Image Segmentation Based on World Cup Optimization Algorithm

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ABSTRACT
Image segmentation has been widely used in different applications of the image processing. The main objective of image segmentation is to subdivide the input images to their main components. Generally, the main purpose of the segmentation is to simplify or change an image representation into something that is more meaningful and easier to analyze. In this paper, World Cup Optimization Algorithm (WCO) is proposed to classify the main components of an image (pixels) into different groups. In the experiment, the proposed method performance is measured by comparing with Otsu as a classic method and GA based and APSO based image segmentation algorithms as the heuristic based algorithms for segmentation. When compared with the other segmentation methods, the proposed WCO based method achieved good performance. The final efficiency of the proposed system is compared with the described methods. Experimental results show that the proposed method has overcome the others in the performance.

KEYWORDS: Image Segmentation; Optimization; World cup optimization, Otsu, Thresholding; Segmentation; GA, APSO; Entropy based segmentation.

1. INTRODUCTION

Image segmentation is one of the key tools in low level image processing which aims to classify an input image into its components. This procedure can be performed by assigning labels to all forming pixels of the image where the pixel with common features are labeled in the same class [1]. This process plays important role in most of computer vision applications [2]. From the literature review, we can classify the image segmentation into four different types: texture analysis based methods, clustering based methods, histogram thresholding based methods and region based split and merging methods [3].

Among different methods of image segmentations, thresholding is a technique which classify the components of an image whereas the pixels with the same features include a special range of grey levels.

There are two different kinds of thresholding: optimal thresholding methods [4-7] and property-based thresholding methods [8], [9].

In simple terms, thresholding based segmentation has been given a considerable attention in the last few years [10]. In addition, because of their ability in obtaining near optimal solutions for many applications, heuristic algorithms have been recently utilized to achieve the proper solutions for the problem of image segmentations.

In a different point of view, multilevel image thresholding techniques can be classified into two other categories including parametric and non-parametric methods [11]. In the non-parametric approach, the main purpose is to find a proper objective function which makes good segmentation by maximizing (minimizing) it based on optimization algorithms, like the Otsu's method [12] and Kapur's entropy method [4]. In parametric based methods, the distribution of grey level for the classes has a histogram such that assumed to follow the given distribution.

Least-squares method can be considered as another method which is introduced to find the fittest histogram data. Generally, the main problem of this method is its time consuming in order to leading a nonlinear optimization problem. There is a gat deal of thresholding techniques which have been proposed in order to perform bi-level thresholding [2, 13, 14]. In[15], a fast recursive method within a look-up table is utilized for improving and optimizing the Otsu's function.

In 2003, Lin proposed a fast thresholding computation by using the Otsu's function. This method occurs by using a successive substitution technique [16].

In 2003, wavelet transform is used to reduce the resolution of the histogram [17]. By this reduction, a comprehensive search is utilized for optimizing the

Otsu's function to characterize the optimal thresholds. Afterwards, the obtained values for threshold are employed to the original scale.

Generally, Optimization algorithms are based on an objective function. In other words, in optimization based methods, the main purpose is to maximize or minimize a definite cost function. Entropy-based methods are one of the most used methods among the optimization algorithms. The maximum entropy method has been used as image segmentation tool for different applications [18], [19].

In the maximum entropy methods, the entropy for every gray value should be achieved. In order to the computational complexity, in this paper, World Cup Optimization Algorithm as a new optimization algorithm is employed to find the optimum results.

2. MAXIMUM ENTROPY THRESHOLDING

The entropy with *n* status can be defined by the Shannon equation as follows:

$$H = -\sum_{i=0}^{n} P_i \log P_i \tag{1}$$

Where *H* describes the entropy of the system information and P_i is the occurrence probability for the event *i* , $\sum_{i=0}^{n} P_i = 1,\ 0 \le P_i \le 1$. Here, inverse probability of the occurrence can be achieved from the information of the event.

By extending the equation above to form the perspective of image processing, and by assuming the *i* as gray value of the image and P_i as the pixel probability being *i*. The main purpose of the maximum entropy is to maximize the *H* by proper selecting of *i*.

Let's consider *T* as the thresholding value. In this condition, the pixels with less grey values than *T* includes the area of interest while the pixels with more grey values illustrate the background region.

$$P_O = -\sum_{i=0}^{T-1} P_i,\ where \quad i = 0,1,\ldots,T-1, \tag{2}$$

$$P_B = -\sum_{i=T}^{255} P_i,\ where \quad i = T, T-1,\ldots 255, \tag{3}$$

Where, P_O, P_B are the grey level probabilities of the background region and object region, respectively.

