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PATIENT FACING SYSTEMS

Personal Authentication Mechanism Based on Finger Knuckle Print

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Abstract
For authentication purposes, the identification and verification of a user is done by biometric traits like finger print, face, iris and gait, etc. Among the various traits finger print is mostly used in commercial applications for recognizing user's identity. The other hand based modalities such as vein, and finger knuckle are gaining importance. This paper proposes a methodology for secure biometrics authentication using Finger Knuckle Print (FKP). The texture patterns from finger knuckle are extracted using Gabor with Exception-Maximization (EM) algorithm and the feature vectors from these texture patterns are acquired using Scale Invariant Feature Transform (SIFT) algorithm. The main focus is to reduce the false rejection rate without increasing the false acceptance rate and to improve the performance over the conventional hand based modalities. The performance is compared with Genuine Acceptance Rate (GAR) and False Rejection Rate (FRR). One of the advantages of FKP authentication is its user friendliness in data collection.

Keywords Knuckle print · Authentication · Soft computing · Cyber security

Introduction

Biometric authentication is the technology used for recognizing a human identity based upon their physiological or behavioural attributes. Biometric system is also a pattern recognition system which captures biometric traits from human and extracts their pattern information. Further, the extracted pattern information must be measured quantitatively for authenticating a person in a simple and automated way. The invariant, measurable, acceptable, permanence properties of biometric traits makes it highly suitable to be incorporated in human identification. Biometric systems are classified into two categories based on the number of modalities used for biometric authentication, viz., unimodal biometric system and multimodal biometrics system. The unimodal biometric system incorporating single biometric trait for recognition has a number of limitations viz., i) lack of uniqueness in the chosen biometric trait ii) spoof attacks which may affect the accuracy of the system are highly probable and iii) errors in the enrolment of sensor captured data may result in poor accuracy. But still, these problems can be overcome by the use of multimodal biometrics. The multimodal biometric system uses the evidence of multiple sources extracted from different biometric identifiers like fingerprints, face, palm prints, iris and hand geometry. The advantage of the multimodal biometric is that, it is highly sustainable to noise which improves the matching accuracy and also provides high resilience to attacks. Hand-based biometric authentication systems are widely used in most of the access control applications due to i) their low cost data capturing units ii) their high potentialities towards the identification of individuals iii) their high user acceptance rate and iv) their performance especially in terms of speed. The various hand patterns include finger prints, palm prints, hand shape features, hand vein structures and finger knuckle surfaces. Finger knuckle surface is one of the emerging hand-based biometric traits for personal identification. These unique patterns of finger knuckle surface have greater potentiality towards the distinctive identification of individuals which in turn contributes a high precise and computationally economic biometric system. This paper focuses on the extraction of features from finger knuckle using different algorithms. The performance comparison is based on

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the parameters such as Accuracy, False Acceptance Rate (FAR) and False Rejection Rate (FRR.

Literature survey

Research has been conducted extensively in the field of finger knuckle print and the significant works are discussed in this section. The rapid growth in the use of e-commerce applications and penetration of information technology into the daily life requires reliable user identification for effective and secured access control. The hand-based biometrics has received considerable attention in recent years which exploits several internal and external features that are quite distinct in an individual [1]. Further, finger knuckle has a high potentiality towards discriminating individuals with high accuracy. From the review conducted on finger knuckle biometric techniques, it is recommended to do the following considerations (i) development of texture analysis techniques which makes use of subset of finger knuckle features for the generation of feature templates and, (ii) incorporating knuckle shape information along with its angular measurements into the feature template [2]. A specific data acquisition device is constructed to capture the FKP images, and then an efficient FKP recognition algorithm is used to process the acquired data in real time. The local convex direction map of the FKP image is extracted based on which a local coordinate system is established to align the images and a region of interest is cropped for feature extraction. For matching two FKPs, a feature extraction scheme, which combines orientation and magnitude information extracted by Gabor filter, is used [3, 4]. Specifically, the local orientation information is extracted by the Gabor filters as the local feature because, local orientation has been successfully used in palm print recognition systems and FKP recognition systems. By increasing the scale of the Gabor filters, more and more global information will be involved, yet the characterization of image local structures will be weakened rapidly. The Fourier transform coefficients are naturally taken as the global features [5], and the finest resolution is got for the global frequency analysis of the image. At the matching stage, two matching distances are computed by comparing the local features and the global features separately.

