Comparative Study of Palmprint Authentication System using Geometric Features

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ABSTRACT

Biometrics, particularly palmprint authentication has been a stimulating research area due to its nascent stage and abundance of features. Stable features and effective matching are the most crucial steps for an authentication system. In conventional palmprint authentication systems, matching is based on flexion creases, friction ridges, and minutiae points. Currently, contactless palmprint imaging is an emerging technology. However, they tend to involve fluctuations in the image quality and texture loss due to factors such as varying illumination conditions, occlusions, noise, pose, and ghosting. These variations decrease the performance of the authentication systems. Furthermore, real-time palmprint authentication in large databases continues to be a challenging task. In order to effectively solve these problems, features which are invariant to these anomalies are required. This paper proposes a robust palmprint matching framework by making a comparative study of different local geometric features such as Difference-of-Gaussian, Hessian, Hessian-Laplace, Harris-Laplace, and Multiscale Harris for feature detection. These detectors are coupled with Scale Invariant Feature Transformation (SIFT) descriptor to describe the identified features. Additionally, a two-stage refinement process is carried out to obtain the best stable matches. Computer simulations demonstrate that the accuracy of the system has increased effectively with an Equal Error Rate of 0.86% when Harris-Laplace detector is used on IITD database.

Keywords: palmprint-authentication, palmprint-segmentation, geometric-features, SIFT-matching, contactless-palmprint

1. INTRODUCTION

Presently, a high demand for personal identification/verification (I/V) is desired in the field of information security. As technology progresses, it is vital to provide maximum security to an authentic individual. Besides, the current generation is in a digital realm and it is necessary to provide reliable, automated, and secured I/V. There are various approaches which facilitate this process, and biometrics is the most prominent. This technique refers to automatic I/V of individual based on identifiers/traits, which are categorized into (i) anatomical characteristics: fingerprints, signature, face, DNA, iris, finger shape, retina, ear features, hand geometry, and (ii) behavioral characteristics: typing gestures, rhythm, gait, and voice [1]. These modalities have been studied extensively to improve the privacy of an individual. The biometric financial market is projected to increase at a rate of 16.79% per Global Information, Inc. The market is estimated to be valued at USD 32.73 billion in 2022 [2].

The aptness of the identifiers/traits to be used for a biometric application depends on attributes such as distinctiveness, permanence, universality, acceptability, and performance [1]. A fingerprint is one such biometric which is widely used in automated fingerprint identification systems (AFIS) for I/V. However, this biometric trait has a few limitations such as, geometric distortions, inaccurate minutiae or image feature extraction from individuals, who are involved in physical work or elderly people [1-3]. Another biometric trait which has gained popularity over the past decade is palmprint recognition. Palmprint refers to the region which lies between the wrist and the fingers. This region includes multiple useful features such as flexion creases also called principal lines, secondary creases known as wrinkles, singular points, minutiae points, ridges, and texture [4]. Using a palmprint has several advantages over the fingerprint in a few aspects namely (i) they are unique and relatively stable features; (ii) palmprint database construction is non-intrusive and comparatively easy when compared to the acquisition of other biometric traits, (iii) it requires minimal user cooperation, (iv) palmprint recognition is relatively cheaper [5], (v) it is less constrained when compared to touch based methods, (vi) palmprints have much larger surface area, hence more distinctive features are available, (vii) forging a palmprint is difficult due to the increased area, and (viii) it is more robust to damage and dirt when compared to the fingertips [6].

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There are numerous ways to procure a palmprint, for example two-dimensional touch based and touchless based methods. The touch based system can be categorized into offline and online methods. The offline methods capture a palmprint using ink and it is digitized using a digital scanner, whereas online methods perform acquisition using optical devices, digital scanners and CCD scanners [2]. Touch based systems necessitate controlled procedures or require the individual to place a hand on fixed support, which raises concerns over hygiene and discomfort [7]. Furthermore, these systems are inconvenient for real-time applications. They are generally used in investigative and forensic sectors. On the contrary, modern biometric systems use touchless based palmprint recognition system which employ CCD cameras, smartphone cameras or video cameras. Conversely, touchless based online palmprint recognition systems have become prominent for real time applications due to its capability of attaining a greater number of fine details at an intermediate resolution. The accuracy of recognition software can be improved with sensors with higher resolution.

