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Multilevel thresholding for image segmentation using Krill Herd Optimization algorithm

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ABSTRACT

In this paper a novel multilevel thresholding algorithm using a meta-heuristic Krill Herd Optimization (KHO) algorithm has been proposed for solving the image segmentation problem. The optimum threshold values are determined by the maximization of Kapur's or Otsu's objective function using Krill Herd Optimization technique. The proposed method reduces the computational time for computing the optimum thresholds for multilevel thresholding. The applicability and computational efficiency of the Krill Herd Optimization based multilevel thresholding is demonstrated using various benchmark images. A detailed comparative analysis with other existing bio-inspired techniques based multilevel thresholding techniques such as Bacterial Foraging (BF), Particle Swarm Optimization (PSO), Genetic Algorithm (GA) and Moth-Flame Optimization (MFO) has been performed to prove the superior performance of the proposed method.

1. Introduction

Image segmentation is considered to be the first and basic operation to analyze and interpret the acquired image in various computer vision applications such as autonomous target recognition, medical imaging, robotic vision, geographical imaging, etc. In general, *Image-Segmentation* is defined as the partitioning of an image into foreground and background with respect to some features such as gray level values or textures. Most of the image segmentation methods are based on two basic characteristics of intensity values namely, similarity and discontinuity. The technique of similarity is widely used which utilizes the similarity among the image objects with a pre-defined criteria for partitioning. Thresholding, region growing, region splitting and merging are the major techniques under similarity based approaches. While considering all existing segmentation methods, thresholding holds the prime position in terms of accuracy, simplicity and robustness. Thresholding based segmentation subdivides an image into smaller segments, using at least one gray level value to define their boundary. Gray level histograms of all real world images are multi-modal and so it is difficult to choose the threshold values by selecting a value in the valley between the histogram peaks. Further researches are going on in this field worldwide since it is more complex than a *bi-model* gray level histogram.

Many thresholding based segmentation techniques have been reported in the literature over the past few years. As part of a survey M. Sezgin et al. (Sezgin and Sankur, 2004) found that global histogram based techniques are being commonly used to determine the threshold in multilevel thresholding. Among the tremendous amount of image thresholding techniques, Otsu's method which works on the principle of between-class variance (Otsu, 1979) and Kapur's method which works on the principle of entropy (Kapur et al., 1985) are proved to be two best thresholding methods. Otsu's and Kapur's methods find the optimum thresholds that divide the region of gray level values of an image in an optimum manner in terms of some predefined criteria. In order to choose the optimal threshold values, maximization of between class variance of gray levels of histogram is used in Otsu's method where as maximization of the histogram entropy is used in Kapur's method. Conventional Otsu's and Kapur's method are proposed for solving *bi-level* thresholding problem. Both the methods suffer a serious drawback of exponential growth in time complexity and hence cannot be practically extended to multilevel thresholding problem. Many methods have been reported in the literature to improve the efficiency and reduce the time complexity of multilevel

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thresholding methods. Recursive algorithms (Liao et al., 2001; Yin and Chen, 1993; Yin and Chen, 1997) reduce the long processing time to determine the optimum threshold values with the help of a look up table. But when the number of threshold increases the method will again suffer long computational time (Song et al., 2017).

In order to overcome the above problems, bio-inspired computing paradigms have been utilized for multilevel thresholding. Evolutionary algorithms such as Genetic algorithms (GA) (Yin and Peng-Yeng, 1999; Lai and Tseng, 2004), ant colony optimization (Ye et al., 2006), honey bee optimization (Horng et al., 2009), particle swam optimization (PSO) (Maitra and Chatterjee, 2008; Shi and Eberhart, 1998; Gao et al., 2010) and bacterial foraging algorithm (BF) (Sathya and Kayalvizhi, 2011) are effectively used in the domain of image segmentation based on multilevel. Among these algorithms, GA, PSO and BF are the most prominent. Genetic algorithms are inspired by the evolutionary ideas of natural selection which finds the optimal thresholds effectively**.** But, recent researches (Fogel, 2000) showed genetic algorithm have a tendency to converge towards local optima rather than the global optimum value of the problem which results misclassification of objects in segmented image. On the other hand, PSO showed a few dissatisfactory problems such as the inability to find global optimization value, low convergence speed and so on**.** Recently P. D. Sathya et al. (Sathya and Kayalvizhi, 2011) proposed bacterial foraging based optimum multilevel thresholding, motivated by the foraging behavior of the E. Coli bacteria present in human intestine. BF algorithm is simple and straight forward and it provides good performance based on the quality of the solution and the fastness of the convergence than the other existing multilevel thresholding methods. But the robustness and efficiency of the BF algorithm depends on the chemo taxis step size; large step size helps bacteria to find optimum position faster but not ensure the global optimum. On the other hand small chemo taxis step size guarantees that bacteria will find global optimum but it requires large processing time. A few state-of-the-art methods have been reported in the literature for multilevel thresholding based on bio-inspired computing paradigm such as Improved Bat Algorithm (Alihodzic, 2014), Honey Bee Mating optimization (Horng, 2010), Artificial Bee Colony algorithm (Horng, 2011) and Firefly Algorithm (MTF) (Horng and Liou, 2011). Uroš Mlakar et al. (2016) proposed an optimal multilevel image thresholding using a hybrid differential evolution technique. Multilevel image thresholding using honey-bee-mating method has been proposed by Yunzhi et. al. (Jiang et al., 2017). In 2017, Nipotepat et al. (Muangkote et al., 2017) proposed a multilevel thresholding technique using differential evolution algorithm. Recently, a bio-inspired algorithm for multilevel image thresholding based on whale optimization algorithm and moth-flame optimization has been proposed by Mohamed Abd El Aziz et al. (2017). Though the above methods perform satisfactorily, achieving best values for the objective function, the computational cost incurred is high.

In this paper we present a new method to solve multilevel thresholding using a bio-inspired computing paradigm such as Krill Herding Optimization (KHO) algorithm. Krill Herd Optimization algorithm, introduced by Amir Hossein Gandomi et al. (Gandomi and Alavi, 2012), is one of the novel swarm intelligent techniques based on the simulation of the aggregation behavior of Krill individual. KHO algorithm has better convergence speed as compared to existing bio-inspired optimization techniques. The proposed method maximizes the Otsu's or Kapur's objective function using KHO algorithm in order to find the optimal values for the thresholds for multilevel image segmentation. After getting the thresholds the given image is subdivided into smaller segment based on the threshold obtained using KHO based multilevel thresholding method.

Detailed description related to the implementation and theoretical aspects of the proposed method is provided in the later sections. The rest of the paper is structured as follows: a brief review of Kapur's and Otsu's method is presented in Section 2. Section 3 highlights KHO algorithm and Section 4 illustrates the application of Krill Herd Optimization algorithm for multilevel thresholding problem. Experimental analysis and results are discussed in Section 5 and conclusions are drawn in Section 6.

2. Optimum multilevel thresholding

The objective of an optimization problem is to find the variable values that optimizes an objective/fitness function and at the same time satisfies the constraints. In this paper, the objective functions for the KHO algorithm for multilevel thresholding has been designed based on entropy criterion and also based on between-class variance.

2.1. Kapur's entropy criterion method

Kapur's entropy criterion method finds the optimal values for the thresholds based on the maximization of entropy (Kapur et al., 1985).

