Point Based Features for Contact-less Palmprint Images

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Abstract— **In this paper, feature extraction and authentication scenarios for contact-based and contact-less palmprint images are investigated. The point-based feature extraction techniques like: Scale Invariant Feature Transform (SIFT), Harris corner detector, and Histogram of Gradient (HOG) in combination to Gabor filter are experimented for contact-based and contact-less palmprint authentication. In our experiments, we have used publicly available IITD database consisting of unconstrained contact-less palmprint images and compared its performance on these features with HongKong PolyU database acquired under constant illumination and constrained conditions. The presented work establishes that majority of the previous methods for palm print authentication, may work well with contact-based images, (with constrained environment) but fail to produce substantial results with unconstrained natural contact-less palmprint images. The proposed techniques give high recognition rate (97.5% and 93% GAR with Harris and SIFT respectively) for contact-less palmprint database. The experimental results in this paper have shown significant improvement for contact-based palmprint as well.**

Key words: palmprint, contact-based, contact-less, constrained, ROI

I. INTRODUCTION

Biometric authentication refers to the automatic identification of a person based on human physiological (e.g., fingerprint, iris) or behavioural (e.g., signature) or chemical (e.g. chemical composition of human perspiration) characteristics or traits [34]. The traditional methods require the pin number or the password to be remembered for identification/authentication and thus are more vulnerable to attacks. As a result, biometric systems are being deployed to enhance security and reduce financial fraud [34][43]. Various biometric traits are being used for real-time recognition, the most popular being fingerprint, face and iris [41][44]. Among the various biometric techniques used for authentication, hand based biometrics is well established trait, with some advantages over the already prevalent competitor techniques. It is so, because of the textural details which can be extracted from hand based features for authentication is high and the human hand data acquisition is convenient and user-friendly. Also, it is less exposed to anatomic variations and environmental artifacts. Higher recognition rates in most hand based modalities rely on a contact device with pegs for image acquisition[5].Hand-based biometrics has been used in personal identification by using fingerprint[44],palmprint [5][29-33], hand geometry [15][35], 3-D finger geometry [36-37], hand vein [38-40] and finger knuckles [6-9]. Fingerprint is a widely used and reliable modality since it is easy to use and gives accurate results. However, as investigated by NIST, approximately 2% of the population do not have useful and accessible fingerprints thus fingerprint identification is useless for such people [1]. Palmprint is a highly accurate biometric modality as there is a larger surface area for feature extraction, and thus they carry more information for personal identification. Moreover, capture devices are much low in cost and memory requirement is less for the storage of low resolution palm images.

The literature works show that, most of the available efforts are on contact-based palmprint acquisition. There is growing concern over using contact-based (constrained) palmprint images as it does not give a user friendly real life scenario. It has resulted in inclination of research interest towards constrained free natural contact-less palmprint authentication. The contacts-less palmprint acquisition systems are more convenient to the user and have negligible hygiene issues. However, a contact-less palmprint acquisition may suffer from scale, rotation, occlusion and translational variations which can reduce authentication accuracy. The available approaches for palmprint authentication can be categorized into following categories: (i) texture-based approaches (Gabor filter, Discrete Fourier Transform) [5][21-22] (ii) line-based approaches (Line matching, Morphological Operators) [23-24], and (iii) appearance-based approaches(PCA, LDA)[25-27]. Most of the reported works have shown satisfactory results on constrained images. The difficulties faced by user in contact-based system, are mainly due to constrained applied like application of pegs, limitation in orientations, and necessity of contact with surface, which may be unhygienic. Nowadays, a growing trend towards the idea of peg-free, contact-less, hand biometrics has emerged. The contact-less imaging increases user convenience [28][30][37][39], enhances real life scenario and results in less imposter attacks. There are various challenges in designing a contact-less system. It involves a careful selection of distance between the hand and input sensor and adds variations like rotational variations, translational variations, scale variations, blurring etc., since there is no restriction on hand placement during image acquisition [42].Therefore, the usage of traditional palmprint feature extraction methods on contact-less imaging schemes remains questionable and hence most of

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the popular palmprint feature extraction methods may not be useful in contact-less frameworks.

