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Fuzzy Multilevel Image Thresholding Based on Modified Discrete Grey Wolf Optimizer and Local Information Aggregation

LINGUO LI[1,2], LIJUAN SUN[1], WEI KANG[2], JIAN GUO[1], CHONG HAN[1], AND SHUJING LI[2]
[1]School of Computer, Nanjing University of Posts and Telecommunications, Nanjing 210003, China
[2]School of Information Engineering, Fuyang Normal University, Fuyang 236041, China

Corresponding author: L. Li (llg-1212@163.com)

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ABSTRACT Fuzzy entropy and image thresholding are the most direct and effective methods for image segmentation. This paper, taking fuzzy Kapur's entropy as the optimal objective function, with modified discrete Grey wolf optimizer (GWO) as the tool, uses pseudotrapezoid-shaped to conduct fuzzy membership initialization so as to achieve image segmentation finally by means of local information aggregation. Experiment results show that the proposed fuzzy-based GWO and aggregation algorithm and fuzzy-based modified discrete GWO and aggregation (FMDGWOA) algorithm can search out the optimal thresholds effectively and accurately. In this paper, electro-magnetism optimization based on Kapur's entropy, standard GWO and fuzzy entropy-based differential evolution algorithm are experimentally compared with the proposed method, respectively. It shows that FMDGWOA enjoys obvious advantages in segmentation quality, objective function, and stability.

INDEX TERMS Evolutionary computation, fuzzy sets, information entropy, image segmentation, optimization methods.

I. INTRODUCTION

Image thresholding is one of the simplest, direct and effective image segmentation methods which can discriminate objects from image background with a set of thresholds. Automatic separation between objects and background remains the most difficult yet intriguing domain in the field of image processing and pattern recognition [1]. The method not only shows well defined areas and clustering results, but also can be a preprocessing step for more complex segmentation methods (e.g., level-sets or active contours [2]). Therefore, image thresholding has been widely used in various fields of image processing, such as medical diagnosis [3], image classification [4], object recognition [5], saliency detection [6], etc.

Basically, image thresholding can be classified into parametric and nonparametric. In general, parametric is time consuming and computationally expensive while nonparametric determine optimal thresholds by optimizing some standards. With the introduction of the optimization methods, nonparametric can not only get better time and computational complexity, but also can achieve good robustness and accuracy [7].

Nonparametric obtains a set of global thresholds by optimizing some standards (objective function) [8]. Common objective function: maximization of the entropy (e.g., Kapur's entropy) [9], maximization of the between-class variance (e.g., Otsu's method) [10], the use of the fuzzy similarity measure [11], and minimization of the Bayesian error [12]. In the beginning, all these technologies have been primarily used for bi-level image thresholding, and now have been extended to multi-level image thresholding (MT). However, the computational complexity increased rapidly after adopting multi-level thresholding [13]. Scholars massively use evolutionary and swarm based intelligent computation to improve computing efficiency and thresholding accuracy. Unfortunately, because global threshold approach neglects the complexity of uneven illumination and soft transitions between gray levels, and spatial location relationship between pixels are not considered, so the performance of segmentation is not perfect enough [1].The main drawback of this approach is due to it being pixel oriented rather than region oriented, and therefore those pixels having the same gray value will always be segmented into the same class. If connectivity or closed objects are not considered, the method tends to produce isolated pixels.

From the body of study concerning MT segmentation methods, we find that each method tends to solve one specific kind of images. Sezgin [14] first divided image thresholding methods into six categories, and Aja-Fernández et al. [1] merged them into three practical methodologies: a) Methods that calculate a global threshold for the whole image. b) Methods that use an adaptive local threshold. c) Methods that use spatial local information for classifying the pixels. Because of the drawback of global thresholding, the last two methodologies attracted more attention though the first one is the earliest used. The second kind of method is an improvement and supplement of the first by choosing thresholds in local areas adaptively to avoid inadaptability caused by global thresholds, but the computational complexity will also correspondingly increase. The third methodology mainly solves the lack of spatial information of pixels, in which spatial local information is applied to thresholding so as to improve the segmentation effect. In this paper, the spatial local information is taken into account in solving the problem, and the applications of fuzzy logic and fuzzy theory in MT is also touched on at the same time. The starting point of introducing spatial local information is that the membership of a pixel in a particular class or object will be highly correlated with the membership in that class of the surrounding pixels [1]. And in order to improve the effectiveness of segmentation, each pixel will be assigned to a set of fuzzy values of different classes through a fuzzy membership function. The traditional hard assignment is replaced by a soft assignment according to the basic theory of fuzzy sets.

The rest of this paper is organized as follows: Section II introduces the correlation work of fuzzy entropy and intelligent optimization algorithms in the field of image thresholding. Section III formulates hard thresholding and soft thresholding, and presents the corresponding fuzzy Kapur's entropy. The detailed process of standard GWO and MDGWO are presented in Section IV. Section V analyzes the initialization of fuzzy membership of a pixel with MT as centroids and the aggregation method. Experimental comparisons and discussion are presented in Section VI in detail. Finally, Section VII concludes.

II. RELATED WORKS

Fuzzy theory and fuzzy logic [15] are known to be flexible tools in classification problems which have been widely used in the field of system control, and there are also a great amount of applications in the image processing field [16]–[18]. Methods based on fuzzy logic and fuzzy measures have been proposed for image thresholding [19]. In these methods, fuzzy logic is respectively combined with clustering methods [20], fuzzy measures [21], fuzzy entropy [22], fuzzy compactness [23], the interpretation of thresholds as type-2 fuzzy logic [24] and other soft computing methods such as the heuristic methods based on ant, bees and bacteria colonies [13], which are mainly used to search the optimal thresholds, but many times they do not take into account spatial information. And fuzzy clustering methods are often used in these techniques which have high time complexity. With constant updating and progressing of the intelligent optimization algorithms, fuzzy optimization has gained growing attention in image thresholding.

Using intelligent optimization to solve MT problem has proved to be feasible theoretically and experimentally [8]. An extensive literature indicates that intelligent optimization algorithms are better than traditional algorithms in accuracy, speed and robustness [7], [8]. Olivaa [25] et al. introduced electro-magnetism optimization into MT, compared with GA, PSO, and BF by taking Kapur's entropy and Otsu's entropy as objective functions respectively. Experiment results showed the advantages of electro-magnetism optimization in terms of standard deviation, mean and segmentation accuracy. Kurban [8] et al. deeply studied the applications of evolutionary and swarm based intelligent computation in the field of MT. According to his statistical analysis on objective value, swarm based algorithms can solve the problem more accurately. In his further analysis, swarm based algorithms mainly regarded Otsu's method, between-class variance, Tsallis entropy, Kapur's entropy as objective functions, and experiments showed that Kapur's entropy based method achieve better image segmentation results. Bhandari [26] et al. have made a comparative and thorough analysis of Kapur's, Otsu and Tsallis functions, proved that Kapur's entropy generally performs better for segmentation of satellite remote sensing images.

