

# Fingerprint Recognition using Scale Invariant Feature Transform (SIFT)

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**Abstract**— The main object of this project to design a fingerprint recognition system which can perform the task of fingerprint verification with greater accuracy. One of the problems of fingerprint authentication system that it perform poorly in case of poor quality fingerprint image. Extraction of minutia from the poor quality fingerprint image is difficult and not all the minutia is extracted. Different number of minutia fingerprint image creates the problem of accurate matching. Moreover most of the fingerprint recognition system performs poorly in case of rotated version of the query fingerprint image. In this project a Scale Invariant Feature Transform (SIFT) based fingerprint recognition system has been designed to overcome above-mentioned problem. In this system, first, minutia's or called featured points are extracted from the fingerprint images. These minutia points are then used to match the identity of the fingerprint image. The SIFT algorithm is basically an approach for extracting distinctive invariant features from images. Since SIFT is rotation invariants therefore it gives better result in case of rotated fingerprint image. Simulation results that this system is able to verify the fingerprint with good accuracy.

**Key words:** Automated Fingerprint Identification System, Scale Invariant Feature Transform, Style, False Acceptance Rate, False Rejection Rate

## I. INTRODUCTION

Individuality, Uniqueness and reliability make the biometric fingerprint as an ideal tool for identification of the person. A Human fingerprint is basically a pattern of valleys and ridges. Among all the biometrics system, fingerprint authentication is most widely used authentication system. Most of the fingerprint authentication system perform the authentication task by using three methods i.e. Minutia Based Fingerprint authentication system, Correlation based Authentication system and Hybrid authentication system.

Details of the human fingerprint lie on the minutia points which are rich in human fingerprint. These minutia points are used for identifying the fingerprint. The main object of this paper is to design a fingerprint recognition system which can perform the task of fingerprint verification with greater accuracy. One of the problems of fingerprint authentication system that it perform poorly in case of poor quality fingerprint image. Extraction of minutia from the poor quality fingerprint image is difficult and not all the minutia is extracted. Different number of minutia fingerprint image creates the problem of accurate matching. Moreover most of the fingerprint recognition system performs poorly in case of rotated version of the query fingerprint image. In this project a Scale Invariant Feature Transform (SIFT) based fingerprint recognition system has been designed to overcome above-mentioned problem. In this system, first, minutia's or called featured points are extracted from the fingerprint images. These minutia points are then used to match the identity of the fingerprint image. The SIFT algorithm is basically an

approach for extracting distinctive invariant features from images. Since SIFT is rotation invariants therefore it gives better result in case of rotated fingerprint image. Simulation results that this system is able to verify the fingerprint with good accuracy. Details of the human fingerprint lie on the minutia points which are rich in human fingerprint. These minutia points are used for identifying the fingerprint. The main object of this project is to design a fingerprint recognition system which can perform the task of fingerprint verification with greater accuracy.

One of the problems which is facing by the fingerprint identification is the amount of time and computational complexity. Since most of the identification system is already loaded with the rage database therefore these system takes some times to match the fingerprint image. Apart from these, most the fingerprint system are suffering from the scaling and rotating fingerprint problems. These systems are not able to recognize or identify the rotated or scaled version of the fingerprint image.

In this paper, local descriptor based fingerprint recognition is presented. Minutia cylinder code is used as local descriptors. Block diagram of proposed methodology is described in the next section.

## II. PROPOSED METHODOLOGY

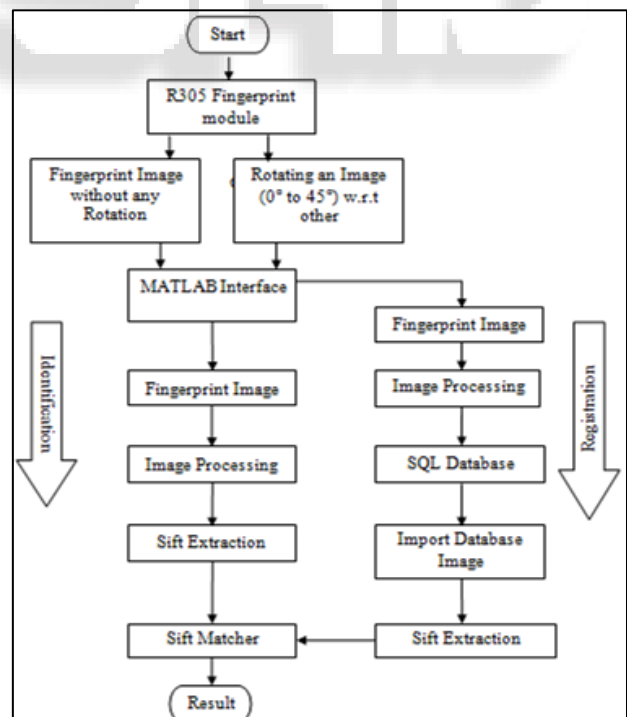


Fig. 1: Proposed methodology

The proposed methodology adopted in this project is shown in figure 1. First of all, with the help of scanner, i.e. R305 fingerprint module, fingerprint image of the finger is registered. Minutia extraction block is used to extract out the minutia from the image.

