Toward Application of Extremal Optimization Algorithm in Image Segmentation

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Abstract—**Extremal optimization (EO) algorithm is a kind of evolutionary optimization method which has been applied successfully in different fields. In this paper a new framework is proposed for applying extremal optimization in image segmentation. oversegmented images are the initial to EO which works on two levels: segments and pixels. A new energy function is defined for segments and the energy function in markov random fields (MRF) is used for pixels. Applying EO in segment level accelerates the speed of the algorithm. The results show that by defining a suitable energy function, EO can be succeed in merging similar segments and provide a visually good segmentation.**

Keywords-extremal optimization; segmentation; oversegmented images; markov random fields

I. Introduction

Extremal optimization (EO) [1-3] is a general-purpose local search optimization method that obtains its main idea from the concept of self-organized criticality (SOC). Such as simulated annealing (SA) [4] or genetic algorithm [5], it was inspired by previous attempts of using physical intuition for optimization. It appears to be a powerful addition to the mentioned heuristics in its generality and its ability to explore complicated configuration spaces efficiently [6].

The base of EO is developing a single solution composed of a number of components, each of which is a variable of the problem.

Extremal optimization has been applied in different fields such as scheduling, network, TSP, graph coloring etc. In this work, EO is proposed to be applied in image segmentation.

Image segmentation [7] is one of the important stages in image analysis. A lot of applications like Object Recognition, Scene Understanding and analysis, Automatic Traffic control systems, Medical Imagining for Detection of Tumors and Pathologies need segmentation either at pre-processor level or at advanced level. Segmentation consists in partitioning an image into its constituent segments or objects, where segment is set of pixels. The segmentation result is the labeling of the image pixels that have common property (brightness, texture, color…).

Previous work on image segmentation based on EO employed the fitness function in markov random field (MRF) model. MRF modeling has been widely used for edge detection [8], image restoration [9], image segmentation, stereovision, long range motion and image classification [10].

Image segmentation based on MRF has been considered as the problem of recovering a "true" image consisting of a few homogeneous segments from a noisy image by labeling individual pixels [11].

This paper is based on a different framework. The algorithm uses oversegmented images as the initial, so the method is extended to work both on segment and pixel level. Besides the MRF energy function used for pixels, a new energy function is defined for segments to be optimized by the algorithm. The advantage of working on segment level is increasing the speed of the algorithm and improving the quality of result images.

The rest of the paper is organized as the following: section 2 reviews some previous work. In section 3, definitions and concepts of MRF and EO are summarized. Section 4 states our proposed model for image segmentation. In section 5 we discuss about the results of our technique. Finally, Section 6 contains the conclusion.

II. Related Work

Few previous work on image segmentation based on EO employed the energy function in MRF model.

The two major MRF based algorithms for image segmentation, the Simulated Annealing (SA) and Iterated Conditional Modes (ICM), are used in [12]. Compared to the SA, the ICM provides reasonable segmentation and shows robust behavior in most of the cases but strongly depends on the initialization phase.

In [13] a new Markov Random Fields model-based algorithm for image segmentation by Extremal Optimization is presented. The general-purpose of this algorithm is to find a label configuration $x=\{x_1, .., x_{MN}\}$ according to the maximum a-posteriori probability estimation method, using τ-EO algorithm which needs only the local energies of sites for affecting the updates. Images which are corrupted by correlated noise are given to the algorithm and after the initialization phase, the worst sites (which have the lowest fitness) of a single sub-optimal solution are consecutively updated by the algorithm which assigns them new random values. As a result, huge fluctuations called *avalanches* come forward to explore various local optima in an efficient way. The robustness of the τ-EO algorithm was tested on different images and provided good segmentation (for initial noisy images) and was the most robust among other two algorithms SA and ICM. Experiments realized with real images demonstrate and indicate that the algorithms (ICM, SA and τ-EO) may fail to enhance the quality of segmentation.