Although the above image thresholding methods have made great progress in accuracy, effect and quality than the traditional methods, hard thresholding will easily result in blurry boundary and isolated points [27]. MT methods based on fuzzy theory have become the research focus in recent years, and the adopted soft thresholding strategy can solve the problem. Zhao et al. [28] first defined three membership functions and applied them to three-level thresholding. Based on this, Tao et al. [29] proposed three-level fuzzy entropy thresholding approach, the three fuzzy functions (Z-function, F-function and S-function) were defined in detail and applied. This approach used Genetic Algorithm (GA) to maximize global fuzzy entropy to get the optimal threshold. These two methods only provided the vision effect without quantitative analysis. Pratamasunu et al. [21] assigned fuzzy coefficients for each pixel on the basis of S-function and Z-function, and then realized the automatic image thresholding by defining a distance function between fuzzy set and crisp set. Though this method has presented the advantage against

Lopes method and the Otsu thresholding, the experimental results are applicable only for bi-level thresholding but not for multi-level thresholding. Muppidi et al. [22] used Triangular membership function, Trapezoidal membership function and Bell shaped membership functionto define three fuzzy entropies respectively, and search optimal parameter sets by GA. The results showed Trapezoidal membership function has better effect. This method was also only compared with Otsu thresholding, and did not give sufficient quantitative comparisons. Based on histogram and fuzzy entropy theory, Sarkar et al. [27] realized MT by using Differential Evolution algorithm. The authors have conducted lots of experiments and comparisons with PSO and GA to prove the speed and accuracy of their method. Aja-Fernández et al. [1] have come up with the solution program for MT segmentation by adopting fuzzy Kapur's entropy and aggregation methods, and also provided solutions to histogram and fuzzy entropy. The most important thing is that they noticed the drawback of MT failing to consider the pixels' spatial relations, so local information aggregation was adopted in their methods to avoid isolated points and finally obtained better results. In this scheme of local information aggregation, authors described median aggregation, average aggregation and iterative average aggregation methods which are all confirmed to be effective. Synthesize the above fuzzy and non-fuzzy multi-level thresholding methods, using fuzzy entropy and intelligent optimization algorithms combining with spatial local information to image thresholding is suggested.

Wolf Pack Algorithm (WPA) is a new swarm intelligent method proposed by Husheng et al. [30] and Wu et al. [31]. According to the wolf pack intelligent behavior, the researchers abstracted three intelligent behaviors, scouting, calling, and besieging, and two intelligent rules, winner-take-all generation rule of lead wolf and stronger-survive renewing rule of wolf pack. The experiments show that WPA has better convergence and robustness, especially for high-dimensional functions. Coincidentally, Tao et al. [29] proposed Grey Wolf Optimizer (GWO) inspired by grey wolves in 2014. The GWO algorithm mimics the leadership hierarchy and hunting mechanism of grey wolves in nature. Four types of grey wolves such as alpha, beta, delta, and omega are employed for simulating the leadership hierarchy. The three main steps of hunting, searching for prey, encircling, and attacking, are implemented. Compared to well-known heuristics such as PSO, GSA, DE, EP, and ES [30]–[33], the GWO [29] algorithm shows better global convergence and higher robustness. Moreover, the GWO has high performance in solving challenging problems in unknown search spaces, and the results on semi-real and real problems also prove that GWO can show high performance not only on unconstrained problems but also on constrained problems. This paper takes Kapur's entropy as objective function with the modified discrete grey wolf algorithm (MDGWO) as the tool to solve the optimal threshold problem, which can serve as the basis for future fuzzy aggregation methods.

III. FORMULATION OF THE MULTILEVEL THRESHOLDING

MT needs to set a group of thresholds, based on that, the image can be segmented into different regions. By means of intelligent optimization to obtain the optimal thresholds, the process of image segmentation has to be formulated before taking image elements or image features as parameters, to determine the optimized objective functions with the purpose of getting close to the optimal threshold values.

A. PIXEL GROUPING BASED ON THRESHOLDS

Assume that an image can be represented by L gray levels. The gray-level for each pixel can be represented by f(x, y), where x, y stand for the positions of the coordinate. As used in [25] and [27], the output image can be formulated as (1).

$$\begin{cases} t_0/2 & 0 \leq \text{f(x,y)} < t_0 \\ (t_i + t_{i+1})/2 & t_i \leq \text{f(x,y)} < t_{i+1} \\ (t_m + L)/2 & t_m \leq \text{f(x,y)} < L \end{cases} \tag{1}$$

Where t_i (i=0, 1,…,m) stands for the ith threshold value, and m is the last number of thresholds. Formulating the output is not the focus, the key point is to determine t_i and its optimization. The maximization or minimization of the objective function represents the optimal value and also ensures the optimization of thresholds.

B. CONCEPT OF KAPUR'S ENTROPY FOR HARD THRESHOLDING

Intelligent optimization algorithm is linked with MT through objective functions so as to get better thresholds. Based on this analysis, the intelligent optimization method using Kapur's entropy as the objective function could get better results. Entropy of the discrete information can be obtained by the probability distribution p = $\text{p}_\text{i} p_i$, where p_i, is the probability of the system in possible state i. The probability for each gray level i is its relative occurrence frequency, equalized by the total number of gray levels as shown in (2).

$$p_i = h(i) \Big/ \sum_{i=0}^{L-1} h(i) \quad \text{i} = 0, 1, \ldots, \text{L-1} \tag{2}$$

Where $h(i)$ is the number of gray level i, L is the number of gray levels. Kapur's entropy is used to measure the compactness and separability of classes. For MT, Kapur's entropy can be described as (3)

$$\begin{aligned} H_0 &= -\sum_{\text{i}=0}^{t_1-1} \frac{p_i}{\omega_0} \ln \frac{p_i}{\omega_0}, \quad \omega_0 = \sum_{\text{i}=0}^{t_1-1} p_i \\ H_1 &= -\sum_{\text{i}=t_1}^{t_2-1} \frac{p_i}{\omega_1} \ln \frac{p_i}{\omega_1}, \quad \omega_1 = \sum_{i=t_1}^{t_2-1} p_i \\ H_j &= -\sum_{\text{i}=t_j}^{t_{j+1}-1} \frac{p_i}{\omega_j} \ln \frac{p_i}{\omega_j}, \quad \omega_j = \sum_{\text{i}=t_j}^{t_{j+1}-1} p_i \\ H_m &= -\sum_{\text{i}=t_m}^{L-1} \frac{p_i}{\omega_m} \ln \frac{p_i}{\omega_m}, \quad \omega_m = \sum_{\text{i}=t_m}^{L-1} p_i \end{aligned} \tag{3}$$

Thus, the function f (T) can be obtained by (4), which is used as a parameter of MDGWO's fitness function in section IV.

$$f(T) = \sum_{i=0}^{m} H_i \quad T = [t_1 \quad t_2 \quad \cdots \quad t_m] \tag{4}$$

Where, T represents a vector quantity of thresholds.

C. CONCEPT OF FUZZY KAPUR'S ENTROPY FOR SOFT THRESHOLDING

Let the set R be a collection of element that can either belong to or not belongs to region r, according to the theory of fuzzy sets, this array can be defined as:

$$R = \{(i, \mu_r(i))|i \in I\}, \quad 0 \leq \mu_r(i) \geq 1, \ r \in [1, N] \quad (5)$$

Where $\mu_r(i)$ is called the membership function, which measures the closeness between the pixel i and the region r. The higher the $\mu_r(i)$ is, the probability of pixel to be partitioned into the region r will be greater. N is the number of regions.

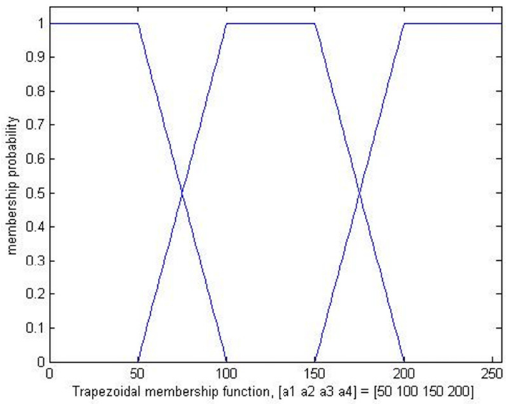

FIGURE 1. Fuzzy trapezoidal membership function.

