An Efficient Finger-Knuckle-Print Based Recognition System Fusing SIFT and SURF Matching Scores

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Abstract. This paper presents a novel combination of local-local information for an efficient finger-knuckle-print (FKP) based recognition system which is robust to scale and rotation. The non-uniform brightness of the FKP due to relatively curvature surface is corrected and texture is enhanced. The local features of the enhanced FKP are extracted using the scale invariant feature transform (SIFT) and the speeded up robust features (SURF). Corresponding features of the enrolled and the query FKPs are matched using nearest-neighbour-ratio method and then the derived SIFT and SURF matching scores are fused using weighted sum rule. The proposed system is evaluated using PolyU FKP database of 7920 images for both identification mode and verification mode. It is observed that the system performs with CRR of 100% and EER of 0.215%. Further, it is evaluated against various scales and rotations of the query image and is found to be robust for query images downscaled upto 60% and for any orientation of query image.

1 Introduction

Biometric based authentication system has been used widely in commercial and law enforcement applications. The use of various biometric traits such as fingerprint, face, iris, ear, palmprint, hand geometry and voice has been well studied [4]. It is reported that the skin pattern on the finger-knuckle is highly rich in texture due to skin folds and creases, and hence, can be considered as a biometric identifier [11]. Further, advantages of using FKP include rich in texture features [3], easily accessible, contact-less image acquisition, invariant to emotions and other behavioral aspects such as tiredness, stable features [16] and acceptability in the society [7].

Despite of these characteristics and advantages of using FKP as biometric identifier, limited work has been reported in the literature [5]. Like any other recognition system, a FKP based recognition system also consists of four stages i.e., image acquisition, extraction of region of interest, feature extraction and matching. Systems reported in literature have used global features, local features and their combinations [16] to represent FKP images. Efforts have been made to build a FKP system based on global features. In [6], FKP features are extracted using principle component analysis (PCA), independent component analysis (ICA) and linear discriminant analysis (LDA).

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These subspace analysis methods may be effective for face recognition but they are not found to be effective to represent the FKP [14]. In [13], FKP is transformed using the Fourier transform and the band-limited phase only correlation (BLPOC) is employed to match the FKP images.

Global feature gives the general appearance (holistic characteristics) of the FKP which is suitable for coarse level representation, while local feature provides more detailed information from specific local region and is appropriate for finer representation [16]. There exist systems where local features of FKP are extracted using the Gabor filter based competitive code (CompCode) [12] and combined orientation and magnitude information (ImCompCode&MagCode) [14]. Further, in [7], orientation of random knuckle lines and crease points (KnuckleCodes) of FKP which are determined using radon transform are used as features. In [11], FKP is represented by curvature based shape index. Morales et. al., [10] have proposed an FKP based authentication system (OE-SIFT) using scale invariant feature transform (SIFT) from orientation enhanced FKP. In [3], an hierarchical based verification system using probabilistic hough transform (PHT) for coarse level classification and the speeded up robust features (SURF) for finer classification has been proposed. SIFT and SURF features of FKP are matched using similarity threshold [10]. In [15], features are extracted using Hilbert transform (MonogenicCode). Further, Zhang *et.al* [16] have proposed a verification system which is designed by fusing the global information extracted by BLPOC [13] and the local information obtained by Compcode [12]. However, there does not exist any system which is robust to scale and rotation.

This paper uses local-local information extracted from SIFT and SURF for a FKP recognition. An approach to correct the non-uniform brightness and to improve the texture of the FKP is proposed. The nearest-neighbour-ratio method [9] which is better than similarity-threshold based matching for SIFT and SURF based matching has been used to obtain the SIFT and SURF matching scores between the enrolled and the query FKPs. These matching scores are fused using weighted sum rule to obtain final matching score. The proposed system has been evaluated on publicly available PolyU [1] database of 7920 FKP images of 4 fingers of 165 users. Further, it is also tested for its performance against changes due to scales and orientations of the query image and has been observed that the proposed system is robust to scale and rotation.

