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Advanced Palm Print Recognition Using Curve Let And Recursive Histogram Equalization

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Abstract: The Palm print enhancement is a preprocessing stage of palm print authentication. The performance and accuracy of the system can be improved by incorporating effective palm print enhancement methods. So far, only little work has been done in palm print enhancement. Little attention is given to incorporate the enhancement techniques in palm print authentication system to achieve performance improvement. Most of the works attempt to improve the performance either by fusing palm print features or using different matching algorithms. This work presents a few effective enhancement methods which provide better performance and accuracy. Advanced palm print recognition using curve let and Recursive Histogram Equalization (RHE) overcomes the drawbacks of the existing systems and makes palm print recognition simpler and more accurate. Palm print recognition system uses the Symbolic Aggregate Approximation (SAX) features from the palm print. Curve let transform is used for removing noise in the input image, while RHE is used to improve the contrast of images. The recognition rate is optimum when both curve let and RHE methods are used for enhancement of palm print.

Key words: Enhancement · Noise · AST · Recognition · Palm print · Histogram

INTRODUCTION

There exist three different categories for palm print authentication [1], divided on the basis of extracted features; (i) line-based approaches [2-4] (ii) appearance-based approaches [5] and (iii) texture-based approaches.

Line-based methods are based on line matching, line detection, crease detection, morphological operators etc. Morphological operators can be used in the feature extraction process in order to obtain the feature vectors. Datum point invariant and the line feature matching technique for the verification process are not appropriate for many on-line security systems, since it is difficult to extract principal lines from a low resolution palm print image. The required recognition rates and computational efficiency are not fully achieved here. Other issues in the line-based approaches include the existence of similar line features in many palm prints, and the thickness and width of the different lines are not taken into account which is very critical for differentiating palm prints.

Appearance-based approaches are based on the analysis of principal component and linear discriminate. The original training palm prints are transformed into small groups of characteristic feature images called Eigen palms [5] by means of Karhunen–Loeve (K–L) transform. But the authentication performance of these Eigen palms is reduced when it is applied in real time applications.

In texture-based approach, texture features are extracted by means of gabor filter, discrete cosine transform, ordinal filter, laws mask, discrete Fourier transform, wavelets and so on. Even though the Gabor filter [6] gives accurate time-frequency location and robustness against varying image's brightness and contrast, it involves high computational cost and time delay. Difficulty in setting an appropriate filter parameter causes identification performance to depend much on the training set used for parameter selection. Orthogonal line ordinal feature [7] is currently the best ordinal measure for palmprint representation; still its theoretical foundation has not been well formulated. Wavelet Energy

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Feature technique's [8] ability to distinguish palms is very strong because it can reflect the wavelet energy distribution of the principal lines, wrinkles and ridges in different directions at varying wavelet decomposition levels. Disadvantages of this method are its sensitiveness towards noise, the requirement of high resolution images, implementation cost and time complexity. Fourier transform method [9] is used to ignore the abundant textural details of a palm, and the extracted features are highly influenced by the lighting situations. A huge storage of database to store image templates affects the system's simplicity.

Personal verification using palm print and hand geometry biometric [10] does verification by integrating hand geometry features. Palm print and hand geometry features are acquired using a digital camera. These images are aligned and then used to extract palm print and hand geometry features. These features are then examined for their individual and combined performances. The image acquisition setup used in this work is inherently simple and it does not employ any special illumination, nor does it use any pegs to cause any inconvenience to the users.

Hierarchical palm print identification via multiple feature extraction [11] describes a new method to authenticate individuals based on palm print identification and verification. A texture-based dynamic selection scheme is used to facilitate the fast search for the best matching of the sample in the database in a hierarchical fashion. The global texture energy, which is characterized with high convergence of inner-palm similarities and good dispersion of inter-palm discrimination, is used to guide the dynamic selection of a small set of similar candidates from the database at coarse level for further processing. Multiple palm print features are used by [12] for accurate palm print recognition.

Combining multiple classifiers by averaging or by multiplying [13] combines observations from different sources. Palm print-based recognition system using phase difference information [14] uses histogram equalization for enhancing the contrast of the palm print image. Most of the works did not give any attempt to incorporate the enhancement techniques in biometric palm print images to achieve performance improvement. In most of the prior systems, the enhancement stage got little attention. The enhancement of the input image can deeply affect the output of the system. This work incorporates curve let and RHE techniques for enhancement of the palm print image. Curve let is used for removing noise in the palm print image, and RHE is used for improving the contrast of the palm print image. Applying curve let and RHE improves the overall performance of the system.