The choice of membership function is the key of fuzzy thresholding, large amount of literature adopted different membership function for testing the validity, trapezoidal membership function is the most popular and effective one [22]. The curve of its fuzzy values is shown in Fig. 1, which have four fuzzy parameters.

The four parameters trapezoidal membership function can be derived for n (n-2*(m+1)) fuzzy parameters as follows:

$$\mu_0(k) = \begin{cases} 1 & k \leq a_1 \\ \dfrac{k-a_2}{a_1-a_2} & a_1 < k \leq a_2 \\ 0 & k > a_2 \end{cases}$$

$$\mu_1(k) = \begin{cases} 0 & k \leq a_1 \\ \dfrac{k-a_1}{a_2-a_1} & a_1 < k \leq a_2 \\ 1 & a_2 < k \leq a_3 \\ \dfrac{k-a_4}{a_3-a_4} & a_3 < k \leq a_4 \\ 0 & k > a_4 \end{cases}$$

$$\vdots$$

$$\mu_m(k) = \begin{cases} 0 & k \leq a_{n-1} \\ \dfrac{k-a_{n-1}}{a_n-a_{n-1}} & a_{n-1} < k \leq a_n \\ 1 & k > a_n \end{cases} \quad (6)$$

Where $a_1, a_2, \cdots a_n$ is fuzzy parameters of trapezoidal membership function, k is the gray value of single pixel. Based on trapezoidal membership function, Kapur's entropy in Section III.B can be expressed as:

$$\begin{aligned} H_0 &= -\sum\nolimits_{i=0}^{L-1} \frac{\mu_0(i)*p_i}{\omega_0} \ln(\frac{\mu_0(i)*p_i}{\omega_0}), \\ \omega_0 &= \sum\nolimits_{i=0}^{L-1} (\mu_0(i)*p_i) \\ H_1 &= -\sum\nolimits_{i=0}^{L-1} \frac{\mu_1(i)*p_i}{\omega_1} \ln(\frac{\mu_1(i)*p_i}{\omega_1}), \\ \omega_1 &= \sum\nolimits_{i=0}^{L-1} (\mu_1(i)*p_i) \\ H_j &= -\sum\nolimits_{i=0}^{L-1} \frac{\mu_j(i)*p_i}{\omega_j} \ln(\frac{\mu_j(i)*p_i}{\omega_j}), \\ \omega_j &= \sum\nolimits_{i=0}^{L-1} (\mu_j(i)*p_i) \\ H_m &= -\sum\nolimits_{i=0}^{L-1} \frac{\mu_m(i)*p_i}{\omega_m} \ln(\frac{\mu_m(i)*p_i}{\omega_m}), \\ \omega_m &= \sum\nolimits_{i=0}^{L-1} (\mu_m(i)*p_i) \end{aligned} \quad (7)$$

To be able to acquire n parameters in (6), this paper adopts MDGEO to maximize the fuzzy Kapur's entropy, as is shown in (8). The comparison of (3) and (7) clearly shows that fuzzy entropy (Eq. (7)) involves more complicated computing procedures. As a result, it is of necessity to adopt the intelligent optimization method.

$$\begin{aligned} &\phi(a_1, a_2, \cdots a_n) \\ &\quad = f(T) = \sum\nolimits_{i-0}^{m} H_i, \quad T = [t_0 \quad t_1 \quad \cdots \quad t_m] \end{aligned} \quad (8)$$

After obtaining n fuzzy parameters, the corresponding entropy can be expressed as:

$$t_0 = \frac{a_1+a_2}{2}, t_1 = \frac{a_3+a_4}{2}, \cdots, t_m = \frac{a_{n-1}+a_n}{2} \quad (9)$$

IV. BRIEF EXPLANATIONS OF MODIFIED DISCRETE GREY WOLF OPTIMIZER (MDGWO)

A. STANDARD GREY WOLF OPTIMIZER

The GWO algorithm [32] abstracted four types of grey wolves such as alpha, beta, delta, and omega. The alpha wolf is also called the dominant wolf, they are the most brilliant wolves and the best in terms of managing the pack. The second level in the hierarchy of grey wolves is beta. The betas are subordinate wolves that help the alpha in decision-making or other pack activities. The third level in the hierarchy of grey wolves is delta. Delta wolves have to submit to alphas and betas, but they can order the omega. They are the backbones of the pack and play multiple roles such as scouts, sentinels, hunters, protectors and even caretakers. The lowest ranking grey wolf is omega. It seems that the omega is not an important individual in the pack, but it is observed that the whole pack will face internal fighting and other problems when the omega is absent, which is harmful to the group organization.

In addition to the social hierarchy of wolves, group hunting is another interesting social behavior of grey wolves. The main phases of grey wolf hunting are as follows:

Searching for the prey; tracking and approaching the prey; pursuing, encircling, and harassing the prey until it stops moving; attack towards the prey.

In order to mathematically model the social hierarchy of wolves in GWO [32], the fittest solution is considered as the alpha. Consequently, the second and third best solutions are named beta and delta respectively. The rest of the candidate solutions are assumed to be omega. In the GWO algorithm the hunting (optimization) is guided by alpha, beta and delta α. The omega wolves follow these three wolves.

For solving MT problems, based on standard GWO, the corresponding relationships between MDGWO and image segmentation in the improved algorithm is shown in table 1:

TABLE 1. **The corresponding relationships between MDGWO and image segmentation.**

MDGWO	Image segmentation
Positions	Threshold segmentation solution
Alpha_Pos	Optimal solution
Alpha_score	The largest fitness value
fitness	Fitness function value
Best_R	Best fitness

B. MODIFIED DISCRETE GREY WOLF OPTIMIZER (MDGWO) FOR IMAGE THRESHOLDING

The size of the wolf pack is assumed as SN. SN candidate solutions (the position of the wolf is the threshold value) are generated randomly in the initialization phase of MDGWO. Standard GWO is used to solve continuous variables and problems while threshold is a group of discrete values. So the GWO needs to be discretized. The initial solution is:

$$x_i = \lfloor rand(1, SN) \cdot (ub - lb) + lb \rfloor \tag{10}$$

Where ub and lb represent the upper limit and the lower limit of parameters (namely boundaries of parameter), $rand(1, SN)$ is a stochastic function, $\lfloor\rfloor$ is the integral function.

After the initialization of candidate solutions, MDGWO judges whether the initial solution X_i is in the range of [ub, lb]. If it is there, the fitness value will be calculated, otherwise the search agent will be pulled back in the search space by (11), and then the fitness value will be recalculated by rounding toward zero.

$$x_i = \left\lfloor (x_i \cdot \overline{(u + l)}) + ub \cdot u + lb \cdot l \right\rfloor \tag{11}$$

Where $u = x_i > ub$, $l = x_i < lb$.

In the all fitness values calculated by (12) of candidate solutions, MDGWO chooses three optimal candidate solutions to assign to $X_\alpha, X_\beta, X_\delta$, and records all the fitness values and candidate functions (namely locations of the wolves).

$$fit(x_i) = \begin{cases} 1/(1 + f(x_i)) & f(x_i) \geq 0 \\ 1 + abs(f(x_i)) & f(x_i) < 0 \end{cases} \tag{12}$$

Where $f(x_i)$ is calculated by fuzzy Kapur's entropy as shown in (8).

After the initialization, all the search agents have to update their current locations to optimize the candidate solutions in the iterating process. In the range of the maximum iteration (Max_iter), all the update process and optimization process will be completed.

