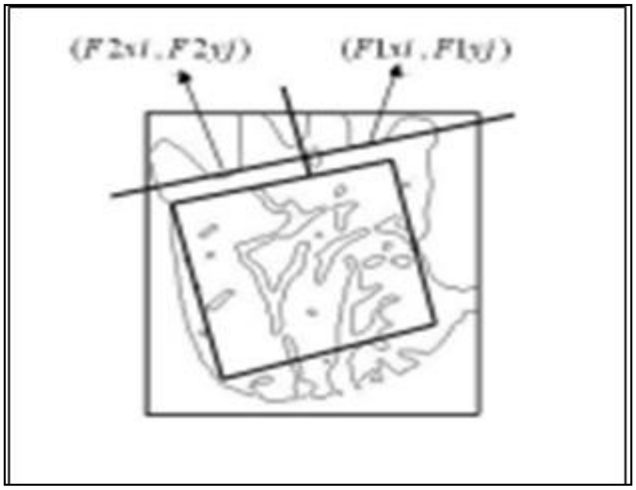

Fig.5 *ROI Extraction*

3.2 Feacture Extraction and Matching

Extracting the vein pattern or features from the background is a prominent step in the palm vein authentication systems 0. Zhang et al. 0 proposed a multi-scale scheme to improve the performance of vein detection. They made use of Gaussian shaped filter to de-noise and the zero-sum to suppress the background pixels. Bhattacharyya et al. 0 proposed three different algorithms for processing palm vein pattern image of an individual to be executed serially; namely Vascular Pattern Marker Algorithm (VPMA), Vascular Pattern Extractor Algorithm (VPEA) and Vascular Pattern Thinning Algorithm (VPTA). In VPMA, smoothening of image is carried out by use of a two pass masking; horizontal and vertical kernels. In VPEA, a binarized image is created with only 2 colors, black (0) and white (255). Image thresholding helps in getting rid of the unimportant parts or noise and retaining the significant part of an image. Ladoux et.al0 observed that the grey level is low where the hemoglobin absorbs the NIR light. In their palm vein based authentication system, the authors have performed local matching of specific feature points, Scale Invariant Feature Transform (SIFT) descriptors, extracted in the reference and test images. Data from 24 persons, in two sessions, was collected. After ROI extraction, local thresholding depending on the mean value of the neighborhood of each pixel is applied to obtain the vein pattern. The SIFT detector and descriptor are constructed from the Gaussian scale space of the source image. The algorithm also makes use of another scale space, called difference of Gaussian (DOG).Extracted key-points are defined as points of local extremum of the DOG scale space. The descriptor is created by sampling the magnitudes and orientations of the image gradients in a neighborhood of each key-point and building smoothed orientation histograms that contain the important aspect of the neighborhood. Each local descriptor is composed on a 4x4 array (histogram). To each coordinate of this array, an 8 orientation vector is associated. A 128-elements vector is then built for each key-point. SIFT descriptors are used as feature points also in 000. In 0 a biometric identification system based on near-infrared imaging of dorsal hand veins is presented where SIFT is used for matching the key points that are extracted from the dorsal hand vein images. A Rank-1 recognition rate of 99.29% is achieved using this method. In 0, two different feature extraction techniques are described; Neighborhood Matching Radon transform (NMRT) based feature extraction and Hessian-Phase based feature extraction. CASIA Multi-Spectral Palmprint Image Database V1.0 which has been acquired from the contactless palm imaging of 100 subjects was used initially. The second database used is the PolyU Multispectral Palmprint Database where all the images were acquired with a constrained device composed of images from 250 individuals with 12 images from each individual. The first three images from the CASIA database and first six images from the PolyU database were used as gallery images and the rest as probe images. In the NMRT based feature extraction, the palm vein vessels are approximated by small line segments which are rather curved. The Radon transform is an effective tool to identify continuous line structures in the