Comparing Local Invariant Algorithms for Dorsal Hand Vein Recognition System

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ABSTRACT

In the field of biometrics, vascular or vein pattern matching is a technology that analyses the patterns of blood vessels that can be visible on the surface of the hand through near infrared illumination. This paper presents a comparative analysis of Oriented FAST and Rotated BRIEF (ORB) and Scale Invariant Feature Transform (SIFT) as feature descriptor algorithm for dorsal hand vein recognition. The hardware implementation is a portable and inexpensive image scanning device using Raspberry Pi, 850nm near infrared lights, IR sensitive CCD camera; and OpenCV Libraries as programming platform. Both algorithms are local invariant making it more suitable for dorsal vein patterns because they are resistant to noise and rotation. Images are pre-processed using CLAHE, low pass filter, and morphological operators. Two algorithms are used independently to extract feature points, and finally, Brute Force Matcher and FLANN are used as image classifiers that implements distance calculation between feature points in the image. Independent testing is performed to assess the performance of the two algorithms. Experimental results shows that ORB delivers better performance than SIFT with overall Accuracy rate of 97.22%, Recall of 94.15%, lowest FAR of 0.0662, and FRR of 0.0541. It also generates the lowest recognition time of 2.33seconds when ORB is used with Brute Force Matcher classifier.

CCS CONCEPTS

- **Computing methodologies → Feature selection**

KEYWORDS

Oriented FAST and Rotated BRIEF (ORB); Scale Invariant Feature Transform (SIFT); FLANN (Fast Library for Approximate Nearest Neighbour); Brute Force Matcher; Vascular vein pattern

1. INTRODUCTION

Vascular or vein pattern matching is a technology that analyses the patterns of blood vessels that can be visible on the surface of the skin through near-infrared illumination [10]. In the field of biometric technology, using vein patterns of the hand either in dorsal or palm, in particular, gained interest in recent years due to its vast physiological information that are relatively constant, distinct lifelong, stable, cannot be forged, tampered nor copied, less intrusive and more hygienic [6]. Finger scan is most widely used today, however with hygienic issues; it is less user-friendly because the finger has to be positioned more precisely on the scanner. The smaller surface area taken from finger scan means that there are fewer reference points, making it more difficult to recognize the pattern correctly [1]. Palm or dorsal vein covers a larger area and more reference points for pattern recognition; thus it can provide greater level of security and convenience. However, the selection for ROI (regions of interest) in terms of using it for biometric application; the physiological structure of the hand entails careful technical consideration [17]. The palm vein, in particular, provides rich information because it can capture both vein patterns as well as palm prints that are both unique to every individual [12]. Conversely, the palm is more covered with thicker skin tissues and could have remarkable wrinkles depending on the nature of the subject. This is in contrast to dorsal hand which does not have remarkable wrinkles, but the elasticity of skin tissues could affect the appearance of vein patterns [8]. The dorsal part also contains melanin in the epidermis layer such that NIR (near infrared light) is needed because it propagates more deeply into the skin tissues thus provides better vessel image quality.

Most of the works in vascular vein recognition used algorithms that analyze entire image only to locate similarity features from different images. A multi-level wavelet analysis was performed by [14] to extract texture feature of hand vein while [15] combined multiple classifiers from a single feature recognition. In [15] minutiae features of dorsal vein was used by locating bifurcation and ending points in the vein pattern. Though these approaches were found effective, the results were sensitive to hand orientation and affected recognition results. In this case, an algorithm invariant to scale and orientation, that were known to be more robust in object detection [9], [5] and generic pattern recognition can be applied for vein recognition. Selection of image classifier is also crucial to implement this work. In [11] Hamming distance was applied while [6], on the other hand, used natural image statistics like Chi-square, Cityblock, Euclidean and Minkowski Random forest classifier was also a good method found by [4] using WEKA when images of dorsal vein were extracted using curvelets.

This paper aims to compare the performance of two local invariant algorithms: ORB and SIFT as descriptor generators for dorsal vein patterns in a portable and inexpensive recognition device using

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Raspberry pi and OpenCV libraries. The performance of the two algorithms is evaluated and compared based on standard biometric performance parameters like Accuracy, Recall, FAR, FRR, and recognition time.

