Routing Protocols of Mobile Ad-hoc Network MANET

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Abstract

Today persons sitting at either end of the world can speak with each other with the aid of wireless technology. Mobile ad hoc Network (MANET) is a type of wireless ad hoc network which is a collection of mobile devices that creates a random topology for communication. The advantage of MANET is that it does not require any central controller or base station. MANET is only a network in which devices work as a host as well as a router. Routing in ad hoc networks has become a popular research topic. There are several routing protocols developed for ad hoc networks. In MANET, it is a very difficult task to predict the performance of routing protocol under varying network conditions and scenarios. This review paper is discussing the three approaches of routing protocols such as Reactive (On demand), Proactive (table driven) and Hybrid routing protocols with their advantages and disadvantages.

Keywords: MANET; AD HOC; Reactive; Proactive; Hybrid;

1. Introduction

Key points are the points of the image that are in scale space of the extremum image. The image scale space contains a set of images. The images of this set are produced using the original image convolution with Gaussian filters and different scales. Simultaneous robust watermarking methods are categorized into three classes including moment-based, histogram-based, and feature-based.
Some of the most important algorithms of feature points are described below.

2. Feature extraction algorithms

2.1 Harris detector

In this section, the Harris-Laplace detector, constructed from an autoregressive scale matrix adapted from Laplace-Gauss scale and practice, is used [1].
Initially, the space for the input image scale I is calculated through the L function in a set of scale in order to display different levels of resolution, the equation of which is as follows:

$$(L(x,\sigma\neg D) = G(x,\sigma D)*I(x \qquad (1)$$

In which, **x** = (x,y) represents the spatial constituents of the image, σ_D is the differential scale, "*" shows the convolutional action, and the uniform Gaussian kernel G is defined as:

$$G(\mathbf{x},\sigma_D)\frac{1}{2\pi\sigma_D^2}e^{-(x^2+y^2)/2\sigma_D} \qquad (2)$$

Then, the autoregressive scale matrix $\mu(x,\sigma_1,\sigma_D)$ is used in scale space to describe the local image structure and its equation is as follows:

$$m(x,s_D,s_D) = s_D^2 G(x,s_1) * \begin{cases} L_x^2\,(x,s_D) & L_x L_y\,(x,s_D) \\ L_x\,L_y\,(x,s_D) & L_y^2(x,s_D) \end{cases} \qquad (3)$$

In which, σ_1 is the integral scale and L_i is the first derivative calculated in path i in which the answer to the cornerstone of the principle of the curvature of this matrix through its trace and its determinants is as follows:

$$C(x,\sigma_1,\sigma_D) = \det(\mu(x,\sigma_1,\sigma_D)) - 0.04\ \mathrm{tarce}(\mu(x,\sigma_1,\sigma_D)) \quad (4)$$

The feature point with a large corner response that indicates a significant rotation (curvature) has a higher repeatability. Then, the candidate points are determined if the corner response is a local maximum and larger than the threshold TR used to filter the non-stable feature regions (variables). Setting a constant value for different input images is difficult [2].

The threshold should be set on 1% of the maximum value of all extracted property regions. In order to achieve scalability variability, the integral scale of all candidate points is compared with the local scale image characteristic scale. The characteristic scale, which is relatively independent of scale change, is obtained by searching for a local extreme across multiple levels of Laplace-Gauss scale. Candidate points are determined for a set of levels of the scale σ_n by setting $\sigma_1 = \sigma_D$ and $\sigma_D = 0.7\sigma_1$, where $\sigma_n = \{\delta^i \sigma_0 | \sigma_0 = 1.5, \delta = 1.1, i = 1, 2, \ldots, n\}$.

The value of σ should be small to achieve high accuracy, which is set to 1.1 in this work according to [3]. The level number of scale n depends on possible scale variations in a picture for different applications and set to 15 in our experiments. Laplace Gauss Candidate points are calculated as follows:

$$|\mathrm{LoG}(\mathbf{x},\sigma_n)| = \sigma_n^2 \,|L_{xx}(\mathbf{x},\sigma_n) + L_{yy}(\mathbf{x},\sigma_n)| \quad (5)$$

The candidate point on the ith scale iM as a characteristic point with characteristic scale σ_c ($\sigma_c = \delta^i\sigma_0$), if Laplace Gauss is a local extreme across the scale levels above the predefined threshold as follows:

$$|\mathrm{LoG}(\mathbf{x},\sigma_i)| > T_{LoG} \quad (6)$$

T_{LoG} threshold is set to 10 according to [15]. In order to achieve the invariance of rotation in the output of extraction features, each point of the property is used as the center of the conclusion of the region. The circular character corresponding to the key-dependent radius is used as follows:

$$r = \alpha \cdot \sigma c \quad (7)$$

Which is formulated using the secret key α and characteristic scale of the feature point σ_c. Obviously, the circular character regions obtained through autoregressive scale matrix and autoregressive scale matrix are highly distinctive and consistent with high repeatability with respect to various image distortions [5].