Rest of the paper is organized as follows. Section 2 describes SIFT and SURF which are used to extract the local features of FKP. Next section presents the proposed system. Performance of the system has been analyzed in Section 4. Conclusions are presented in the last Section.

2 Local Information

This section describes SIFT [8] and SURF [2] which are used to extract the local features from a FKP image. Both of them determine scale invariant key-points and then describe these key-points by means of local patterns around key-points.

2.1 Scale Invariant Feature Transform

Feature vectors through SIFT are formed by means of local patterns around key-points from scale space decomposed image [8]. Following are the major steps to generate SIFT features of a given image.

1. *Scale-space extrema detection*: The first step of computation searches over all scales and image locations. It is implemented efficiently by using a Difference-of-Gaussian function to identify potential interest points that are invariant to scale.
2. *Key-point localization*: At each candidate location, a detailed model is fitted to determine location and scale. Key-points are selected based on measures of their stability.
3. *Orientation assignment*: Consistent orientation is assigned to the key-point following local image properties to make the key-point descriptor rotation invariant.
4. *Key-point descriptor*: Feature vector of 128 values is computed from the local image region around the key-point.

2.2 Speeded up Robust Features

Feature vectors through SURF are formed by means of local patterns around key-points which are detected using scaled up filter [2]. Following are the major steps to determine the SURF feature vectors of a given image.

1. *Key-point detector*: At this step, SURF key-points are detected using Hessian-matrix approximation. The second order Gaussian derivatives for Hessian matrix are approximated using box filters. Key-points are localized in scale and image space by applying a non-maximum suppression in a $3 \times 3 \times 3$ neighbourhood.
2. *Key-point descriptor*: This stage describes the key-points. It fixes a reproducible dominant orientation based on information from a circular region around the interest point. Feature vector of 64 values is computed from the oriented square local image region around key-point.

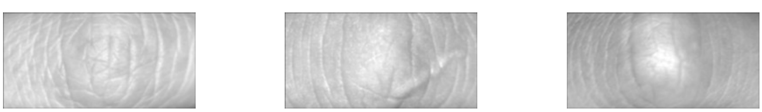


Fig. 1. Sample of finger-knuckle-print images from PolyU database [1]

3 Proposed System

This section presents a robust FKP based recognition system which is designed by fusing SIFT and SURF features at matching score level. Sample of FKP images of PolyU database [1] are shown in Fig. 1. The FKP image is subjected for non-uniform brightness correction and contrast enhancement. SIFT and SURF features are extracted

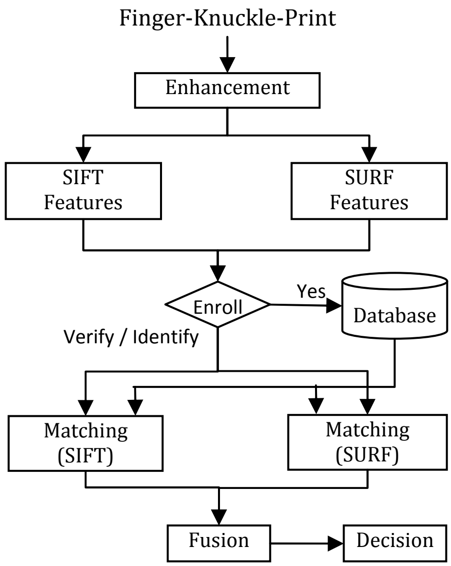
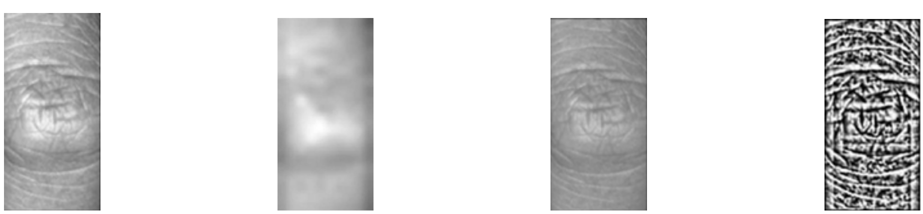


