Palmprint Recognition Using Kekre's Wavelet's Energy Entropy Based Feature Vector

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ABSTRACT

Palmprints are one of the oldest biometric traits used by mankind. It is highly universal and moderate user co-operation is required in implemented system. Palmprints are rich in texture information which can be used classification purpose. Wavelets are very good in extracting localized texture information. In this paper a new and faster type of wavelets called kekre's wavelets are used for extracting feature vector from palmprints. Multilevel decomposition is performed and feature vectors are matched using Euclidian distance and Relative Energy Entropy. The results indicate that kekre's wavelets are viable option for extracting texture information from palmprints and provide good accuracy with faster performance.

Categories and Subject Descriptors

D.4.6 [Security and Protection]: Access Controls, Authentication
I.4.7 Image Processing and Computer vision

General Terms

Algorithms, Design, Experimentation, Security, Human Factors, Verification.

Keywords

Biometrics, Palmprint Recognition, Kekres's Wavelets, Entropy.

1. INTRODUCTION

Palmprints are believed to have the critical properties of universality, uniqueness, permanence and collectability for personal authentication [1]. What's more, palmprints have some advantages over other hand-based biometric technologies, such as fingerprints and hand geometry. Palms are large in size and contain abundant features of different levels, such as creases, palm lines, texture, ridges, delta points and minutiae. Faking a palmprint is more difficult then faking a fingerprint because the palmprint texture is more complicated; and one seldom leaves his/her complete palmprint somewhere unintentionally.

As with fingerprint palmprint is also a multistage process. It consists of Palmprint Acquisition, Palmprint Enhancement, Feature Extraction & Matching.

ICWET'11, February 25–26, 2011, Mumbai, Maharashtra, India.

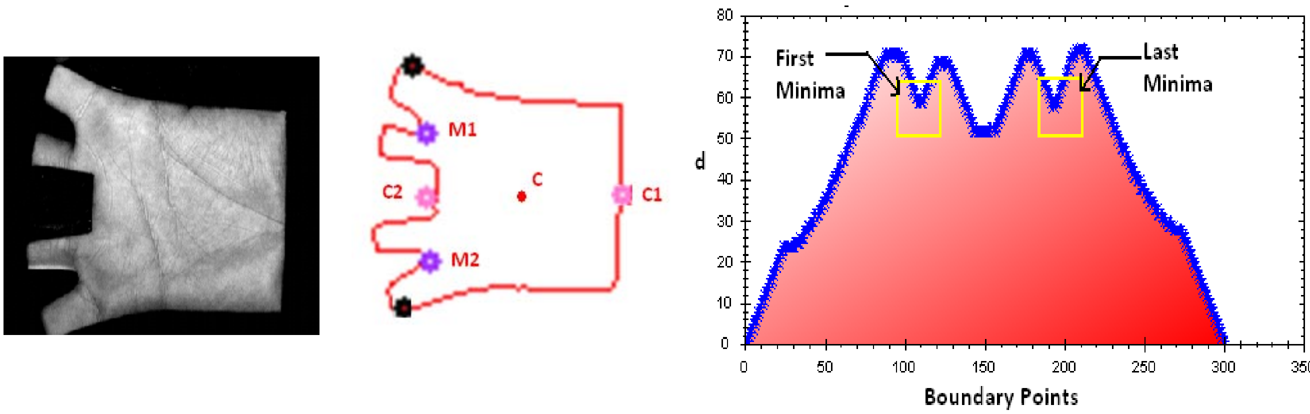
In this paper palmprint feature extraction using kekre's wavelets is performed, the wavelet coefficients are used to calculate localized energy distributions. The paper is organized as follows first we discuss some of the existing technique for palmprint recognition. Next we present generation of kekre's wavelets & palmprint feature vector extraction. Finally the experimentation methodology is discussed.

