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Diffie–Hellman-Merkle Longer Key Usage On Minutiae, Orientation, And Density Based Palmprint Pattern Matching

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ABSTRACT

Palmprint based biometric recognition has proven to be a reliable source of pattern matching between the tests and training images with variety of features. Recently, the Palm print biometric system is fast and reliable on correct matches but longer key based matching was not exhibited. The shorter key distribution is not effective on detecting the correlation pattern matching output. On the other hand, managing the non-linear deformation palm print is a crucial task since the matching rate is affected especially on minutiae, orientation, and density mapping. A better classifier index and matching method is needed to be employed on the palmprint biometric recognition system. In this paper, Diffie–Hellman-Merkle (DHM) Longer Key Exchange based Palmprint Pattern Matching method is employed. DHM based palmprint pattern matching comprises of three processes. Initial process, palmprint image classification is carried out using the Mahalanobis distance based classifier. Then the classified palmprint image is segmented based on the Higher Order Neighborhood Statistical (HONS) approach. Proposed HONS approach in the second process performs the morphological palmprint image segmentation on different non-linear deformation texture variance. Final processing step is the decision control process (i.e.,) pattern matching on minutiae, orientation, and density. Diffie–Hellman-Merkle longer key set is used to exchange between the two ends of the communication channel to improve the matching rate. The pattern matching rate in Diffie–Hellman-Merkle method essentially consists of finding the best matching between the template (i.e., stored palmprint image in database) and test user palmprint image. Experiment is conducted on factors such as false rejection rate, palmprint matching rate, rate of classification errors.

Keywords: Diffie–Hellman-Merkle Longer Key Exchange, Palmprint Pattern Matching, Higher Order Neighborhood Statistical Approach, Decision Control Process.

1. INTRODUCTION

Biometrics system is used for the personal recognition of the secret information. The palmprint biometric system is the most consistent physiological characteristics which differentiate the individuals. Palm print recognition refers to the process of mapping the two palm print based on the minutiae, orientation, and density range. Palm print is referred to the principal lines, wrinkles and folds come out on the palm images. The present research work with different biometric authentication system has some limitations. However, palm print serves as the identifier with the individual consistency level, where the print patterns of the palm are not able to be duplicated. The rich composition of the palm print has the ample functional information such as higher decision accuracy rate, low intrusiveness, secures features and higher accept rate. The palm print is chosen in our research work, because it is distinctive and easily captured by the devices for the easy extraction of the palm features. The palm feature extracted based on the texture, indents and marks.

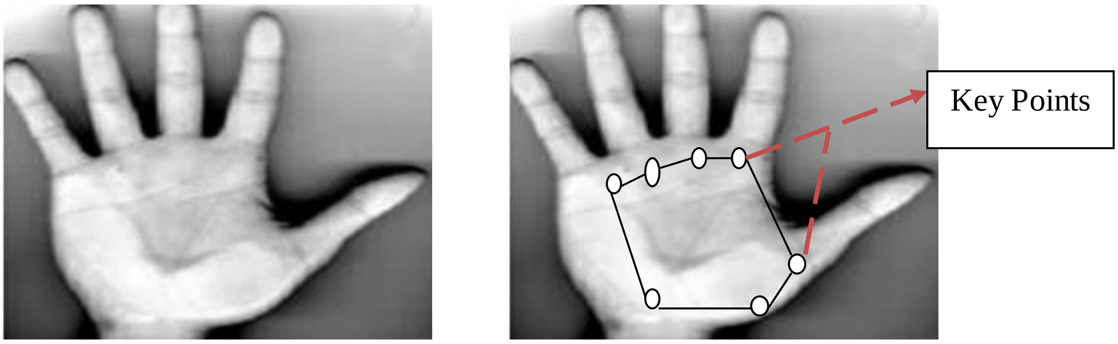

Fig 1 (a) Palm Print Image (b) Palm Print Image with Key Points

As illustrated in Fig 1, the palm print image is acquired through the scanner. The obtained image uses the key points to perform the effective matching operation on set of sampled images. The key points are plotted based on the ridge flow and fold individuality of the palm epidermis. In our research work, the scanned palmprint images are segmented into smaller areas to attain the matching performance. The robustness of the system mainly based on matching the test and training samples to extract the user information with higher security level. Circular Strip based Palmprint Recognition as shown in [8] demonstrates with the image acquisition, preprocessing and image enhancement. Image acquisition gathers the palmprint images from the users and stored in the database. Preprocessing aligns the palmprint images at lowest stage of concept with both input and output intensity value. Circular strip based segmentation carried out to improve the image enhancement rate. Convex hull oriented feature based machine learning approach for palmprint recognition is described in [4], where the pixel wise Niblack's binarization method is accepted. Palmprint endpoints are identified for all the lines sensed which are then used in the building of a convex hull. Machine Learning procedure is clearly employed while performing the palmprint recognition. Dynamic Time Warping (DTW) method as demonstrated in [15] is capable to measure the distance between two different features of the palmprint. DTW method palm recognition consisted of block-based line detection which deals with palm print feature extraction process, and chain code to solve the hand geometric feature extraction. Personal identification system is also not feasible to develop with online system recognition. DTW fails in increasing the accuracy rate an enhancement process.