Let L be the number of gray levels in a given image so that the intensity values are in the range [0, L-1]. We can then define Y_j = b(j)/M, where b(j) denotes the number of pixels with gray level value j and M represents the total number of pixels in the image. Here the aim is to maximize the objective function

$$\mathrm{f}(\mathrm{t}) = E_0 + E_1 \tag{1}$$

where

$$E_0 = -\sum_{j=0}^{t-1} \frac{Y_j}{\omega_0} In \frac{Y_j}{\omega_0}, \quad \omega_0 = \sum_{j=0}^{t-1} Y_j \tag{2}$$

$$E_1 = -\sum_{j=t}^{L-1} \frac{Y_j}{\omega_1} In \frac{Y_j}{\omega_1} \quad \omega_1 = \sum_{j=t}^{L-1} Y_j \tag{3}$$

The above method can also be extended to multilevel thresholding problem, which is defined as follows: The objective here is to find n optimal thresholds $[t_1, t_2, \ldots . t_n]$ which maximizes the following objective function.

$$f(\mathrm{t}_1, \mathrm{t}_2, \mathrm{t}_3 \ldots \ldots \mathrm{t}_n) = \mathrm{E}_0 + \mathrm{E}_1 + \mathrm{E}_2 + \ldots \mathrm{E}_n \tag{4}$$

where,

$$E_0 = -\sum_{j=0}^{t_1-1} \frac{Y_j}{\omega_0} In \frac{Y_j}{\omega_0} \quad \omega_0 = \sum_{j=0}^{t_1-1} Y_j \tag{5}$$

$$E_1 = -\sum_{j=t_1}^{t_2-1} \frac{Y_j}{\omega_1} In \frac{Y_j}{\omega_1} \quad \omega_1 = \sum_{i=t_1}^{t_2-1} Y_j \tag{6}$$

$$E_2 = -\sum_{j=t_2}^{t_3-1} \frac{Y_j}{\omega_2} In \frac{Y_j}{\omega_2} \quad \omega_2 = \sum_{j=t_2}^{t_3-1} Y_j \tag{7}$$

$$E_n = -\sum_{j=t_n}^{L-1} \frac{Y_j}{\omega_n} In \frac{Y_j}{\omega_n} \quad \omega_n = \sum_{j=t_n}^{L-1} Y_j \tag{8}$$

2.2. Otsu's between-class variance method

Otsu's between-class variance method (Otsu, 1979) finds the optimal threshold values based on the between-class variance

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maximization. Otsu's method can then be defined as maximizing the following objective function.

$$\mathrm{f(t)} = \varphi_0 + \varphi_1 \tag{9}$$

where,

$$\varphi_0 = \omega_0(\infty_0 - \mu_T)^2, \quad \infty_0 = \sum_{j=0}^{t-1} \frac{jY_j}{\omega_0(t)} \tag{10}$$

$$\varphi_1 = \omega_1(\infty_1 - \mu_T)^2, \quad \infty_1 = \sum_{j=t}^{L-1} \frac{jY_j}{\omega_1(t)} \tag{11}$$

Global intensity mean, $\mu_T = \omega_0\infty_0 + \omega_1\infty_1$where,

$$\omega_0 + \omega_1 = 1 \tag{12}$$

and

$$\omega_0 = \sum_{j=0}^{t-1} Y_j \tag{13}$$

$$\omega_1 = \sum_{j=t}^{L-1} Y_j \tag{14}$$

The above method can also be extended to multilevel thresholding problem, which is defined as follows: Maximize Otsu's Objective function

$$\mathrm{f(t)} = \varphi_0 + \varphi_1 \ldots\ldots + \varphi_\mathrm{n} \tag{15}$$

where,

$$\varphi_0 = \omega_0(\infty_0 - \mu_T)^2 \tag{16}$$

$$\varphi_1 = \omega_1(\infty_1 - \mu_T)^2 \tag{17}$$

$$\varphi_n = \omega_n(\infty_n - \mu_T)^2 \tag{18}$$

As the number of thresholds n increases, Exhaustive search for n + 1 segments will result in exponential growth in computational time. Therefore, Otsu's and Kapur's methods are unsuitable choice for the real world multilevel image segmentation applications. To overcome the above drawback a new Kapur's or Otsu based Krill Herd Optimization (KHO) algorithm is proposed here as a solution for multilevel thresholding problem. The goal of the proposed method is that within the limited computational time find the optimal thresholds for segmenting the image by maximizing Kapur's or Otsu's objective function.

3. Krill Herd Optimization (KHO) algorithm

KHO algorithm (Gandomi and Alavi, 2012) is one of the new swarm intelligent optimization technique based on the simulation of the Krill (*Euphausia superba*) individual herding behavior in response to environmental and biological processes. KHO algorithm simulates the behavior of Krill where each individual of the krill herd will make its own contribution in the moving process depending upon its fitness It also depends on whether the adjacent krill individual possess either an attractive or repulsive effect on each other, acting as a local search for each one. The overall fitness of the krill individuals leads to the identification of the food center which is considered as the best global estimation. KHO algorithm is based on the Lagrangian and the evolutionary behavior of the krill individuals with the ability to do both exploration and exploitation in optimization problem simultaneously. Since random values plays a major role in this algorithm, coupling with an adaptive technique changes the positions of the current solution towards best solution, thus leading to better convergence speed as compared to other bio inspired optimization technique. Another remarkable advantage is that less number of parameters is needed to create krill behavior for finding global best in KHO algorithm as shown in Table 9.

The time-dependent location of an individual krill can be computed based on the following three actions: Krill individual movement induction (Nk_i), foraging activity (Fk_i), and random diffusion (Dk_i).

A d-dimensional search space Lagrangian model has been adopted by the Krill Herd Optimization algorithm (Hofmann et al., 2004)

$$\frac{\mathrm{dX_i}}{\mathrm{dt}} = \mathrm{Nk_i + Fk_i + Dk_i} \tag{19}$$

The algorithm of the Krill Herd Optimization is as follows:

Step 1 Initialize parameters I_{max} (maximum number of iteration), N^{max} (maximum induced speed),V_f (maximum foraging speed), D^{max} (maximum diffusion speed), n (number of Krill) and X (position of Krill).
Step 2 Repeat the Step 3 to Step 7 for i = 1 to I_{max}
Step 3 For each Krill calculate movement
Step 4 Movement due to other Krill individuals

Communal effects among the krill individuals lead to the movement since they always attempt to preserve a high density. Motion induction direction denoted by α_i is estimated from the local target and a repulsive swarm density.

$$\mathrm{Nk_i^{new}} = \mathrm{N^{max}}\phi_\mathrm{i} + \omega_\mathrm{n}\mathrm{Nk_i^{old}} \tag{20}$$

ω_n is the inertia weight associated with the motion induced and has a value in the range [0,1]. Nk_i^{old} represents the last motion induced.

Step 4.1

$$\phi_i = \phi_i^{local} + \phi_i^{target} \tag{21}$$

Step 4.1.1 The neighbors provides a local effect denoted by ϕ_i^{local} and it can be defined as follows:

$$\phi_i^{local} = \sum_{j=1}^{Nn} \widehat{K}_{i,j}\widehat{X}_{i,j} \tag{22}$$

where,

$$\widehat{X}_{i,j} = \frac{X_j - X_i}{||X_j - X_i|| + z} \tag{23}$$

$$\widehat{K}_{i,j} = \frac{K_i - K_j}{K^{worst} - K^{best}} \tag{24}$$

K^{worst} and K^{best} are the best and worst Krill individuals' fitness values,K_i is the i^{th} Krill individual's fitness, K_j is the j^{th} neighbor's fitness, z is a small positive number to avoid singularities, and N_n represents the number of neighbors .

Step 4.1.2 Effect of target direction denoted by ϕ_i^{target} is provided by the best Krill individual and is determined as follows

$$\phi_i^{target} = C^{best}\widehat{K}_{i,best}\widehat{X}_{i,best} \tag{25}$$

Krill individual effective coefficient with best fitness to i^{th} $k$rill individual denoted by C^{best} is given by,

$$C^{best} = 2(rand + \frac{I}{I_{max}}) \tag{26}$$

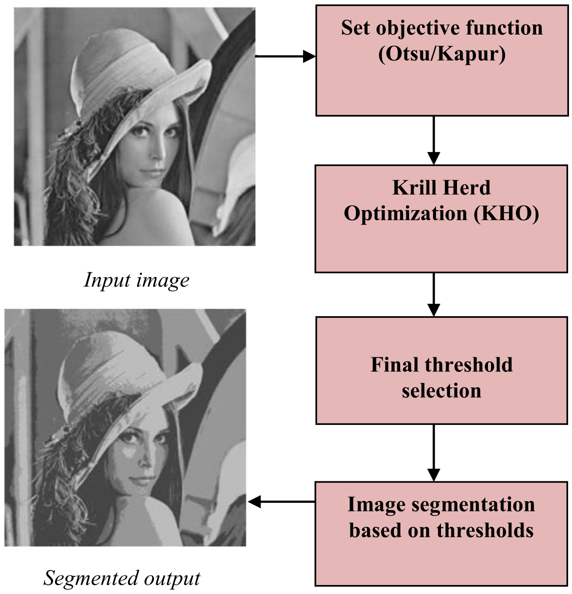

Fig. 1. Block diagram of KHO based image segmentation.