One of the advantages of FKP is its user friendliness in data collection. However, the user flexibility in positioning fingers also leads to a certain distortions such as degree of pose variations in the collected FKP images. The widely used Gabor filtering based competitive coding scheme is sensitive to such variations, resulting in many false rejections. So, a new technique is proposed to alleviate the variation problem by reconstructing the image sample with a dictionary learned from the template samples in the gallery set [6]. The survey of finger knuckle recognition has given a conclusion that the existing algorithms are successful but has a high equal error rate (EER). To reflect on the above problem, the proposed authentication method has a scope to prepare the own database and improve the quality of images using pre-processing techniques so that it improves the performance parameters by reducing the EER [7]. In this paper, a new finger print recognition methodology is defined and is tested for use FKP recognition systems. Compared with the other existing FKP recognition systems, the proposed approach performs better in terms of both the recognition accuracy and the speed of the execution. The rest of this paper is organised as follows: Third section introduces the proposed approach; fourth section reports the experimental results and discussions. Finally, conclusions are presented in the fifth section.

Proposed approach

The proposed approach consists of 4 stages Image Acquisition, Pre-processing, Localization of Region of Interest and Feature Extraction. In each stage various operations are executed to authenticate the user. Figure 1 represents the work flow diagram of the proposed system model.

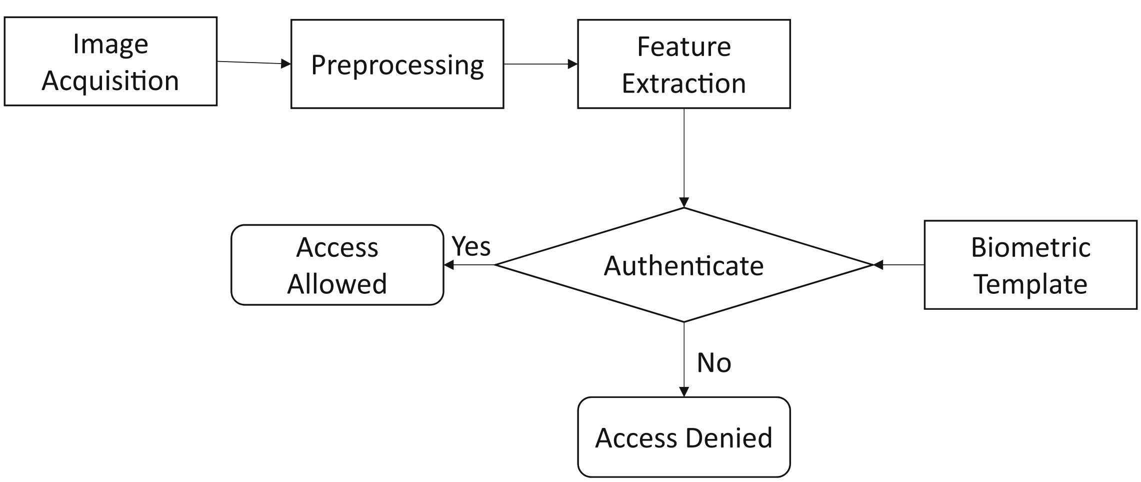

Fig. 1 Proposed system model

Image acquisition

Finger knuckle print images are collected from Poly U FKP database. Here, the images are acquired using a standalone embedded FKP recognition system. Such a system can work alone without depending on any general-purpose computer. Users can operate the system via the touch screen. This system has the merits of small size, fast speed, and low cost. The proposed system utilizes images from the Poly U database and real time test images acquired using a Mobile Phone camera with the pixel intensity of 20 M pixel.

