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A NOVEL PERSONAL AUTHENTICATION USING KNUCKLE MULTISPECTRAL PATTERN

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ABSTRACT

With the increased use of biometrics for identity verification, there have been similar increases in the use of unimodal biometric system. The finger knuckle print recognition is one of the newest biometric techniques research today. In this paper, one of the reliable and robust personal identification approaches using finger knuckle print is presented. Many researchers are going on in face, finger print and iris recognition and which finds its usage in many applications. These biometric which find its usage in many applications are easily duplicated for fraudulent activities. But the finger knuckle print recognition is the unique pattern to identify the individuality at a high level of accuracy. This paper proposes new algorithms for finger knuckle print recognition using SIFT algorithm and this algorithm presents, extracting a new original constant features from images As the proposed method matches the different angles of finger knuckle print with the database, its reliability is very high when compared to other biometrics. The features of SIFT which are invariant to image scale and rotation, are shown to provide robust matching across a substantial range of fine distortion, change in 3D viewpoint, addition of noise, and change in illuminance. The features are highly distinctive, in the sense that a single feature could be correctly matched with high probability against a large database of features from many images.

Keywords: unimodal, SIFT, finger knuckle print, biometric, recognition.

INTRODUCTION

Finger knuckle prints have been used to secure commercial transactions where the finger knuckle prints have been found among the ruins on clay seals attached to business documents. Each finger knuckle print contains cosmic features, which can be seen with the plain eye, and local features, also called minutiae points, the tiny, unique characteristics of finger knuckle print ridges. As, ridge patterns can be looped, arches, or whorls; minutia types associated with a ridge pattern include ridge endings, bifurcations, divergences (ridges so small that they appear as dots or islands), and closures points (Ridges that bifurcate and reunite around a ridge less area).

Finger knuckle print scanners detect ridge patterns are very small then it will be indicate the some trivial details based upon the orientation (the direction the minutia are facing), spatial frequency (how far apart the ridges are around a particular mark), curvature (rate of orientation change), and location (X, Y points are relative to some fixed point). There is about 60 to 70 minutia points on everyone finger, and even match have different minutia points. These details are describing the very small points and provide the crucial components of the patterns are calculated from the enrollment and advance sample pattern. Whereas Police finger knuckle printing stores the entire image, finger knuckle print scanning systems store only the instruction. A pattern image cannot be created from its data pattern alone. An original image cannot be constructed from its data template alone. Some of the complication that alters unimodal biometric systems can be alleviated by using multimodal biometric systems.

Hand-based person identification provides a reliable, inexpensive and easy to use viable solution for a range of access control applications. In fact, in contrast to other modalities like face and iris, the human hand contains a extensive collection of modalities, which are fingerprinted, hand geometry, palm print and Finger-Knuckle-Print (FKP). These modalities can be by far used by biometric systems because of some advantages that the biometric of human hand offers. First, data acquisition is relatively easy and economical via commercial low-resolution cameras. Second, hand-based access systems are very suitable for indoor and outside usage, (acceptance) and can work well in extreme elements and illumination conditions. Third, hand features of adults are more stable over time and they are not susceptible to major changes. Finally, human hand-based biometric information is very reliable and it can be successfully used for recognizing people among several populations.

Most of the biometric systems which are currently used, typically use a single biometric trait to establish identity (i.e., they are unibiometric systems). With the proliferation of biometric-based solutions in civilian and law enforcement applications, it is important that the vulnerabilities and limitations of these systems are clearly understood. Some of the challenges generally experienced by biometric systems are listed below.

a) Noise in sensed data: The biometric data being presented to the system may be contaminated by noise due to imperfect acquisition conditions or subtle variations in the biometric itself. For example, a defect can change a subject's fingerprint while the common cold can alter the voice characteristics of a speaker. Similarly, unfavorable illuminance conditions may significantly affect the face and iris images acquired from an independent. The noisy data can result in an independent being incorrectly labeled as an impostor thereby improves the False Reject Rate (FRR) of the system.