Fig. 2. Block diagram of the proposed recognition system

from the enhanced FKP images. During recognition, corresponding feature vectors of query and enrolled FKPs are matched using nearest-neighbourhood-ratio method [9] to obtain the respective matching scores and these SIFT and SURF matching scores are fused using weighted sum rule. The block diagram of the proposed FKP based system for recognition is shown in Fig. 2.

3.1 Enhancement

The finger-knuckle surface represents a relatively curvature surface and results in non-uniform reflections. FKP has low contrast and non-uniform brightness (as shown in Fig. 3(a)). To obtain the well distributed texture image following operations are applied on FKP.



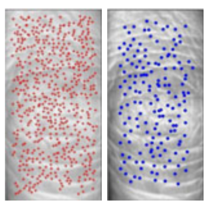
(a) (b) (c) (d)

Fig. 3. (a) Finger-knuckle-print (b) Estimated coarse reflection (c) Uniform brightness knuckle-print image (d) Enhanced Knuckle-print image

Each FKP image is divided into sub-blocks of 11×11 pixels. Mean of each block is calculated which estimates the reflection of the block. The estimated coarse reflection is expanded to the original size of the FKP image using bi-cubic interpolation. For the coarse estimate of reflection, if the block size is very small, the estimate is almost same as the extracted FKP and if the block size is high, the estimate becomes improper. Based on the experiments, block size of 11×11 pixels has been chosen for computing the coarse estimate of reflection. Estimated coarse reflection is shown in Fig. 3(b). The estimated reflection is subtracted from the original image to obtain an uniform brightness of the image which is shown in Fig. 3(c). Histogram equalization is performed on blocks of 11×11 pixels to improve the contrast in the texture of FKP and then is subjected to perform filtering to smooth the boundaries between blocks. Enhanced image is shown in Fig. 3(d).

3.2 Feature Extraction

Features are extracted from all FKP images. SIFT and SURF are used to extract the local features of FKP. Both SIFT [8] and SURF [2] have been designed for extracting highly distinctive invariant features from images. Further, extracted feature vectors are found to be distinct, robust to scale, robust to rotation and partially invariant to illumination. Thus features can be matched correctly with high probability against features from a large database of FKPs. SIFT and SURF key-points extracted from the FKP images are shown in Fig. 4.



(a) SIFT (b) SURF

Fig. 4. Key-points

3.3 Matching and Fusion

In this paper, feature template of the FKP is represented by two local feature vectors extracted using SIFT and SURF. During recognition, SIFT and SURF features of the query FKP are matched with the corresponding features of all the knuckle-prints in the database. The matching scores between corresponding feature vectors are computed using nearest-neighbour-ratio method [9] as follows.

Let Q and E be vector arrays of key-points of the query and the enrolled FKP respectively obtained using either SIFT or SURF

$$Q = \{q_1, q_2, q_3, \cdots q_m\} \tag{1}$$

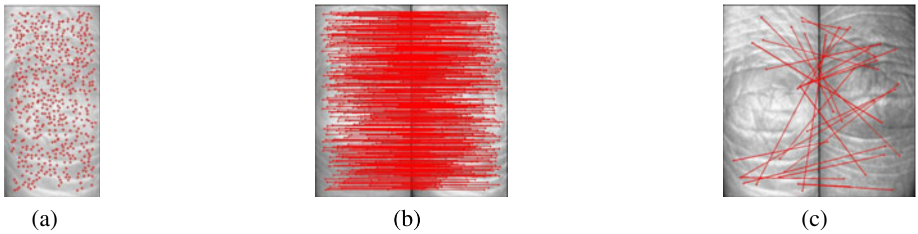


Fig. 5. (a) SIFT key-points detected (b) Genuine matching of SIFT key-points (c) Imposter matching of SIFT key-points

