Finger-knuckle-print based Recognition System

A Report Submitted
in Partial Fulfillment of the Requirements
for the Degree of
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in
Information Technology

by
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ALLAHABAD
April, 2018

UNDERTAKING

I declare that the work presented in this report titled "*Finger-knuckle-print based Recognition System*", submitted to the Computer Science and Engineering Department, Motilal Nehru National Institute of Technology, Allahabad, for the award of the ***Bachelor of Technology*** degree in ***Information Technology***, is my original work. I have not plagiarized or submitted the same work for the award of any other degree. In case this undertaking is found incorrect, I accept that my degree may be unconditionally withdrawn.

April, 2018
Allahabad

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CERTIFICATE

Certified that the work contained in the report titled "*Finger-knuckle-print based Recognition System*", by *Saksham Agrawal*
Aditya Gangwar
Sridhar Addagatla
Ram Lakhan Meena
Rohit Ranjan, has been carried out under my supervision and that this work has not been submitted elsewhere for a degree.

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April, 2018

Preface

This project has been undertaken by the team as a part of the B.Tech curriculum of Information Technology.
Through this project we have hoped to achieve a nuanced insight into the world of Image Processing and Machine Learning.
We also hope our theoretical report along with the accompanying implementations find relevance and importance in the field of Computer Science.

Acknowledgements

We would like to take this opportunity to acknowledge and appreciate the efforts of the people who have helped us during our research and documenting this thesis. First and foremost, we would like to express our deep-felt gratitude towards our thesis adviser - Dr. Suneeta Agarwal for her excellent guidance and invaluable support. Her invaluable and continuous exposure, not only to research but also to other aspects of life have helped in constructive development and shaping of our ideologies and understanding.
We would also like to thank all the teachers of the Computer Science and Engineering Department, who have helped us develop a deep love and passion for this stream.

Abstract

Finger-Knuckle print recognition is carried using detection and matching interest points after pre-processing of image. The non-uniform brightness of the FKP due to relatively curvature surface is corrected and texture is enhanced. The pre-processing involves contrast stretching, Gaussian filtering and adaptive histogram equalization of image. 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 en- rolled 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.

Contents

Chapter 1

Introduction

Biometric identifiers are the distinctive, measurable characteristics used to label and describe individuals. Biometric identifiers are often categorized as physiological versus behavioral characteristics. Physiological characteristics are related to the shape of the body. Examples include fingerprint, palm veins, face recognition, DNA, palm print, hand geometry, iris recognition, retina and odour/scent. Behavioral characteristics are related to the pattern of behavior of a person, including typing rhythm, gait, and voice. Proper biometric use is very application dependent. Certain biometrics will be better than others based on the required levels of convenience and security. No single biometric will meet all the requirements of every possible application.

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 [8]. 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 [9] and acceptability in the society [6].

Finger knuckle bending produces a highly unique texture pattern and it can be used as a distinctive biometric identifier. Like any other recognition system, a FKP based recognition system also consists of four stages -

- Image acquisition
- Pre-processing
- Interest points extraction
- Matching

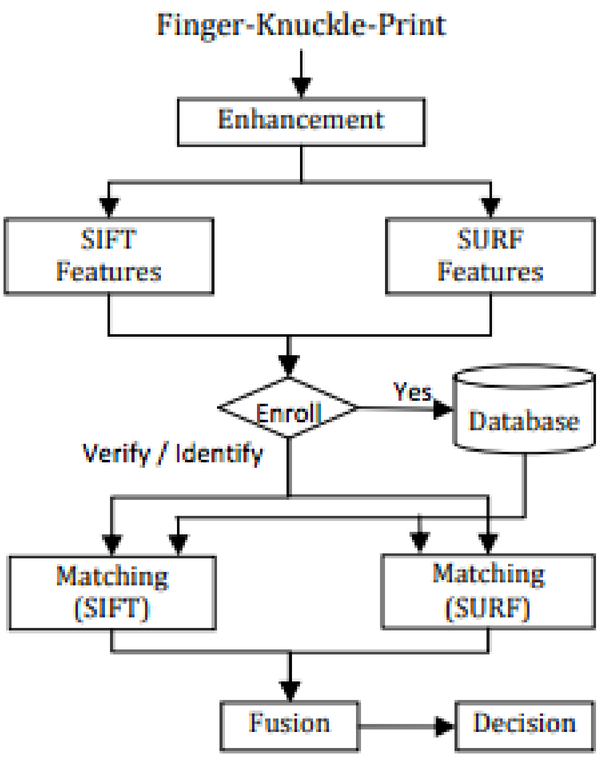


Figure 1: Basic block diagram of Finger-knucke-print Recognition System

We use local information extracted using SIFT and SURF algorithms for FKP recognition. The nearest-neighbour-ratio method based matching has been used to obtain the SIFT and SURF matching scores between the enrolled and the query FKPs. The scores are fused using the weighted sum rule to obtain final matching score. The proposed system has been evaluated on publicly available PolyU database of 7092

FKP images of 4 fingers of 148 users. Further, it is also tested for its performance against changes due to scales query image and has been observed that the proposed system is robust to scale.