Palm Print Recognition Using Sax Features: The symbolic demonstration of time series is called SAX. It transforms the original time-series data into symbolic strings where Piecewise Aggregate Approximation (PAA)-based algorithm is used that provides simplicity and low computational complexity. Since SAX requires less storage space, it is used for solving many challenges associated with the present data mining tasks. In addition, the symbolic representation allows researchers go further to the available wealth of data structures and string manipulation algorithms in computer science, and also for many applications in bioinformatics and data mining [15].

SAX algorithm transforms a time-series X of length 'n' into the string of arbitrary length w, where w < n, using a table that contains the breakpoints. Each value in the table corresponds to each level in the time series graph which is further represented by symbols in the alphabet array of size>2 which finally forms the string of length 'w'. Dimensionality reduction is based on two parameters named 'sax length' (w) and 'number of symbols used in the alphabet array'. The algorithm consists of two steps. In the first step, it transforms the original time-series into a PAA representation ($\bar{c}$) and this intermediate representation is further converted into alphabetic string ($\hat{c}$) in the second step. Usage of PAA approach in the first step gives the advantage of being simple and efficient in dimensionality reduction and provides lower bounding property. The second step, where the actual conversion of PAA coefficients into alphabets is also computationally efficient, shows the contractive property of symbolic distance.

Generating SAX from PAA representation of a time series is implemented in a way which produces symbols that correspond to the varying magnitude of time-series data [16]. Figure 1 shows the conversion of times series into SAX representation. Figure 1 (a) is the original time series data. Figure 1 (b) shows the corresponding PAA representation and Figure 1(c) shows the SAX representation.

Advanced Palm Print Recognition System: The proposed palm print recognition system using SAX features is shown in Figure 2. It composes input acquisition, enhancement, feature extraction and recognition stages. The input acquisition and enhancement steps are discussed in chapter I, II, and III. This chapter mainly focuses on the feature extraction and recognition steps. The block diagram of palm print recognition using SAX features is shown in Figure 2.

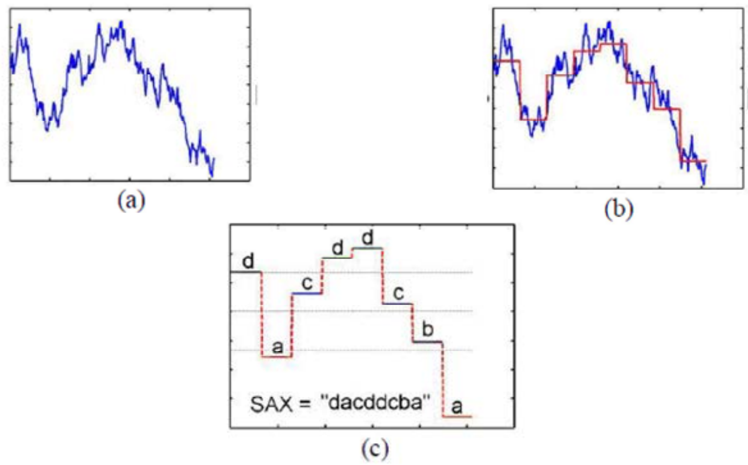

Fig. 1: Times series to SAX representation (a) Time series (b) PAA representation (c) SAX representation