images. However if the length of the line is significantly shorter than the image dimension, as in case of detecting the palm-veins, then the process may not be able to locate that line as line segments. The palm vein vessels also may suddenly change their direction to an almost perpendicular orientation, and break the long curve into several short line segments. To avoid this, NMRT utilizes the idea of restricting the radon transformation in the local area and selecting the size of the local region to be small enough so that the target shortest line segments in the images can be detected. NMRT further simplifies the transformation by fixing the intercept term and restricting the integration in a confined width (line width).A method similar to NMRT, called Localized Radon Transform (LRT) was used for feature extraction in 0 The Hessian Phase based feature extraction is based on the fact that the eigenvector of a matrix corresponds to the basis/principal directions of the matrix. Thus the magnitude of the corresponding eigenvalues of the Hessian matrix (second-order derivative), will reflect the curvature of the principal orientation in the local image. Two local characteristics of image can be measured by analyzing the eigen values. First, the norm of the eigen values will be small at the location where no structure information is shown since the contrast difference is low, and it will become larger when the region occupies higher contrast since at least one of the eigenvalues will be large. Second, the ratio between the eigen values will be large when the blob-like structure appears in the local area, and will be very close to zero when the structure shown is line-like. Yingbo Zhou et al, in 0 have also used Hessian phase based features. By systematically adapting the parameters to fit palm vein structures, the Local Binary Pattern (LBP) operator, the Local Derivative Pattern (LDP) operator and the fusion of the two are used to create efficient descriptors for palm vein recognition. It is found that the proposed local texture can be adapted to the vein description task for biometric recognition and that the LDP operator consistently outperforms the LBP operator in palm vein recognition 0. 0 introduced complex spectral minutiae which utilize the orientation in addition to the minutiae location; therefore a minutiae orientation extraction algorithm based on a fast convolution approach is proposed. Location and complex spectral minutiae when fused at the score level results in increased recognition rate. In addition to the feature extraction techniques described above, many other techniques such as , Gaussian filter 000, shock filter 0, PCA 0, Gabor filters 0, Laplacian palm 00 and Ordinal Code00 are frequently used to extract palm vein pattern from the palm vein images. Also different distance measures have been used for matching such as Euclidean distance, Hamming distance, Cosine similarity, Exclusive-or operator, AND operator, and OR operator. Also some models of neural networks have been used for matching step such as Adaptive Resonance Theory 1 (ART1) networks, Learning Vector Quantization (LVQ) and Cellular. Creating fast and modality-dependent feature extractors is one of the open challenges in this field Reducing noise in the palm vein images is a problem that needs more analysis. The external lights can also affect the infrared light source so that some images have very poor quality.

