Journal of the Earth and Space Physics, Vol. 46, No. 4, Winter 2021, P. 49-64 (Research)

DOI: 10.22059/jesphys.2020.281849.1007120

Automatic Satellite's Streak Detection in Astronomical Images Based on Intelligent Methods

Farzaneh, S.[1*], Sharifi, M. A.[2] and Kosary, M.[3]

1. Assistant Professor, Department of Surveying and Geomatics Engineering, Faculty of Engineering, University of Tehran, Iran
2. Associate Professor, Department of Surveying and Geomatics Engineering, Faculty of Engineering, University of Tehran, Iran
3. Ph.D. Student, Department of Surveying and Geomatics Engineering, Faculty of Engineering, University of Tehran, Iran

(Received: 25 May 2019, Accepted: 29 Sep 2020)

Abstract

The orbit determination in one sentence is the application of a variety of techniques for estimating the orbits of objects such as the moon, planets and spacecraft. In dynamic astronomy, the orbit determination is the process of determining orbital parameters with observations. Considering the visibility of the satellite motion trace and the fundamental need to determine and modify satellites' orbital parameters as well as identify special satellites, determining the positional parameters of the satellite is also one of the modern and important applications of vision-based astronomical systems. In the modern vision-based astronomical systems, data collection is done using a charge-coupled device (CCD) array. In this paper, a new method is presented for satellite streak detection through an optical imaging system. This automatic and efficient method, which has the ability of real-time data analysis, is based on the sidereal image using CCDs. The images captured by this method have a large amount of information about stars, galaxy, and satellites' streaks. In this paper, an automatic method is presented for streak detection. The purpose of this research is to find an optimal method for satellite streak detection and different methods in clustering such as k_means, particle swarm optimization (PSO), genetic algorithm (GA), and Gaussian mixture model (GMM). Finally, some assessment criteria were compared and concluded that GA is an optimal algorithm in satellite streak detection.

Keywords: Satellite tracking, Satellite streak detection, MSAC, Clustering, Swarm intelligence.

1. Introduction

In recent years, a limited number of countries have achieved some advancements in the aerospace industry and the ability of building, launching, and infusing satellites in low orbits. In order to complete the entire cycle of the space industry, the satellite navigation, and control, which has been neglected since the beginning of the movement of space science in the country, has to be considered specifically. The orbit determination can be expressed as the application of a variety of techniques for estimating the orbits of objects such as the moon, planets, and spacecraft. Today, satellite orbit determination is known as primary part of space surveillance in design and control of them after launch. Therefore, the ability of tracking and satellite orbit determination is among the most important issues in the space program of each country. From ancient times, orbit determination has been a challenge for space scientists. Due to increasing space missions and the number of satellites, it is necessary to establish new methods for accurate detection of orbits and identify spy satellites. In particular, orbit determination of planet of the solar system is an adjustment of noisy orbital observation that consists of random and systematic error for force models and estimation of model parameters by observations, such that to achieve a mathematical model that illustrates the path of the celestial object in the path before and after the observation time. To simplify, this process is divided into two parts. First, the initial orbit is estimated and then corrections are made to the determined orbit. The purpose of initial orbit determination of the object moving around the earth is to calculate object orbital parameters by few observations; furthermore, initial orbit determination is used for detecting a missing object in space. To determine the precise orbit, it is necessary to

*Corresponding author: farzaneh@ut.ac.ir

determine the initial orbit with good accuracy, which indicates the importance of the initial orbit determination (Vallado and Agapov 2010; Swanzy, 2007; Farnocchia et al., 2010).

In general, tracking and orbit determination procedure can be divided into two sections: observation and calculation. The first is extraction of position and velocity of the satellite and in part of the calculation, numerous methods and algorithms about tracking and satellite orbit determination are applied to them. Satellite altitude determination and positioning requires sufficient information on physics of the motion and other controlling parameters. Since the physics of earth and atmosphere is not adequately known, orbit determination is not possible with the available model. Therefore, for a highly accurate orbit determination of civilian satellite, it is necessary to directly observe the satellite. Different types of observations are used to make an initial orbit determination. These observations can be collected by ground stations that contain angular angles, elevations, distance and distance range. These observations are made by the radar and the telescope because the collection of observations without an instrument and the naked eye does not have enough precision and sensitivity for the determination of the space object orbit. However, because the distante observation is expensive and sometimes impossible, angular observation is used. Thus, the optical tracking system is more accurate and simpler and requires low-cost equipment. Accordingly, optical tracking has higher flexibility against the environmental condition (Lee, 2003; Lee et al., 2004).

Fundamental of orbit determination using optical system is astronomical imaging using a CCD. Images captured with this method contain large amount of information about stars, galaxies, and satellite streak (Schildknecht 1994, 2007). Orbit determination method based on this method used stars' position for attitude determination of satellite, so coordinates of satellite and stars should be detected in images. Since a satellite appears as a streak in the captured image, the model of the streak satellite must be extracted accurately, because the misdiagnosis of the beginning and end points of the streak directly affect the accuracy of the determined orbit. Automatic method is imperative for streak detection because satellite recognition manually is tedious, time-consuming, and erroneous. Manual streak detection was used in initial methods when technology was not available or it was not affordable. With the advancement of technology, the dependency on manual methods has drastically decreased (Hejduk et al., 2004).

In satellite detection, streak can sever as a line such that the efficient line detection method affects the diagnosis of beginning and end points. There are some studies regarding line detection in image processing. The first method in this regard was proposed by Hough in 1962 as a Hough Transform (HT) algorithm, which transfers an edge image in parameter space. Another type of HT is Probabilistic Hough Transform that determines the start and end points of lines. Lévesque performed the matched filter algorithm for satellite streak detection detection. (Levesque, 2009; Levesque and Buteau, 2007). Also, a number of algorithms have been developed for line detection using PSO, which performs faster than HT (Simms, 2011; Kirchmaier et al., 2010).

There is a need to develop algorithms and software that can automatically detect and report the presence of satellite streaks and start and end points in the acquired images. The algorithms presented in this paper were developed for this purpose. The main objective of this study is to develop a streak detection algorithm based on the clustering. The basic idea of the method is to use numerous clustering algorithms to improve accuracy and speed and decrease run-time.

The remainder of this paper is organized as follows. Section 2 describes the proposed methodology. Section 3 provides a quantitative and comparative experimental validation of the proposed approach using simulated and real astronomical images. Results of streak detection on two datasets are presented in Section 4, and conclusions are provided in Section 5.

2. Method

An automatic streak detection for optical images is developed in this study. In addition to streaks of the satellite, the observed images contain noise, star, and space debris. Therefore, it is imperative to illuminate all non-streak components from the image before the streak detection algorithm is performed on the image. The overall process includes four steps: 1) noise reduction in the optical image, 2) extraction of star centers, 3) star removal, and 4) clustering and segmentation. Figure 1 illustrates the global processing. The basic approach consists of using PSO to detect the streak.

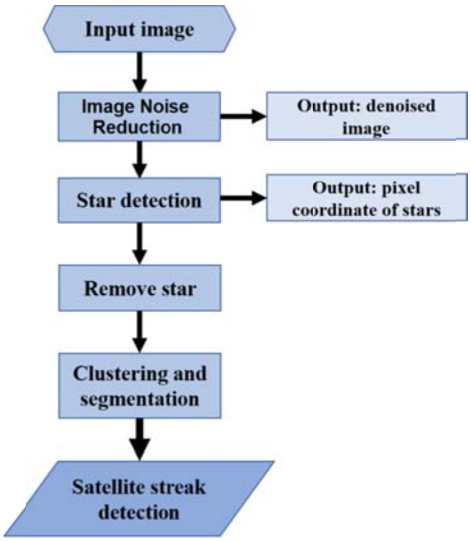


Figure 1. General procedure for satellite's streak detection.