b) Upper bound on identification accuracy: The matching performance of a unibiometric system cannot be continuously improved by tuning the feature extraction and matching modules. There is an constant upper bound on the number of distinguishable patterns (i.e., the number of distinct biometric feature sets) that can be represented using a patterning. The capacity of a patterning is strained by the variations observed in the feature set of each subject (i.e., intra-class variations) and the variations between feature sets of different subjects (i.e., inter-class variations). As error rates associated with four biometric modalities - fingerprints, face, voice, iris- are very less they for novel public tests. These statistics suggest that there is a tremendous scope for performance improvement, especially in the context of large-scale authentication systems.

c) The Multimodal systems establish identity, based on the evidence of multiple biometric attributes. For example, some of the earliest multimodal biometric systems utilized face and voice features to establish the identity of an individual. Physically uncorrelated traits (e.g., fingerprint and iris) are expected to result in a better improvement in performance than correlated traits (e.g., voice and lip movement). The recognition accuracy can be improved by utilizing an increasing number of traits, although the dimensionality phenomenon would impose abound on this number. The dimensionality limits the number of attributes (or features) used in a pattern classification system when only a small number of training samples is available Takita (2012). The number of traits used in a specific application will also be restricted by practical considerations such as the cost of distribution, enrollment time, throughput time, normal error rate etc.

RELATED WORK

Different approaches have been proposed in the literature for developing unimodal and multimodal biometric systems. Multi-biometric systems are developed by fusing different biometric features pertaining to various biometric modalities at different levels. Many researchers have shown that the multimodal systems outperform the unimodal systems, giving better discrimination of genuine from imposters. A unimodal finger knuckle print-based identification system is presented in Liao (2009). For system development, firstly, a simple alignment method called direction, alignment based on morphology was used.

Then, for database development, finger knuckle print features were extracted from ROIs and classified into Local Features, Global Features and Combination Features. Finally, Euclidian distance classifier differentiates between genuine and imposters. Chang and Lin (2001) proposed finger knuckle print Recognition based on binarization methods and neural Network. In the paper, binarizations are utilized as knuckle features and a neural network (NN) is used as a classifier. Experimental results on PolyU knuckle print database Gayathri Ramamurthy (2012) have demonstrated the identification (99.5%) and recognition (98.7%) rate of the proposed method. In the approach proposed in Michael (2010), SIFT fingerprint feature is used for fingerprint matching. SIFT is used to find minutiae pairs, which are further used for a preliminary matching to ensure reliability and for fine matching to overcome possible distortion. Snelick *et al*. (2012) present a multimodal biometric authentication system using fingerprint and face biometric systems with a population of 1,000 individuals. After normalizing the scores, different fusion methods, including Simple-Sum (SS), Min-Score (MIS), Max-Score (MAS), Matcher Weighting (MW) and User Weighting (UW) are utilized. The minimum EER achieved out of these methods is 0.63%. Debole and Sebastiani (2003) proposed a multimodal system by combining palm print and finger knuckle print. For fusion purposes, matched minutiae scores from fingerprint images are combined with the scores of palm print images that are based on distance of feature vectors. Cortes and Vapnik (1995) combined palm print and palm vein images to develop a multimodal system at image level fusion. Integrated Line preserving and contrast enhancing fusion methods are used to perform fusion. Fused images are obtained by combining modified multiscale edges of palm print and knuckle print images. The resultant interaction points (IPs) of the palm prints and finger knuckle print image contrast are enhanced. The Laplacian palm feature is extracted from the fused images and further used for recognition purposes.

MATERIALS AND METHODS

Data acquisition

A snapshot of a specified knuckle region is captured by a CCD camera under a wavelength range of near Infrared - (700nm-1400nm). Need of near Infrared range in the acquisition stage of knuckle image is required to detect the vein because the vein carrying deoxygenated blood absorbs this range while the rest of the knuckle like skin, hair and arteries reflects this range of illumination. Array of LED source illuminating NIR wavelength is

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placed around the CCD camera in the form of concentric circular structure. The Figure-1 shows the setup of the captured knuckle image viewed on PC a structure of dark patterns is visible on the hands which are knuckle patterns due to penetration. Figure-2 shows the snatch finger knuckle image is applied to various enhancement techniques. The proposed algorithm is simulated on the PolyU FKP database.