Considerably, less work has been reported using the contact-less images in the literature. Cui Xin *et al.* have done work on contact-less hand shape identification system [11]. Analysis of 3-D finger geometry features has been done by Malassiotis *et al.* using peg-free imaging [37].Morales *et al.* has also done some significant work on contact less palmprint images [42]. Tee Connie *et al.* [10] have given a robust approach on knuckle and palmprint recognition using contact-less databases. Badrinath *et al.* used SIFT to extract features from constrained palmprint images [12]. Julien Doublet *et al* used skin color and hand shape information to classify users into imposter and genuine [45]. In this work some methods have been proposed which can be used for contact-less databases. The proposed methods Gabor –SIFT and Gabor-Harris give highly improved the authentication rate of the PolyU database (contact-based palmprint), though other approach Gabor-HOG results are comparable .The proposed approaches degrades the performance with the IITD database (contact-less) as compare to earlier approaches. But, SIFT, Harris and HOG give efficient results for IITD database. Thus the work establishes that Gabor based approaches are not suitable for contact-less palmprints, but improves authentication results remarkably for contact-based palmprints. So, the authentication schemes that can efficiently detect rotation and scale invariant features has been used in the proposed approach. The basic steps in palmprint authentication are: pre-processing, feature extraction, matching.

The organization of rest of this paper is as follows; Section 2 describes the process of feature extraction, Section 3 details the proposed approaches, and section 4 presents results and discussion. Finally the conclusion of this work is summarized in section 5.

II. FEATURE EXTRACTION

Feature point detection is the vital step in palmprint authentication in which the input data captured is transformed into a reduced representation of feature vector set on which different similarity measure like Euclidean distance, L-norm, cosine similarity are used. The visual features comprise of domain specific features (e.g. fingerprints, human faces) or general features (viz. color, texture and shape). The most popular and intuitive choice for similarity measure, the cosine function is considered for this work. The experiments have shown that most of the existing approaches are not so promising with contact less databases, there is a need for such detectors which can deal with the images having variations and gives the best authentication results. The detectors explained below will address these variations. Here, the acquisition is considered to be done under constant fluorescent illumination circumstances. Interesting features are extracted from the pre-processed image i.e. ROI. Every image consists of some particular features, points or key points that need to be extracted from the image.

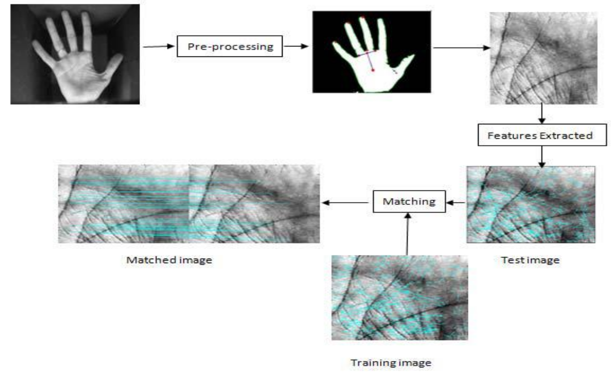

Fig. 1: Basic Steps of palm print authentication system

The palm consists of principal lines, wrinkles (secondary lines) and epidermal ridges. Detectors used for extracting these features are SIFT, HARRIS, AND HOG. SIFT is an approach for detecting and extracting local feature descriptor which are invariant to scale and rotation. HARRIS is an approach to detect and extract corners from the palmprint image which are invariant to scale and illumination. HOG are feature descriptors that represent occurrences of gradient orientation in localized portions of an image. Descriptor is anything which describes the properties of an image like color, orientation, texture, pixel intensity, edges etc. In palmprint, unique properties can be texture, orientation, scale etc. Descriptor with edge orientation information (SIFT, HOG) in this work have been used. Local feature descriptors of palmprint images are then matched using cosine similarity measure.

III. PROPOSED APPROACHES FOR PALMPRINT AUTHENTICATION

In the proposed approach, Gabor filter is utilized to improve the features in palmprints. SIFT feature detector is used with Gabor to result the Gabor-SIFT approach, which is experimented with contact-based and contact-less palmprints. HARRIS, feature detector, which were earlier used for contact-based palmprints is experimented for contact-less database. The system with combination of Gabor and HARRIS, called Gabor-HARRIS, is also proposed. In this approach SIFT descriptor is used for describing the feature obtained through HARRIS. Another feature detector HOG is also experimented for both type of uses i.e. alone and combination with Gabor (Gabor-HOG).