2. METHODOLOGY

2.1 Proposed Method

The architecture for the project is shown in Figure 1, where dorsal vein pattern is acquired from an image scanning device and undergoes pre-processing prior to extracting key feature point descriptors which are matched by an image classifier algorithm to generate verification results.

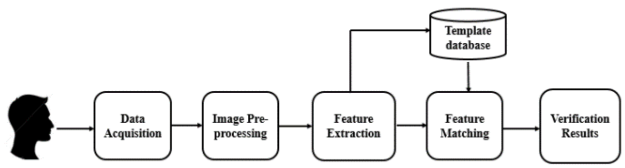


Figure 1. Architecture dorsal hand vein recognition.

The project flow of the system is depicted in Figure 2. At the enrolment phase, each subject makes registration to the system and is given a UserID for profiling. Dorsal vein is captured using the image scanning module with infrared LEDs of 850nm, IR sensitive “no-filter” camera module, Raspberry pi microcontroller, visible light filter, and diffuse paper. The lighting LEDs are connected to Raspberry Pi and SQLite is use for the template database.

The user can register both left and right hand and will be prompted through an LCD for correct hand orientation. Once the hand is detected, the region of interest (ROI) is automatically identified. The images captured are stored in the database template and notification is displayed in the LCD. The dataset is consist of 200 images taken from left & right dorsal hands of 100 persons. Pre-processing steps are applied to raw image to enhance image quality while ORB and SIFT are used independently to extract key point descriptors of the image and store it in the Reference database.

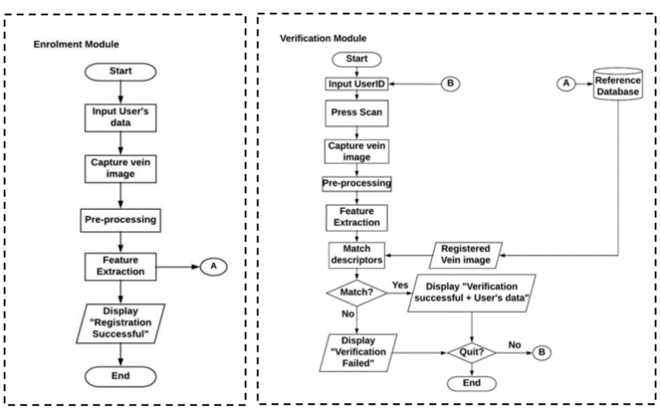


Figure 2. Project system flow.

For verification stage; UserID is inputted first prior to scanning the test vein image. It undergoes pre-processing steps and feature extraction prior to feature matching. Matching score is check between key point descriptor then, generates verification results displayed in the LCD.

2.2 Image Pre-processing

Pre-processing facilitates the removal of noise and perform image enhancement steps to reduce complex task in feature extraction. ROI (Region of Interest) is automatically detected by drawing a rectangular area at a fixed position around the dorsal hand. The original image taken from 640x480 camera resolution is converted to grayscale and resized to a maximum of 256x256 pixels to reduced computational task and create a standard image size. After resizing the image, contrast is adjusted to avoid loss of information due to over-brightness. CLAHE method is used as described in [18] where contrast limiting function is applied to each 8x8 blocks until it reach required threshold value by using bilinear interpolation. Afterward, a low pass filter is successively applied to sharpen edges and smoothen the image [10]. Two morphological operations are performed at the last stage: dilation which enlarges bright regions and shrinking dark regions at pixel points set at (i, j) and erosion that performs opposite function at all neighboring pixel values.

2.3 Feature Extraction & Matching

Feature extraction algorithms like ORB and SIFT generates key point descriptors in the image for object detection and pattern recognition. Both algorithms implement feature descriptors that are invariant to scale, rotation or image translation [16]. The latter, however, is less preferred because of its patent features and high computational requirements.

