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Segmentation of Infrared Images and Objectives Detection Using Maximum Entropy Method Based on the Bee Algorithm

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Abstract

Thresholding is a popular image segmentation method that converts a gray-level image into a binary image. Many thresholding techniques have been proposed in the recent years. Among them, the maximum entropy thresholding has been widely applied. Image entropy thresholding approach has drawn the attentions in image segmentation. In this paper, the image thresholding approach with the index of entropy maximization of the grayscale histogram based on a novel optimization algorithm, namely, the bee algorithm is proposed to deal with infrared images. The bee algorithm is realized successfully in the process of solving the maximum entropy problem. The proposed algorithm uses the bee algorithm which proved to be the most powerful unbiased optimization technique for sampling a large solution space. Because of its unbiased stochastic sampling, it was quickly adapted in image processing and thus for infrared image segmentation as well. The experiments of segmenting of the infrared images are illustrated to prove that the proposed method can get ideal segmentation result with less computation cost. The proposed algorithm is also applied to the segmentation of standard images with very promising results.

Keywords- Image Segmentation; Bee Algorithm; Infrared Images; Maximum Entropy.

1. Introduction

Image Thresholding is an important technique in image segmentation, enhancement and object detection. However, the segmentation results depend heavily on the used image thresholding methods. The image thresholding is widely used in halftone reproduction [1], infrared image segmentation [2], automatic target recognition [3], color image segmentation [4] and mixed-type document analysis [5]. The main goal of image segmentation is to determine a threshold for bi-level thresholding or several thresholds for multi-level thresholding for image segmentations. While one include pixels with gray values that are below or equal to a certain threshold, the other includes those with gray values above the threshold. Many thresholding methods have been reported in the literature [6-10]. An early review of thresholding methods was reported in [6]. A comparative performance study of global thresholding techniques was reported by Lee et al. [7]. Another comparative analysis of the performance of eleven histogram-based thresholding algorithms was carried out by Glasbely [11]. Among early works on thresholding, Prewitt and Mendelson [12] suggested to select the threshold at the valleys of the histogram, while Doyle [13] advocated the choice of the median. Image segmentation is the first and key step of target recognition, which separates the objects from the background and makes preparation for the post processions. Of particular interest is an information theoretic approach that is based on the concept of entropy introduced by Shannon in information theory [14]. There are many methods of image segmentation such as Hough transformation, Template matching, Neural Network, and etc. [15-16], among which threshold segmentation is the most important one. Image thresholding is a basic component of many computer vision systems. While humans can easily differentiable an object from complex background, image thresholding is a difficult task for separate them. The gray-level histogram of an image is usually considered as efficient tools for development of image thresholding algorithms.

Li and Lee's method [17] minimizes relative cross entropy or Kullback-Leibler (KL) distance between the probability distribution functions of the original and the thresholded image. Kitler and Illingworth [18] developed a thresholding method that minimizes the notion of a segmentation error derived using an information-theoretic approach, while Dunn et al.'s method [19] is based on a uniform error criterion. Recently, Leung and Lam [20] developed a method that maximizes segmented image information derived using information-theoretic approaches and demonstrated that their method is better than the methods based on minimum error [18] and uniform error [19] criteria. [6] As well as Abutaleb's 2-D histogrambased approaches were discussed in the work of Yang et al. [21], there is no need to repeat their work here.

Instead, this paper is primarily focused on a comparative study and analysis among Kittler and Illingworth's MET, the three co-occurrence matrix-based entropy thresholding techniques and three relative entropy thresholding methods plus Otsu's [22] method. While the methods of Wong and Sahoo [23] and Pal and Pal [24], [25] incorporate some spatial image information in their methods, others are mostly histogram-based techniques. Although researchers have used spatial image information in several non thresholding image segmentation methods [26-28], thresholding is a fundamentally different and simple operation. Further, final segmentations using these methods depend on initial segmentations which are not needed by thresholding. One common trait of all histogram based approaches is that they do not utilize the considerable amount of information that is captured in the spatial distribution of intensities and in image morphology. It is obvious that, in real-life imaging applications, it is very difficult to select a threshold from the histogram only without seeing the image, while the latter has a clear object morphology. Yin [29] developed a recursive programming techniques to reduce the order of magnitude of computing the multilevel thresholds and further used the PSO algorithm to minimize the cross entropy.

