

Finger Knuckle Print Authentication based on KWT Transform using FKP Capture Device

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ABSTRACT

The main purpose of using biometrics is to avoid the risks related to password such as easy to find or Stoll. To make safe and authenticated access control it is true alternatives for passwords and identifiers. In contrast to existing methods, finger knuckle image authentication system employs a low resolution knuckle print images to achieve effective personal identification. In this paper, efforts are concentrated to develop a biometric authentication system that consists of a finger knuckle print sensor which acts as a biometric sensor unit with a direct interface to an external PC for storing finger knuckle print templates. Finger knuckle print sensor consists of a set of digital camera that captures the raw image of finger knuckle print. The image is processed through an algorithm to extract the features set and form the finger knuckle print template for biometric authentication using KWT transform using division method of original templates. We propose a principle method for implementing Kekre's transform for the feature extraction as it performs well on every size of image.

Keywords

Sensor, biometrics, finger knuckle images, KWT, monomodality.

1. INTRODUCTION

Biometric-based solutions are able to provide for confidential financial transactions and personal data privacy. They can be used to distinguish between individuals based on their inherent physical and behavioral characteristics and hence can serve as an ideal solution to this problem. In palm print recognition, the features used for matching are the principal lines and wrinkles. The outer surfaces of finger joints have even more obvious line features as opposed to the palm surface, in spite of very tiny comparable area. This motivates us to propose a new biometric technique — the finger-knuckle print (FKP), which refers to the image of the outer surface of the finger phalange joint

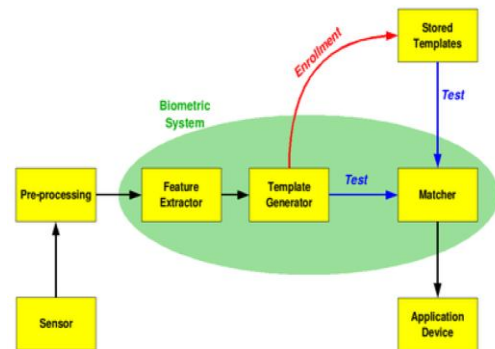


Fig.1: Block diagram of biometric system

2. PROPOSED BIOMETRIC SYSTEM

All biometric systems works in a four-stage process that consists of the following steps: In the step of capture, Collection of the sample of biometric features like fingerprint, voice etc of the person who wants to login to the system is performed. Extraction of data is done uniquely from the sample and a template is created to extract the unique features and converted into a digital biometric code. This sample is then stored as the biometric template for that individual. After comparison with the new sample, the biometric data are then stored as the biometric template or template or reference template for that person. After matching or a non-matching with the template when identity needs checking, the person interacts with the biometric system, a new biometric sample is taken and compared with the template. If the template and the new sample match, the person's identity is confirmed else a non-match is confirmed.

2.1 Problem Definition

We proposed to authenticate the individuals based on the knuckle lines and the textures on the outer finger surface. A database to implement the designed algorithm which will run on created database. The comparison of trainee knuckle

$$k_{xy} = \begin{cases} 1; & x \leq y \\ -N + (x - 1); & x = y + 1 \\ 0; & x > y + 1 \end{cases} \quad (2)$$

Fig.7 shows the generalised form of $M \times M$ Kekre's Wavelet transform matrix generated from $128 \times N$ Kekre's transform matrix. The matrix generated of size is 128×128 compatible to the size of original image [3]. First 128 number of rows of Kekre's wavelet transform matrix are generated by repeating every column of Kekre's transform matrix P times which is the spreading factor [1]. In this case we use spreading factor i.e. $p = 4$ for getting accuracy. To generate remaining $(M-N)$ rows, extract last $(P-1)$ rows and last P columns from Kekre's transform matrix and store extracted elements in to temporary matrix say T of size $(P-1) \times P$.

Values of matrix T can be computed as (3),

$$T(x, y) = K(N - P + (x+1), N-P+ y); 1 \leq x \leq (P-1), 1 \leq y \leq P \quad (3)$$

First row of T is used to generate $(N+1)$ to $2N$ rows of Kekre's Wavelet transform matrix. Second row of T is used to generate $(2N+1)$ to $3N$ rows of Kekre's wavelet transform matrix. Likewise last row of T is used to generate $((P-1)N + 1)$ to PN rows.

Kekre's transform matrix compatible to the block size is generated of size 128×128 . After down sampling the KWT size is reduced to 64×64 and then 32×32 .