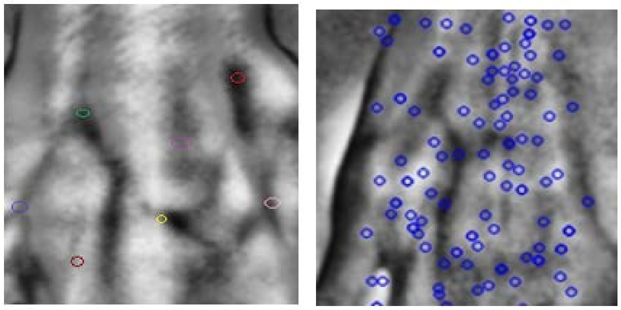
2.3.1 Oriented FAST and Rotated BRIEF (ORB)

ORB (Oriented FAST and rotated BRIEF) as feature detector was presented by [13] and [2] implements feature point detection using FAST (Features from Accelerated Segment Test) and descriptor generator using BRIEF (Binary Robust Independent Elementary Features).

First, we locate corner points using FAST which are set of ‘n’ adjoining pixels around a centroid of 16 pixels. To localize feature point, its intensity pixel point is compared to the sum of the surrounding pixels from its four corner boundaries of center point. The best key point is selected using Harris method and orientation is assigned along intensity centroid. Next, binary descriptor is extracted using BRIEF where processed feature point is set around area with to nearby coordinate p(x) and p(y) are assigned [3]. Random of 256 9x9 pairs are compared. If p(x) is smaller than p(y) then, the binary descriptor is 1, else it is 0. The process is repeated 256 times until a 256-bit string descriptor is generated.

2.3.2 Scale Invariant Feature Transform (SIFT)

Scale Invariant Feature Transform (SIFT) is one of the popular choice algorithms for detecting and describing local features of an image in a computer vision technology [20]. In the pre-processed image, the SIFT algorithm starts when key points are detected in the images by searching the scale-space extrema in Difference-of-Gaussian (DoG). The local extrema corresponds to keypoint in the blurred image and refined using the Taylor Series expansion. Once potential key point locations are found, the Taylor series is applied to expand scale space to make the location of extrema more accurate. By Harris corner detector, edges are removed and 2x2 Hessian matrix computes the principal curvature so that only the strongest key points remain. Once key points are found, an orientation is assigned by finding a neighbor around a key point location and compute the magnitude and direction of the region. An orientation histogram is produced with 16x16 key point descriptor of the same location and scale of different directions which constitutes the vector of 128 bin key point descriptor. Figure 3 illustrates feature points generated by the two algorithms wherein ORB performed dimensionality reduction by focusing only on strongest key point rather than entire image features.



(a)ORB feature points (b) SIFT feature points

Figure 3. Generated Feature Points

2.3.3 Feature Matching

A classifier's role is to find matches between reference image and a query image needed to come up with a decision result. In this paper, FLANN (Fast Library for Approximate Nearest Neighbour) and Brute-Force Matcher is used for SIFT and ORB respectively. Both classifiers implement a nearest neighbor search among key points independently generated by ORB and SIFT. Figure 4, depicts a sample of classifier matching results between test and reference image. In FLANN, search is obtained by setting the kd-tree parameters to organize keypoints in a space with k dimensions and number of times the trees in the index should be recursively traversed [7]. To determine the two nearest neighbors of a query feature from the reference image, we define: d1 as the distance to the nearest neighbor and d2 be the distance to the next one. To generate a "match", d1/d2 ratio should be smaller than a given threshold of 0.77. In cases when the second closest-match may be very near to the first the ratio, the Lowe's ratio test is used [5]; if the ratio is greater than 0.8, they are rejected.

Brute-Force Matcher, on the other hand, uses Hamming distance measurement using a WTA_K parameter to decide the number of points to produce each element on the oriented BRIEF descriptor. Matcher returns only best match as the closest distance between the i-th descriptor in set A (test image) and j-th descriptor in set B (reference image).

