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Finger Knuckle Print Recognition Techniques-A Survey

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ABSTRACT

Biometric traits are now highly explored by researchers to establish a system that can be used to accurately identify a person. Personal identification based on biometric features is becoming more popular these days because it is more reliable than traditional methods and has got numerous applications. The performance of such a system depends on the biometric characteristic that is utilized. Many traits like fingerprint face iris, palm vein, DNA and many others have been used for personal identification. One new biometric trait that has attracted researchers in the recent years is the finger knuckle print. The finger knuckle print refers to the inherent skin patterns that are formed at the joints in the finger back surface. Recently it has been found that the finger knuckle print is highly rich in textures and can be used to uniquely identify a person. Hand based biometrics have the advantage of higher user acceptability and this new trait has an added advantage of not getting easily damaged. This paper presents some of the methods used by the researchers for acquisition and techniques used for recognition systems based on finger knuckle print. Most of the researchers have made use of the database containing 7920 samples collected from 660 individuals that is publicly made available by the Hong Kong Polytechnic University. Performance comparison of the different techniques proposed in the literature is also presented.

KEYWORDS *: Biometrics, finger knuckle print, features, recognition system.*

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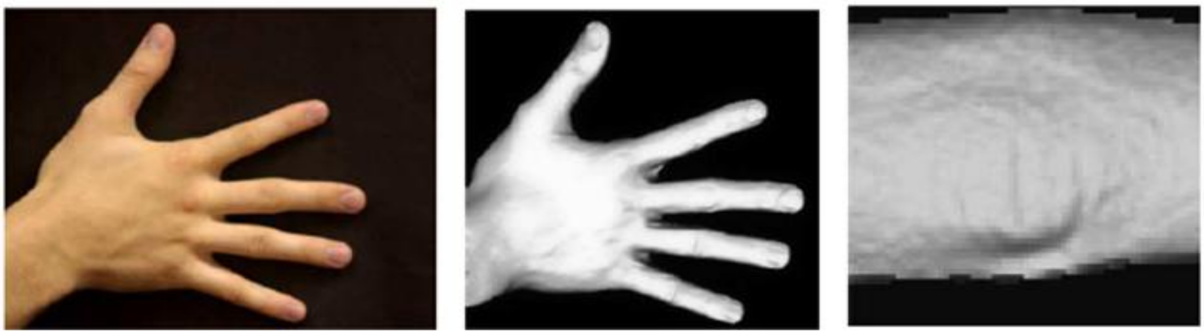
I. INTRODUCTION

Biometric features have been widely used in personal authentication system because it is more reliable when compared to conventional methods like knowledge based methods e.g. password, PIN number and token based methods eg.passports, ID cards. Different physical or behavioral characteristics like fingerprint, face, iris, palmprint, hand geometry, voice, gait, signature etc., have been widely used in biometric systems. Among these traits hand based biometrics such as palmprint, fingerprint and hand geometry are very popular because of their high user acceptance. Recently it has been found that image patterns of skin folds and creases, the outer finger knuckle surface is highly unique and this can serve as distinctive biometric identifier [19]. It has got more advantages when compared to finger prints. First it is not easily damaged since only the inner surface of the hand is used widely in holding of objects.. Secondly it is not associated with any criminal activities and hence it has higher user acceptance [17]. Third it cannot be forged easily since people do not leave the traces of the knuckle surface on the objects touched/ handled. Also the FKP is rich in texture and has a potential as a biometric identifier. The rest of this paper is organized as follows: Section 2 discusses about the various methods used for capturing finger knuckle print (FKP), section 3 summarizes the various technique used for personal identification system based on FKP and section 4 the concluding remarks