A distributed image segmentation algorithm structured as a multiagent system is proposed in [14] which is composed of a set of segmentation agents and a coordinator agent. Starting with an initial image, each segmentation agent performs the iterated conditional modes method, known as ICM, in applications based on Markov random fields, to obtain a sub-optimal segmented image. The coordinator agent diversifies the initial images with the help of genetic crossover and mutation operators along with extremal optimization. This combination increases the efficiency of the algorithm and ensures its convergence to an optimal segmentation. In this segmentation, EO is just a help for diversifying the solution and GA has the basic role for segmentation.

In [15] Bak–Sneppen model and Markov Random Fields are combined to define a multiresolution image segmentation approach in order to speed up the segmentation process and to improve the restoration process. Image pixels are viewed as lattice species of Bak–Sneppen model. At each cycle, some objectionable species are chosen for a random change in their fitness values. Furthermore, the change in the fitness of each species causes fitness changes of its neighboring species. After a certain number of iteration, the system converges to a Maximum A Posteriori estimate. In this multiresolution approach, a wavelet transform is used to reduce the size of the system. The initial images are still noisy images and it doesn't have good results for real images.

In fact to the best of our knowledge, segmentation of images containing realistic photos are never studied before. Few published results of EO in the field of image segmentation [13-15] are mainly concerned with removing the effects of noise from synthetic images.

One of the major differences between this work and the mentioned previous work is the proposed framework for image segmentation.

III. BACKGROUND

A. Definitions and Notations

First, in this section, we define briefly our notations and give an introduction to the theory of MRF. The MRF is a discrete stochastic process and its global properties are controlled by means of local ones. The Ising model, which is the best known and the most used in MRF image segmentation, highlights MRF and facilitates its use in different domains of application.

An image $S = \{1, .. t, .., MN\}$ specifies the gray levels for all pixels in an M×N lattice where t is called a site. The gray levels belong to the set A= {0,..., 255}. The labeled image is denoted by the vector random variable $X = (X_1, .., X_t, .., X_{MN})$, $Xt \in \{1, .., C\}$ where C is the number of categories. If C=2 then the problem can be viewed as a special case of pixel labeling called edge detection (edge and no edge). The image observed is represented by the MN-vector random variable $Y= (Y1,...,Y_{MN})$, $Yt \in \{0,.., 255\}$.

A neighborhood system $N = (Ni \subset S, i \in S)$ is formed by the subsets Ni of S which are neighbors to pixel i that verifies: (1) $i \notin Ni$ and (2) $j \in Ni \Leftrightarrow i \in Nj$.

A clique $c \subset S$ is a set of points which are all neighbors to each other: $\forall\, r, t \in c, r \in Nt$.

The structure of the neighborhood system (see Fig. 1) determines the MRF order. In a first order the neighborhood of a site consists of its four nearest neighbors. For a second order the neighborhood of a site consists of the eight nearest neighbors. In this paper second order neighborhood system is used.

This model as stated in [15] is defined formally as:

Let $X = (X_1, .., X_{MN}) \in \Omega$ where Ω is the set of all possible configurations for labels. X is a MRF according to the neighborhood system N if:

1. $\forall\; x \in \Omega : P(X = x) > 0$.
2. $\forall\; t \in S\; x \in \Omega$: $P(x_i/x_j, j \in S - \{i\}) = P(x_i/x_j, j \in Ni)$.

$P(X=x)$ is a Gibbs distribution defined by:

$$P_{Gibbs}(X=x) = e^{-U(x)} \big/ Z \quad (1)$$

Where $Z = \sum_{x \in \Omega} e^{-U(x)}$ is the partition function and $U(x)$ is the energy function given by:

$$U(x) = \sum_{t=1}^{MN} \sum_{r \in N_t} \left(\theta_r \delta(x_t, x_r)\right) \quad (2)$$

Where θ_r are the clique parameters. $\delta(a, b) = -1$ if $a = b$, 1 if $a \neq b$. $P(X = x)$ is called the a-priori probability.

