International Journal of Science and Research (IJSR)
ISSN (Online): 2319-7064
Impact Factor (2012): 3.358

A New Method for Noisy Image Segmentation using Firefly Algorithm

Bhavana Vishwakarma[1], Amit Yerpude[2]

[1] M. Tech Scholar, Department of Computer Science and Engg., CSVTU University
Rungta College of Engineering & Technology, Bhilai (C.G.), India

[2]Associate Professor, Department of Computer Science and Engg., CSVTU University
Rungta College of Engineering & Technology, Bhilai (C.G.), India

Abstract: ***Segmentation of noisy images is one of the most challenging problems in image analysis. In this paper, we propose a new method for image segmentation, which is able to segment all type noisy images. The performance of existing (K-means) and proposed (Firefly) algorithm was tested on three images. The experimental results prove that Firefly algorithm performs better for all types of noisy images.***

Keywords: Image segmentation, Image Noise, Firefly Algorithm, K-means

1. Introduction

Image segmentation [2] is an important process in many computer vision and image processing applications. It divides an image into a number of discrete regions such that the pixels have high similarity in each region and high contrast between regions. Purpose of dividing an image is to further analyze each of these objects present in the image to extract some high level information. In order to facilitate practical manipulation, recognition, and object-based analysis of multimedia resources, partitioning pixels in an image into groups of coherent properties is indispensable. This process is regarded as image segmentation [3].

Noise in images represents unwanted information which degrades the image quality. Noise is defined as a process which affects the acquired image quality that is being not a part of the original image content [4] The main source of noise in digital images arises during image acquisition (digitization) or during image transmission. The principal sources of noise in the digital image are:

a) The imaging sensor may be affected by environmental conditions during image acquisition.
b) Insufficient Light levels and sensor temperature may introduce the noise in the image.
c) Interference in the transmission channel may also corrupt the image.
d) If dust particles are present on the scanner screen, they can also introduce noise in the image.

We can consider a noisy image to be modelled as follows:

$$g(x, y) = f(x, y) + \eta(x, y)$$

Where f(x, y) is the original image pixel, η(x, y) is the noise term and g(x, y) is the resulting noisy pixel. [5]

2. Different Noise Models

Noise [6], [7] is a random variation of image intensity and visible as grains in the image. Image noise is the random variation of brightness or color information in images produced by the sensor and circuitry of a scanner or digital camera. Different factors may be responsible for introduction of noise in the image. Image noise can be classified as:

- Amplifier noise (Gaussian noise)
- Salt-and-pepper noise
- Shot noise (Poisson noise)
- Speckle noise

A. Amplifier Noise (Gaussian Noise)

Gaussian noise [8] model is additive in nature and follow Gaussian distribution. Each pixel in the noisy image is the sum of the true pixel value and a random, Gaussian distributed noise value. The noise is independent of intensity of pixel value at each point.

B. Salt-and-Pepper Noise

The term impulse noise is also used for salt-and-pepper noise [8], [6]. Black and white dots appear in the image as a result of this noise and hence the name salt and pepper noise. This noise arises in the image because of sharp and sudden changes of image signal. This type of noise can be caused by dead pixels, analog-to-digital converter errors, bit errors in transmission, etc.

C. Poisson Noise

Poisson noise [6], [4] is also known as shot noise. It is a type of electronic noise. It occurs when the finite number of particles that carry energy, such as electrons in an electronic circuit or photons in an optical device, is small enough to give rise to detectable statistical fluctuations in a measurement.

D. Speckle Noise

Speckle noise [6], [8] is a type of granular noise that commonly exists in and causes degradation in the image quality. This noise deteriorates the quality of active radar and Synthetic aperture radar (SAR) images. Speckle noise occurs due to random fluctuations in the return signal from an object in conventional radar that is not big as single image-processing element. It increases the mean grey level of a local area.

3. Firefly Algorithm

Fireflies are one of the most special creatures in nature. Most of fireflies produced short and rhythmic flashes and have different flashing behavior. Fireflies use these flashes for communication and attracting the potential prey. Xing She Yang used this behaviour of fireflies and introduced Firefly Algorithm in 2008 [9] [10]. Firefly algorithm (FFA) [11] is a new meta-heuristic nature- inspired algorithm. It has been shown that the algorithm is very effective in solving some optimization problems and can be better than the other traditional algorithms. And the stability of the algorithm proved to be superior to other well- known optimization algorithm [12].