1) ENCIRCLING PREY

Grey wolves encircle prey before hunting. During the process of threshold optimization, the wolf pack has to update the position (namely the threshold value) constantly to approach the prey. In the algorithm, all the agent position updated by (13) in the course of encirclement:

$$\vec{x}(t+1) = \vec{x_p}(t) - \vec{A} \cdot \vec{D} \tag{13}$$

Where t indicates the current iteration, $\vec{A}$ is the coefficient vectors, $\vec{X_p}$ is the position vector of the prey, and $\vec{X}$ indicates the position vector of a grey wolf. $\vec{D}$ and $\vec{A}$ are calculated by (14), (15).

$$\vec{D} = \left| \vec{C} \cdot \vec{x_p}(t) - \vec{x}(t) \right| \tag{14}$$

$$\vec{A} = 2\vec{e}\,\vec{r_1} - \vec{e} \tag{15}$$

Where $\vec{C}$ in (14) is calculated by (16)

$$\vec{C} = 2\vec{r_2} \tag{16}$$

Where components of $\vec{e}$ are linearly decreased from 2 to 0 in the course of iterating and $\vec{r_1}$, $\vec{r_2}$ are random vectors in [0, 1]. The detailed selection of the two vectors can be found in [32].

2) THE BEHAVIOR OF HUNTING

The hunt is usually guided by the alpha. The beta and delta might also participate in hunting occasionally. The only optimal solution usually plunges into local optima, the alpha, beta, and delta have better knowledge about the potential location of prey in GWO for improving the efficiency. The concrete procedures are as follows: the algorithm saves the first three best solutions obtained so far and obliges the other search agents (including the omegas) to update their positions according to the position of the best search agents. The original GWO algorithm [32] updates search agents by the first three best solutions (namely new candidate solutions) as follows:

$$\vec{x_1} = \vec{x_\alpha} - \vec{A_1} \cdot \vec{D_\alpha}, \quad \vec{x_2} = \vec{x_\beta} - \vec{A_2} \cdot \vec{D_\beta}, \quad \vec{x_3} = \vec{x_\delta} - \vec{A_3} \cdot \vec{D_\delta} \tag{17}$$

$$\vec{D_\alpha} = \left| \vec{C_1} \cdot \vec{x_\alpha} - \vec{x} \right|, \quad \vec{D_\beta} = \left| \vec{C_2} \cdot \vec{x_\beta} - \vec{x} \right|, \quad \vec{D_\delta} = \left| \vec{C_3} \cdot \vec{x_\delta} - \vec{x} \right| \tag{18}$$

Where $\vec{x_\alpha}$, $\vec{x_\beta}$, $\vec{x_\delta}$ are the first best solutions, A_1, A_2, A_3 are calculated by Eq. (15), C_1, C_2, C_3 are calculated by (16).

The position of the best search agents is obtained by the average of x_1, x_2, x_3 [32]. In order to let the best solutions play a greater role, the proposed modified algorithm updates the position of best solutions by means of weighting.

$$\vec{x}(t+1) = w_1 \cdot \vec{x_1} + w_2 \cdot \vec{x_2} + w_3 \cdot \vec{x_3} \tag{19}$$

The corresponding weights w_1, w_2, w_3 in (19) are calculated by (20):

$$w_1 = {f_1}/{F}, \quad w_2 = {f_2}/{F}, \quad w_3 = {f_3}/{F} \tag{20}$$

Where f_1, f_2, f_3 calculated by Eq.(12) are the corresponding fitness values of α, β, δ. $F = f_1 + f_2 + f_3$. It needs to be particularly emphasized that, distinct from the way GWO updates its search agents, it is the first time to employ weighting method to update the location of search agents as shown in (19) and (20), it is also the major contribution this paper makes to improving GWO.

3) ATTACKING PREY

The grey wolves finish the hunt by attacking the prey when it stops moving. The process is completed by decreasing the value of $\vec{e}$ to narrow the fluctuation range of $\vec{A}$. In other words $\vec{A}$ is a random value in the interval [−e, e] where $\vec{e}$ is decreased from 2 to 0 in the course of iterating. When random values of $\vec{A}$ are in [−1, 1], the search agent will approach the best solution gradually.

The search agents will get distant from the prey when the value $\vec{A}$ is greater than 1 or less than −1. in the case of $\left|\vec{A}\right| > 1$, the grey wolves will keep away from the prey and turn to search for a better one.

V. THE FUZZY MEMBERSHIP ASSIGNMENT AND LOCAL SPATIAL INFORMATION AGGREGATION

Based on Fuzzy theory, each pixel in the image will be assigned a membership degree, namely fuzzy membership assignment. Based on this, image segmentation is completed by combining spatial information for aggregation. Fuzzy membership assignment is based on a group of thresholds by (8).

A. THE MEMBERSHIP ASSIGNMENT USING PSEUDO TRAPEZOID- SHAPED (PTS) MEMBERSHIP FUNCTION

The membership assignment is classified as histogram based approach and centroids based approach [1]. The histogram based approach needs to predict the probability distributions like Gaussian distributions. But different types of distributions of histogram always follow different probability models [1]. As a result the universality will be poor, while centroids based approach only needs to select appropriate centroids. This paper treats the thresholds obtained from (8) as centroids, using PTS membership function to assign fuzzy degree to every pixel. Fig. 2 shows the PTS with three fuzzy sets.

Similar to the formulations of trapezoidal membership function, the PTS membership function in cases of n centroids

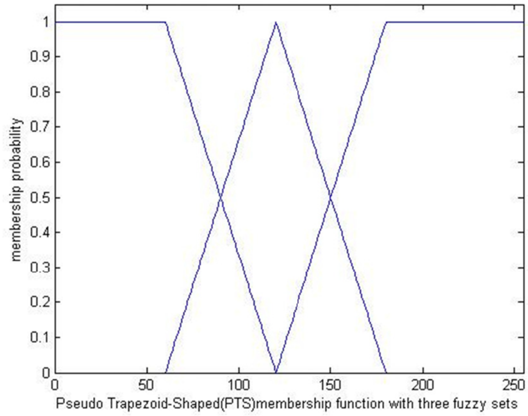

FIGURE 2. Fuzzy pseudo trapezoid-shaped membership function.

can be formulated as:

$$\mu_0'(k) = \begin{cases} 1 & k \le a_1 \\ \dfrac{k-a_2}{a_1-a_2} & a_1 < k \le a_2 \\ 0 & k > a_2 \end{cases}$$

$$\mu_1'(k) = \begin{cases} 0 & k \le a_1 \\ \dfrac{k-a_1}{a_2-a_1} & a_1 < k \le a_2 \\ \dfrac{k-a_3}{a_2-a_3} & a_2 < k \le a_3 \\ 0 & k > a_3 \end{cases}$$

$$\vdots$$

$$\mu_m'(k) = \begin{cases} 0 & k \le a_{n-1} \\ \dfrac{k-a_{n-1}}{a_n-a_{n-1}} & a_{n-1} < k \le a_n \\ 1 & k > a_n \end{cases} \tag{21}$$

Where $\mu_0'(k), \mu_1'(k), \cdots \mu_m'(k)$ are fuzzy membership functions, $a_1, a_2, \cdots a_n$ are fuzzy parameters of PTS membership function, k is the gray value of a pixel.

Any random pixel i in image I in rth class can be expressed by $\mu_r(I(i))$. After using PTS membership function to initialize the fuzzy membership of the whole image, each pixel corresponds to a membership vector $\mu(I(i))$ as shown in (22).

$$\mu(I(i)) = [\mu_0(I(i)) \quad \mu_1(I(i)) \quad \cdots \quad \mu_m(I(i))] \tag{22}$$

B. THE MEMBERSHIP AGGREGATION BASED ON LOCAL SPATIAL INFORMATION

When the fuzzy memberships are assigned, every pixel could be divided into two different regions (two nonzero values at most in (22)). Spatial aggregation therefore can be used to improve segmentation accuracy and avoid the issues as isolated pixels on the basis of adjacent fuzzy degrees.

