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A comparative study of image feature detection and matching algorithms for touchless fingerprint systems.

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Abstract

Usually, in touchless 3D Fingerprint recognition system the effective area is increased by taking multiple images of the finger. This is done to mosaic or stitch these images together. The key problem here is the need to effectively extract feature points from these images individually and match them. There has never been a complete survey on the different methods of image feature detection specific for fingerprints. The goal of this paper is to have a comparative study visualizing the merits and demerits of the methods. We evaluate the performance of existing image feature detection techniques, such as, Difference-of-Gaussian, Hessian, Hessian Laplace, Harris Laplace, Multiscale Hessian, Multiscale Harris and OpenSURF, on a database that contains multiple images of a finger. The process involves (i) feature detection, (ii) feature matching and validation, and (iii) image stitching. Also we evaluate the performance by visually examining the mosaicked images as well as the number of matches. Computer simulation are presented and the goal is to make a comparison of the existing feature detection algorithms.

1 Introduction

Tremendous growth has been made in the field of Fingerprint recognition [1]. It is being widely used for person identification in a number of commercial, civil, and forensic application [2-6]. It is a known fact that as compared to other biometric features, fingerprint-based technique is the most scientifically proven technique for person authentication [7]. Fingerprint matching techniques can be coarsely classified in three groups: minutiae-based, correlation-based and ridge feature-based matching techniques [8]. But they are generally classified into two, minutiae based and texture based. Fingerprints are represented based on local landmarks called minutiae. A good quality fingerprint contains about 25 to 80 minutiae and can be used to compare one print to another [9]. Minutiae include Ridge endings, Ridge bifurcation, island, etc.,[10]. Although minutiae based verification system has shown fairly high accuracies, further improvements in their performance is required, especially in applications that involve a large scale database [11].

Registering fingerprint images is not an easy task as it faces several problems, such as, non-linear plastic distortions which are due to non-uniform pressure applied by the subject onto the scanner, accumulation of dirt, improper finger placement and sensor noise. Therefore, to provide a more accurate, faster and hygienic method, the contactless fingerprint identification system was developed [2].

Few sensors, such as the ultrasound sensor, work without touch. But due to its production cost and large size, it was unsuitable for the market. Also, an on-line authentication system needed quick capture time, which wasn't the case in an ultrasound sensor. So, for the advancement of fingerprint recognition, a few contactless/touchless identification system were fabricated [1-3, 7, 8, 12-19]. The systems used were less expensive as it only requires few cameras. Earlier implementations used single-camera mode touchless imaging devices. Song et al. [8] designed a touchless system using a monochrome CCD camera and double ring-type illuminators with blue LEDs. Touchless fingerprint sensor products from companies (e.g., Mitsubishi [20], TST Biometrics [21], and Lumidigm [22]) are on sale. Chen [19] devised a system that generated a 3D model of a finger using structured light from a projector, and a camera. Kumar and Zhou [2] used a web camera to capture low resolution images of the finger. The above mentioned devices faced a common problem of view difference due to curvature of the finger shape. Also, in fingerprint recognition systems, the performance is degraded by the restricted overlapping area between fingerprints caused by view difference. To deal with the above mentioned problem and increase the effective area of the finger image, multiview touchless sensing techniques have been proposed [3, 7, 12, 18, 23]. The process involves (i) feature detection (ii) feature matching and validation and (iii) Image stitching. Also we evaluate the performance by visually examining the mosaicked images as well as the number of matches.

Touchless fingerprint sensor products also provide us with multiple images of the finger [3, 7, 14]. After obtaining multiple views of the same finger, they need to be stitched together in some fashion. . To assess the quality of a stitched image, methods provided in[24-28] There exist two approaches. (i) Combine at an image level [29, 30], (ii) combine at a feature level [31]. Since a portion of these images will have the same texture, Scale-invariant

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feature transform (SIFT) can be used for feature extraction to obtain correspondences between these images. Noisy SIFT features should be removed. Matching is done by comparing these feature points. A number of false matching points are generated and they need to be removed using geometric constraints [32].

