Multilevel Thresholding for Image Segmentation Using an Improved Electromagnetism Optimization Algorithm

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Received 11 March 2018 | Accepted 3 September 2018 | Published 22 September 2018

Abstract

Image segmentation is considered one of the most important tasks in image processing, which has several applications in different areas such as; industry agriculture, medicine, etc. In this paper, we develop the electromagnetic optimization (EMO) algorithm based on levy function, EMO-levy, to enhance the EMO performance for determining the optimal multi-level thresholding of image segmentation. In general, EMO simulates the mechanism of attraction and repulsion between charges to develop the individuals of a population. EMO takes random samples from search space within the histogram of image, where, each sample represents each particle in EMO. The quality of each particle is assessed based on Otsu's or Kapur objective function value. The solutions are updated using EMO operators until determine the optimal objective functions. Finally, this approach produces segmented images with optimal values for the threshold and a few number of iterations. The proposed technique is validated using different standard test images. Experimental results prove the effectiveness and superiority of the proposed algorithm for image segmentation compared with well-known optimization methods.

Keywords

Image Segmentation, Multilevel Thresholding, Otsu's Entropy, Electromagnetic Optimization, Levy Function.

DOI: 10.9781/ijimai.2018.09.001

I. Introduction

Recently, image processing has several applications in different areas such as; industry agriculture, medicine, etc. Image segmentation is considered the most important step in image processing [1]. This process is classifying the pixel in the image depending on its intensity value. In literature, different methods have been proposed for image segmentation, including edge based method [2] neural network based method [3],watershed based method [4], clustering based method [5], and artificial threshold based method [6].

Thresholding method is a simple and effective tool to isolate objects of interest from the background. Its applications include several classics such as document image analysis, whose goal is to extract printed characters [7] logos, graphical content, or musical scores; also it is used for map processing which aims to locate lines, legends, and characters [8]. It is also used for scene processing, aiming for object detection and marking [9];; Similarly, it has been employed to quality inspection for materials discarding defective parts[10].

Thresholding techniques are used for segmenting the image into two (bi-level) or more classes (RGB). The binary level thresholding is taking only one threshold value (t) and then testing every pixel with specific intensity value, if it is higher, the threshold value (t) classified as the first class and the other pixel with a different intensity value are classified as second class. In multilevel thresholding, the pixels in the image are divided into more than one class, where, every class is taken a specific threshold value [11-13]. Basically, two approaches called parametric and nonparametric can be used to determine the optimal threshold value [12]. In parametric approach, some parameters of a probability density function should be estimated for classifying the classes of image. But this approach is computationally expensive and time consuming whereas that non parametric approach optimizes several criteria such as; the error rate, the entropy, etc, in order to determine the optimal threshold values However, there are two methods can be used for binary level thresholding; Otsu's and Kapur. Otsu method uses the maximization of between classes variance [14].

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Kapur method maximizes the entropy to measure the homogeneity of the classes [15]. The computational complexity of the two methods for multilevel thresholding is increasing for each new threshold [16].

Many optimization techniques deal with multilevel thresholding (MT) for image segmentation such as; Particle Swarm Optimization (PSO) [17] , Moth Flame Optimization (MFO) [18], Genetic Algorithm (GA) [19], Whale Optimization Algorithm (WOA) [18], Ant Colony Optimization (ACO) [20].

Recently, EMO contributed to solving many engineering problems such as; control systems [22], array pattern optimization in circuits [23],neural network training [24], vehicle routing [25], communications [26], flow-shop scheduling [27], image processing [28] Although EMO algorithm is consistent with characteristics of other approaches, EMO's performance generates a better precision and computation time in most of the studied cases when it is compared with other metaheuristic optimization techniques such as; Cuckoo Search (CS), Sine Cosine algorithm (SCA) and MFO, and WOA. However, EMO algorithm simulates the mechanism of attraction-repulsion which subject to the electromagnetic law of physics to develop the individuals of population based on their objective function values [21]. The main idea of EMO is to move a particle through the space following the force exerted by the rest of the population. Using the charge of each particle depending on its objective function value, the force is calculated.

This paper proposes an improved EMO algorithm based on levy function (EMO-levy) for multilevel thresholding of image segmentation. Different standard images are used to validate the proposed technique compared with other well-known optimization techniques such as; original EMO, CS, SCA, MFO and WOA. The developed approach produces a multilevel segmentation of digital images with few number of iterations and fast computational time.

The organization of the paper is as follows. In Section II, presents the developed Electromagnetism Optimization Algorithm with levy function (EMO.levy). Section III illustrates the problem definition of multilevel thresholding (MT) and the application of developed optimization algorithm for solving it. Section IV presents comprehensive results obtained by the developed algorithm, comparing with other techniques. Section V provides the outstanding features of the proposed algorithm. Finally, Section VI gives the final conclusions of the paper.

II. Improved Electromagnetism Optimization Algorithm

A. EMO

The EMO formulation has been developed to find a global solution of a nonlinear optimization problem with satisfying the operating constraints as [12]:

$$\max f(x), x = (x_1, x_2, x_3, ..x_k) \in Z \tag{1}$$

Subject to $x \in X$

where, f: Z→Z is a nonlinear function, $X = \{x \in Z | l_k \le x_k \le u_k, k = 1, \dots, n\}$, l_k is the lower limit and u_k is the upper limit.

EMO technique uses some variable such as:

m → number of population inside one iteration

n → dimensional control variable $x_{j,t}$ and t refers to the iteration number of the algorithm.

$E_t=(E_{1,t},E_{2,t},E_{3,t},\dots\dots\dots\dots E_{m,t})$→is the initial population in the same iteration t which is taken by random samples from search space X of image histogram. After the initialization of E_t, EMO continues its iterative process until reaching to the maximum number of iterations [30].