A. Gabor SIFT: Gabor Scale Invariant Feature Transform

Scale-invariant feature transform (SIFT) is a powerful detector extensively used in the pattern recognition and computer vision fields. The pre-processed palm print ROIs are used in SIFT feature extraction. In case of palmprint authentication, features consist of principal lines, wrinkles (secondary lines) and epidermal ridges. However, these principal lines are not sufficient to represent the uniqueness of each individual's palmprint because different people may have similar principal lines in their palmprints as in Fig. 2.

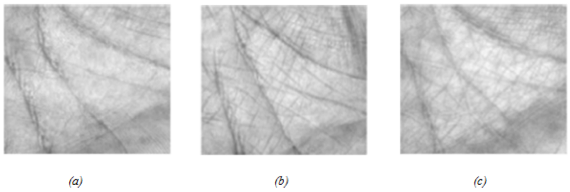

Fig. 2: ROI's of different users having similar *principal lines*

Therefore in the proposed approach, to extract texture features especially, fine features of palmprint images, Gabor filter (Gab) is applied for enhancement of textural features.

$$\mathrm{Gab}(x, y, \theta, u, \sigma)=\left(\frac{1}{2\Pi\sigma^2}\exp\left(-\frac{x^2+y^2}{2\sigma^2}\right)\mathrm{x}\exp\left(2\Pi i(ux\cos\theta + uy\sin\theta)\right)\right) \quad (1)$$

Where 'u' is the frequency of the sinusoidal wave, 'θ' controls the orientation of the function 'σ' is the standard deviation of the Gaussian envelope and (x, y) is any location in the image plane. The images obtained after applying Gabor filter are called as Gabor enhanced images (GROI) as shown in Fig. 3.

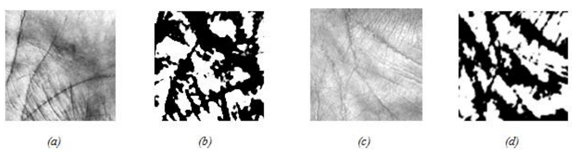

Fig. 3: a) ROI of the left palm print of a user (IITD database), (b) GROI of (a), (c) ROI of the left palm print of a user (PolyU database), (b) GROI of (c).

Each image is convolved with Gabor filter to enhance the details of the image and to increase the number of key points detected. The image obtained is the pre-processed image. This image can now be used for feature detection. The scale space of an image is defined as a function, Lap(x, y, σ), this is produced from the convolution of a variable-scale Gaussian function, Gauss(x, y,σ), with an input image, I(x, y): as in

$$\mathrm{Lap}(x,y,\sigma)=\mathrm{Gauss}(x,y,\sigma)*I(x,y) \quad (2)$$

where '∗' represents the convolution operation and the Gaussian function is given by:

$$\mathrm{Gauss}(x,y,\sigma)=\frac{1}{2\pi\sigma^2}\exp\left(-\frac{x^2+y^2}{2\sigma^2}\right) \quad (3)$$

Detection process is then done by selecting key locations at local maxima and minima of a Difference of Gaussian (DoG) function applied in scale space, which is computed by successively down sampling the input image. Maxima and minima of this scale space function are determined by comparing each pixel to its neighbors. The scale of the key point is used to select the Gaussian smoothened image with the closest scale. For each image sample, at this scale, the gradient magnitude, *mag(x, y)*, and orientation, *arg(x, y)*, are precomputed using pixel differences:

$$\mathrm{mag}(x,y)=\sqrt{\begin{matrix}\left(\mathrm{Lap}(x+1,y)-\mathrm{Lap}(x-1,y)\right)^2+\\ \left(\mathrm{Lap}(x,y+1)-\mathrm{Lap}(x,y-1)\right)^2\end{matrix}} \quad (4)$$

$$\arg(x,y)=\tan^{-1}\left(\frac{Lap(x,y+1)-Lap(x,y-1)}{Lap(x+1,y)-Lap(x-1,y)}\right) \quad (5)$$

Orientations are assigned to each key point location based on local image gradient directions and orientation histogram obtained. The peaks in the orientation histogram amount to dominant directions of local gradients. Any local peak that is within 80% of the highest peak is used to create a key point with that orientation. More detail description of this process can be found in Lowe [16]. Fig. 4 shows sample palm print SIFT extraction results.