Since the theory of entropy was brought into the thresholding selection technology, many methods have been proposed to deal with the problem of image segmentation. The maximum entropy method is proved to do good results for the infrared image segmentation. But it needs to compute the entropy of every gray value. Over the last decade, modeling the behavior of social insects, such as ants and bees, for the purpose of search and problems solving has been the context of the emerging area of swarm intelligence. Ant colony algorithm [30] and particle swarm optimization [31] are two most popular approaches in swarm intelligence. The honey bee mating optimization [32] may also be considered as a typical swarm-based approach for optimization, in which the search algorithm is inspired by the process of mating in real honey bees. In the literature, the honey bee mating optimization algorithm had been adopted to search for the optimal solution in many applications such as clustering [33], market segmentation [34] and benchmark mathematical problems [35]. Taking the consideration the complexity of its computation, we proposed a new heuristic optimization algorithm, called the bee algorithm to search the result for infrared image segmentation.

The bee algorithm may also be considered as a typical swarm-based approach for optimization, in which the search algorithm is inspired by the real bees. The behavior of bees is the interaction of their (1) genetic potentiality, (2) ecological and physiological environments, and (3) the social conditions of the colony, as well as various prior and ongoing interactions between these three parameters. This paper introduces a new approach for optimization of the maximum entropy based on the bee algorithm. The rest of the paper is organized as follows. Section (2) the theory of maximum entropy is presented. Section (3) the bee algorithm is explained. Section (4) the simulation results are presented. Section (5) Conclusions are presented.

2. The Theory of Maximum Entropy

2.1. The Shannon Entropy

The most generally accepted form of entropy was derived by Shannon (Shannon and Weaver, 1949) [36] in connection with information theory. Given a discrete probability distribution P_i , $i = 1,2,..., N$, the entropy is given by

$$H = -\sum_{i=0}^{n} p_i \log(p_i) \ , \sum_{i=0}^{n} p_i = 1, \quad (1)$$
$$0 \le p_i \le 1$$

Where $i = 1,2,..., N$, are a set of possible outcomes or states of a discrete information source modelled as a Markov process. Shannon's measure is used as a measure of information gain, choice and uncertainty.

Shannon points out a number of interesting properties of (1), including:

i) H=0 if and only if $p_i = 0 \quad \forall i \neq j, P_j = 1$, where j can indicate any position in the distribution. Otherwise H is positive. This makes intuitive sense, since $P_j = 1$ indicates certainty of the outcome, and the information gained by the occurrence of event j is thus zero.

ii) For a given number of discrete states N, H is a maximum when all the P_i are equal, i.e. $P_i = 1/N$, $i = 1,2,..., N$. Intuitively this is the most uncertain situation: all outcomes are equally likely, making accurate prediction impossible.

2.2. Image Thresholding Based on the Maximum Entropy

In general, an image can be described by a discrete function. For discrete values we deal with probabilities and summations. The probability of occurrence of gray level i in an image is approximated by

$$P_i = \frac{n_i}{n}, \ i = 0,1,2,..., L-1. \quad (2)$$

where, as noted at the beginning of this section, n is the total number of pixels in the image, n_i is the number of pixels that have gray level i, and L is the total number of possible gray levels in the image (L=256). If we consider a threshold that is named T (0<T<L-1) we have two regions C_O, C_B . Where, C_O is the object region and C_B is the background region. Shannon defines the entropy of a system, which has n status, as

$$H = -\sum_{i=0}^{n} p_i \log(p_i) \quad (3)$$

Where p_i is the probability of the occurrence of the event i, and the entropy H is the measuring of the system information. The value of the information obtained from an event is the inverse probability of the occurrence. Now formula (2) is analyzed from the point of an image. The event i can be regarded as a gray value of an image while p_i is the probability of the pixel being i. The theory of maximum entropy is to select i which makes H be maximum value [37]. p_O , p_B are denoted as the probabilities of grey levels of the object and background regions respectively.