I represent the actual iteration number, *rand* represent a random value between 0 and 1.

Step 4.2 Compute sensing distance

$$d_{s,i} = \frac{1}{5N}\sum_{j=1}^{N} X_i - X_j \tag{27}$$

where N is the number of krill individuals and X_i represents the related position of ith Krill. If the distance of X_i and X_j is less than the defined sensing distance then X_j is a neighbor of X_i.

Step 5 Movement due to foraging activity

The foraging motion is defined based on the location of the food as well as the previous experience about the location of the food. Foraging motion Fk_i is given by,

$$\mathrm{Fk_i} = \mathrm{V_f}\gamma_\mathrm{i} + \omega_\mathrm{f}\mathrm{Fk_i^{old}} \tag{28}$$

where ω_f is the inertia weight of foraging motion (a random value in the range [0,1]), and γ_i^{best} represents i^{th} Krill's best fitness so far.

Step 5.1

$$\gamma_i = \gamma_i^{food} + \gamma_i^{best} \tag{29}$$

Step 5.1.1 Food attractive β_i^{food} is given by,

$$\gamma_i^{food} = C^{food}\widehat{K}_{i,food}\widehat{X}_{i,food} \tag{30}$$

C^{food} is the food coefficient which is computed as:

$$C^{food} = 2\left(1 - \frac{I}{I_{max}}\right) \tag{31}$$

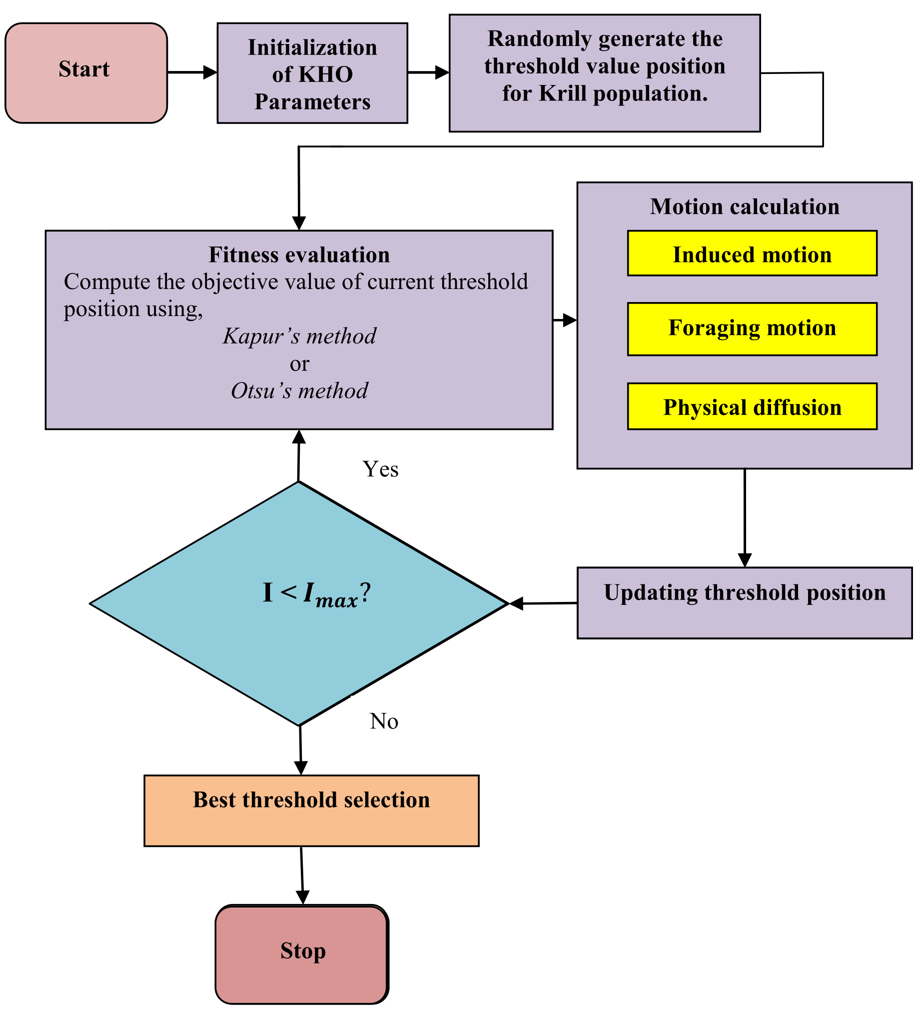

Fig. 2. Flowchart of KHO based image segmentation.

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Step 5.1.2 γ_i^{best} is the i^{th} Krill individual's best fitness which is determined as:

$$\gamma_i^{best} = \widehat{K}_{i,ibest}\widehat{X}_{i,ibest} \tag{32}$$

$\widehat{K}_{i,ibest}$ represent the i^{th} Krill individual's previously visited best position.

Step 5.2 Compute food centre for each iteration as follows:

$$X^{food} = \frac{\sum_{i=1}^{N}\frac{1}{K_i}X_i}{\sum_{i=1}^{N}\frac{1}{K_i}} \tag{33}$$