2-1. Noise reduction

In the modern vision-based astronomical systems, data collection is done using CCD array. During the process of light collision to the surface of the CCD, reading and measuring the number of photoelectrons, and converting them to the digital numbers to store them as grey degree in each pixel, the smallest mistakes that result in the loss or adding of electrons on each pixel can lead to distortion and noise in the image. Noise can be generated by external factors such as temperature and physical conditions, or internal factors associated with CCD. Noise reduction is performed as a primary step in processing. The noise removal process should not only eliminate or reduce the noise, but also avoid blurring the image and removing or relocating the edges of the image (Gonzalez, 2009). To determine the primary orbit of the satellite using an optical method, the streak of the satellite must be extracted accurately because, the misdiagnosis of the beginning and end points of the streak directly affects the accuracy of the determined orbit. Therefore, a method should be used that imposes the lowest possible effects to the key complications of the astronomical images such as star and satellite streak. There are several noise reduction methods such as average filter (Said et al., 2016), median filter (Arias-Castro and Donoho, 2009), and Gaussian filter (Buades et al., 2005). Negative points of these filters are smoothing and converting the edge with simultaneous removal of noise, so they are not appropriate for optical orbit determination.

If the gray levels of the image are considered as temperature, then heat transfer process decreases the gray levels over time and thus helps noise reduction. In order to preserve the edges, the thermal conductivity coefficient is determined by the position of these gray levels. This method provides constancy of both edge shapes and noise removal. Thermal conductivity coefficient depends on the position of current and surrounding pixels. Therefore, the image is smoothed in the direction of edges. However, they do not change in the perpendicular direction to them and thus the position and direction of edges remain unchanged (Weeratunga and Kamath 2002, 2003). In this study, it is attempted to eliminate the noise in the optical image using the diffusion equation. Furthermore, to identify the accurate position of the edges, the gradient is calculated through the convolution of the main image by the Gaussian filter.

There is a wide range of methods to solve the diffusion equation. In this study, this equation was solved by an iteration-based numerical method (Gerig et al., 1992). Generally, the more the paces and iterations in the equation, the smoother the image would be. One parameter must be chosen such that the image brightness does not exceed the main range. For this purpose, the noise must be eliminated from the image by choosing an appropriate number of iterations. In this research, the structural similarity index (SSI) is used to select the optimum number of iterations. This index considers gray level changes. Also, it expresses contrast information and structures in comparison of images. Thus, SSI is based on a weighted combination of three criteria such as luminance ($l(x.y)$),contrast ($c(x.y)$), and structure ($s(x.y)$), as stated in Equation (1) (Wang, 2017; Wang et al., 2004).

$$SSI = [l(x.y)]^{\alpha} \cdot [c(x.y)]^{\beta} \cdot [s(x.y)]^{\gamma} \quad (1)$$

2-2. Detection and Removal of Stars from the Image

The second step in the proposed algorithm is star center extraction. In order to extract these objects, scale invariant feature transform (SIFT) have been used as an index to describe the local feature in the image. These features are invariant to uniform scaling, orientation, illumination changes, and partially invariant to local geodetic distortion (Lowe, 1999). In this method, the features are extracted efficiently and then, through a multi-stage filtering method, stable points (i.e., key points) are identified in a scaled space. In this algorithm, without the need to the distribution function, the position of the star center is determined with sub-pixel precision automatically. Figure 2 presents an overview of star detection procedures.

Because star appeared as a circle in the astronomical image, it is necessary to identify pixels that are located in this circle and determine their centers using the SIFT algorithm. The problem faced in this regard is that radii of the circles are unknown; so they were calculated repeatedly. This means that for different radii, the mean gray level of pixels outside the circle was calculated and a radius with no bright pixels outside it was selected.

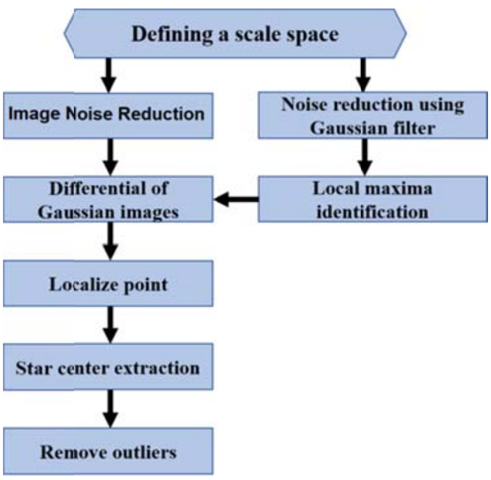


Figure 2. Star recognition process using SIFT algorithm.

2-3. Satellite Streak Detection

As noted previously, since satellite streak appears as a line in the astronomical image, it is imperative to detect start and end points of line precisely. Therefore, determination of mathematical model for satellite streak plays a key role in this procedure. In this study, satellite streak was detected using a clustering algorithm.

Clustering is one of the unsupervised classification methods and a set of objects is grouped in some classes automatically. The purpose of any clustering algorithm is to evolve a dataset in such a way that objects in the same class are based on the minimum squared distance criterion and distance between different classes should be maximum. Data clustering is considered among the most common techniques for statistical data analysis; furthermore, it can be used in a wide range of issues such as machine learning, pattern recognition, data mining, image analysis, and other fields (Grira et al., 2004).

Among various clustering algorithms, hierarchical and density-based partitional clustering methods are widely used in different topics. These methods, which are often based on the cost function, employ optimization algorithms for clustering. The optimum classifier is found by minimizing the cost function (Grira et al., 2004).

Many algorithms for data clustering have been proposed. In this regard, the k_{means} method is one of the common and simple methods (Jain, 2010). Recently, heuristic and evolutionary algorithms have been utilized for data analysis and optimization algorithm inspired by PSO. As one of the newest growing methods, PSO is a function of collective behavior in artificial intelligence (Lim, 2009). The theoretical foundations of PSO come from the behavior of agents that interact locally with one another or their environments, such as some insects (i.e., bee, ant, and termite) or even humans. In population, agents have a simple structure but their collective behavior can be complicated.

The purpose of this study is to identify satellite streak as a clustering problem using PSO algorithm and Gaussian mixture model (GMM). In the following, these algorithms are discussed.

2-3-1. The k-Means Algorithm

The k-means is one of the simplest unsupervised clustering algorithms (Jain, 2010). The main idea of this algorithm, which was presented by MacQueen in 1967, is to define k-center for each cluster through the following steps:

- From N data, K data $z_1, z_2, ..., z_k$ is chosen as cluster centers.

- Assigns data $x_i, i = 1, 2, ..., n$ to a specific cluster if Equation (2) is held:

$$\|x_i - z_j\| < \|x_i - z_p\| \quad , \quad p = 1, 2, ..., K \quad , \quad j \neq p \tag{2}$$

- When all samples are assigned to clusters, the position of the K class centers is recalculated. New class centers are determined by Equation (3):

$$Z_i = \frac{1}{n_i \sum x_j} \quad , \quad i = 1, 2, ..., k \quad , \quad x_j \in C_j \tag{3}$$

n_i illustrates the number of data in C_i class.

- The second and third steps are repeated until class centers do not change.