3.3 Feature Extraction

The extracted knuckle images obtained are of size (128×256) . The kekre's wavelet transform matrix is chosen of size 128×128 . To extract all the features of the knuckle the extreme left end, the extreme right end and center of the region of interest is selected each of size 128×128 . the transformation is performed on these blocks. The blocks are shown in fig. 8.

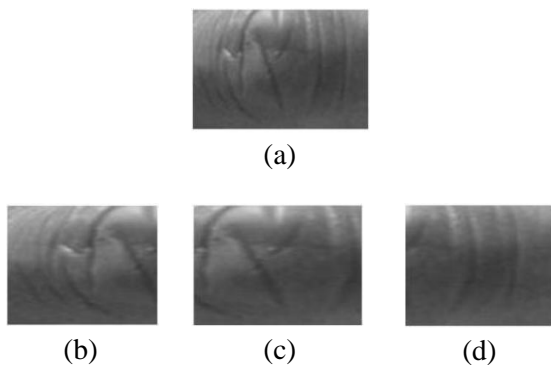


Fig 6: (a) original image(128x256) (b) left block (128x128) (c) center block (128x128) (d) right block(128x128)

The feature vector is extracted using kekre's wavelet transformation.

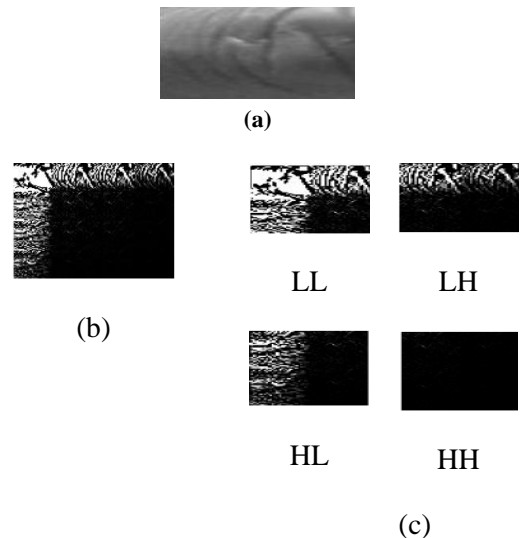


Fig. 7: (a) Forepart of knuckle (b) Kekre's Transformed image (c) Wavelet decomposition of knuckle forepart

The first level decomposition of the transformed knuckle images gives four set of coefficients, i.e. LL, LH, HL, and HH. These coefficients are used as feature vector to perform pattern recognition. The LL sub band is associated with the texture of knuckles, while the higher order sub bands related to the knuckle edges which form the basis of their classification. The approximate coefficients are made to undergo a further 3 level decomposition to obtain finer resolution frequency components. The wavelet coefficients obtained at this level of decomposition are used as feature vectors for inter and intra matching of knuckle data. The LH is divided into 2×2 parts of size matrix $(N/4 \times N/4)$. A set of four wavelet coefficients is obtained as (3)

$$WC = \sum_{i=0}^{w-1} \sum_{j=0}^{w-1} wc(i, j)^2 \quad (3)$$

Where $w=N/4$. The values of these three set of coefficients give twelve features from the first transformation.

The aforementioned procedure is elaborated for knuckle image of size 128×108

For second transformation the LL from the transformed matrix is taken and padded with zero to keep the size of matrix 128×128 . This matrix is inverted transformed and down sampled by selecting alternate rows and columns. The images with padding zeros are shown below [6].

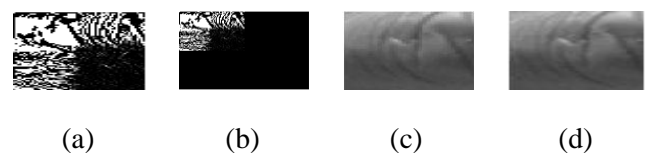


Fig 8.(a) LL part of original image (64x64) (b) LL with dimensions (128x128) (c) inverse of LL (d) Down sampling of image

The new matrix is of size 64×64 . the KWT of size (64×64) is used for second transformation and the same procedure is carried out on LL1 to extract another set of 12 features. The

third level of transformation is done with the down sampled LL1 in 2nd stage and transformed using KWT of size 32 × 32. Thus the feature vector have 36 wavelet coefficients. On performing the same procedure on fore and hind part of knuckle gives the set of hundred and eight feature vectors. The values of the feature vector are taken without normalization. Such feature vector is generated for the training samples i.e. seven samples of each user and the database is of 50 users hence the training samples are 350. A matrix file is created of all the feature vector of 350 samples (1 × 108 × 350).