Key-dependent radius blocks the attacker's access to the feature area by controlling the size of its uncertainty, while watermarking is not included in the area, and the information leakage also decreases.

2.2 The SIFT descript

Rotation, magnification, view point change, noise, lighting, and stretching.

The first step in all methods that work on specific points of the image is finding key points. In this method, Gaussian differences (DoGs) are used to find key points in the image.

The process of finding these points begins by constructing a pyramid of images and the convolution of the image I (x, y) with the Gaussian filter G (x, y, σ). So the scale space is displayed as follows.

$$L(x,y,\sigma)=I(x,y)*G(x,y,\sigma) \tag{8}$$

'*' Represents the convolutional operator in x and y and:

$$G(x,y,\sigma)=\frac{1}{2\pi\sigma^2}e^{-(x^2+y^2)/2\sigma^2} \tag{9}$$

The blurring rate is controlled with the standard deviation parameter σ by the Gaussian function. The DoG scale space is also obtained by subtracting adjacent scale levels:

$$D(x,y,\sigma)=[G(x,y,k\sigma)-D(x,y,\sigma)]*I(x,y) \tag{11}$$

Using (10), then:
The stages of producing DoG scale space are shown in Figure 1.

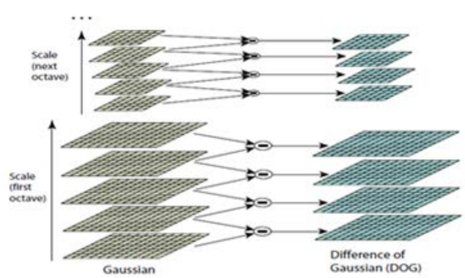

Fig.1.For each octave from the scale space

Reactive (On-demand) Protocol:

For each octave from the scale space, the initial images are convoluted and they make the left-hand side. Adjacent Gaussian images are subtracted from each other and form the DoG set on the right.Images in each octane are halved [6].

The next step is to find the maximum or minimum points in each octave. This is done by comparing each pixel with 26 neighbors in the 3 × 3 region of all adjacent DoG levels in the same octet. If the desired point is larger or smaller than all its neighbors, it is chosen as the point.In the key point descriptor stage, the main feature vector stage will be created. Initially, the gradient range and direction around the key point are sampled. David Low used 4 × 4 arrays with 8 directions per histogram instead of 2 × 2 arrays. Therefore, the attribute vector length is 128 = 8 × 4 × 4 elements for each point. Figure2 shows histogram for gradient direction and Figure 3 shows the application of SIFT algorithm to Lena test image

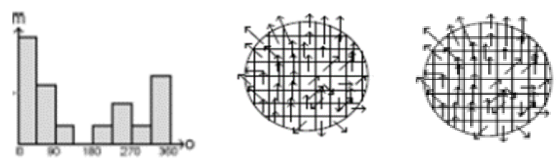

Fig.2. Histogram for gradient direction.a) Histogram b) 4 x 4 pixel gradient and direction c) Total gradients [6]

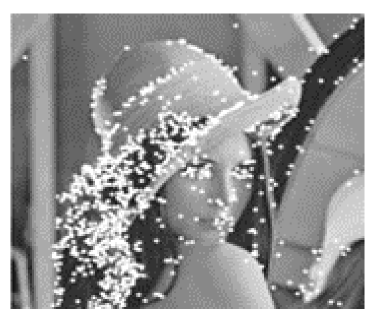

Fig.3. Feature points extracted by the SIFT algorithm [17].

The matching stage of the feature vectors is that the matching phase is at the diagnostic stage, by comparing each of the key points related to the training image.

The best candidate points are related to the training image, the best candidate points for matching, are found through the detection of the nearest neighbor in the key points of the training image. The nearest neighbor has the smallest distance with its corresponding point [6].