2. PALMPRINT RECOGNITION METHODS

Palmprints are very rich in texture. We can form the feature vector by extracting texture information. Various approaches are followed by researchers. Pan & Ruan [2] used 2D Gabor filters at different angles to extract the feature information. A phase based palmprint matching approach is suggested in [3] by K. Ito, T. Aokit et al. They used a Band Pass phase only correlation method to extract the spectral information. Another correlation based method is presented by N. E. Othman et al. recognition. They proposed an approach based on the application of unconstrained minimum average correlation energy (UMACE) filter is proposed for palmprint feature extraction and representation [4]. The UMACE methodology determines a different filter for each palmprint of authentic class, the correlation function gives peak for authentic palmprint, and this property is used for classification.

Principal component analysis based approaches are suggested in [5], [6], [7], [8], [9]. They include PCA on PCA & 2D PCA analysis of Gabor Wavelets, Moment invariants etc. Wavelet energy based feature vector are also possible for palmprints. K. Wong, G. Sainarayanan and A. Chekima [10] used wavelet energy of the palmprint ROI. Palmprint image was decomposed using different types of wavelets for six decomposition levels. Two different wavelet energy representations were tested. The feature vectors were compared to the database using Euclidean Distance or classified using feed forward and back propagation neural network.

X. Wu, K. Wang, D. Zhang [11] used 3 level decomposition of palmprint and formed the wavelet energy based feature vector for matching. We have proposed a feature based on wavelet energy entropy. kekre's Wavelet for extraction of feature vector and the palmprint was decomposed into five levels is proposed in this paper. For classification relative wavelet energy entropy as well as Euclidian distance based classifier is used.



(a) (b) (c)

Figure 1. (a) POLYU Palmprint Database Image (b) Palmprint Boundary and Reference Points (c) Boundary points distance w.r.t the Reference Point

3. PALMPRINT SEGMENTATION METHODS

The captured palmprint may be full palm or may a restricted palm area as discussed above, we have to extract the region of interest from it. This will be used for extracting feature vector for classification. Palmprint has center part which is rich in principal lines; we have to consistently locate a region (ROI) from this part. Many researchers are using a technique based on border tracing and locating extreme points [2], [3], [4],[10],[12],[13]. Pan & Ruan [2] have used border tracing and minima location to fit a co-ordinate system to palmprint. Gan & Zou have used similar approach of the partial template of palmprint [13].

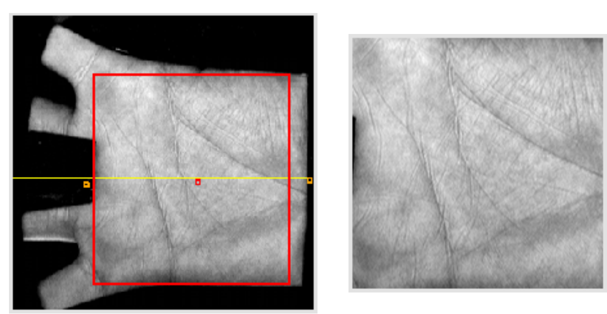
4. PALMPRINT ROI EXTRACTION

In order to match the palmprint using the feature vector, consistent region from palm should be selected, this is called as Region of Interest (ROI). This results in matching feature vector. If the selected region is having shifts or varying orientations the accuracy decreases. In literature various methods to fit a co-ordinate system to a palm are discussed [5], [6], [8], [14]. We have implemented a border tracing based method to fit a reference coordinate system to a palmprint.

Fig. 1 (a) shows a typical image from PolyU database. We want to find a consistent reference point for ROI Selection. This is done by fitting a coordinate system consisting of reference points on a palmprint as shown in Fig. 1 (b). This is done in following steps.

1. First we threshold the palmprint and trace the boundary pixels of the palmprint.
2. We decide the start point ‘C1’ on the boundary as the center of Left hand side part of boundary line. This is shown in Fig. 1(b).
3. We trace the boundary in upward direction starting from point ‘C1’ and find the distance of every pixel with ‘C1’.
4. The Distance Vs point plot is shown in Fig. 1(c), we find first and last minima (Points M1 & M2) on this plot as shown.
5. In case of PolyU database these points correspond to minima between the index finger second finger pair and third finger and last finger pair. (In case of full palmprint we have to find second and last minima on the plot.)
6. We find the center (Point C2) of the line joining M1 & M2.
7. The center point is given as center (Point C) of line joining point C1 & C2.
8. We select 192*192 pixels size region of interest surrounding the reference pint ‘C’.
9. As the structure of all the images in PolyU database is same the proposed method consistently determines point ‘C’ on each palmprint hence we can select a consistent ROI from each palmprint.
10. This algorithm is universal and can be applied to palmprints from any source.