Pre-processing

The images acquired are to be pre-processed before the operations like segmentation or feature detection which are the important processes in image processing. To denoise an image without affecting the image quality and edges in an image, edge preserving filters are used. The filtering methods perform several successive independent processing steps which respectively correct non-uniform illumination, poor contrast, motion blur and defocusing.

Localization of ROI

Each of these images requires localization of region of interest for the feature extraction. The region of interest is the region having maximum knuckle creases. It is necessary to construct a local coordinate system for each FKP image. With such a coordinate system, an ROI can be cropped from the original image for reliable feature extraction and matching. The ROI is decided based on the basal block, as the finger is kept placed straight in 90 degrees during each acquisition process. The top of the finger boundary is calculated mathematically. The layer of hair over the finger is considered to be a noise and dull razor hair removing algorithm [8] is applied to eliminate the unwanted noise.

Feature extraction of finger knuckle print

The enhanced knuckle image mainly consists of curved lines and creases as shown in Fig. 2.

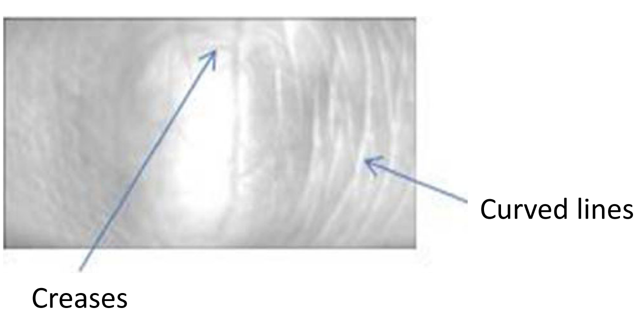

Fig. 2 Finger Knuckle print

Knuckle texture patterns such as curved lines and creases are extracted using Modified Gabor filter. The Scale Invariant Feature Transform (SIFT) is the most reliable feature extraction technique that is used in authentication systems on FKP. The feature descriptors detected by SIFT claim to be capable of distinguishing each and every image in the dataset from one another with cost involved in its operations. The Key-Point descriptors that are invariant to scaling are computed using SIFT algorithm.

Texture pattern extraction

In the proposed method the original image is segmented into two divisions and is given as an input to the Gabor filter. The segmentation is accomplished by using the Expectation Maximization (EM) algorithm. The extraction of textures using Gabor with EM algorithm is done as shown in Fig. 3. The EM algorithm is an iterative approach to compute maximum-likelihood estimates when the observations are incomplete. In the mixture density estimation, the information that indicates the component from which the observable sample originates is unobservable. Expectation Maximization (EM) is one of the most common algorithms used for density estimation of data points in an unsupervised setting. In EM, alternating steps of Expectation (E) and Maximization (M) are performed iteratively till the results converge. The E - step computes an expectation of the likelihood by including the latent variables as if they were observed, and the M – step computes the maximum likelihood estimates of the parameters by maximizing the expected likelihood found on the last E step. The parameters found on the M step are then used to begin another E step, and the process is repeated until convergence.

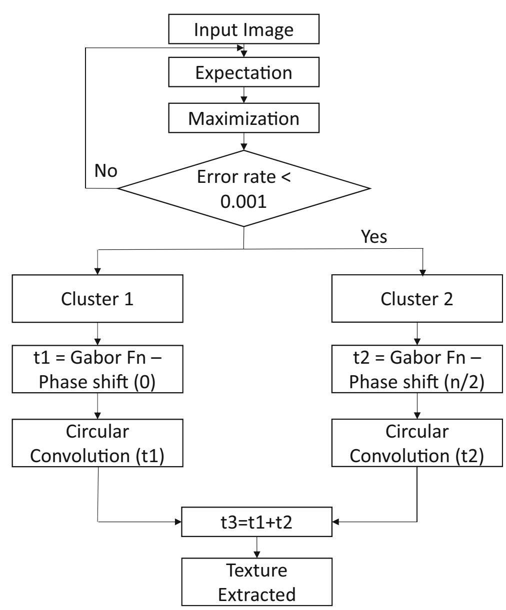

Fig. 3 Extraction of textures using Gabor with EM algorithm

The EM algorithm is frequently used for the research of the parameters involved in achieving the maximum likelihood. The criteria to stop the algorithm, is either a maximum number of iterations to limit the time of calculation or a lower mistake. The EM algorithm requires the initialization of model parameters of Gaussian mixture.