The rest of the paper is organized as follows. In Section 2 and 3, we talk about the different feature detectors and descriptors. In Section 4, we take a glance at the computer simulations and the results obtained. Section 5 concludes the paper and suggests the future directions.

2 Feature Detectors

Feature extraction from images captured by camera sensors are mainly dealt under Computer Vision and has quite a few applications including classification of objects, matching images, image retrieval etc. The features to be extracted can be broadly classified into two categories, namely, local and global features. Global features are good, in the context of image retrieval, Object recognition etc. [33, 34], to describe the information of the image but they end up mixing the information of foreground and background and hence cannot distinguish between the two [4]. Further, they consider the image as a whole, irrespective of the isolated pixels. These features are well suited for most of the shape and texture description, but they are affected by partial occlusion and clutter [35]. Thus they are not suitable for localization of objects spatially. Since for fingerprint applications we need to detect features only on the fingerprint and not on the background, it is better to use local features than global. Local features are invariant i.e. they differ from immediate neighbors and allow matching local structures between the images efficiently [4]. Local features may be points, edges, lines, segments or objects that have specific structures in the image [36, 37]. These features are also referred to as corner points, key points or feature points [38, 39].

There are a number of feature detectors and descriptors that are proposed in the literature (e.g. [20, 23, 40, 41]). In this paper we have focused on 7 feature detectors which include Difference-of-Gaussian [40], Hessian, Hessian Laplace [4], Harris Laplace [4, 22], Multiscale Hessian, Multiscale Harris and Open SURF [42, 43]. As a common descriptor we have used the SIFT descriptor [21] with all the above mentioned detectors. The method followed in order to perform feature detection, matching and image stitching is as follows: 1) Detect the features using one of the detectors, 2) Describe each of the detected keypoints using a SIFT descriptor, 3) Match these descriptors using nearest neighbor method, 4) Perform geometric verification to validate the matches, 5) Based on the matches select parameters for stitching. Each of the 7 feature detectors considered are explained in the following section. A brief introduction and steps along with the advantages and disadvantages are given below.

The Difference-of-Gaussian (DoG) Detector [41]

Using the local extrema of the Laplacian-of-Gaussian (LoG) as the point of interest was first suggested by Lindeberg in [41]. Based on this concept, Lowe proposed the Difference-of-Gaussian detector [40]. It is a translation, rotation and scale invariant feature detector. The overall procedure for detection includes detecting the extrema in the scale space i.e. over multiple scales and locations and selecting keypoints based on a measure of stability. Steps involved: 1) Produce the scale space of an image by convolving the different scales of Gaussian kernel to the image, 2) Separate the generated scale space into a number of octaves, 3) Each of the generated octave is again convolved with the Gaussian to create a set of scale space image for that particular octave, 4) Adjacent sub-octave scale space are subtracted to produce the DoG, 5) To proceed to next octave, the Gaussian image is down-sampled by 2. 6) Detect the maxima and minima of DoG in scale space by comparing each point with 8 neighbors in the current image and 9 neighbors each in the scales above and below. Advantages: 1) Better compared to Harris operator as it is scale, rotation and translation invariant [44]. 2) This produces a lot of features for even small objects. Robust to occlusion and clutter [44]. Disadvantages: 1) Slow when compared to SURF [45]. 2) Computationally expensive [46].