ROI Extraction results are shown in Fig 2.



(a) (b)

Figure 2. Palmprint ROI Extraction (a) Coordinate System and Palmprint ROI (b) Segmented ROI (192*192 Pixels)

5. KEKRE’S WAVELETS

Kekre’s wavelets are orthogonal family of wavelets. For generation of kekre’s wavelets we need basis function as in case of other families, this basis functions are generated from Kekre’s Transform matrix.

5.1 Kekre's Transform [15], [16]

Let us generate the Kekre's Matrix [K] for size m x m where m can be any integer not necessarily the power of 2 as required for many other conventional transforms. This matrix has all 1's on the main diagonal and upper triangle of the matrix. The sub-diagonal just below the main diagonal has the value (-m + i) where 'm' is the order of matrix and 'i' is the column number. Rests of the elements of lower triangle below the sub diagonal are all zeros. The general form of Kekre's matrix [K] can be written as

$$K_{NxN} = \begin{bmatrix} 1 & 1 & 1 & \ldots & 1 & 1 \\ -N+1 & 1 & 1 & \ldots & 1 & 1 \\ 0 & -N+2 & 1 & \ldots & 1 & 1 \\ . & . & . & \ldots & . & . \\ . & . & . & & . & . \\ . & . & . & & . & . \\ 0 & 0 & 0 & \ldots & 1 & 1 \\ 0 & 0 & 0 & \ldots & -N+(N-1) & 1 \end{bmatrix}$$

The formula for generating the element Kxy of Kekre's transform matrix is,

$$K_{xy} = \begin{cases} 1 & ; x \le y \\ -N + (x-1) & ; x = y + 1 \\ 0 & ; x > y + 1 \end{cases} \qquad (1)$$

5.1.1 Properties of Kekre's Transform

1) The Kekre's transform is real and orthogonal transform.

   a. $[K]^T [K] = [\mu]$ (2)

   Where $[k]^T$ is transpose of [K] and [μ] is a diagonal matrix and its elements are given by $\mu_{11} = m$

   $\mu_{ii} = (m-i+1)(m-i+2)$ (3)

2) It has a fast algorithm as it contains m(m+1)/2 number of ones and (m-1)(m-2)/2 number of zeros leaving only (m-1) integer multiplications and only (m-1)(m/2) additions for transforming a column vector of dimension mx1. For a normal matrix transformation we require m^2 multiplications and m (m-1) additions.

3) The transform of a vector **f** is given by

   $$\mathbf{F} = [\mathbf{K}]\, \mathbf{f} \qquad (4)$$

   And inverse is given by

   $$\mathbf{f} = [\mathbf{K}]^T [\mu]^{-1} \mathbf{F} \qquad (5)$$

5.2 Kekre's Wavelets [15]

Kekre's Wavelet transform is derived from Kekre's transform. From NxN Kekre's transform matrix, we can generate Kekre's Wavelet transform matrices of size (2N) x (2N), (3N) x (3N),……, up to maximum (N2) x (N2). For example, from 5x5 Kekre's transform matrix, we can generate Kekre's Wavelet transform matrices of size 10x10, 15x15, 20x20 and 25x25.

In general M x M Kekre's Wavelet transform matrix can be generated from N x N Kekre's transform matrix, such that M = N * P where P is any integer between 2 and N that is, 2 ≤ P ≤ N. Consider the Kekre's transform matrix of size N x N shown in Fig. 3. M x M Kekre's Wavelet transform matrix generated from N x N Kekre's transform matrix is shown in Fig 4. First 'N' number of rows of Kekre's Wavelet transform matrix is generated by repeating every column of Kekre's transform matrix P times. 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) x P . Fig. 4 shows extracted elements of Kekre's transform matrix stored in T.

$$K_{NxN} = \begin{array}{|c|c|c|c|c|c|} \hline K_{11} & K_{12} & K_{13} & \ldots & K_{1\,(N-1)} & K_{1N} \\ \hline K_{21} & K_{22} & K_{23} & \ldots & K_{2\,(N-1)} & K_{2N} \\ \hline K_{31} & K_{32} & K_{33} & \ldots & K_{3\,(N-1)} & K_{3N} \\ \hline . & . & . & \ldots & . & . \\ . & . & . & & . & . \\ \hline K_{N1} & K_{N2} & K_{N3} & \ldots & K_{N\,(N-1)} & K_{NN} \\ \hline \end{array}$$

Figure 3. Kekre's Transform (KT) matrix of size NxN.