II. FINGER KNUCKLE PRINT ACQUISITION

Woodward and Flynn are the first scholars who made use of the finger knuckle surface in their work. They set up a 3D finger back surface database with the Minolta 900/910 sensor. This sensor captures both a 640x 480 range image and a registered 640x480 24 bit colour intensity image nearly simultaneously. The sensor dimensions are 213mm x 413mm x 271mm and it weighs around 11 kg. The sensor cost, size and weight, limits the use of this sensor in a commercial biometric system. During data collection, the sensor is positioned approximately 1.3 m from a flat wall which has been covered with a black piece of cloth. Black cloth was chosen as the background to simplify the hand data segmentation task. Prior to data collection, the subject was instructed to remove all jewelry. The presence of jewelry during range image capture causes the emitted light from the sensor to scatter when contact is made with its reflective surface. The result is missing or inaccurate range image data near and at that location. The subject was instructed to place his or her right hand flat against the wall with the fingers naturally spread as the image is captured. Between image captures, the subject is instructed to remove his or her hand from the wall and then return it to approximately the same position. A total of 1191 hand range images were collected by the researchers which are publicly available.



(a) (b) (c)

Figure 1 (a) intensity image sample (b) range image sample (c) range image detail

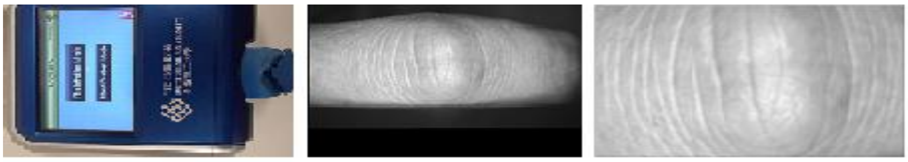
Figure1 (a) shows a sample 640x480 color image of a hand. Figure 1(b)is a pseudo intensity of the same hand rendered using the 640x480 range image as a polygonal mesh. Figure1(c) depicts the surface detail detected near a knuckle. The only requirement for hand placement is that the fingers are placed such that there is space between two adjacent fingers. No constraints like pegs were used for acquiring the images. After preprocessing and segmenting the fingers they used the 3D range image of the hand to calculate the curvature surface representation of the index, middle and ring fingers. Normalized correlation coefficient was used for similarity comparison.[18]

Next C.Ravikanth et al.[19] developed a system for acquiring the finger back surface images. This imaging system uses a digital camera focused against a white background under uniform illumination. The camera has been set and fixed at a distance of 20 cm from the imaging surface. Non-uniform illumination cast shadows and reflections at the hand boundaries which significantly reduces the performance. Therefore, the image acquisition is uniformly illuminated by a fixed light source above the hand. The resolution of the acquired image is 1600 x 1200 pixels. Each subject is requested to place the hand on the support with their back hand facing the sensor. The subject can visualize the placement of their hand from the live-feedback on small plasma display. The acquisition of a sample image is shown in figure 2(b).

(a) **(b)**

Figure 2 (a) acquistion of finger back image (b) acquired image

Next Lin Zhang et al. [1] development a system for FKP acquisition. This consists of four components FKP image acquisition, ROI (region of interest) extraction, feature extraction and feature matching. The figure 3(a) shows the FKP recognition system, Figure 3(b) shows the captured image and figure 3(c) the extracted ROI which is now publicly available in the PolyU database. The FKP images were captured using this device in figure from 165 persons. The people who provided the database were in age group from20-50 years. The samples were collected in two different sessions and the time interval between these two sessions was around 25 days. Six samples was collected from left index, left middle, right index and right middle fingers of each person and thus a total of 48 samples was available. The database thus consists of 7920 images from 660 fingers.