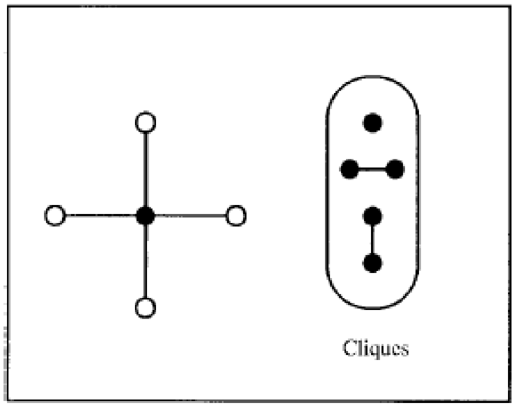

Figure 1. First order neighborhood-system with cliques [11]

The a-posteriori probability $P(x/y)$ follows a Gibbs distribution defined by:

$$P(x/y)= e^{-U(x/y)} / Z_y \quad (3)$$

Where Z_y is the normalization constant and $U(x/y)$ is the energy function given in equation (4):

$$U(x/y) = \sum_{t=1}^{MN}\left[\ln\left(\sqrt{2\pi}\,\sigma_{xt}\right)+\frac{(y_t-\mu_{xt})^2}{2\sigma_{xt}^2}+\sum_{r\in N_t}\left(\beta\delta(x_t,x_r)\right)\right] \quad (4)$$

Where β is a positive model parameter that controls the homogeneity of the image segments and σ_{xt}^2 and μ_{xt} are respectively variance and mean of a segment.

We can define image segmentation as the estimation of configuration label x which maxmizes the fitness function $P(x/y)$ called the MAP estimation.

B. Bak-Sneppen Model And Extremal Optimization Heuristic

One of successful application of the Self-Organized Criticality (SOC) concept is the bak–sneppen model of evolution. In this model, species are placed on lattice-system sites. Each species has a fitness value in [0, 1], where the higher the fitness, the better the chance of species survival.

Inspired by the bak-sneppen model, Boettcher and Percus proposed the EO algorithm, successively replaces the value of extremely undesirable variables in a sub-optimal solution with new, random ones. Large, avalanche-like fluctuations in the cost function self-organize from this dynamics, making the system explore local optima in distant neighborhoods of the configuration space while eliminating the need to tune parameters. To avoid getting trapped in local optimum and also for global improvement of results, Boettcher et al. introduced τ – EO algorithm by adding a single parameter τ to the basic EO. In the τ-EO heuristic, the process is based on the selection against several objectionable variables. Therefore, all variables are selected for state-updating indiscriminately. Because of this property, τ – EO heuristic is the base of this work.

IV. THE PROPOSED MODEL FOR IMAGE SEGMENTATION

this model starts with oversegmented initial images. The aim of EO is optimizing the energy function to obtain good segmentation. The algorithm is consisted of two phase as the following:

A. The First Phase

In this phase, the algorithm just works on segment level. In fact, we apply EO on the segments of the created initial oversegmented images.

To define the Energy function for segments, we inspired by the squared Fisher's distance (equation (5)) in [16] for merging similar segments.

$$D(R_1,R_2)=\frac{(n_1+n_2)(\mu_1-\mu_2)^2}{n_1\sigma_1^2\, n_2\sigma_2^2} \quad (5)$$

The aim of the proposed method in this phase is merging similar segments to minimize the energy function given as:

$$U(s_i) = n_i * \sigma_i^2 + \frac{|v_i|}{\sum_{j\in v_i}\left((n_i+n_j)(\mu_i-\mu_j)^2 / n_i\sigma_i^2\, n_j\sigma_j^2 \right)} \quad (6)$$

The number of pixels, the average color and the variance of colors within segment s_i are respectively n_i, μ_i, σ_i^2. The neighbors of segment s_i represented by v_i and $|v_i|$ is the number of neighbors of s_i.

In fact, for every segment s_i, we are using the average of squared Fisher's distance between its neighbors. The larger the distance, the smaller the energy function, the higher the fitness and the higher the chance of survival of the segment. Each segment which has the smaller distance has more similarity with its neighbors. So, there is no need for this segment to be survived and it can be merged with one of its similar neighbors.