In general M x M Kekre's Wavelet transform matrix can be generated from N x N Kekre's transform matrix, such that M = N * P where P is any integer between 2 and N that is, 2 ≤ P ≤ N. Consider the Kekre's transform matrix of size N x N shown in Fig. 3. M x M Kekre's Wavelet transform matrix generated from N x N Kekre's transform matrix is shown in Fig 4. First 'N' number of rows of Kekre's Wavelet transform matrix is generated by repeating every column of Kekre's transform matrix P times. 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) x P . Fig. 4 shows extracted elements of Kekre's transform matrix stored in T.

$$T = \begin{array}{|c|c|c|c|} \hline K_{(N-P+2)\,(N-P+1)} & K_{(N-P+2)\,(N-P+2)} & .. & K_{(N-P+2)\,N} \\ \hline K_{(N-P+3)\,(N-P+1)} & K_{(N-P+3)\,(N-P+2)} & .. & K_{(N-P+3)N} \\ \hline . & . & .. & . \\ . & . & .. & . \\ . & . & .. & . \\ \hline K_{N(N-P+1)} & K_{N(N-P+2)} & .. & K_{NN} \\ \hline \end{array}$$

Figure 4.Temporary Matrix T of size (P-1) x P.

Values of matrix T can be computed as,

$T(x, y) = K(N-P+(x+1), N-P+ y)$; $1 \le x \le (P-1)$, $1 \le y \le P$ (3.43)

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, Like wise last row of T is used to generate ((P-1) N + 1) to PN rows [12].

We have used Kekre's Wavelet Transform Matrices of Size 128, 64, 32 Generated from kekre's Transform Matrix of Size 64, 32, 16 respectively. We calculate Wavelet energy feature for the Palmprint image using these wavelet matrices.

5.2.1 Properties of Kekre's Wavelet Transform:

1. Orthogonal- The transform matrix K is said to be orthogonal if the following condition is satisfied.

$[K][K]^T = [D]$, Where D is a diagonal matrix.

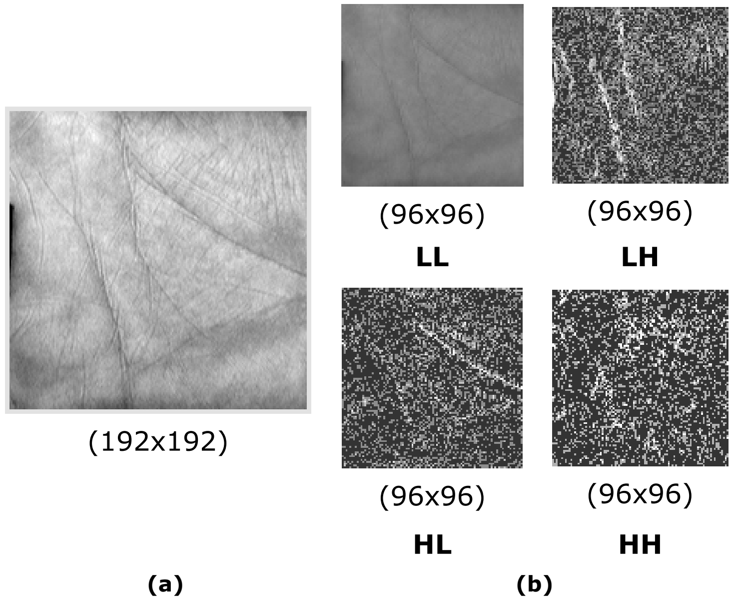


Figure 5. Wavelet Decomposition of Selected ROI of Palmprint Image (a) Selected ROI (b) Kekre's Wavelet First level Components