Table1. The threshold, the number of found points and the time of calculations in detectors in this comparison [7].

Detector	Threshold	Nb of points	Comp. time(ms)
FH-15	60,000	1813	160
FH-9	50,000	1411	70
Hessian-Laplace	1000	1974	700
Harris-Laplace	2500	1664	2100
DoG	Default	1520	400

2.3 SURF feature points

SURF (speeded up robust features) is a detector and descriptor of rotation-resistant properties and scale changes, which even acts better than other methods in the field of repeatability, differentiation, and resistance, and can be much faster and more robust in comparisons and calculations .The higher speed of this algorithm is due to the use of integral image techniques [18].

However, the use of the integral image is used to quickly compute the image convolution with box filters. First, the integral matrix of the photo matrix is constructed. In order to obtain the value of each pixel in the integral matrix, the first pixel with the same address in the image matrix is considered. Then, the total of all the pixels on the left and the top of that pixel, as well as the pixel itself, is calculated and placed in the integral matrix instead of the pixel value with the address specified so that the heuristic and the smallest pixel in the integral image represents the total of all the pixels of the original image. The procedure for generating an integral image matrix is shown in the following equation.

$$\mathbf{I}_{\Sigma}(\mathbf{x}) = \sum_{\mathbf{i=0}}^{\mathbf{i \le x}} \sum_{\mathbf{j=0}}^{\mathbf{j \le y}} \mathbf{I}(\mathbf{i}, \mathbf{j}) \tag{13}$$

Thus, the total pixels inside the rectangle can be calculated for any dimension in the original image with three complementary actions, regardless of the size of the rectangle using the integral image. For this reason, using the integral image method to calculate the results of applying different filters on the image increases the speed.

The Freak algorithm is inspired by fast retina key points. Freak is a method that uses circular shapes that are more intense than the points nearest to the center. Each sample needs to be flattened to have less sensitivity to noise. To accommodate the retina pattern, different core sizes are used for each instance, such as the Brisk algorithm. Exponential variations in size and overlapping strings are the differences in this algorithm with the Brisk algorithm [8].On the next page, we will give a brief overview of the most famous feature points in this section.

Some geometric attacks and compression apply to standard images, and two versions of the fast Hessian detector are compared with the Gaussian filter size, which is shown alongside Hsian's fast detectors, which has the best performance for this FH-9 index.

Repeatability factor is referred to as the rate between the corresponding key points and the lowest total number of visible key points in the two images. The corresponding points are identified by looking at the overlapping regions of an image and projection of the points of the region from another image. If the intersection area is larger than 50% of the union, it will be recognized as the corresponding point, which is strongly dependent on the radius of the desired circle. In the other sense, repeatability refers to the number of points discovered after attacks. This factor has been taken using the threshold of the BRISK detector during a sequence. In fair conditions, the SURF detector has been used for Hessian's threshold. A comparison chart is shown in the figure below. The number of points discovered after the attacks is displayed above the column of each of the two types of BRISK and SURF detectors. The results indicate that the SURF descriptor shows higher resistance after attacks, and thus, the more points that can be recovered after the attack has been recovered [7]. Figures 4 and 5 show the number of repetitions in the test images.

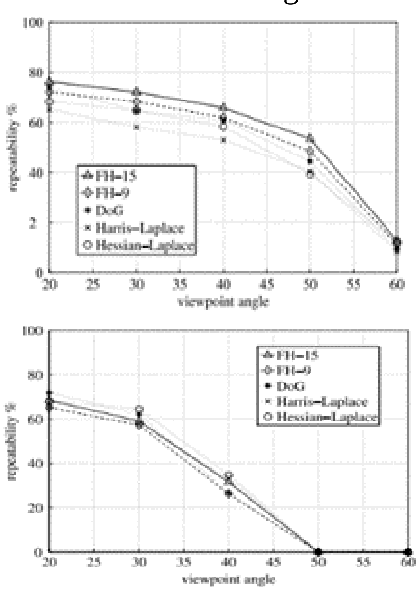

Fig.4. Repeat number of Graffiti images (right)and Wall image (left) [7].