Firefly algorithm employs three idealized rules:

a) All fireflies are unisex so that one firefly will be attracted to other fireflies regardless of their sex;
b) Attractiveness is proportional to their brightness, thus for any two flashing fireflies, the less bright one will move towards the brighter one. The attractiveness is proportional to the brightness and they both decrease as their distance increases. If there is no brighter one than a particular firefly, it will move randomly;
c) The brightness of a firefly is affected or determined by the landscape of the objective function.

A. Attractiveness Function

Since, the brightness of the fireflies decreases with the distance from the light source, therefore, the attractiveness of a firefly function determined by the following monotonically decreasing function.

$$\beta - \beta_0 e^{-\gamma r^2}$$

Where 'r' is the distance between each two fireflies and β_0 is their attractiveness at r = 0, γ is the absorption coefficient.

The *distance between any two fireflies* i and j at x_i and x_j can be Cartesian distance given by:

$$r_{ij} = \| x_i - x_j \|_2 = \sqrt{\sum_{k=1}^{d} (x_{i,k} - x_{j,k})^2}$$

B. Movement of Firefly

The firefly 'i' *movement* is attracted to another more attractive (brighter) firefly 'j' is determined by:

$$x_i = x_i + \beta_0 e^{-\gamma r^2}(x_j - x_i) + \alpha \varepsilon_i$$

Where, the second term is due to the attraction, while the third term is randomization.

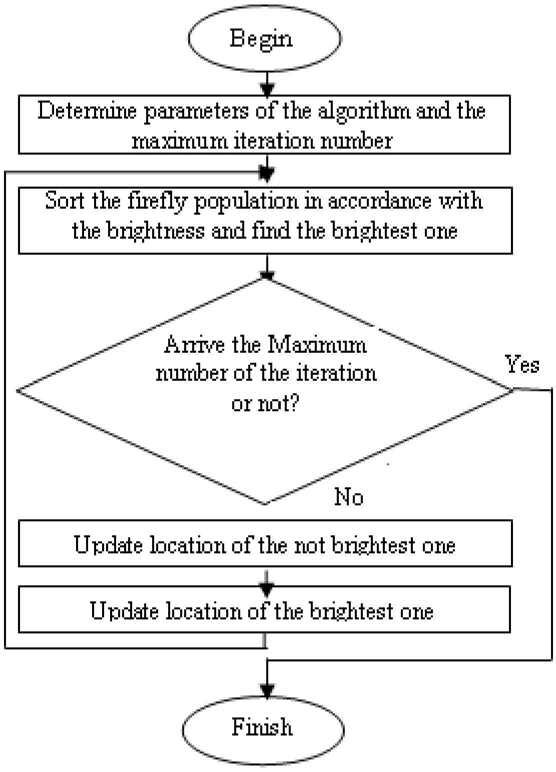

Figure 3.1: (Execution Process of Firefly Algorithm)

4. Proposed Method

Image segmentation using firefly algorithm has proved its superiority over K-means clustering technique for segmentation [13]. It could effectively overcome the problem that K-means algorithm is sensitive to the initial center and local optimal convergence. The initial centroids are calculated using firefly algorithm and it also speed up the clustering process by achieving early convergence.

We propose a robust method for noisy image segmentation using Firefly Algorithm (FFA) because FFA is more potentially powerful in solving noisy non-linear optimisation problems. The FFA seems to be a promising optimisation tool in part due to the effect of the attractiveness function which is a unique of firefly behaviour. The FFA has not only the self improvement process with the current space, but it also includes the improvement among its own space from the previous stages [11].

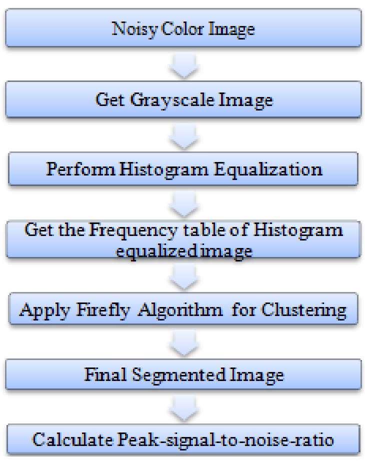

Figure 4.1 Flow Diagram of the Proposed Approach

5. Experimental Results and Discussions

We tested the proposed method on three images with different types of noises added. Figure 5.1, 5.2 and 5.3 represents the images flower.jpg, dogs.jpg, and tiger.jpg. These images are tested for segmentation using basic K-means algorithm and the proposed method. The outputs in table 5.1, 5.3 and 5.5 depict the computational efficiency of proposed method over K-means. Similarly, the outcomes of table 5.2, 5.4, and 5.6 illustrate that the peak-signal-to-noise-ratio for the proposed method is far better compared to the K-means. Graph of figure 5.4, 5.5, 5.6, 5.7, and 5.8 clearly demonstrates that the proposed method is better and more effective as compared to K-means algorithm.