B. Lévy Electromagnetism Optimization Algorithm (EMO.levy)

Lévy flight distribution is integrated in EMO technique to enhance the searching capability and exploration ability of this optimization algorithm by increasing its probability of producing new solutions to avoid stagnation of algorithm and to avoid trapping in local minima. Levy flight is a random process for generating a new solution based on random walk where its steps are captured from a Lévy distribution. The new population position that is based on Lévy distribution can be found as follows [35]:

$$X_i^{new} = X_i + \propto \oplus Levy(\beta) \tag{2}$$

where, ∝ represents a random step size parameter. ⊕ is the entry wise multiplication and β is a Lévy Flight distribution parameter. The step size can be found as:

$$\propto \oplus Levy(\beta) \sim 0.01 \frac{u}{|v|^{1/\beta}} \left(X_i^t - X_{best}^t \right) \tag{3}$$

where, u and v are normally variables produced by normal distribution where,

$$u \sim N\left(0, \phi_u^2\right), \quad v \sim N\left(0, \phi_v^2\right) \tag{4}$$

$$\phi_u = \left[\frac{\Gamma(1+\beta) \times \sin(\pi \times \beta / 2)}{\Gamma[(1+\beta)/2] \times \beta} \right]^{1/\beta}, \phi_v = 1 \tag{5}$$

where Γ, is the standard gamma function and, $0 \le \beta \le 2$. To enhance the exploitation of EMO the best search agent is updated by using variable bandwidth as follows:

$$X_{best}^{new} = X_{best}^t \pm C_5 \times K_w \tag{6}$$

where, C_5 is a random number in [0, 1]. K_w is a variable bandwidth that decreases dynamically as:

$$K_w = K_{\max} e^{(s \times t)} \tag{7}$$

$$s = \left(\frac{\ln\left(\frac{K_{\min}}{K_{\max}}\right)}{T_{\max}} \right) \tag{8}$$

where, K_{max} and K_{min} are the maximum and the minimum limits. t is the current iteration and T_{max} is the maximum number of iterations.

However, the solution process of EMO technique is going through basic steps:

Step1- Input variable $iter_{max}$, $iter_{local}$, α local search parameter, m number of population, n dimensional of x.

Step2- The algorithm in this step makes initialization by taking random particles from the search space between lower and upper bound at same iteration=1 ,then the objective function values

f ($x_{i,t}$) are calculated over all population $E_{i,t}$, (where i=1,….,m) from the results, the best value of $E_{i,t}$ is E^b that represents the optimum objective function value $f(x_{i,t})$ which is generated from the best point x_t^b.

where,

$$E_{i,t} = f(x_{i,t}) \tag{9}$$

$$x_t^b = \arg\max f(x_{i,t}) \tag{10}$$

$$E_t^b = f(x_t^b) \tag{11}$$

Step3- The force value must be calculated for each individual of the population in E_t, It is known that each individual of the population has a value of objective function $f(x_{i,t})$ therefore a value the electromagnetic charge ($q_{i,t}$) can be calculated based on the value of its function as:

$$q_{i,t} = \exp\left(-n \frac{E_{i,t} - E_t^b}{\sum_{i=1}^{m} E_{i,t} - E_t^b} \right) \tag{12}$$

Simply the force between two points $x_{i,t}$, $x_{j,t}$ (where i≠j) can be calculated as:

$$F_{i,j}^{t} = \begin{cases} \left(x_{i,t} - x_{j,t}\right) \dfrac{q_{i,t} \bullet q_{j,t}}{\left\| x_{j,t} - x_{i,t} \right\|^{2}}, & \text{if } f\left(x_{i,t}\right) > f\left(x_{j,t}\right) \\ \left(x_{j,t} - x_{i,t}\right) \dfrac{q_{i,t} \bullet q_{j,t}}{\left\| x_{j,t} - x_{i,t} \right\|^{2}}, & \text{if } f\left(x_{i,t}\right) \le f\left(x_{j,t}\right) \end{cases} \tag{13}$$

The total force that affects the point xi,t can be calculated as:

$$F^{T} = \sum_{j=1, i \neq j}^{m} F_{i,j}^{t} \tag{14}$$

In this step, each point $x_{i,t}$ except x_b is moving from its place to another using attraction or repulsion force depending on its charge which is based on objective function value of each other. Hence, the points which have strong charge with a better objective function value will be attracted to each other, and the point $x_{i,t}$ will move to point $a_{i,t}$

$$x_{i,t} = x_{i,t} + \frac{F_{i}^{t}}{F_{i}^{t}} (RNG),\ i = 1, 2, , \ldots ..m \quad i \neq b \tag{15}$$

where, RNG → the range of movement toward the lower or upper bound.

l → the standard uniform distribution with minimum 0 and maximum 1.

Step4- In this step, the algorithm makes local search. After all points are moved from its place except x^b point on search space, the iteration of local search ($iter_{local}$) is generated and each point performs a local search for neighbor points of $a_{i,t}$ and generates its δ neighbor points for selecting a better point $d_{i,t}$ which generates a better objective function more than the current. Then, the local search process will be stopped when the iteration ($iter_{local}$) is finished.

After all these steps, the algorithm goes to next iteration, while the point $x_{i,t}$ becomes either $a_{i,t}$ or $d_{i,t}$ in next iteration (t+1).

III. Image Segmentation Using Improved Emo Method

The effective way for image segmentation is thresholding method. This method is used for classifying the binary level image and multilevel image based on the value of its intensity level (L). This process converts the image into (m×n) pixel. Each pixel carries an intensity level (L) value that can be classified to the class which it belongs.