Kekre's Wavelet Transform matrix satisfies this property and hence it is orthogonal. The diagonal matrix value of Kekre's transform matrix of size NxN can be computed as

$$D(x,y)=\begin{cases} 2 & ,\text{if } x=y=N \\ N & ,\text{if } x=y=1 \\ 0 & ,\text{if } x\neq y \\ D(x-1,y-1)-2(N-x+1) & ;\text{if } x=y=p \text{ and } p\neq 1 \text{ or } N \end{cases} \quad (6)$$

2. Asymmetric- As the Kekre's transform is upper triangular matrix, it is asymmetric.

3. Non Involutional - An involutionary function is a function that is its own inverse. So involution transform is a transform which is inverse transform of itself. Kekre's transform is non-involution transform.

4. Transform on Vector -The Kekre's Wavelet transform on a column vector f is given by

$$F = [KW]\ f \quad (7)$$

And inverse is given by

$$f = [KW]T\ [D]^{-1}\ F \quad (8)$$

5. Transform on 2D Matrix- Kekre's Wavelet transform on 2D matrix f is given by

$$[F] = [KW]\ [f]\ [KW]^T \quad (9)$$

Obtaining Inverse:

Calculate Diagonal matrix D as,

$$[D] = [KW][KW]^T \quad (10)$$

D =

D1	0	0	0	0	0
0	D2	0	0	0	0
0	0	D3	0	0	0
0	0	0	...	0	0
0	0	0	0	...	0
0	0	0	0	0	DN

Inverse is calculated as

$$[f] = [KW]T\ [\ Fij\ /\ Dij\ ]\ [KW] \quad (11)$$

Where Dij = Di * Dj ; $1\leq i \leq N$ and $1\leq j \leq N$

6. PALMPRINT FEATURE VECTOR EXTRACTION & MATCHING

With the development of wavelet theory, Wavelet Analysis has been valued highly in various domains of research. It is a powerful tool of multi-resolution analysis. Here we construct wavelet energy feature (WEF) by the high frequency to describe the palmprint images' texture and use it to describe the ridges & principle lines. We take the kekre's Wavelet (KW) Transform of the selected palmprint ROI. The wavelets will capture localized spectral information from the ROI. We have the ROI of Size 192 X 192 Pixels. At each level Mth order KW matrix (of MXM Size) is generated by M/2 order Kekre's Transform Matrix (N=M/2, P=2).

The wavelet energy in horizontal, vertical and diagonal directions at the *i*-level can be, respectively, defined as:

$$E_i^h = \sum_{x=1}^{M}\sum_{y=1}^{N}(H_i(x,y))^2 \quad (12)$$

$$E_i^v = \sum_{x=1}^{M}\sum_{y=1}^{N}(V_i(x,y))^2 \quad (13)$$

$$E_i^d = \sum_{x=1}^{M}\sum_{y=1}^{N}(D_i(x,y))^2 \quad (14)$$

These energies reflect the strength of the images' details in different direction at the *i*-level decomposition. Hence the feature vector $(E_i^h, E_i^v, E_i^d)_{i=1,2,3,\ldots,k}$ where K is the total number of wavelet decomposition level, can describe the global details feature of palmprint texture.

Using above mentioned vector, the features extracted from the whole ROI don't preserve the information concerning the spatial location of different details of ridges and principle lines, so its ability to describe palmprint uniqueness is weak. In order to deal with this problem, we divide the detail images into $S \times S$ non-overlap blocks equally, and then compute the energy of each block. Then, the energies of all blocks are used to construct a vector. This is shown in Fig 6. Finally the vector is normalized by the total energy. We are also normalizing this vector each level and Component wise also. These normalized vectors are named as wavelet energy feature. WEF has a strong ability to distinguish palmprints. According to these figures, WEFs of the same palmprints are very similar while those of different palmprints are quite dissimilar. This is helpful for palmprint recognition.