Multi feature-Based High-Resolution Palmprint Recognition in [2] noticeably improves the matching performance with dissimilar resolution palmprint images. Quality-based and adaptive orientation field estimation algorithm with Neyman-Pearson rule achieves the good performance, yet non-linear deformation and matching efficiency are not up to the grade. Relative nonlinear deformation amongst dissimilar impressions of the same palm is obvious in the case of a contact-based palm scanner image searching process. Cuckoo Search Algorithm is briefly explained in [5] using Active Shape Model and Gabor Filtration method. Active Shape Model helps on extracting the features and Gabor Filter removes the unwanted palmprint structures for the easier searching process. The searching form a new technique with Woods knocks to find the shortest path for the searching of palm images. Palmprint images are converted to the frequency domain using a log-Gabor filter to mine the phase symmetry information in [13]. 2D Fourier Transform takes the series of the palm images over the space domain in terms of orthogonal basis functions. Symmetry is a useful mechanism for identification of palm image objects in an image, without some of the prior segmentation of objects. However combining of this concept with the Moment Invariance and Legendre Moments does not provide the robust classifications. Coupled Nonlinear Dynamic Filters (CNDF) in [6] generates the privacy preserving palmprint templates using the chaotic stream cipher with various orientation palmprint features. The features obtained from a bank of Gabor filters and determined in a phase-coding scheme with classification procedure. Matching is performed directly with the encryption domain parallel to speed up matching and to provide the users privacy.

Principle Component Analysis (PCA) based Gaussianization technique in [11] uses the classifier to match the features. Gaussianization extracts of multiple features from palmprint and reduces the dimensionality of feature vector length. However, the features are not effective to enhance the indexing technique and reduce the time required for matching. Phase-Difference Trained for effective authentication of the users in [14]. Probability Neural Networks extract with PCA and improves the effectual security level by presently increasing hidden layer count. Principle component analysis unable to develop with Kontorovich-Lebedev-Neural (KLN) transforms. The fusion of multimodal biometric is not in carried out with phase-different method. Biometric key-binding framework as illustrated in [1] applied on the image pattern maps the required user information with rotation, scaling, transformation operation. During authentication, the query is matched with the pattern and the image transformation parameters are predictable. The output of the palmprint matching process from which the information bound to the template is recovered but the classifier is not designed with this key binding framework.

In this paper, a palm print matching method to achieve the higher false rejection rate. Based on multiple orientation of PolyU database information, Diffie–Hellman-Merkle (DHM) Longer Key Exchange is employed to generate the high matching template and test users' palmprint image. The Mahalanobis distance based classifier classifies the palmprint training images. The palmprint classification on the training image used as an initial step to perform the higher matching rate. Higher Order Neighborhood Statistical (HONS) approach is introduced in DHM pattern matching method for different non-linear deformation texture segmentation. Final part matches the minutiae, orientation, and density value between the two ends of the communication channel to improve the matching rate. The experimental results worked to demonstrate that the proposed template protection scheme meets the requirements of diversity, revocability, high recognition performance and also provides significant template matching ability. The structure of this paper is as follows. In Section 1, describes the basic problems in biometric recognition based on the palmprint. In Section 2, present an overall view of the Diffie–Hellman-Merkle (DHM) Longer Key Exchange based Palmprint Pattern Matching method. DHM pattern matching also introduces the segmentation process. Section 3 and 4 outline experiment results with parametric factors and present the result graph for research on palmprint recognition. The palmprint results are compared against the existing work using (PolyU) Multispectral Palmprint Database. Finally, Section 5 demonstrates the related work and Section 6 concludes the work with better result outcome.

2. DIFFIE–HELLMAN-MERKLE LONGER KEY EXCHANGE BASED PALMPRINT PATTERN MATCHING METHOD

Palmprint Biometric Matching system using the Diffie–Hellman-Merkle Longer Key exchange consists of the three processes, namely the image classification, segmentation and decision control process. The key exchange between the communication channels is effective in matching of the training and test palmprint patterns. The palmprint test images are collected using the appropriate palmprint scanner in our Diffie–Hellman-Merkle (DHM) Longer Key Exchange method. The image classification step is introduced on classifying the palmprint images to different class indexes. The class index based palmprint collection minimizes the distance between the feature matching. The minimization of distance rate reduces the classification time drastically. Mahalanobis distance based classifier is employed in DHM Longer Key Exchange method. Then the classified palmprint images result are used for performing morphological segmentation operation. The morphological texture segmentation uses the higher order neighborhood statistical approach and it is represented as,

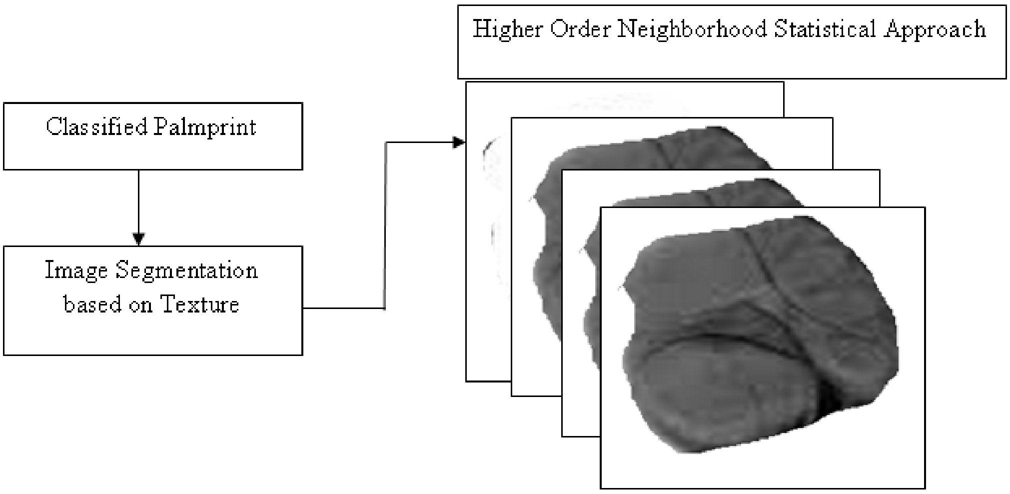

Fig 2 Morphological Texture Segmentation Procedure

Fig 2 briefly explains about the morphological segmentation based on different texture features. The variance in the texture features is clearly analyzed in Diffie–Hellman-Merkle (DHM) Longer Key Exchange method using the Higher Order neighborhood statistical approach. The statistical based texture analyzing of gray scale computes the higher order neighborhood features values at each point of the palmprint images. All points are derived together to analyze the variance on the neighborhood features of the images. Architecture Diagram of DHM based Palmprint Pattern Matching method is described in Fig 3.