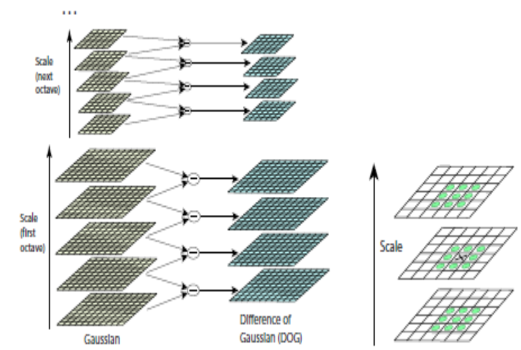

Figure 1: *a) subtract the adjacent sub-octave Gaussian to get DoG. b) Compare each point with the 26 neighbors to find the extrema.*

Hessian Detector [4, 22]

The Hessian matrix is composed of second order partial derivatives [4, 22]. This matrix has been used to analyze local image structures. The algorithm is described below:

1) Find the determinant of the Hessian matrix as it is used to detect image structures which have strong signal variation in two directions. So, we use this property to detect the interest points.
2) We then build a scale-space representation by convolving the image with Gaussians of increasing size. The Gaussian kernels are chosen such that successive images differ by a particular scale ratio.
3) The Hessian matrix has to be made invariant to scale. Hence a factor σ2 is multiplied with the Hessian matrix, where σ represents the scale of the image [4].
4) Next a 3 x 3 search window is swept over the entire image. If the value of the pixel is larger than the values of all 8 immediate neighbors and also above a given threshold, then a feature point is associated with the present location. An example is shown in figure 2.

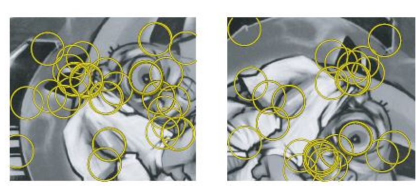

Figure 2: *Output of the Hessian detector applied to a given scale to example images with rotation[4].*

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Harris-Laplace Detector [47]

The Harris-Laplace Algorithm is described below:

1) The initial points are realized with the Harris detector [48]. The Harris function is used to create a scale-space representation and it is used to determine local maxima for all scales [4].
2) Check whether the LoG reach maximum at the scale. Non-corner points will have finer and coarser scales [49].
3) Remove those points for which the Laplacian did not reach the threshold. Thus we get characteristic points for each scale [48] [47].

There still may exist certain points which do not belong to the selected scale. These points reduce the accuracy and should be removed [50].

Advantages:

1) This approach brings forth a tightly packed and characteristic set of points from the image [47] [22].
2) This approach is simple.

Dis-advantage:

1) This approach has lower accuracy.

Hessian-Laplacian Detector [51]

It is very similar to Harris-Laplace. The difference being that they start from the determinant of the Hessian rather than the Harris corners. This is described as a viewpoint invariant blob-detector method. An example is shown in Figure 3.

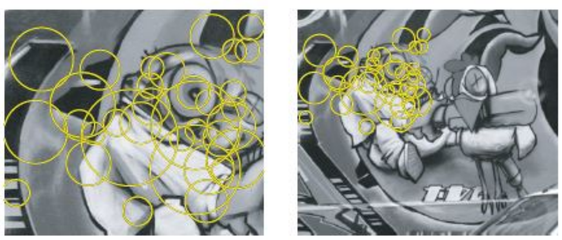

Figure 3:*Output of Hessian-Laplace detector applied to example images with scale change[4].*

The Hessian-Laplace Algorithm [4, 51] is described below:

1) The initial points are realized with the determinant of the Hessian. The Hessian function is used to create a scale-space representation and it is used to determine local maxima for all scales[51].
2) Check whether the corner points reach maximum at the scale. Non-corner points will have finer and coarser scales.
3) Remove those points which did not reach the threshold. Thus we get characteristic points for each scale.

Advantages:

1) It is more robust than the Harris-Laplace detector[51].
2) More features are detected when compared to Harris-Laplace detector[4].

Disadvantages:

1) It cannot be used for region detection[51].
2) Ii is not affine invariant[51].

Multiscale Hessian Detector [52]

Since the image dimensions can be different, it is necessary to introduce a measurement scale which changes within a certain range[53]. The algorithm is described below:

1) Calculate the Taylor expansion in the vicinity of the point under consideration. This expansion will approximate the structure of the image upto the second order[54].
2) Normalization is performed to compare the response of different operators at multiple scales.
3) The eigenvalues of the Hessian are used to determine the possibility of a blob feature being present.