Figure 5.1.1 (Original Image without noise)

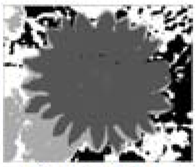
Figure 5.1.2 (Segmented Image using Kmeans)

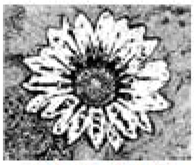
Figure 5.1.3 (Segmented Image using FFA)


Figure 5.1.4 (Image with Gaussian Noise)

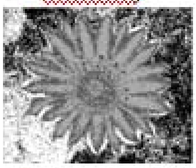
Figure 5.1.5 (Segmented Image using Kmeans)

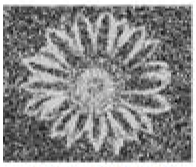
Figure 5.1.6 (Segmented Image using FFA)

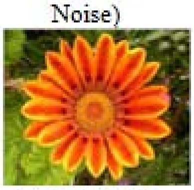
Figure 5.1.7 (Image with Salt & Pepper Noise)


Figure 5.1.8 (Segmented Image using Kmeans)

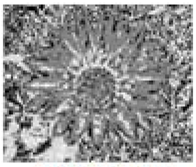
Figure 5.1.9 (Segmented Image using FFA)


Figure 5.1.10 (Image with Poisson Noise)


Figure 5.1.11 (Segmented Image using Kmeans)

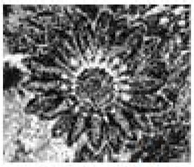
Figure 5.1.12 (Segmented Image using FFA)


Figure 5.1.13 (Image with Speckle Noise)


Figure 5.1.14 (Segmented Image using Kmeans)

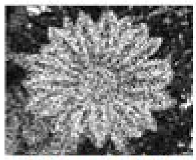
Figure 5.1.15 (Segmented Image using FFA)


Figure 5.2.1 (Original Image without noise)


Figure 5.2.2 (Segmented Image using Kmeans)


Figure 5.2.3 (Segmented Image using FFA)


Figure 5.2.4 (Image with Gaussian Noise)

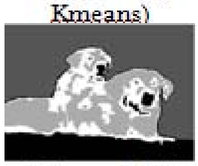
Figure 5.2.5 (Segmented Image using Kmeans)


Figure 5.2.6 (Segmented Image using FFA)


Figure 5.2.7 (Image with Salt & Pepper Noise)

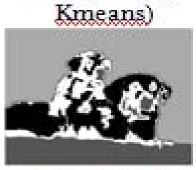
Figure 5.2.8 (Segmented Image using Kmeans)

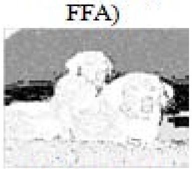
Figure 5.2.9 (Segmented Image using FFA)


Figure 5.2.10 (Image with Poisson Noise)


Figure 5.2.11 (Segmented Image using Kmeans)

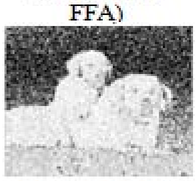
Figure 5.2.12 (Segmented Image using FFA)


Figure 5.2.13 (Image with Speckle Noise)

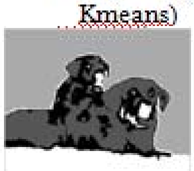
Figure 5.2.14 (Segmented Image using Kmeans)


Figure 5.2.15 (Segmented Image using FFA)


Figure 5.3.1 (Original Image without noise)


Figure 5.3.2 (Segmented Image using Kmeans)


Figure 5.3.3 (Segmented Image using FFA)


Figure 5.3.4 (Image with Gaussian Noise)


Figure 5.3.5 (Segmented Image using Kmeans)

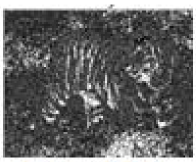
Figure 5.3.6 (Segmented Image using FFA)