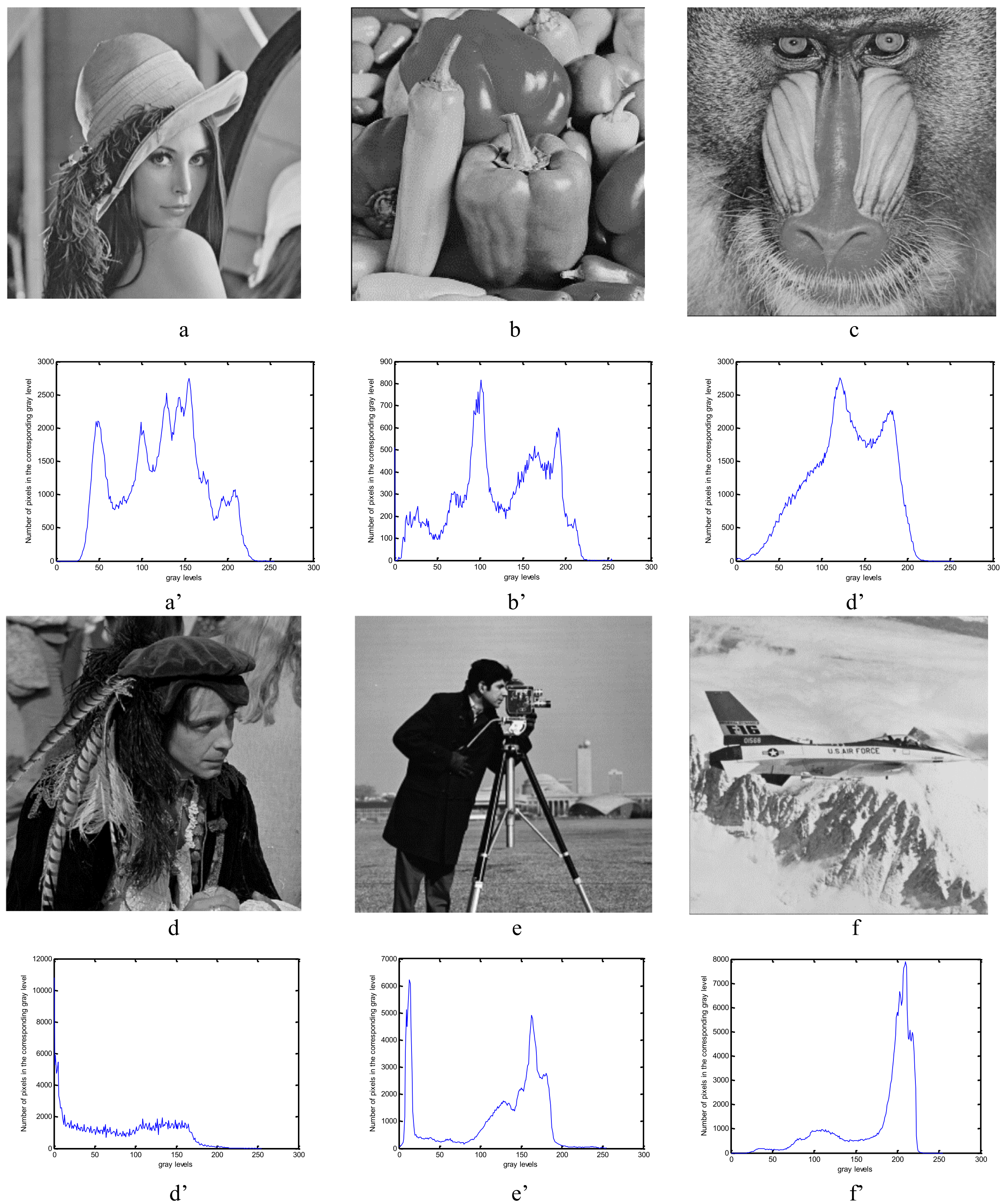

Fig. 3. Test images and their corresponding histogram (a-Lena, b-Pepper, c-Baboon, d-Hunter, e-Cameraman and f-airplane).

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Table 1
Parameter values for KHO.

Parameter		Value
Number of iterations (I_{max})		20
Motion parameters	Induced Motion(N_{max})	10
	Foraging motion (V_f)	5
	Physical diffusion (D_{max})	20

Table 2
Parameter values for GA.

Parameter	Value
Size of the Population (N)	20
Iteration Number	100
Probability of Crossover (P_c)	0.8
Probability of Mutation (P_m)	0.05

Table 3
Parameter values for PSO.

Parameter	Value
No. of particles (s)	20
Iteration Number (I_{max})	100
Inertia Weight (W_{max})	0.9
Inertia Weight (W_{min})	0.4
PSO random parameter	C1 = 2
	C2 = 2

Table 4
Parameter values for BF.

Parameter	Value
Bacterium Number (s)	20
Chemotatic Steps Number (N_c)	10
Length of Swimming (N_s)	10
Reproduction Steps Number (N_{re})	4
Elimination of Dispersal Events Number (N_{ed})	2
Attractant Depth ($d_{attract}$)	0.1
Attract Width ($x_{attract}$)	0.2
Repellent Height ($h_{repellent}$)	0.1
Repellent Width ($x_{repellent}$)	10
Elimination and Dispersal Probability (P_{ed})	0.02

Step 6 Physical diffusion

Physical diffusion motion can be defined in terms of diffusion speed at maximum and a random directional vector as follows:

$$\mathrm{Dk_i} = \mathrm{D^{max}}\left(1 - \frac{\mathrm{I}}{\mathrm{I_{max}}}\right)\Psi \tag{34}$$

Ψ represents the random directional vector in the range $[-1, 1]$

Step 7 Genetic operators

To improve the KHO performance, mechanisms of genetic reproduction namely crossover and mutation are integrated with KHO algorithm.

Step 7.1 Crossover

$x_{i,m}$ is the m^{th} component of X_i obtained from the following formula:

$$x_{i,m} = \begin{cases} x_{r,m}, rand_{i,m} < Co \\ x_{i,m}, else \end{cases}$$

Co (crossover probability) = 0.2 $\widehat{K}_{i,ibest}$

Step 7.2 Mutation

$$x_{i,m} = \begin{cases} x_{gbest,m+}\mu(x_{p,m} - x_{q,m}), rand_{i,m} < Mt \\ x_{i,m}, else \end{cases}$$

M_t (Mutation probability) is defined as:

$Mt = 0.05/\widehat{K}_{\mathrm{i,ibest}}$

Step 8 A krill individual's position vector during the interval $[t, t + \Delta t]$ can be determined as follows based on the different parameters of the movement:

$$X_i(t + \Delta t) = X_i(t) + \Delta t\frac{dX_i}{dt} \tag{35}$$

Table 5
Comparative analysis of objective function values obtained by Kapur based KHO method with other bio-inspired multilevel thresholding methods.

Test images	No. of thresholds	Objective value				
		KHO	BF	PSO	GA	MFO
LENA	2	**12.3713**	12.3470	12.3459	12.3344	12.3523
	3	**15.2628**	15.2206	15.1336	14.9956	15.2367
	4	**18.0431**	17.9333	17.8388	17.0892	17.9456
	5	20.1617	**20.6099**	20.4427	19.5492	20.2145
PEPPER	2	12.3520	**12.5191**	12.5168	12.5133	12.5098
	3	**15.5523**	15.3998	15.0939	14.7122	15.4287
	4	**18.2835**	18.2697	18.0974	17.6958	18.2756
	5	20.9282	**20.9999**	20.7338	20.0691	20.8854
BABOON	2	**12.2385**	12.2164	12.2134	12.1847	12.2256
	3	**15.2398**	15.2114	15.0088	14.7457	15.2147
	4	**18.0493**	17.9920	17.5743	16.9356	17.9968
	5	20.6433	**20.7200**	20.2245	19.6622	20.7102
HUNTER	2	**12.3772**	12.3733	12.3708	12.3496	12.3714
	3	**15.5563**	15.5533	15.1286	14.8381	15.5428
	4	**18.4673**	18.3819	18.0401	17.3189	18.3965
	5	20.9743	**21.2565**	20.5339	19.5635	20.9874
CAMERAMAN	2	**12.2842**	12.2646	12.2595	11.9414	12.2789
	3	**15.2900**	15.2507	15.2110	14.8278	15.2698
	4	**18.5348**	18.4066	18.0009	17.1665	18.3558
	5	21.1641	**21.2111**	20.9631	19.7950	21.1785
AIRPLANE	2	**12.1817**	12.1759	12.1503	12.1153	12.1745
	3	10.4628	**15.3605**	15.2925	14.8059	15.2654
	4	**18.1824**	18.1777	18.0300	17.8923	18.0897
	5	**20.7729**	20.7515	20.3964	19.4465	20.7645

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4. Proposed method

In the proposed work KHO algorithm (Gandomi and Alavi, 2012) is utilized to find the optimal thresholds for segment the image by maximizing the objective function of Otsu's or Kapur's method. Step by step procedure for the proposed multilevel thresholding method based on Krill Herd Optimization is as follows:

Step I: Parameter initialization

a) Initializes KHO motion parameters and maximum number of iteration I_{max}
b) Set the lower boundary and upper boundary of the threshold values
c) initialize number of threshold values (number of threshold is equal to the number of Krill in the KHO algorithm)

Step II: Position calculation

Generate the position of thresholds randomly (in the range [0,255])

Step III: Object /fitness function calculation

Calculate the fitness of current threshold position using Otsu's or Kapur's objective function given in Section 2 (using Eq. (4) or Eq. (9))

Step IV: Motion calculation

For each threshold value perform the following actions

a) Calculate motion induced by other individual using equations in Step 4 given in Section 3.
b) Evaluate foraging motion using equations in Step 5 given in Section 3.
c) Calculate physical diffusion motion using equations in Step 6 given in Section 3.

Step V: Update positions for each threshold using the motion vector obtained from Step IV (using Steps 7 & 8 in Section 3).

Step VI: If the number of iterations reaches the maximum go to Step VII. Otherwise go to Step III.

Step VII: Select the threshold values associated with the overall best Krill (threshold).