$$E = \{e_1, e_2, e_3, \cdots e_n\} \tag{2}$$

where q_i and e_j are the feature vectors of key-point i in Q and that of key-point j in E respectively. If $\|q_i - e_j\|$ and $\|q_i - e_k\|$ are the Euclidean distance between q_i and its first nearest-neighbour e_j and that between q_i and its second nearest-neighbour of e_k respectively, then

$$q_i = \begin{cases} \text{Matched with } e_j & \text{if } \frac{\|q_i - e_j\|}{\|q_i - e_k\|} < T \\ \text{Unmatched} & \text{Otherwise} \end{cases} \tag{3}$$

where T is a predefined threshold.

The matched key-points q_i and e_j are removed from Q and E respectively. The matching process is continued until there are no more matching points either in Q or E. Total number of matching pairs M is considered as the matching score. More the number of matching pairs between two images, greater is the similarity between them. Matching between FKP images of same user is called genuine matching while that of different users is known as imposter matching. An example of genuine matching and imposter matching using SIFT is shown in Fig. 5. Similarly, Fig. 6 shows an example of genuine matching and imposter matching using SURF.

Let M_T and M_S be SIFT and SURF matching scores respectively between the query and an enrolled FKP. These SIFT and SURF matching scores are fused by weighted sum rule to obtain the final matching score S as

$$S = W_T * M_T + W_S * M_S \tag{4}$$

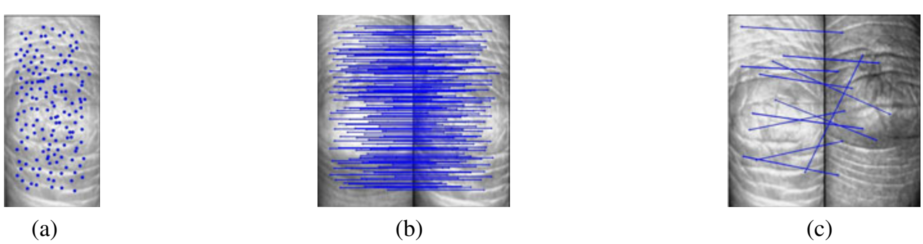


Fig. 6. (a) SURF key-points detected (b) Genuine matching of SURF key-points (c) Imposter matching of SURF key-points

where W_T and W_S are weights assigned to SIFT matching score M_T and SURF matching score M_S respectively, with $W_T + W_S = 1$. In this paper, $W_T = C_T/(C_T + C_S)$ and $W_S = C_S/(C_T + C_S)$ are considered where C_T and C_S are the correct recognition rate (CRR) of the system using SIFT alone and SURF alone respectively.

4 Experimental Results

This section analyses the performance of the proposed system on a publicly available PolyU FKP database [1]. This database contains 7920 FKP images of 4 different fingers obtained from 165 users [12]. The users comprise of 125 males and 40 females. Out of 165 users, 143 users are of age lying between 20 years and 30 years while remaining are between 30 years and 50 years. Images of each user are collected in two separate sessions. For each user, six images of 4 fingers, *viz.* index and middle finger of each hand have been acquired in each session. Images collected in first session are considered for training while remaining are used for testing.