Recent progressions in research have improved the less-constrained touchless based palmprint recognition systems. The approaches employed in the existing system can be divided into five categories, namely, ridge-based, line based, Subspace-based, Statistical, and Coding-based. Ridge- based techniques use minutiae, ridges, and crease points as features to perform I/V. Rotinwa et al., [8] proposed a method to extract palm lines using the Sobel operator. The edges and cross points information available from the palm lines are used to create a feature vector. Zhu and Zing [9] detected and extracted the principal lines by overlapping the gradient images computed using four different directions. Laadjel et al., [10] employed local minutiae descriptors, which was a combination of minutiae with SIFT features for touch based partial palmprint matching. The matching score was computed based on the Euclidean distance. Line based approaches use lines such as principle lines and wrinkles. Subspace-based approaches use the features extracted using Principal Component Analysis (PCA), Linear Discriminant analysis (LDA), or Independent Component Analysis (ICA). Sang and Liu [11] used two-dimensional PCA based approach for processing defocused palmprint images. Matching was performed using nearest neighbor classifier. Imtiaz and Fattah [12] proposed a Discrete Wavelet Transform (DWT) based recognition system in which, enhancement and extraction of features were conducted using 2D-DWT. Additionally, the feature set was reduced using PCA. Statistical approaches are based on local or global statistics. Generally, in local statistics, the means or variance of the subdivided regions of an image are considered as features. In contrast the global statistics use the entire image for feature extraction. Wong et al.,[13] computed features by extracting energy values from different wavelet transforms. Later, a neural network was employed to generate the matching score. Yih et al., [14] used the entropy obtained from Haar wavelet transform for generating feature vector. The matching score was generated using Euclidean distance. In coding-based approaches, an entire database is searched using a matching function. Kong and Zhang [15] introduced a competitive coding scheme by extracting the orientation information of palm lines. This extracted information is stored in the competitive code. An angular match was used for matching purposes. Zhang et al., [7] proposed a system, which extracted local phase information using a single Gabor filter.

Practically, for satisfactory I/V, palmprint matching systems should meet several requirements [16] such as: (i) its invariance to central position of the palmprint; (ii) insignificance to geometric transformation such as translation and rotation; (iii) tolerance to nonlinear distortion such as palmprint displacement, skin moisture content, imaging methods, and sensor noise; (iv) elimination of false feature matching, and (v) provide a reference dataset of candidates for decision making. The touchless acquisition system challenges are (i) lower contrast, (ii) more complex background, (iii) non-uniform acquisition distances, and (iv) non-uniform illumination. Additionally, the traditional acquisition techniques are assumed to be well aligned due to the fixed support during acquisition. But in contactless acquisition techniques, the images are not aligned, due to less constrains. Thus, causing significant intra-class variations, which include hand deformation like shifting, rotation, scaling and transformation. These variations can be dealt by using local invariant features which further improve feature extraction. A local invariant feature is a point detected on an image, and is dependent on image properties like intensity, and texture [17]. Various researchers have investigated palmprint authentication using Difference of Gaussian (DoG) and Scale Invariant Feature Transform (SIFT) [6, 18, 19]. However, there are various local feature detectors available which are not delved into, and perform better than DoG.

This paper provides a comparison of various local invariant detectors, which include DoG, Hessian, Hessian-Laplace, Harris-Laplace, and Multiscale Harris on palmprint segmented images. A detailed study of these detectors can be found in [20, 21]. These detectors identify keypoints on the image, and a SIFT descriptor is used to describe the representation of texture around the detected points. Additionally, this system solves the problem of minimal overlap in partial palmprints. The rest of the paper is organized as follows: section 2 provides details of the matching framework, section 3 provides a glance at the computer simulations, and section 4 concludes the paper and suggests the future work.

2. MATCHING FRAMEWORK

Feature detection and description is a broadly used technique for object classification, image matching, and image retrieval in the field of Computer Vision [20, 21]. Detailed survey can be found in [20]. Features can be detected locally and globally, but it makes more sense to detect local features in palmprint images. This is because local features are computed as collection of points, which are generally invariant to many factors depending on the type of detector employed. Compared to conventional touch based methods, contactless image acquisition techniques possess severe rotation and scaling. Furthermore, the rate of nonlinear distortion is comparatively higher. Few examples of these translations and distortions are displayed in Figure 1.

(a) (b) (c)

Figure 1. (a) and (b) are palmprint images from the same person but captured at different angles, (c) is an example of displacement caused during acquisition in IITD database.