$$p_O = \sum_{i \in C_O} p_i \text{, Where } i = 0,1,2,...,T-1; \quad (4\text{-}1)$$

$$p_B = \sum_{i \in C_B} p_i \text{ ,} \quad (4\text{-}2)$$

Where $i = [T, T+1, T+2, ..., 255]$ and the entropy of the object region and the background region can be denoted as follows:

$$H_O(T) = -\sum_{i=0}^{T-1} [(p_i / p_O) \log(p_i / p_O)], \quad (5\text{-}1)$$

$$H_B(T) = -\sum_{i=T}^{255} [(p_i / p_B) \log(p_i / p_B)], \quad (5\text{–}2)$$

Thus, the function of the entropy is:

$$Fitness = H(t) = H_O(t) + H_B(t) \text{ ,} \quad (6)$$

The maximum entropy formalism attempts to maximize the equation (6), subject to known constraints about the parameters we are trying to estimate P_i , $i = 1,2,..., N.$ Effectively, by maximizing the entropy, we are attempting to maximize our information gain or, equivalently, arrive at a solution which fits our prior knowledge but makes no assumptions beyond what is known. In the absence of any prior information, the maximum entropy distribution is simply the uniform distribution, as indicated by Shannon's point (ii) above. It can thus be aptly viewed as an application of Laplace's principle of insufficient reason, which states that the uniform distribution is the most unbiased when one has no prior knowledge regarding a probabilistic event. We solve equation (6) to get the optimized threshold $(T = t^*)$ which can make $H(t)$ maximum. The threshold T is selected as the one which maximizes $H(t)$.

$$T = t^* = Arg(\max H(t)) \text{,} \quad (7)$$

Where $0 \le T = t^* \le 255$, directly to solve the equation (7) will cost lots of time. In order to enhance the speed and accuracy of the proposed algorithm, the bee algorithm is used to extract the optimized threshold.

3. The Bee Algorithm

A colony of honey bees can extend itself over long distances (more than 10 km) and in multiple directions simultaneously to exploit a large number of food sources [38-39]. A colony prospers by deploying its foragers to good fields. In principle, flower patches with plentiful amounts of nectar or pollen that can be collected with less effort should be visited by more bees, whereas patches with less nectar or pollen should receive fewer bees [40-41]. The foraging process begins in a colony by scout bees being sent to search for promising flower patches. Scout bees move randomly from one patch to another. During the harvesting season, a colony continues its exploration, keeping a percentage of the population as scout bees [39]. When they return to the hive, those scout bees that found a patch which is rated above a certain quality threshold (measured as a combination of some constituents, such as sugar content) deposit their nectar or pollen and go to the “dance floor” to perform a dance known as the “waggle dance” [38].

The bee algorithm is an optimization algorithm inspired by the natural foraging behavior of honey bees to find the optimal solution [42]. Table 1 shows the pseudocode for the algorithm in its simplest form. The algorithm requires a number of parameters to be set, namely: number of scout bees (n), number of sites selected out of n visited sites (m), number of best sites out of m selected sites (e), number of bees recruited for the other (m-e) selected sites (n1), number of bees recruited for best e sites (n2), initial size of patches (ngh) which includes site and its neighborhood and stopping criterion. The algorithm starts with the n scout bees being placed randomly in the search space.