Steps:

Input: H = Histogram, k = Gaussian number ε = Error
Output: Model parameters ($\alpha_1, \alpha_2, \ldots, \alpha_k, \theta_1, \theta_2, \ldots \theta_k$)
Evaluation expectancy (E):

$$\varphi\left(i/x_{j,}\theta\right) = \frac{p_i f_i\left(x_j|\theta_i\right)}{\sum_{k=1}^{K} \alpha_k f_k\left(x_j|\theta_k\right)}$$

- Maximization step (M): GMM parameters update

$$\alpha_i^{new} = \frac{1}{N}\sum_{j=1}^{N} \varphi\left(\mathrm{i}|\mathrm{X_j}, \theta^{\mathrm{old}}\right)$$

$$\mu_i^{new} = \frac{\sum_{j=1}^{N} \mathrm{X_j}\varphi\left(\mathrm{i}|\mathrm{X_j}, \theta^{\mathrm{old}}\right)}{\sum_{j=1}^{N} \varphi\left(\mathrm{i}|\mathrm{X_j}, \theta^{\mathrm{old}}\right)}$$

$$\Sigma_i^{new} = \frac{\sum_{j=1}^{N} \varphi\left(\mathrm{i}|\mathrm{X_j}, \theta^{\mathrm{old}}\right)\left(\mathrm{X_j} - \mu_j^{new}\right)\left(\mathrm{X_j} - \mu_j^{new}\right)^T}{\sum_{j=1}^{N} \varphi\left(\mathrm{i}|\mathrm{X_j}, \theta^{\mathrm{old}}\right)}$$

Stopping Criteria:

$$\|\theta^{new} - \theta^{old}\| \leq \varepsilon$$

The Gabor filtering technique can simultaneously extract the spatial-frequency information from the original signal. The Gabor filter has a real and an imaginary component. These two components may be formed into a complex number or used separately in different systems. The EM algorithm is combined with Gabor filter to increase the performance of the proposed system. The combined algorithm is given below.

Gabor with EM algorithm

1. Original image is taken as input
2. Image is segmented using EM algorithm
3. Image is classified as two clusters C1 and C2.
4. For Cluster 1: $G(x, y, \lambda, \theta, \psi, \sigma, \gamma = \exp\left(-\frac{x'^2 + \gamma^2 y'^2}{2\sigma^2}\right)$
5. For Cluster 2: $\mathrm{G}(\mathrm{x}, \mathrm{y}, \lambda, \theta, \psi, \sigma, \gamma = \exp\left(\mathrm{i}\left(2\pi\frac{\mathrm{x}'}{\lambda} + \psi\right)\right)$

where $x' = x\cos\theta + y\sin\theta$ *and* $y' = -x\cos\theta + y\sin\theta$).

Extraction of Feature Vector

The Scale Invariant Feature Transform (SIFT) algorithm is used to extract local features of an image, based on their inherent advantages such as (i) features are invariant on rotation, scale scaling, and illumination change of images; (ii) features maintain a certain degree of stability on perspective changes, affine transformation, and robustness to the noise; (3) features are uniqueness and informative. The extraction of feature descriptor procedure is as follows:

- Scale-Space Extrema Detection – The first step of SIFT process is to find the Difference of Gaussian (DOG) function convoluted with the finger knuckle print image to detect the key point locations.
- Key-Point Localization – The next step is to detect the local maxima and minima of DOG by comparing each pixel value of FKP image with the neighbour pixel values. They are selected, if the pixel value is higher or lower related with the neighbour pixels.
- Assign an orientation – These selected values are named as key points. The orientations of key points are assigned for the selected key points. The key points selected are scale invariant points.
- Key-Point Descriptor – Feature vector of 128 values are computed from the local image region.