Entropy value of the object and the background regions can be achieved by the following equations:

$$H_O = -\sum_{i=0}^{T-1} P_i / P_O \log P_i / P_O, \tag{4}$$

$$H_B = -\sum_{i=T}^{255} P_i / P_O \log P_i / P_O, \tag{5}$$

Where H_B, H_O describe the entropy value of the background and object regions, respectively.

From the above equations, the entropy function can be evaluated as below:

$$H = H_B + H_O \tag{6}$$

From the illustrated considerations, the threshold value T^* should result in the function in below:

$$T^* = \max \mathrm{H} \tag{7}$$

3. WORLD CUP OPTIMIZATION ALGORITHM

World Cup Optimization (WCO) algorithm is a new optimization algorithm which is derived from the challenges among national teams to achieve the championship cup. Teams are usually stand in the seeds according to their Ranks [20]. One of the most important principles of FIFA is Rank in order to their fails and wins in the past challenges [21].

Generally, 'rank' has direct effect on the success of the teams; because the team's strength defines the seeding.

By this way, *n* first stronger teams have been given to the first seed, the teams with less strength have been given to the next seed, etc. At first, strong teams survive from competition with each other to save and upgrade them into the higher level. After the seeding step, the competition starts. Here, all the teams challenge with each other to gain victory to collect more points for improving their ranks to the next competitions. The competition starts with an early challenge among the teams into each seed. After these competitions, two high point teams in the groups (these teams can belong to a common continent) mount to the next level and the rest are omitted.

The challenges have different rules which have been changed in each series of competitions. The third place of each competition belongs to a team which can compete with the rest teams and win them all to get a chance to enhance its ability to rise into the higher level of competitions (Play-Off). The final challenge has been hold between two teams with high points toward the rest teams to select the champion of the competition. WCO algorithm can be summarized as follows:

Step 1) Initializing step for selecting the continents and their teams

By considering an N dimensional (N_{var}) optimization problem with *M* continents, continents will have an array of $1\times N_{\text{var}}$, which has representing the teams in competition, we have:

$$Continent = [country_1, country_2, \ldots, country_{N_{\text{var}}}] \tag{8}$$

$$country_i = [x_1, x_2, \ldots, x_{N_{\text{var}}}] \tag{9}$$

here x_i defines the i^{th} team in the country. The variable's values ($x_1, x_2, \ldots, x_{N_{var}}$) are floating point number. We can also achieve the rank of the continents by considering the rank points f_r in a continent ($x_1, x_2, \ldots, x_{N_{var}}$). Since,

$$Rank = f_r(continent) = f_r(x_1, x_2, \ldots, x_{O_{var}}) \quad (10)$$

$$O = N \times M \quad (11)$$

Where M describes the number of continents and N illustrates the variables dimension. One of the best profits of the WCO algorithm is Initializing step; in this step, continents include different values of random teams by different standard deviation. For enhancing the convergence time, an interval is selected and get the random values and then, it is divided into parts which these parts comprise the continents. This characteristic makes this algorithm to have a faster convergence rather than the other algorithms. The generated continents are matrices of size $N_{pop} \times N_{var}$; where N_{var} describes the number of variables in the problem and N_{pop} shows the number of teams. There is also a number of random number of teams for the initial continents. Generally, the real FIFA competitions include 5 continents with some teams in them.

Step 2) Fitness function Evaluation

After initial competition among teams and describing their points, the next step is to evaluate the continent's point. The achieved points are not so clear. The reason is behind the fact that there may be a continent with some teams which includes the most point (optimum fitness) while the others have weak points in the continents. A solution in the WCO has been done by computing the mean value and the standard deviation of the continents:

$$\overline{X} = \frac{1}{n}\sum_{i=1}^{n} X_i \quad (12)$$

$$\sigma = \sqrt{\frac{1}{n-1}\sum_{i=1}^{n}(X_i - \overline{X})^2} \quad (13)$$

here n describes the number of members in X , $\overline{X}$ shows the mean value of the continent X, and σ shows the standard deviation of the continent X.