The common drawback of thresholding methods is that only gray levels are considered, but the spatial local information between pixels is ignored. In this paper, every pixel will have one or two fuzzy values through fuzzy membership function, these uncertainty values provide an excellent precondition for spatial aggregation.

In the neighborhoods of pixels, the correlation of fuzzy degree can be maximized by average operator or median operator, etc. As described in [1], there are three aggregation methods.

1) Median Aggregation: The memberships of each pixel are aggregated using the median operator with N neighborhoods

$$\mu^{aggr}(I(i)) = \underset{I(i)\in N(I(i))}{median}\{\mu_0(I(i))\mu_1(I(i))\cdots\mu_m(I(i))\} \quad (23)$$

Where $\mu^{aggr}()$ is the fuzzy degree after aggregation, $median\{\}$ is the median operation for vectors, $N(I(i))$ is N neighbor pixels of the ith pixel.

2) Average aggregation: In the neighborhood of each pixel (3*3), search for the average value of all pixels including itself and take the value as the pixel's fuzzy membership value, as is shown in (24)

$$\mu^{aggr}(I(i)) = \frac{1}{N(I(i))} * \sum_{I(i)\in N(I(i))} \mu(I(i)) \quad (24)$$

3) Iterative averaging aggregation: In order to enhance aggregation effect, we adopt iterative procedure to replace only one time average aggregation. But too much iteration will blur the boundaries, so we set different weights for different space distance of neighborhood pixels as shown in (25). This kind of method is presented in (26), in which $\mu^{aggr}(I(i)_t$ is the iteration result of (24).

$$w = \frac{1}{3} * \begin{bmatrix} 0 & 0.5 & 0 \\ 0.5 & 1 & 0.5 \\ 0 & 0.5 & 0 \end{bmatrix} \quad (25)$$

$$\mu^{aggr}(I(i)_{t+1} = w * \mu^{aggr}(I(i)_t \quad (26)$$

When the aggregations are completed, each pixel will get a fuzzy degree vector as shown in (22), and the area that the pixel belongs to will be determined by taking the biggest value.

VI. EXPERIMENTS AND DISCUSSION

A. THE DISCUSSION OF INITIALIZATION PARAMETERS AND THE SELECTION OF AGGREGATION METHODS

The proposed algorithm has been tested under a set of benchmark images which are chosen on purpose from the Berkeley Segmentation Data Set Benchmarks 500 (BSD500 for short, see [36]), as shown in Fig.3. The experiments were carried out on a Lenovo Laptop with an Intel Core i3 processor and 4GB memory. Based on large amount of contrast experiments, this paper proves the superiority of the proposed algorithm through images, data and quantitative analysis. In the following sections, the proposed method will be compared with electro-magnetism optimization [25] and fuzzy entropy Based multi-level image thresholding using differential evolution [27] respectively. Electro-magnetism optimization is the latest intelligent optimization method which uses Kapur's entropy as the objective function. And the differential evolution algorithm is also a novel algorithm on the basis of fuzzy theory. And the comparison between MDGWO and GWO is mainly used to test the advantages of MDGWO.

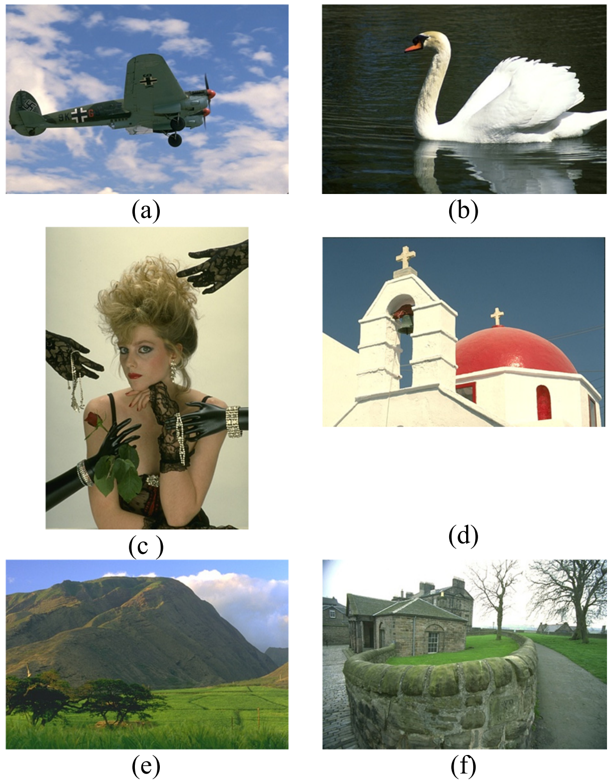

FIGURE 3. The original images and their histograms (a) Aeroplane, (b)Swan, (c) Ladyhand, (d) Church, (e) Mountain, (f) Building.

According to [7], [8], [25], and experimental results, thresholds in this paper are M=2, 3, 4, 5, the maximum number of iteration is 150, specified parameters are as shown in Table 2:

TABLE 2. Parameters settings.

Parameters	Population size	Threshold	No. of iterations	Lower bound	Upper bound
Value	50	2,3,4,5	150	1	256

TABLE 3. Comparison of image segmentation quality with different thresholds and aggregation.

M	2	3	4	5
Median Aggregation	17.0304	20.1923	21.2965	21.2566
Average aggregation	16.9702	20.0421	21.0762	21.0263
Iterative averaging	17.0094	20.1346	21.1580	21.1360

The stability of the proposed algorithm can be tested by conducting qualitative comparisons of the standard deviation (STD) of objective function values and peak signal noise

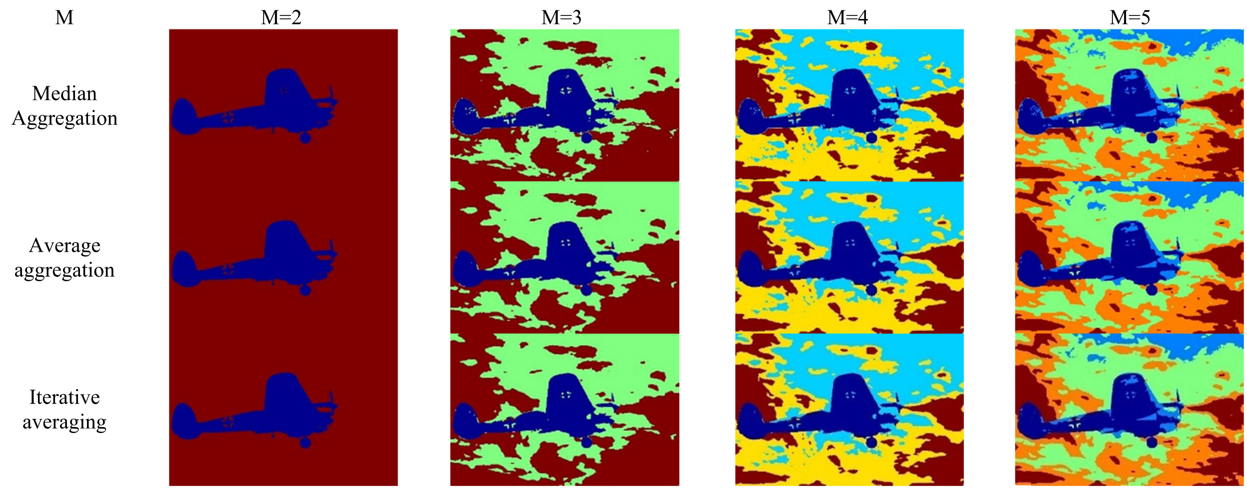

FIGURE 4. The segmentation results of Aeroplane with different thresholds and aggregation.