With the help of minutia, a cylindrical code for minutia is formed. Minutia cylindrical code represents minutia local structure of the minutia distribution. Once, minutia cylindrical code is generated for each finger print then a database is created which contain the minutia cylindrical codes of the entire fingerprint image. The last step of this method is matching or testing. Next section describes the functioning of last four block of this algorithm.

#### A. Sift Algorithm

After enhancing the fingerprint of the desired area, the next step is to extract the key points from the fingerprint image. The SIFT feature extraction process comprises of four stages- scale space extrema detection, keypoint localization, orientation assignment, keypoint descriptor

##### 1) Scale-Space Extrema Detection

It has been described by Lindeberg [8] that the scale space of an image is produced from the convolution of a variable-scale Gaussian with an input image. Therefore, this stage identifies keypoints that are invariant to scale and orientation in scale-space by using the difference-of-Gaussian (DoG) function [4, 5]. The DoG images are generated by subtracting two nearby scales which are separated by a constant multiplicative factor  $k$ . After each octave, the Gaussian image is downsampled and the process is repeated until the entire DoG pyramid is built up. After the DoG pyramid has been produced, the local extrema is detected by comparing a pixel to its 26 neighbours in a  $3 \times 3$  region at the current and adjacent scales. The scale space [2] is defined by the function

$$L(x, y, \sigma) = G(x, y, \sigma) \times I(x, y) \quad (1)$$

Where  $G()$  is variable scale Gaussian convolved with an image  $I()$ . Difference-of-Gaussian is defined as

$$D(x, y, \sigma) = L(x, y, k\sigma) - L(x, y, \sigma) \quad (2)$$

These extrema are selected as candidate key points which will be filtered in the next stage.

##### 2) Keypoint Localization

In this stage the final keypoints are selected and determined based on the stability of the candidate keypoints. In order to perform a detailed fit to the nearby data for location, scale and ratio of curvatures, the candidate keypoints with low contrast or that are poorly localized along an edge will be eliminated.

$$D(x) = D + \frac{\partial D}{\partial x} x + \frac{1}{2} x^T \frac{\partial^2 D}{\partial x^2} x \quad (3)$$

Where  $D$  and its derivatives are evaluated at the sample point and  $x = (x, y, \sigma)^T$  is the offset from this point and derivative of  $D$  are approximated by using differences of neighboring sample points.

##### 3) Orientation Assignment

Based on local image gradient directions, each keypoint location assigns one or more orientations. All future operations are performed on the transformed image data relative to the assigned orientation, scale, and location for each feature, thus the invariance to these transformations is provided. Each keypoint is assigned to one or more orientations. These orientations are based on the local image gradients around the keypoint. The gradient magnitude is given by

$$m(x, y) = \sqrt{(L(x+1, y) - L(x-1, y))^2 + (L(x, y+1) - L(x, y-1))^2} \quad (4)$$

From this point and derivative of  $D$  are approximated by using differences of neighboring sample points.

##### 4) Keypoint Descriptor

During the previous stages, a stable location, scale and orientation for each keypoint have been detected and determined. This stage measures the local image gradients at a selected scale in the region around each keypoint, and computes a descriptor for the local image region that is highly distinctive.

The previous operations have assigned an image location, scale, and orientation to each keypoint. These parameters impose a repeatable local 2D coordinate system in which to describe the local image region, and therefore provide invariance to these parameters. The next step is to compute a descriptor for the local image region that is highly distinctive yet is as invariant as possible to remaining variations, such as change in illumination or 3D viewpoint.

The SIFT features can be extracted by following the steps presented in subsection 4.2. It can be noted that the SIFT extraction for fingerprint images highly affects the verification results. In order to detect the local extrema reliably, the frequency of sampling in the scale and spatial domain needs to be determined properly. To achieve the precise translation and rotation, and precise prediction of each SIFT keypoint in the original image can be generated.

##### 5) SIFT Matcher

Each SIFT keypoint specifies 5 parameters: 2D location, scale, orientation and a keypoint descriptor which is a multidimensional vector. In previous work [3], the algorithm was based on Euclidean Distance. Point wise matching followed by trimming false matches is based on the Fast Nearest-Neighbor algorithm or known as dot product of their keypoint descriptors. Assuming that image  $I$  needs to be matched with image  $T$ , for each keypoint  $k_i$  in  $I$ , The point wise matching is used to find the closest distance  $d_1$  than a predefined threshold (0.7 for example),  $k_i$  is considered as a matched keypoint. The number of matched keypoints is considered as the output score. This is due to the fact that the closest neighbor should be significantly closer than the closest incorrect match to achieve reliable matching. Trimming false matches selects a value of majority orientation and length, and keeps the matching pairs that have the majority orientation and length using the Template.