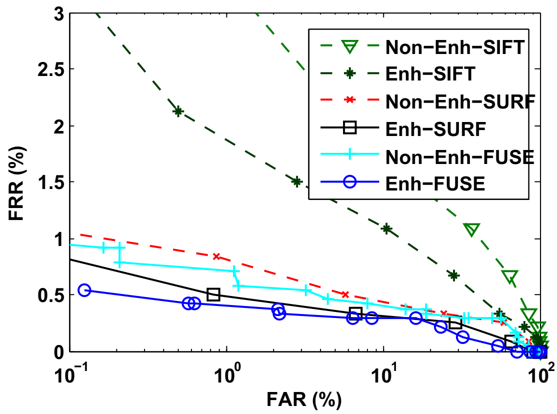


Fig. 7. ROC curves of the proposed system

Metrics like correct recognition rate (CRR) for identification and the receiver operating characteristic (ROC) curve and equal error rate (EER) for recognition are used to measure the performance of the system. CRR of the system is defined as

$$CRR = \frac{N_1}{N_2} \times 100 \tag{5}$$

where N_1 denotes the number of correct (Non-False) recognitions of FKP images and N_2 is the total number of FKP images in the testing set.

At a given threshold, the probability of accepting the imposter, known as false acceptance rate (FAR) and probability of rejecting the genuine user, known as false rejection rate (FRR) are obtained. Equal error rate (EER) is the error rate where $FAR = FRR$. Again, the receiver operating characteristics (ROC) curve which is another measure

Table 1. Performance of the proposed system and [10, 12–16]

Systems	CRR (%)	EER (%)
CompCode [12]	-	1.658
BLPOC [13]	-	1.676
ImCompCode&MagCode [14]	-	1.475
MonogenicCode [15]	-	1.720
OE-SIFT [10]	-	0.850
LGIC [16]	-	0.402
Proposed Non-Enh-SIFT	98.667	2.691
Proposed Enh-SIFT	99.125	1.900
Proposed Non-Enh-SURF	99.902	0.833
Proposed Enh-SURF	99.916	0.317
Proposed Non-Enh-FUSE	100.00	0.508
Proposed Enh-FUSE	**100.00**	**0.215**

used for measuring performance of a verification system is generated by plotting FAR against FRR at different thresholds. Besides, the testing of the proposed system using the fusion of SIFT and SURF matching scores of FKP images, we have studied the performance of the system using only SIFT matching scores or SURF matching scores on FKP images with or without enhancement. In Fig. 7, there are six ROC curves. Non-Enh-SIFT, Enh-SIFT, Non-Enh-SURF, Enh-SURF, Non-Enh-FUSE and Enh-FUSE are ROC curves of the proposed systems using SIFT matching scores on FKP images without enhancement, using SIFT matching score on enhanced FKP images, using SURF matching scores on FKP images without enhancement, using SURF matching score on enhanced FKP images, using fusion on FKP images without any enhancement and using fusion on enhanced FKP images respectively.

It is observed that the proposed system based on fusion of SIFT and SURF matching scores on enhanced FKP images is found to perform better than that on FKP images without enhancement. Further, it is observed that at low FAR, the proposed system with the fusion has low FRR compared to system using either SIFT or SURF scores on enhanced or non enhanced FKP images. Hence the proposed system with the fusion of the SIFT matching scores and SURF matching scores improves the performance. The proposed system has been compared with existing systems presented in [10, 12–16]. All these systems have used PolyU database for testing. Table 1 shows the claimed EER of these systems along with EER of the proposed system under different constraints. It has been observed that EER of the proposed system with fusion of SIFT matching scores and SURF matching scores on enhanced FKP images which is 0.215% is lowest. Further, the existing systems are not evaluated for identification mode; hence CRR are not known. The performance of the proposed system could not be compared with the existing systems. However, the proposed system using fusion of SIFT matching scores and SURF matching scores on enhanced FKP images has achieved 100% CRR.

4.1 Performance of the System against Scale

The proposed system with the fusion of SIFT matching scores and SURF matching scores have used the local features of FKP images extracted with the help of SIFT and SURF which describe an image using local regions around the key-points. The extracted key-point features using SIFT and SURF are invariant to scale of the image; so the proposed system is robust to scale (spatial resolution).

In order to investigate the performance of the proposed system against scale, each FKP image in the query set are down scaled to 90%, 80%, 70%, 60% and 50% size of original image using bi-cubic interpolation. Matching points between the enrolled image and the scaled query FKP images of the same user using SIFT and SURF are shown in Fig. 10 and Fig. 11 respectively.