Figure 5.3.7 (Image with Salt & Pepper Noise)

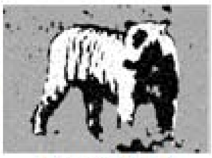
Figure 5.3.8 (Segmented Image using Kmeans)

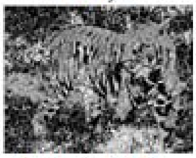
Figure 5.3.9 (Segmented Image using FFA)


Figure 5.2.10 (Image with Poisson Noise)

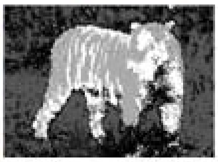
Figure 5.3.11 (Segmented Image using Kmeans)

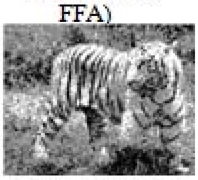
Figure 5.3.12 (Segmented Image using FFA)


Figure 5.3.13 (Image with Speckle Noise)


Figure 5.3.14 (Segmented Image using Kmeans)

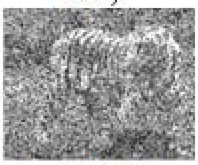
Figure 5.3.15 (Segmented Image using FFA)

Table 5.1: Time Required for Execution

Image	*Execution Time (in seconds)*	
Flower.jpg	For K-means	For Firefly
Original Image	2.253437	1.32014
Image with Gaussian Noise	3.847061	0.73097
Image with Salt & Pepper Noise	1.764102	0.980379
Image with Poisson Noise	1.640579	0.984251
Image with Speckle Noise	2.604798	0.952194

Table 5.2: Comparison of Peak-Signal-to-Noise Ratio

Image	*Peak-Signal-to-Noise-Ratio (in db)*	
Flower.jpg	For K-means	For Firefly
Original Image	-6.9623	9.6205
Image with Gaussian Noise	-7.572	12.3288
Image with Salt & Pepper Noise	-7.9786	9.3235
Image with Poisson Noise	-8.1046	8.4915
Image with Speckle Noise	-8.5163	10.0545

Table 5.3: Time Required for Execution

Image	*Execution Time (in seconds)*	
Dogs.jpg	For K-means	For Firefly
Original Image	2.037268	0.966357
Image with Gaussian Noise	1.823511	0.931063
Image with Salt & Pepper Noise	1.271649	0.843848
Image with Poisson Noise	1.526217	0.9541
Image with Speckle Noise	1.592517	1.001513

Table 5.4 Comparison of Peak-Signal-to-Noise Ratio

Image	*Peak-Signal-to-Noise-Ratio (in db)*	
Dogs.jpg	For K-means	For Firefly
Original Image	-6.3237	16.593
Image with Gaussian Noise	-6.192	11.7353
Image with Salt & Pepper Noise	-7.3479	20.608
Image with Poisson Noise	-7.8212	18.7378
Image with Speckle Noise	-8.0788	16.848

Table 5.5: Time Required for Execution

Image	*Execution Time (in seconds)*	
Tiger.jpg	For K-means	For Firefly
Original Image	1.908765	0.748992
Image with Gaussian Noise	4.097758	0.619067
Image with Salt & Pepper Noise	2.869185	0.62982
Image with Poisson Noise	2.026278	0.889227
Image with Speckle Noise	2.078839	0.704611

Table 5.6: Comparison of Peak-Signal-to-Noise Ratio

Image	Peak-Signal-to-Noise-Ratio (in db)	
Dogs.jpg	For K-means	For Firefly
Original Image	-7.6981	8.618
Image with Gaussian Noise	-7.0052	11.2154
Image with Salt & Pepper Noise	-7.7965	11.2235
Image with Poisson Noise	-6.0981	17.446
Image with Speckle Noise	-7.8398	13.5465