(a) (b) (c)

Figure 3 (a) FKP recognition System (b) Captured image (c) extratcted ROI

III. RECOGNITION ALGORITHMS

A bio metric system can recognize a person based on the algorithm built in to the system. These recognition algorithms are generally of two types1) Identification algorithm which computes the template of the user and compares it with the templates stored in the database. It is also referred to as one to many matching. 2) Verification algorithm requires identity such as ID card, smart card or ID number for authentication. The user template is then matched with the master template for recognition. It is also known as one to one matching. The verification algorithms must be accurate and identification algorithms must be accurate and very fast. The performance of a biometric system is based on the error rates. Two types of error rates are defined; False Acceptance Rate (FAR) and False Rejection Rate (FRR).They are defined as:

$$FAR = \frac{Number\ of\ false\ acceptances}{Total\ munber\ of\ impostor\ attempts} \qquad (1)$$

$$FRR = \frac{Number\ of\ false\ rejections}{Total\ munber\ of\ genuine\ attempts} \qquad (2)$$

The threshold value at which the FAR equals the FRR value is called the Equal Error Rate (EER) [30].The accuracy of the biometric system is defined as:

$$\text{Accuracy} = \max\ (100 - (FRR+FAR)/2) \qquad (3)$$

The same formula was used by Rattani et al. in [26]

The recognition algorithms proposed in the literature may be grouped under the following categories (i) Subspace based methods (ii) Coding methods (iii) Other methods (iii) fusion methods. Some of the algorithms are discussed as follows.

3.1Subspace based Methods

The subspace techniques [2, 3, 14, 27] that can create spatially localized features are receiving increasing attention in the literature. Such techniques are expected to be more tolerant to the occlusion as the localized features help to implement region-based identification [19].These techniques include Principal Component analysis (PCA) Linear Discriminant Analysis (LDA) and Independent Component Analysis (ICA).The subspace coefficients are used to represent the feature vector and for matching distance measure or classifiers are employed. They are also used for dimensionality reduction,

Jun et al.[14] proposed a new linear feature extraction approach called Weighted Linear Embedding(WLE).It combines Fisher criterion with manifold learning criterion like local discriminant embedding analysis. From the manifold learning theory it is understood that local information is more important than non local information and hence both these features are extracted. Gaussian weighting is utilized to combine local and non local information.WLE aims to find a mapping vector such that the ratio between weighted class scatter to the weighted within class scatter is maximized. The classification is based on the nearest neighbor classifier. The authors have also tested the same algorithm on palmprint and have made a comparative study of PCA, LDA, LDE and WLE .The WLE is applied on right index finger of 1000 persons and a recognition rate of 78.2%is achieved.Yang et al. [2] inspired by the work that Gabor wavelets have been applied successfully in image analysis and pattern recognition, used it for feature representation in FKP. PCA was used to transform Gabor features in to low dimensional space. Further orthogonal linear discriminant analysis (OLDA) transformation in

PCA subspace is done and classified using nearest neighbor classifier and efficiency as high as 98% was obtained. This paper compares the performance of the individual fingers and shows that the left index finger provides better performance.Jing et al.[3]simultaneously considered distances and angles between image data vectors to measure data similarities in hope of more sufficiently capturing the manifold structure. In order to highlight the distinction among angles between different data and enhance the complimentary information of angles compared with distance, a

new type of image angle measurement in a shifted image space that is centered at the data mean is proposed. Both angle and distance are fused using the parallel fusion strategy based on which the complex locality preserving projection is used extract the low dimensional feature that can better preserve the manifold structure of the input data set. In order to remove the redundant information, orthogonal complex locality preserving projections (OCLPP) is used. Four images were randomly selected during the training process and recognition rate of 88% was achieved for the left index finger. This method is compared with other subspace methods like PCA, CPCA, LPP, CLPP and OCLPP in their proposed work.