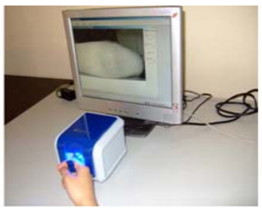

Figure 1. FKP device.

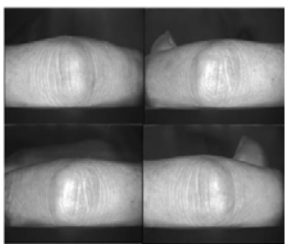

Figure-2. A captured digital finger knuckle image.

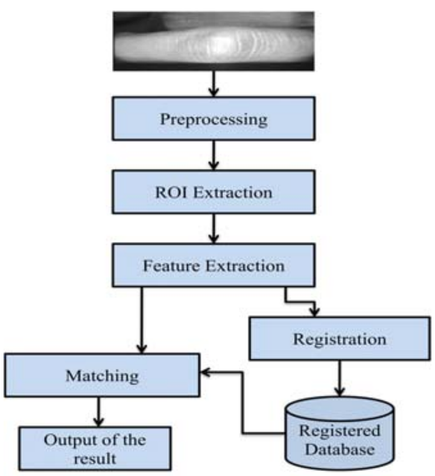

Figure 3. Structure of the proposed FKP-based personal authentication system.

The Figure-3 represents the proposed method of the finger knuckle print authentication system. It based on the preprocessing, feature extraction, matching and classification. The unimodal biometric involves for FKP modalities are image matching and classification module. The matching between the registered and registration image. Depends on the separate matching score, a final decision made (the user is identified or rejected). This improved structure takes advantage of the proficiency of each unimodal biometric and can be used to overcome some of their limitations.

The captured image is converted from RGB to grayscale format. If we convert the grayscale format it easy to identify the matrix value, because in grayscale format only have black and white images. When capturing a knuckle print, the position, direction and stretching degree may vary from time to time. As a result, even the knuckle prints from the same knuckle could have a little rotation and translation. Also, the sizes of knuckle are different from one another, so the preprocessing algorithm is used to align different knuckle prints and extract the corresponding central part of feature extraction. In our knuckle print system, both rotation and translation are constrained to some extent by the capture device panel, which positions the knuckles with several pegs. Then, the images to be registered often have scale differences and contain noise, motion blur, haze and sensor nonlinearities. Pixel sizes of FKP images are generally known and therefore, either image can be resampled to the scale of the other, or both images can be resampling to the same scale.

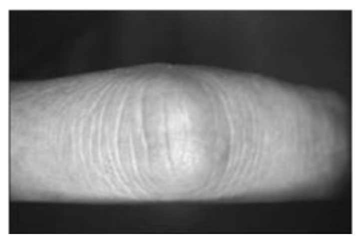

Figure-4. Preprocessing Output.

The noises are removed by using median filter. Denoting the image after smoothing by figure 4, assuming image figure 5 contains M × N pixels, and the filter is of Radius r pixels, median filtering is measure from

$$F(i,j) = MEDIAN(f,i,j,r) = 0, M-1, j = 0...N-1 \quad (1)$$

Where MEDIAN (f, i, j, r) is a function that returns the median intensity in image f in a circular window of radius r centered at (i, j). If a part of the window falls outside the image, intensities within the portion of the window, falling inside the image are used to measuring the median. As specified earlier, circular windows are used to make smoothing independent of image orientation.

Segmentation

Image segmentation is the process of partitioning an image into meaningful parts and is perhaps the most

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studied topics in image analysis. This can be attributed to the importance of segmentation in image analysis and the fact that a universal method does not exist that can portion all images. The advanced method taking into consideration the properties of a particular class of images.

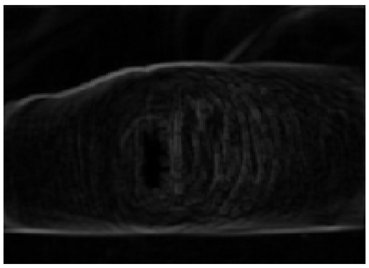


Figure-5. Segmentation output.