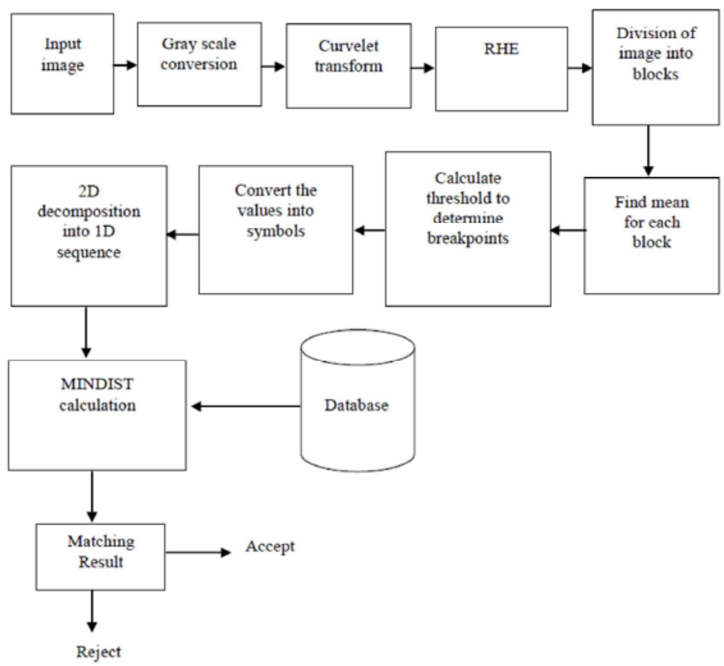

Fig. 2: Block Diagram of Palm Print recognition using SAX features

Here, an extension of the SAX is used which represents the 2D data using a 2D matrix of symbols. The method uses the gray scale information of captured images in order to reduce the complexity of execution.

The size of the gray scale image matrix Q, is m x n. It is then divided into equal size blocks of size w_1 x w_2 and the mean value of the data inside each block is calculated to form the dimensionality reduced representation. The newly formed mean value matrix is named as $\bar{Q}$ of size w_1 x w_2. The (i^{th}, j^{th}) element of $\bar{Q}$ or the mean value of each block in $\bar{Q}$ can be calculated by using the Equation (1)

$$\bar{Q}(i,j) = \frac{1}{w_1 w_2} \sum_{x=\frac{m}{w_1}(i-1)+1}^{\frac{m}{w_1}i} \; \sum_{y=\frac{n}{w_2}(j-1)+1}^{\frac{n}{w_2}j} Q(x,y) \qquad (1)$$

Breakpoints have to be applied to convert $\bar{Q}$ into a symbol matrix S or the 2D SAX representation. For this, a 'threshold' value is used so that breakpoints can be calculated easily. Threshold value is calculated using the Equation (2).

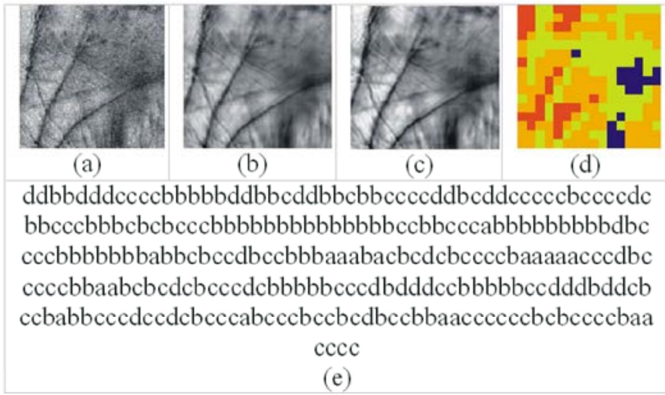

Fig. 3: Palm print enhancement and feature extraction. (a) The input image. (b) image after applying curve let (c) RHE equalized image (d) SAX representation (e) SAX string

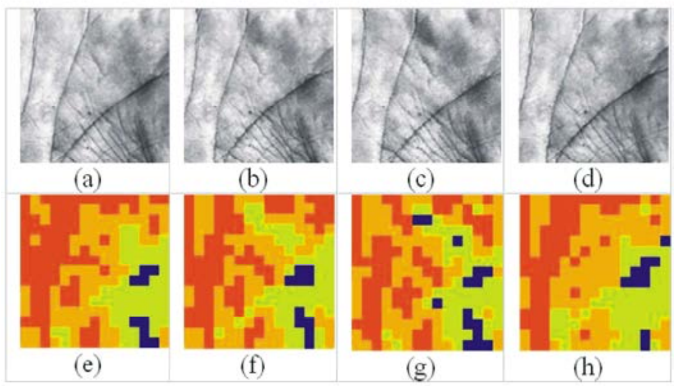

Fig. 4: (a),(b),(c) and(d) palm prints from the same palm, (e),(f),(g) and (h) corresponding SAX representation

Table 1: Lookup table for calculating dist () function with four SAX level

	a	b	c	d
a	0	0	0.67	1.34
b	0	0	0	0.67
c	0.67	0	0	0
d	1.34	0.67	0	0

$$T = \frac{\max - \min}{SAX_{level}} \tag{2}$$

where 'max' is the maximum value in the $\overline{Q}$ matrix, 'min' is the minimum value in the $\overline{Q}$ matrix and SAX $_{level}$ is equal to number of symbols to be used.