1.1 Motivation

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 bio-metric identifier. It ensures easy accessibility, contact-less image acquisition, in-variance to emotions and other aspects such as tiredness.

There are many cases in which people involved in manual labour such as farmers, construction workers deteriorate their finger prints. Hence they can not be uniquely recognized using their finger prints. The knuckle portion is not much prone to deterioration as compared to finger prints.

Moreover, in some cases voice is used as a recognition parameter. A major drawback in this scenario is that voice of a person is not always the same. It changes based on age and emotions. For example - a person who is sad or crying speaks with a shivering voice whereas one who is angry speaks in a bold voice.

The biometric identifiers have their advantages and disadvantages in terms of the precision and user acceptance. Currently, passwords and smart cards are used as the authentication tool for verifying the authorized user. However, passwords are easily cracked by dictionary attacks, as well as the smart cards are stolen by anybody, and then we cannot check who the authorized user is.

Chapter 2

Related Work

Finger-knuckle-print based recognition system is a lesser researched area compared to finger print and other bio-metrics. "Finger surface as a bio-metric identifier" by Damon L. Woodard, Patrick J. Flynn, Department of Computer Science and Engineering, University of Notre Dame, Notre Dame, IN 46556, USA was the first paper accepted in this field in 2005.

Since then, there have been few more research papers published in this field. Some of them are - "An Efficient Finger-knuckle-print based Recognition System Fusing SIFT and SURF Matching Scores" by G S Badrinath, Aditya Nigam and Phalguni Gupta Department of Computer Science and Engineering Indian Institute of Technology, Kanpur, 208016, India. "Finger-Knuckle-Print ROI Extraction Using Curvature Gabor Filter for Human Authentication" by Aditya Nigam and Phalguni Gupta, School of Computer Science and Electrical Engineering, Indian Institute of Technology Mandi (IIT Mandi), Mandi, India 2National Institute of Technical Teachers Research (NITTTR), Salt Lake, Kolkata, India. "A New Finger-Knuckle-Print ROI Extraction Method Based on Two-Stage Center Point Detection" by Hongyang Yu, Gongping Yang, Zhuoyi Wang and Lin Zhang School of Computer Science and Technology, Shandong University Jinan 250101, P.R. China. "Finger-Knuckle-Print Based Recognition System using LBP and SURF" by Salil Kumar Verma1 , Maitreyee Dutta2, National Institute of Technical Teachers Training and Research ,Chandigarh, India.

Chapter 3

Tools and Libraries Used

3.1 Python

Python is a widely used high-level programming language for general-purpose programming, created by Guido van Rossum. An interpreted language, Python has a design philosophy which emphasizes code readability and a syntax which allows programmers to express concepts in fewer lines of code than possible in languages such as C++ or Java. Python features a dynamic type system and automatic memory management and supports multiple programming paradigms, including objectoriented, imperative, functional programming, and procedural styles. It has a large and comprehensive standard library.

3.2 Open Source Computer Vision

Open Source Computer Vision, also known as OpenCV, is a real time computer vision library with many image processing functions developed by Intel. OpenCV is written in C++ and its primary interface is in C++. There are bindings in Python, Java and MATLAB. This API provides functions to perform various complex Image processing operations. We used the python interface of OpenCV.

Chapter 4

Proposed Work

4.1 Pre-processing

The aim of pre-processing is improvement of the image data that suppresses unwilling distortions or enhances some image features important for further processing. Following pre-processing techniques are implemented in the current work with corresponding images are shown for the illustration. Figure 2 is used as original image in this work.

Figure 2: Original Image

4.1.1 Image contrast stretching

The Finger-knuckle surface represents a relatively curvature surface and results in non-uniform reflections. FKP(finger-knuckle-print) has low contrast and non-uniform brightness. To obtain the well distributed texture, image contrast stretching is used. This method usually increases the global contrast of images, especially when the usable data of the image is represented by close contrast values. This allows for areas of lower local contrast to gain a higher contrast. As we can see in Figure 3 contrast is improved globally.

Figure 3: Contrast Stretched Image

4.1.2 Image smoothing

The Finger-knuckle surface has much noise due to non-uniform reflections of light and curvature surface. So, it is better to remove noise before applying algorithms which depend on quality of image. For this purpose, we used Gaussian blur method with a kernel size of 3x3. Gaussian filtering is done by convolving each point in the input array with a Gaussian kernel and then summing them all to produce the output array. After removing the noise image looks like Figure 4.