Advantages:

1) A large increase in the detected feature points.
2) It can extract features from images which have different dimensions.

Disadvantages:

1) Computational time is large.
2) High redundancy.

Multiscale Harris Detector [52]

In, Multiscale Harris Detector, the Harris corner indicator is applied at successive integration scales [52]. This algorithm determines many points which repeat in the neighboring scales. In the Harris detector, an auto-correlation matrix is used. It helps in ascertaining feature detection. The Multiscale Harris algorithm is described below:

1) To make the detector, multi-scale, this matrix must be able to change scale to make it independent of the image dimension [48] [22].

This matrix now describes the gradient distribution of a point within its vicinity.

2) The Harris measure combines the trace and determinant of the auto-correlation matrix [49].
3) The local maxima of this measure determines position of the points [48].

Advantages:

1) It can be used to perform feature matching of images of different dimensions.

Dis-advantages:

1) It increases the probability of a mismatch[52].
2) It increases the complexity [47].

OpenSURF [46];

Open SURF is one of the efficient implementation of the Speeded Up Robust Features (SURF). SURF was first introduced in [46] and was developed to achieve a fast computation of the features retaining the repeatability, distinctiveness, and robustness properties. The increase in the performance of SURF compared to its predecessors is owed to the use of “Integral Image” [45].Steps involved:

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1) Use of integral images to get major speed boost. Integral image is nothing but an intermediate image representation which contains summed up pixel values in gray scale. The time required for the computation of a rectangular area is simplified to the addition of four points (S = A + D – (C + B) as shown in figure 4) and thus is invariant to change in the size of the rectangle.
2) Obtain the Fast-Hessian Detector. This is done by approximating the Laplacian-of-Gaussian with the weighted box filter (mean/average filter) in x, y, and xy – directions.(as shown in the figure 5)
3) Perform the scale – space analysis with constant image size and varying the size of the filter or the kernel (Figure 6)
4) Perform thresholding to accurately estimate the interest point location.
5) Perform non-maximal suppression to find the final candidate points. This step is similar to the one in the DoG detector, i.e. compare each pixel in the scale space to its 26 neighbors.

Advantages:
1) Computation time is much faster when compared to its predecessors [44].
2) Good at handling image rotation [45].
3) Repeatability property of the feature is good [45].

Disadvantages:
1) Change in viewpoint is poorly handled.
2) Poor performance for variation in illumination [44].

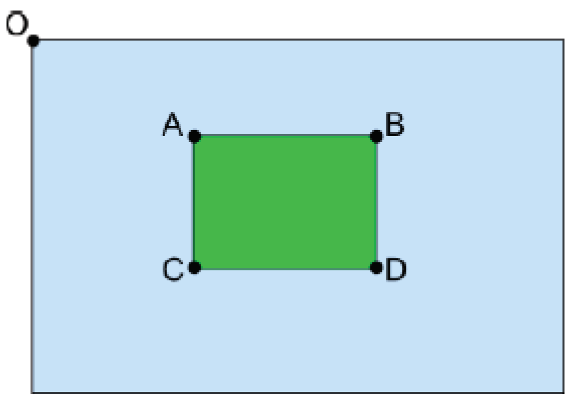

Figure 4: *Describes how the sum of intensities inside a rectangle can be simplified to three addition operations using integral images [42].*

