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Electromagnetism Like Optimization (EMO) Based Image Thresholding

Vijaya Chandu.G[1], Fahimuddin Shaik[2] and Abdul Rahim.B[3]

[1]*M.Tech Scholar, A.I.T.S, Rajampet*
[2,3]*A.I.T.S, Rajampet*
E-mail: [1]chandugudaru35@gmail.com, [2]fahim6285@gmail.com, [3]hodece.aits@gmail.com

Abstract: *In day-to-day life, new technologies are emerging in the field of Image processing. Here, we are proposing to use Electromagnetism-like Optimization (EMO) which is a global optimization algorithm, particularly well-suited to solve problems featuring non-linear and multimodal cost functions in Image processing. The Electro-magnetism-Like algorithm (EMO) is an evolutionary method which mimics the attraction-repulsion mechanism among charges to evolve the members of a population. However, EMO usually requires a large number of iterations for a local search procedure; any reduction or cancelling over such number, critically perturbs other issues such as convergence, exploration, population diversity and accuracy. By introducing a multilevel thresholding (MT) algorithm based on the EMO is introduced in image processing and some advantages in either image segmentation or image restoration can be achieved. The approach combines the good search capabilities of EMO algorithm with objective functions proposed by the popular MT methods of Otsu and Kapur to obtain optimized results.*

Keywords: *Image Segmentation, EMO, MT, Meta-Heuristic, evolutionary algorithms, Image Histogram.*

1. INTRODUCTION

Image processing is the analysis and manipulation of a digitized image, especially in order to improve its quality and it has several applications in areas such as medical, industrial, agricultural, etc. Almost all the methods of image processing require a first step called segmentation. This task consists in classify the pixels in the image depending on its gray (or RGB in each component) level intensity (histogram). In this way, several techniques had been studied [1], [2].

Thresholding is the easiest method for segmentation as it works taking a threshold (*th*) value and the pixels which intensity value is higher than *th* are labeled as the first class and the rest of the pixels correspond to a second class. When the image is segmented into two classes, the task is called bi-level thresholding (BT) and it requires only one *th* value. On the other hand, when pixels are separated into more than two classes, the task is named as multilevel thresholding (MT) and demands more than one *th* values [3], [4]. Threshold based methods are divided into parametric and nonparametric [1], [4]. For parametric approaches it is necessary to estimate some parameters of a probability density function which models each class. Such approaches are time consuming and computationally expensive. On the other hand, the nonparametric employs several criteria such as between-class variance, the entropy and the error rate [5], [6] that must be optimized to determine the optimal threshold values. These approaches result an attractive option due their robustness and accuracy .

For bi-level thresholding there exist two classical methods, the first maximizes the between classes variance and was proposed by Otsu [5]. The second submitted by Kapur in [6] uses the maximization of the entropy to measure the homogeneity of the classes. Their efficiency and accuracy have been already proved for a bi-level segmentation. Although both Otsu's and Kapur's can be expanded for multilevel thresholding, their computational complexity increases exponentially with each new threshold.

As an alternative to classical methods, the MT problem has also been handled through evolutionary optimization methods. In general, they have demonstrated to deliver better results than those based on the classical techniques in terms of accuracy, speed and robustness.

Numerous evolutionary approaches have been reported in the literature. Hammouche et al. provides a survey of different evolutionary algorithms such as Differential Evolution (DE), Simulated Annealing (SA), Tabu Search (TS) etc.), used to solve the Kapur's and Otsu's problems [7]. In [1],[7],[8] Genetic Algorithms-based approaches are employed to segment multi-classes. Similarly in [9],[10], Particle Swarm Optimization (PSO) has been proposed for MT proposes, maximizing the Otsu's function. Other examples such as including Artificial Bee Colony (ABC) or Bacterial Foraging Algorithm (BFA) for image segmentation.