4 Fusion Techniques For Multimodal Systems

To improve the performance of the biometric system and make it immune to spoof attacks, a combination of modalities is used and is called as multimodal biometric system [113]. The most compelling reason to combine different modalities is to improve the recognition rate. This can be done when biometric features of different biometrics are statistically independent 0. A multimodal biometric system fuses the individual modalities by integrating the information obtained from these modalities. Fusion can be performed at the four different levels; at the sensor level, at the feature-extraction level, at the matching-score level and at the decision level as shown inFig.6.

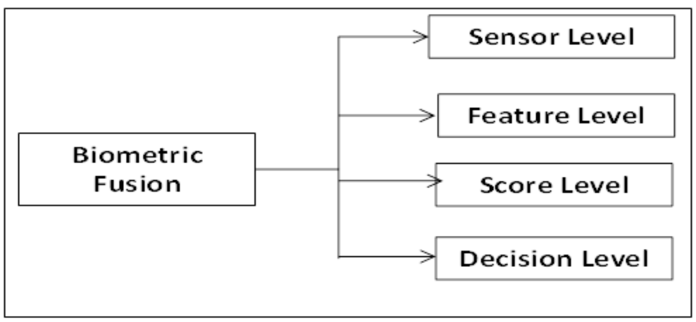

Fig.6 *Fusion Levels in Multimodal Biometrics*

Fusion at the sensor level is performed by integrating information from different sensors before feature extraction takes place. Although fusion at such a level is expected to enhance the biometric recognition accuracy 0[126], it cannot be used for multimodal biometrics because of the incompatibility of data from different modalities 0. Fusion at the feature-extraction level is performed by concatenating feature vectors obtained from different modalities. Integration at the feature extraction level is expected to perform better than fusion at other levels 0. The main reason is that the feature level contains richer information about the raw biometric data. The extracted features are also relatively robust to position variations and can be made invariant to size, orientation and/or lighting. However, such a fusion type is not always feasible 0[126]. For example, in many cases the given features might not be compatible due to differences in the nature of modalities and also such concatenation may lead to a feature vector with a very high dimensionality which increases the computational complexity. It is reported that a significantly more complex classifier design might be needed to operate on the concatenated data set at the feature level space 0. Fusion at the matching-score level is performed by combining matching scores obtained from multiple matchers. Matching-score level fusion is widely used owing to its good performance, intuitiveness and simplicity 0. Normalization step for fusion at the matching-score level is necessary as the matching scores at the output of the individual matchers can be represented in different ways. The output of a matching algorithm varies; it can be distances (as a measure of dissimilarity), proximities (as a measure of similarity). The matcher outputs can be in different numerical ranges. Genuine and impostor matching scores from different modalities may not follow the same statistical distributions. In general, normalization is performed by using a normalization function, whose parameters are obtained based on a training set. Various heuristic normalization functions are used such as linear, hyperbolic tangent, double-sigmoid 0 or piece-wise linear function 0. Normalization can also be performed based on Bayes theorem 0, which assumes independence of different modalities. The piecewise-linear normalization, which has proven to work well for many applications 00transforms the matching scores into a common interval [0-1]. Normalized scores can be combined into a unique similarity measure by one of the following fusion rules: simple sum, weighted sum, minimum score, maximum score or product rule. In fusion at the decision level, accept/reject decision of multiple systems is consolidated into unique decision. This can be performed either by voting, weighted voting (in which each system is given a weight according to its accuracy) or decision trees. Fusion at the decision level is considered to be rigid due to the availability of limited information 0. It is generally believed that a combination scheme applied at an early stage for example at sensor or feature level, in the recognition system is more effective than at a later stage (decision level).

4.1 Fusion Techniques: Palm Vein as Modality

In 0, the authors collected palm print and palm vein images from 500 different volunteers from the Shenzhen Graduate School of Harbin Institute of Technology and The Hong Kong Polytechnic University. For palm print, orientation texture-based coding features were extracted and for palm vein, matched filters based coding features were extracted. Hamming distance was used as a distance measure in both the cases to obtain individual matching scores. Fusion, after normalization, was then performed at score level to obtain a Genuine Acceptance Rate (GAR) of 99.7% in the verification mode. In 0, palm vein and signature biometrics were fused at feature level. A database of 37 palm vein image and signatures was collected from employees of Center of Scientific Computing located in Mansoura University. Features extracted (Morphological and SIFT features) were concatenated using a simple sum rule. The dimensionality of the resultant feature vector was reduced using Discrete Cosine Transform (DCT) algorithm. The feature vector is then fed to LVQ classifier. A Genuine Acceptance Rate (GAR) of 96.98% is obtained using this system. Feature level fusion of palmprint and palm vein images using 16, entropy based features with a recognition rate of 99% has been proposed in 0.As feature level fusion was performed; normalization is avoided, thus simplifying the verification process.

4.2 Fusion Techniques: Face as Modality

In0, M.I.Ahmed et al, introduced a multimodal biometric system for face and palmprint images using fusion techniques at the feature level. Gabor based image processing is utilized to extract discriminant features, while PCA and LDA are used to reduce the dimension of each modality. The output features of LDA are serially combined and classified by a Euclidean distance classifier. The experimental results based on Olivetti Research Laboratory (ORL) face and Hong Kong Polytechnic University (Poly-U) palm print databases, with 40 individuals, yielded a recognition rate of 99.5%. Sheetal Chaudhary et al in0, presented a multimodal biometric system integrating palm print, fingerprint and face based on score level fusion. The block diagram of the system is shown in Fig.7. In this system, different feature extraction techniques are applied for each modality; PCA is used for feature extraction of palm print and face, while a minutia matching is used for fingerprint feature extraction. The matching score between two palm print(and eigen face) feature vectors was calculated using the Euclidean distance while a similarity score is generated for minutiae based finger print matching. The matching scores from the individual recognizers are then passed to the fusion module. A GAR of about 95% was obtained.