Proposed work maximizes the objective functions of conventional between class variance or entropy criterion methods. The optimal threshold values determined by the KHO based multilevel thresholding algorithm used to segment the given image. The detailed multilevel image segmentation using

Krill Herd Optimization algorithm is presented in Figs. 1and 2

5. Experimental analysis and results

5.1. Experimental setup

Experiments with various standard test images having different histogram are performed to highlight the efficiency of the proposed algorithm in determining the optimal threshold values. KHO based image thresholding algorithm is validated through simulations in MATLAB on a Computer with the following configuration: Pentium(R) Dual core T4500 @ 2.30 GHz and 2 GB of memory with Microsoft Windows 7 system. The objective values along with corresponding thresholds and CPU time obtained using proposed method are compared already reported multilevel thresholding algorithms based on bio-inspired computing paradigms such as BF (Sathya and Kayalvizhi, 2011), PSO (Gao et al., 2010), GA (Yin and Peng-Yeng, 1999) and MFO (Aziz et al., 2017) algorithms. The input images namely Lena, Baboon, Pepper, Cameraman, Hunter, Airplane and their respective histograms are shown in Fig. 3. Except the pepper image, which is of size 256 × 256, all other images are of size 512 × 512.

5.2. Parameter setting

The parameters for KHO algorithms for multilevel thresholding are determined through empirical analysis. The parameter values used in the proposed KHO algorithm is shown in Table 1. The parameter values used for other paradigms such as GA, PSO and BF are shown in Tables 2, 3 and

Table 6
Comparative analysis of threshold values obtained by Kapur based KHO method with other bio-inspired multilevel thresholding methods.

Test images	No. of thresholds	Threshold values				
		KHO	BF	PSO	GA	MFO
LENA	2	**97,167**	97,164	99,165	104,167	98, 163
	3	**75,134,186**	88,142,188	86,151,180	72,151,180	85,150,181
	4	**69,106,151,188**	92,129,162,191	92,129,162,191	57,110,178,184	56,111,174,180
	5	**91,104,137,176,196**	74,115,145,170,197	74,115,145,170,197	96,112,151,186,198	92,110,148,182,192
PEPPER	2	**86,156**	79,146	79,146	82,146	84,145
	3	**57,105,148**	104,141,180	104,141,180	108,127,186	105,129,185
	4	**35,66,124,174**	57,110,162,199	57,110,162,199	72,102,172,204	70,101,165,198
	5	**44,80,108,170,196**	70,116,138,166,200	70,116,138,166,200	77,107,124,178,209	75,103,127,180,211
BABOON	2	**86,148**	76,144	76,144	93,152	85,148
	3	**44,112,166**	72,130,181	72,130,181	64,151,181	68,145,181
	4	**43,85,120,147**	65,121,153,180	65,121,153,180	90,106,152,188	85,105,153,185
	5	**50,89,123,148,171**	73,110,142,166,192	73,110,142,166,192	96,126,150,172,197	91,120,145,170,195
HUNTER	2	**83,176**	83,179	83,179	75,178	83,179
	3	**51,100,184**	85,128,166	85,128,166	70,148,167	85,128,167
	4	**63,99,133,176**	74,131,174,200	74,131,174,200	64,100,189,200	75,131,175,200
	5	**47,69,123,157,192**	90,120,164,190,219	90,120,164,190,219	87,96,128,196,213	87,102,150,190,210
CAMERAMAN	2	**121,195**	115,196	115,196	76,195	80,195
	3	**49,94,202**	96,138,191	96,138,191	111,165,189	96,140,190
	4	**40,92,152,198**	77,116,151,202	77,116,151,202	71,80,141,192	71,110,141,200
	5	**46,98,136,198,221**	64,95,121,156,198	64,95,121,156,198	66,110,169,180,209	64,111,155,190,210
AIRPLANE	2	**73,164**	80,175	80,175	90,176	80,175
	3	**70,124,178**	72,121,191	72,121,191	75,110,199	75,120,199
	4	**74,111,144,190**	74,129,162,188	74,129,162,188	87,124,154,187	86,125,160,190
	5	**61,102,138,161,187**	81,118,144,167,192	81,118,144,167,192	95,121,141,151,196	95,118,144,167,196

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4, respectively. The parameters for MFO algorithm has been assigned to the default values mentioned in (Aziz et al., 2017). To evaluate the performance of the proposed algorithm, Kapur's and Otsu's objective functions are considered. The proposed KHO based multilevel thresholding algorithm was run 50 times and the threshold values associated with the highest objective function value among the 50 values are reported in this paper.

Fig. 4. Segmented images obtained by Kapur based KHO method (A_1 - E_1, A_2 - E_2, A_3 - E_3 and A_4 - E_4 represent the 3, 4, 5 and 6 level thresholding respectively).

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Table 7
Comparative analysis of objective function values obtained by Otsu based KHO method with other bio-inspired multilevel thresholding methods.

Test images	No. of thresholds	Objective values				
		KHO	BF	PSO	GA	MFO
LENA	2	1953.4594	1961.5556	1961.4149	1960.9603	**1961.5641**
	3	**2130.6895**	2128.0706	2127.7771	2126.4107	2128.7456
	4	**2202.0382**	2189.0267	2180.6868	2173.7148	2145.7895
	5	**2219.1174**	2215.6092	2212.5555	2196.2745	2215.3649
PEPPER	2	2469.3335	**2474.8090**	2469.5788	2457.1517	2469.6585
	3	**2627.0501**	2625.3627	2623.2739	2614.0841	2625.8547
	4	**2704.9597**	2697.7838	2695.8867	2682.8391	2697.5417
	5	**2737.8604**	2735.6447	2733.5097	2725.8750	2735.4514
BABOON	2	1519.2698	1548.0125	1547.9977	1547.6588	**1549.2123**
	3	**1639.6731**	1637.0079	1635.3623	1633.5220	1635.2465
	4	**1691.9699**	1690.7220	1684.3363	1677.7052	1690.2144
	5	**1726.3819**	1716.7283	1712.9582	1699.3909	1720.2315
HUNTER	2	3045.8980	**3064.1188**	3064.0688	3064.0156	3064.0212
	3	**3219.0872**	3213.4460	3212.0585	3211.7947	3212.2121
	4	**3300.7276**	3266.3504	3257.1767	3231.1313	3265.2457
	5	**3315.9949**	3291.1339	3276.3173	3244.7387	3297.5682
CAMERAMAN	2	3608.3062	3609.4995	3609.3703	3609.0761	**3609.6214**
	3	**3686.4993**	3682.5693	3677.1783	3643.2153	3683.2897
	4	**3768.1051**	3737.1201	3722.6447	3710.7311	3745.5214
	5	**3799.8781**	3769.2239	3764.9571	3755.5529	3756.2145
AIRPLANE	2	**1845.4991**	1837.7517	1837.7222	1837.7144	1837.5264
	3	**1930.3693**	1910.7434	1905.7664	1844.5642	1928.5465
	4	**1959.0381**	1954.2480	1953.8872	1950.5919	1956.2478
	5	**2003.1870**	1978.4335	1977.9742	1973.0894	1979.5545

Table 8
Comparative analysis of threshold values obtained by Otsu based KHO method with other bio-inspired multilevel thresholding methods.