Although k-means have been developed during the last decades, it cannot find optimum solution accurately and has several significant drawbacks such as:

- The major disadvantage of the k-means algorithm is that the final solution depends on a number of clusters and their primary centers; in addition, this algorithm is sometimes stuck at suboptimal values.

- There is no obvious procedure for calculating the primary class centers.

- If the number of data in one class is zero, there is no way to continue the method.

2-3-2. Particle Swarm Optimization (PSO) Algorithm

PSO is a computational method that optimizes a problem iteratively based on a simulation of birds or fish collective behavior (Eberhart and Kennedy, 1995). PSO is originally attributed to Kennedy and Eberhart. They first intended to develop a kind of artificial intelligence using social models that did not require individual abilities. Their primary simulation was performed in 1995 for the simulation of bird behavior for finding seeds (Eberhart and Kennedy, 1995).

In PSO, agents in a particle have simple behavior and follow achievement of neighbors and themselves. The collective behavior that appears from this simple behavior will cover optimal areas of a multi-dimensional search space. In PSO, a group of particle is used each having a strong potential to solve the problem (Esmin et al., 2008).

To update the particle's position, it is necessary to calculate the particle's velocity. In PSO, in accordance with Equation (4), the velocity consisted of three components: momentum, cognitive, and social (Van der Merwe and Engelbrecht, 2003).

$$v_{ij}(t+1) = \underbrace{v_{ij}(t)}_{\text{Momentum}} + \underbrace{c_1 r_{1j}(t)[pbest_{ij}(t) - x_{ij}(t)]}_{\text{Cognitive}} + \underbrace{c_2 r_{2j}(t)[gbest(t) - x_{ij}(t)]}_{\text{Social}} \tag{4}$$

In PSO, pbest and gbest play crucial roles in guiding the particle's search. In the above equation, $pbest_{ij}(t)$ represents the best position that i^th^ particle has experienced since the process has started, $gbest(t)$ represents the best position of neighbors, and $v_{ij}(t)$ is the previous velocity of the i^th^ particle. $x_{ij}(t)$ is particle's position, c_1, c_2 are acceleration constant parameters that play the role of weighting for cognitive and social parts, and $r_{1j}(t)$ and $r_{2j}(t)$ are random values between 0 and 1, which are sampled from a uniform distribution. Finally, the particle's position in each stage is updated according to Equation (5).

$$x_i(t+1) = x_i(t) + v_i(t+1) \tag{5}$$

PSO algorithm is influenced by several factors such as data dimension, particle number, neighbor size, number of repetitions, and acceleration coefficients (Suganthan, 1999).

2-3-3. Genetic Algorithm

Genetic algorithm (GA) employs Darwins natural selection principles to find the optimal formula for predicting or matching the pattern. This algorithm is a search technique to find the optimal solution and is a type of metaheuristic algorithms inspired by biological functions such as mutation, crossover, and selection (Coley, 1999).

A GA involves several steps. At first, depending on the data and problem, unknown variables are specified. Then, these variables are properly encoded and represented as a chromosome. Based on the cost function, a fitness function is defined for chromosomes and, initially, the population is selected randomly. Afterward, the value of the fitness function is calculated for each chromosome. Later, according to Figure 3, other steps are performed sequentially. Each step is described in more details below (Coley, 1999).

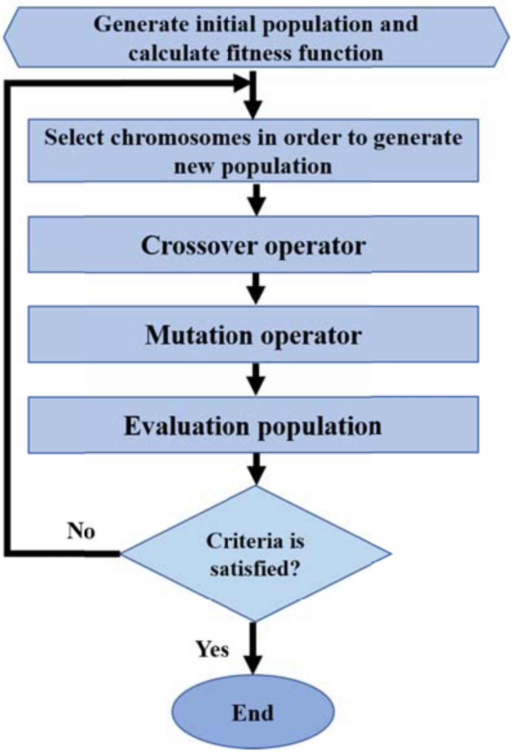


Figure 3. General overview of Genetic algorithm procedure during satellite's streak detection.

- In this step, a sufficient number of chromosomes based on their fitness values are selected and are later used in the next steps.
- The crossover operator with P_c probability is applied to parent chromosomes and new chromosomes are generated.
- The mutation operator with P_m probability is performed on chromosomes resulting from a crossover operator and with changing the bits of these chromosomes make a way to enter new information.
- At this step, the fitness value of new chromosomes is calculated in order to evaluate the daughter chromosomes.
- New population is selected to enter the next step of the algorithm by comparing the chromosomes' fitness values.
- All the new populations are evaluated. If the algorithm is terminated, it will be finished; otherwise, the current population is used as the initial population for the next step.

The termination condition of the GA can be determined by a problem (Scrucca, 2013).

2-3-4. GMM Algorithm

The GMM is one of the novel methods for data analysis and clustering. The satisfactory results with high speed make this method very useful. This method is the most statistically mature method for clustering because each type of distribution can be approximated by a sufficient number of Gaussian function (Zivkovic, 2004). In a GMM, it is assumed that each x_i is created independently by a mixture with the following density:

$$p(\vec{x} \mid \lambda_l) = \sum_{i=1}^{M} p_i b_i(\vec{x}) \tag{6}$$

p_i is a weighting of model i[th] (by assumption $0 < p_i < 1$ for each k and $p_1 + \cdots + p_M = 1$) and $b_i(\vec{x})$ are d-dimensional Gaussian distribution function with average $\vec{\mu}_i$ and covariance matrices $\vec{\mu}_i$, respectively.

$$b_i(\vec{x}) = \frac{1}{(2\pi)^{D/2}\left|\Sigma_i\right|^{1/2}} \exp\left(\frac{-1}{2}(\vec{x}-\vec{\mu}_i)' \Sigma_i^{-1} (\vec{x}-\vec{\mu}_i)\right) \tag{7}$$

The clustering process thereby is transformed such that to estimate the parameters of the GMM. Expectation-maximization algorithm is used in this study to estimate the unknown parameters of the GMM (Zivkovic, 2004).

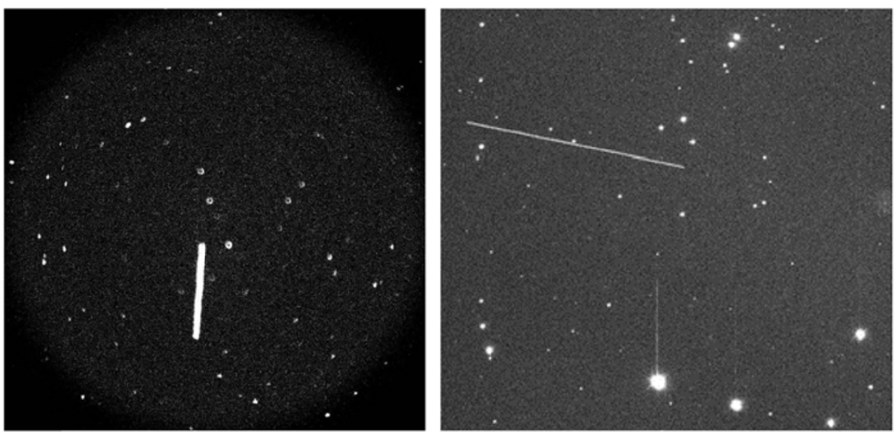
The output of clustering is a binary image in which only satellite streak pixels are found bright. Sometimes, images include some satellite streaks that necessitate separating each streak. Therefore, the proposed algorithm involves connected component labeling process to detect each of them (Suzuki et al., 2003). Since there are some outliers in streak class, RANSAC algorithm is executed for line detection (Fischler and Bolles, 1981). With this algorithm, the fitted line becomes closer to the stable position by some iteration and, as a result, start and end points of streak are identified precisely.