4.3 Fusion Techniques: Palm Vein and Face as Modalities

In 0, S.F.Bahgat et al, proposed a bi-modal biometric authentication system that fuses the features of the palm veins with that of the face. The palm vein and face images were collected for 18 persons. The functional flow of the system is shown in Fig.8.

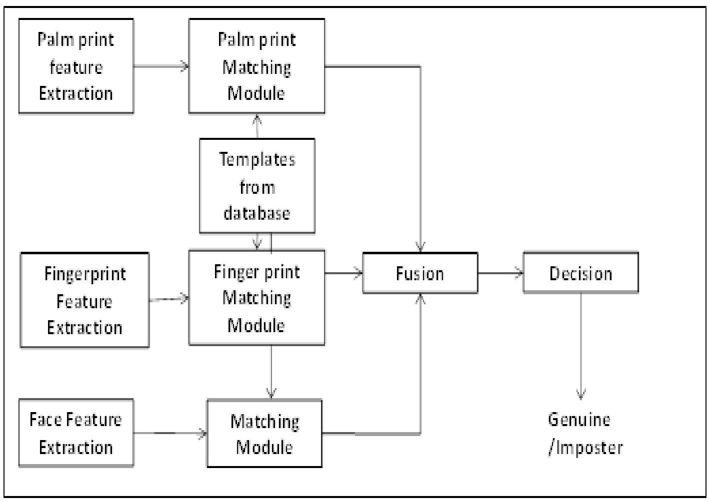

Fig.7 *Block-diagram of the multimodal biometric recognition system using Palm print, fingerprint and face features*

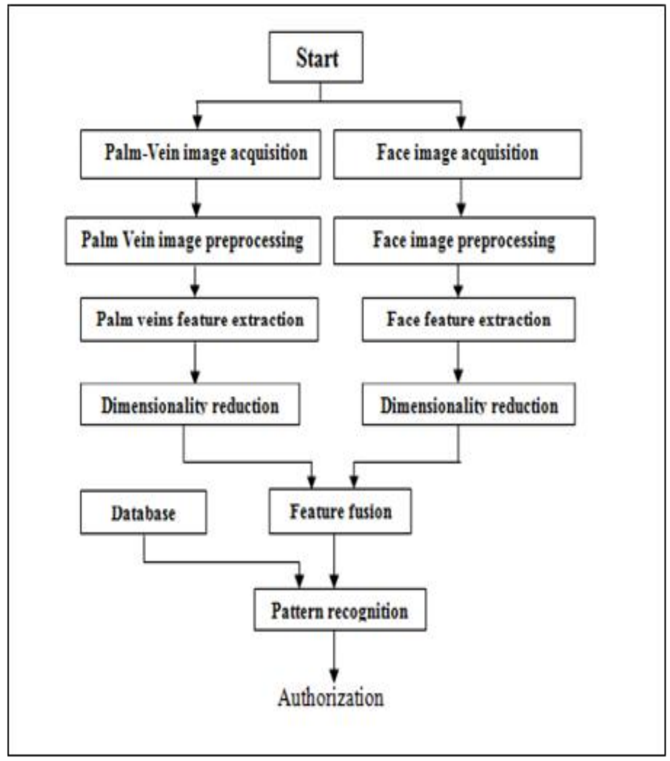

Fig.8 *Functional Flow of Bimodal System using Palm Vein and Face 0*

Among all the approaches studied, Moment Invariants (MIs) feature vector guaranteed better recognition rates. Fusing the MI feature vectors improved the recognition rate by 30% 0. A recognition rate of 96.22% was obtained in verification mode even when the input images were corrupted with noise (salt and pepper) in this system. In Table.I, the recognition rates of the multimodal biometric systems discussed above are compared. It can be seen from the table that, the recognition rates of multimodal biometric systems are significantly high (above 95%).It can also be noted that fusion at feature level (by concatenating features of different modalities), seems to be the preferred technique in multimodal biometric authentication as feature level data has richer raw data information of the biometric trait without the additional complexity of normalization during fusion.