Figure 4: Smoothed Image with Gaussian blur

4.1.3 Contrast Limited Adaptive Histogram Equalization

It is also known as CLAHE, which is much better algorithm than Adaptive histogram equalization at improving the contrast while maintaining the contrast limit. Adaptive histogram amplifies the noise. To avoid this, contrast limiting is applied. If any histogram bin is above the specified contrast limit (by default 40 in Open CV), those pixels are clipped and distributed uniformly to other bins before applying histogram equalization. After equalization, to remove artifacts in tile borders, bi-linear interpolation is applied.

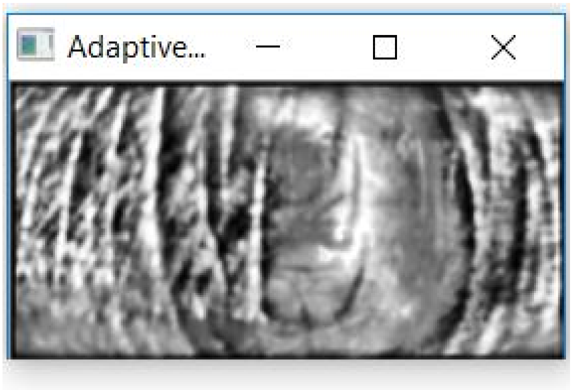


Figure 5: Image after applying CLAHE

4.2 Feature extraction

Feature extraction and matching is an important step in any biometric identification system. The features extracted from the preprocessed image can be either global features or local features. The global features take the entire preprocessed images and features may be extracted using Fourier descriptors, Hu moments or Eigen vectors. The advantages of these algorithms based on global features are simple and fast but they do not provide reliable recognition under illumination changes and pose variations. On the other hand, local features based algorithms are more suitable for textured objects and are also more robust to illumination and pose variations (Alhwarin et al 2008). The extraction of local features in Finger knuckle print involves determining the key points in the image. A key point may represent an isolated pixel with maximum or minimum intensity, or a corner point, line endings or a point on the curve where the curvature is locally maximal. A descriptor is then determined around the key point which represents the feature vector. Some of the techniques used to find the key points and descriptors include Harris corner detector, SIFT(Scale invariant feature transform), SURF(Speeded up robust features). The Harris corner detector proposed by Harris Stephens (1998) can be used to efficiently recognize images with occlusion and clutter but it fails when the images undergo scale changes. Lowe (2004) introduced the Scale Invariant Feature Transform (SIFT) used to detect local features that is invariant to scaling, rotation, affine transformation, and partially invariant to changes in illumination and view angle.

4.2.1 Scale Invariant Feature Transform

Scale Invariant Feature Transform (SIFT) was developed by Lowe (2004) and it presents a method for detecting distinctive invariant features from images that can be used to perform reliable matching. This algorithm is used in palmprint recognition (Chen Moon 2008, Badrinath Phalguni Gupta 2008), face recognition (Geng et al 2009), iris recognition (Fernandez et al 2009). The extraction of SIFT features involves the following steps explained below.

■ *Detection of Key points*

This step involves finding the points of interest known as the keypoints that are invariant to scale and orientation. The keypoints are detected using cascade filtering approach and for each of these keypoints the scale and location is determined and then gradient operators are used for orientation assignment. The identification of keypoints is summarized as follows

Detection of Scale Space Extrema: The first step of keypoint detection is to find the positions and scales that can be assigned again and again with different views of same object. The locations that remain consistent to variations in scale can be found by finding the stable features at different scales using a continuous function of scale known as scale space. The scale space of an input image (I) is obtained when it is convolved with Gaussian kernel G(x, y,σ) and is given by

$$L(x, y, \sigma) = G(x, y, \sigma) * I(x, y) \tag{1}$$

where * is the convolution operator and σ the width of Gaussian filter. The Difference of Gaussian (DOG) images are computed from two nearby scales that differ by constant multiplicative factor k

$$D(x, y, \sigma) = L(x, y, k\sigma) - L(x, y, \sigma) \tag{2}$$

The scale space is divided into different octaves, with each octave containing a series of smoothed images that is obtained by convolving the input image with Gaussian kernels for different values of σ. Thus each scale space is divided into an integer number of intervals s. The nearby images are subtracted to give the DOG images. The scale space for the jth and (j+1)th octave is shown in Figure 6. The next octave is obtained by down sampling the Gaussian image that has twice the initial value of σ.

Keypoint Localization: The DOG images obtained in the above step are used to find the keypoints with the help of local maxima or minima across different scales. Each pixel in the DOG image is compared with its eight and nine neighbours in the scale above and below respectively. The pixel is then selected to be the candidate

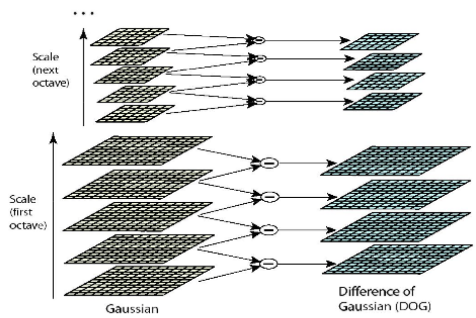


Figure 6: The Gaussian convolved images at different scales, and the computation of the Difference-of-Gaussian images

keypoint if it is either a local maxima or minima in 333 regions at current and adjacent scales. The next step is to reject the keypoints that are associated with an edge or that which has a low contrast because they are easily corrupted by noise.