3. Experimental result

The theory of noise reduction, star center extraction, and streak detection was explained in Section 2. In this section, the proposed method is implemented on the two images that have been used by CCDs of iXON Ultra 888 for experiments and analyses. The device was equipped with back-illuminated technology and an electron magnifying setup to record the single photons, that arrive at the CCD’s surface. Table 1 presents the key specifications of the machine. As can be observed, the machine has 1024×1024 square pixels with a pixel size of 13 µm. The high reading rate of this sensor provides an appropriate capability for consecutive imaging of celestial bodies. The studied images are demonstrated in Figure 4.

Table 1. Key specification of iXON Ultra 888

Active pixel (H x V)	1024×1024
Pixel size (W x H; µm)	13×13 µm
Image area (mm)	13.3×13.3
Active Area Pixel Well Depth (e-)	e -80
Max Readout Rate (MHz)	30MHZ
Frame rates (fps)	26(full frame)-9690
Read noise (e-)	<1 with EM gain
QE Max	>90%



(a) (b)

Figure 4. sample images used in this study using Ixon Ultra 888 CCD with different Exposure time a) 0.5 sec and b)1 sec.

3-1. Noise Reduction

The image noise reduction was implemented on the images using the diffusion equation. As noted previously, this method is a function of the number of iteration and this parameter is unknown. In order to find an optimal number of iterations, the SSI index was utilized. The range of 0 to 10 is considered as iteration and the expected value is given by the maximum index. The variation of SSI index and result of noise reduction are presented in Figures 5 and 6.

3-2. Star Extraction

Star extraction algorithm is applied to the denoised image and the SIFT algorithm parameters for two images presented in this paper (Table 2). Also, the center of stars is presented in Figure 7.

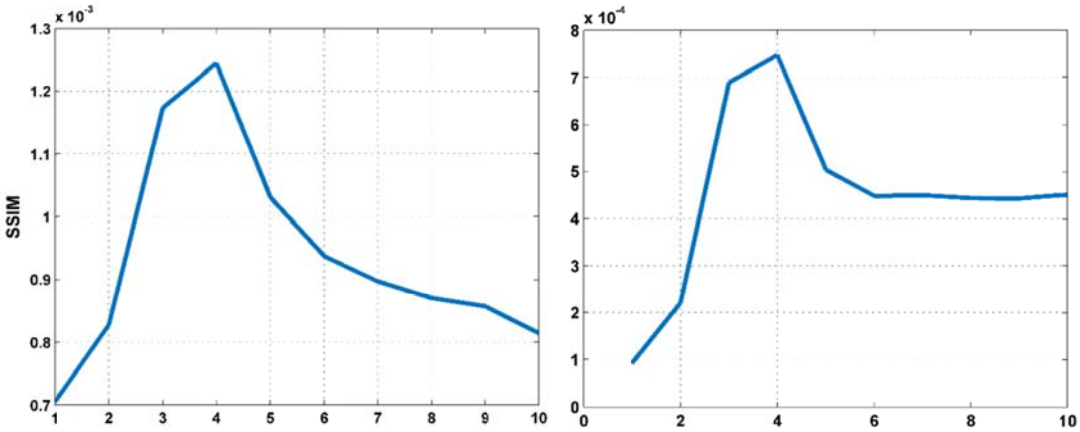


Figure 5. Variation of structural similarity index in range of 10 iteration.

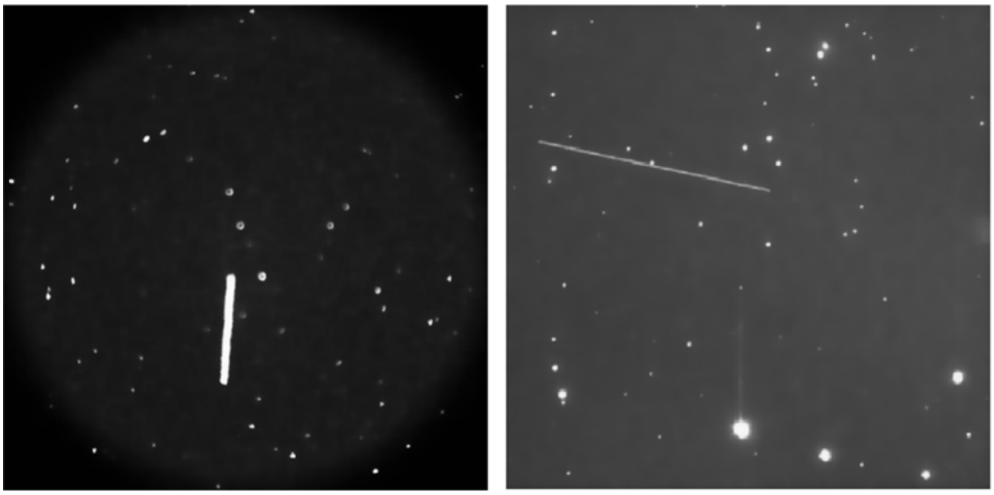


Figure 6. Result of removing noise in sample images using diffusion equation.

Table 2. The SIFT algorithm parameters for star extraction.

SIFT Parameters	
Scl	2.1
Threshold	10
Radius1	4
Radius2	4
Radius3	4
Octaves	5
Sigma	1.5
Edge Ratio	5

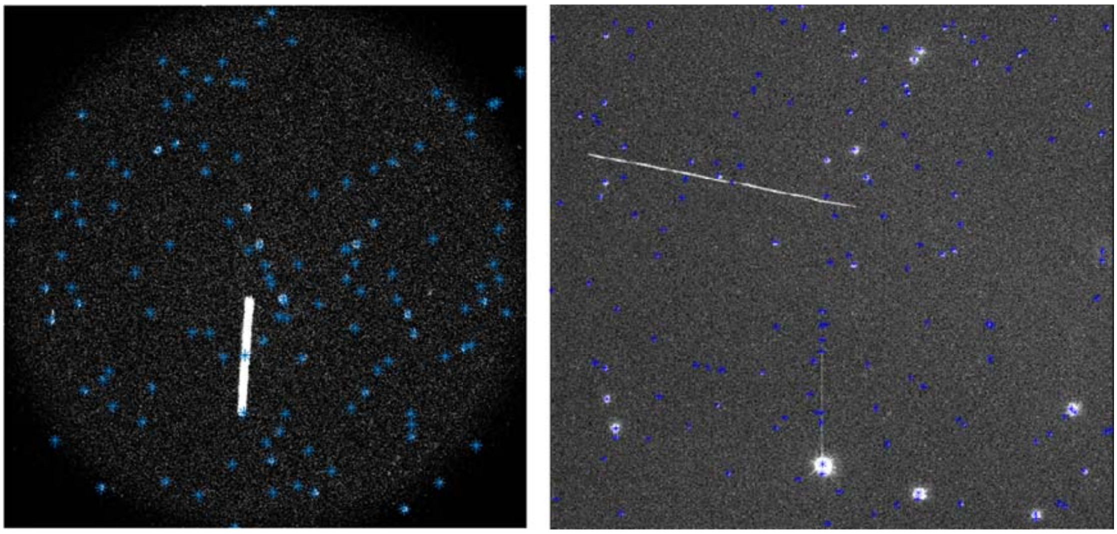


Figure 7. Display of star's center pixel coordinate using SIFT algorithm.