Segmentation of these images were carried out using the technique proposed by Khan et al.,[22]. This method was initially proposed for multispectral images. It is based on identifying landmarks more specifically the valleys between the fingers, which are invariant to the movement of the hand. However, this segmentation technique was tailored to segment visible palmprint images instead of multispectral images. The segmented images were preprocessed by enhancing the edges (flexion lines, ridges, wrinkles) using a technique called guided filtering [23]. This is an edge preserving filter and performs remarkably well due to its non-approximate means of implementation. Furthermore, it yields better quality and the computation time is greatly reduced due to its filter size invariance. It can be defined as shown in equation (1).

$$F_x = \sigma_y I_x + \rho_y \in \emptyset_y \tag{1}$$

$$\sigma_y = \frac{\frac{1}{|\emptyset|}\sum_{x\in\emptyset_y} I_x\, G_x - \mu_y\, \widehat{G_y}}{\varphi_y + \varepsilon}\,;\; \rho_y = \widehat{G_y} - \sigma_y \mu_y \tag{2}$$

where $\emptyset_y$ is an odd-sized window, φ_y and μ_y are variance and mean of I respectively, $|\emptyset|$ and $\widehat{G_y}$ provides the count of the pixels and mean of G respectively, in $\emptyset_y$.

The matching algorithm utilized these enhanced palmprint images. A general algorithm for matching two palmprints is provided below.

Algorithm for matching two palmprints

1. *Input two segmented palmprint images- I and T.*
2. *Perform preprocessing operations such as enhancement [24-27], palmprint edge detection, [28-30].*
3. *Detect geometric feature points in both palmprint images using various detectors.*
4. *Describe the keypoints using SIFT descriptor.*
5. *Perform matching and geometrically verify them using two-stage refinement process.*
6. *Provide the matching score.*

Two palmprint images namely the original image *I*, and the template image *T* are provided as input to the recognition system. The geometric features are extracted from each image using the detectors, which include Difference-of-Gaussian, Hessian, Hessian-Laplace, Harris-Laplace, and Multiscale Harris. Each detector identifies points uniquely and is invariant to various kinds of transformation. This is displayed in Table 1 [21, 31]. The features points detected using different detectors are shown in Figure 2 and the number of features detected in accordance with the feature detectors are displayed in Table 2.

Table 1 Characteristics of the Detectors

# no	Feature Detector (FD)	Feature Detected	Rotation Invariant	Scale Invariant	Accuracy	Robustness
1	Difference of Gaussian	Corner + Blob	Yes	Yes	2	2
2	Hessian	Blob	Yes	No	2	2
3	Hessian-Laplace	Corner + Blob	Yes	Yes	3	2
4	Harris-Laplace	Corner + Blob	Yes	Yes	3	3
5	Multiscale Harris	Corner	Yes	No	2	3

* On a scale of 1 to 3, 1 being lowest and 3 being highest in terms of performance.