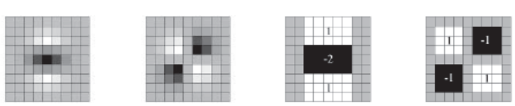

Figure 5: *Shows the Laplacian-of-Gaussian approximation used in SURF [46].*

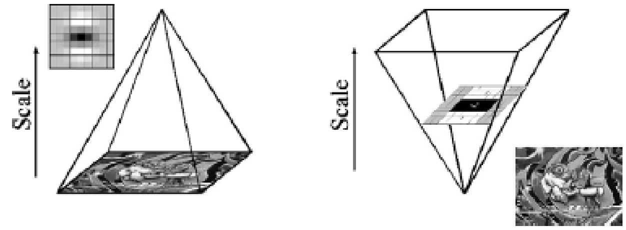

Figure 6: *Shows the traditional approach (left) where the image size is varied and convolved with the Gaussian filter to get the scale space. The SURF approach (right) where the filter size is varied and the image is left unchanged [45].*

3 Scale Invariant Feature Transform (SIFT) Descriptor

The SIFT descriptor which is widely used, was introduced by David G. Lowe. This descriptor combines the Difference of Gaussians (DoG) interest region detector and a corresponding feature descriptor [36, 40]. This descriptor provide unique features which makes it invariant to complications such as rotation, translation and object scaling[55] . Many studies have been conducted regarding the performance of the descriptor and SIFT generally provides good performance when compared with other local descriptors [47].

SIFT Descriptor encodes the image information in a localized set of gradient orientation histograms by providing minor shifts in the positions , thus achieving robustness to lighting variations [51]. Cascade filtering approach was introduced which reduced the cost of extracting features by allowing expensive operations to be executed only after passing the initial test [40].

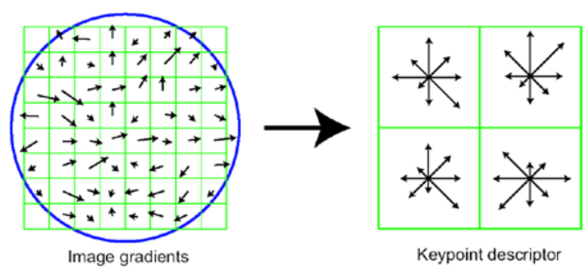

Figure 7: *The above images show the image gradient and the keypoint descriptors.*

The keypoint descriptors are produced using the data obtained from the DoG. The orientation of the data created has to be altered so that it matches with the orientation of the keypoint. After this, it is weighted by Gaussian with variance which is 1.5 times the scale of the keypoint. Using this data, a histogram which is centered on the keypoint is created.

The following process describes the Scale-Invariant Feature Transform:

1) The SIFT of a neighborhood of the image gradients give a 128 dimensional vector of histograms.

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2) This region with a proper scale and rotation is further split into a 4x4 square grid as shown in figure 7.
3) Every cell in this grid contains a histogram with eight orientation bins.

4 Computer Simulations

The above mentioned feature detecting methods were applied to our finger image as shown in figure 8.

(Left) (Center) (Right)

Figure 8: *Multiview images of a finger*

The features were detected for the red, green, blue, gray and modified gray channel images using MATLAB as shown in figure 9. The blue-channel images are used for matching and the final mosaicking. Visually analyzing the results, we observe that for Hessian detector, 64 matches were found after verification. For Hessian Laplace detector, only 1 match was found and hence the matching failed. For the Harris Laplace detector, only 2 matches were found after verification and hence the matching failed. For the Multiscale Harris detector, 39 matches were found after verification. For the Open SURF with SIFT descriptor, 10 matches were found after verification. For the Difference of Gaussian (DoG) detector, 24 matches were found after verification but alignment mismatch exists. And finally for Multiscale Hessian detector, 1600 matches were found. Even though DoG, Multiscale Harris, and Open SURF helped provide mosaicked images, the quality and alignment of the mosaicked image are poor as shown in figure 10. Hessian and Multiscale Hessian provide good mosaicked images.

The number of feature detected for the images are tabulated as shown in table 1, table 2 and table 3. Hessian-Laplace and Harris-Laplace for modified gray level have very few features because they are overlapping. They have the same or very close location and/or vary in scale and orientation. The multiscale Hessian can be used to detect features in images with different dimensions, i.e. the scale is adaptable. This property is very useful for fingerprint feature detection as the multiple finger images can have dimension mismatch. Also, blob feature detection used in Hessian extracts more features than the corner features that are extracted using Harris. But, due to the complexity of multiscale Hessian/Harris, the computation time is very high. On the other hand, the computation time of Open SURF is faster but the features detected are much lower.