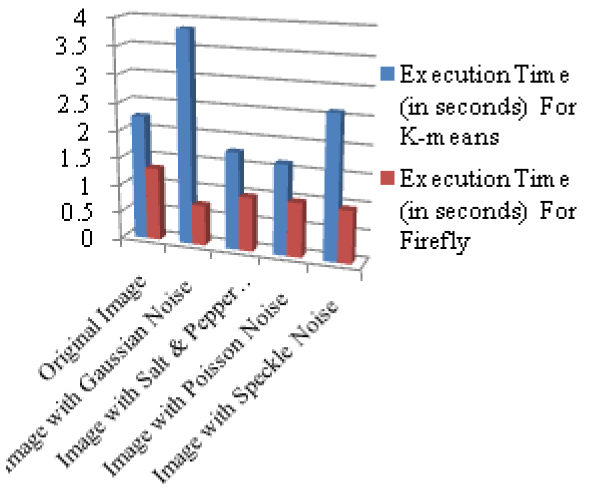

Figure 5.3 (Graph for difference in time between Kmeans and Firefly Algorithm for image Flower.jpg)

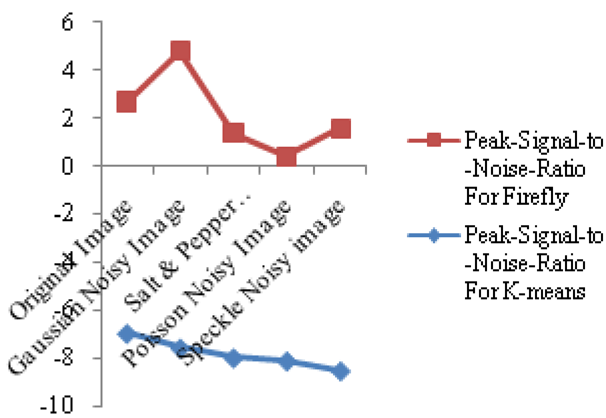

Figure 5.4 (Graph for Comparison of PSNR between Kmeans & Firefly for image Flower.jpg)

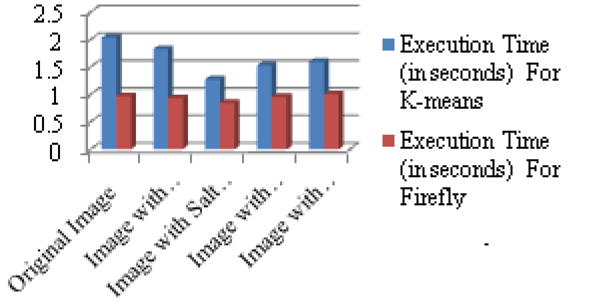

Figure 5.5 (Graph for difference in time between Kmeans and Firefly Algorithm for image Dogs.jpg)

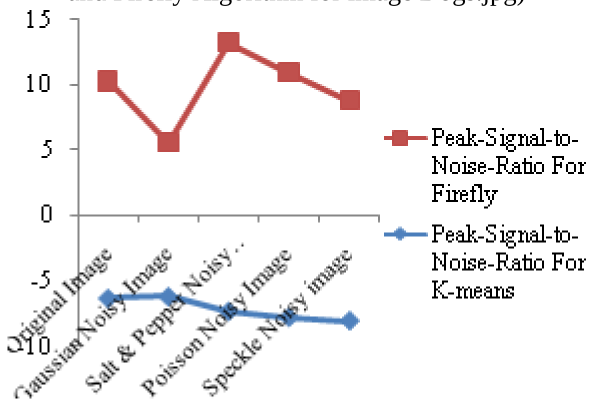

Figure 5.6 (Graph for Comparison of PSNR between Kmeans & Firefly for image Dogs.jpg)

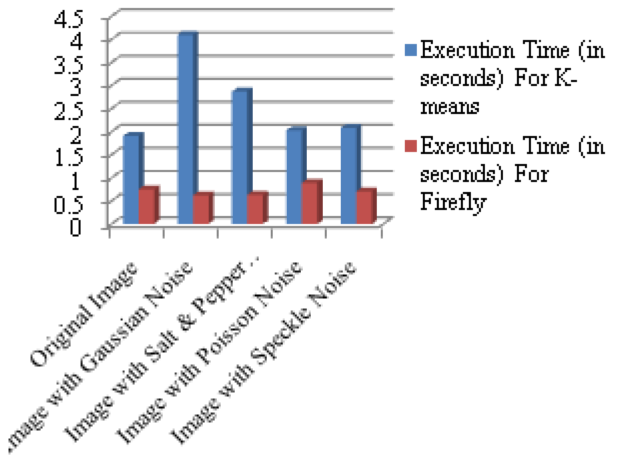

Figure 5.7: Graph for difference in time between Kmeans and Firefly Algorithm for image Tiger.jpg