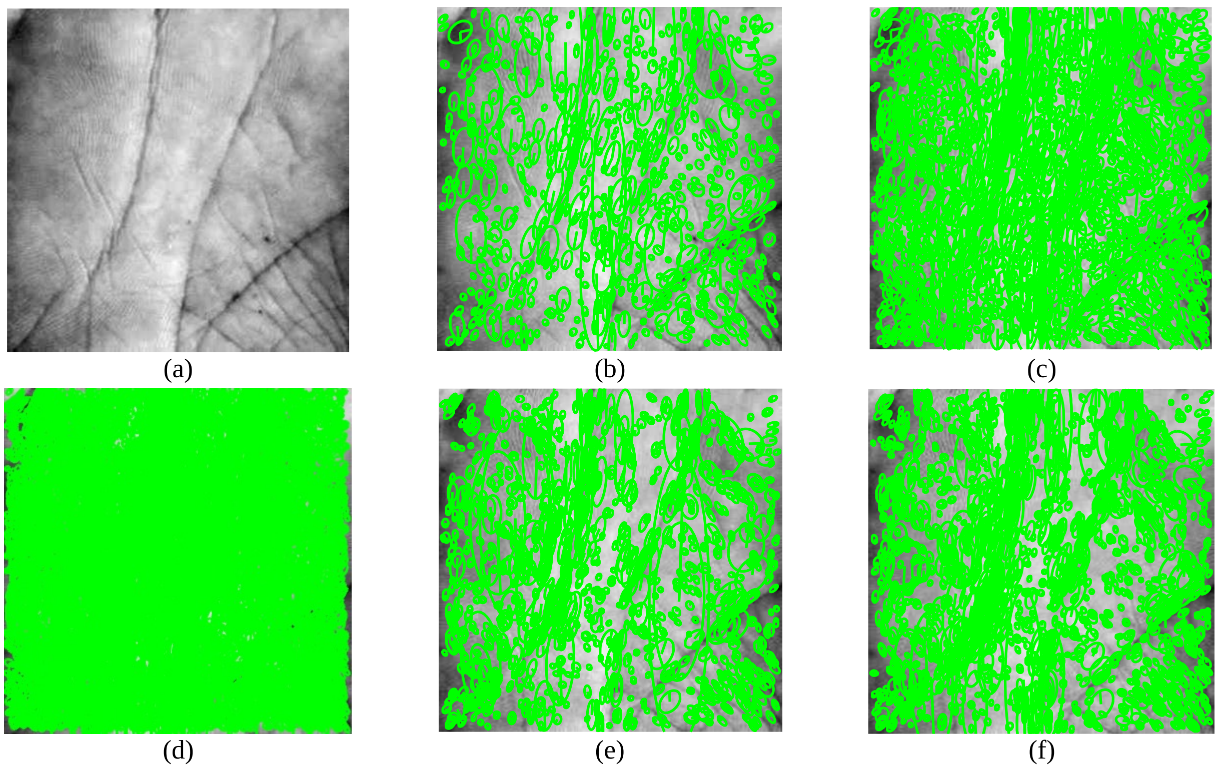


Figure 2. Feature detection: (a) is the original image, panel [b-f] show the features detected using (b) DoG, (c) Hessian, (d) Hessian-Laplace, (e) Harris-Laplace, and (f) Multiscale Harris. It can be seen that the Hessian-Laplace detector detects many keypoints.

The SIFT descriptor is used to describe the characteristic points depending on the texture around them. Detected and described keypoints contain four attributes, namely, 2-D location, scale, orientation, and its description.

Table 2 Number of Features Detected using the Detectors

Detector	Difference of Gaussian	Hessian	Hessian-Laplace	Harris-Laplace	Multiscale Harris
# of features detected	756	2098	7861	1253	1763