Segmentation methods can be grouped into thresholding, boundary detection and region growing. Thresholding methods assign pixels with intensities below a threshold value into one class and the remaining pixels into another class and form regions by connecting adjacent pixels of the same class. Thresholding methods work well on simple images where the objects and background have different intensity distributions. Boundary extraction methods use information about intensity differences between adjacent regions to separate the regions from each other. If the intensities within a region vary gradually but the difference of intensities between adjacent regions remains large, horizon detection methods can successfully delineate the regions. Region growing methods form regions by combining pixels of similar properties.

ROI extraction

The image region to be extracted is known as a region of interest (ROI). It's important to fix the ROI in the same position in different knuckle images to ensure the stability of the principal extracted knuckle features. It also Significant influence on the accuracy of verification. However, it is difficult to fix the ROI at the same position in different knuckle images without using a docking device to constrain the knuckle position. Then, we use the binarization method to extract the knuckle print images.

Binarization method

This method is widely used in binary finger knuckle print image. The image usually passes through a thinning process that reduces the line thickness to one pixel, resulting in an FKP image. Although these steps are time-consuming and may cause some information loss, they allow the minutiae detection with simple images can and they greatly benefit from previous enhancement processes such as the approaches presented in some methods of this type are, and an approach based on peak detection along sections orthogonal to the ridge orientation. The ROI extraction algorithm can then locate the coordinate system of the knuckle prints quickly by the following five steps:

a) As a threshold to convert the original grayscale image into a binary image, then use a low-pass filter to smooth the binary image.

b) Trace the boundary of the gaps between the fingers.

c) Compute the common tangent of the boundaries of the gaps.

d) To determine the Y-axis of the knuckle print coordination system and make a line passing through the midpoint of the two points, which is perpendicular to this Y-axis to determine the origin of the system.

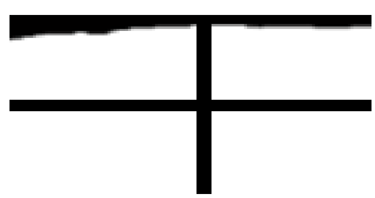
e) Extract the central part of the image to be used for feature extraction.

Step-1:

Determine the *X*-axis of the coordinate system. The bottom boundary of the finger can be easily extracted by a binarization method. By fitting this boundary as a straight line, the *X*-axis of the local coordinate system is determined.

Step-2:

Crop a sub-image *IS*. The left and right boundaries of *IS* are two fixed values evaluated empirically. The top and bottom horizons are predicted according to the boundary of real fingers and they can be obtained by a binarization. Apply a binarization method *IS* to obtain the edge map.



Step-3:

Then the binary images change into the grayscale image. Then the ROI extraction output is shown in Figure-6.

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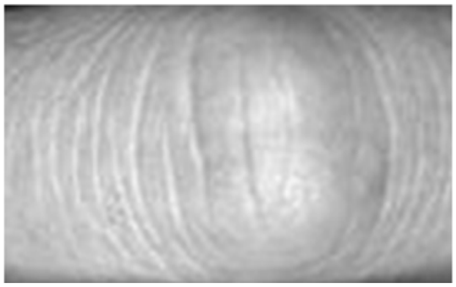

Figure-6. ROI extraction output.

Feature extraction

The feature extraction technique is mainly used to find the unique point of the finger knuckle print and palm print. In existing work, the various applications are implemented in finger knuckle print recognition, they include in Principal Component Analysis (PCA), Local Feature Analysis (LFA), Linear Discriminant Analysis (LDA), and Independent Component Analysis (ICA). Those methods are derived from an ensemble statistics of giving training images. In proposing work we extract the knuckle print from Figure-7 and palm print by using the discrete wavelet transform. The discrete wavelet transform bases are not adapted to represent the functions of the Fourier transforms have a narrow high frequency support. The wavelet transform provides an appropriate basis for image handling because of its favorable features. The resources of the wavelet transform are:

The capability to bunched most of the signal's energy into a few transformation coefficients, which is called energy compaction.

The capability to snatch and represent effectively low frequency components (such as image backgrounds) as well as high frequency transients (such as image edges). The variable corruption with almost uncorrelated coefficients.

The ability of a continuous transmission, which facilitates the reception of an image at different qualities.

Algorithm

First, we load the input image from the database. Then, set the colour value is 256 and double the maximum value of the given database.

Then, the doubled image will be decomposed and set the approximation coefficient storage value.