Step 3) Ranking the teams as below:

$$\begin{aligned} X_1 &= [X_{11}, \ldots X_{1n}]^T, \\ X_2 &= [X_{21}, \ldots X_{2n}]^T, \\ &\ldots, \\ X_5 &= [X_{51}, \ldots X_{5n}]^T \end{aligned} \quad (14)$$

$$X_{Total} = [X_{11}, \ldots X_{1n}, X_{21}, \ldots X_{2n}, \ldots, X_{51}, \ldots X_{5n}]^T \quad (15)$$

where T is the transpose operator and n describes the number of teams for the continents. During this process, two optimal quantity of each continent has been selected and perched to the other vector (X_{Rank}) for the next competitions and the optimal quantities of X_{Total} have been selected as the first cup's champion:

$$X_{Rank} = [X_{11}, X_{12}, X_{21}, X_{22}, \ldots, X_{51}, X_{52}]^T \quad (16)$$

$$\begin{aligned} X_{champion} &= \min(X_{Total}) = \\ &\min([X_{11}, \ldots X_{1n}, X_{21}, \ldots X_{2n}, \ldots, X_{51}, \ldots X_{5n}]^T) \end{aligned} \quad (17)$$

Where, $X_{champion}$ describes the minimum value of the solutions.

Step 4) start the next stage of competition among teams

After the first competition among teams, new continents and teams including them will be regenerated according to the previous championship competitions and their ranking. In this step, the algorithms perform different from the real FIFA competition. For this process, a vector with two parts can be considered:

$$Pop = X_{total} = [X_{Best}, X_{Rand}] \quad (18)$$

here X_{Rand} illustrates a random quantity in a described interval, $Pop(X_{total})$ describes the new generated teams of the size ($N \times M$) and X_{Best} is a vector as follows:

$$L < X_{Best} < U \quad (19)$$

$$U = \frac{1}{2} \times ac \times (Ub + Lb) \quad (20)$$

$$L = \frac{1}{2} \times ac \times (Ub - Lb) \quad (21)$$

where ac describes a coefficient between L_b and U_b as low and high bounds for the problem.

Step 5) Exploration and exploitation

X_{Rand} and X_{Best} are utilized as the exploration and the exploitation terms. X_{Best} is the process of possession of the formerly search space and X_{Rand} is the process of generating new random quantities in the search space. The size of X_{Best} and X_{Rand} are separated by Cross Point (CP) as follows:

$$\begin{aligned} X_{Rand} &= Pop(1: CP, M) \\ X_{Best} &= Pop(CP+1: N, M) \end{aligned} \quad (22)$$

The new population is divided into m teams of n continents:

$$Pop=[X_{Best},X_{Rand}]\rightarrow \begin{array}{l} X_{1new}=[Pop(1:k)] \\ X_{2new}=[Pop(k+1:l)] \\ X_{1new}=[Pop(l+1:r)] \\ X_{1new}=[Pop(r+1:s)] \end{array} \quad (23)$$

Step 6) If the criterion is reached, end the algorithm; otherwise repeat the algorithm.

4. OPTIMIZING THE IMAGE SEGMENTATION TECHNIQUE BASED ON WCO ALGORITHM

From the WCO algorithm and the maximum entropy method for thresholding, the grey value for the pixel t is described as the teams which are in competition. The objective is to maximize the entropy function which is given above. The optimized solution can be reached by the iterative challenging. The procedure is illustrated as follows:

Randomly initializing the n number of quantities in the interval 0-255 to comprise the teams. Then compete the teams based on their ranks and points. Evaluate the fitness function of the teams according to formula. Apply exploration and exploitation terms. In the event that the point of the team is greater than 255, the quantity zero will be chosen for the rank; otherwise, the rank returns to 255 if the point is smaller than 0.

5. EXPERIMENTAL RESULTS

In this section, images from different databases are taken to be analyzed with the proposed method. MATLAB tool is utilized to develop and implement the proposed technique and the method is run on a 2.6 GHz Core i7 CPU, on Windows 10 platform. For efficiency analysis of the proposed optimized method, three different thresholding algorithms including classic, GA based and APSO based optimization of the entropy function [22] are employed [5].

Thresholding technique is analyzed on USC-SIPI benchmark [23]. The introduced dataset includes 44 real complex images with different contrasts, brightness and sizes.

This benchmark is one of the primarily benchmarks which has been used to support research in image processing and machine vision purposes. Images have different sizes from 256×256 and 512×512 to1024×1024 in pixels. The quality of images is 8 bits/pixel for gray-level images, 24 bits/pixel for color images.