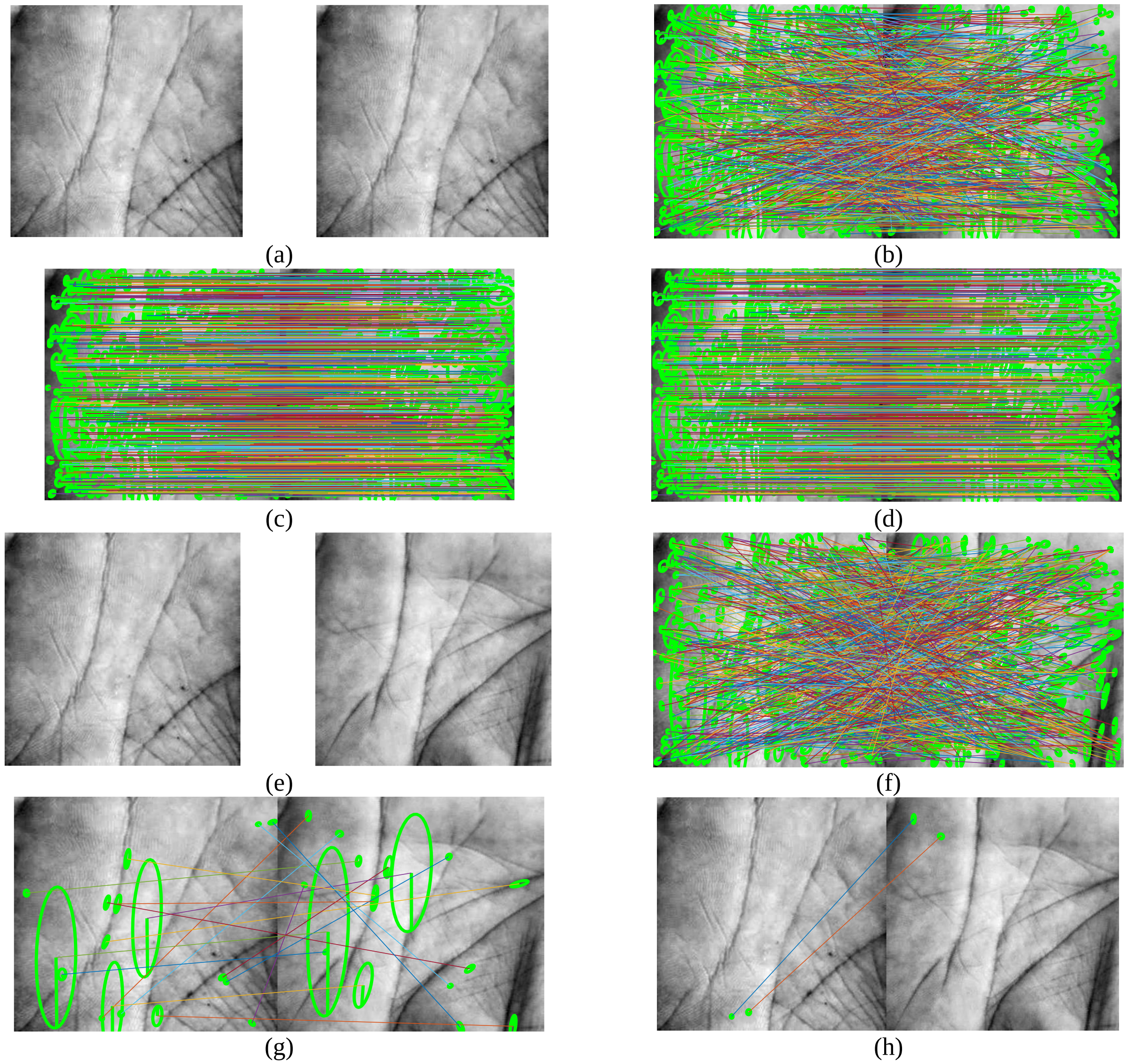


Figure 3. Feature matching: (a) are palmprint images of same user and (e) are palmprint images of different users, (b) and (f) are the matches produced for genuine and imposter respectively, (c) and (g) are the matches found after first refinement for genuine and imposter respectively, (d) and (h) are the matches after second refinement for genuine and imposter respectively.

2.1 Matching

Matching is conducted by applying the nearest neighbor technique for finding matches. For example, consider an image *I* with a keypoints *k1* and an image *T* with a keypoint *k2*. These two keypoints are successfully matched if the distance between them is significantly smaller than any other keypoint in *T*. This significant distance is defined by the threshold set during matching. The points detected and described are matched using this concept. During this process, irrelevant matches are produced, which can be seen in Figure 3(b) and (f). These matches are incorrect and a refinement procedure is necessary. Refinement is done in two steps to remove all the mismatches. The first step involves using a second nearest neighbor test to identify ambiguous matches. The main idea behind this is setting a threshold for the ratio between the second nearest neighbor against the first neighbor. This process removes most of the mismatches depending on the threshold. This can be seen in Figure 3 (c) and (e). Once these mismatches are removed, a second refinement is executed by applying geometric verification. The geometric verification [21] is conducted by applying a technique, which is based on similarity transformations.

The steps involved for geometric verification are as follows:

- Compute the similarity transformation, it can be calculated using equation(3)

$$\begin{bmatrix} x' \\ y' \end{bmatrix} = s\,R(\theta)\begin{bmatrix} x \\ y \end{bmatrix} + \begin{bmatrix} t_x \\ t_y \end{bmatrix} \tag{3}$$

- Trace all the keypoints from one image to the other using this transformation
- Choose inliers when the distance between them is below a provided threshold
- Count the number of matched inliers and choose the transformation with the highest count of inliers, which consists of a rotation by θ, an isotropic scaling by s, and a translation by a vector (t_x, t_y)

Once all the mismatches are removed using the two-stage refinement process, the matching score is provided. The score is based on the ratio of geometrically verified matches and the maximum number of points extracted from image *I* and *T*. This score is normalized between 0 and 1, which indicate no match and perfect match respectively.