Orientation Assignment: In this step a consistent orientation is assigned to the keypoint. This makes the feature invariant to rotation when the descriptor for the keypoint is expressed in reference to orientation. The local image gradients are used to assign the orientation to the keypoints. To determine keypoint orientation, a gradient orientation histogram is computed in the neighbourhood of the keypoint. The scale of keypoint is used to select Gaussian smoothed image L. For each Gaussian smoothed image L(x, y), magnitude m(x, y) and orientation θ(x, y) are computed as

$$m(x,y) = \sqrt{(L(x+1,y) - L(x-1,y))^2 + (L(x,y+1) - L(x,y-1))^2} \quad (3)$$

$$\theta(x,y) = tan^{-1}\Big(\frac{L(x,y+1) - L(x,y-1)}{L(x+1,y) - L(x-1,y)}\Big) \quad (4)$$

Orientation histogram is then formed from the gradient orientation of the sample points around each keypoint. The histogram has 36 bins for 360 degree range of orientations and each sample is weighed by gradient magnitude and Gaussian weighted circular window with σ of 1.5 times of scale of keypoint before adding it to histogram. Peaks in the histogram correspond to dominant orientation of the local gradients and any other local peak within 80% of largest peak is used to create keypoint with the computed orientation. This is done to increase stability during matching.

▮ *Extracting SIFT descriptor*

After the selection of orientation, the feature descriptor is computed. This is done by computing as a set of orientation histograms on 44 pixel neighbourhoods. The orientation histograms are relative to the keypoint orientation as shown in Figure 7. These histograms contain 8 bins each and each descriptor contains an array of 16 histograms around the keypoint. This generates SIFT feature descriptor of 448=128 element feature vector for each keypoint. The descriptor vector is invariant to rotation, scaling and illumination. The FKP image and the detected keypoints are shown in Figure 8.

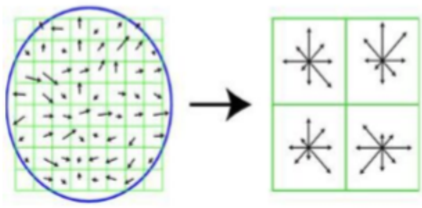


Figure 7: (a) Image gradients (b) Keypoint descriptor

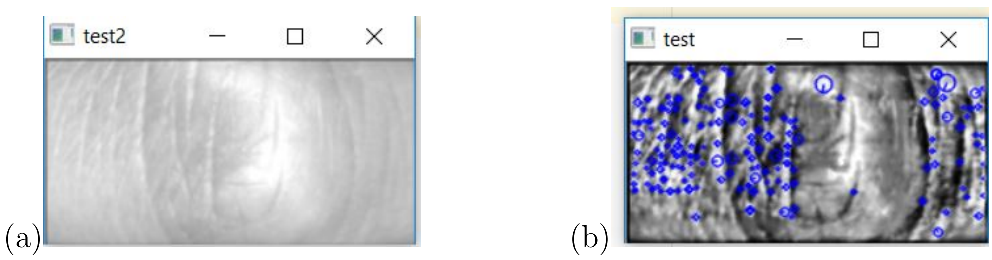


Figure 8: (a) Original (b) Detected SIFT keypoints

4.2.2 Speeded Up Robust Features

Speeded Up Robust Features (SURF) is a scale invariant and rotation invariant interest point detector and descriptor. This algorithm has been used in face (Li et al 2011), iris (Mehrotra et al 2009) and ear (Rathore et al 2013) based personal identification systems and is used in the proposed work because it provides good distinct features and is robust to scale, rotation, illumination and view point changes (Le-qing 2011).This algorithm uses a keypoint detector and descriptor method which is explained as below.