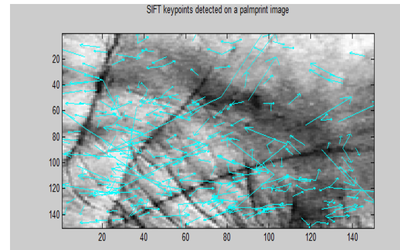

Fig. 4: SIFT keypoints detected in a palmprint ROI

B. Gabor-Harris Corner Detector

The Harris corner detector is a popular interest point detector that addresses the issues like invariance to rotation, scale, illumination variation and image noise. In the proposed approach Gabor filter is used for enhancement of the fine features similar to the Gabor-SIFT approach. The Harris corner detector [48] is based on the local auto-correlation function of a signal, where the local auto-correlation function measures the local changes of the signal with patches shifted by a small amount in different directions. Given a shift (Δx, Δy) and a point (x, y), the auto-correlation function is defined as,

$$c(x,y)=\sum w(I(x_i,y_i)-I(x_i+\Delta x,y_i+\Delta y))^2 \quad (6)$$

where $I(x_i,y_i)$ denotes the image function and (x_i,y_i) is i^{th} point window (Gaussian) w centred at (x,y). The shifted image is approximated by a Taylor expansion truncated to the first order terms,

$$I(x_i+\Delta x,y_i+\Delta y)\approx I(x_i,y_i)+[\,I_x(x_i,y_i)\;\; I_y(x_i,y_i)][\,\Delta x\;\Delta y]^T \quad (7)$$

where $I_x(x_i,y_i)$ and $I_y(x_i,y_i)$ denote the partial derivatives with respect to x and y, respectively. Using (6) and (7) and various mathematical operations we get

$$c(x,y) = [\Delta x\;\Delta y]c(x,y)[\Delta x\;\Delta y]^T \quad (8)$$

Where updated matrix c(x,y) captures the intensity structure of the local neighborhood. The Eigen values for matrix c(x,y) are calculated and if both eigen values are high and the local auto-correlation function is sharply peaked, then shifts in any direction will result in a significant increase; this indicates a corner. Once the corners are detected then Sift descriptor is applied, as described by David Lowe to get feature vectors [16]. Harris Corners are described in Fig. 5.

A. Gabor-HOG-Gabor Histogram of Gradients

Originally HOG has been first proposed by Dalal and Triggs, as an image descriptor for localizing pedestrians in complex images. Here in this approach, Gabor filter is applied to palmprint images as done in Gabor-SIFT and Gabor-HARRIS approaches to enhance the features of the palmprint image. The HOG descriptor [46] represents an image by a set of local histograms which count occurrences of gradient orientation in a local cell of the image. In this the image is divided into small spatial regions (cells), for each cell accumulating a local 1-D histogram of gradient directions or edge orientations over the pixels of the cell. The gradients can be computed using the Eqn. 9. The combined histogram entries represent the whole image. For invariance to illumination, the local responses are contrast normalised before using them. This is done by accumulating a measure of local histogram energy over larger spatial regions called blocks.

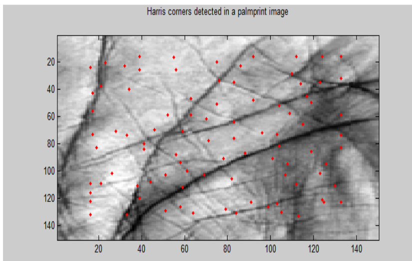

Fig. 5: Harris Corners detected in a palmprint ROI

These results are used to normalize all the cells in the block using any of the normalization schemes like *L2 - norm, L1-sqrt, L2- Hys* etc[46].

$$g(x,y)=\sqrt{g_x(x,y)^2 + g_y(x,y)^2} \qquad (9)$$

Here, $g_x$and g_y represent 1-D filters. HOG had been used as a detector as well as a descriptor which divides the images into blocks and cells, and then return its full feature vector which is used for authenticating the palmprint images.

IV. RESULTS AND DISCUSSIONS

The experimentation in this work is carried out on Hong Kong Polytecnic University(PolyU) palmprint database[49] and IITD database[48]. The characteristics of both the databases are shown in the table 1. Zhang's *et al* method [5] gave promising results with contact-based images, PolyU images(GAR=99.7 at FAR=0.01) but the result were not that satisfactory for the contact-less database, IITD images (GAR=60 at FAR=0.01). So there was a need for better authentication schemes particularly for contact-less images. ROCs of this experiment are given in Fig. 6.