As seen in figure 11, (a) represents the original images of the fingers from the database. The features extracted are shown in (b) and the mosaicked images are shown in (c). From visual and statistical results, Multiscale Hessian was chosen for feature detection and matching.

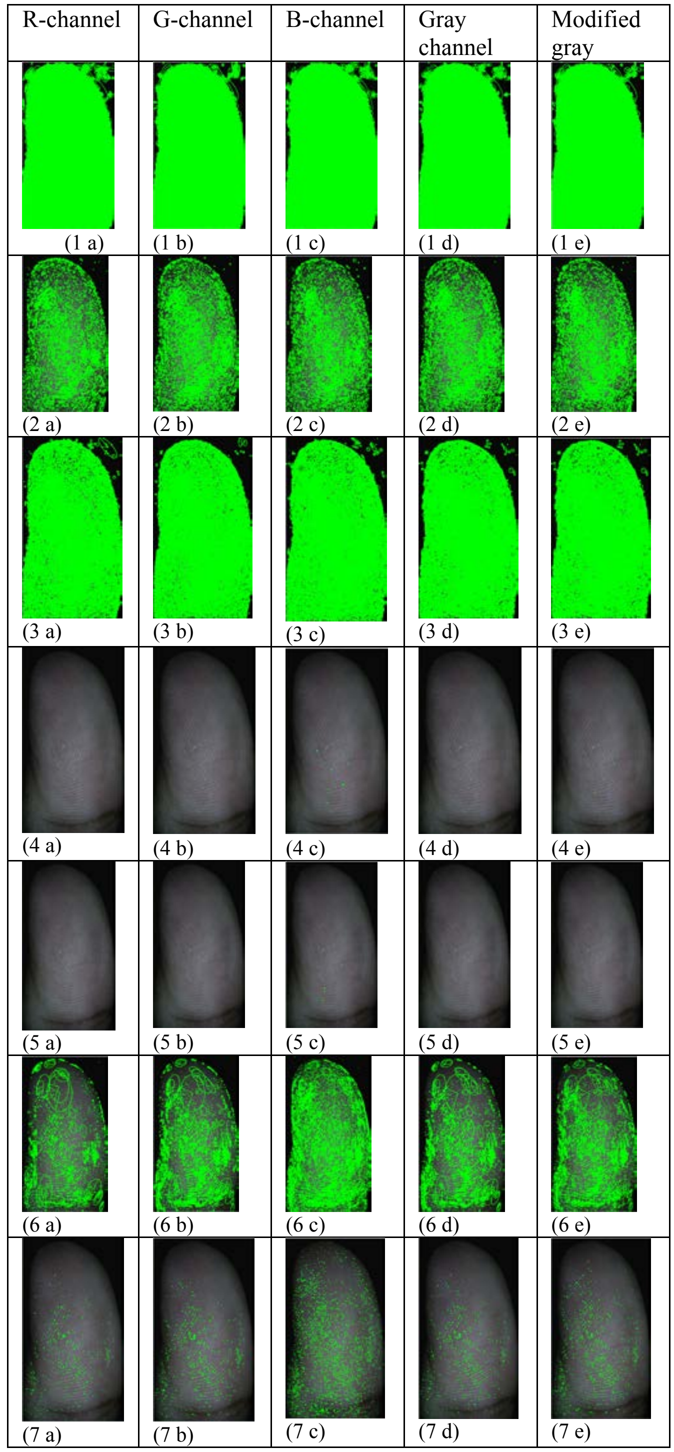

Figure 9: *Feature detection methods applied to figure 1(left). (1) Features detected using the Multiscale Hessian Detector. (2) Features detected using the DoG Detector. (3) Features detected using the Hessian Detector. (4) Features detected using the Hessian-Laplace Detector. (5) Features detected using the Harris-Laplace Detector. (6) Features detected using the Multiscale Harris Detector. (7) Features detected using the Open SURF.*

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Table 1: Number of feature found for the Center image shown in figure 1.