- *Detecting key points with Fast-Hessian*

SURF makes use of Hessian matrix to detect the keypoints in the image. Let P(x,y) represent a point in the image , and then the Hessian matrix H(P,σ) at scale σ is defined as

$$H(P,\sigma) = \begin{bmatrix} \mathrm{L}_{xx}(P,\sigma) & \mathrm{L}_{xy}(P,\sigma) \\ \mathrm{L}_{yx}(P,\sigma) & \mathrm{L}_{yy}(P,\sigma) \end{bmatrix} \tag{5}$$

where, $L_{xx}(P,\sigma), L_{xy}(P,\sigma), L_{yx}(P,\sigma), L_{yy}(P,\sigma)$ are the convolution of the Gaussian second order derivative $\frac{\delta^2}{\delta x^2}g(\sigma)$, $\frac{\delta^2}{\delta xy}g(\sigma)$, $\frac{\delta^2}{\delta yx}g(\sigma)$, $\frac{\delta^2}{\delta y^2}g(\sigma)$ with image I at point P. The box filters are used to approximate the second order Gaussian derivatives in the Hessian matrix and this serves to speed up the computation. The keypoints at different scales are obtained by convolving the image with the box filters. Instead of iteratively reducing the image size as in sift algorithm, the scale space is analyzed by up scaling the filter size. Next to localize the keypoints in the image and over scales, non maximum suppression in a 3 x 3 x 3 neighbourhood is applied. Figure 9 shows the SURF points detected in an FKP image.

- *Extracting SURF Descriptor*

The extraction of the SURF descriptor first involves orientation assignment around the keypoint and then the extraction of the descriptor with reference to the orientation.

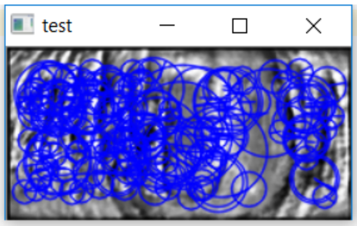
(a)  (b) 

Figure 9: (a) Original Image (b) Detected SURF keypoints

Orientation Assignment: First a circular region is considered around the selected keypoints to determine the dominant orientation based on the information in the circular region. The Haar wavelet response in both horizontal and vertical directions is computed and the dominant orientation is obtained by summing the wavelet responses and the maximum response yields the dominant orientation of the keypoint. The feature vector is then computed relative to the dominant orientation thus making it invariant to rotation.

Descriptor Components: Next a square region aligned along the dominant orientation is considered around the selected keypoint. This region is then divided into 44 subregions and for each of these subregions the Haar wavelet response is computed. The sum of the wavelet responses d_x and d_y in the horizontal and vertical directions for each subregion represents the feature vector. Next the sum of the absolute value of the responses $|d_x|$ and $|d_y|$ are computed which provides the information about the polarity of the changes in image intensity. Thus the feature vector V_j for the j^{th} subregion is given as

$$V_j = \left[\Sigma d_x, \Sigma d_y, \Sigma|d_x|, \Sigma|d_y|\right] \tag{6}$$

Concatenating the entire feature vector for the sixteen subregions surrounding the keypoint provides the descriptor vector of length 64(16 x 4).

4.3 Matching and Fusion

The feature template of the FKP is represented by local feature vectors extracted using SIFT, SURF. During recognition, the feature set of the test FKP image is matched with the corresponding features of all the knuckle prints in the database. For SIFT and SURF feature the matching scores are computed based on the number of key points matched between the test image and template stored in the database. Both SIFT and SURF algorithms generate matching score. These scores combined using weighted sum to generate unique matching score. The matching scores between corresponding feature vectors are computed using nearest-neighbour-ratio method as follows.

4.3.1 Nearest Neighbour Ratio Algorithm

Let S and T represent the vector array of the keypoint descriptor for the images in the database and the test image as given below

$$S = (s_1, s_2, s_3, ..., s_m) \tag{7}$$

$$T = (t_1, t_2, t_3, ..., t_n) \tag{8}$$

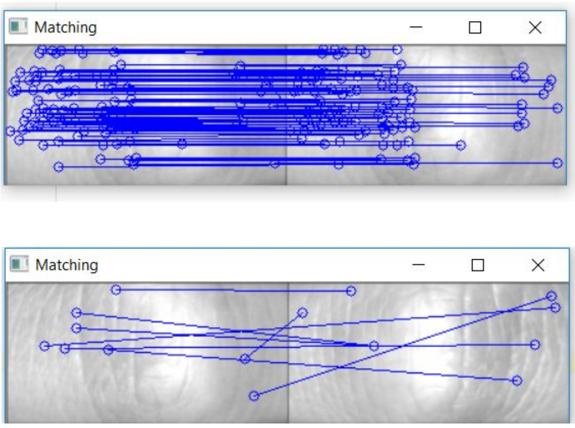
Where s_i and t_j are the descriptor for the keypoint in the database and the test image. The nearest neighbour ratio is computed using the relation

$$R = \frac{||s_i - t_j||}{||s_i - t_k||} \tag{9}$$

where $||s_i - t_j||$ and $||s_i - t_k||$ represents euclidean distance between s_i and it's first nearest neighbour t_j and that between s_i and its second nearest neighbour t_k. A match is said to be found for s_i with t_j if the following condition is satisfied.

$$s_i = \begin{cases} \text{Matched if R < threshold} \\ \text{Not matched Otherwise} \end{cases} \tag{10}$$