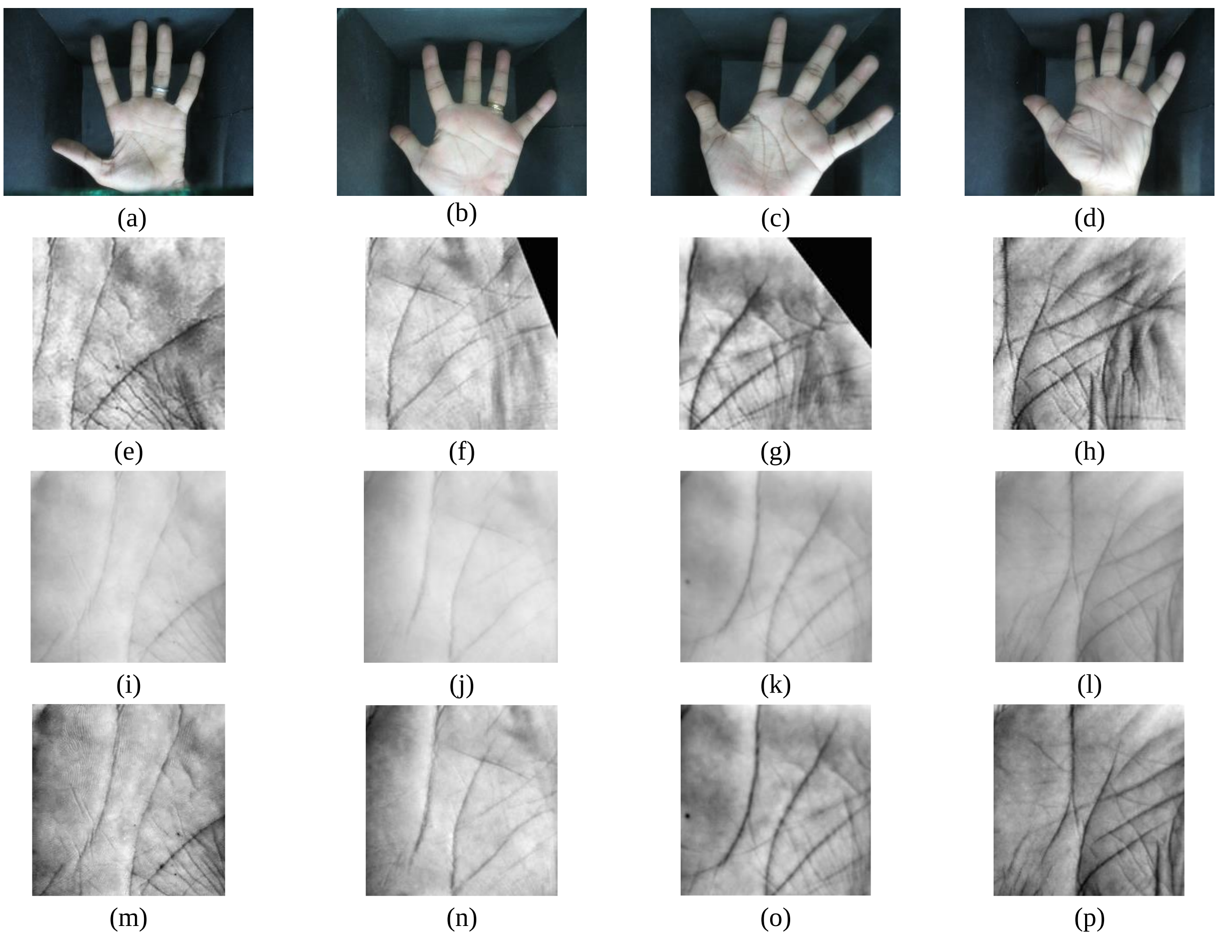
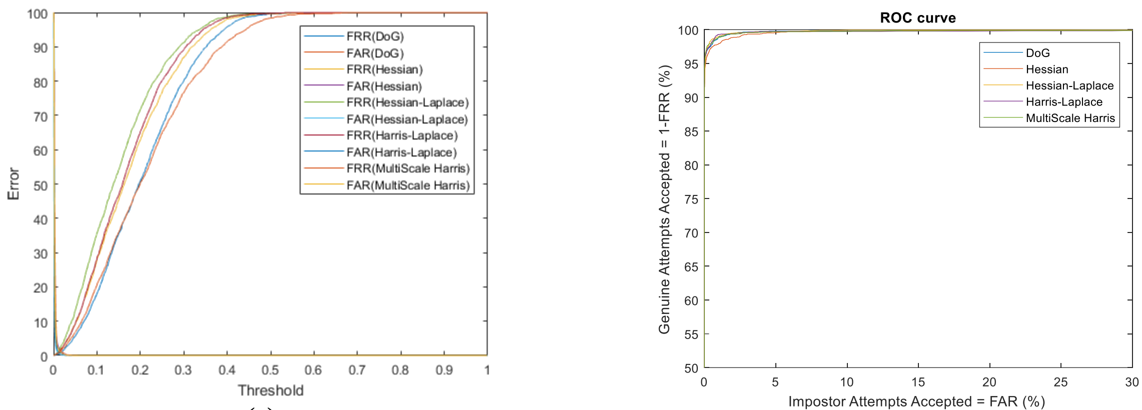