According to the fitnesses of the sites visited by the scout bees are evaluated. In step “select m sites for neighborhood search”, bees that have the highest fitnesses are chosen as “selected bees” and sites visited by them are chosen for neighborhood search. Then, in steps “recruit bees for selected sites” and “select the fittest bee from each patch”, the algorithm conducts searches in the neighborhood of the selected sites, assigning more bees to search near to the best e sites. The bees can be chosen directly according to the fitnesses associated with the sites they are visiting. Alternatively, the fitness values are used to determine the probability of the bees being selected. Searches in the neighborhood of the best e sites which represent more promising solutions are made more detailed by recruiting more bees to follow them than the other selected bees. Together with scouting, this differential recruitment is a key operation of the bee algorithm. However, in step “select the fittest bee from each patch”, for each patch only the bee with the highest fitness will be selected to form the next bee population. In nature, there is no such a restriction. This restriction is introduced here to reduce the number of points to be explored. In step “assign the (n-m) remaining bees to random search”, the remaining bees in the population are assigned randomly around the search space scouting for new potential solutions. These steps are repeated until a stopping criterion is met.

3.2. The Determination of the Bee Algorithm Parameters

In this section, the proposed algorithm is employed as an optimized method to extract ideal threshold. Considering the maximum entropy method and bee algorithm together, we set the threshold vector (t) as the sites, and H(t) as the fitness to guide the search. After getting the histogram of the image, we adopt the bee algorithm procedure to explore the optimum result of (t*) which can produce the maximum fitness. Then, the infrared image can be segmented according to the value of (t*). All programs are designed by using the Matlab program. In the simulation of the proposed algorithm, it needs many parameters that are predefined. Table.1 shows predefined values of parameters for the max-entropy & bee algorithm and also Fig. 1 describes the process of the proposed algorithm. The values were determined empirically in table. 1.

Table 1. Parameters of the Bee Algorithm

The Bee Algorithm Parameters	Symbol	Value
Number of scout bees	n	30
Number of best selected sites	m	25
Site radius for neighbourhood search	ngh	1
Number of elite sites out of m selected sites	e	20
Number recruited bees around best selected sites	n1	15
Number of recruited bees around elite selected sites	n2	20

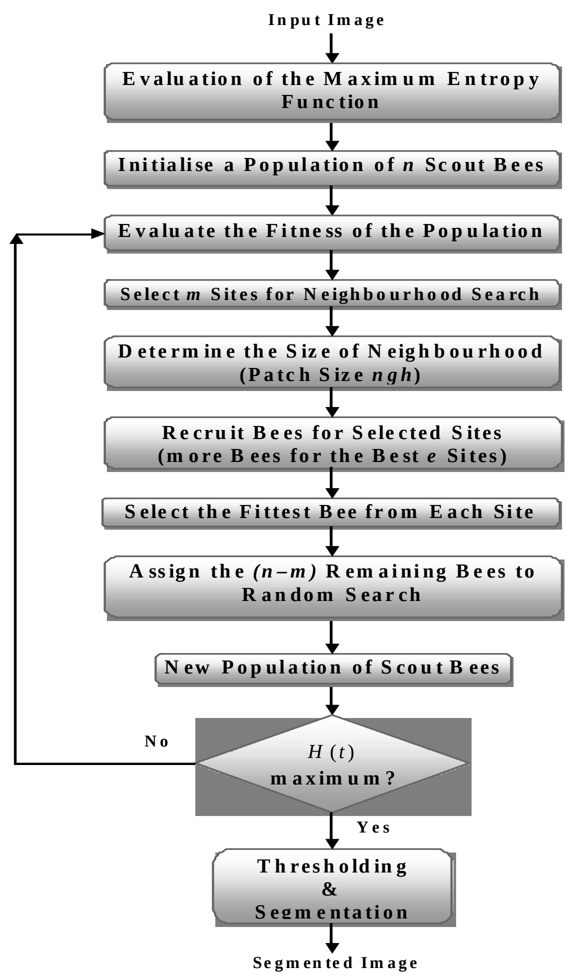

Figure 1. Flow chart of the proposed method

4. Results

The manual segmented results of six different images based on the maximum entropy that is supplied by the bee algorithm are shown in Fig. 2 and Fig. 3. Considering the segmented images, we think the results obtained by our method can be regarded as reasonably good and applicable in subsequent processing. Experiments on infrared images segmentation are used to illustrate the validation of the proposed algorithm. The proposed algorithm is tested on the six different original images. The original images are named FLOWERS, STEALER, DOGS, AIRPLANE, SHIP and TANK images. And the images used contains (500*375), (320*240), (350*155), (320*240), (255*195) and (300*202) pixels respectively, which are shown as Fig. 2 and Fig. 3.