TABLE 1. *RECOGNITION RATE OF MULTIMODAL SYSTEMS IN VERIFICATION MODE*

Biometric Traits	Fusion level	Fusion Technique	Normalization	Database details	Recognition Rate (%)
Palm Vein and Palm Print	Score level	weighted sum rule	Yes.	500 (local)	99.7
Palm Vein and Signature	Feature Level	Concatenation	No	37 (local) 5 training and 5 testing	96.98
Palm Vein and Palm Print	Feature Level	Concatenation	No	100 (local)	99

Face and Palm Print	Feature Level	Concatenation	No	40 (ORL & Poly-U) 5 training and 5 testing	99.5
Face, Palm print and Fingerprint	Score level	weighted sum rule	Yes	Not indicated	95
Palm Vein and Face	Feature Level	Concatenation	No	18 (local)	96.22*

**Recognition rate obtained on input images that are corrupted with noise*

5 CONCLUSIONS
In this paper, a survey of various techniques for face, palm vein recognition and fusion of both the modalities was presented. Owing to its non-intrusive nature, person authentication based on face recognition has good user acceptability and such systems have reached a certain degree of maturity when operating under constrained conditions. However, they have not been able to achieve reliable performances where factors like pose, occlusion, illumination conditions, expression, etc. cannot be controlled. Feature based face detection techniques have overcome some of the limitations. In these techniques, depending upon the actual condition, it may be necessary to use more features thus increasing the dimensions of the feature vector. Reduction in dimensionality can be achieved by selecting optimal features. However, automating feature detection and selection process, to reduce dimensionality, remains an open issue in these techniques. Holistic approaches have been successful in reducing dimensionality while achieving good recognition rates. However, retaining discriminative information, while reducing computational complexity, is a challenge. Though 3D face recognition techniques seem to overcome the problem of occlusion that can be seen in 2D face recognition systems, they are computationally expensive. Designing systems that are invariant to factors like age which affect the permanence of the face biometric also remains an open problem in this area. Palm veins present some desirable properties like high permanence and distinctiveness that help in discriminating different classes accurately. It is also difficult to spoof, since vascular patterns lie under the skin and is not affected by adverse sensing environments. These advantages, in addition to high recognition rates, make palm vein based recognition a favored technology at high security establishments. However, palm vein based recognition is relatively new technology and has not been explored fully for real-world applications. There is a need to develop new algorithms and techniques that will exploit the full potential of palm vein based recognition. Creating fast and modality-dependent feature extractors is one of the open challenges in this field. Another challenge faced by the researchers is to reduce noise in the palm vein images due to illumination, external light intensity and temperature conditions. Reducing the computational complexity and shortening the authentication time are goals to be achieved in future.The performance of face based recognition systems, affected by factors like pose and illumination, can be enhanced by combining it with a different modality. Palm vein being statistically independent (with face) and difficult to spoof, is ideal for such fusion. Fusion can be achieved at different levels. However feature level fusion is preferred, as it contains richer information about the raw biometric data and can be made invariant to size, orientation and lighting. Fusion at feature level also ensures that the additional complexity of normalization, needed at score level fusion, is not needed. However, fusion of features results in high dimensional feature vector which increases computational complexity and makes the classifier design complex. Thus dimensionality reduction and the problems faced by individual modalities need to be addressed to reduce the computational complexity and time. Simple algorithms, to achieve real time recognition performances in practical applications, need to be designed.

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