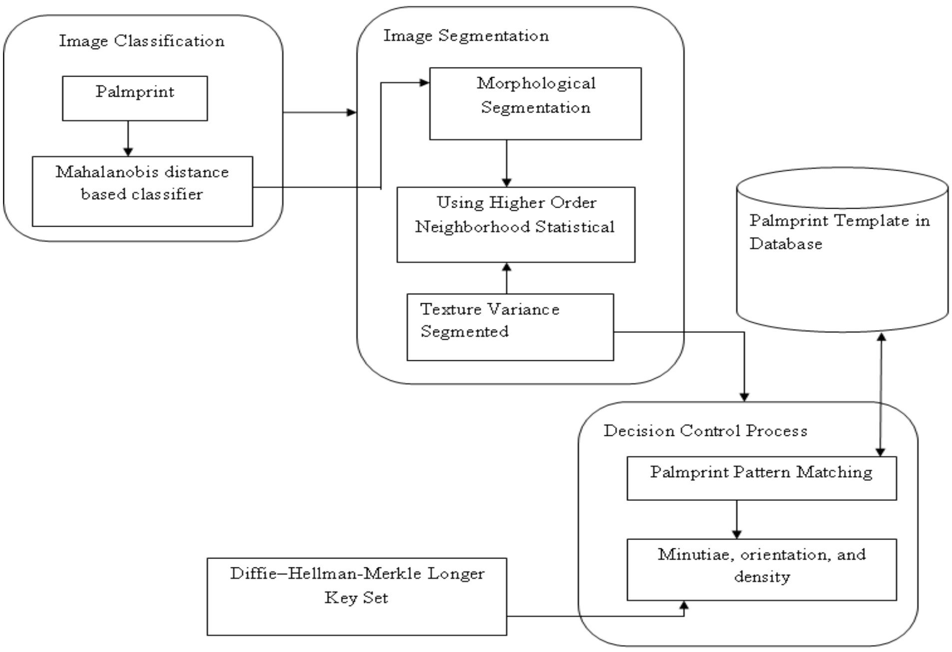

Fig 3 Architecture Diagram of DHM based Palmprint Pattern Matching

Fig 3 demonstrates about the DHM based Palmprint Pattern Matching using the longer key distribution set. Initial process in the DHM based Palmprint Pattern Matching is the classification process, where the Mahalanobis distance based classifier is employed. The DHM method carries the classification process based on the palmprint training image feature of the distance from the test image feature classifiers. Second major process in the DHM based Palmprint Pattern Matching is the image segmentation. The classifier result is used for performing the morphological segmentation based on the texture.

The morphological texture segmentation in proposed work partitions the palmprint images into regions with some feature characteristics. The statistical structure is typically viewed on the neighborhood points through the texture primitives. The Higher Order Neighborhood Statistical approach is briefly used on locating the correlation between the non-linear deformation palm prints. Texture variance segmentation is based on computing the neighborhood intensity range. Final processing step in the DHM based Palmprint Pattern Matching is the decision control process. The pattern matching process is carried out using Diffie–Hellman-Merkle Longer Key Set. The longer key set is used on the training and test sample communication end to improve the matching rate. The pattern matching on Minutiae, orientation, and density range are carried out to attain the best result.

2.1 Image Classification based on Mahalanobis distance

Assume 'I' user's palmprint image of 'n' dimensional vector with 'x' sample test images. The set of palmprint image is formulized as,

$$User\ Palmprint\ Image\ Set\ 'S' = [I_x(1), I_x(2), I_x(3) \ldots I_x(n)] \ldots\ldots \text{Eqn (1)}$$

The palmprint image classifier distance of user 'I' is measured through the Mahalanobis on 1, 2, 3…n dimensional points. The same set of dimensions are identified for the all the users biometric verification. Mahalanobis distance of the 'x' sample test images covariance matrix is measured as,

$$Covariance\ Classifier\ Matrix\ (CCM) = D\sqrt{(x-\mu)^{Test}\, P^{-1}(x-\mu)^{Training}} \quad \text{Eqn (2)}$$

The test and training samples distance is measured. The 'μ' is the mean point of the palmprint image and p denotes the similarity metrics. The inverse of similarity (i.e., dissimilarityP^{-1}) is also measured. The class indexes hold the value in the diagonal matrix, and then the resultant classifier distance is a normalized classifier distance measure.

2.2 Morphological Texture based Segmentation

Proposed DHM based Palmprint Pattern Matching method develops the Morphological texture based segmentation using classifier result. The dissimilarity removed classified class index is used for the texture region segmentation. The texture region segmented based on the high order neighborhood statistical approach, where the quantitative measure of the palmprint image intensities is identified. Statistical approach is used in proposed method to easily compute the natural biometric image textures variances.