If the image is grey level, the thresholding method classifies it into two classes R_1, R_2 with only a threshold value (th), hence, if the pixel has an intensity level value > th, it can be classified as the first class R_1 and otherwise classified to second class R_2.

$$\begin{aligned} & R_1 \leftarrow p \quad if \quad 0 < p < th \\ & R_2 \leftarrow p \quad if \quad th < p < L - 1 \end{aligned} \tag{16}$$

For multilayer image, the image is divided into more than two classes, every class has a specific threshold value, Therefore for multilayer image TH=(th_1,th_2,th_3,……….th_{L-1}), the classes are (R_1,R_2,….R_N).

where, N is the number of classes

$$\begin{aligned} & R_1 \leftarrow p \quad if \quad 0 < p < th_1 \\ & R_2 \leftarrow p \quad if \quad p > th_1 \\ & R_3 \leftarrow p \quad if \quad p > th_2 \\ & \ldots\ldots\ldots\ldots. \\ & R_N \leftarrow p \quad if \quad p > th_{N-1} \end{aligned} \tag{17}$$

The problem for both bi-level and multilevel thresholding is to select the *th* values which correctly identify the classes. Otsu's and Kapur's methods are well-known approaches for determining such values. Both methods propose a different objective function which must be maximized in order to find optimal threshold values, just as it is discussed below.

A. Otsu's Method

Otsu method is one of the methods used to segment the image by maximizing variance value σ among classes then calculating the value of objective function as:

$$f\ (th)_{otsu} = \max(\sigma_{b}^{2^{r}}\ (\mathrm{th})) \tag{18}$$

where, $0 \leq \mathrm{th} \leq \mathrm{L} - 1$

The optimization problem is decreased to get a better intensity level (threshold) that maximizes (18). The previous objective function is used for grey level image because it contains one threshold (th). However, equation (18) can be rewritten to be used in the case of RGB images as;

$$f\ (TH)_{otsu} = \max(\sigma_{b}^{2^{r}}\ (\mathrm{TH})) \tag{19}$$

where,

$0 < th_i < \mathrm{L} - 1 = 1, \ldots, \mathrm{k}$

TH=($th_1, th_2, \ldots..th_{k-1}$) and k is number of class

$$\sigma_{B}^{2^{r}} = \sum_{i=1}^{k} \sigma_{i}^{r} \tag{20}$$

$$\sigma_{i}^{r} = w_{i}^{r} (m_{i}^{r} - m_{t}^{r})^{2} \tag{21}$$

where,

i→ refers to a certain class, and k is number of classes

r→ refers to a constant number equal to 1 in grey level image (r=1,2,3 in RGB image)

σ_i^r → refers to the variance among classes R (Otsu´s variance)

m_i^r →refers to the mean of a class

$$\begin{aligned} & m_{0}^{r} = \sum_{i=1}^{th_1} \frac{iph_{i}^{r}}{w_{0}^{r}(th_1)} \\ & m_{1}^{r} = \sum_{i=th_1+1}^{th_2} \frac{iph_{i}^{r}}{w_{1}^{r}(th_2)} \\ & \ldots\ldots. \\ & m_{k-1}^{r} = \sum_{i=th_k+1}^{L} \frac{iph_{i}^{r}}{w_{1}^{r}(th_k)} \end{aligned} \tag{22}$$

where, w_1^r → refers to the probability of occurrence

$$w_{1}^{r}(th) = \sum_{i=1}^{th_1} ph_{i}^{r}$$

$$w_{2}^{r}\left(th\right) = \sum_{i=th_1+1}^{th_2} ph_{i}^{r}$$

…..

$$w_{k-1}^{r}(th) = \sum_{i=th_k+1}^{L} ph_i^{r} \tag{23}$$

where, that ph_i^r is the probability distribution of the intensity level values which can be calculated as:

$$ph_i^{r} = \frac{h_i^{r}}{N}, \mathrm{r} = \begin{cases} 1 & in \;\; grey\, image \\ 1,2,3 & in \;\; RGBimage \end{cases} \tag{24}$$

where,

$$\sum_{i=1}^{N} ph_i^{r} = 1 \tag{25}$$

h_i^r are histogram distribution values which indicate the number of pixels corresponding to the i intensity level, N is total number of pixel in the image.

Electromagnetism optimization is used to find the optimal decision variable which is considered in the segmentation problem as threshold (TH)[20] as:

Maximize $f\ (TH)_{ostu}$

Subject to TH ∈ x , TH = $(th_1, th_2, \ldots . th_k)$

where, $0 < th_i < 255$ this is lower and upper bounded of threshold i=1,..,k and here k refers to different thresholds (TH).

B. Kapur Method

Another nonparametric method that is used to determine the optimal threshold values has been proposed by Kapur [15]. It is based on the entropy and the probability distribution of the image histogram. This method aims to find the optimal *th* which maximizes the overall entropy. The entropy of an image measures the compactness and separability among classes. In this sense when the optimal *th* value appropriately separates the classes, the entropy has the maximum value. For the bi-level example the objective function of the Kapur's problem can be defined as:

$$f_{kapur}(th) = H_1^{c} + H_2^{c}, c = \begin{cases} 1,2,3 & if \;\; RGB\ image \\ 1 & if \;\; grey\, image \end{cases} \tag{26}$$

where, the entropies H_1 and H_2 are computed by the following model:

$$H_1^{C} = \sum_{i=1}^{th_1} \frac{ph_i^{c}}{w_0^{c}} \ln\left(\frac{ph_i^{c}}{w_0^{c}}\right), \quad H_2^{C} = \sum_{i=th+1}^{L} \frac{ph_i^{c}}{w_1^{c}} \ln\left(\frac{ph_i^{c}}{w_1^{c}}\right) \tag{27}$$

where, ph_i^c is the probability distribution of the intensity levels which is obtained using (24). w_0^c and w_1^c are probabilities distributions for C_1 and C_2, respectively. Similar to the Otsu's method, the entropy-based approach can be extended for multiple threshold values, for such a case it is necessary to divide the image into *k* classes using the similar number of thresholds. Under such conditions, the new objective function is defined as:

$$f_{kapur}(TH) = \sum_{i=1}^{k} H_i^{c}, \quad c = \begin{cases} 1,2,3 & if \;\; RGB\ Image \\ 1 & if \;\; grey\ Image \end{cases} \tag{28}$$

where,

$$\begin{aligned} H_1^{C} &= \sum_{i=1}^{th_1} \frac{ph_i^{c}}{w_0^{c}} \ln\left(\frac{ph_i^{c}}{w_0^{c}}\right) \\ H_2^{C} &= \sum_{i=th_1+1}^{th_2} \frac{ph_i^{c}}{w_1^{c}} \ln\left(\frac{ph_i^{c}}{w_1^{c}}\right) \\ &\ldots\ldots\ldots\ldots\ldots \\ H_k^{C} &= \sum_{i=th_k+1}^{L} \frac{ph_i^{c}}{w_{k-1}^{c}} \ln\left(\frac{ph_i^{c}}{w_{k-1}^{c}}\right) \end{aligned} \tag{29}$$

The solution process of image segmentation using the developed optimization algorithm can be shown in Fig. 1.

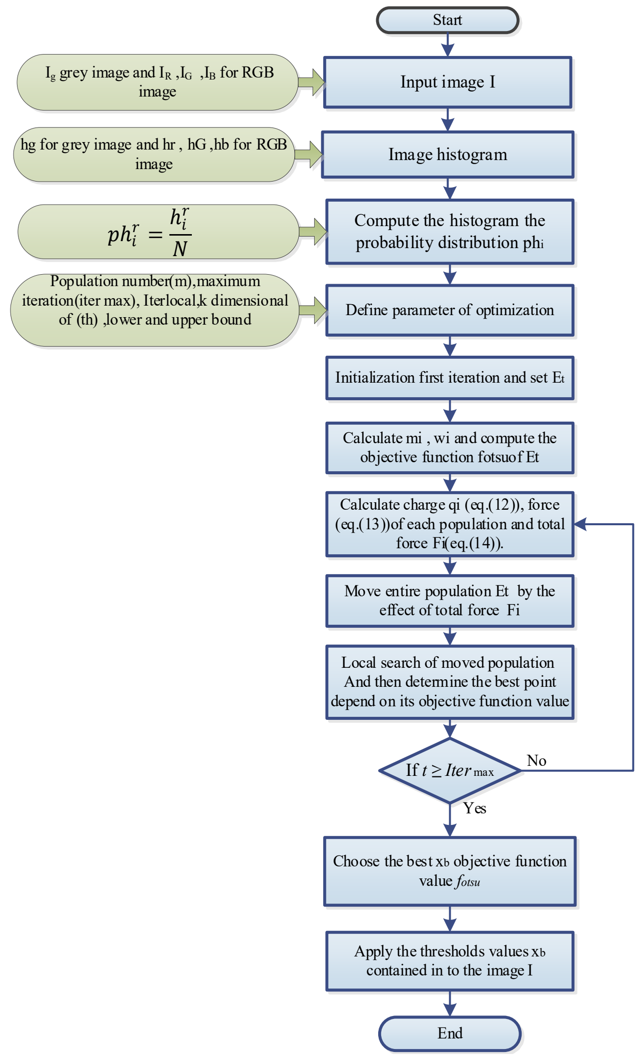


Fig. 1. Flowchart of the proposed method for image segmentation.

IV. Results and Discussion

In this section, different test images are used to validate the proposed EMO with levy algorithm

A. Standard Test Images

In this section, three test images; Baboon, Peppers, and Camera Man, are used to check the effectiveness of the optimization algorithm. These images are taken from USC-SIPI image database which are of size 512 ×512 each [36].