The energy function is defined in order to be applicable for EO. Like MRF energy function for pixels, Energy function in [6] has two parts. The first part is related to the segment s_i itself and the second part is related to the neighbors of the segment s_i. in every step, one segment with the worst energy function is selected for merging in order to minimize the inter-segment variance and also to maximize intra-segment distances. Therefore similar segments can be merged to minimize the energy function defined.

In segment level, we consider segments as species and the image as a lattice-system as in bak–sneppen Model. The worst segment which has the worst fitness are more likely to extinction.

The fitness value of segment s_i is λ_{si} given by equation (7):

$$\lambda_{si} = e^{-U(s_i)} \tag{7}$$

We present the segment level EO algorithm as following:

1) Input data y(0): y(0) represents the observed image of size M × N.

2) Create an initial solution x(0) (an oversegmented image sized MN):

For t = {1, ..,L}(L is the number of segments) Do compute λt. Compute F = U(t).

3) Let x_{best} = x, F_{best} =F and Iteration = 1.

4) rank the segments according to their fitnesses.

5) For s = 1..L Do

a) Compute probability Ps α $s^{-\tau}$ where τ is a parameter

b) Generate a uniform random number μs in [0, 1].

c) If μs <=Ps Then merge this segment with one of it's neighbors which has the nearest mean of colors.

6) For t = 1...L Do evaluate λt of x. Compute F = U(t).

7) If F <F_{best} Then x_{best} = x and F_{best} = F.

8) Iteration = Iteration +1.

9) If (Iteration ≤ a given number of iterations) Then goto 4.

10) Output x_{best} and F_{best}.

B. The Second Phase

In this phase, the algorithm works on pixel level. After merging similar segments, EO tries to find better labels for some pixels to optimize the energy function defined for pixels in equation (4).

We consider site labels as species and the image as lattice- system as in bak–sneppen model.

The fitness value of species x_i is λ_i given by equation (8):

$$\lambda_i = P(x_i / x_j,\ j \in N_i) \tag{8}$$

We present the pixel level EO algorithm as following:

1) An initial solution x(0) (segmented image from previous phase

For t = {1, ..,MN} Do compute λt. Compute F = U(x/y).

2) Let x_{best} = x, F_{best} =F and Iteration = 1.

3) Rank the pixels according to their fitness (the worst site label has rank 1 and the best site label has rank MN) (note that according to the fitness function defined for pixels, most of the pixels at the edges of each segments has lower fitness than other pixels. So the labels of these pixels are more likely to change)

4) For s = 1..MN Do

a) Compute probability Ps α $s^{-\tau}$ where τ is a parameter

b) Generate a uniform random number μs in [0, 1].

c) If μs <=Ps Then modify the label of the site s to one of it's nearest neighbors label.

5) For t = 1...MN Do evaluate λt of x.

Compute F = U(x/y).

6) If F <F_{best} Then x_{best} = x and F_{best} = F.

7) Iteration = Iteration +1.

8) If (Iteration ≤ a given number of iterations) Then goto 3.

9) Output x_{best} and F_{best}.

V. Experimental Results

In this section several results of the algorithm on different test images are displayed in the following figures.

The problem parameters are tuned as: β = 0.5, τ = 1.9 for segment level EO and τ = 0.8 for pixel level EO.

One result of the proposed method compared with the base EO is presented in Fig. 2. The oversegmented of the true image is used as the initial and both base EO and the proposed method are applied to optimize it.

Visual examination shows that base EO works well at labeling some pixels that seems to be like noise but it fails to give a simple segmented image. The proposed method can successfully merge similar segments while recognizing the main segments in initial image and improving the segmentation result.