2.2.1 Higher Order Neighborhood Statistical Approach

The classified features from the palm print images are segmented into regions. The region based texture segmentation takes the higher order neighborhood values to reduce the computational complexity rate of palmprint segmentation processing. Each element of the computed covariance matrix is used for the effective texture segmentation of the palmprint regions.

$$Segmentation\ of\ palmprint = CCM\ (R1, R2, R3 \ldots Rn) \qquad \text{Eqn (3)}$$

Segmentation of the palmprint texture is a contiguous set of intensity measurement for analyzing the correlation of regions. The correlation between the texture regions are pair wise dependent or mutually dependent. The pair wise or mutually dependent of the neighborhood regions in the palmprint images initially takes the center pixel intensity ‘c’ to compute the process. The invariance on the texture based segmentation of the palmprint images uses the ‘c’ value to identify the difference point. On using the statistical approach on texture based segmentation, DHM based Palmprint Pattern Matching attains the easier segmentation of palmprint images with lesser computational complexity rate. Defining the soft texture based segmentation, uses the Fisher Texture Variance Segmentation Score to work with non-linear deformation. Fisher Texture Variance Segmentation Score is defined as,

$$Fisher\ Score\ (R|\beta) = \sum_{c=1}^{N} \alpha_x N(R|(\mu_x, \epsilon_x)) \quad \ldots\ldots\ldots \qquad \text{Eqn (4)}$$

The fisher score of the ‘R’ a region is identified with parametric vector ‘β’.

The center pixel intensity value is used for computation of all neighborhood pixel values with mean range. The different classified dimension of single user ‘x’ with higher order texture variations 'ϵ' is used to compute fisher score in DHM based Palmprint Pattern Matching. Higher Order Neighborhood Statistical approach is formularized as,

//Higher Order Neighborhood Statistical

Step 1: Classifier Distance Measure covariance matrix value is initialized

Step 2: Palmprint Image ‘I’ of ‘x’ image region is segmented based on texture variance

For Every Region ‘R’

Step 3: Intensity of the center pixel is computed

Step 4: Fisher Texture Variance Segmentation Score computed for non-linear deformation

Step 4.1: Computes $\sum_{c=1}^{N} \alpha_x N(R|(\mu_x, \epsilon_x)$ on all sample palmprint segmented regions

Step 5: Compute the average score of the 'R' region through $Each\ Fisher\ Score\ Value$

End

The higher order texture variation is used to compute the fisher score in DHM based Palmprint Pattern Matching. The mean of all the samples are computed together to manage the non-linear deformation on the palmprint images.

2.3 Decision Control Process

The final process is the decision control process, where the pattern matching operation is carried out. The Diffie–Hellman-Merkle is a specific method used in the proposed work to implement the longer key distribution. Diffie–Hellman-Merkle longer key exchange activity carried out between the two communications terminals. The key used to match the training and test sample palmprint images to jointly establish the secure biometric authentication system.

2.3.1 Minutiae Pattern Matching

Minutiae based pattern matching makes effectual decision process using the minutiae representation of palmprint. The similarity score of the training and test palmprint images is described

$$Minutiae\ Pattern\ Matching = n^2\ (Size\ of\ test\ (I)) \equiv n^2\ (Size\ of\ training\ (I)) \qquad \text{Eqn (5)}$$

Size of the test image and training palmprint image 'I' is matched with 'n' number of minutiae. The number of the matched minutiae is equivalent in test and training image using the longer key set, thereby matching the pattern.

2.3.2 Orientation Pattern Matching

The orientation based denotes the ridges mapping on the palmprint images. The ridges of test and training image are matched in Diffie–Hellman-Merkle and represented as,

$$Orientation\ (test\ (I), Training(I)) = \sum_{I=1}^{n}(Count\ of\ Rid) \qquad \text{Eqn (6)}$$

The orientation field of matched palmprint block is measured. The matching of the orientation is carried based on the 'Rid' ridges.

2.3.3 Density Mapping

The longer key exchange between the system helps to improve the matching accuracy rate of the test and training palmprint samples. The density mapping on the palmprint image is carried out using the chi-square match properties.

$$Density\ (Test\ (I), Training(I)) = \sum_{I=1}^{n} \frac{(Training_{\ n} - Test_n)^2}{Training_{\ n} + Test_n} \qquad \text{Eqn (7)}$$

Chi-square match properties of sample test and training image is measured, which produces the higher matching rate in Diffie–Hellman-Merkle (DHM) Longer Key Exchange based Palmprint Pattern Matching method.

3. EXPERIMENTAL EVALUATION

Experiment is carried out in MATLAB to recognize the palmprint matching accuracy. Diffie–Hellman-Merkle (DHM) Longer Key Exchange based Palmprint Pattern Matching method is compared against the existing Biometric Key-Binding Framework and Multi feature-Based High-Resolution Palmprint Recognition. The images used for the experimental work are taken from the Hong Kong Polytechnic University (PolyU) Multispectral Palmprint Database. Palmprint is a distinctive and consistent Biometric characteristic with high usability rate. With the increasing order of extremely precise and robust palmprint matching system, multispectral imaging has been employed and enlarges the anti-spoof ability of palmprint. Multispectral palmprint images used for the experimental work were composed from 250 volunteers, including 195 males and 55 females for DHM performance evaluation. The age distribution is from 20 to 60 years old and with different separate sessions. In every session, the subject offers 6 palm images for each set. Therefore, 24 images of every elucidation from 2 palms were composed from each subject. Entirely, the database contains 6,000 images from 500 different palms for one illumination. The average time interval between the first and the second sessions was about 9 days time period.

The ‘rar’ files contains all the original palmprint images collected with our device by blue, green, red and NIR illumination. Experiment is conducted on factors such as false rejection rate, texture variance segmentation efficiency, true acceptance rate, palmprint matching rate, and rate of classification errors.