TABLE 4. The result of fuzzy entropy values, STD and MEAN acquired by FMDGWO.

Image	M	Thresholds	fuzzy entropy	STD	MEAN
Aeroplane	2	37 164.5	13.8150	0.0169	13.8105
	3	39 110 199.5	17.4472	0.0512	17.4142
	4	36 117 168.5 215	20.8525	0.0910	20.7548
	5	42.5 93 136.5 179 218	24.0734	0.1162	23.7150
Swan	2	62 159	12.0181	0.0340	12.0039
	3	69 126 191	15.5387	0.0426	15.5002
	4	35 69 126.5 192	19.1692	0.0864	18.9652
	5	31.5 64 113.5 164.5 211.5	22.6611	0.1972	22.3534
Ladyhand	2	73 200.5	14.1208	0.0120	14.1161
	3	54 123 197.5	17.9898	0.0644	17.9607
	4	38.5 88.5 122.5 199.5	21.3452	0.1434	21.2114
	5	40.5 82 123.5 163 210	24.7622	0.2660	24.4464
Church	2	126 212.5	11.9929	0.0353	11.9787
	3	117 166 212.5	15.6651	0.0458	15.6128
	4	42 117.5 163.5 212	19.3724	0.0735	19.2266
	5	46.5 106.5 136 174.5 224	22.6491	0.2222	22.2623
Mountain	2	51.5 179	12.7894	0.0207	12.7758
	3	75.5 155.5 208.5	16.4899	0.0433	16.4414
	4	48 122 156 209.5	19.7866	0.1452	19.6364
	5	51 107.5 139 165 210.5	22.8371	0.2478	22.4280
Building	2	50 129.5	12.6856	0.0228	12.6682
	3	79.5 148.5 205.5	16.4213	0.0515	16.3554
	4	54.5 135 167 214	19.7916	0.1085	19.6435
	5	39.5 94 139 170 215	22.9501	0.1545	22.6598

ratio (PSNR), where STD can be calculated by (27).

$$STD = \sqrt{\sum_{i=1}^{Max_iter} \frac{(\theta_i - \varepsilon)^2}{Max_iter}} \tag{27}$$

In addition, PSNR is mainly used to compare the similarity between segmented images and original images.

$$PSNR(i,j) = 20\log_{10}({}^{255}/_{RMSE(i,j)}) \tag{28}$$

Where RMSE is the root mean-squared error, the detail defined can be found in [25].

In order to compare the effects different aggregation methods have on the segmentation results and when the number of thresholds varies, a great number of experiments are conducted. Fig. 4 demonstrates the results by average, median and iterative median aggregations of Airplane images. It can be seen that with the increasing number of thresholds, the segmentation accuracy is improved. However, the threshold number cannot infinitely increase because the information unit of each image is limited. So too many thresholds have no help for segmentation, but improve the complexity. We test the segmentation effect with threshold number between 2 and 5 respectively. The results show that the three methods are not different significantly when the number of thresholds is the same. For more accurate comparison, Table 3 gives PSNR values corresponding to the results in Fig. 4. It is clearly observed that under the same number of thresholds, median aggregation method obtains the best results, and the iterative average outperforms the average aggregation method.

B. THE FUZZY IMAGE SEGMENTATION RESULT BASED ON FMDGWO WITH DIFFERENT THRESHOLDS

In order to compare the segmentation effects, Fig. 5 illustrate the segmentation results for the images in Fig. 3 when the number of thresholds range from 2-5. When the number of

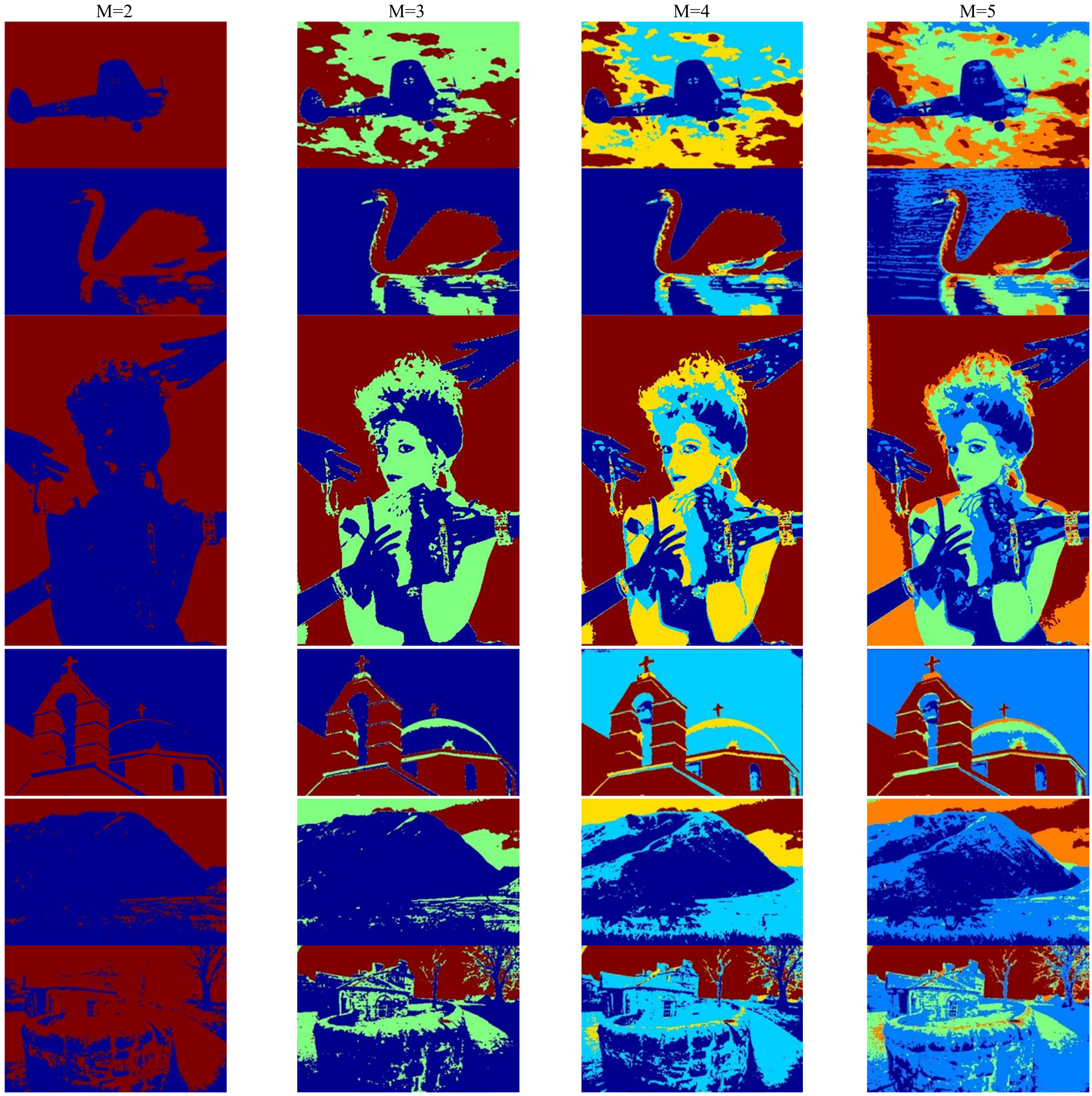

FIGURE 5. The segmentation results of (a)-(f) in Fig. 3.

thresholds increases, the results are more accurate, while the number of regions and accuracy are lower when the threshold number is small. In extreme cases, when threshold number is 2, our algorithm becomes bi-level image thresholding (namely segmentation of foreground and background). Certainly, the number of regions are related to the concrete applications and demands, our method just sets the corresponding threshold number M. Segmentation performances among different methods are hard to be distinguished visually. So various data are provided such as Thresholds, fuzzy entropy values, STD, MEAN in Table 4. Quantitative analysis of effect and performance is provided in Section VI.C, VI.D.