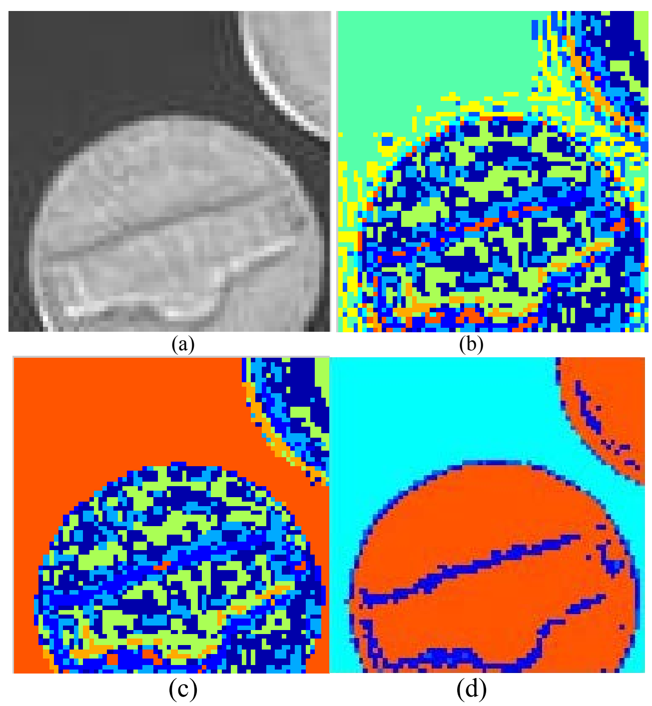

Figure 2. Segmentation results: (a) true image (b) initial oversegmented image, (c) base EO segmentation, (d) proposed method segmentation

In Fig. 3 we show different experimental results of the proposed segmentation method. Merging similar segments can be seen in some internal steps of the algorithm (Fig. 3.c, 3.d and 3.e). The result of segment level EO (Fig. 3.f) contains main segments and is an initial image to pixel level EO. Finally, pixel level EO adjusts some pixels and lead to a good segmentation result; however some pixels containing improper labels may remain (Fig. 3.g).

Fig. 4 is another example which shows different experimental results of the proposed segmentation method.