False Rejection is a part to overcome the negative obstacles in biometric security systems. The system is effective in recognizing an authorized person and rejects that person as a fraud, measure the rejection rate performance in percentage (%). False reject rate is a way used to measure biometric performance when operating in the verification task and typically calculated as the proportion of times the structure produces a false rejection. The classification operation through the Mahalanobis distance based classifier improves the performance, thereby reducing the error rate. The percent of the precise error value is measured to perform the rate of the classification error.

$$Classification\ Error\ Rate = \frac{Approximate\ Classification - Exact\ Classification}{Exact\ Classification}$$

The approximation value is used to identify the difference with exact classification, which measured in terms of percentage. Matching rate of the palmprint is defined as the context of the feature segmented is used to identify the success rate. The success of matching depends on the percentage of higher satisfaction given to the users.

$$No.of\ test\ samples\ image\ key\ points = No.of\ training\ sample\ key\ points$$

The comparison of the key points between the test and training samples improves the matching rate. The number of region segmented in the palm print based on the key points is used to improve the efficiency rate of biometric system. The larger the segmentation based on the texture improves the efficiency variance.

The true accept rate is used to calculate the biometric performance when performing the verification task. It is the percentage of times a system correctly confirms an accurate assert of identity users through the palmprint matching. The higher matching of the user test samples with the training samples improves the acceptance rate.

$$True\ Acceptance\ Rate = \left[\frac{Training\ Sample\ Key\ Points \cap Tested\ Key\ Points}{Overall\ Palmprint\ Image\ Sample} * 100\right] \quad \text{Eqn (8)}$$

The true acceptance rate is denoted as accuracy rate. The overall palmprint image is used to identify the true acceptance percentage. The larger the database collection of palmprint images takes higher processing time to test the user requested biometric authentication system.

4. RESULTS DISCUSSION

In section 4, Diffie–Hellman-Merkle (DHM) Longer Key Exchange based Palmprint Pattern Matching method is compared against the present existing work Biometric Key-Binding (BKB) Framework and Multi feature-Based High-Resolution Palmprint Recognition (MFHPR) System. Different parametric analyses showing the effectiveness of the Diffie–Hellman-Merkle (DHM) Longer Key Exchange have been shown. Hong Kong Polytechnic University (PolyU) Multispectral Palmprint Database is experimented through table and graph values.

Table 1 Tabulation of False Rejection Rate

Average Key Set Size (KB)	**False Rejection Rate (Rejection %)**		
	BKB Framework	MFHPR	DHM Method
5	1.81	2.55	2.88
10	2.38	3.21	3.82
15	6.13	8.15	9.23
20	5.13	6.68	7.62
25	3.48	4.46	5.66
30	6.36	9.17	10.21
35	7.88	10.3	11.27

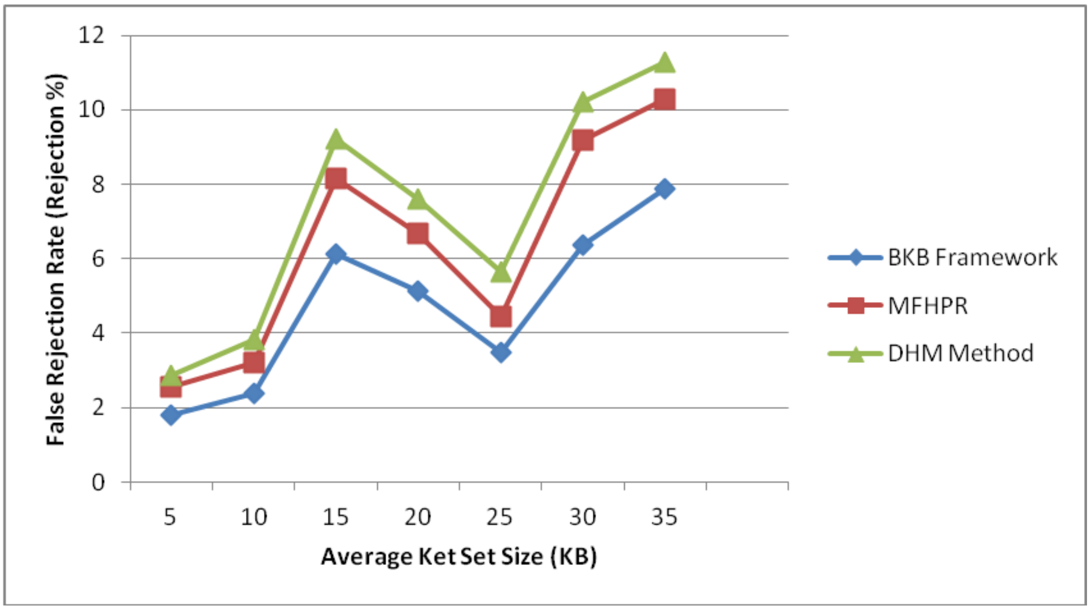

Fig 4 Measure of False Rejection Rate

Fig 4 demonstrates the false rejection rate based on the average key set size. Similarity between the test and training image are measured and the dissimilar key points are removed. The dissimilarity removal helps to reject the false samples. The avoidance of the false rejection rates about 43 – 62 % higher in DHM Method when compared with BKB Framework [1]. Statistical approach is used in proposed method to easily compute the natural biometric image textures variance dissimilarity thereby improves the false rejection rate by 9 – 26 % when compared with existing MFHPR. Average Key Set size is measured in Kilobytes. For instance, 5 KB key size performs the false rejection by 12.94 % higher in DHM Method when compared with MFHPR system [2].