This paper introduces a multilevel threshold method based on the Electromagnetism-like Algorithm (EMO) is to segmentation process. EMO is a global optimization algorithm that mimics the electromagnetism law of physics. It is a population-based method which has an attraction-repulsion mechanism to evolve the members of the population guided by their objective function values. The main idea of EMO is to move a particle through the space following the force exerted by the rest of the population. The force is calculated using the charge of each particle based on its objective function value.

In this paper, a segmentation method called Multilevel Threshold based on the EMO algorithm (MTEMO) is introduced. The algorithm takes random samples from a feasible search space which depends on the image histogram. Such samples build each particle in the EMO context. The quality of each particle is evaluated considering the objective function employed by the Otsu's or Kapur's method. Guided by this objective value the set of candidate solutions are evolved using the attraction-repulsion operators.

Image Multilevel Thresholding

Thresholding is a process in which the pixels of a gray scale image are divided in sets or classes depending on their intensity level (L). For this classification it is necessary to select a threshold value (th) and follow the simple rule of

$$C1 \leftarrow p \text{ if } 0 \leq p < \text{th},$$
$$C2 \leftarrow p \text{ if } \text{th} \leq p < L-1,$$

where p is one of the $m \times n$ pixels of the gray scale image Ig that can be represented in L gray scale levels $L = \{0, 1, 2, \ldots, L-1\}$. $C1$ and $C2$ are the classes in which the pixel p can be located, while th is the threshold. The rule in (5) corresponds to a bilevel thresholding and can be easily extended for multiple sets:

$$C1 \leftarrow p \text{ if } 0 \leq p < \text{th1},$$
$$C2 \leftarrow p \text{ if } \text{th1} \leq p < \text{th2},$$
$$Ci \leftarrow p \text{ if } \text{th}i \leq p < \text{th}i{+}1,$$
$$Cn \leftarrow p \text{ if } \text{th}n \leq p < L-1,$$

where {th1, th2, . . . , th$i$, th$i$+1, th$k$} represent different thresholds. The problem for both bilevel and MT is to select the th values that correctly identify the classes. Although, Otsu's and Kapur's methods are well-known approaches for determining such values, both propose a different objective function which must be maximized in order to find optimal threshold values.

Optimization

In general, an optimization problem can be written as minimize f1(x),...,fi(x),...,fI(x),x=(x1,...,xd),

subject to $hj(\mathbf{x})=0,(j=1,2,\ldots,J)$ and

$$gk(\mathbf{x}) \leq 0,(k=1,2,\ldots,K),$$

where $f1,\ldots,fI$ are the objectives, while hj and gk are the equality and inequality constraints, respectively. In the case when $I=1$, it is called single-objective optimization. When $I \geq 2$, it becomes a multi objective problem whose solution strategy is different from those for a single objective.

2. LITERATURE SURVEY

Optimization Algorithms

To solve the optimization problem, efficient search or optimization algorithms are needed. There are many optimization algorithms which can be classified in many ways, depending on the focus and characteristics.

If the derivative or gradient of a function is the focus, optimization can be classified into gradient-based algorithms and derivative-free or gradient-free algorithms. Gradient-based algorithms such as hill-climbing use derivative information, and they are often very efficient. Derivative-free algorithms do not use any derivative information but the values of the function itself. Some functions may have discontinuities or it may be expensive to calculate derivatives accurately, and thus derivative-free algorithms such as Nelder-Mead downhill simplex become very useful. From a different perspective, optimization algorithms can be classified into trajectory-based and population-based. A trajectory-based algorithm typically uses a single agent or one solution at a time, which will trace out a path as the iterations continue. Hill-climbing is trajectory-based, and it links the starting point with the final point via a piecewise zigzag path. Another important example is simulated annealing which is a widely used Meta heuristic algorithm. On the other hand, population-based algorithms such as particle swarm optimization (PSO) use multiple agents which will interact and trace out multiple paths (Kennedy and Eberhardt, 1995) [3].

Optimization algorithms can also be classified as deterministic or stochastic. If an algorithm works in a mechanical deterministic manner without any random nature, it is called deterministic. For such an algorithm, it will reach the same final solution if we start with the same initial point. Hill-climbing and downhill simplex are good examples of deterministic algorithms. On the other hand, if there is some randomness in the algorithm, the algorithm will usually reach a different point every time the algorithm is executed, even though the same initial point is used. GAs and PSO are good examples of stochastic algorithms.