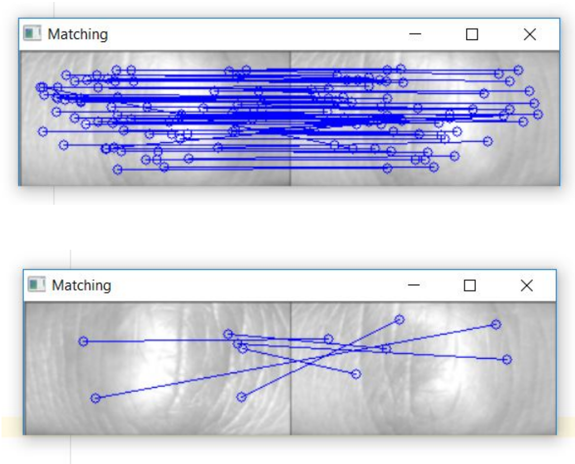
Where threshold is taken as 0.8, Once a match is found for a keypoint in S and T, then the matched keypoint is removed and the process is repeated till no more matches are found. The total number of matches thus found gives the matching score. This nearest neighbour ratio matching scheme is used for both SIFT and SURF feature matching. An example of genuine matching and imposter matching using SIFT is shown in Figure 10. Similarly, Figure 11 shows genuine matching and imposter matching of SURF.



(a)

(b)

Figure 10: (a) Genuine matching of SIFT keypoints (b) Imposter matching of SIFT keypoints



(a)

(b)

Figure 11: (a) Genuine matching of SURF keypoints (b) Imposter matching of SURF keypoints

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

$$S = W_T * M_T + W_S * M_S \tag{11}$$

Where W_T, W_S are subjective to experimental analysis.

4.3.2 Score Normalization

The scores generated from the different matchers may not lie in the same range. One matcher may provide scores that lie in the range [0, 1] and another matcher in the range [10, 100].If these scores lying in different ranges are fused directly, then score contribution from the first matcher is effectively eliminated. Hence score normalization is a necessary step before fusion to transform the scores from different matchers to a common range. In the proposed work Min-max normalization is used which transform the scores to a range [0, 1] (Jain et al 2005).Let s represent the matching score from a set S of the matching scores from a particular matcher and let the normalized score be represented as n and is given by

$$n = \frac{s - min(S)}{max(S) - min(S)} \tag{12}$$

where max (S) and min (S) are the maximum and minimum scores from the given set S.

Chapter 5

Experimental Results

This section analyses the performance of the proposed system on a publicly available PolyU FKP database [10]. This database contains 7092 FKP images of 4 different fingers obtained from 148 users [11]. For each finger 12 images are acquired out of which 8 images are used for training and 4 for testing. For testing metrics like correct recognition rate(CRR), false acceptance rate(FAR) and FRR(false recognition rate) are used.

$$CRR = \frac{N1}{N2} \tag{13}$$

where N1 denotes the number of correct (Non-False) recognitions of FKP images and N2 is the total number of FKP images in the testing set.

At a given threshold, the probability of accepting a imposter, known as false acceptance rate (FAR) and probability of rejecting a genuine user, known as false rejection rate (FRR) are obtained. As the threshold is increases the FRR decrease but FAR increases and vice-versa.

$$FAR = \frac{N1}{N2} \tag{14}$$

where N1 denotes the number of imposters accepted in the system and N2 is the total number of imposter images in the testing set.

$$FRR = \frac{N1}{N2} \tag{15}$$

where N1 is the total number of genuine users rejected by the system and N2 is the total number of genuine user images in the testing set.

For a good biometric system both FRR and FAR should be minimum. Both FAR and FRR converge to minimum at a point which is called equal error rate(EER) where FAR = FRR at a certain threshold. Hence, to measure the performance of a biometric system EER should be taken into account instead of FAR and FRR as EER is independent of threshold used.
We have approximated the value of EER by finding the threshold at which the difference between FAR and FRR is minimum and then we took mean of FAR and FRR as the value of EER.

$$EER = \frac{FAR + FRR}{2} \tag{16}$$

where FAR and FRR are false acceptance rate and false rejection rate at the threshold where the difference between FAR and FRR is minimum.
The proposed method achieves a CRR of 99.3% and FAR of 0.733% and FRR of 0.7% so EER=0.717%.