C. COMPARISON OF FUZZY ENTROPY VALUES, STD AND MEAN BETWEEN FMDGWO AND FUZZY GWO (FGWO)

In this section, the results of fuzzy entropy values, STD and MEAN acquired by various images are discussed. Table 5 depicts the values of fuzzy entropy, STD and MEAN obtained by FMDGWO and FGWO methods. From Table 4 we can see that FMDGWO and FGWO both obtain good fuzzy entropy values with different thresholds for all test images. When M=2, the objective function value of FMDGWO is to be equal or slightly higher than FGWO, and with the increasing number of thresholds, the objective function values of FMDGWO are all higher than FGWO. From the angle of STD, only Mountain images show lower STD by FMDGWO

TABLE 5. COMPARISONS of fuzzy entropy values, STD and MEAN between FMDGWO and fuzzy GWO (FGWO).

IMAGE	M	The result of FMDGWO			The result of FGWO		
		Fuzzy Entropy	STD	MEAN	Fuzzy Entropy	STD	MEAN
Aeroplane	2	13.8150	0.0169	13.8105	13.8150	0.0293	13.8079
	3	17.4472	0.0512	17.4142	17.4469	0.0618	17.4191
	4	20.8525	0.0910	20.7548	20.8396	0.1397	20.7335
	5	24.0734	0.1162	23.7150	23.9392	0.1957	23.7539
Swan	2	12.0181	0.0340	12.0039	12.0181	0.0389	11.9924
	3	15.5387	0.0426	15.5002	15.5222	0.0441	15.4656
	4	19.1692	0.0864	18.9652	18.9541	0.1504	18.8352
	5	22.6611	0.1972	22.3534	22.6340	0.2081	22.4099
Ladyhand	2	14.1208	0.0120	14.1161	14.1208	0.0472	14.1087
	3	17.9898	0.0644	17.9607	17.9894	0.0647	17.9490
	4	21.3452	0.1434	21.2114	21.2813	0.1558	21.1764
	5	24.7622	0.2660	24.4464	24.7212	0.2708	24.4208
Church	2	11.9929	0.0353	11.9787	11.9915	0.0364	11.9686
	3	15.6651	0.0458	15.6128	15.6625	0.0556	15.6089
	4	19.3724	0.0735	19.2266	19.3649	0.0804	19.1991
	5	22.6491	0.2222	22.2623	22.6089	0.2273	22.2420
Mountain	2	12.7894	0.0207	12.7758	12.7865	0.0209	12.7799
	3	16.4899	0.0433	16.4414	16.4896	0.0836	16.3984
	4	19.7866	0.1452	19.6364	19.7700	0.1173	19.5660
	5	22.8371	0.2478	22.4280	22.8188	0.3222	22.3547
Building	2	12.6856	0.0228	12.6682	12.6856	0.0287	12.6739
	3	16.4213	0.0515	16.3554	16.4140	0.0653	16.3583
	4	19.7916	0.1085	19.6435	19.7851	0.1115	19.6628
	5	22.9501	0.1545	22.6598	22.9143	0.1693	22.6157

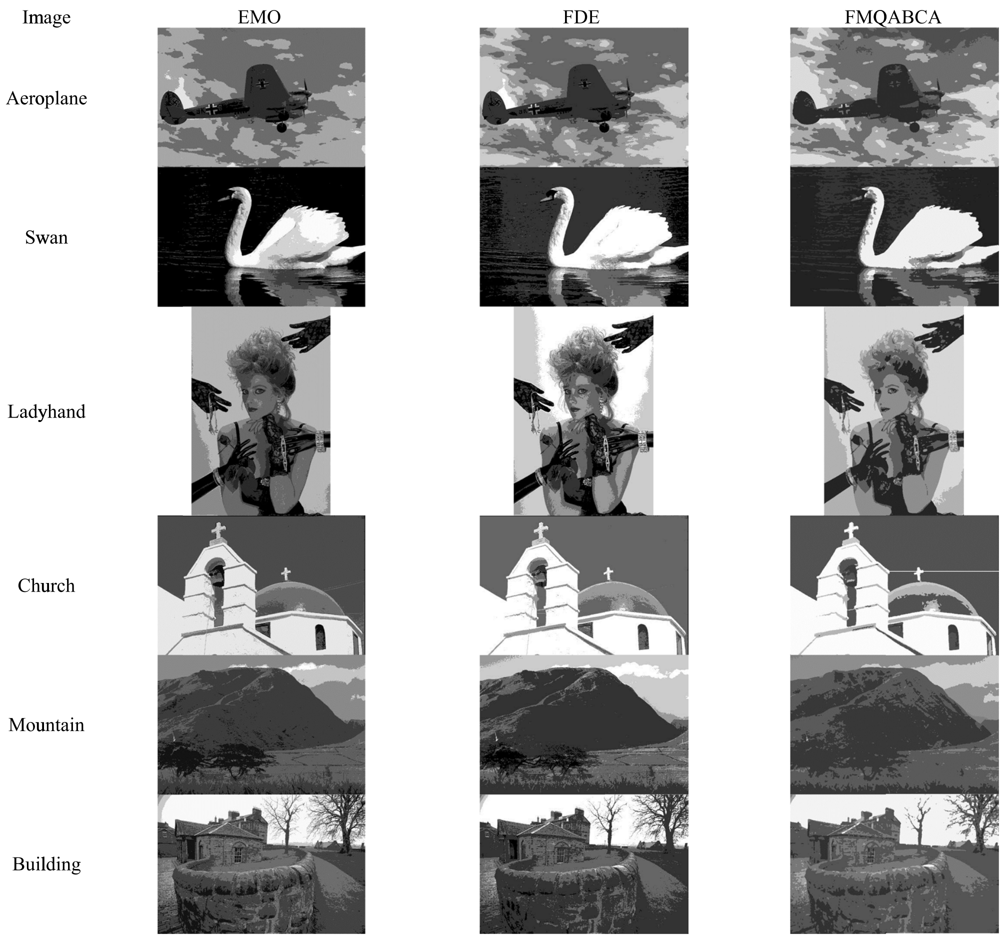

FIGURE 6. The comparison of grayscale segmentation results about (a)-(f) in Fig. 3.

than FGWO when M=4 while STD is higher by FGWO method under any other situations. It needs to be emphasized that when M=2, the STD of Ladyhand images increases by 75%. And it can be calculated that the STD of FMDGWO is increased averagely by 17% than FGWO from Table 5. In the respect of MEAN, FMDGWO shows better

TABLE 6. PSNR metrics of the test images segmented with different threshold.