Table 1: Characteristics of IITD and PolyU Database

Characteristics	IITD database	PolyU database
No of Users	235	345
No of Samples	7(1645 in total)	7(2415 in total)
Hands Acquired	Left	Left
Acquisition Method	Contact-less, Unconstrained(Pegs free)	Contact-based, Constrained
Background	Uncontrolled	Controlled
ROI size	150 × 150	128 × 128

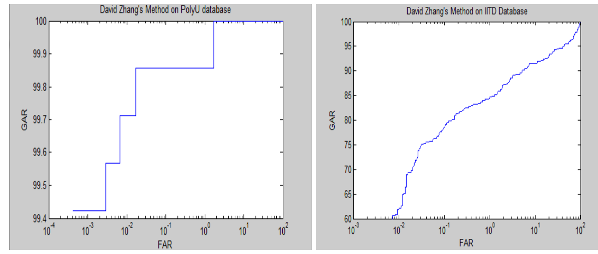

Fig. 6: ROC for IITD and PolyU database using Zhang's et al method.

Throughout our experimentation process, values used for the Gabor filter are $\theta = \pi / 4, \sigma = 5.6179, u = 0.0916$ .The images obtained after convolving Gabor filter are named as GROI(Gabor-Region of Interest). First we explain the experiments designed to assess the robustness and capabilities of the different region detectors and the descriptors. PolyU images are contact-based palm images. The results after application of SIFT on GROI images of contact-based database were considerably good(97.5% GAR) although it was very low(51% GAR) for images that were not convolved with the Gabor filter. However the results after application of SIFT on IITD GROI images were not significantly improved (70% GAR). The ROC curves are shown in figure 7 and 8. The Red curve is the curve for original images (WOG- WithoutGabor) and the Blue Curve is for GROI images (WG- With Gabor). This color notation for curves is used throughout this paper.

In the second set of experiments, the Harris corner points are detected at different scales and are described at different scales. The range of scale taken is 's'∈ (4, 12). As the scale is further increases the number of keypoints detected are less and it gradually decreases the matching performance also. The performance at different scales is cited in table 2 and ROC plots are shown in figure 9, 10 and 11. By observing the ROCs at different scales it was found that GAR was maximum for scale 8(GAR=87 at FAR=0.01) for IITD database.

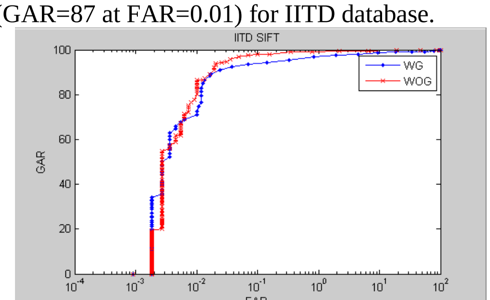

Fig. 7: ROC curve for IITD database for GROI images and the original images using SIFT detector.

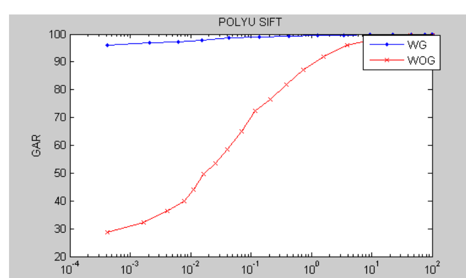

Fig. 8: ROC curve for PolyU database for GROI images and the original images using SIFT detector.

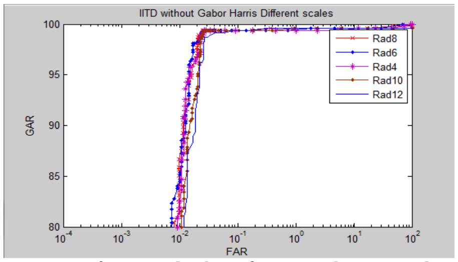

Fig. 9: ROC curve for IITD database for original images. The curve is obtained for Harris detector at different scales (4,6,8,10 and 12).