5.1 Performance of 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 Figure 12, Figure 13 respectively.

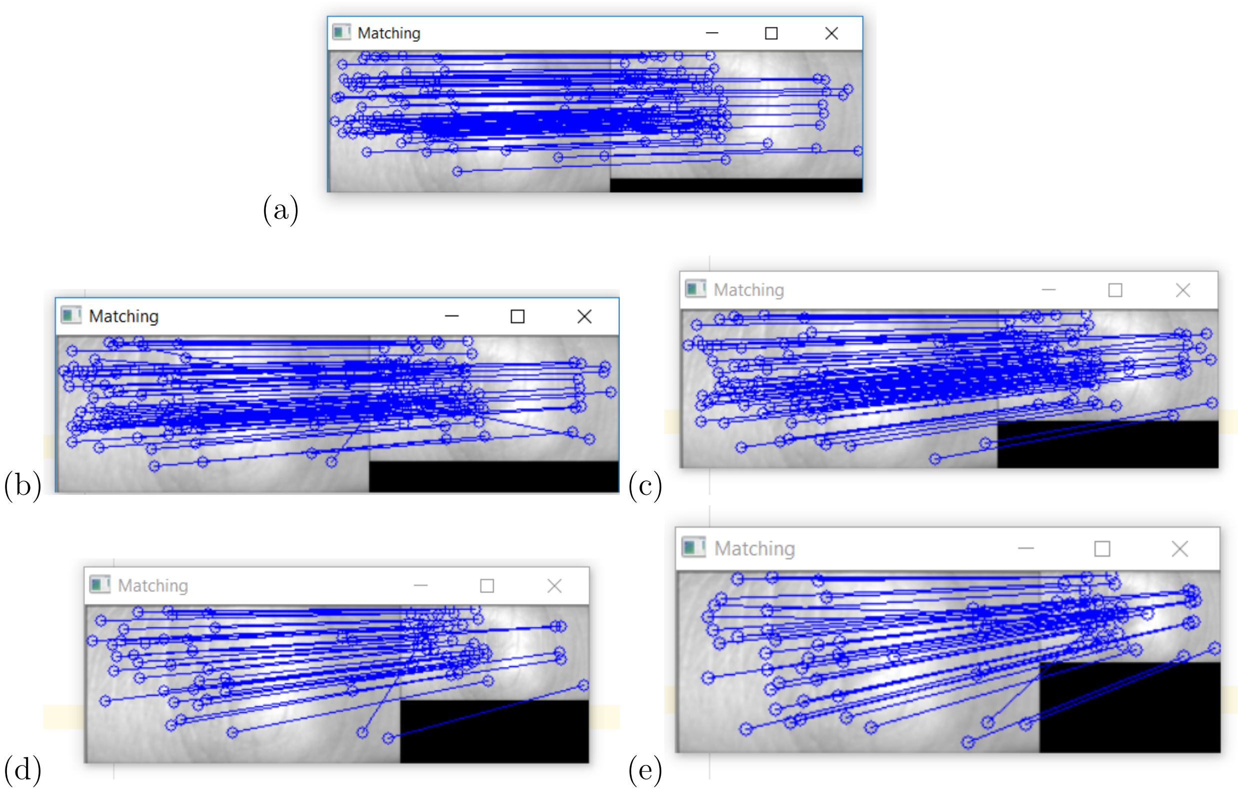


Figure 12: Matching of SIFT points with (a) 90% scaling (b) 80% scaling (c)70% scaling (d) 60% scaling (e)50% scaling

Table 1: Performance of the proposed system for various scales of query image

Scale%	CRR%	FRR%	FAR%	EER%
100	99.3	0.7	0.733	0.717
90	99.4	0.6	0.549	0.575
80	99.05	0.9	0.916	0.908
70	98.75	1.25	1.19	1.22
60	96.9	3.05	3.022	3.036
50	90.35	9.25	9.341	9.296

It can be observed from Table 1 that when query images are downscaled by 60%, the propsed gives CRR of 96.9% and EER% 3.036. Hence, it can be said that the