Table.2 presents the segmentation results that are obtained by the proposed Algorithm for the six different images. It is seen from the segmented image that the computed thresholds are our favorite results.

Table 2. Experimental Results

Image	Computed Threshold	Number of Iterations
FLOWERS	128	200
STEALER	129	600
DOGS	124	50
AIRPLANE	132	100
SHIP	127	50
TANK	123	50

It is possible to reveal from the selected thresholds in table.2 that the maximum entropy image segmentation based on the bee algorithm can find a better threshold and because of its selected threshold, can detect and extract the favorite object from the background of the image. Also, the experiments of segmenting the infrared images are illustrated to show that the proposed method can get ideal segmentation result with less computation cost. The presented detection method is not limited to infrared images segmentation. On the other hand, this approach could be extended and modified to segmentation and detection of other types of standard images.

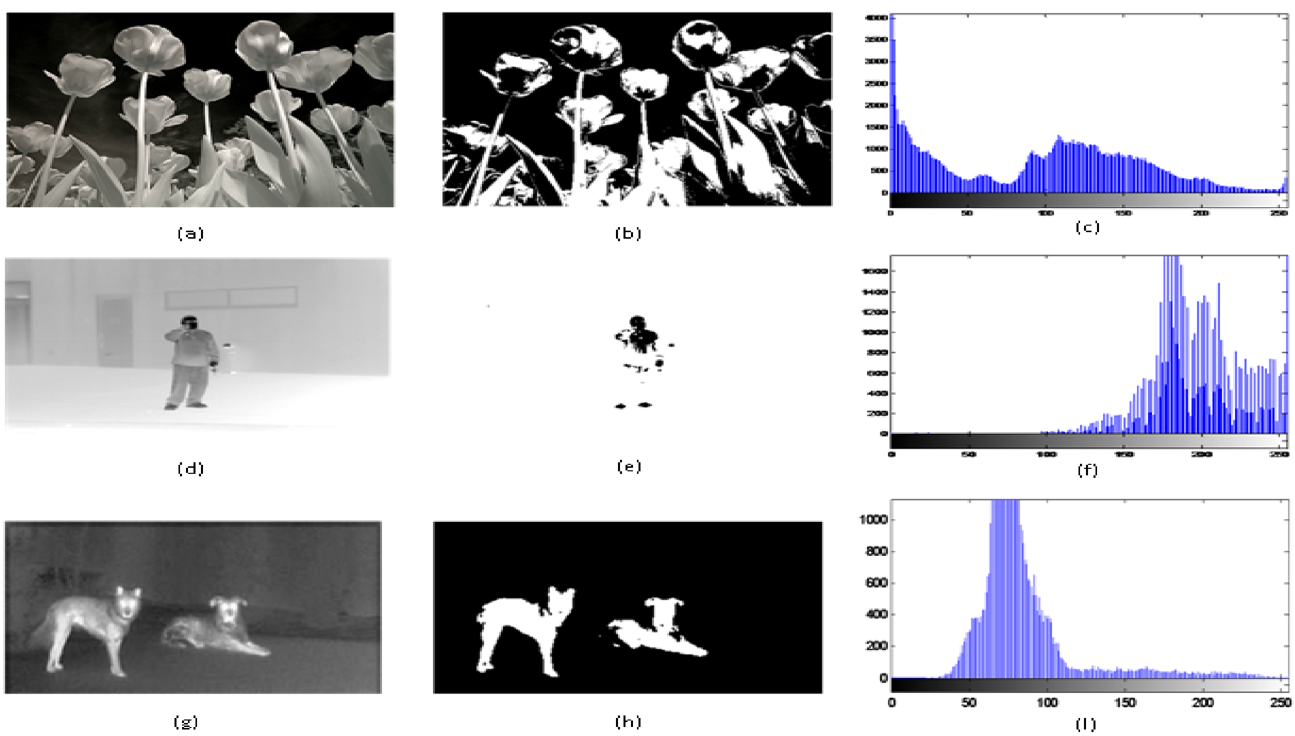

Figure 2. (a) Original Image of FLOWERS (b) Segmented Image of FLOWERS (c) Histogram of FLOWERS Image (d) Original Image of STEALER (e) Segmented Image of STEALER (f) Histogram of STEALER Image (g) Original Image of DOGS (h) Segmented Image of DOGS (l) Histogram of DOGS Image