Table 2 Tabulation of Classification Error Rate

.Incoming Palmprint for Classification	Rate of Classification Error (Error %)		
	BKB Framework	MFHPR	DHM Method
20	0.40	0.38	0.36
40	0.41	0.39	0.37
60	0.45	0.43	0.41
80	0.47	0.45	0.43
100	0.48	0.49	0.45
120	0.52	0.50	0.46
140	0.55	0.51	0.49

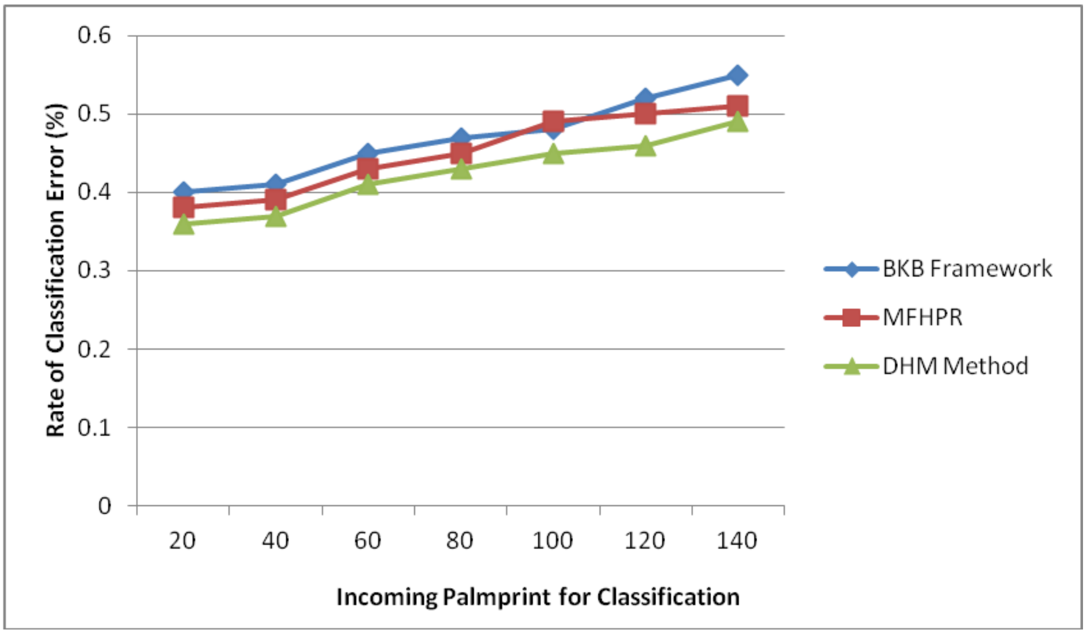

Fig 5 Measure of Classification Error Rate

Error rate on classification are analyzed through the incoming palmprint images. The palmprint images taken for the classification process uses the Mahalanobis distance based classifier in DHM. The image classification step is introduced on classifying the palmprint images to different class indexes. Class indexing reduces the error rate in DHM by 6 – 11 % when compared with existing BKB Framework [1]. The palmprint image classifier distance of user 'I' is measured through the Mahalanobis distance form. As the palmprint image count increases, the error rate on classification in proposed work is reduced when compared with existing work. The class indexes which reduce the error rate when compared with [1] method holds the value only in the diagonal matrix structure. The minimization of distance rate reduces the classification error to 4 – 8 % in DHM when compared with MFHPR [2].

Table 3 Tabulation of Palmprint Matching Rate

User Count	Palmprint Matching Rate (%)		
	BKBFramework	MFHPR	DHM Method
10	85.8	90.2	96.1
20	80.5	87.2	95.2
30	83.6	91.6	97.3
40	82.2	90.4	95.2
50	84.4	91.1	98.2
60	80.9	89.2	96.6
70	85.2	90.7	96.5

Palmprint matching is typically based on the training and test samples in DHM Method. DHM Method compares the existing work with the BKB Framework and MFHPR. The matching of the different set of user count such as the ‘10’, ‘20’ ’30’, ‘40’ are used on experimental work. A high intensity value on the palm lines are effectively matched in DHM Method when compared with BKB Framework [1] and MFHPR [2]. The higher the result percentage can be used for the high end real time applications.