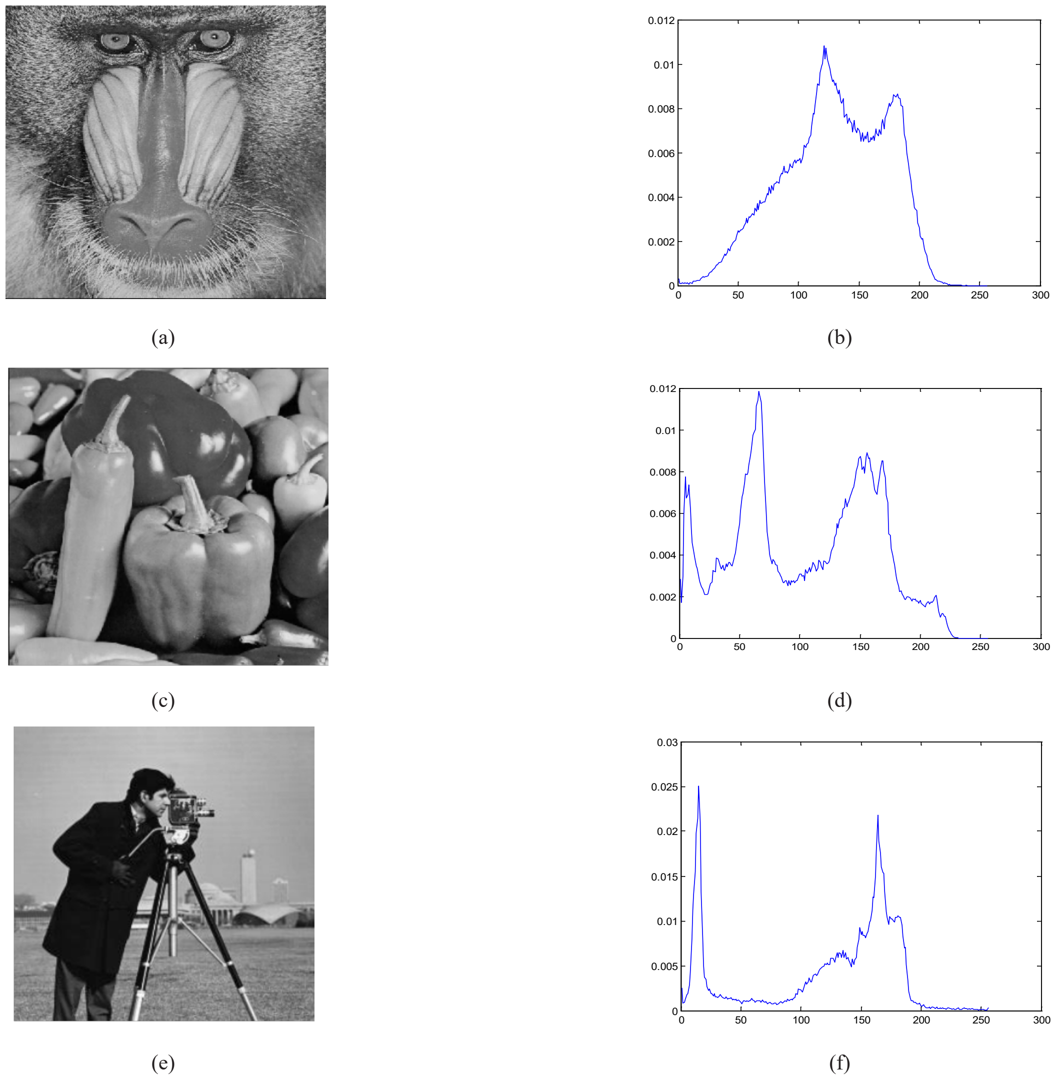


Fig. 2. Benchmark test images: (a) Baboon, (c) pepper, (e) Cameraman, (b), (d), (f) histogram of these images, respectively.

Fig. 2 indicates these test images and their histogram distributions which refer to the number of pixels in the images at each different intensity value found in these images.

The performance of proposed EMO with levy algorithm based multilevel thresholding is compared with some well-known optimization algorithms such as; CS [31, 32], MFO [18], WOA [18], SCA [33, 34]. All algorithms have been tested with the same condition of stop criterion;100 iterations and 25 population. At the end of each test, the Peak Signal-to-Noise Ratio (PSNR) is computed as:

$$PSNR = 20\log_{10}\left(\frac{255}{RMSE}\right) \tag{30}$$

The PSNR is an important value which measures the accuracy of a segment image comparing with the original image.

where, RMSE is the root mean square error, which can be calculated as:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{ro}\sum_{j=1}^{co}\left(I_0^r(i,j)-I_{th}^r(i,j)\right)}{ro \times co}} \tag{31}$$

where, ro is the total number of rows of an image, co is the total number of column of the image, r is depending on the type of image (RGB image r=1,2,3), I_{th}^r refers to the segmented image, I_o^r refers to the original image.

In each experiment the stop criteria is set to 100 iterations. In order to verify the stability at the end of each test the standard deviation (STD) is obtained (Eq. (32)). If the STD value increases the algorithms becomes more instable.

$$STD = \sqrt{\sum_{i=1}^{iter_{max}}\frac{(s_i - m)}{Ru}} \tag{32}$$

Table I indicates the parameters of EMO with Levy function (EMO.levy). The maximum number of iterations is taken as 100, this parameter represents the stop criterion of the optimization process. However, which the stop criterion is taken as the number of times in which the best fitness values remains without change. $Iter_{local}$=100 is the number of times that the algorithm do local search with 25 population at every external iteration.

TABLE I. Parameters of Emo With Levy

Itermax	Iterlocal	d	M(population)
100	10	0.025	25

TABLE II. Results After Applying the Emo with Levy Using Otsu´S Function

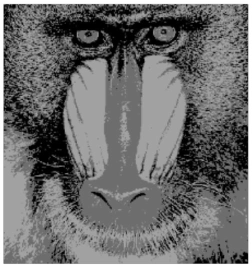
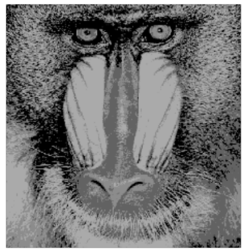
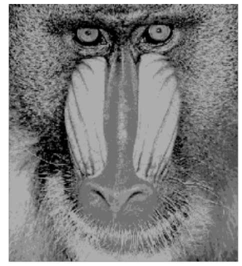
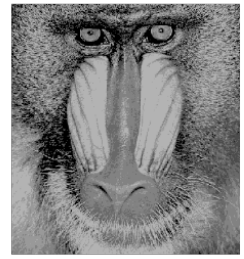
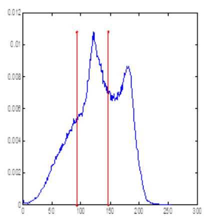
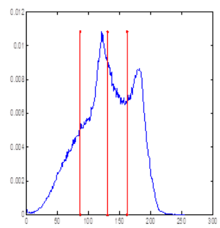
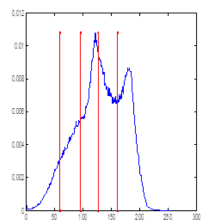
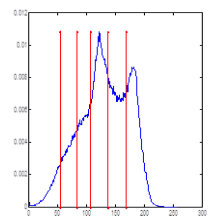
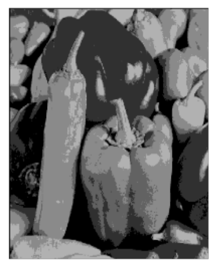
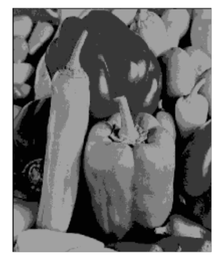
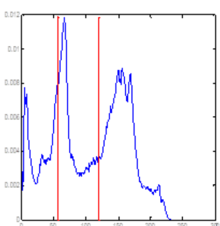
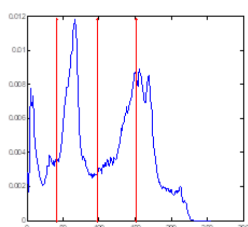
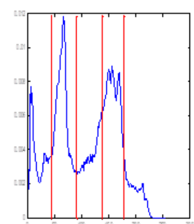
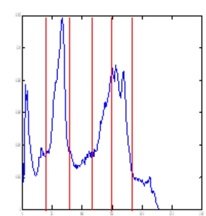
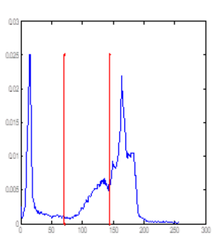
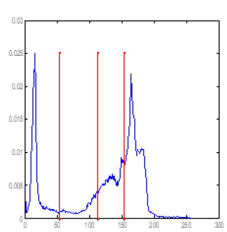
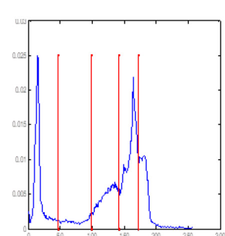
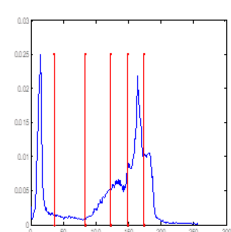
TH=2	TH=3	TH=4	TH=5
			