Then, find the horizontal, vertical and diagonal detail coefficient storage image.

Then, apply the n-level decomposition and show the feature extraction output.

Then, the wavelet equations are represented by,

$$\varphi(t) = \sqrt{2\sum_{k} g_k \phi(2t-k)} \tag{2}$$

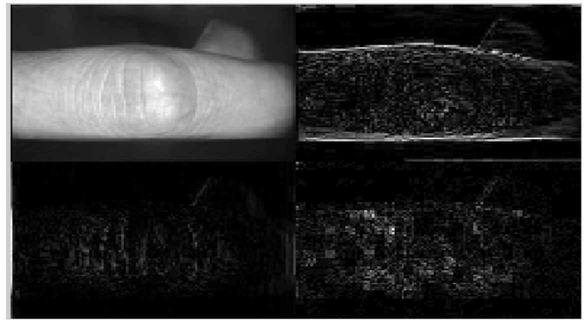

Figure-7. Feature extraction output.

Matching

Matching high quality fingerprints with small intra subject variations is not difficult and every reasonable algorithm can do it with high accuracy. The absolute challenge is matching the pattern which might be affected by: I) large displacement and/or rotation; ii) non-linear distortion; iii) different pressure and skin condition; IV) Feature extraction errors. To avoid this we implement in the SIFT level matching algorithm. The Key properties of local features are locality, robust against occlusions, must be highly distinctive, a good feature should allow for correct object identification with low probability of mismatch, easy to extract and match, efficiency, quantity: many appearances from small objects, invariance to noise, and changes in illumination, scaling and rotation, viewing direction (to a certain extent). The main steps of the SIFT algorithm are scale-space extreme a detection, key point localization and orientation assignment.

Finding key points

Detect points in which the Laplacian (of Gaussian) of the image is large (Lindeberg). It has been practically shown to be a balanced image feature compared to gradients or Harris corner detection functions as in Figure-8.

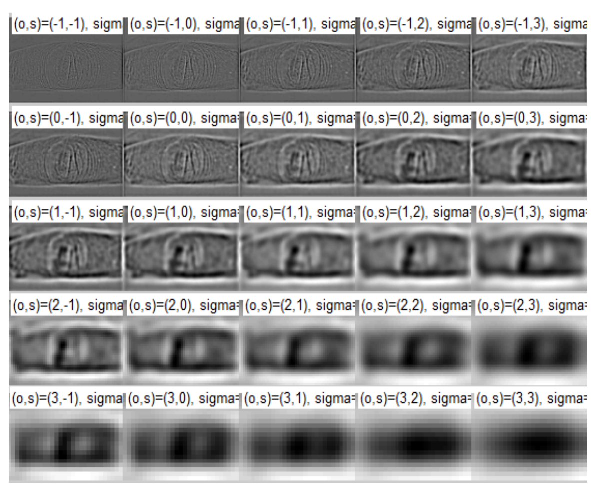

Figure-8. SIFT feature extraction.

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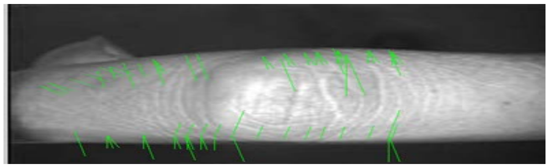

Figure-9. Key points detection.

The matching outputs are shown in the Figure-9 and Figure-10. Then find the time taken for calculating the SIFT key descriptor value is 2.759094 then it also calculates the matching percentage is 0.000187.the matching percentage between 2 images is 56.060606 is respectively.

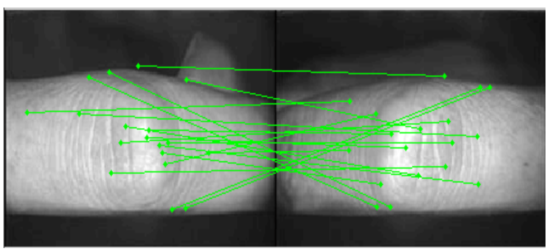

Figure-10. Matching output.

Classification

Classification is the problem to mention to which of a various types (subpopulations) a new research belongs, on the basis of a practiced set of data enclose observations (or instances) whose category group is known. Th specific measurements are analyzed into a set of measurable properties, known as various demonstrative variables, features, etc.