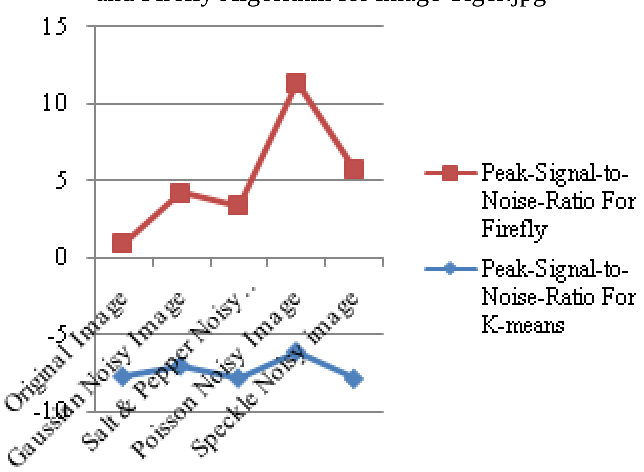

Figure 5.8: (Graph for Comparison of PSNR between Kmeans & Firefly for image Tiger.jpg)

6. Conclusions and Future Scope

In this paper we presented a new robust method for the segmentation of noisy images. The experimental results show that the proposed method turn out better results than K-means algorithm. Thus, we conclude that we can efficiently use this new algorithm for noisy image segmentation.

References

[1] Mandar Sohani, Avinash Shrivas Vijay Jumb, "Color Image Segmentation Using K-Means Clustering And Otsu's Adaptive Thresholding," International Journal Of Innovative Technology And Exploring Eng Ineering (IJITEE), Vol. 3, No. 9, Pp. 72-76, February 2014.

[2] Rajneet Kaur Gurjeet Kaur Seerha, "Review On Recent Image Segmentation Techniques," International Journal On Computer Science And Engineering (IJCSE), Vol. 5, No. 2, Pp. 109-112, February 2013.

[3] Dr. Sipi Dubey Amit Yerpude, "Colour Image Segmentation Using K – Medoids Clustering," Int.J.Computer Techology & Applications, Vol. 3, No. 1, Pp. 152-154, February 2012.

[4] Sengottaiyan.G Govindaraj.V, "Survey Of Image Denoising Using Different Filters," International Journal Of Science, Engineering And Technology Research (IJSETR), Vol. 2, No. 2, Pp. 344 - 351, February 2013.

[5] Woods.R. Gonzalez.R., Digital Image Processing, 2nd Ed., Englewood Cliffs, Ed. New Jersy: Prentice-Ha, 2001.

[6] Dr. Sipi Dubey Amit Yerpude, "Robust Method For Noisy Image Segmentation," International Journal Of Computer Science Engineering & Technology (IJCSET), Vol. 2, No. 2, Pp. 891-895, Februaray 2012.

[7] Sonali R. Mahakale & Nileshsingh V. Thakur, "A Comparative Study Of Image Filtering On Various Noisy Pixels," International Journal Of Image Processing And Vision Sciences, Vol. 1, No. 2, Pp. 69-77, 2012.

[8] Dr. Jahid Ali Mr. Rohit Verma, "A Comparative Study Of Various Types Of Image Noise And Efficient Noise Removal Techniques ," International Journal Of Advanced Research In Computer Science And Software Engineering, Vol. 3, No. 10, Pp. 617-622, October 2013.

[9] Tahereh Hassanzadeh And Mohammad Reza Meybodi, "A New Hybrid Algorithm Based On Firefy Algorithm And Cellular Learning Automata," IEEE, Pp. 628 - 633, 2012.

[10] Xin-She Yang, Nature-Inspired Metaheuristic Algorithms, 2nd Ed. United Kingdom: Luniver Press, 2010.

[11] P. Aungkulanon, and P. Luangpaiboon N. Chai-Ead, "Bees And Firefly Algorithms For Noisy Non-Linear Optimisation Problems," In Imecs, Hong Kong, March 2011.

[12] Zhongqiang Gao And Weihua Zhao Chang Liu, "A New Path Planning Method Based On Firefly Algorithm," IEEE, Pp. 775-778, 2012.

[13] Amit Yerpude Bhavana Vishwakarma, "A Meta-Heuristic Approach For Image Segmentation Using Firefly Algorithm," International Journal Of Computer Trends And Technology (IJCTT), Vol. 11, No. 2, Pp. 69-73, May 2014.