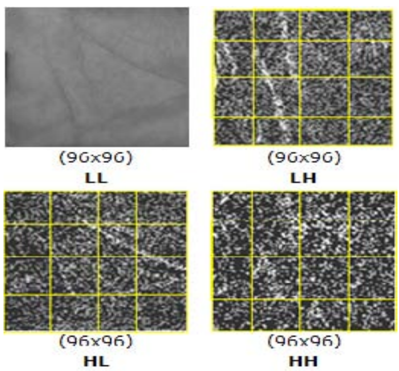


Figure 6. Dividing Wavelet Components into 4x4 non overlapping blocks
Only Horizontal, Vertical and Diagonal Components are divided into 4x4 blocks. Each component gives 16 values and per level we get 48 values of wavelet energy.

Each component is divided into 4x4 (SxS) non overlapping blocks; hence for a single component (LH, HL or HH) we have 16 wavelet energy values. In a single decomposition we have 3 components (LH, Hl & HH) hence we get total 48 components. We Normalize the feature vector by dividing energy of components at each levels by the sum of all the components energy at that level. We have such 5 levels (J) of decompositions hence we have total 3xSxSxJ i.e. 240 (3*4*4*5) values in the wavelet energy feature vector. We call this feature vector as KWEFV.

KWEFV = {WE0, WE1, ….., WEn) n=3xSxSxJ. (15)

For the palmprint shown in Table 3.8 Set1 & Set 2 the plot of Wavelet Energy Coefficients (KWEFV) are shown in Fig.7. KWEFV for palms of same person are similar and follow common pattern and this varies for palm from different persons.

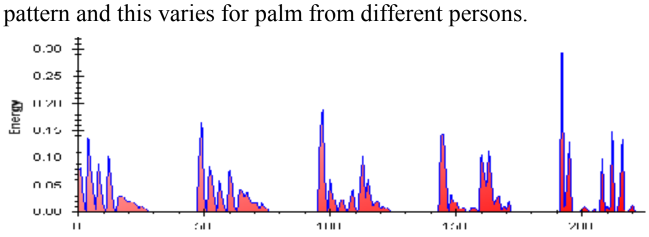


Figure 7. Kekre's Wavelet Energy Feature Vector Plot for the Palmprint shown in Fig. 6.

Total 15 Components (3*J) are generated, total energy of each component for analysis is also calculated. The component energy is normalized by total energy at the level. The distribution is a coarser estimate of spectral content. It is seen that for different palm higher components energy distribution is different amounting to the variations in ridges and principal lines.

6.1 Relative Wavelet Entropy

Two metrics for analyzing similarity between two energy distributions (Kekre's Wavelet Energy Feature Vector) are used; Wavelet Energy Entropy [233] as one of the similarity measure. We have normalized the wavelet energy feature vector hence this can be treated as a probability distribution.

Let us now suppose that there are two different probability distributions $\{p_i\}$ and $\{q_j\}$, with $\sum_j p_j = \sum_j q_j = 1$. Here consider them as wavelet energy distributions. Relative Wavelet Entropy is defined as ,

$$S_{wt}(p \mid q) = \sum_{j=0}^{n} p_j \ln\left[\frac{p_i}{q_j}\right] \tag{16}$$

Which give degree of similarity between to probability distributions with respect to each other; the RWE is a positive real number and it vanishes when $p_j \equiv q_j$.

6.2 Palmprint Enrollment & Matching

Palmprint database of Hong Kong Polytechnic University is used for testing proposed method. This is called as PolyU database [18]. In this database has 384 different persons palmprints taken in two different sittings & for each palm 10 samples are available. We have enrolled 125 persons from this database. For each person 6 samples were taken for training and remaining samples were used for testing. Imposter palm were selected from other person's samples. We have extracted Wavelet Energy Feature Vectors using Kekre's Wavelets and Haar Wavelets (Modified). As discussed earlier the feature vector is normalized per level. Fig. 7 shows one of these feature vectors. We are representing the palm by its feature vector (KWEFV). We analyze similarity in three modes.