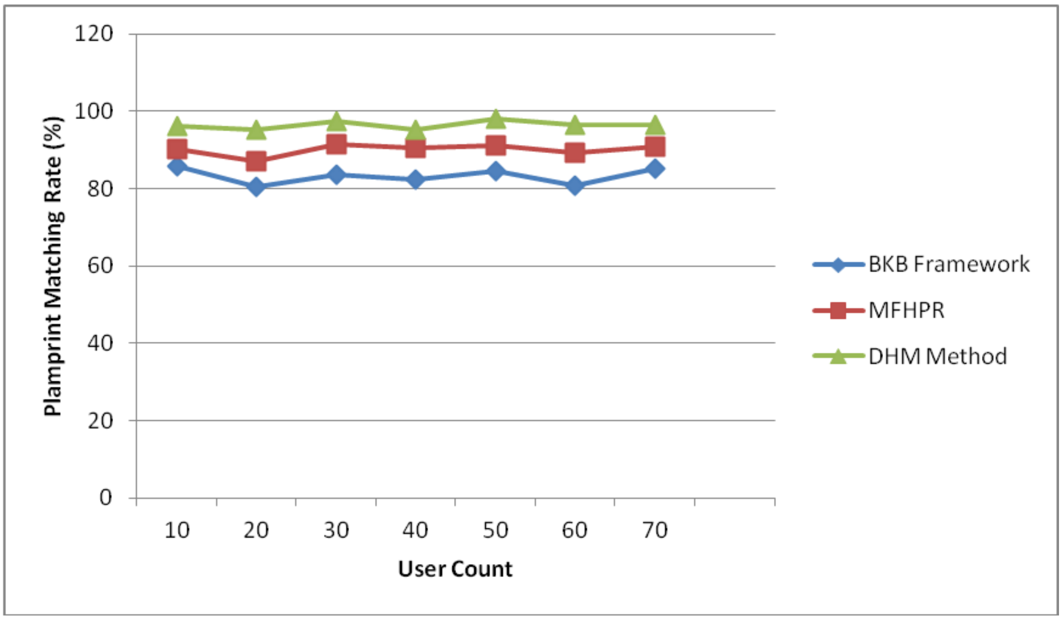

Fig 6 Performance of Palmprint Matching Rate

Fig 6 illustrates the Longer Key Set in DHM method for performing the accurate palmprint matching. The palmprint is matched in DHM based on the Minutiae, orientation, and density range. The accurate matching result on the above three features improves the matching rate by 12 – 19 % in DHM method when compared with BKB Framework [1]. The longer key set is used on the training and test sample communication to improve the matching rate. The matching rate of the palmprint is also increased by 5 – 9 % when compared against the MFHPR system. For instance, on illustrating with ‘10’ sample users, the DHM method attains the 6.54 % higher result rate when compared with MFHPR system.

Table 4 Texture Variance Segmentation Tabulation

Palmprint Test Images	**Texture Variance Segmentation Efficiency (%)**		
	BKB Framework	MFHPR	DHM Method
100	71	79	83
200	73	81	86
300	74	83	88
400	75	85	91
500	77	88	92
600	79	89	95
700	81	89	96
800	83	90	97

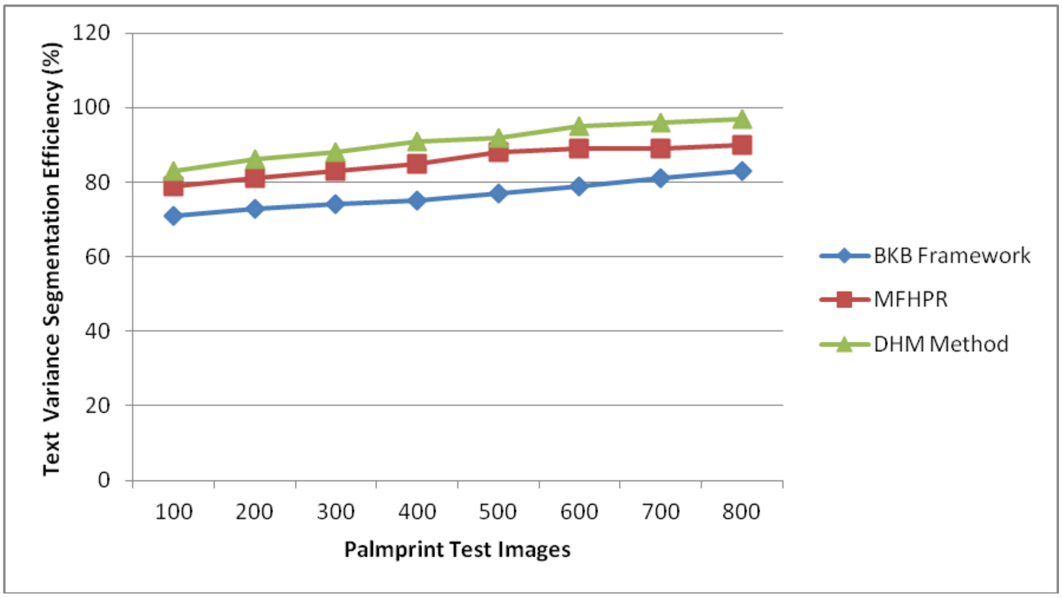

Fig 7 Texture Variance Segmentation Rate Measure

Fig 7 demonstrates the texture variance segmentation rate of the BKB Framework [1], MFHPR system [2] and DHM Method. The morphological texture segmentation uses the higher order neighborhood statistical approach to improve the variance rate by 16 – 21 % when compared with BKB Framework. The morphological texture segmentation partitions the palmprint images into regions with some feature characteristics through the texture primitives. As the palmprint test image count increases, the segmentation efficiency is also improved drastically. Morphological Segmentation is carried out based on the neighborhood intensity range. The morphological segmentation in DHE method still improves the segmentation efficiency by 4 – 7 % when compared with MFHPR system [2].

Table 5 Tabulation of True Acceptance Rate

Average Key points (K) on different sample Range	**True Acceptance Rate (Accept %)**		
	BKB Framework	MFHPR	DHM Method
20 (K7)	30	32	35
40 (K20)	45	48	50
60 (K35)	52	55	58
80 (K60)	70	72	75
100 (K75)	68	71	75
120 (K75)	55	59	62
140 (K100)	65	68	71
160 (K140)	82	85	87.5

Average key points in the palmprint image are set to easily compute the true acceptance rate. The different samples are fetched for the experimental work and also the key points are set to the samples for computing the true acceptance rate. True Acceptance rate is lesser improved when compared with the MFHPR system [2] and improved drastically when compared with BKB Framework [1].