ROC curves for matching with different scales of query images are shown in Fig. 8. CRR and EER obtained for the different scales of query images are given in Table 2. It can be observed that when the query images are downscaled upto 60%, the proposed system performs with CRR more than 98.625% and EER less than 5.25%. Hence, it can be inferred that the proposed system is robust to downscaled query FKP images of size upto 60%.

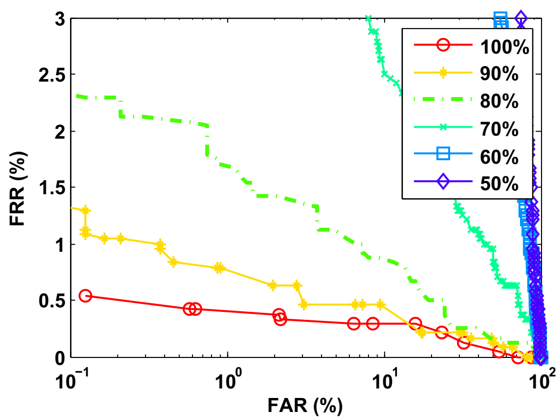


Fig. 8. ROC curves of the proposed system for various scales of query image

Table 2. Performance of the proposed system for various scales of query image

Scale (%)	CRR (%)	EER (%)
100	100.00	0.215
90	100.00	0.458
80	99.917	1.458
70	99.792	3.708
60	98.625	5.25
50	95.000	12.75

4.2 Performance of the System against Rotation

Further, feature vector of a key-point described by SIFT and SURF are relative to the dominant orientation of the key-point. Hence the key-point features remain the same irrespective of the orientation of the FKP image. Thus, the proposed system is robust to the rotation of FKP image.

In order to investigate the performance of the system against rotation, FKP images in the query set are synthetically rotated using bi-cubic interpolation by $2°$, $5°$, $10°$, $45°$, $70°$, $90°$ and $180°$. Matching points between the enrolled and the query FKP images of a user for various rotations using SIFT and SURF are shown in Fig. 12 and Fig. 13 respectively. ROC curves obtained for different rotations of query image are shown in Fig. 9. CRR and EER of the system for different rotations of the query image are given

Table 3. Performance of the proposed system for various angles of query image

Angle	CRR (%)	EER (%)
$0°$	100.00	0.215
$5°$	99.875	0.833
$10°$	99.833	0.416
$45°$	99.792	0.925
$70°$	99.917	0.750
$90°$	99.958	0.358
$180°$	99.917	0.441