### III. RESULTS AND DISCUSSION

In previous work [3], the algorithm was based on Euclidean Distance. Point wise matching followed by trimming false matches is based on the Fast Nearest-Neighbor algorithm or known as dot product of their keypoint descriptors. Assuming that image  $I$  needs to be matched with image  $T$ , for each keypoint  $k_i$  in  $I$ , The point wise matching is used to find the closest distance  $d_1$  than a predefined threshold (0.7 for example),  $k_i$  is considered as a matched keypoint. The number of matched keypoints is considered as the output score. This is due to the fact that the closest neighbor should be significantly closer than the closest incorrect match to achieve reliable matching. Trimming false matches selects a value of majority orientation and length, and keeps the matching pairs that have the majority orientation and length.

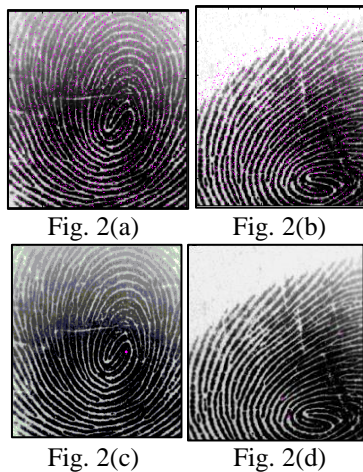


Fig. 2: The positions of SIFT key points for two impressions from the same finger

Based on the work in Ref. [3,5], the SIFT matcher is modified and expanded into two steps as follows. In the first step, An example is shown in Fig.2 to explain the reason that fixed ratio is not suitable. Fig.2 (a) and Fig.2 (b) show the positions of SIFT key points for two impressions from the same finger. One of the key points in Fig.2 (a) is also shown in Fig.2(c). After matching all the key point descriptors in Fig.4.5 (b), d1 and d2 are calculated. Fig.2 (d) shows the closest neighbor which is the below one and the second closest neighbor which is the upper one. The closest neighbor is the genuine keypoint but d1/d2 for the key point shown in Fig.2(c) is as low as 0.4.

#### IV. CONCLUSION

Since from its inception, finger- print matching area has been in the search of some robust technique for matching the fingerprint accurately. We have achieved till now precised processed Image in order to get accurate matched fingerprint recognition system. And the featured points of the fingerprint image are extracted in efficient way. The requirement of rotation, scale invariants are the need of the hour. Image based, minutia based and ridge based fingerprint authentication system has been designed earlier. Each and every method has its own advantages and drawbacks. Recently, Minutia cylindrical code (MCC) has emerged as an efficient way of fingerprint way of fingerprint matching. Lots of research is on the way to use MCC in its full capability. In this project a MCC based fingerprint matching algorithm is implemented and presented. The performance of the proposed system is satisfactory as very clear. Even after rotating and scaling the fingerprint, proposed system is able to achieve very good accuracy not only for the good quality fingerprint image but also for poor quality fingerprint image.

#### REFERENCES

- [1] Ru Zhou, SangWoo Sin, Dongju Li, Tsuyoshi Isshiki and Hiroaki Kunieda, "Adaptive SIFT Based Algorithm for Specific Fingerprint Verification", pp.978-1-4577-0490-1/11. 2011 IEEE
- [2] Jakub Sobek, Damian Cetnarowicz, Adam Dąbrowski, "Fingerprint Classification using Scale-Invariant Feature Transform", 2012 IEEE
- [3] Unsang Park, Sharath Pankanti and A.K.jain, "Fingerprint Verification Using SIFT Features",

Proceeding of SPIE Defense and Security Symposium 2008, pp. 0277-786X, SPIE, Orlando, Florida.

- [4] David G.Lowe, "Object recognition from local scale-invariant features", International Conference on Computer Vision, Corfu, Greece, pp. 1150- 1157, 1999
- [5] D.G.Lowe, "Distinctive Image Features from Scale-Invariant Keypoints", International Journal of Computer Vision, 60(2), pp. 91-110, 2004
- [6] User Manual of "R30X Series Fingerprint Identification Module"
- [7] Datasheet of CP2102/9 SINGLE-CHIP USB TO UART BRIDGE, <http://www.silabs.com> Silicon Laboratories Inc., 400 West Cesar Chavez , Austin, TX 78701, USA
- [8] Davide Maltoni, Dario Maio, Anil K. Jain, Salil Prabhakar, "Handbook of Fingerprint recognition", New York: Springer, ISBN.0387954317, Mar.2005.
- [9] Ali Ismail Awad, Kensuke Baba, "Evaluation of a Fingerprint Identification Algorithm with SIFT Features", IIAI International Conference on Advanced Applied Informatics, pp. 978-0-7695-4826-5/12, DOI 10.1109/IIAI-AAI.2012.34, 2012 IEEE
- [10] Jialiang Peng, Ning Wang, Ahmed A. Abd El-Latif, Qiong Li, Xiamu Niu, "Finger-vein Verification using Gabor Filter and SIFT Feature Matching", Eighth International Conference on Intelligent Information Hiding and Multimedia Signal Processing, pp. 978-0-7695-4712-1/12, DOI 10.1109/IIH-MSP.2012.17, 2012 IEEE