After extraction star's center, pixels have been occupied by star are removed from images using proposed method, and Figure 8 is a result of this step.

3-3. Satellite Streak Detection Using Swarm Intelligence Algorithms

In this study, four clustering algorithms (i.e., PSO, GA, GMM, and k-means) were implemented on images to detect satellite streak cluster. GA and PSO algorithms require some initial parameters, thus it is necessary to calculate optimal parameters before the clustering. The number of iteration and initial population play important roles in the PSO method and directly affect the solution. To determine the number of iteration for PSO and GA, the problem was run for 1 to 50 iterations in one image. Also, the Sum of Squared Error (MSE) between binary image after clustering and the image with only satellite streak, each iteration was plotted in Figure 9. The plot shows that adding more iteration does not improve the results considerably. Therefore, 5 and 4 iterations were selected as the optimal iteration parameter for GA and PSO, respectively. This procedure is repeated for a number of populations, but the difference is that the problem was run for 1 to 100 populations and the MSE for each number of the sample was presented in Figure 10. As a result, 49 and 7 samples opt as the optimal number of population.

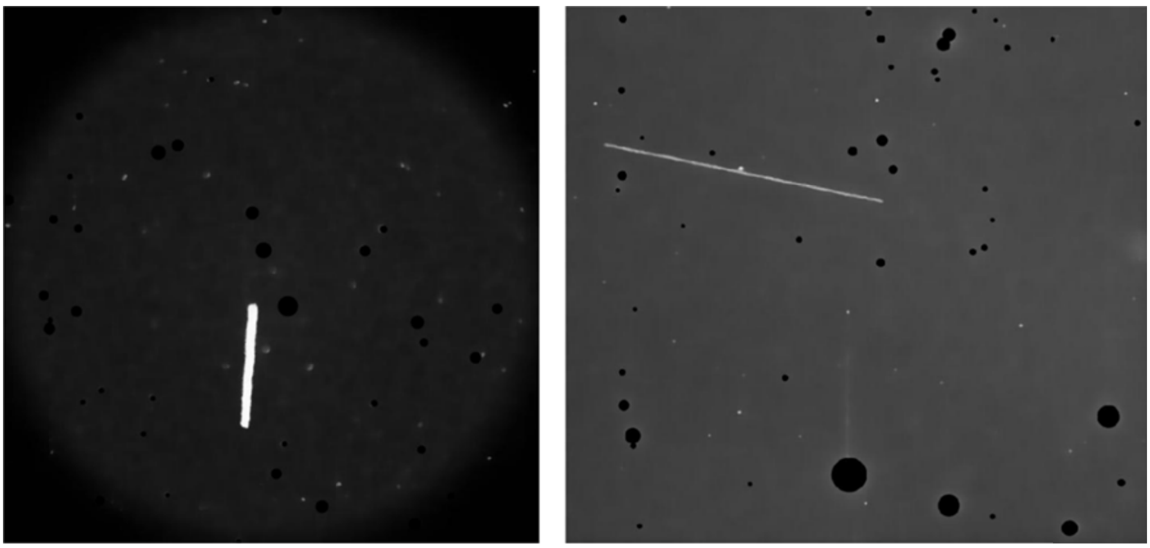


Figure 8. Removing star pixels from images using proposed algorithm.

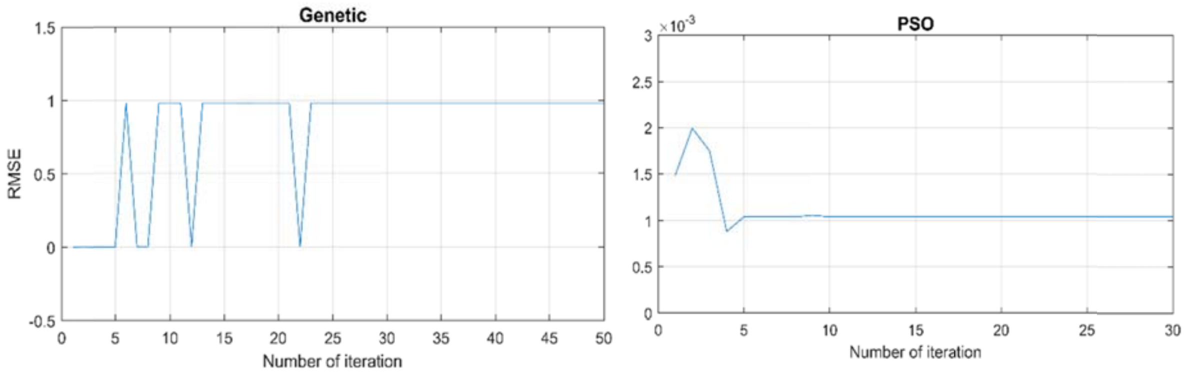


Figure 9. MSE for different iteration using PSO and Genetic.

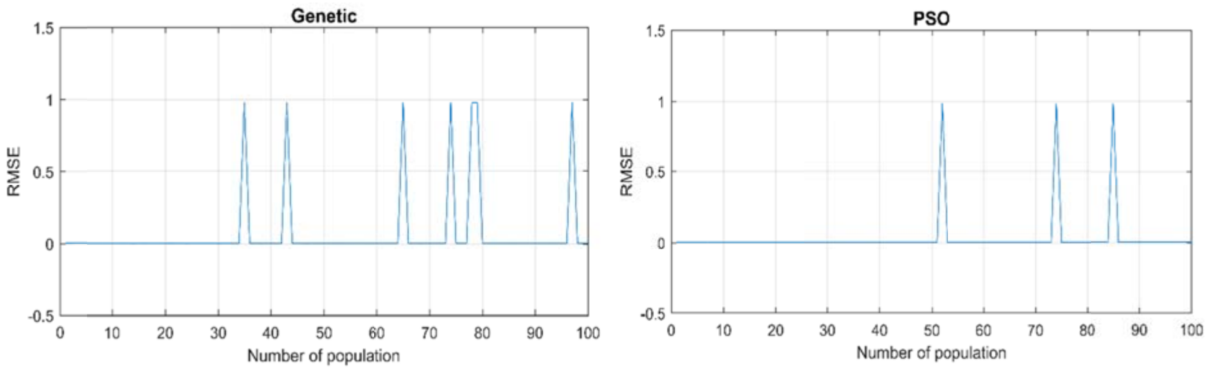


Figure 10. MSE for different population using PSO and Genetic.

As stated previously, k_means algorithm sometimes converges to a local minimum. In order to solve this problem, combination method between k_means and PSO algorithm is proposed. In this procedure, centers of the initial clusters are calculated using PSO, GA, and GMM. Afterward, clustering is performed using the k_means algorithm. Eventually, the satellite streak model is determined using RANSAC methods. The outputs of seven algorithms (i.e., PSO, GA, k_means, GMM, PSO_K_means, GA_K_means, and GMM_K_means) are illustrated in Figures 11 to 17.