Search capability can also be a basis for algorithm classification. In this case, algorithms can be divided into local and global search algorithms. Local search algorithms typically converge towards a local optimum, not necessarily (often not) the global optimum, and such an algorithm is often deterministic and has no ability to escape from local optima. Simple hill-climbing is such an example. On the other hand, for global optimization, local search algorithms are not suitable, and global search algorithms should be used. Modern Metaheuristic algorithms in most cases tend to be suitable for global optimization, though not always successful or efficient. A simple strategy such as hill-climbing with random restarts can turn a local search algorithm into an algorithm with global search capability. In essence, randomization is an efficient component for global search algorithms.

3. ELECTROMAGNETISM - LIKE OPTIMIZATION ALGORITHM (EMO)”,

EMO algorithm is a simple and direct search algorithm which has been inspired by the electro-magnetism phenomenon. It is based on a given population and the optimization of global multi-modal functions. In comparison to GA, it does not use crossover or mutation operators to explore feasible regions; instead it does implement a collective attraction–repulsion mechanism yielding a reduced computational cost with respect to memory allocation and execution time. Moreover, no gradient information is required as it employs a decimal system which clearly contrasts to GA. Few particles are required to reach converge as has been already demonstrated in EMO algorithm can effectively solve a special class of optimization problems with bounded variables in the form of:

$$\begin{aligned} &\min f(x) \\ &x \in [l, u] \end{aligned}$$

where $[l, u] = \{x \in \Re^n \mid l_d \le x_d \le u_d, d = 1,2...n\}$ and n being the dimension of the variable x, $[l, u] \subset \Re^n$, a nonempty subset and a real-value function f: $[l, u] \rightarrow \Re$. Hence, the following problem features are known:

- n : Dimensional size of the problem.
-
- u_d : The highest bound of the k^{th} dimension.
- l_d : The lowest bound of the k^{th} dimension.
- $f(x)$: The function to be minimized.

EMO algorithm has four phases [6]: initialization, local search, computation of the total force vector and movement. A deeper discussion about each stage follows.

Initialization, a number of m particles is gathered as their highest (u) and lowest limit (l) are identified.

Local search, gathers local information for a given point $\mathbf{g}^p$, where $p \in (1,\mathrm{K},m)$.

Calculation of the total force vector, charges and forces are calculated for every particle.

Movement, each particle is displaced accordingly, matching the corresponding force vector.

Initialization

First, the population of m solutions is randomly produced at an initial state. Each n-dimensional solution is regarded as a charged particle holding a uniform distribution between the highest (u) and the lowest (l) limits. The optimum particle (solution) is thus defined by the objective function to be optimized. The procedure ends when all the m samples are evaluated, choosing the sample (particle) that has gathered the best function value.

Local Search

The local search procedure is used to gather local information within the neighbourhood of a candidate solution. It allows obtaining a better exploration and population diversity for the algorithm.

Considering a pre-fixed number of iterations known as *ITER* and a feasible neighbourhood search δ, the procedure iterates as follows: Point $\mathbf{g}^p$ is assigned to a temporary point **t** to store the initial information. Next, for a given coordinate d, a random number is selected (λ_1) and combined with δ as a step length, which in turn, moves the point **t** along the direction d, with a randomly determined sign (λ_2). If point **t** observes a better performance over the iteration number *ITER*, point $\mathbf{g}^p$ is replaced by **t** and the neighbourhood search for point $\mathbf{g}^p$ finishes, otherwise $\mathbf{g}^p$ is held.