4. KNUCKLE MATCHING

4.1 Intra Matching

Intra matching is done for genuine matching. In the intra matching we compare the sample of particular user to that user itself to ensure about identity of that user. A set of three test samples are selected of each user. In intra class matching the feature vector of the selected test sample (test1) is matched with the seven training (train1-train7) samples of the same user. The Euclidian distance matching is performed. Seven Euclidian distances are calculated using equation (4)

$$ED = \sqrt{\sum_1^m (test(1, m) - train(1, m))^2} \quad (4)$$



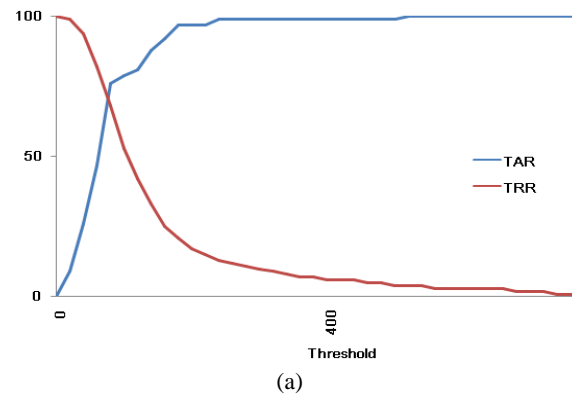
Fig.9 GUI used for matching purpose

4.2 Inter Matching

Inter matching is done for imposter identification. In imposter identification the purpose of authentication is satisfied to allow user to enter in the system. A set of three test samples are selected of each user. In inter class matching the feature vector of the selected test sample (test1) is matched with the seven training (train1-train7) samples of each user present in the database except for the same user. The Euclidian distance matching is performed. Using the Euclidian distances of intra and inter matching technique a threshold is calculated. The threshold is used to decide whether the user is authentic or not. If the average Euclidean distance is less than the threshold value the user is authenticated otherwise the user is not authenticated.

5. EXPERIMENTAL RESULTS

The graphs are shown below is the plot between the FAR (False Acceptance Ratio) and FRR (False Rejection Ratio) which is exact opposite replica of TAR (True Acceptance Ratio) against TRR (True Rejection Ratio).



This graph is a relation between the genuine matching (TAR) & (TRR) percentage on the Y-axis. The X-axis represents a scaled down Euclidian distance (threshold).

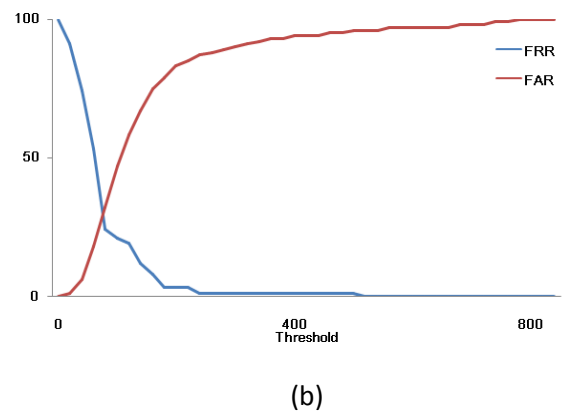
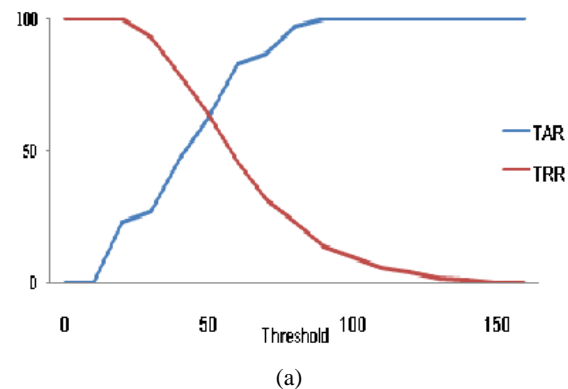
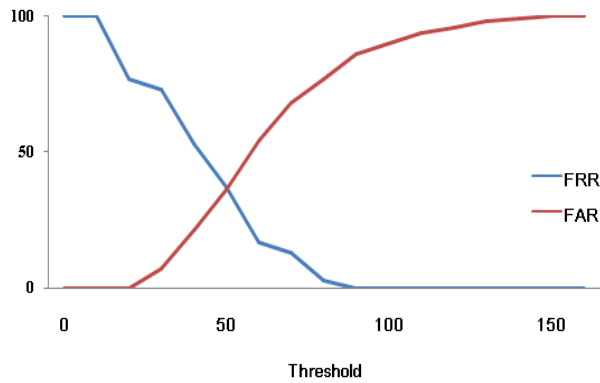