For example, if four SAX $_{level}$ are chosen, five breakpoints have to be calculated. The breakpoints are min, min+T, min+2T, min+3T and max. Then, one symbol is used to represent the values between min and min+T, and another symbol is used for the values between min+T and min+2T and so on. In this manner, the symbol matrix S, the 2D SAX representation can be obtained. Then, this two dimensional data is decomposed into one dimensional (1D) sequences using a progressive scan [17]. These 2D SAX representations as strings are stored in the database as palm print template.

The MINDIST between two corresponding strings is measured and this is adopted as the similarity measurement of the corresponding two palm prints. Given two SAX strings $\hat{Q} = \hat{q}_{11}, \hat{q}_{12}, \ldots \hat{q}_{w_1 w_2}$ and $\hat{C} = \hat{c}_{11}, \hat{c}_{12}, \ldots \hat{c}_{w_1 w_2}$, their MINDIST can be calculated using the Equation (3) where dist() can be implemented using lookup table as given in Table 1. If the MINDIST is smaller, then the two palm prints are more similar.

$$\mathrm{MINDIST}(\hat{Q},\hat{C}) = \sqrt{\frac{mn}{w_1 w_2}} \sqrt{\sum_{i=1}^{w_1} \sum_{j=1}^{w2} \mathrm{dist}(\hat{q}_{ij},\hat{c}_{ij})^2} \tag{3}$$

where m x n is the size of the image and w_1 x w_2 is the SAX length.

Few samples of palm prints are shown in Figure 5, in which palm prints in the same column are from the same palm, and the palm prints in the first and second rows are from session one and session two respectively. Figure 3 shows the output of the palm print enhancement and

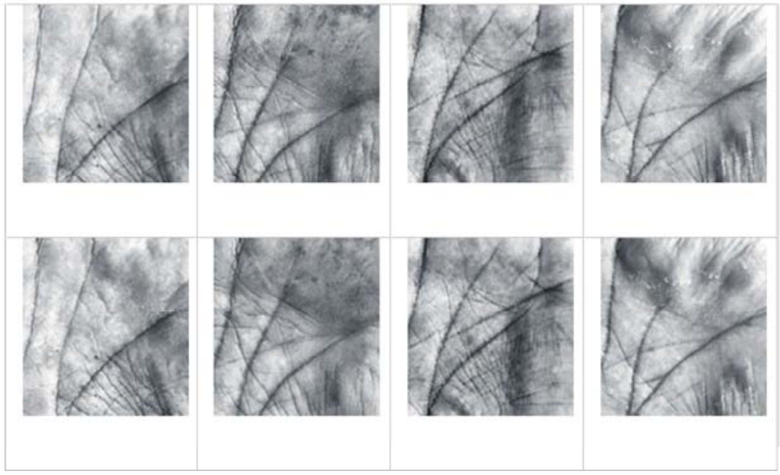

Fig. 5: Sample palm prints

feature extraction process where block size (w1×w2) is set as 8×8 and the SAX $_{level}$ as 4. The SAX string is used as palm print templates for experiment-matching process. Figure 4 shows the four samples of a palm print from an individual and their corresponding SAX representation.

RESULTS AND DISCUSSIONS

234 subjects from IIT Database are used for recognition. Four samples are taken for each subject. The features of the palm print image to be recognized are checked with the features of the palm print images stored in the system's database. If a match is found, then the person is authenticated, otherwise the person is unauthenticated. Verification is done with HE, curve let, RHE and curve let & RHE methods. It is proceeded with two phases in which in the first phase, 117 random palm print images from the IIT database that are also contained in the system's database were tested. In the second phase, 117 palm print images were taken for testing from the IIT database that is not in the system's database.

The performance of a palm print authentication system can be measured by three metrics, namely FAR(False Acceptance Rate),FRR(False Rejection Rate) and TSR(Total Success Rate).