			
			
			
			
			

TABLE III .The Best Fitness Value Obtained from all Algorithms for Test Image

Image	K	EMO.levy	EMO	CS	SCA	MFO	WOA
Baboon	2	1552.5	1550.2	1552.5	1455.2	1538.81	1545.92
	3	1644.7	1645	1645	1527.8	1592.98	1635.7
	4	1699.4	1691	1699.5	1663.4	1647.93	1669.83
	5	1725.6	1720	1725.8	1628.2	1705.93	1682.48
pepper	2	2858.5	2857.5	2861.1	2324.5	2435.5	2433.36
	3	3059.9	3059.8	3059.9	2550.4	2574.7	2493.18
	4	3145.7	3144.8	3145.7	2537.9	2647.67	2632.9
	5	3189.8	3189.4	3189.7	2603.8	2669.47	2682.01
Cameraman	2	3646.6	3646.5	3643.6	3515.8	3643.31	3649.36
	3	3721.8	3721	3718.7	3680.5	3720.25	3690.11
	4	3778.2	3777.4	3774.5	3749.18	3748.75	3760.5
	5	3809.4	3809.4	3805.7	3718.18	3758.72	3795.86

TABLE IV. The Best Threshold Values Obtained from All Algorithms for the Test Image

Image	k	EMO with levy	EMO	CS	MFO	WOA	SCA
Baboon	2	97,149	93,147	97,149	111,133	83,151	103,150
	3	86,126,162	85,124,160	84,123,160	74,137,168	27,83,144	81,112,145
	4	71,105,136,167	60,96,127,161	71,106,137,168	44,84,133,173	96,109,134,152	61,82,128,164
	5	64,95,121,146,173	54, 83,107,137,168	68,100,125,149,174	46,94,158,189,219	32,77,101,148,207	75,99,140,159,188
pepper	2	82,143	56,120	49,116	100,182	56,152	66,143
	3	43,99,153	43,100,154	43,99,153	92,124,161	72,119,165	59,127,163
	4	41,89,135,175	43,91,138,178	41,89,135,175	41,139,157,187	47,74,132,155	68,94,136,167
	5	39,81,119,151,183	39,79,116,149,183	39,80,118,150,183	59,81,121,165,207	29,85,97,133,157	38,81,125,181,183
Camera man	2	70,144	71,144	70,144	96,167	94,146	86,145
	3	57,117,155	53,112,153	59,119,156	65,155,197	59,143,208	73,151,196
	4	41,94,140,170	47,99,142,172	41,94,140,170	59,117,133,203	77,135,200,222	76,126,166,188
	5	36,83,122,149,173	36,83,122,149,173	37,84,123,150,174	47,85,110,173,210	3,53,111,166,184	80,126,171,202,207

TABLE V. The Average of the Psnr Measure of All Algorithms

Image	K	EMO	EMO .levy	CS	MFO	WOA	SCA
Baboon	2	15.4129	15.6662	15.4129	15.8636	16.0311	15.2642
	3	17.6283	17.7558	17.8713	18.5521	18.3643	16.6058
	4	20.2143	20.9297	20.3029	20.0673	20.4056	17.5951
	5	21.9684	22.5824	21.4839	22.6505	20.2745	18.0885
Pepper	2	15.5245	16.4296	16.2354	16.6278	16.2716	14.2092
	3	18.8675	18.8469	18.8675	18.1623	18.0953	16.466
	4	20.4503	20.4749	20.4503	20.63	19.7982	16.9392
	5	21.8329	21.8597	21.855	21.4056	21.608	19.5709
camera man	2	17.253	17.3213	17.253	17.3744	18.2862	15.8362
	3	20.2116	20.2304	20.1796	20.0161	19.9084	18.0557
	4	21.4177	21.625	21.4177	21.9564	21.1897	20.219
	5	23.2749	23.2749	23.2735	21.6302	22.1592	18.6505