3.2Coding Methods

Different coding algorithms are proposed in the literature. [5, 13, 15, 17] and basically iris code is the foundation of these coding algorithms. These coding techniques have been used widely for palmprint recognition [21, 22, 23, 24, 25, 29] and have provided good recognition results. The finger knuckle surface is highly rich in lines and creases which are curved but are highly unique in individuals. Hence Ajay Kumar [17] in his work exploited the local information in comparison to the global information for reliable performance. The preprocessing step accentuates texture features and helps to cope with illumination variations. To avoid wrap around due to inherent modulo operation Finite Radon Transform (FRT), the Modified Finite Radon Transform (MFRT) is used to efficiently and effectively ascertain the orientation of the knuckle lines/greases in the local neighborhood region. The dominant direction at every pixel is then coded using b binary bits and it is known as the knuckle code. Normalized Hamming distance was used for similarity measurement and provided a recognition accuracy of 98.6%. Lin et al.[13] designed a system to capture FKP images and proposed a method to align the FKP images by adaptively constructing a local coordinate system for each image. The bottom of the FKP image is stable because of acquisition method. Hence this is considered as X axis of the ROI coordinate system by fitting this boundary as a straight line. A curve model for FKP was established and the convexity magnitude is determined. This magnitude will reach the minimum at the center of the phalangeal joint and this position can be used to set the Y axis of the coordinate system. Once this coordinate system is fixed then an ROI sub image of 110 x 220 is extracted. Gabor filtering is used from which the orientation information is extracted and represented as Competitive Code. Angular distance is used for matching and an EER of 1.09% was achieved. Next the author in [1] developed an Improved Competitive and Magnitude code by extracting the orientation and magnitude information using Gabor filters .These features are used to set up a code map based on the competitive code. Angular distance and magnitude distance is computed for the code maps during matching. The two distances are fused and the minimum of the resulting distance is considered to be the final distance. The proposed method is compared with the other standard coding methods and found to show better performance. Fusion of features from all four fingers resulted in an equal error rate (EER) of zero percent.

Lin et al. [15] proposed a fast feature extraction and coding method called the Monogenic code based on the Monogenic signal theory and is used for FKP recognition. For a two dimensional signal f(x) the monogenic signal is defined as the combination of f and its Riesz transform which is a vector valued extension of the Hilbert transform in the 2D Euclidean space. The code represents each pixel as a 3 bit code obtained by extracting the signs of the three components of the monogenic signal. It reflects the local orientation and phase information of the pixel under consideration. This method is shown to achieve similar verification accuracy in comparison to the state of art FKP verification methods. Lin Zhang et al. [5] used coding method because they have the merits of high accuracy, robustness, compactness and high matching speed. Hence, based on the findings that Riesz transform can well characterize the visual patterns this work proposes to encode the local patches of FKP images by using second order Riesz transform. A six bit coding scheme namely the Riesz Compcode was developed. This code integrates the advantages of Riesz transform and Compcode in characterizing the local image features together. At the matching stage the normalized Hamming distance is employed. This coding scheme is shown to have a better performance in terms of verification accuracy when compared to other coding based methods.

3.3Other Methods

In the literature [7, 8, 11, 16] various image processing techniques are employed either independently or combined to extract the texture, local, global or line feature from the finger knuckle print. The local and global information have been combined [8.11] to provide more information and better recognition results. To explore FKP recognition technology Zhu Lei Quing [9] proposed a robust FKP feature presentation and matching method based on Speeded-Up Robust Features (SURF). It is an improvement on scale invariant feature transform. First a coordinate system is defined based on the local convex direction map of FKP to align the images and a ROI is cropped for feature extraction. Secondly the key points are extracted using Fast Hessian detector to which an orientation was assigned accordingly to the Haar wavelets responses inside the neighbor circle area of the keypoint and an orientation invariant descriptor is constructed for each key points. In matching the distance of the closest neighbor that of the second closest neighbor is compared and all matches in which the distance ratio is less than 0.6 is retained. Thus the initial tentative correspondence between two key point set of training image and template are got. Then RANdom SAmple Consensus (RANSAC) is employed to establish a geometric constraint for removing the false matching. The amount of final matched point pairs is referred to decide the consistency of the palm images. This method is invariant to rotation, scale and view point changes which proves its robusticity. The method provides an accuracy of 90.63% for verification and 96.91% for identification.