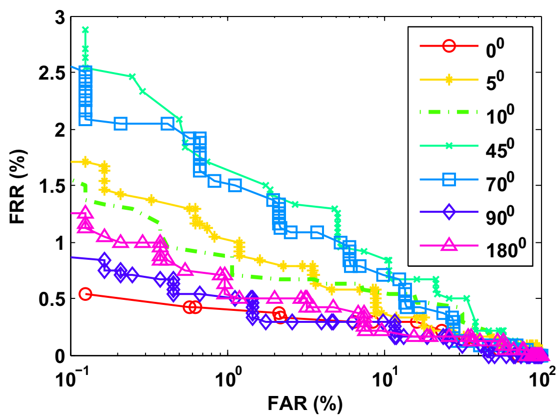
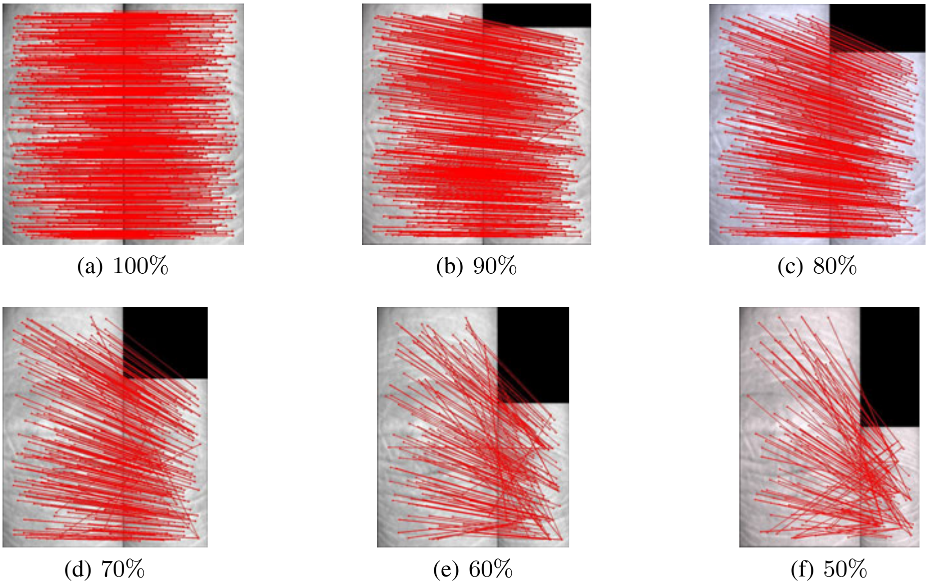


Fig. 9. ROC curves of the proposed system for various orientation of query image

Table 4. Speed of the Proposed System

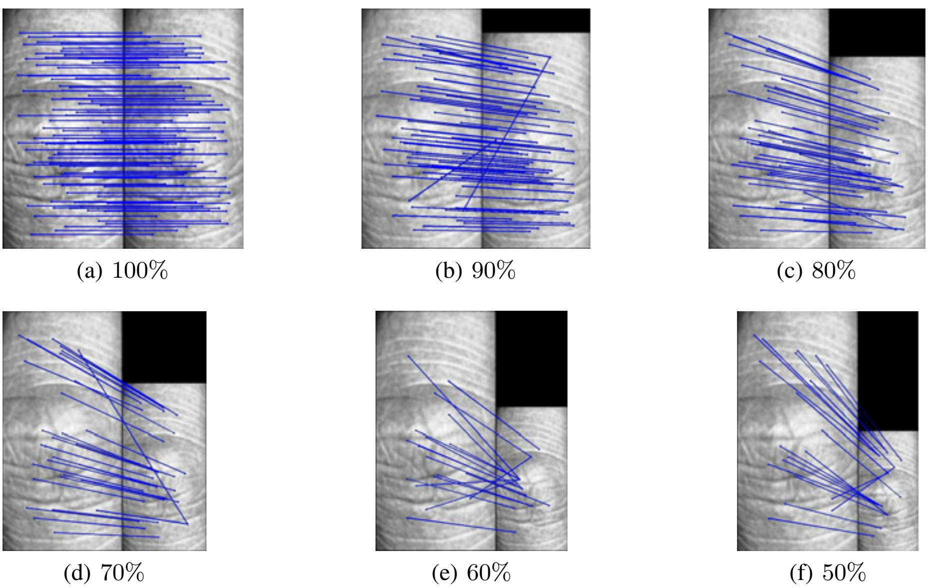
	SIFT	SURF	Total
Feature Extraction (ms)	58.091	17.970	76.061
Matching (ms)	4.782	0.083	**4.865**
Total (ms)	62.873	18.053	**80.926**