Test images	No. of thresholds	Threshold values				
		KHO	BF	PSO	GA	MFO
LENA	2	**89,157**	92,151	94,152	91,149	92,149
	3	**74,117,167**	79,125,170	79,127,170	80,124,173	79,125,170
	4	**74,111,144,190**	76,117,151,182	78,112,134,175	80,126,159,185	78,117,134,185
	5	**48,62,81,131,169**	66,92,122,149,183	79,110,140,167,188	80,116,146,179,213	80,110,122,175,210
PEPPER	2	**60,136**	73,137	76,144	84,144	76,137
	3	**56,128,181**	63,125,174	72,124,171	65,116,175	65,125,175
	4	**33,92,125,167**	54,89,128,171	57,92,130,172	62,108,142,177	57,92,130,177
	5	**23,77,112,168,183**	47,86,123,158,183	56,84,115,150,179	52,90,128,166,191	52,86,121,165,183
BABOON	2	**121,226**	98,150	96,149	98,151	98,151
	3	**90,134,162**	84,126,159	85,126,166	86,125,155	85,125,159
	4	**82,116,160,184**	77,109,139,169	79,105,140,174	82,122,146,173	79,109,146,175
	5	**57,110,137,168,191**	70,99,127,154,177	74,104,134,161,180	73,106,140,167,199	72,104,138,167,197
HUNTER	2	**37,111**	51,117	52,116	51,115	51,117
	3	**25,84,143**	36,86,135	39,86,135	36,89,133	39,86,133
	4	**27,65,118,155**	31,80,120,152	36,84,130,157	39,93,142,163	35,80,132,157
	5	**24,55,111,140,178**	31,73,109,141,178	37,85,125,154,177	39,94,130,169,204	37,94,131,168,201
CAMERAMAN	2	**70,146**	70,143	71,143	72,145	71,143
	3	**73,148,165**	61,118,155	71,134,166	71,143,196	71,138,196
	4	**30,81,144,172**	48,104,142,170	65,121,147,172	59,119,155,203	65,123,145,178
	5	**71,123,152,163,171**	40,86,125,151,174	45,78,121,146,172	51,106,141,167,194	51,103,139,165,192
AIRPLANE	2	**103,162**	117,175	117,174	116,175	117,174
	3	**96,156,198**	91,147,190	99,158,193	86,133,204	97,152,195
	4	**56,105,172,210**	84,127,169,202	84,125,168,201	71,119,164,200	72,127,168,202
	5	**75,90,131,158,203**	71,110,138,175,203	60,101,138,177,204	84,124,164,188,204	75,109,138,175,204

5.3. Results and discussion

The objective values and corresponding threshold values achieved using Kapur based KHO method, BF, PSO and GA are shown in Tables 5 and 6. Segmented images obtained by Kapur based KHO method is presented in Fig. 4. The objective function values and the threshold values determined by the Otsu based KHO, BF, PSO and GA are presented in Tables 7 and 8. The mean and the standard deviation values of the objective functions over 50 runs obtained by Kapur and Otsu based KHO method are shown in Table 9. Wilcoxon signed ranks test (Wilcoxon, 1945) was conducted to test the statistical significance between the proposed KHO method (Kapur based) and the other bio-inspired methods such as BF, PSO, GA and MFO. The significance value alpha was taken as 0.05 with the sample space of 50. Table 10 gives the result of Wilcoxon test with p-value for evaluation, and from the table it is evident that KHO outperforms other methods since the p-value in all cases proves statistical significance. Segmented images (Lena, Pepper, Baboon, Hunter, and Cameraman) of Otsu based KHO method shown in Fig. 5. The higher value of objective function leads to better visual effect for segmented image. The experimental results indicate that the proposed method yields the highest objective values, for almost all the cases when compared to BF, PSO and GA, while for the rest

Table 9
Mean values and standard deviations of the objective function over 50 runs obtained by Kapur based and Otsu based KHO method.

Test images	No. of thresholds	Kapur based KHO		Otsu based KHO	
		Mean	Standard Deviation	Mean	Standard Deviation
LENA	2	12.3701	5.2342E-6	1953.4586	6.4526E-4
	3	15.2612	4.2254E-5	2130.6885	8.5874E-4
	4	18.0425	5.0147E-4	2202.0374	6.2178E-3
	5	20.1611	6.1459E-3	2219.1162	4.1475E-2
PEPPER	2	12.3508	3.5213E-7	2469.3327	2.9841E-4
	3	15.5512	9.2547E-5	2627.0498	5.6321E-3
	4	18.2824	8.3654E-5	2704.9586	7.4532E-3
	5	20.9264	2.3654E-3	2737.8597	5.2247E-2
BABOON	2	12.2376	7.4523E-6	1519.2687	3.2123E-4
	3	15.2382	5.9821E-4	1639.6722	3.7841E-4
	4	18.0473	7.2135E-4	1691.9691	7.2784E-3
	5	20.6425	6.3215E-3	1726.3814	4.1257E-2
HUNTER	2	12.3765	3.3633E-7	3045.8975	9.5862E-4
	3	15.5549	2.2128E-5	3219.0868	5.2148E-3
	4	18.4668	7.1254E-5	3300.7269	7.8951E-3
	5	20.9732	8.2968E-3	3315.9942	1.2348E-2
CAMERAMAN	2	12.2831	7.4187E-6	3608.3057	6.3521E-4
	3	15.2889	8.1247E-4	3686.4988	5.8912E-4
	4	18.5341	6.3654E-4	3768.1047	3.2258E-3
	5	21.1638	4.5897E-3	3799.8777	7.8852E-2
AIRPLANE	2	12.1815	1.2354E-7	1845.4988	8.3361E-4
	3	10.4626	4.9821E-5	1930.3687	6.2158E-3
	4	18.1820	5.2147E-5	1959.0374	5.6568E-3
	5	20.7726	9.3654E-3	2003.1864	1.2453E-2

Table 10
p-values produced by Wilcoxon test comparing KHO versus other bio-inspired methods over the Kapur based objective function values.

Test images	No. of thresholds	KHO versus BF	KHO versus PSO	KHO versus GA	KHO versus MFO
LENA	2	2.5418E-4	4.3217E-5	2.7845E-4	8.2314E-4
	3	5.2148E-3	5.4877E-4	7.3652E-4	9.3218E-4
	4	3.3298E-3	4.5478E-3	9.3287E-3	8.5789E-3
	5	4.3621E-3	1.3625E-2	5.7854E-3	9.8854E-3
PEPPER	2	3.2511E-5	4.4463E-4	4.3321E-5	4.3621E-5
	3	8.5241E-4	9.3321E-4	5.2236E-4	5.6612E-4
	4	7.7742E-3	7.3325E-3	8.2389E-3	7.3328E-4
	5	6.3289E-3	8.2214E-3	3.4541E-3	8.2114E-3
BABOON	2	1.3621E-5	8.3652E-4	3.5478E-5	2.9887E-4
	3	6.3477E-4	5.3398E-4	5.4488E-4	4.5589E-4
	4	4.5562E-4	1.2547E-3	7.2963E-3	6.2478E-3
	5	7.3369E-3	4.8895E-3	6.6654E-3	8.3327E-3
HUNTER	2	5.2147E-4	3.4498E-5	7.2345E-4	9.4432E-5
	3	2.0014E-4	6.4777E-4	2.8841E-4	6.3142E-4
	4	7.6631E-3	9.1247E-3	8.2347E-3	9.4413E-4
	5	1.6547E-2	3.1146E-3	4.6218E-3	7.5852E-3
CAMERAMAN	2	3.1699E-5	5.3197E-5	7.4663E-4	8.4129E-5
	3	6.3745E-4	2.3123E-4	8.2211E-4	2.3787E-5
	4	4.3578E-3	7.6589E-3	4.5981E-3	1.2679E-4
	5	7.3346E-3	2.1452E-2	6.3748E-3	3.7951E-3
AIRPLANE	2	4.9832E-5	3.2887E-4	4.3982E-5	1.8523E-5
	3	8.2588E-4	7.3328E-4	4.2888E-4	4.3617E-4
	4	9.4135E-3	1.9985E-3	4.1136E-4	3.7411E-3
	5	7.9953E-3	2.2259E-2	8.2647E-3	8.4459E-3

of the cases results are analogous, while considering the computational time.

Table 11 illustrates the computational efficiency of the proposed method. KHO based multilevel thresholding algorithm is compared with the existing bio-inspired methods based on the convergence time (CPU time taken in seconds on an average). From the Table 11, it is evident that the proposed KHO based multilevel thresholding method is much faster than the other bio-inspired computing algorithms. Table 12 shows the comparative analysis of Kapur and Otsu based KHO methods with exhaustive search method in terms of objective function and threshold values. A comparative analysis of the proposed method with recently reported state-of-the-art techniques such as MTABC (Horng, 2011) & MTHBMO (Horng, 2010) are performed and the quantitative results are shown in Table 13.