Lin et al. [11] based on the results of psychophysics and neurophysiology studies which show that both global and local features are crucial for image perception, proposed, the Local Global Information Combination (LGIC) technique. For local feature extraction, the orientation information extracted from Gabor filters using four scales and six orientations is coded using the competitive coding scheme. This method is suitable for images containing abundant line like structures and has the advantages like high accuracy, robustness to illumination variations, and fast matching. Next the scale of the Gabor filter is increased to infinity by which the Fourier transform of the FKP image is obtained. The Fourier coefficients of the image are taken as the global feature. For matching two competitive code maps, angular distance based on normalized Hamming distance is used. Band Limited Phase Only Correlation (BLPOC) is used to measure the similarity between Fourier transforms (Global Information) of the images. Thus the local and global features are matched separately and two distances, d1 and d2 is achieved which are fused according to the Matcher Weighting (MW) rule distance. An Equal Error Rate (EER) as low as 0.402 is achieved using this technique. Rui Zhao et al.[16] proposed a novel approach using a single knuckle print only, for personal identification. This method reduces the burden of a large data base to train the classifier. The edges of an image are characterized by discontinuities in the gray levels. Thus the main lines in a finger knuckle print are the result of grey level discontinuity. Hence to eliminate the noise and to extract the main lines a self defined convolution template of 3x5 is in the spatial domain is used as a gradient operator for edge detection and extracting the line features. Further he used a method to reduce the possibility of wrong decision that may be caused by the variation in the precise location of the acquisition device of the different standing posture of the user during the collection of images. Eight different images were obtained by translation operation and this along with the original image totaling to nine was used for confirming the user's identity by maximum of cross correlation coefficient. The experiments verified that the knuckle print is reliable as one of the biometric traits and provided a recognition rate of 95.68% at 30 threshold value.

Z.S.Shariat Madar and Karim Faez [7] in their work used a bank of Gabor filters to extract the orientation information from the FKP images. Five different scales and eight different orientations were selected keeping the remaining parameters constant Next principal component analysis is applied for dimensionality reduction. Since a combination of PCA and LDA provides good effect on feature selection LDA is applied on PCA weights. Euclidean distance is used for matching .The proposed algorithm was tested on all four fingers and it is found that right middle finger provides better performance with an recognition rate of 75.25%.Feature level information fusion was carried out for different finger combinations and a maximum recognition rate of 98.79% was obtained for all four fingers.

3.4 Fusion Method

Fusion is a promising technique that is used to increase the accuracy of the biometric systems [20]. Different biometric traits are combined using different fusion methods[2,4,6,8.27] These include (i) Sensor level fusion (ii) Feature level fusion (iii) Rank level fusion (iv) Sore level fusion. In finger knuckle print recognition score level fusion has been used widely.Z.S.Shariat Madar and Karim Faez [8] proposed an efficient method for FKP recognition by using information fusion at different levels. For each image two feature vectors were extracted. The ROI image was divided in to twenty two segments of 1100 pixels each and Average Absolute Deviation (AAD) was computed in individual segments.

Next for the same ROI, Log Gabor transform of five scales and ten orientations is obtained and for each of these fifty images, the AAD is computed. By this process 1100 features were obtained. For dimensionality reduction, a combination of PCA and LDA algorithm was applied and 164 most important features were selected. The two feature vectors were combined and minimum Euclidean distance was used for comparing. Two experiments were conducted in which each finger was evaluated separately and then different combinations of the fingers were used to get the best recognition result. Left index finger gave an accuracy of 89.9% and the fusion of all four fingers provided 96.56% using feature level fusion.Abadallah Meraoumia et al.[4] have designed a biometric recognition system based on the fusion of FKP and palmprint modalities. This scheme uses Phase Correlation Function (PCF) for matching. Two dimensional DFT of the palmprint image to be verified and registered are obtained. The cross correlation of the two dimensional inverse DFT of the phase components is got. This is known as PCF. The PCF has a distinct impulse which is used for matching. When two images are similar, the PCF gives a distinct sharp peak and when they are different the peak drops significantly. Analysis is done for separate fingers and the right index finger is shown to have better performance. The two modalities are combined and fusion at matching score level is applied. L.Shen et al.[2] in his work aims to improve the accuracy of the personal identification when only a single sample is registered as a template by integrating multiple hand based biometrics i.e. the Palmprint and FKP. To extract Gabor features for the palmprint, the image is convolved with a set of wavelets of different frequencies, orientations and scales. A two bit code representing the local feature information at a pixel is then defined. The same process is applied to the FKP images and a fusion code is obtained. Then the scores are combined at decision level fusion strategy and Hamming distance measure is used to calculate the similarity between two subjects.