Figure 4. Segmentation: panel [a-d] are the original hand images obtained from IITD database, panel [e-h] are the corresponding segmented palmprint images included in the database, panel [i-l] are the segmented images obtained by using the technique provided by Khan et al., and panel [m-p] are the enhanced image after applying guided filtering.

3. COMPUTER SIMULATIONS

For computer simulations, IIT Delhi (IITD) Touchless Palmprint Database version 1.0 [32, 33] is used. This database contains images from more than 230 subjects and each subject contributed at least 5 hand image samples. Each image has a resolution of 800 x 600. All the subjects in the database are in the age group 12-57 years. Few examples of images provided in this database are displayed in Figure 1 and Figure 4. The segmented images provided by the database is shown



(a) (b)

Figure 5. (a) shows the FAR vs FRR graph (normalized), and (b) shows the ROC curve for all the detectors

in Figure 4 panel [e-h]. But due to their incorrect segmentation, the segmented images were not employed. Hence, the segmentation by Khan et al., is used and can be seen in Figure 4 panel [i-l]. The enhanced palmprint images used in this paper is displayed in Figure 4 panel [m-p]. The presented system is evaluated based on accuracy and efficiency. Accuracy of the system is based on False Rejection Rate (FRR), False Acceptance Rate (FAR) and Equal Error Rate (ERR) of the system. FRR is the fraction of genuine palmprints, which are rejected. FAR is the fraction of imposter palmprints, which are accepted. The FAR vs FRR graphs for all the detectors used is shown in Figure 5 (a). EER is the rate at which the FAR and FRR are equal. Complete dataset of right hand images was considered for simulation purpose. The detectors were applied and described independently. Matching was conducted and two-stage refinement was applied. EER values were computed and are provided in Table 3. Additionally, a receiver operating characteristic (ROC) curve is shown in Figure 5 (b). Results show that the matcher performs exceptionally well when Harris-Laplace detector is used along with the SIFT descriptor. The EER is low because, Harris-Laplace is a detector, which has better discriminative power when compared to others. Furthermore, resulting points obtained are robust to changes in scale, image rotation, illumination, and camera noise.

Table 3 Verification performance

Detector	**DoG**	**Hessian**	**Hessian-Laplace**	**Harris-Laplace**	**Multiscale Harris**
EER (%)	1.04	1.48	0.99	0.86	1.12

4. CONCLUSION

In the field of Computer Vision, various detectors such as Difference-of-Gaussian, Hessian, Hessian-Laplace, Harris-Laplace, and Multiscale Harris are extensively used for feature detection. However, only DoG is used in palmprint authentication systems. In this paper, a palmprint matching system is presented by comparing the afore mentioned local geometric detectors along with the SIFT descriptor. These detectors provide stable features depending on the characteristics of the image and perform efficiently in low quality images. The reduction of accuracy due to hand deformations is overcome by employing the above-mentioned detectors. The extracted features are invariant to most of the characteristics such as scaling, rotation, translation, noise, affine transformations, and partially or completely invariant to illumination changes. As a result of these invariances, the problems caused by pose, scaling, and illumination are overcome. Accuracy is significantly improved due to the consideration of edges, blobs or corners in palmprint image and not just conventional palmprint information. Moreover, registration or alignment of palmprint is not required at any stage; thus, making it suitable to be employed for partial palmprint matching systems. Computer simulations indicate a 0.86 % EER by Harris-Laplace detector, which is significantly lower when compared to other detectors. Consequently, it can be concluded that Harris-Laplace detector is by far the best detector among the afore detectors with all kinds of invariance required. As a part of future work, the authors intend to test the theory of attaining higher accuracy when multispectral imaging is used. Secondly, the accuracy of the system will be further determined by executing it on various databases available.

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