TABLE VI. CPU Time for All Algorithms (Per Second)

image	k	EMO.levy	EMO	CS	WOA	MFO	SCA
Baboon	2	9.34	10.39	11.67	12.55	12.88	12.97
	3	12.19	13.96	14.67	15.40	16.06	16.98
	4	14.53	18.82	19.31	20.01	21.55	22.89
	5	16.01	19.66	20.39	21.83	22.09	22.77
Pepper	2	9.67	10.31	12.31	13.95	14.33	14.87
	3	12.16	14.47	15.48	15.78	16.09	16.59
	4	14.78	16.26	17.45	18.66	19.23	20.01
	5	16.38	18.43	19.85	20.28	21.91	22.01
Camera man	2	5.34	7.53	10.32	11.03	12.22	12.83
	3	8.90	10.95	12.36	13.02	13.89	14.66
	4	12.29	14.39	16.23	17.15	17.87	18.32
	5	16.26	18.29	19.43	20.33	20.85	21.22

TABLE VII. Comparison Between Otsu And Kapur Thresholding Methods

		Otsu method			Kapur method		
Image	**K**	**Threshold**	**STD**	**PSNR**	**Threshold**	**STD**	**PSNR**
Baboon	**2**	97,149	6.92 E-13	15.6662	79, 144	1.08 E-14	15.016
	3	86,126,162	7.66 E-01	17.7558	79, 143, 232	3.60 E-15	16.018
	4	71,105,136,167	2.65 E-02	20.9297	44, 98, 152, 231	2.10 E-03	18.485
	5	64,95,121,146,173	4.86 E-02	22.5824	33, 74, 115, 159, 231	1.08 E-14	20.507
Pepper	**2**	82,143	1.38 E-12	16.4296	67, 143	7.21 E-15	16.265
	3	43,99,153	4.61 E-13	18.8469	62, 112, 162	2.80 E-03	18.367
	4	41,89,135,175	4.61 E-13	20.4749	62, 112, 162, 227	1.28 E-01	18.754
	5	39,81,119,151,183	2.33 E-02	21.8597	48, 86, 127, 171, 227	1.37 E-01	20.643
Camera man	**2**	70,144	1.40 E-12	17.3213	128, 196	3.60 E-15	13.626
	3	57,117,155	3.07 E-01	20.2304	97, 146, 196	4.91 E-02	18.803
	4	41,94,140,170	8.40 E-03	21.625	44, 96, 146, 196	1.08 E-14	20.586
	5	36,83,122,149,173	2.12 E+00	23.2749	24, 60, 98, 146, 196	6.35 E-02	20.661

TABLE VIII. Proposed Algorithm For Low Contrast Images

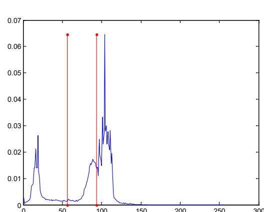
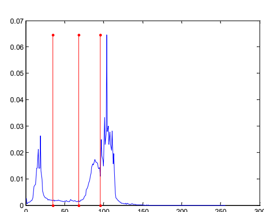
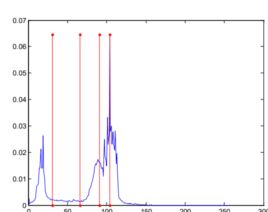
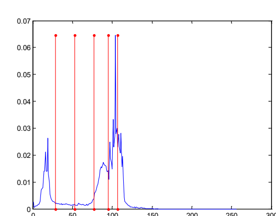
Th=2	Th=3	Th=4	Th=5
			
			

TABLE IX. Proposed Algorithm for High Contrast Images

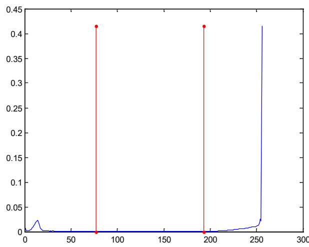
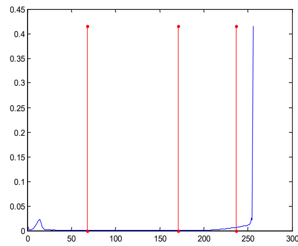
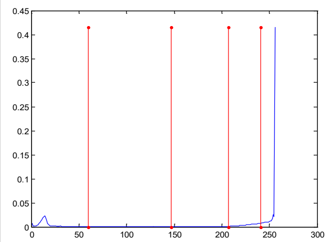
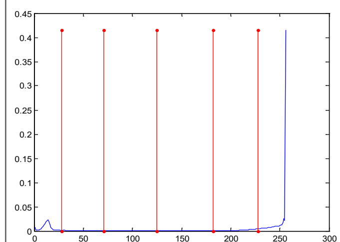
Th=2	Th=3	Th=4	Th=5
			
			

Table II shows the results of segmented images after applied four optimal thresholds TH= {2,3,4,5} based on Otsu's objective function.

Table III and Table IV show the result of the best fitness function and threshold values of three images obtained by all algorithms using Otsu's function.

From Table III, it can be observed that the proposed algorithm (EMO.levy) has a better fitness value than other algorithms when TH={2,3,4,5} .

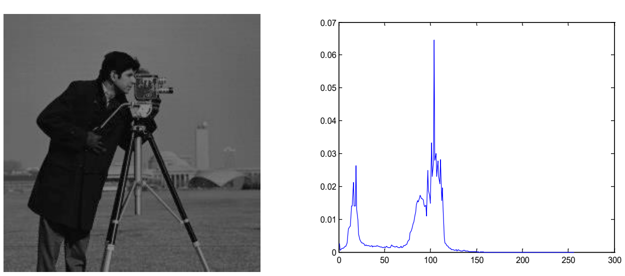
Table V shows that the proposed algorithm has mostly the highest values for PSNR compared to other multilevel algorithms (EMO, CS, MFO, WOA, SCA) also note whenever the number of threshold values increases, PSNR value also is increased for all algorithms.

Table VI presents the CPU time for all algorithms when applied on multilevel thresholding problem Experiments were conducted on MATLAB R2014 a running on an Intel®CoreTM i5 PC with 2.50 GHz CPU and 8 GB RAM. From this table, it can be observed that the developed algorithm gives low CPU time compared with the traditional EMO and CS algorithm.