Feature Detector	R	G	B	Gray	Modified Gray
Difference of Gaussian	9393	9755	10064	9458	9838
Hessian	37007	37209	40999	36665	38144
Hessian Laplace	1	0	6	0	2
Harris Laplace	0	0	4	0	1
Multiscale Hessian	**208911**	**201832**	**211394**	**201204**	**204458**
Multiscale Harris	7216	10277	19379	9071	12557
Open SURF	702	1159	4039	980	1633

Table 2: Number of feature found for the Right image shown in figure 1.

Feature Detector	R	G	B	Gray	Modified Gray
Difference of Gaussian	9606	9929	10118	9655	9900
Hessian	37535	38295	41742	36990	38191
Hessian Laplace	1	1	10	2	2
Harris Laplace	1	1	4	1	2
Multiscale Hessian	**216432**	**209106**	**218217**	**208525**	**210336**
Multiscale Harris	5167	8058	18569	6683	10245
Open SURF	332	614	3111	514	992

Table 3: Number of feature found for the Left image shown in figure 1.

Feature Detector	R	G	B	Gray	Modified Gray
Difference of Gaussian	9493	9816	10181	9474	10037
Hessian	36852	37052	41401	36022	38067
Hessian Laplace	0	0	14	0	5
Harris Laplace	0	0	17	0	2
Multiscale Hessian	**213090**	**206960**	**216786**	**206261**	**208692**
Multiscale Harris	5423	7894	18321	6733	10242
Open SURF	702	1159	4039	980	1633