False Acceptance (FA) is the number of times the system accepts an unauthorized user (imposter) and FAR is the ratio of number of false acceptances to the total number of imposter accesses. FAR is measured as in Equation (4)

$$\text{FAR} = \frac{\text{Number of false acceptances}}{\text{Total number of imposter accesses}} \times 100 \ \% \qquad (4)$$

False Rejection (FR) is the number of times the system rejects an authorized user (genuine) and FRR is the ratio of number of false rejections to the total number of genuine accesses. FRR is measured using Equation (5)

$$\text{FRR} = \frac{\textit{Number of false rejections}}{\text{Total number of genuine accesses}} \times 100 \ \% \qquad (5)$$

TSR (Connie et al 2005) represents the recognition rate of the system and it is measured using Equation (6)

$$\text{TSR} = \left(1 - \frac{\text{FA} + \text{FR}}{\text{Total number of accesses}}\right) \times 100 \ \% \qquad (6)$$

Performance of Palm print Recognition Using SAX Features: The comparison of FAR of the RHE & curve let method with other methods is given in Figure 6. RHE& curve let method has the lowest FAR.

The comparison of FRR of the RHE & curve let method with other methods is given in Figure 7. RHE& curve let method has the least FRR. The comparison of TSR of the RHE & curve let method with other methods is given in Figure 8. RHE& curve let method has the highest TSR. Here, the proposed technique provides TSR of 98.29%.

The optimum result is obtained when both curve let and RHE are used. The FAR, FRR and TSR values are measured as 1.7094%, 1.7094%, 98.2905%. Michael et al (2008) used contrast adjustment and smoothing as enhancement technique in contactless palm print and recognition system. They obtained a recognition rate of 98.10 % without image enhancement and recognition rate of 98.68% with image enhancement. An improvement of

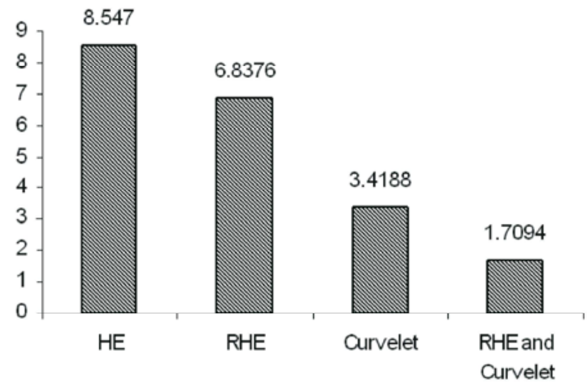

Fig. 6: Comparison of FAR of RHE & curve let method with HE, RHE and curve let

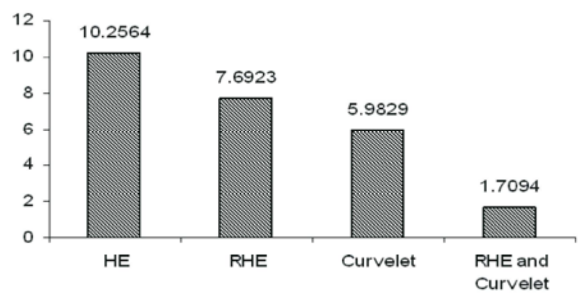

Fig. 7: Comparison of FRR of RHE & curve let method with HE, RHE and curve let

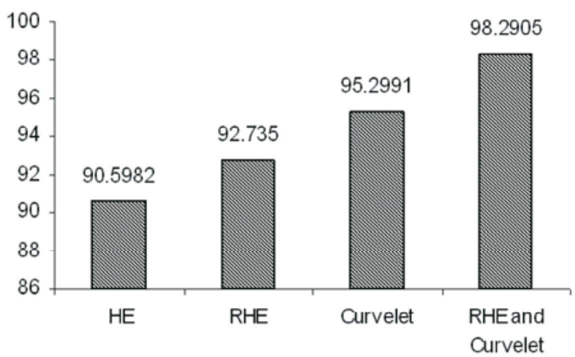

Fig. 8: Comparison of TSR of RHE & curve let method with HE, RHE and curve let

0.58 % is obtained using enhancement. The proposed system provides an improvement of 8% than the HE method using RHE and curve let.

CONCLUSION

To improve the accuracy of palm print authentication system, curve let and RHE are applied prior to the 2D SAX conversion. As these procedures remove the noise and enhance the contrast, the proposed system ensures high performance with competitive accuracy. Since it is a texture-based approach, the computational complexity of the feature extraction process is much lower and thus can be efficiently implemented for even slow mobile embedded platforms. Also, the proposed approach does not rely on any parameter training process.

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