One of the important parameters of KHO algorithm is the No. of iterations, I_{max}. The proposed method has been applied on *lena* image with different I_{max} values and the corresponding objective function values (both Kapur and Otsu method) has been computed. The graph representing the No. of iterations (I_{max}) versus objective function values associated with Kapur and Otsu method for different threshold values are shown in Figs. 6 and 7, respectively. From the graph it is evident that the best objective function value is obtained at $I_{max} = 20$, for both Kapur and Otsu based method.

Fig. 5. Segmented images obtained by Otsu based KHO method (a_1 - e_1, a_2 - e, a_3 - e_3 and a_4 - e_4 represent the 3,4,5,6 level thresholding respectively).

6. Conclusion and future works

This paper presents a novel Krill Herd Optimization (KHO) based algorithm for multilevel thresholding, which can be effectively used for solving image segmentation problems. The proposed KHO algorithm simulates the krill herding behavior to select the optimum thresholds for multilevel thresholding. In order to evaluate the performance of the proposed KHO algorithm two

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Table 11
Comparative analysis of average CPU time (in sec) obtained by KHO based method with other bio-inspired multilevel thresholding methods.

Test images	No. of thresholds	KHO		BF		PSO		GA		MFO	
		Kapur's	Otsu's	Kapur's	Otsu's	Kapur's	Otsu's	Kapur's	Otsu's	Kapur's	Otsu's
LENA	2	**2.2645**	**2.2584**	7.2063	3.2969	7.8594	3.5781	8.5469	3.9688	5.2347	3.2625
	3	**2.2770**	**2.3007**	7.6060	3.8281	8.3594	4.4031	8.8594	5.2969	5.9775	3.4589
	4	**2.2964**	**2.3306**	8.5000	4.2188	9.1719	4.7500	9.5156	5.6094	6.7489	4.5142
	5	**2.3218**	**2.3314**	8.8125	4.7813	9.4063	5.2031	10.1250	5.8938	6.9686	4.9875
PEPPER	2	**0.9694**	**0.9185**	6.5001	2.9889	7.1358	3.4010	8.6492	3.8569	5.1278	3.2897
	3	**0.9778**	**0.9296**	6.8625	3.2157	7.6250	4.3125	9.1056	4.9787	5.8745	3.8547
	4	**1.0022**	**0.9317**	7.4706	3.5875	8.1254	4.6719	9.6406	5.5156	6.4716	4.3257
	5	**1.0047**	**0.9669**	7.8177	3.6094	8.4844	4.8125	9.9688	5.9844	6.8741	4.8756
BABOON	2	**2.2572**	**2.2837**	7.6250	3.2813	8.0016	3.8469	8.3563	4.3969	5.0234	3.0145
	3	**2.2746**	**2.2894**	8.2824	3.7969	8.7188	4.3125	9.3750	4.7969	5.6478	3.5874
	4	**2.9860**	**2.3263**	8.7188	4.2813	9.1084	4.9063	9.6750	5.6094	6.0214	4.1415
	5	**2.3117**	**2.3305**	9.1875	4.8206	9.7813	5.3281	10.1875	6.0109	6.541	4.6512
HUNTER	2	**2.2726**	**2.2639**	7.3594	3.2344	8.0000	3.8438	8.6406	4.4063	5.1412	3.1216
	3	**2.2872**	**2.3022**	8.2813	3.9063	8.7031	4.4844	9.9844	4.8625	3.7841	3.9652
	4	**2.3212**	**2.3082**	8.7344	4.1875	9.0313	4.8125	9.6219	5.3906	4.2419	4.2547
	5	**2.3291**	**2.3106**	9.6250	4.8128	10.1406	5.3031	10.6094	6.1563	4.7891	4.8741
CAMERAMAN	2	**2.2778**	**2.2816**	7.7813	3.0625	8.4844	3.4844	9.2500	3.9531	5.0369	3.2468
	3	**2.2821**	**2.3010**	8.2720	3.6875	9.0625	4.1250	9.7000	4.8125	5.6874	3.9712
	4	**2.3040**	**2.3031**	8.5938	4.2344	9.1250	4.7406	9.9844	5.2500	6.1423	4.2578
	5	**2.3231**	**2.3368**	9.2969	4.6719	10.1094	5.2656	10.9688	6.0025	6.8547	4.8874
AIRPLANE	2	**2.2630**	**2.2392**	7.3094	3.0250	7.9844	3.4688	8.7188	4.0000	5.1128	3.1487
	3	**2.2724**	**2.2857**	8.2500	3.8531	8.9688	4.5938	10.4844	5.1875	5.7568	3.7551
	4	**2.2981**	**2.2943**	8.5625	4.0125	9.2031	4.7969	9.9531	5.3594	6.0227	4.0669
	5	**2.3231**	**2.3269**	9.0156	4.7500	9.9688	5.0781	10.4031	5.8125	6.7411	4.7885

Table 12
Comparative analysis of objective function values and threshold values computed by Kapur and Otsu based KHO methods with Exhaustive search method.

Test images	No. of thresholds	Exhaustive search method				KHO method			
		Exhaustive search based on Kapur method.		Exhaustive search based on Otsu method.		Kapur based KHO		Otsu based KHO	
		Threshold values	Objective value	Threshold values	Objective value	Threshold values	Objective value	Threshold values	Objective value
LIVING ROOM	2	94, 175	12.40	87, 145	1627.90	**90,174**	**12.42**	**82,143**	**1625.50**
	3	47, 103, 175	15.55	76, 123, 163	1760.10	**36,107,176**	**15.46**	**79,120,178**	**1735.79**
	4	47, 98, 149, 197	18.47	56, 97, 132, 168	1828.86	**54,102,161,187**	**18.36**	**58,98,139, 171**	**1830.22**
	5	42, 85, 124, 162, 197	21.15	49, 88, 120, 146, 178	1871.99	**144,198, 206,224, 225**	**20.97**	**65,110,140,162,193**	**1872.30**
BARBARA	2	96, 168	12.66	82, 147	2608.61	**120,184**	**12.56**	**108,167**	**2589.09**
	3	76, 127, 178	15.74	75, 127, 176	2785.16	**130,150, 177**	**15.59**	**36,78,154**	**2666.92**
	4	60, 99, 141, 185	18.55	66, 106, 142, 182	2856.26	**74,113,180,224**	**18.45**	**34,61,74, 134**	**2869.43**
	5	58, 95, 133, 172, 210	21.24	57, 88, 118, 148, 184	2890.97	**85,95,122, 146,194**	**20.91**	**57, 88, 118, 148, 184**	**2890.97**
BOATS									
	2	107, 176	12.57	93, 155	1863.34	**160,172**	**12.56**	**87,169**	**1840.52**
	3	64, 119, 176	15.82	73, 126, 167	1994.53	**72,130,172,188**	**15.63**	**25,98,154**	**1932.91**
	4	48, 88, 128, 181	18.65	65, 114, 147, 179	2059.86	**70,130,172,188**	**18.31**	**33,96,133, 178**	**2050.17**
	5	48, 88, 128, 174, 202	21.40	51, 90, 126, 152, 183	2092.77	**44,103,173,180,201**	**20.92**	**81,104,145,154,173**	**2066.26**

Table 13
Comparative analysis of objective function values and threshold values computed by Kapur based KHO method with other state-of-the-art methods.