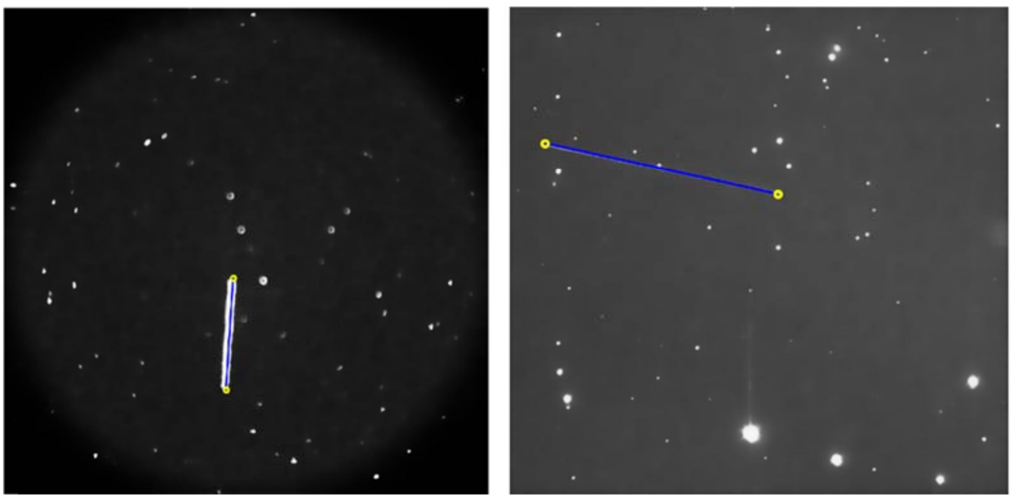


Figure 11. Detected satellite's streak using k_means algorithm.

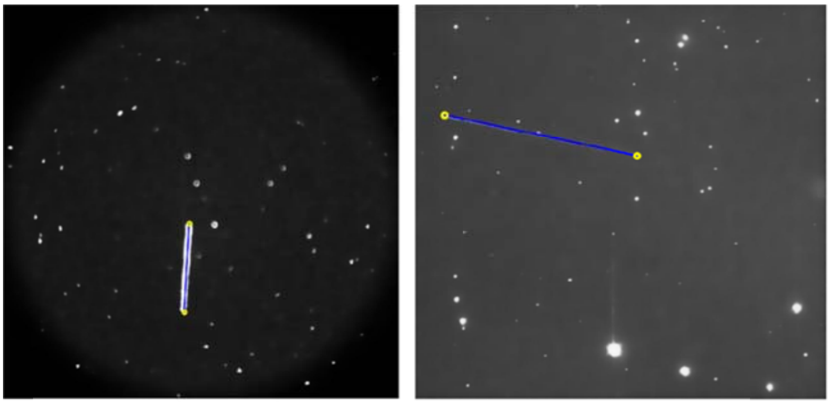


Figure 12. Detected satellite's streak using PSO algorithm.

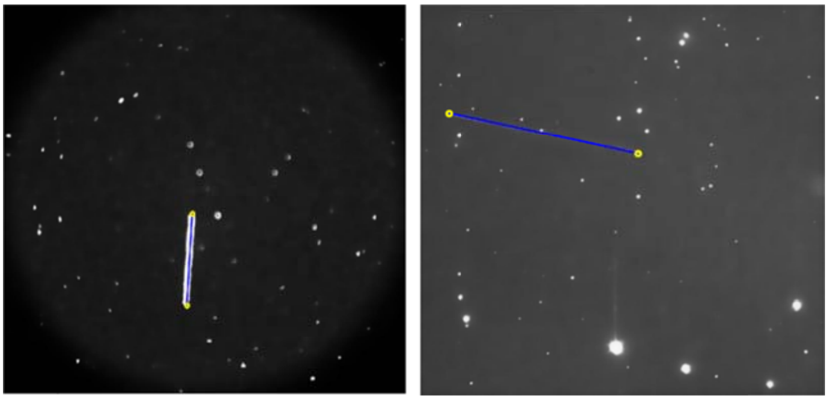


Figure 13. Detected satellite's streak using Genetic algorithm.

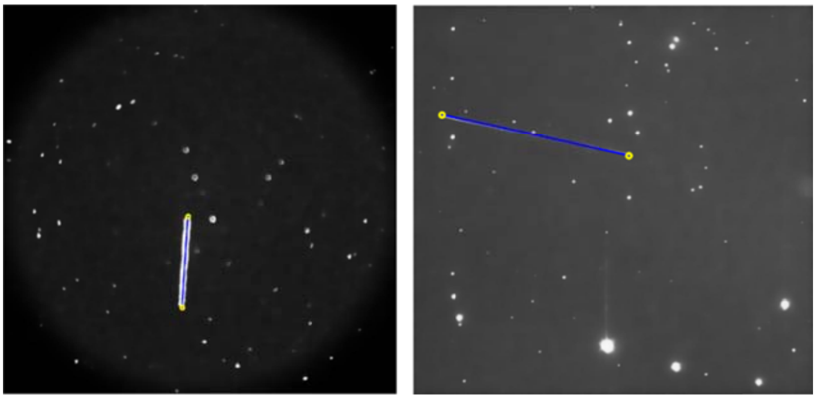


Figure 14. Detected satellite's streak using GMM algorithm.

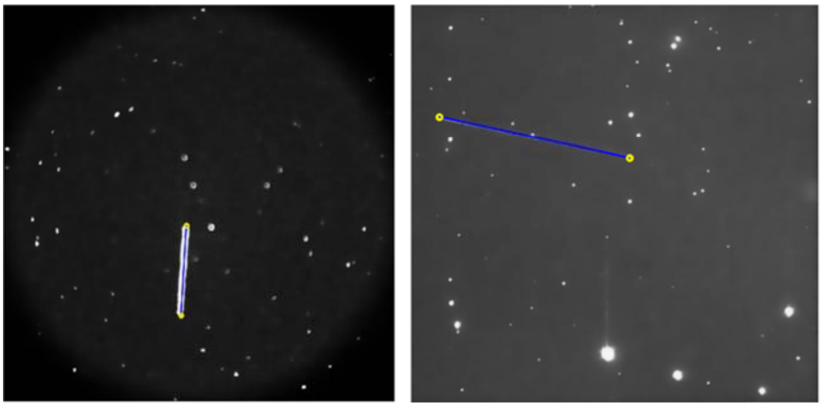


Figure 15. Detected satellite's streak using PSO and k_means algorithm.

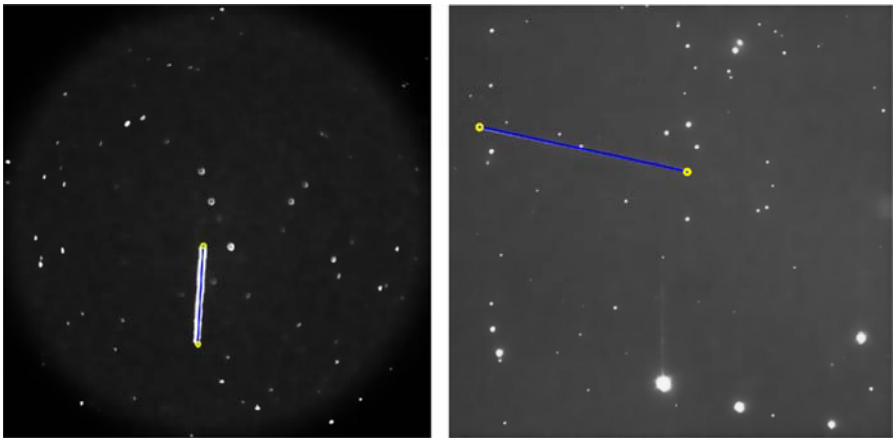


Figure 16. Detected satellite's streak using Genetic and k_means algorithm.