Two multilevel thresholding-based segmentation methods; Otsu and Kapur are compared in Table VII. From this table, it can be observed that the Otsu thresholding method generates segmented images with high accuracy and higher values of PSNR and STD compared with Kapur method.

B. Low and High Contrast Test Image

In order to validate the effectiveness of the proposed algorithm, high and low contrast are applied to benchmark camera man image [36].

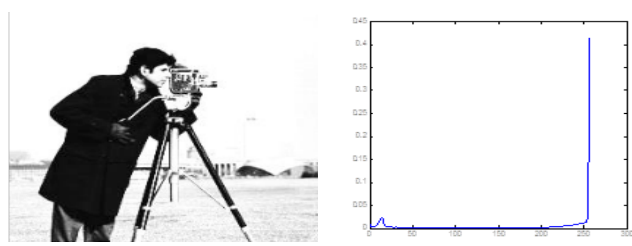


(a) (b)

Fig. 3. Low contrast camera man image and its histogram.

TABLE X. Result of Low Contrast Images

Comparison of Fitness values between algorithms				
Image	K	EMO.levy	EMO	CS
Cameraman	2	1.1517e+03	1.1516e+03	1.1516e+03
	3	1.1806e+03	1.1802e+03	1.1804e+03
	4	1.1922e+03	1.1923e+03	1.1922e+03
	5	1.1989e+03	1.1966e+03	1.1984e+03
Comparison of thresholds values between algorithms				
Image	k	EMO.levy	EMO	CS
Cameraman	2	52 ,95	52,94	52,93
	3	35,68,96	34,69, 96	34,67,96
	4	31,66,91,104	34,68,93,106	34,68,92 106
	5	29,53,77,95,107	33,67,92,104,118	32,65,87,98,109
Comparison of PSNR values between algorithms				
Image	K	EMO.levy	EMO	CS
Cameraman	2	21.4769	21.3387	21.4768
	3	24.5621	24.4175	24.5621
	4	25.6215	25.5492	25.6210
	5	27.3095	25.7825	26.8439



(a) (b)

Fig. 4. High contrast camera man image and its histogram.

TABLE XI. Result Of High Contrast Images

Comparison of Fitness values between algorithms				
Image	K	EMO.levy	EMO	CS
Camera man	2	9.2645e+03	9.2646e+03	8.6620e+03
	3	9.3622e+03	9.3622e+03	8.7206e+03
	4	9.4934e+03	9.4028e+03	8.7585e+03
	5	9.4170e+03	9.4012e+03	8.7738e+03
Comparison of PSNR values between algorithms				
Image	k	EMO.levy	EMO	CS
Camera man	2	18.9340	13.9395	12.8589
	3	19.6216	19.5743	19.2122
	4	22.3761	21.3739	20.8283
	5	22.7940	22.0383	22.4284
Comparison of thresholds values between algorithms				
Image	K	EMO.levy	EMO	CS
Camera man	2	77,193	78,193	73,184
	3	68,171,237	68,169,236	66,163,228
	4	60,147,207,241	42,108,185,238	41,106,180,232
	5	28,71,125,182,228	39,100,169,218,244	37,93,154,204,236

Tables VIII, shows the proposed algorithm for low contrast images, when (th=2,3,4,5). Table IX, shows the proposed algorithm for high contrast images, (th=2,3,4,5). Table X, shows a comparative study between the proposed algorithm and other algorithms in case of low contrast images. Table XI, shows a comparative study between the proposed algorithm and other algorithms in case of high contrast images. Fig. 3 depicts the low contrast camera man image and its histogram. Fig. 4 depicts the high contrast camera man image and its histogram. From Fig. 3, 4 and Table VIII, IX, X, XI, it can be observed that the proposed algorithm still keeps with better performance compared to the other algorithms in terms of threshold, PSNR and fitness.

From the obtained results, the proposed algorithm has a powerful computational, outperforms, high converges speed, consuming less time and saves energy to perform the computational tasks. The drawback of the proposed algorithm is that the threshold and fitness function values are not usually the best for the studied cases.

V. Outstanding Features of Proposed Algorithm

In this section, the main features of the proposed optimization algorithm (EMO.levy) are summarized as follows:

- Based on the obtained results, the proposed algorithm gives the highest values for PSNR in the most studied cases compared to other algorithms (EMO, CS, MFO, WOA, and SCA) as presented in Table V.
- The proposed algorithm (EMO.levy) gives the best fitness values in the most cases compared with the other optimization algorithms when TH={2, 3, 4, 5} as presented in Table III.
- The computation time of the proposed algorithm is lower than those obtained by the other optimization techniques as presented in Table VI.
- The reliability of the proposed algorithm has been proved using different high and low contrast images.

However, the proposed optimization algorithm has a distinguished performance in the most studied cases compared with other well-known optimization algorithms. In a few cases, the PSNR and fitness values of the proposed algorithm are little bit worse than those obtained by the other optimization techniques.

VI. Conclusion

In this paper, we have proposed an improved version for electromagnetism optimization based on levy function for multilevel thresholding of image segmentation. The aim of this algorithm is to determine the best threshold values that segment the tested image accurately, producing better results compared with the original EMO version. The peak signal-to-noise ratio (PSNR) value has been used to measure the segmentation quality and similarity between original image and segmented image. The PSNR measure proved the efficiency of the algorithm compared with the other algorithms. From the experimental results of the proposed algorithm comparing with original EMO, CS, SCA, MFO and WOA algorithms, the developed algorithm has good performance regarding to the fitness function and PSNR in all images.

The future work will focus on applying the proposed optimization algorithm for higher numbers of thresholds, solving dynamic multilevel thresholding and multi-objective problems. In addition, recent optimization techniques will be applied to in order to attain better segmentation results.

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