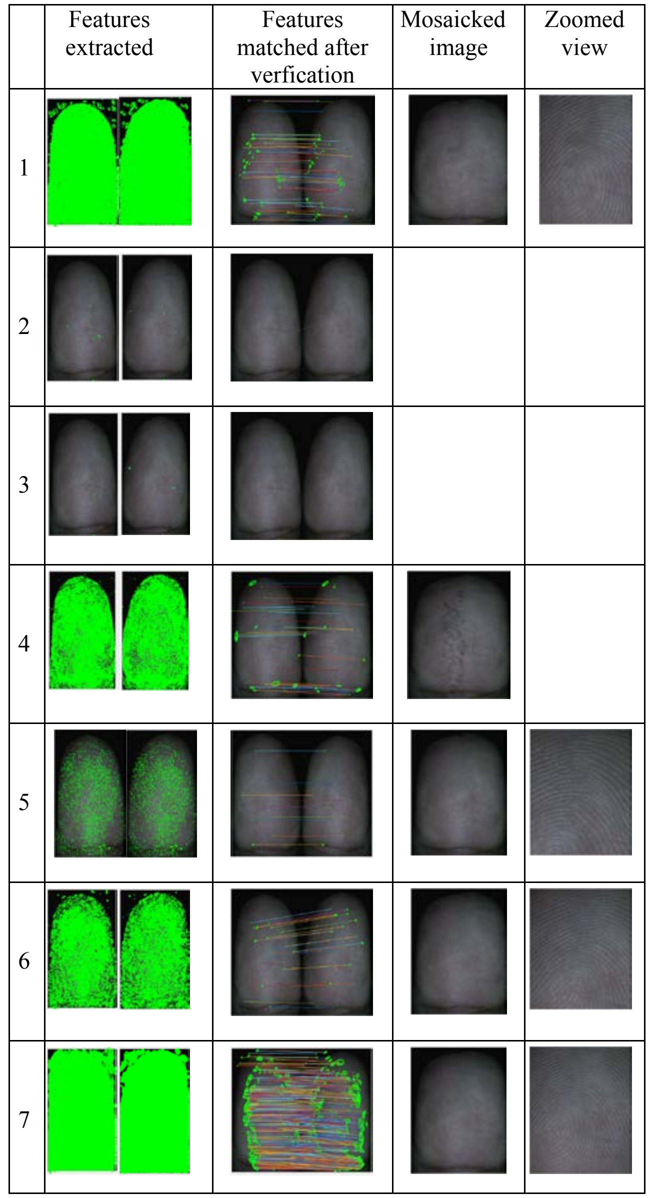

Figure 10: *Feature detection methods applied to figure 1(right and center) using the following detectors: (1) Features detected using the Hessian Detector. (2) Features detected using the Hessian-Laplace Detector. (3) Features detected using the Harris-Laplace Detector. (4) Features detected using the Multiscale Harris Detector. (5) Features detected using the OpenSURF Detector. (6) Features detected using the DoG Detector. (7) Features detected using the Multiscale Hessian.*

5 Conclusion

This paper attempts to provide a visual and statistical comparative study of the existing feature detectors, namely, Difference-of-Gaussian, Hessian, Hessian Laplace, Harris Laplace, Multiscale Hessian, Multiscale Harris and Open SURF. Detection of feature points in fingerprint images will help solve the dilemma of increasing the effective area of the fingerprint. We performed feature detection using different detectors and then matched the

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extracted features to obtain the final mosaicked image. The merits and demerits of the various detectors were realized. After performing computer simulations in MATLAB, we have found out that the **Multiscale Hessian detector** extracts the best features for the multiple finger images and provides us with the finest mosaicked image.

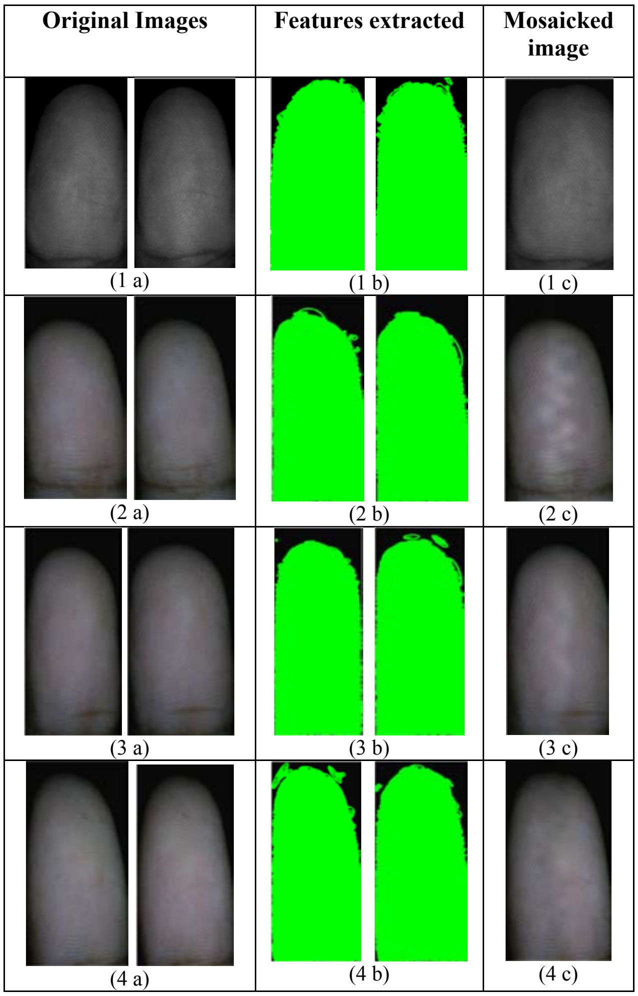

Figure 11: *(1), (2), (3), (4) are Multiview images of different fingers on which Multiscale Hessian detection is performed.*

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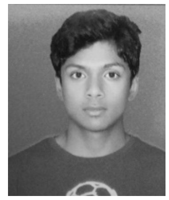

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