(a) 100% (b) 90% (c) 80%

(d) 70% (e) 60% (f) 50%

Fig. 10. SIFT matching for various scales of query image

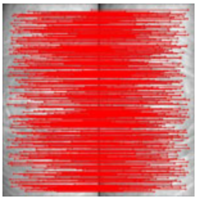


(a) 100% (b) 90% (c) 80%

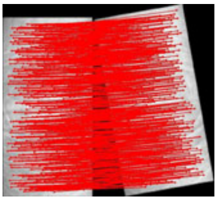
(d) 70% (e) 60% (f) 50%

Fig. 11. SURF matching for various scales of query image

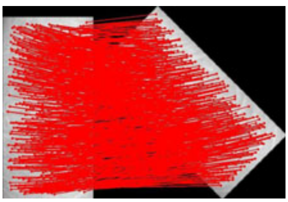
in Table 3. It is observed that the system performs with CRR minimum of 99.79% and maximum EER of 0.92% for any orientation of query images. Hence, it can be said that the system is robust to rotation.



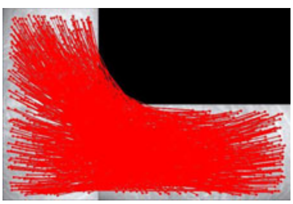
(a) 0°



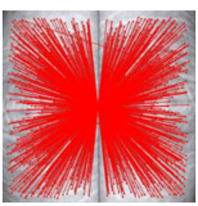
(b) 10°



(c) 45°

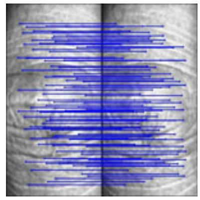


(d) 90°

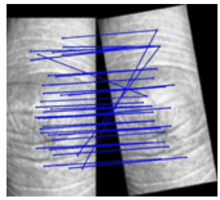


(e) 180°

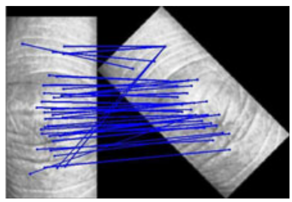
Fig. 12. SIFT matching for various orientations of query image



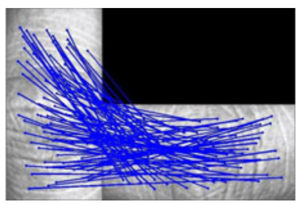
(a) 0°



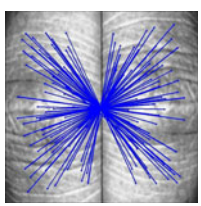
(b) 10°



(c) 45°



(d) 90°



(e) 180°

Fig. 13. SURF matching for various orientations of query image

4.3 Speed

This sub-section discusses the time taken by the proposed system for feature extraction and matching. The system has been implemented on a Oct-Core $(8 \times 2.5GHz)$ workstation with 8 GB RAM. Time taken by the system for feature extraction and matching are given in Table 4. The feature extraction time is the time taken to extract SIFT and SURF features on entire database and dividing by the total number of images. It is found that the system takes $58.091ms$ and $17.970ms$ for extracting SIFT and SURF features respectively. For average matching time, all possible matches that include both genuine and imposter cases are considered. It is observed that the system takes $4.782ms$ and $0.083ms$ for matching SIFT and SURF feature vectors respectively. Total time taken by the system is $80.926ms$, out of which matching takes $4.865ms$ only and is significantly fast.

5 Conclusions

This paper has proposed an FKP based recognition system which is robust to scale and rotation. Local information of the FKP are extracted using SIFT and SURF and they are fused at matching score level. An approach to correct the non-uniform brightness and to improve the contrast is proposed. During recognition, the corresponding features of enrolled and query FKPs are matched using nearest-neighbourhood-ratio method and the derived SIFT and SURF matching scores are fused using weighted sum rule to obtain fused matching score. The proposed system has been evaluated using publicly available PolyU database [1] of 7920 images. It is observed that the proposed system performs with CRR of 100.00% and EER of 0.215%, and is found to be better than best known systems [10, 12–16]. Further, the system is evaluated for various scales and rotations of the query image. It is observed that the system performs with CRR of atleast 98.62% and EER of atmost 5.25% for query image downscaled upto 60% and performs with CRR of 99.75% and EER of 0.925% for any orientation of query image.

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