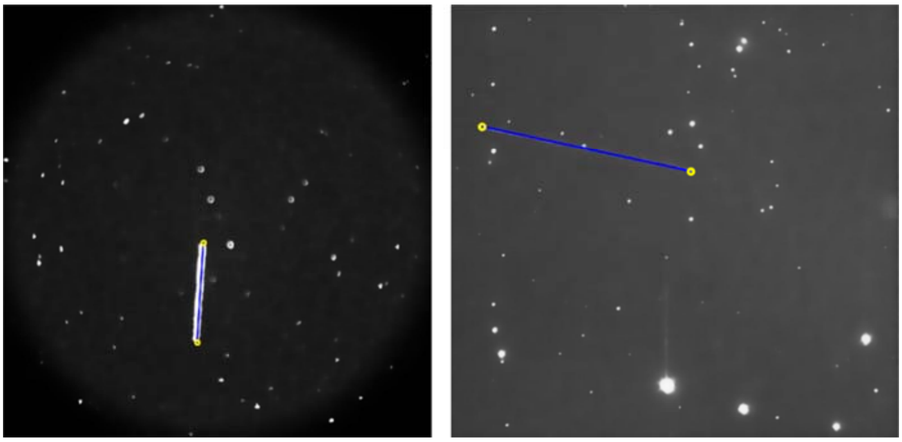


Figure 17. Detected satellite's streak using GMM and k_means algorithm.

4. Discussion

It is obvious that all algorithms can detect satellite streak and no significant difference is seen visually. In order to compare methods, it is also necessary to evaluate quantitative results. The approach used to compare different methods is to assess some precision parameters using the confusion matrix and execution time. In this study, the confusion matrix is calculated between the outputs illustrated in the previous section and the binary image in which satellite streak pixels are bright. The evaluation criteria presented in Tables 3 and 4 are described as follows.

Table 3. Evaluation criteria with different methods in the sample image (a) in Figure (4).

	PSO	genetic	EMGMM	K-means	PSO_kmeans	Genetic_kmeans	EMGMM_kmeans
Misclassification	0.0010	6.69 e -4	0.0015	9.086 e -4	0.0013	0.0014	9.08 e -4
Specificity	0.494	0.635	0.314	0.534	0.433	0.423	0.534
Performance_rate	971.44	1151.64	965.75	977.70	969.64	969.60	977.70
Time	3.563	3.616	11.696	7.780	5.841	6.560	12.352

Table 4. Evaluation criteria with different methods in the sample image (b) in Figure (4).

	PSO	genetic	EMGMM	K-means	PSO_kmeans	Genetic_kmeans	EMGMM_kmeans
Misclassification	9.92 e -5	1.15 e -4	0.001	3.19 e -4	1.46 e -4	4.76 e -6	3.06 e -4
Specificity	0.998	0.968	0.778	0.917	0.960	1	0.920
Performance_rate	289.03	280.91	280.66	280.86	280.90	281.32	280.86
Time	7.367	3.900	5.061	3.318	8.181	6.354	3.866

Misclassification rate criteria reflect that rate at which classifier is not able to identify the correct class of them. Therefore, according to the purpose of this study, one method with minimum misclassification rate can be chosen as an optimal approach. In this connection, the GA and GA-k_means were identified as an optimal method for the left and right images of figure 4 respectively. The measures of accuracy derived from the confusion matrix represent the proportion of true results and the expected value of these criteria that would be close to 1. According to this parameter, no significant difference was found between the outputs; as a result, the purposed algorithm is not sensitive to this criterion. Specificity measures the rate of the non-streak pixel correctly classified under non-streak class; consequently, the optimal algorithm for satellite streak detection is identified by the maximum value of this factor. Thus, the GA in the left image and GA-K_means in the right image are considered as optimal methods. Another criterion determined in this study is F-measures. This parameter was calculated from the harmonic average of precision and sensitivity. Under ideal and worst conditions, this parameter equals to 1 and 0, respectively. The values of this parameter do not present any variation in the different method; therefore, it is not an appropriate criterion for satellite streak detection. Next parameter evaluated in this study is the performance rate. This criterion shows the proportion of streak pixels that classified correctly and pixels categorized mistakenly; hence, GA and PSO can be determined by the optimal method for the left and right image, respectively, based on the performance rate. The last criterion studied in this research is the execution time. Based on this parameter, PSO and K_means minimize the time required to detect satellite streak. It should be noted that the measured time difference between GA and PSO for the left image was 53 milliseconds. Finally, considering the characteristics of imaging geometry, type of CCD, and exposure time, the assessment of demonstrating that PSO method is more efficient than other clustering methods in the automatic satellite streak detection and GMM can be considered as an appropriate approach for streak detection.

4-1. Multi-Streak Detection

When a multi-satellite streak is found in the sidereal image, it would be reasonable to expect that the proposed algorithm can detect all the streaks in an image. The proposed approach was applied to the simulated image and then the start and end points of each streak were specified by pixel coordinate. The output of this section is shown in Figure 18.

4-2. Comparison of Proposed Method with Precise Orbit

For more evaluation of proposed method, the azimuth and elevation value of the beginning and end points of a sample streak (Figure 19) using the best intelligent method (PSO) can be calculated by precise orbit file, then these results are compared with results of the purposed method. Tables 5 to 7 show the comparison of proposed method with precise orbit. These tables reveal that the proposed method is comparable with real observation, which has a difference of about milliseconds.

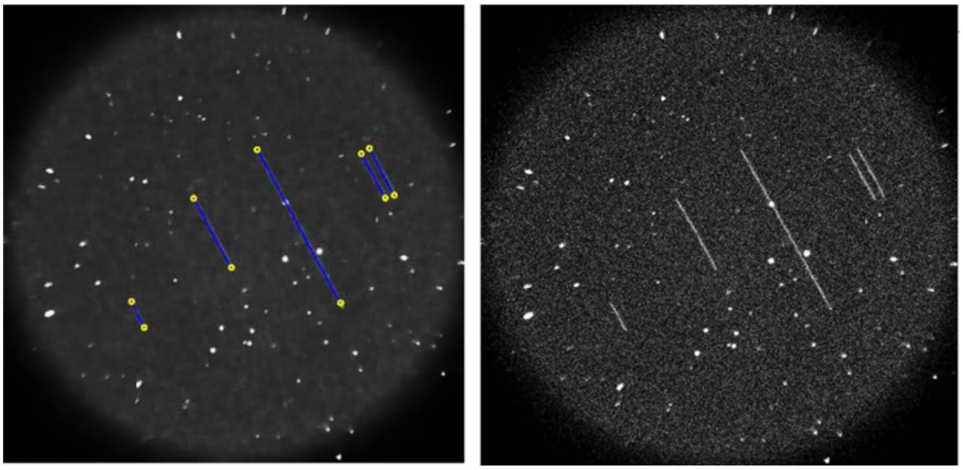


Figure 18. Output of proposed algorithm for multi streak image.

Figure 19. MOUS streak at 24 September 2015 by SBig 16303 blooming CCD.

Table 5. Celestial and pixel coordinates of start and end satellite streak.

	TIME	X_Pixel	Y_Pixel	Ra(J2000)	Dec(J2000)	Az(J2000)	El(J2000)
Start	2015/09/24 12:05:47.66002	277.9091	518.8905	15:25:48.613	63:23:44.43	122.5792	41.541
END	2015/09/24 12:06:17.26004	712.9777	614.9662	15:26:24.533	63:13:29.72	122.7979	41.624

Table 6. Azimuth and elevation of satellite streak using proposed method and precise orbit.