Fig.11. Graph between TAR and TRR with collected database (b) Graph FAR and FRR with collected database

5.1 Hong-Kong University Database Results

The readymade database is selected from the Hong-Kong university database [9]. A set of 10 images is selected for user and 10 users are selected. Thus a database of 100 samples is used. The analysis of this shown





(b)

Fig. 12: Comparison between collected database and Hong Kong university database (a) result of TAR against TRR with collected database (b) result of FAR against FRR with Hong Kong university database

Analysis in the above figures proves that the proposed algorithm shows similar performance for database of different resolution as the observed pattern is same for the both collected database and Hong Kong university database [5].

Table1. Comparison between collected and Hong Kong university database based on matching distance in terms of equal error rate (EER)

Proposed and implemented techniques	EER (TAR-TRR)	EER (FAR-FRR)
Acquired Database (Euclidian distance)	73%	27%
Acquired Database (Absolute Distance)	67%	33%
(Hong-Kong university)	62%	38%

The EER (FAR-FRR) of Hong-Kong University database is higher than developed database this can be reduced if the number of samples is increased.

The original algorithm previously implemented had a spreading factor (p) =2. The spreading factor in this algorithm is p = 4. The total 108 features are obtained in this project while the previously only 27 features were extracted and the accuracy is found to have decreased from 80% to 73%.

6. CONCLUSIONS

In this project a sensor is developed which is comparatively less complex and the resolution of the images acquired is high. The Euclidian distance matching gives a better result than absolute distance matching. The test run on ready-made database using the implemented algorithm gives a lesser accuracy as only 10 user samples were selected. This can be improved by increasing the number of samples.

7. FUTURE SCOPE

In our proposed project we can further enhance our project by using many different modalities for the comparison at a same time, thereby increasing the security of the system. The system is called as mono modality with multiple approaches .In future the proposed FKP can integrate with another correlated modality of finger vein that can boost the conventional parameter along with the security of person authentication which is very chief requirement for authentication. We can also make use of many different transform for the feature extraction of the trainee image .We can also further improve our project by introducing the concept of subset for group of images and then comparing it with the another subset of image of our trainee image .We can also combine the features generated from Haar transform and Kekre’s transform for matching purpose.

8. REFERENCES

- [1] Kekre H.B., Bharadi Vinayak. A. 2011.Finger Knuckle Verification using Kekre’s Wavelet Transform , International conference and workshop on emerging Trends in technology TCET, Mumbai, India
- [2] Ravikant C., Kumar A., 2007. Biometric authentication using finger-back surface. In: Proc. CVPR, pp. 1–6
- [3] Dr. Kekre H. B., Athawale Archana, Sadavarti Dipali, 2010. Algorithm to Generate Kekre’s Wavelet Transform from Kekre’s Transform, International Journal of Engineering Science and Technology, vol. 2(5), 756-767
- [4] Zhang Lin, Zhang Lei, Zhang David and Zhu Hailong: Ensemble of Local and Global Features for Finger-Knuckle-Print Recognition Biometrics Research Centre, Department of Computing, the Hong Kong Polytechnic University.
- [5] Kekre H. B., sonawane Kavita October 2011. Query based Image Retrieval using Kekre’s, DCT and Hybrid wavelet Transform over 1st and 2nd Moment, International Journal of Computer Applications (0975 – 8887) Volume 32– No.4
- [6] Hanmandlu M., Grover J 2012.Feature Selection for Finger Knuckle Print-based Multimodal Biometric System, International Journal of Computer Applications, vol. 38 (10), pp. 975 – 8887
- [7] Badrinath G. S., Nigam Aditya and Gupta Phalguni. An Efficient Finger-knuckle-print based Recognition System Fusing SIFT and SURF Matching Scores.Department of Computer Science and Engineering, Indian Institute of Technology, Kanpur, 208016, India
- [8] Zhang Lin, Zhang Lei and David.Finger-Knuckle PRINT: A NEW BIOMETRIC IDENTIFIER, Zhang Biometrics Research Centre, Department of Computing, The Hong Kong Polytechnic University , Hong Kong, China.
- [9] The Hong Kong Polytechnic University (PolyU) Finger-Knuckle-Print Database