The most widely used classifiers are the neural network (multilayer perceptron), support vector machine, K-nearest neighbor, Gaussian mixer model, Gaussian, naïve bayes decision tree and RBF classifier.

PCNN models are proving to be highly applicable in the field of image processing, a sequence of steps being developed for contour detection and especially image segmentation. Taking PCNN process into application, the performance depends on the appropriate selection of the parameters. Although some researchers tried to find criteria to select adaptively parameters based on intensity statistical properties, image Entropy or other image quality indicator, holistic adjustment are insufficient to reach an optimal standoff between false negative and false positive. We propose an extended PCNN using fast linking, and make some improvement to extend PCNN to work completely. Some specifications are modify based on its neighborhood for individual pixel, and the neighborhood is formed exactly to a ratio. We practice this PCNN to different types of image under various conditions of illuminations and demonstrate the effectiveness of this model through experiments.

The Pulse-Coupled Neural Network (PCNN) algorithm is based on the neurophysiology models evolving from studies of small mammals. The PCNN will receive both stimuli by feeding and also inhibitory linking. These combine in an internal activation system. This accumulates the signal until it exceeds a dynamic threshold, appear in an output. This alters the threshold as well as linking and feeding neurons, as will be discussed below. The PCNN produces a temporal series of outputs. Depending on time as well as the parameters, this changing output enclose to the information, which makes it possible to identify the edges, achieve segmentation, detect the edges, do segmentation, identify textures and perform other feature extractions. The PCNN can achieve on distinctive types of data since it is very generic in its nature. F channel and L channel combine in a second order fashion to create the total subjective activity *U*, which is then compared to the change neuromime and create the output Y as in Figure-11.

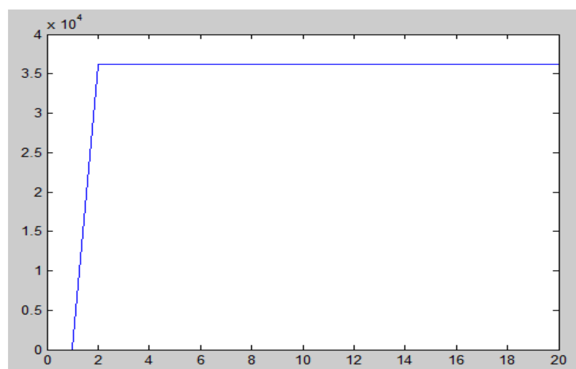

Figure 11. Classification output

EXPERIMENTAL RESULTS

Finger knuckle based verification performance

The next experiment was carried out to effectiveness of the knuckle print system. The proposed SIFT coding scheme yields the matching percentage between 98 to 100.The reported result was the best result obtained by rotating and translating the knuckle print images when matching was performed.

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Table-1. Performance of ROC Curve (Right Middle) using Poly U Database.

Finger	Comp code	Ordinal code	Imp code and mag	SIFT
Sample 1	0.96	0.97	0.97	0.99
Sample 2	0.97	0.97	0.98	0.99
Sample 3	0.98	0.98	0.98	1
Sample 4	0.98	0.98	0.98	1

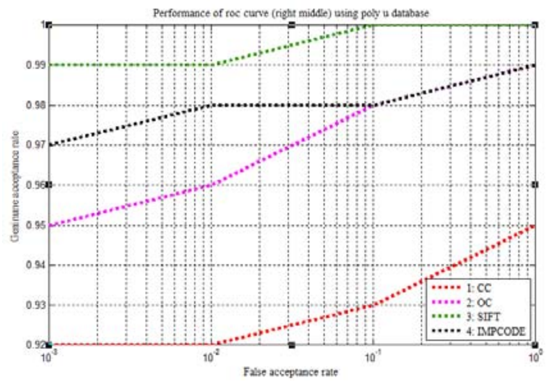

Figure-12. Compare the performance of ROC (right middle) with different coding.

Table-2. Performance of ROC Curve (Right Index) using Poly U Database.