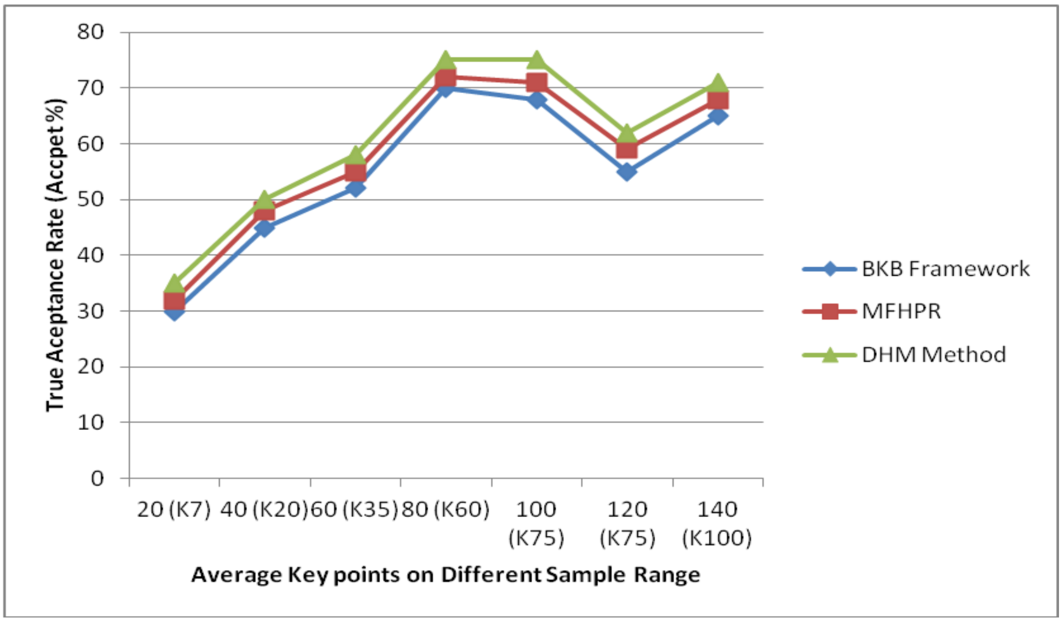

Fig 8 Measure of True Acceptance Rate

Fig 8 demonstrates the true acceptance rate based on the average key point fixed different sample count. The sample of 20, 40, 60 up to 140 ranges are taken for the experimental work. Defining the soft texture based segmenting, uses the Fisher Score to work with non-linear deformation and measure the true acceptance rate. For instance, on taking the single sample count of '7' key points with '20' different sample palmprint achieves the 35 % acceptance rate in DHM method, whereas the 32 % in MFHPR system [2] and 30 % in BKB Framework [1]. The different classified dimension of single user 'x' with higher order texture variations $'\epsilon'$ is used to compute fisher score and improve the acceptance rate by 7 – 16 % when compared with BKB Framework [1] and also improved by 4 – 9 % when compared with the MFHPR system [2].

Finally, Diffie–Hellman-Merkle (DHM) Longer Key Exchange achieves the higher matching accuracy between the test and training images. The classification and segmentation procedure is DHM improves the matching accuracy rate. High recognition performance with significant palmprint template is matched.

5. RELATED WORK

Biometric-based personal identification techniques use physiological characteristics of the individual to establish automatic personal recognition. The iris and palmprint are changed into the set of features autonomously in [3]. The fusion modalities with the pyramid based algorithms and wavelet based algorithms. Image fusion is good to each of the images to form the resultant high secured system through biometric image verification. Multimodal biometric with face and palmprint in [12] using Bipartite Rank Boost Approach improves the score level. Adaptive Boosting weight the data instead of arbitrarily sampling and discarding. The AdaBoost algorithm is a well-known method to build ensembles of classifiers with incredibly good performance. RankBoost 'B' provide the bipartite feedback for two sets of instances and ranks all instances of one set above an additional set.

Adaptive histogram equalization technique is employed on preprocessing the palmprint images in [9]. The preprocessed palmprint images are analyzed using Discrete Curvelet Transform for the recognition of the persons however the segmentation process is not carried out. Curvelet transform characterize edges and other singularities along palm curves with collection of fold fragments and then uses fold let transform to symbolize each fragment. Eigen-space and a robust code signature as produced in [16] include tonal and lighting variations. The larger number of classes are fused together to improve recognition accuracies. An additional restriction is that the data model has low dimensionality and computational overheads while implementing on real-time applications.

Sparse representation method in bimodal biometrics [10] uses the weighted sum procedure to produce the approximate representation. The approximate representation of the test image is based on the classification. The linear combination is obtained by solving the group of the linear equation combination. Hybrid learning algorithm such as Particle Swarm Optimization, Bacterial Foraging and Reinforcement learning in [7] is developed to learn the fuzzy densities and the interaction factor of the multimodal fusion. Error rate identification utilizes the t-norms that do not demand no learning which results in the higher performance rate.

6. CONCLUSION

The palm prints biometric system being designed by using the Diffie–Hellman-Merkle (DHM) Longer Key Exchange, whose output is fed to achieve the higher matching rate. The tabulation result provides us the added information that the users training palmprint being in the database provide us the higher matching accuracy rate. Diffie–Hellman-Merkle (DHM) Longer Key Exchange performs the three processes such as the classification, segmentation and matching based on minutiae, orientation, and density. The palmprint test images are matched with the training images in a quickly executable form in our proposed work. Even in the real world scenario, the result reverts that the original performance still achieves the higher level of matching rate. Classification in DHM is carried out through the Mahalanobis distance based classifier. Then the palmprint image segmentation is carried out using Higher Order Neighborhood Statistical (HONS) approach. Final matching is carried out with the decision controlling process in DHM. Achieves a better matching of the genuine and the impostor user's palmprint test images based on the minutiae, orientation, and density. Thus, they are able to minimize the classification error by 6.02 % as well as the false rejection rate is 15.276 % improved.

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