K-Means clustering

The main concept of the k -means approach is that, every object in the database must be present in any of the clusters or group, and then every cluster should contain a minimum of one object. The key points which are taken from the feature extraction process are clustered using this algorithm.

Consider the key points are given as the input data vectors' M = (m_1, m_2, ...m_n)

- K-Means algorithm starts by initializing the first coordinate value as the centroid and defines the number of clusters to be split.
- With reference to the initial centroid value, distance between the centroid and the key points is calculated using Euclidean distance.
- Clusters are formed with minimum distance and the process is repeated until optimum number of clusters is reached.
- At optimum level, centroid value is calculated from the key-points.
- The centroid values calculated from k-means clustering are converted into 128 bit binary values, and are stored in the database.

Table. 1 Performance evaluation of SIFT with K-means method

Metrics	Anisotropic Filter		Homomorphic Filter		Wavelet Denoising by Average Filter	
	Poly U FKP Dataset	Real time FKP Dataset	Poly U FKP Dataset	Real time FKP Dataset	Poly U FKP Dataset	Real time FKP Dataset
Accuracy	84.4	84	84.4	84	85	86
Precision	0.845	0.736	0.845	0.829	0.850	0.806
Recall	0.837	0.854	0.845	0.808	0.849	0.822
F-measure	0.841	0.791	0.845	0.818	0.850	0.814
FAR	0.153	0.500	0.165	0.200	0.153	0.308
FRR	0.157	0.028	0.146	0.143	0.147	0.081

Authentication

The test image is compared with the template images available in the database. If the extracted feature value of the test image is same as that of the trained image, then the user is authenticated else the user is restricted as imposter.

Classification

Classification process is to find the best class that is closest to the classified pattern. Classification comprises of two phases namely, training phase and testing phase. During the training phase, a set of feature vectors of the genuine user is used to build the model for the respective user. The model is built based on the classifier mechanism used. During the testing phase, each test vector is compared with the model developed.

Support vector machine (SVM) classifier

Once the features are extracted using the Modified Gabor filter method and SIFT with K-means mechanism, each feature set is presented to the Support Vector Machine (SVMs) classifier. SVM is a binary classifier that makes its decision by constructing a linear decision boundary or hyper plane that optimally separates data points of the two classes in feature hyper space. There are many hyper planes that might classify the data. One reasonable choice as the best hyper plane is the one that represents the largest separation, or margin, between the two classes. So that, the distance to the nearest data point on each side is maximized. If such a hyper plane exists, it is known as the maximum-margin hyper plane and the linear classifier it defines is known as a maximum margin classifier. In the training phase, two class labels namely authenticated or unauthenticated is assigned. In the testing phase, the classification process is carried out and the features are classified as either authenticated or unauthenticated.

Results and analysis

The real time samples from the users are collected in two separate sessions. In each session, the subject was asked to provide 6 images for each of the left index finger, the left middle finger, the right index finger, and the right middle finger. Therefore, 48 images from 4 fingers were collected from each subject. In total, the algorithm is evaluated using 480 images from 40 different fingers.

Table 2 Performance evaluation of Gabor Method

Metrics	Anisotropic Filter		Homomorphic Filter		Wavelet Denoising by Average Filter	
	Poly U FKP Dataset	Real time FKP Dataset	Poly U FKP Dataset	Real time FKP Dataset	Poly U FKP Dataset	Real time FKP Dataset
Accuracy	88	88	87.77	90	87.77	90
Precision	0.889	0.882	0.876	0.907	0.876	0.910
Recall	0.888	0.880	0.877	0.897	0.877	0.883
F-measure	0.889	0.881	0.877	0.902	0.877	0.896
FAR	0.094	0.087	0.142	0.047	0.141	0.058
FRR	0.126	0.148	0.104	0.137	0.105	0.121