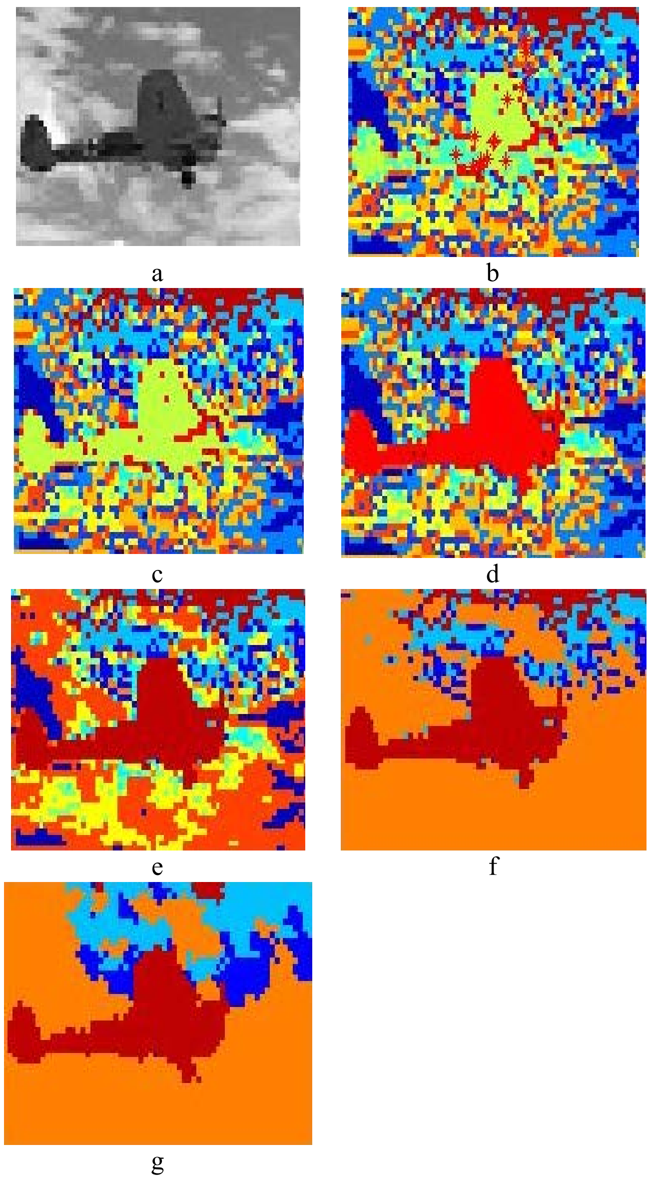

Figure 3. Segmentation results of different steps in the proposed method: (a) true image, (b) initial oversegmented image, (c) , (d) and (e) merging segments after some iterations, (f) result of segment level EO (initial to pixel level EO), (g) final result of pixel level EO

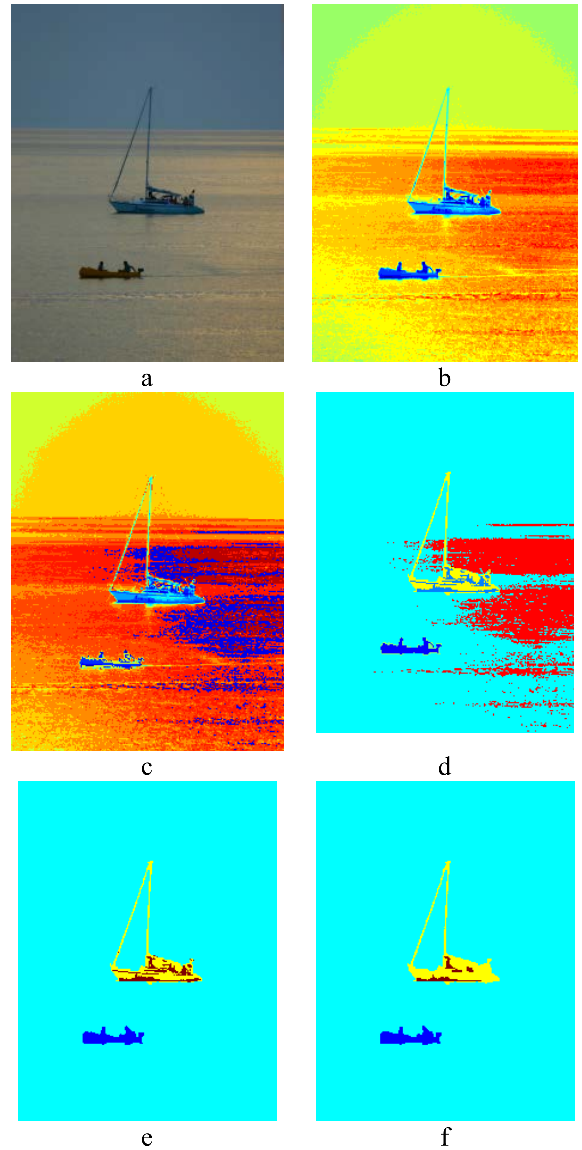

Figure 4. Segmentation results of different steps in the proposed method: (a) true image, (b) initial oversegmented image, (c) , (d) merging segments after some iterations, (e) result of segment level EO (initial to pixel level EO), (f) final result of pixel level EO

VI. Conclusion

In this paper, we have proposed a new framework for image segmentation based on extreaml optimization algorithm. Oversegmented images are used as the initial step and EO was applied in two levels: segment and pixel. Two separate energy function, one for segments and the other for pixels, are stated. The new defined energy function for segments inspired by squared Fisher's distance is employed as a successful measure of merging similar segments. Also the energy function in MRF for adjusting the labels of pixels will help the quality of segmentation result (achieved through a visual judgment).

We propose as a future work the use of other group of objective functions in order to work both on splitting and merging techniques together. In this case, we can detect other new segments that the initial segmentation given to the algorithm has ignored them. In fact, we can improve the algorithm to be independent of the initialization.

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