Finger	Comp code	Ordinal code	Imp code and mag	SIFT
Sample 1	0.92	0.95	0.96	0.98
Sample 2	0.92	0.96	0.97	0.98
Sample 3	0.93	0.98	0.98	0.99
Sample 4	0.95	0.99	0.99	1

Tables 1-4 are compare the performances of the ROC curve using the POLY U Databases. The respective performance comparison are given in Figures 12-15

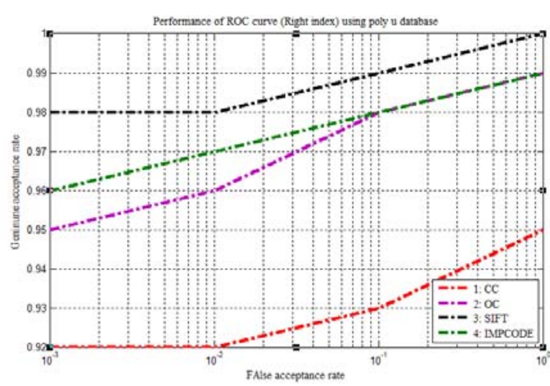

Figure-13. Compare the performance of ROC (right index) with different coding.

Table 3. Performance of ROC Curve (Left Middle) using Poly U Database.

Finger	Comp code	Ordinal code	Imp code and mag	SIFT
Sample 1	0.93	0.97	0.98	0.98
Sample2	0.97	0.98	0.98	0.99
Sample3	0.98	0.98	0.99	1
Sample4	0.98	0.99	0.99	1

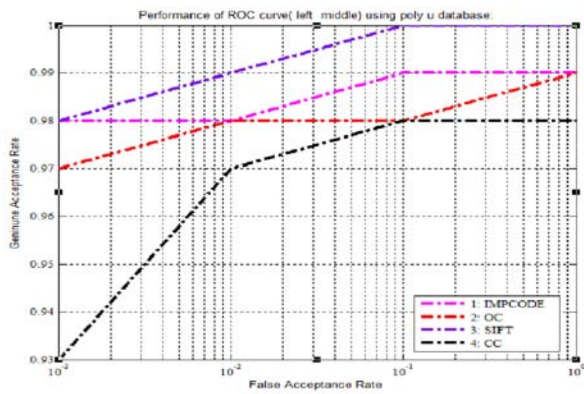

Figure-14. Compare the performance of ROC (left middle) with different coding.

Table-4. Performance of ROC Curve (Left Index) using Poly U Database.

Finger	Comp code	Ordinal code	Imp code and mag	SIFT
Sample1	0. 92	0.95	0.96	1
Sample 2	0.92	0.97	0.98	1
Sample 3	0.97	0.98	1	1
Sample 4	0.98	0.99	1	1

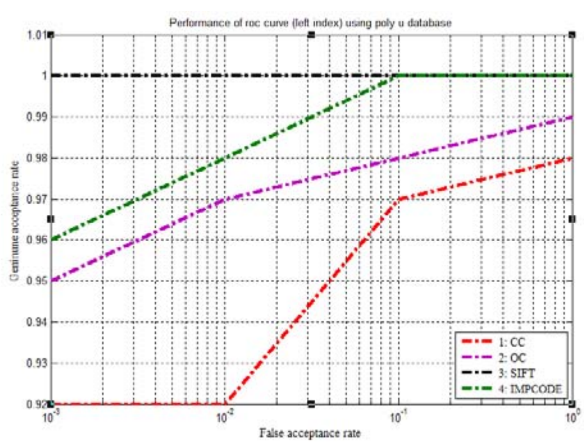

Figure-15. Compare the performance of ROC (left index) with different coding.

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CONCLUSIONS

The proposed work investigates a novel approach for personal authentication. The proposed approach effectively, accommodates the potential image deformation, translational and rotational variation by matching to the corresponding region and generates a more reliable match score. Finger knuckle print image databases are collected and their shift features are extracted and classified using PCNN classifier.

The PCNN classification method is used to find the class to which the test sample belongs. The test samples are matched with trained samples for the personal authentication. The experimental result reveals that using the SIFT analysis as a feature extraction method and PCNN classifier is a most appropriate one among the other methods in term of FKP recognition. The performance achievement from additional training samples is quite significant while the sample size, is still small but redundant information accumulate rapidly as the training sample size increases.

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