Test images	No. of thresholds	KHO		MTABC (Horng, 2011)		MTHBMO (Horng, 2010)	
		Threshold values	Objective value	Threshold values	Objective value	Threshold values	Objective value
LENA	2	**97,167**	**12.37**	80,150	12.69	80,150	12.69
	3	**75,134,186**	**15.26**	60,109,160	15.76	60,109,160	15.76
	4	**69,106,151,188**	**18.04**	56,100,144,182	18.58	56,100,144,182	18.58
	5	**91,104,137,176,196**	**20.16**	44,79,115,148,186	21.24	44,80,115,150,185	21.24
PEPPER	2	**86,156**	**12.35**	72,146	12.63	74,146	12.63
	3	**57,105,148**	**15.55**	61,112,164	15.68	61,112,164	15.68
	4	**35,66,124,174**	**18.28**	57,104,148,194	18.53	57,104,148,194	18.53
	5	**44,80,108,170,196**	**20.92**	42,77,113,153,194	21.28	42,77,113,153,194	21.28
CAMERAMAN	2	**121,195**	**12.28**	128,193	12.16	128,193	12.16
	3	**49,94,202**	**15.29**	44,104,193	15.22	44,104,193	15.22
	4	**40,92,152,198**	**18.53**	44,97,146,197	18.39	44,97,146,197	18.39
	5	**46,98,136,198,221**	**21.16**	40,84,119,155,197	21.08	40,84,119,155,197	21.06

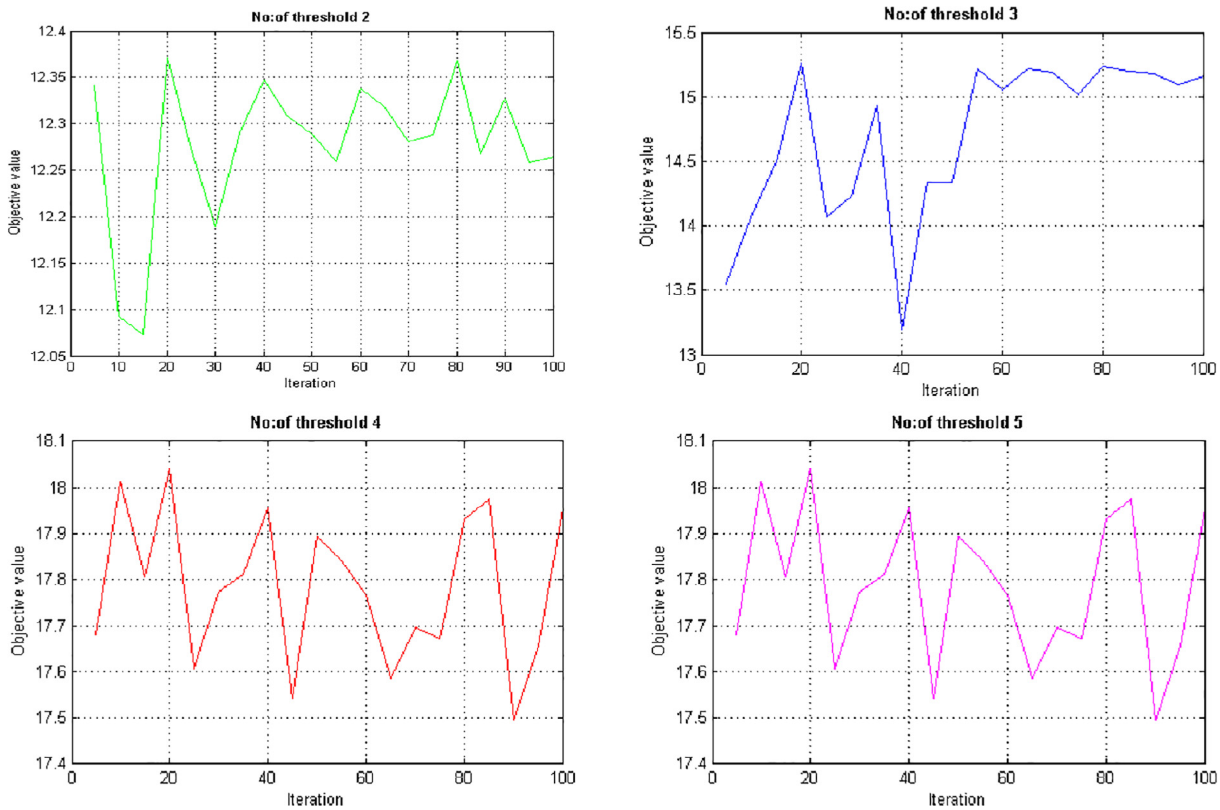

Fig. 6. Graph showing No. of Iterations (I_{max}) versus Objective function value (Kapur's Method) for different thresholds (2, 3, 4 and 5).

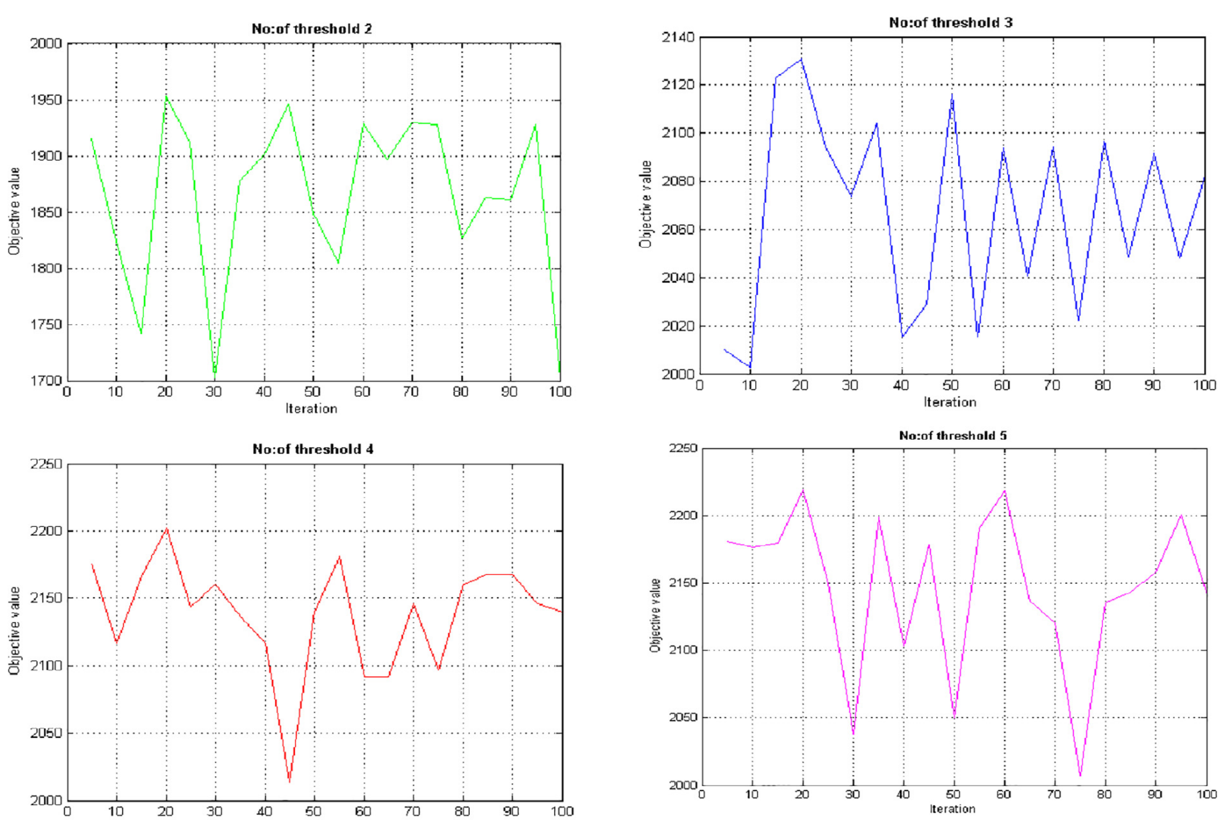

Fig. 7. Graph showing No. of Iterations (I_{max}) versus Objective function value (Otsu's Method) for different thresholds (2, 3, 4 and 5).

objective functions, one based on Kapur's method and other based on Otsu's method, were considered. The performance of the KHO based multilevel thresholding for image segmentation have been tested with standard images and computed the processing time to determine the optimal thresholding, and results are also compared with the other bio-inspired multilevel thresholding methods. KHO based multilevel thresholding observed to be faster than the existing bio-inspired techniques for image segmentation. The segmentation results of KHO algorithm for multilevel thresholding are promising and hence the proposed method can be effectively used for multilevel image segmentation problem. As a future work, the possibility of using Chaotic Krill Herd Optimization algorithm for improving the performance of the proposed method will be explored.

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