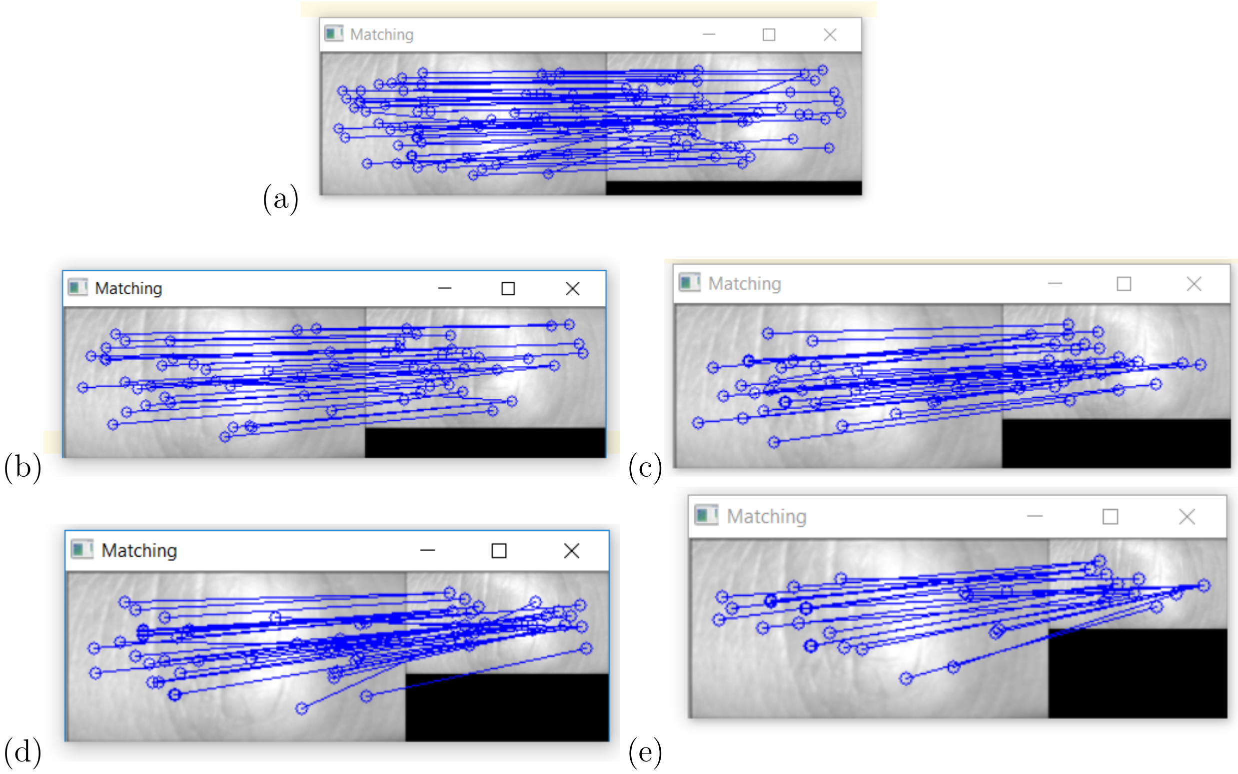


Figure 13: Matching of SURF points with (a) 90% scaling (b) 80% scaling (c)70% scaling (d) 60% scaling (e)50% scaling

proposed system is robust to downscaled query FKP images of size upto 60%.

5.2 Speed

Table 2: Speed of Proposed System

	SIFT	**SURF**	**Total**
Feature Extraction	46.09ms	40.52ms	86.61ms
Matching	6.394s	10.644s	17.038s
Total	6.440s	10.685s	17.125s

This section discusses the time taken for interest point extraction and matching. The system has been implemented on Quad-Core(4*2.5 GHz) workstation with 8GB of RAM. Time taken by the system for feature extraction and matching are given in Table 2. 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 46.09ms and 40.52ms 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 6.394s and 10.644ms for matching SIFT and SURF feature vectors respectively. Total time taken by the system is 17.125s, out of which matching takes 17.038s.

Chapter 6

Conclusion and Future Work

This report has proposed an FKP based recognition system which is robust to scale. 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 [10] of 7092 images. It is observed that the proposed system performs with CRR of 99.3% and EER of 0.717%. Further, the system is evaluated for various scales of image. It is observed that the system performs with CRR of atleast 96.9% and EER of 3.036% for query image downscaled upto 60%.

References

[1] D.Lowe. Distinctive Image Features from Scale-Invariant Keypoints, International Journal of computer vision, 2004
`https://people.eecs.berkeley.edu/ malik/cs294/lowe-ijcv04.pdf`

[2] Herbert Bay, Andreas Ess, Tinne Tuytelaars, and Luc Van Gool. Speeded-up robust features. Computer Vision and Image Understanding, 110:346359, 2008.

[3] M. Choras and and R. Kozik. Knuckle biometrics based on texture features. In International Workshop on Emerging Techniques and Challenges for Hand-Based Biometrics, pages 15, 2010.

[4] Anil K. Jain, Patrick Flynn, and Arun A. Ross. Handbook of Biometrics. Springer-Verlag, USA, 2007.

[5] W. O. Jungbluth. Knuckle print identification. Journal of Forensic Identification, 39:375 380, 1989.

[6] A. Kumar and C. Ravikanth. Personal authentication using finger knuckle surface. IEEE Transactions on Information Forensics and Security, 4(1):98 110, 2009.

[7] A. Kumar and Y. Zhou. Personal identification using finger knuckle orientation features. Electronics Letters, 45(20):1023 1025, 2009.

[8] Damon L. Woodard and Patrick J. Flynn. Finger surface as a biometric identifier. Computer Vision and Image Understanding, 100:357384, 2005

[9] Lin Zhang, Lei Zhang, David Zhang, and Hailong Zhu. Ensemble of local and global information for finger-knuckle-print recognition. Pattern Recognition, 44(9):1990 1998, 2011.

[10] PolyU Finger-Knuckle-Print Database, http://www.comp.polyu.edu.hk/ biometrics/FKP.htm

[11] L. Zhang, L. Zhang, and D. Zhang. Finger-knuckle-print: A new biometric identifier. In International Conference Image Processing, pages 1981-1984, 2009