Total force vector computation

The total force vector computation is based on the *superposition principle* from the electro-magnetism theory which states: “the force exerted on a point via other points is inversely proportional to the distance between the points and directly proportional to the product of their charges”. The particle moves following the resultant Coulomb’s force which has been produced among particles as a charge-like value. In the EMO implementation, the charge for each particle is determined by its fitness value as follows:

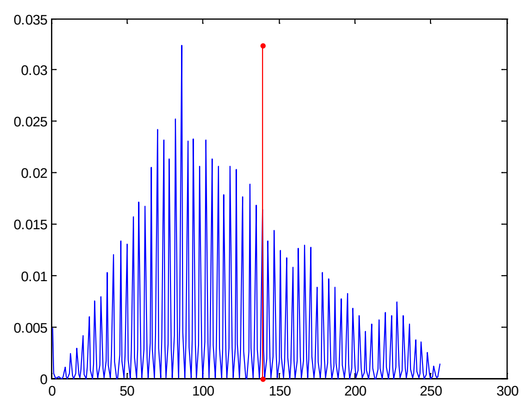
$$q^p = \exp\left(-n \frac{f(\mathbf{g}^p) - f(\mathbf{g}^{best})}{\sum_{h=1}^{m} \left(f(\mathbf{g}^h) - f(\mathbf{g}^{best}) \right)} \right), \forall p ,$$

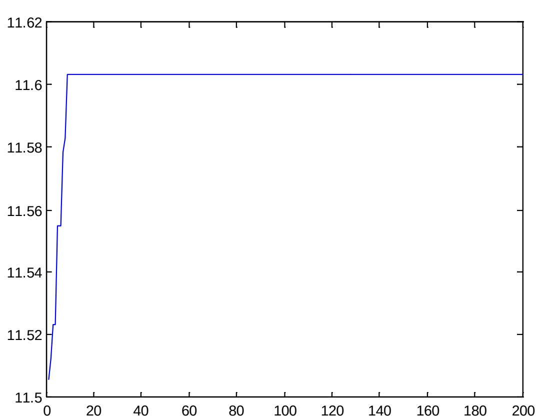
where n denotes the dimension of $\mathbf{g}^p$ and m represents the population size. A higher dimensional problem usually requires a larger population. the particle showing the best fitness function value $\mathbf{g}^{best}$ is called the “*best particle*”, getting the highest charge and attracting other particles holding high fitness values. The repulsion effect is applied to all other particles exhibiting lower fitness values. Both effects, attraction-repulsion are applied depending on the actual proximity between a given particle and the best-graded element.

4. COMPARISON

The study explores three different approaches are used for comparisons and they are performed. The first one involves the two versions of MTEMO are been compared, with the Otsu function and other with the Kapur criterion. The second one the state-of-the-art approaches among the MTEMO are compared with each other. Finally the third one compares the number of iterations of MTEMO and the selected methods, in order to verify its performance and computational effort.

Here, we demonstrate that the MTEMO is an interesting alternative for MT, the proposed algorithm is compared with other similar implementations. The other methods used in the comparison are: Genetic Algorithms (GA), Particle Swarm Optimization (PSO) and Bacterial foraging (BF). The number of iterations will provide evidence that the MTEMO requires less iterations to find a stable value Here, considering MTEMO that finds the EMO requires a low number of iterations depending on the dimension of the problem. Under such conditions, it is from that the computational cost of MTEMO is lower than GA, PSO and BF for multilevel thresholding problems. In order to statistically prove such statement, a non-parametric Wilcoxon ranking test over the number of iterations has been used. The test is divided in three groups MTEMO vs. GA, MTEMO vs. PSO and MTEMO vs. BF. The obtained *p*-values will be observed in below figures.





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6. COOPNCLUSION

This paper presents a new version of the electromagnetism-like optimization algorithm for image segmentation. The approach combines the good search capabilities of EMO algorithm with the use of some objective functions that have been proposed by the popular MT methods of Otsu and Kapur. In order to measure the performance of the proposed approach, it is used the peak signal-to-noise ratio (PSNR) which assesses the segmentation quality, considering the coincidences between the segmented and the original images. The study explores the comparison between the two versions of MTEMO, one using the Otsu objective function and the other with the Kapur criterion. The results show that the Otsu function presents better results than the Kapur criterion. Such conclusion was statistically proved considering the Wilconxon test.

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