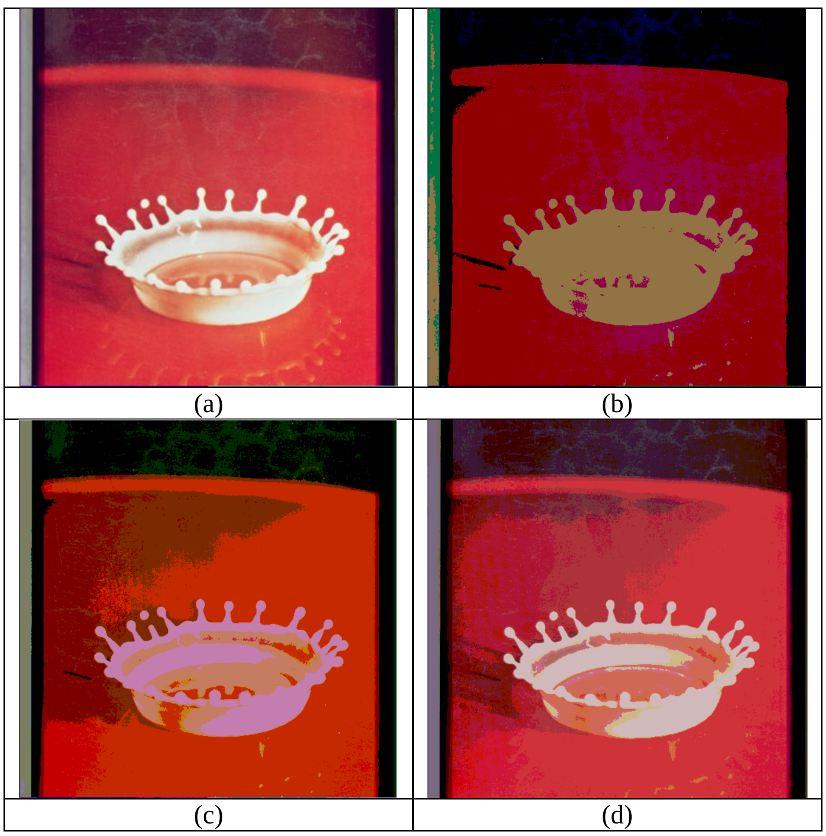

Fig. 1. (a) Input image. (b) segmented image by WCO (c= 3) (c) segmented image by WCO based method (c = 5), (d) segmented image by WCO based method (c = 7).

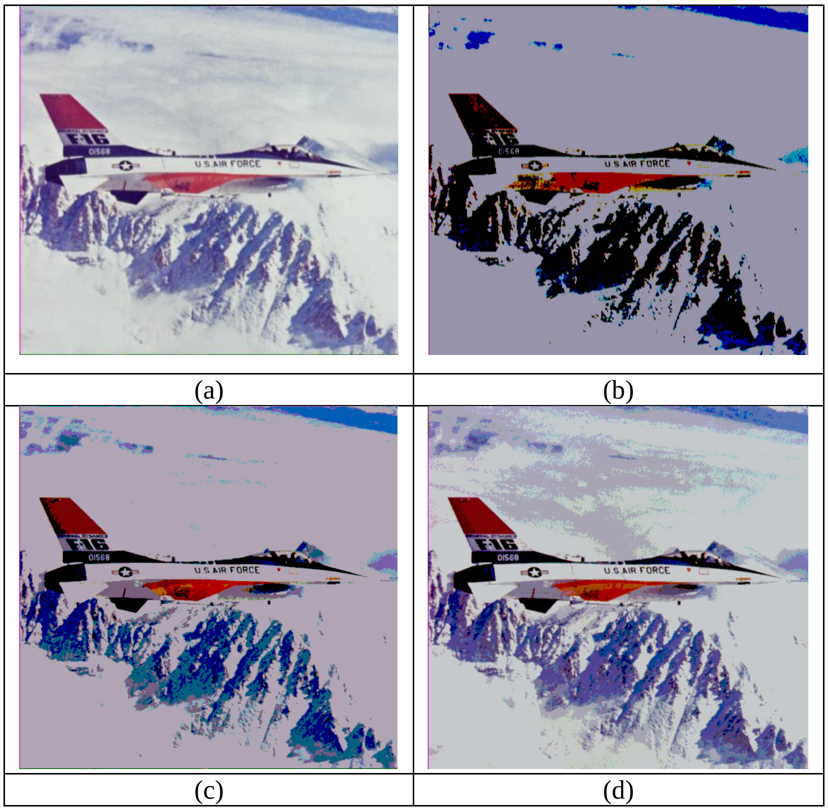

Fig. 2. (a) Input image. (b) segmented image by WCO (c= 5) (c) segmented image by WCO based method (c = 7), (d) segmented image by WCO based method (c = 9).