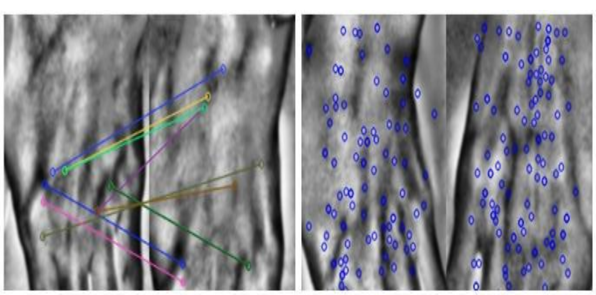


Figure 4. Vein matching results (left: ORB, right: SIFT)

3. RESULTS AND DISCUSSION

Consequently, this section presents the experimental result and performance analysis obtained from the proposed implementation.

3.1 Experimental Results

ORB and SIFT generates different degree of similarity between test and referenced image. Two types of users are considered: Genuine refers to an authorized user and was successfully verified by the system, and Impostor or a registered user who access the system using different UserID. A match is tagged when match score is equal or greater than the threshold value.

For experimentation, 1:1 matching is performed for five iterative tests of 100 randomly selected samples. To illustrate match score from query vs. reference image, test case of 10 select UserID is shown in Table 1 and Table 2. The value of match scores generated by ORB and SIFT constitutes the strongest similarity point and is used to set the threshold value. Consequently, the matching algorithms tagged matched results when similarity score is equal or greater than 4 for ORB and equal or greater than 10 for SIFT.

Iterative test case is summarized in a normalized Confusion matrix in Table 3, showing 100 sample attempts for genuine and impostor users.

Table 1. Match Results for ORB

		Actual									
	UserID	**10**	**79**	**20**	**35**	**19**	**21**	**42**	**56**	**85**	**98**
Predicted	**10**	4	0	0	0	0	0	0	0	0	0
	79	0	5	0	0	2	0	0	0	0	0
	20	1	0	4	0	0	0	0	0	0	1
	35	0	0	1	6	1	0	0	2	0	0
	19	0	2	0	3	5	0	0	0	0	1
	21	0	0	0	0	0	3	1	0	0	0
	42	1	0	0	0	2	0	5	0	0	0
	56	0	0	0	1	0	0	0	4	0	0
	85	0	0	0	0	0	0	0	0	6	0
	98	0	0	0	0	0	0	0	0	0	7

Table 2. Match Results for SIFT

		Actual									
	UserID	**01**	**02**	**22**	**60**	**78**	**41**	**54**	**80**	**90**	**11**
Predicted	**01**	11	2	6	7	4	9	5	5	4	3
	02	4	10	8	5	2	3	5	7	6	5
	22	1	3	14	5	7	8	6	5	5	4
	60	4	2	3	8	1	4	8	2	5	8
	78	5	2	3	3	5	6	8	5	4	3
	41	3	3	5	6	8	15	1	7	8	4
	54	2	4	4	5	2	5	11	4	6	5
	80	8	6	7	1	5	5	8	10	5	9
	90	5	5	4	6	2	4	6	5	12	4
	11	5	5	4	3	4	4	4	8	5	10

Table 3. Sample Confusion Matrix

		Actual	
	N = 100	**Genuine**	**Impostor**
Predicted	**Genuine**	97	3
	Impostor	2	98

3.2 Performance Analysis

In this study, performance of the proposed system is done by evaluating and comparing the performance of ORB and SIFT in terms of Accuracy, Recall, FAR, FRR, and recognition time. FAR is the rate of false acceptance of an impostor access while FRR is the rate of false rejection among a genuine access. We described the following parameters as:

$$FAR = \frac{\#(T \geq \tau \mid T \in \text{Genuine})}{\text{Total number of genuine samples}} \quad (1)$$

$$FRR = \frac{\#(T < \tau \mid T \in \text{Impostor})}{\text{Total number of impostor samples}} \quad (2)$$

Here, T is the match score generated by the algorithm and τ refers to the threshold value. The recognition time refers to the elapsed time for genuine or impostor access as determined by the matching classifier. Accuracy and Recall are another important biometrics indicator of performance which can be described as:

$$Accuracy = \frac{TP+TN}{TP+FP+TN+FN} \times 100\% \quad (3)$$

$$Recall = \frac{TP}{TP+FN} \times 100\% \quad (4)$$

From five iterative test conducted using 100 samples each, the performance of ORB and SIFT can be summarized in Table 4.