Table 2: IITD database without Gabor performance measures using Harris detector with different scales Characteristics of IITD and PolyU Database

Harris scale	FAR	GAR
4	0.01	82
6	0.01	85
8	0.01	87
10	0.01	78
12	0.01	70

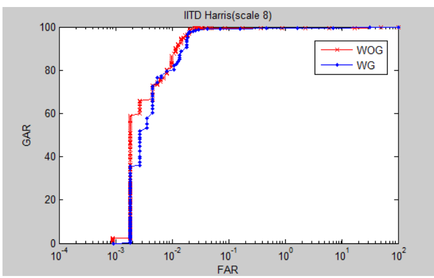

Fig. 10: ROC curve for IITD database for images convolved with GROI images and the original images using Harris detector.

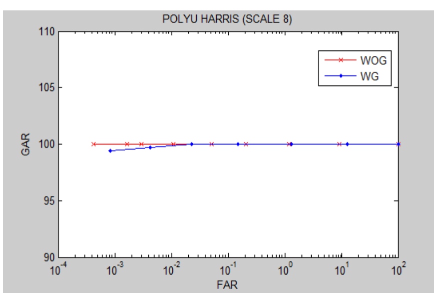

Fig. 11: ROC curve for PolyU database for images convolved with GROI images and the original images using Harris detector.

Harris also proved a very good and better technique for contact-based giving GAR = 100. In the third set of experiments, the results using HOG on GROI images of PolyU database were considerably good (99.4% GAR) although it were also good (99.2% GAR) for images that were not convolved with the Gabor filter. However, the results after application of HOG on IITD GROI images were low (60% GAR). The ROC curves are shown in figure 12 and 13.

The performance measures of different detectors on both the databases are shown in table 3 and 4.

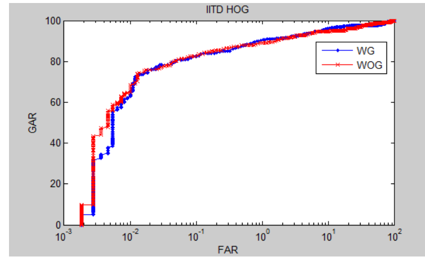

Fig. 12: ROC curve for IITD database for images convolved with GROI images and the original images using HOG.

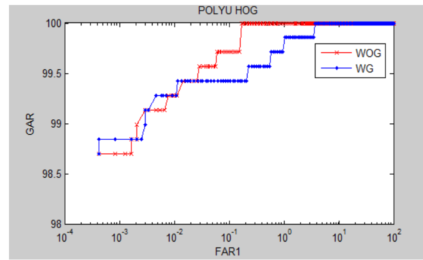

Fig. 13: ROC curve for PolyU database for images convolved with GROI images and the original images using HOG.

Table 3: IITD Database performance measures using different detectors

Different Detectors	**With Gabor (WG)**		**Without Gabor (WOG)**	
	GAR (at FAR 0.1)	***GAR (at FAR 0.02)***	***GAR (at FAR 0.1)***	***GAR (at FAR 0.02)***
SIFT	94	90	98	93
HARRIS	99	97	99.3	97.5
HOG	83	76	83	76

Table 4: PolyU Database performance measures using different detectors

Different Detectors	**With Gabor (WG)**		**Without Gabor (WOG)**	
	GAR (at FAR 0.1)	***GAR (at FAR 0.02)***	***GAR (at FAR 0.1)***	***GAR (at FAR 0.02)***
SIFT	99	98.1	70	51
HARRIS	100	99.97	100	100
HOG	99.7	99.5	98	99.4

V. CONCLUSIONS

All these techniques discussed above could work well for the contact-less databases. An interesting point to note is that application of Gabor on contact-less database did not improve the results but it worked quite efficiently for contact-based database. This has also been proved by the prior method of Zhang [5] which incorporated the use of Gabor on the databases and matching was done by hamming distance. The results on PolyU database were high but not so good for IITD database which supports the fact that Gabor is not efficient for contact-less databases. In fact applying Gabor on PolyU database the results were significantly improved for SIFT and Harris but it remained almost the same for HOG. From the above experiments it was also found that out of all these three techniques Harris corner detector worked best for both the palmprint databases viz. PolyU and IITD. The experimental results on Harris detector can be summarised as: GAR 97.5%

for IITD database and GAR=100% for PolyU. Second in performance is SIFT followed by HOG. It could be concluded that the point based features like Harris (GAR=97.5%) and SIFT (GAR=93%) were most successful in detecting the features for contact-less palmprint images (IITD). For further improvement of the performance of these feature detectors, our future work will focus primarily on finding new and more efficient techniques for contact-less databases which can also work with other biometric modalities like vein, knuckle etc.

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