Y.Zhang et al.[6] presents a novel approach by fusing two kinds of biometrics i.e. palmprint and middle inner surface of the finger. Discriminant features are obtained by combining the statistical information and structural information of each modality which are extracted using locality preserving Projections (LPP) based on wavelet transform to reduce the effect of affine transform, mean filtering is used to enhance the robustness of the structural information in order to improve the discriminant ability of the high frequency sub bands in the palmprint. The two types of features are fused at score level for the final hand based single sample bio metric recognition. A recognition efficiency of 99.56% is obtained.

A summary of the techniques discussed above is given Table I and Table II

Table I:A summary of first three methods

Method	Technique	Database Size		Classifier	EER	Recognition rate
		Class size	No of samples			
Sub space based method	Principal Component analysis(PCA)	100	12	Nearest Neighbor Classifier		55.7
	Liner Discriminant Analysis (LDA)	100	12	Nearest Neighbor Classifier		76.0
	Liner Discriminant Embedding(LDE)	100	12	Nearest Neighbor Classifier		76.2
	Weighted Linear Embedding	100	12	Nearest Neighbor Classifier	-	78.2
	Gabor Feature and OLDA	165	12	Nearest Neighbor Classifier		98.06
	Orthogonal Complex Locality Preserving Projections	165	12	Fused angle and Euclidean distance		87.87
Coding Methods	Modified Finite radon Transform	158	5	Distance measure	1.14	98.6
	Competitive Code	165	12	Angular distance	1.09	97.96
	Improved Competitive Code and Magnitude Code	165	12	Angular distance	1.48	-
	Monogenic Code	165	12	Hamming distance	1.72	
	Riesz Transform based coding	165	12	Hamming distance	1.26	
Other Methods	Speeded-Up Robust Features	165	12	RANSAC matching strategy		96.91
	LGIC technique	165	12	Hamming distance and BLPOC	0.402	
	Edge detection	98	-	Cross Correlation coefficient		95.68
	Gabor filter +PCA+LDA	165	6	Euclidean distance	-	89.9

Table II A summary of fusion method

Method	Technique		Database Size: Class size	Database Size: No of samples	Fusion level	EER	Recognition rate
Fusion Method	Curvature based shape index	Multiple fingers	86	8	score level fusion		98
	PCA+LDA+ICA	Multiple fingers	105	6	score level fusion		98
	Gray level intensity + Log-Gabor feature	Multiple fingers	165	6	feature level fusion		96.56
	Gray level intensity + Log-Gabor feature	Multiple fingers	165	6	score level fusion		95.45
	2D-DFT	Palmprint and FKP	150	12	score level fusion		
	Locality Preserving Projection	Palmprint and FKP	100	10	score level fusion		99.56
	Directional coding and ridgelet transform	Palmprint and FKP	50	10	SVM based score fusion	.0034	

IV. CONCLUSION

Finger knuckle print is anew biometric trait that has entered the biometric family a few years ago. It contains curved line like structures and is rich in texture. Different image processing techniques that were used in personal identification biometric systems have been applied to finger knuckle print and shows promising results. From the above discussions it may be seen that fusion techniques results in high recognition rates. Only a very few works has been reported in this area and it has scope for expansion

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