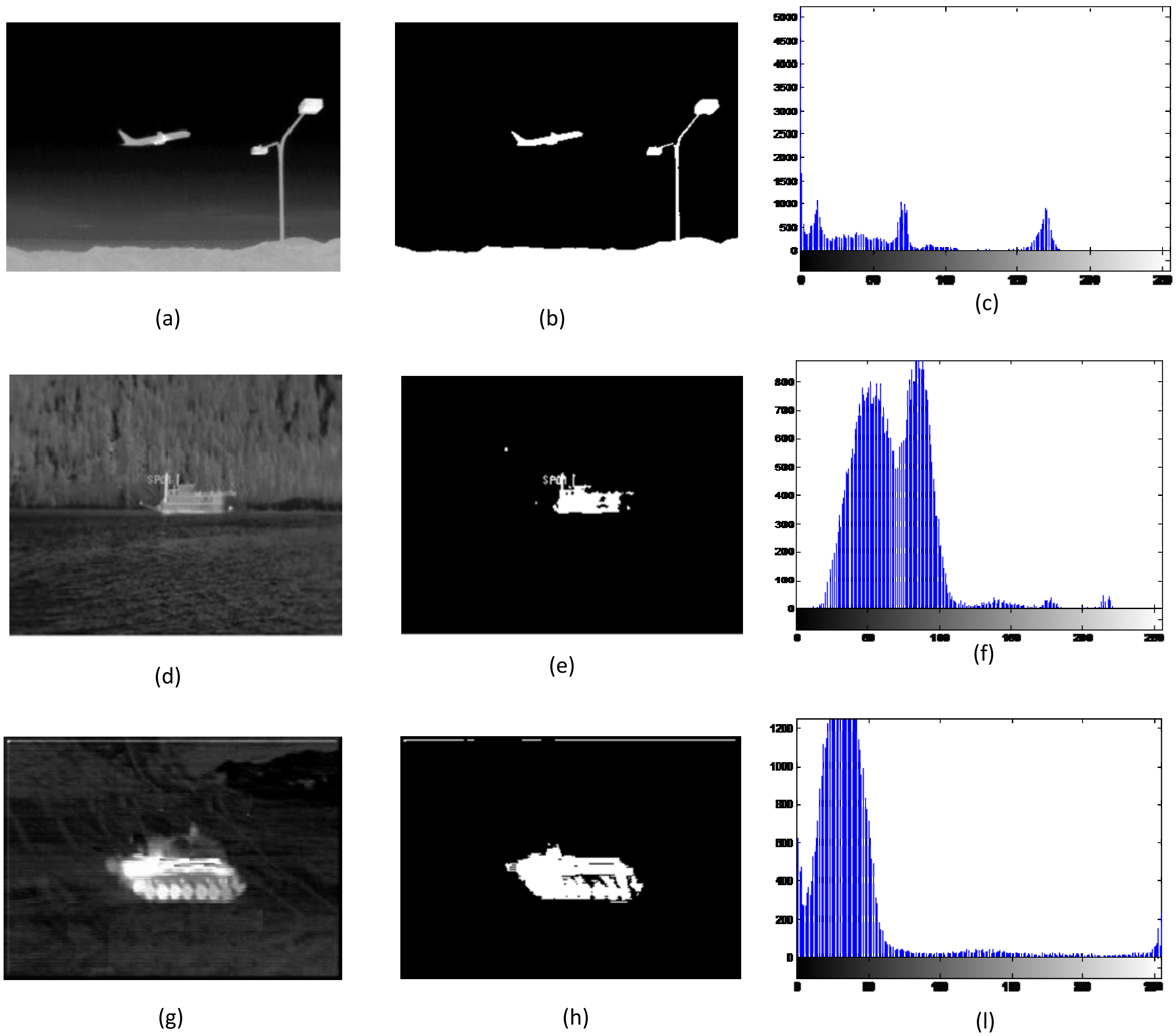

Figure 3. (a) Original Image of AIRPLANE (b) Segmented Image of AIRPLANE (c) Histogram of AIRPLANE Image (d) Original Image of SHIP (e) Segmented Image of SHIP (f) Histogram of SHIP Image (g) Original Image of TANK (h) Segmented Image of TANK (l) Histogram of TANK Image

Fig. 2 shows the segmentation results obtained on the FLOWERS, STEALER and DOGS images by the proposed algorithm. For original images in the first columns (Fig. 2), the segmentation results are shown in the second columns and the histograms of the original images are shown in the third column in Fig. 2. In the first row, the flowers of the image were clearly segmented as black and white colours, as shown in Figs. 2(b). And also the background information was segmented as black colour. As seen from the first row of Fig. 2, the main features of the image were clearly detected by the proposed approach. In the second row, the image "STEALER" mainly consists of one ideal object, the stealer man, and we have decided to detect that from the background objects. It is seen from the segmented image that the proposed algorithm succeeded to detect the stealer man as black colour and segmented the background as white colour, as shown as in Fig. 2(e). In the third row, the image "DOGS" includes two noticable objects, two dogs, that should be segmented and extracted from the background. According to the segmented image in Fig.

2(h), two dogs were evidently segmented as white colour and the background was detected as black colour.

Fig. 3 shows the segmentation results obtained on the AIRPLANE, SHIP and TANK images by the proposed algorithm. For original images in the first columns (Fig. 3), the segmentation results are shown in the second columns and the histograms of the original images are shown in the third column in Fig. 3. In the first row, the original image “AIRPLANE” consists of two favorite objects, the airplane and the light bulb. According to the segmented image, the ideal objects were clearly segmented as white color, as shown in Figs. 3(b). And also the background information was segmented as black color. As seen from the first row of Fig. 3, the main