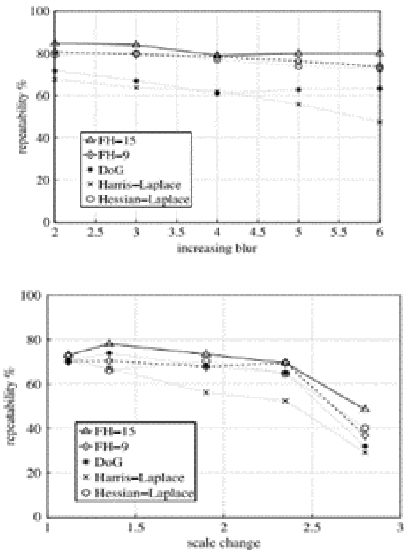

Fig.5. Repeat number of Boat images, resize 7(right) and Bike image, blur (left)

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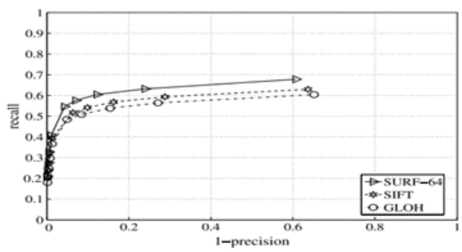

Fig.6. the comparison of recall-precision between SIFT and GLOH has been performed that SURF-64 provided better results.

Figure 6 shows the recall-precision graphs that are presented using the threshold-based similarity matching for different data types. All descriptors are extracted from one area. As shown, .SURF performs well, and BRISK approaches the SURF and the SIFT results do not show a good performance. SIFT results do not show good performance, which shows the limit on the number of duplicate points in these cases.

According to the explanation, the SURF descriptor shows a better performance than other detectors, such as SIFT, BRISK and GLOH, so the descriptor has been used in this study as well.

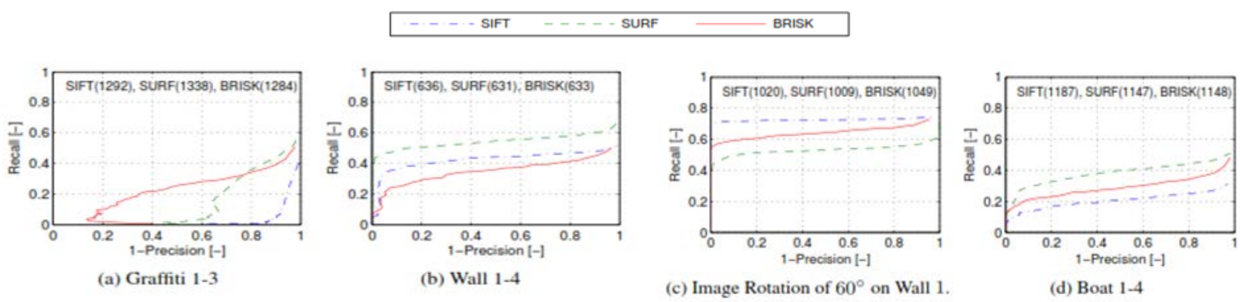

Fig.7. Comparative graph of recall-precision results among the SIFT, SURF, and BRISK algorithms [8].

3. Sustainable feature extraction

SURF is a fast-moving feature points at rising speed of a detector and descriptor of rotation-resist feature and scale modification, which acts better than other extraction methods in the field of repeatability, distinctness, and resistance. Detectors and descriptors are obtained using the integral and convolutional images. In particular, the Hassian-based matrix is introduced for the detector and a distribution-based method (to achieve resistance and speed) is introduced for the descriptor [12].

Figure 9 show the comparison of precision-recalling, results and repeatability factors among the SURF and SIFT algorithms. The precision-recalling results for detection, extraction, and adoption are shown in Figure 8. The best performance is achieved by SURF.

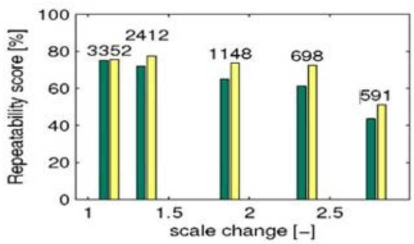

Fig.8. Precision-recalling of SURF, SIFT, and BRSIK [2].

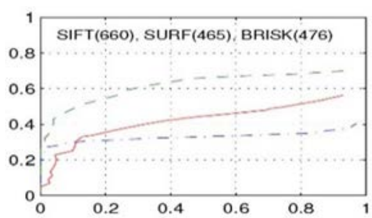

Fig.9.SURF and BRISK repeatability diagrams [2].

Conclusion

As reviewed papers especially the paper [2] show, the SURF algorithm is more resistant to attacks than other algorithms.

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