TIME	Azimuth and Elevation with proposed method		Azimuth and Elevation using precise orbit	
2015/09/24 12:05:47.66002	322.7376636	50.8347074	322.7396420	50.8424562
2015/09/24 12:06:17.26004	322.7421911	50.8414754	322.7312864	50.8320066

Table 7. Difference of azimuth and elevation.

TIME	Azimuth	Elevation
2015/09/24 12:05:47.66002	-0.00197844	-0.0077490
2015/09/24 12:06:17.26004	0.01909047	0.0094688

7. Conclusion

In the current state of colonization of near-Earth space by satellites, there is an increasing need to know exactly the real status of the occupation of this space. Thus, orbital parameters for all objects traveling in this space must be known with a high degree of accuracy. In addition, this knowledge must be periodically updated because this situation is always changing. Atmospheric drag, solar wind, moon, and planetary gravitational perturbations are all sources of interference that generate orbital perturbations beyond what the best orbital model can predict. The solution is to periodically observe all the satellites, particularly the debris (because active satellites themselves contribute to maintaining the knowledge of their orbital parameters), to determine with precision their positions, and update their known orbital parameters. There is a serious need for sky surveillance in order to monitor the satellites or the non-functional space objects for different purposes, such as to correct the satellites deviations from their trajectories, to detect uncatalogued space debris objects, and to avoid possible collisions. In order to define the location of the satellite in the sky and then to update its orbital parameters, an optical satellite tracking system can be designed, which acquires sequences of astronomical images from the sky. Such a system is composed of many sensors like a telescope, a CCD camera, and a GPS receiver. The CCD camera captures some sequences of images in the current time provided by GPS. The star catalogs are employed to calibrate the image plane to the celestial coordinate systems. The TLE database contains the outdated orbital parameters to estimate the satellite position. For this purpose, an algorithm was required to detect satellite streaks automatically in the sidereal image.

References

Arias-Castro, E. and David, L.D., 2009, Does median filtering truly preserve edges better than linear filtering?. The Annals of Statistics, 37, 1172-206.

Buades, A., Bartomeu, C. and Jean-Michel, M., 2005, A review of image denoising algorithms, with a new one. Multiscale Modeling & Simulation, 4, p. 490-530.

Coley, D.A., 1999, An introduction to genetic algorithms for scientists and engineers (World Scientific Publishing Company).

Eberhart, R. and James, K., 1995, A new optimizer using particle swarm theory. In Micro Machine and Human Science.

Esmin, A.A.A, Dilson, L.P. and FPA, D.A., 2008, Study of different approach to clustering data by using the particle swarm optimization algorithm. In Evolutionary Computation.

Farnocchia, D., Giacom, T., Andre, M. and Alessandro, R., 2010, Innovative methods of correlation and orbit determination for space debris. Celestial Mechanics and Dynamical Astronomy, 107, p. 169-85.

Fischler, M.A. and Robert, C.B., 1981, Random sample consensus: a paradigm for model fitting with applications to image analysis and automated cartography. Communications of the ACM, 24. 381-95.

Gerig, G., Olaf, K., Ron, K. and Feren, A.J., 1992, Nonlinear anisotropic filtering of MRI data. IEEE Transactions on medical imaging, 11, 221-32.

Gonzalez, R.C., 2009, Digital image processing: Pearson education india.

Grira, N., Michel, C. and Nozha, B., 2004, Unsupervised and semi-supervised clustering: a brief survey. A review of machine learning techniques for processing multimedia content, Report of the MUSCLE European Network of Excellence (FP6): 1001-30.

Hejduk, M.D, Lambert, J.V., Williams, C.M. and Lambour, R.L., 2004, Satellite detectability modeling for optical sensors. In AMOS Technical Conference.

Jain, A.K., 2010, Data clustering: 50 years beyond K-means. Pattern recognition letters, 31, 651-66.

Kirchmaier, U., Simon, H. and Klaus, D., 2010, A line detection and description algorithm based on swarm intelligence. In Image Processing: Machine Vision Applications III, 75380Q.

Lee, D.J., 2003, kyung-Hee University.

Lee, W., Hyung-Chul, L., Pil-Ho, P., Jae-Hyuk, Y., Hong-Suh, Y. and Hong-Kyu, M., 2004, Orbit determination of GPS and KOREASAT 2 satellite using angle-only data and requirements for optical tracking system. Journal of Astronomy and Space Sciences, 21, 221-32.

Levesque, M., 2009, Automatic reacquisition of satellite positions by detecting their expected streaks in astronomical images. In Proceedings of the Advanced Maui Optical and Space Surveillance Technologies Conference, E81.

Levesque, M. P. and Sylvie, B., 2007, Image processing technique for automatic detection of satellite streaks. In.: DTIC Document.

Lim, C. P. and Satchidananda, D., 2009, Innovations in swarm intelligence. Springer Science & Business Media, 248.

Lowe, D.G., 1999, Object recognition from local scale-invariant features. The proceedings of the seventh IEEE international conference on, 1150-57.

Said, A.B, Rachid, H., Kamal, E.M. and Sebti, F., 2016, Multispectral image denoising with optimized vector non-local mean filter. Digital Signal Processing, 58, 115-26.

Schildknecht, T., 1994, Optical astrometry of fast moving objects using CCD detectors. Geod.-Geophys. Arb. Schweiz, 49.

Schildknecht, T., 2007, Optical surveys for space debris. The Astronomy and Astrophysics Review, 14, 41-111.

Scrucca, L., 2013, GA: a package for genetic algorithms in R. Journal of Statistical Software, 53, 1-37.

Simms, L.M., 2011, Autonomous subpixel satellite track end point determination for space-based images. Applied optics, 50, p. D1-D6.

Suganthan, P.N., 1999, Particle swarm optimiser with neighbourhood operator. Evolutionary Computation., 3.

Suzuki, K., Isao, H. and Noboru, S., 2003, Linear-time connected-component labeling based on sequential local operations, Computer Vision and Image Understanding, 89, 1-23.

Swanzy, M., 2007, Analysis and demonstration: a proof-of-concept compass star tracker, Texas A&M University.

Vallado, D. and Vladimir, A., 2010, Orbit Determination Results for Optical Measurements. In AIAA/AAS Astrodynamics Specialist Conference, 7525.

Van der Merwe, D.W. and Engelbrecht, A.P., 2003, Data clustering using particle swarm optimization. In Evolutionary Computation, 2003. CEC'03, 215-20.

Wang, Y., 2017, 'Reliability Analysis of Spintronic Device Based Logic and Memory Circuits', Télécom ParisTech.

Wang, Z., Bovik, A.C., Sheikh, H.R and Simoncelli, E.P., 2004, 'Image quality assessment: from error visibility to structural similarity', IEEE transactions on image processing, 13, p. 600-12.

Weeratunga, S.K. and Chandrika, K., 2002, PDE-based nonlinear diffusion techniques for denoising scientific and industrial images: an empirical study. International Society for Optics and Photonics, 279-90.

Weeratunga, S.K. and Kamath, C., 2003, Comparison of PDE-based non-linear anistropic diffusion techniques for image denoising. In Image Processing: Algorithms and Systems II, 201-13. International Society for Optics and Photonics.

Zivkovic, Z., 2004, Improved adaptive Gaussian mixture model for background subtraction. In Pattern Recognition, 2004. ICPR 2004. Proceedings of the 17th International Conference on, 28-31. IEEE.