- The feature vector is normalized level wise i.e. for all 48 components (16 LH, 16 HL, 16 HH) and then we can evaluate the Relative Wavelet Energy Entropy for this normalized feature vector, final matching is given by summation of all levels relative entropy.
- Euclidian Distance (ED) between two KWEFV sequences (Seq. X & Seq. Y).

$$ED = \sqrt{\sum_{i=0}^{n} (KWEFV_{x,i} - KWEFV_{y,i})} \tag{17}$$

- RWEE for two normalized KWEFV directly. We take full wavelet energy coefficient sequence and normalize it by total energy. This distribution is then used for finding full sequence relative entropy.

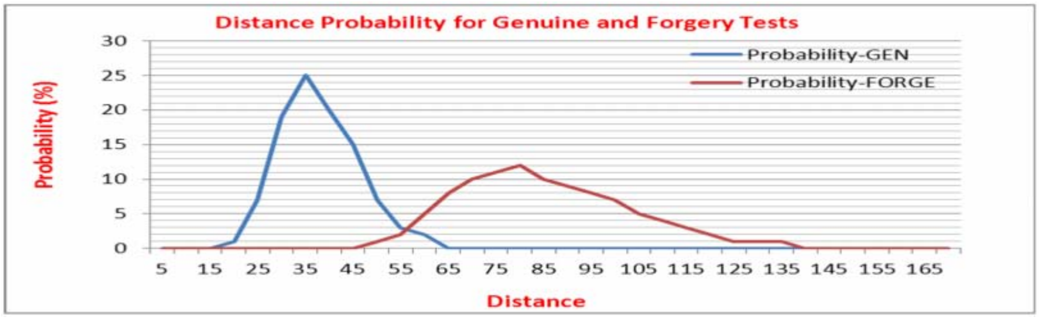


Figure 8. Relative Probability for Matching Distance of Genuine and Forgery Tests.
Two clear classes can be seen, with threshold distance as 55. This can be used for designing classifier.

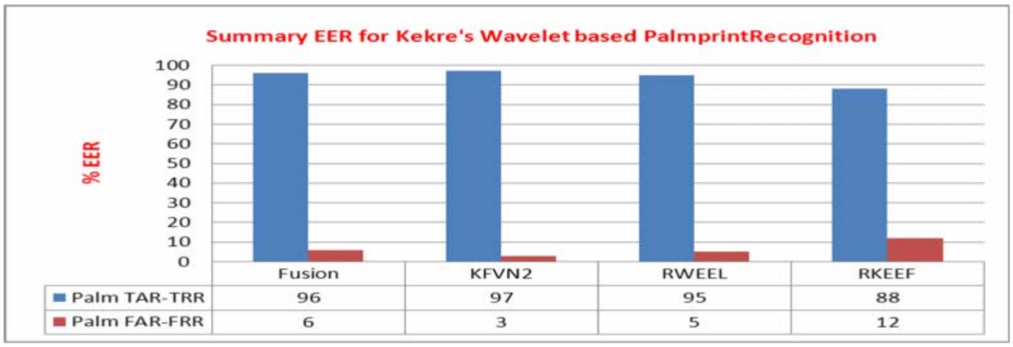


Figure 9. Comparison of Different Palmprint Recognition Methods Implemented (KFVN2 - kekre's Wavelet Feature Vector Normalized Level Wise, RWEEL- Relative Wavelet Energy Entropy Level wise, RKEEF – Relative Kekre's Wavelet Energy Entropy Full Sequence)

7. RESULTS & DISCUSSIONS

Total 508 tests for intra class matching i.e. genuine palmprint testing and more than 5200 tests for intra class matching i.e. cross matching and imposter testing has been performed. Euclidian distance and relative energy entropy for each test is calculated. The test results are divided in two classes as Genuine Tests Distance and Forgery Tests Distance (Imposter distance). The range of distance values against the participation in specific class is shown in Fig. 8. Two peaks for two test classes can be clearly seen. For genuine palms the relative distance lies in the range of 15 to 65 and that for imposter palm lies in the range of 45 to 135. Simple Euclidian Distance based K-nearest neighborhood classifier (K-NN) is used here. Evaluation metrics such as False Acceptance Rate (FAR), False Rejection Rate (FRR), True Acceptance Rate (TAR) and True Rejection Rate (TRR) are evaluated [1].