features of the image were evidently detected by the proposed approach. In the second row, the image “SHIP” mainly consists of one ideal object, the ship, and we have decided to extract it from the background objects. It is seen from the segmented image that the proposed algorithm succeeded to detect the ship as white color and segmented the background as black color, as shown as in Fig. 3(e). In the third row, the image “TANK” includes one ideal object, the tank, which should be segmented and extracted from background. According to the segmented image in Fig. 3(h), the tank was evidently segmented as white color and the background was detected as black color.

5. Conclusions

An automatic thresholding of gray-level images using maximum entropy and bee algorithm is proposed. The proposed approach is based on the bee algorithm to optimization of the maximum entropy method for segmentation of infrared images. The goal of this research was to develop a better segmentation algorithm. In order to achieve this goal, we developed an important thresholding method based on a recent evolutionary algorithm. The proposed algorithm simulates the behavior of honey bees to develop the algorithm to search for the optimum thresholds for segmentation of images. With the help of the bee algorithm, the favorite threshold can be obtained easily with high efficiency. The selected threshold can be segmented images and evidently extracted the ideal objects from background. Experimental results on a large number of different kinds of infrared images show that the proposed method performs fairly well in term of the segmentation and the objectives detection quality. The proposed segmentation method is not limited to infrared images segmentation. On the other hand, this approach could be extended and modified to segmentation of other types of standard images. This result is promising and it encourages further research for applying the maximum entropy and the bee algorithm to develop algorithms for image processing and pattern recognition.

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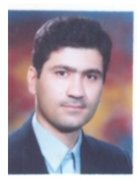

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