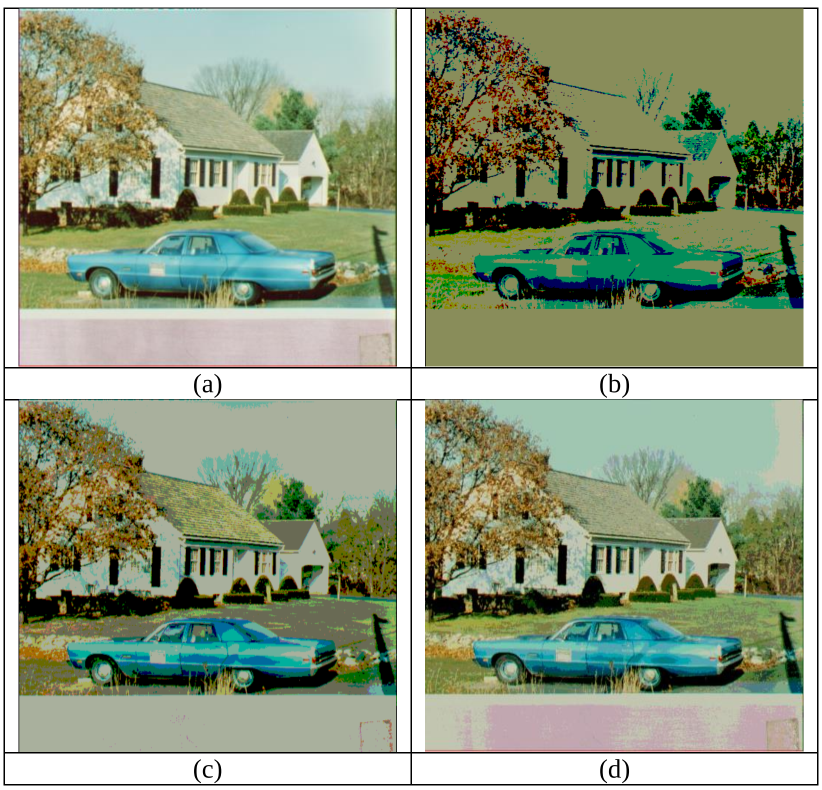

Fig. 3. (a) Input image, (b) segmented image by WCO (c= 3) (c) segmented image by WCO based method (c = 7), (d) segmented image by WCO based method (c = 9).

Figures 1 to 3 show the analysis of three different algorithms on the considered images based of the entropy technique. In here, the segmented parts of the considered image have been marked with color level intensity of the respective cluster centers. Performance comparisons are analyzed by three different number of clusters: 3, 7 and 9 clusters.

Three performance indexes which are employed for the algorithm analysis are: the correct detection rate (CDR), the false rejection rate **(FRR)** which defines the percentage of identification moments in which false rejection occurs, and false acceptance rate **(FAR)** which defines the percentage of identification moments in which false acceptance occurs.

$$CDR = \frac{\text{Number of samples correctly classified in dataset}}{\text{Total number of samples in dataset}} \quad (24)$$

$$FAR = \frac{\text{Number of false accepted samples in dataset}}{\text{Total number of samples in dataset}} \quad (25)$$

$$FRR = \frac{\text{Number of false rejected samples in dataset}}{\text{Total number of samples in dataset}} \quad (26)$$

Table 1 illustrates the average segmentation accuracy on all 44 images in the benchmark dataset, USC-SIPI benchmark for WCO based technique and its comparison by the GA based and APSO based algorithms and the mean time taken by each algorithm to terminate on the image data. Finally, Table 4 contains the mean and standard deviations of the number of classes obtained by the two automatic clustering algorithms

Table 1. The performance comparison in the presented method and some other classic and heuristic methods applied on USC-SIPI benchmark.

Index	**Otsu[12]**	**GA[22]**	**APSO[14]**	**WCO**
CDR(%)	34.09	79.54	93.18	95.45
FAR(%)	43.19	13.63	4.52	0.022
FAR(%)	22.72	6.82	2.27	0.022

From the table, it can be concluded that the proposed segmentation method based on WCO illustrates the highest accuracy in comparison with others.

6. CONCLUSIONS

Segmentation is one of the most significant topics in image processing and machine vision. Among different ways which have been introduced to this purpose, the maximum entropy method has good results. The only problem of this method is its complex computation. Recently, a new algorithm namely WCO is introduced for solving the optimization based complex problems. In this paper, we employ this algorithm for solving this complexity easily and with high efficiency. The proposed method is analyzed based on three different metrics and the results showed that the proposed method have better performance than some different applied algorithms.

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