Table 4. Performance Results for ORB and SIFT

	Accuracy	Recall	FAR	FRR
ORB	97.22%	94.15%	0.0662	0.0541
SIFT	92.80%	87.35%	0.1657	0.1264

Compared to SIFT; ORB obtained higher Accuracy in recognizing genuine and impostor access; also a good Recall rate showed how well it correctly matches a genuine user to the corresponding template in the database. The EER results coming from the ratio of FAR and FRR is lower in ORB indicating better performance.

The two classifier can be described further by its FAR-FRR diagram as depicted in Figure 5 and Figure 6. This is crucial for determining threshold that can be a factor in accuracy and recall trade-off needed to define operating characteristics of the proposed system. The graph clearly shows that when threshold is set at 4 for ORB and 10 for SIFT, the system can exhibit good performance in verifying user access.

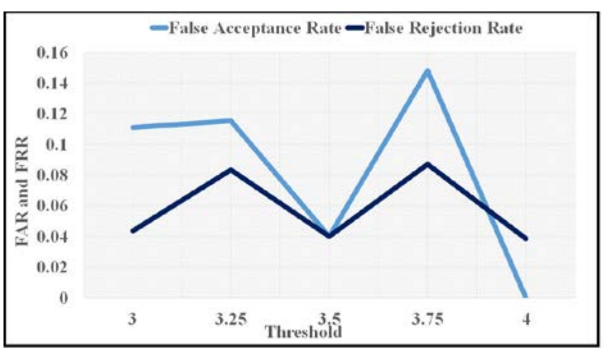


Figure 5. FAR-FRR Diagram for ORB

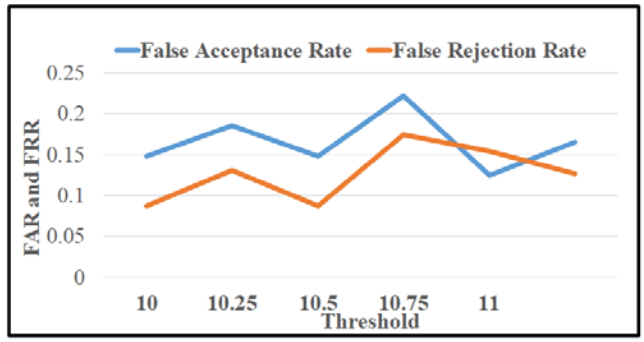


Figure 6. FAR-FRR Diagram for SIFT

In terms of verification speed, the performance of both feature extraction algorithm and matching classifier can be assessed using recognition time. The proposed model utilized ORB-BFMatcher and SIFT-FLANN combination, but it is also noteworthy to determine trade-off between these classifiers. The test is conducted using three trials for 30 randomly selected samples to which recognition time is recorded for each test.

Table 5. Summary Recognition Time

	Average (secs)
ORB-BF Matcher	2.33
SIFT-FLANN	3.20
ORB-FLANN	5.03
SIFT-BF Matcher	4.32

Results in Table 5 shows ORB-BF Matcher as the most robust implementation and its performance is lowered by more than 100% when combined with different classifier like FLANN. In contrast to SIFT; a reduction of about 35% in its recognition speed is notable when FLANN is used as classifier. The rotational invariances of both ORB and SIFT makes it ideal for vein recognition because they are more resistant to noise and orientation, therefore the choice of suitable classifier is needed [14] and [17].

4. CONCLUSIONS AND FUTURE WORKS

The study showed that between the two local invariant algorithm, using ORB for feature extraction proves to be a good choice over SIFT in terms of its overall Accuracy, Recall FAR and FRR results. Although both FLANN and Brute Force Matcher classifiers implement distance calculation, the number of feature points generated by ORB and SIFT differs and thus affects its performance relative to its recognition speed. Hence, Brute Force Matcher need not implement a ratio test for returning best match, making it more suitable use for ORB. In terms of hardware design, Raspberry Pi and OpenCV libraries were effectively utilized in developing a portable, less expensive and contactless hand vein recognition system.

Future researchers may focus on optimizing Raspberry Pi's multiprocessing capability so the system can be integrated for commercial applications.

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