Table 3 Performance evaluation of Proposed Method

Metrics	Anisotropic Filter		Homomorphic Filter		Wavelet Denoising by Average Filter	
	Poly U FKP Dataset	Real time FKP Dataset	Poly U FKP Dataset	Real time FKP Dataset	Poly U FKP Dataset	Real time FKP Dataset
Accuracy	96.66	98	97.22	98	98.33	98
Precision	0.966	0.954	0.972	0.928	0.982	0.968
Recall	0.966	0.987	0.971	0.988	0.983	0.985
F-measure	0.966	0.970	0.972	0.957	0.983	0.977
FAR	0.032	0.090	0.031	0.142	0.010	0.062
FRR	0.034	0	0.023	0	0.024	0

The average time interval between the first and the second sessions was about 25 days. The results of classification of real time images are compared with the finger knuckle print images from PolyU FKP of Hong Kong Polytechnic University.

In order to investigate the performance of the SIFT with K-means algorithm using different filters, each FKP image in the query set are classified to identify an individual identity. The Accuracy, Precision, Recall, False Acceptance Rate (FAR) and False Rejection Rate (FRR) between the enrolled image and the classified FKP images of the same user using SIFT is computed and is shown in Table 1.

From Table 1, it is inferred that the accuracy of the SIFT with K-means algorithm, when tested with Anisotropic, Homomorphic and Wavelet denoising by Average filter appears to be the same.

To investigate the performance of the system against rotation, FKP images in the query set are synthetically rotated by 0, 45, 90,135 and 180 using Gabor feature extraction method. The Accuracy, Precision, Recall, False Acceptance Rate (FAR) and False Rejection Rate (FRR) between the enrolled image and the classified FKP images of the same user using Gabor algorithm is depicted in Table 2.

From Table 2, it is inferred that the accuracy of the Gabor method, when tested with Anisotropic, Homomorphic and Wavelet denoising by Average filter appears to be almost the same.

The proposed methodology is tested for the same samples and the results are tabulated as shown in Table 3.

From Table 3, it is inferred that the accuracy of the proposed algorithm, when tested with Anisotropic, Homomorphic and Wavelet denoising by Average filter appears to be better than the other two conventional approaches.

Comparison of the proposed approach

The comparison of results obtained using various feature extraction algorithms is shown in Table 4. From Table 4, it can be understood that the Genuine Acceptance Rate (GAR) and False Rejection Rate (FRR) of the proposed approach is far better than the existing approach, which makes this system to be employed as standalone or multimodal authentication mechanism**.** The overall performance of this proposed approach is 98%.

Conclusion

The proposed method has been successfully implemented on FKP based authentication system and its performance is evaluated using the using a standard FKP database. Based on the experimental results it is concluded that usage of Finger Knuckle Print (FKP) would enhance the efficiency in authenticating a user. It is also seen that the accuracy

Table 4 Comparison of proposed approach

Algorithm	GAR (%)		FRR (%)	
	Poly U FKP Dataset	Real time FKP Dataset	Poly U FKP Dataset	Real time FKP Dataset
SIFT with K Means Approach	85	92	0.147	0.080
Gabor Approach	88	86	0.125	`0.141
Proposed Approach	98	99	0.020	0.001

varies heavily when the texture features are initially extracted using Gabor with EM algorithm. The results of different filters namely Anisotropic, Homomorphic and Wavelet denoising by average filter are also compared for the obtained PolyU FKP dataset and the real time dataset. It is observed that the proposed mechanism outperforms other conventional methodology in terms of Accuracy, False Rejection Rate (FRR) and False Acceptance Rate (FAR). FKP based system is rich in texture features, easily accessible, invariant to emotions and other behavioural aspects such as tiredness, stable features and acceptability in the society and hence this mechanism can be used as additional step in validating the users.

Compliance with Ethical Standards

Conflict of Interests The authors declare that this article content has no conflict of interest.

Ethical Approval This article does not contain any studies with human participants or animals performed by any of the authors.

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