Image	M	PSNR				
		EMO	MDGWO	FDE	FGWOA	FMDGWOA
Aeroplane	2	12.7187	12.7187	14.5518	17.0304	17.0304
	3	15.9198	15.9198	18.4402	20.1350	20.1923
	4	17.3090	18.4142	21.0083	21.1548	21.2965
	5	18.7284	20.3884	21.0451	21.1891	21.2566
Swan	2	14.8785	14.8785	16.2123	18.2777	18.2777
	3	16.2373	16.2369	16.2334	22.6330	22.6895
	4	16.6445	16.6792	16.7381	23.9026	24.5940
	5	16.9761	16.9803	23.4825	25.7618	25.8041
Ladyhand	2	15.4928	15.4928	15.7940	17.6340	17.6340
	3	17.5422	17.5422	17.9525	20.6992	20.7966
	4	19.0184	18.8069	19.3191	21.6924	21.7043
	5	19.8337	20.6981	20.6115	22.8752	22.9208
Church	2	19.9068	19.9068	15.3281	21.9463	21.9522
	3	21.6779	21.6779	23.3545	22.4576	23.3729
	4	22.5158	22.5158	20.7066	23.8851	23.6241
	5	22.7461	23.0594	22.2338	22.0212	23.2552
Mountain	2	10.8782	10.8857	13.2357	19.6864	19.8276
	3	17.4652	17.4652	21.6381	20.9099	20.9121
	4	19.9008	19.4572	20.1122	22.6798	22.7221
	5	20.8788	20.8256	20.6652	22.6403	22.6645
Building	2	9.9838	9.9838	12.2905	13.3699	13.3699
	3	16.3142	16.3426	18.1586	20.9778	20.8304
	4	19.5233	18.0951	17.4129	21.8416	21.8538
	5	20.7006	21.2341	18.9062	22.0181	22.1664

performance than FGWO. Based on that, FMDGWO has better fuzzy entropy values and STD by adopting fuzzy Kapur's entropy. Although the effects are not as good as FGWO except for a few occasions, the aim of this paper is to get the maximum fuzzy entropy value, the MEAN can only reflect the average performance which doesn't affect the maximum value. Besides, the difference of MEAN between these two methods is less than 0.05.

D. COMPARISON OF FUZZY MULTILEVEL IMAGE SEGMENTATION RESULT AND QUALITY ASSESSMENT BY PSNR

Fig. 5 demonstrates segmentation results by FMDGWOA. Fig. 6 shows the results in 5 thresholds by EMO, FDE and FMDGWOA. The results are processed with gray scaling, and the gray values of a region will be replaced by the average of that region. It is difficult to distinguish the quality among the three methods visually.

In order to compare the difference among these methods further, PSNR values under different thresholds are presented in Table 6. In the case where fuzzy entropy is not applied, MDGWO obtains similar PSNR to EMO, which are higher than EMO in most cases. FMDGWOA gets the highest PSNR values when fuzzy entropy is applied. Thus it proves that FMDGWOA performs better in image segmentation. Compared with fuzzy entropy (FDE, FGWOA, FMDGWOA) and no fuzzy entropy (EMO, MDGWO), PSNR is higher in most cases with fuzzy entropy. Notably, FMDGWOA is much better than other methods.

Compared with EMO, the FMDGWOA method gets the highest increase of 82% for the Mountain images when M=2, the lowest also increases by 2% for the Church images when M=5. On average, the FMDGWOA method shows more than 23% of the PSNR improvement for all the images with different thresholds.

This paper first improved the standard GWO method, from the comparisons offered in Section VI.C, it can be seen that MDGWO performs better than the standard GWO, so only comparison of MDGWO and FMDGWOA is conducted in this section. According to the computation of Table 6, FMDGWO has improved by 4%∼82%, averagely 22%. Therefore, fuzzy entropy and local information can effectively improve the segmentation quality.

Compared with FDE, FMDGWOA has increased by 16% averagely from the perspective of MEAN. And Mountain images have increased by 50% when M=2. Compared with FGWOA, FMDGWOA achieves better PSNR in most cases, especially when M=5.

Through the above data analysis, the proposed FGWOA and FMDGWOA are obviously superior to EMO, MDGWO, FDE methods in segmentation quality. Hence, to achieve image segmentation by fuzzy aggregation in the neighborhoods of pixels is a feasible and effective segmentation method which takes fuzzy Kapur's entropy as the objective function and with GWO and MDGWO as the tools. Through quantitative and visual analysis of Table 3-6 and Fig. 4-6, FMDGWOA achieves better performance in MT and has obvious advantages in accuracy and stability.

VII. CONCLUSION

In this paper, in order to solve the multilevel image thresholding problem as described in section III, the proposed MDGWO is used to optimize fuzzy Kapur's entropy to obtain a set of thresholds. Taking the thresholds as centroids, assign a set of fuzzy values to every pixel by Pseudo Trapezoid-Shaped membership function, and then the aggregation will be taken by average, median and iterative average, finally finish the segmentation. Based on the reasonable parameter setting and efficiency of the MDGWO, the analysis results of VI shows that MDGWO delivers high performance in Multi-level image thresholding. Specifically, by comparing the fuzzy entropy values, STD and MEAN, it can be see that FMDGWO performs better than FGWO. The comparison of PSNR value of MDGWO and EMO also shows that the former is much superior to the latter. In the case where fuzzy methods are applied, FMDGWOA proves to be much better than FDE and FGWOA. Taken together, FMDGWOA improves the stability while ensures higher objective function value and better PSNR than EMO, MDGWO, FDE and FGWOA,During the process of fuzzy aggregation, average aggregation gained better results and the PSNR is also better than EMO, MDGWO and FDE. Therefore, FMDGWOA not only have excellent segmentation performance, but also have obvious advantages in stability and objective function optimization. In the future, we will continue to make further improvements on GWO algorithm and the application of fuzzy theory in image thresholding so as to push the quality of image segmentation to a much higher level.

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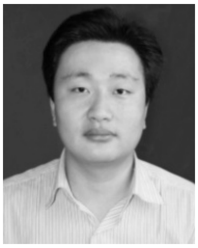

LINGUO LI received the B.S. degree in computer science and technology from Liaocheng University in 2005, and the M.S. degrees in computer application technology from Jiangnan University in 2008. He is currently pursuing the Ph.D. degree in information network with the University of Posts and Telecommunications, Nanjing, China.

He is currently a Lecturer with Fuyang Normal University, Fuyang, China. His research interests are in image and video processing and Information Security.

LIJUAN SUN received the B.S. degree in radio engineering from Southeast University in 1985, the M.S. degree in signal, circuit and system, and the Ph.D. degree in communication and information system from Nanjing University Posts and Telecommunications in 1988 and 2007, respectively.

She is currently a Professor and a Ph.D. Supervisor with the School of Computer Science and Technology and the School of Software, Nanjing University Posts and Telecommunications, Nanjing, China. Her research interests include multimedia wireless sensor networks and evolutionary computation.

WEI KANG received the B.S. degree in mathematics from Fuyang Normal University, Fuyang, China, in 2007, and the M.S. degree in apllied mathematics from the University of Electronic and Technology of China, Chengdu, China, in 2010. He is currently pursuing the Ph.D. degree with the University of Electronic and Technology of China. His current research interests include stability of neural networks and control of time-delay systems.

JIAN GUO received the B.S. and M.S. degrees in computer science , and the Ph.D. degree in information network from the from the Nanjing University of Posts and Telecommunications in 2000, 2007, and 2013, respectively.

He is currently an Associate Professor with the Nanjing University of Posts and Telecommunications, China. His research interests cover evolutionary computation, swarm intelligence, and wireless sensor networks.

CHONG HAN received the M.S. degrees in computer application from Henan University in 2010, and the Ph.D. degree in information network from Nanjing University Posts and Telecommunications in 2013.

He is currently a Lecturer with the Nanjing University of Posts and Telecommunications, Nanjing, China. His research interests include wireless visual/video sensor networks and multimedia information processing.

SHUJING LI received the B.S. degree in computer science and technology from Liaocheng University in 2005, and the M.S. degree in computer application technology from the China University of Geosciences in 2008.

She is currently a Lecturer with Fuyang Normal University, Fuyang, China. His research interests are in information security, and image and video processing.