Analysis for Euclidian Distance of KWEFV normalized level wise is shown in Fig. 10. Here the Euclidian Distance between two KWEFV sequences is calculated. The sequence is normalized for each level. This mode of matching gives maximum accuracy. It gives 97% EER for TAR-TRR and 3% EER for FAR-FRR

Summary of EER for other options is shown in Fig. 9, where it can be seen that the Relative Wavelet Energy Entropy Level wise (RWEEL) based feature vector gives 95% EER for TAR – TRR Analysis. The Relative Wavelet Energy Entropy Full (RKEEF) gives lower EER of 88%. The fusion is discussed next.

7.1 Fusion of Relative Entropy & Euclidian Distance

The score of Relative Entropy and Euclidian Distance based distance is also fused for multi-algorithmic matching. We have used linear fusion of score where the final score D_f is given by fusion of Relative Entropy E_R and Normalized KWEFV distance D_{WN}.

$$D_f = W_1 * E_R + W_2 * D_{WN}. \quad (18)$$

Where W1 & W2 are fusion weights, W_1=10, W_2=0.5. These weights are empirically decided so that their contribution towards final distance is equal. The analysis is shown in Fig. 11, the achieved EER for TAR-TRR is 96% and that for FAR-FRR is 4%.

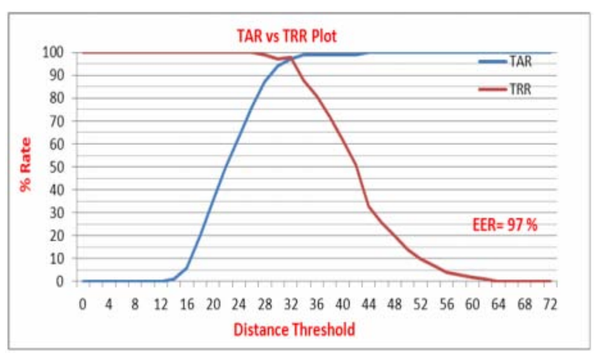


Figure 10. TAR-TRR Plot for Kekre's Wavelet Relative Energy Entropy Level wise .

Table 1. Palmprint Recognition Testing Summary

Test Result	Successful	Failure	Total	% Accuracy
Number of Tests	435	73	508	85.63

Overall accuracy of the palmprint recognition is 85.63%. Out of total 508 (1:1 Matching) recognition tests performed 435 tests were successful, this classification was performed using simple K-NN Classifier. This performance can be improved by implementing training and neural network based classifier.

8. CONCLUSION

In this paper palmprint recognition based on Wavelet Energy Distribution is discussed. kekre's Wavelet for extracting texture features of the palmprints are used. Relative Energy Entropy and Euclidian Distance are used for calculating distance between feature vectors extracted. Kekre's Wavelets have good feature extraction capability; EER of 97% for TAR-TRR analysis of Euclidian distance between KWEFV is achieved. The fusion of Relative Entropy based distance and normalized Euclidian distance is also performed which gave 96% EER for TAR-TRR analysis. K-NN classifier based palmprint recognition gave 85% accuracy. This can be further improved by neural network based classifier. Kekre's wavelet have integer coefficients in the wavelet matrix, this makes the operation faster and the result clearly indicate the feasibility of these wavelets in extracting texture information from images, this facts can be used to explore further dimensions in image processing using wavelets.

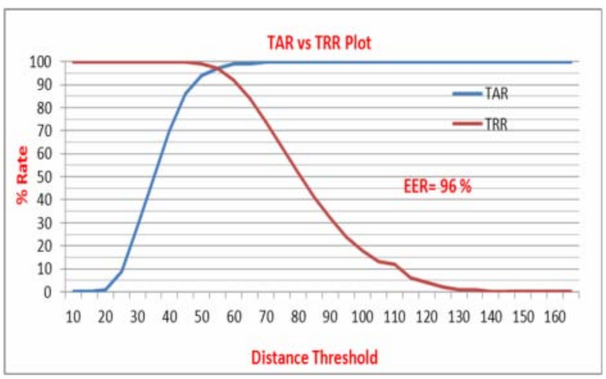


Figure 11. TAR-TRR Plot for Fused Matching Distance based Palmprint Recognition

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