Analysis of Image Thresholding Segmentation Algorithms based on Swarm Intelligence

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ABSTRACT

Swarm intelligence-based image thresholding segmentation algorithms are playing an important role in the research field of image segmentation. In this paper, we briefly introduce the theories of four existing image segmentation algorithms based on swarm intelligence including fish swarm algorithm, artificial bee colony, bacteria foraging algorithm and particle swarm optimization. Then some image benchmarks are tested in order to show the differences of the segmentation accuracy, time consumption, convergence and robustness for Salt&Pepper noise and Gaussian noise of these four algorithms. Through these comparisons, this paper gives qualitative analyses for the performance variance of the four algorithms. The conclusions in this paper would give a significant guide for the actual image segmentation.

Keywords: Swarm Intelligence, Image Segmentation, Otsu Thresholding Segmentation, Performance Analysis, Noise Robustness

1. INTRODUCTION

Image processing is a sub-branch of computer science and engineering in which information from the perception of electromagnetic waves is captured, stored and manipulated. It lies at the core of many applications such as military, medical, remote sensing and so on. As a key and indispensible procedure in image processing, image segmentation could distinguish the target and the background in an image and bring convenience to other works such as image matching and target recognition. The research of image segmentation has been extensively investigated in the past decades [1]. The traditional image processing algorithms include: area-based algorithms, edge-based algorithms and clustering-based algorithms. All of them are based on some fixed models, thus there are two disadvantages existing: 1) the best threshold value is different to find for an image, and 2) these algorithms do not have acceptable performance.

Swarm intelligence is an important technology of artificial intelligence. It was proposed by Beni and Hackwood [2]. Swarm is a set of some agents with inter-correlations, e.g. bee swarm, ant swarm and bird swarm [3]. Since every agent could communicate with others and obtain more information than that from itself. This kind of communication could make all the agents clustering or co-working, and gradually auto-emerging. This powerful ability of evolution comes from the cooperation of the whole swarm, so it is called swarm intelligence. As a new kind of evolution algorithms, swarm intelligence could provide a novel method for many complex and distributed problems, without central control and certain models.

The spring up of novel methods have been proposed recently to address the problems of digital image processing by using swarm intelligence, and these algorithms show better performance and robustness for noise. In this paper, four image thresholding segmentation algorithms based on swarm intelligence are discussed, including fish swarm algorithm, artificial bee colony, bacteria foraging algorithm and particle swarm optimization. Through the comparisons of the segmentation accuracy, time consumption, convergence and robustness for noise of these four algorithms, some analyses and conclusions will be given to make the actual image segmentation better.

The rest of this paper is organized as follows: Section 2 discusses the four image thresholding algorithms based on swarm intelligence. Experiments and performance valuations with these algorithms are reported in Section 3. Finally, we draw conclusions and outline novel research frontiers in Section 4.

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2. IMAGE THRESHOLDING SEGMENTATION ALGORITHMS BASED ON SWARM INTELLIGENCE

Image thresholding segmentation could classify the pixels to separate the target and the background in an image by setting a gray-scale threshold. The traditional algorithms only depended on the gray-scale histogram to make segmentation, thus they would be disturbed by noise seriously besides how to choose a good threshold was difficult. Otsu [4] found the principle that the best threshold should make the distance between the two classes largest and designed a brute-force algorithm to search it. In order to have better robustness for noise, Liu [5] improved Otsu's algorithm and designed 2-D Otsu algorithm. 2-D Otsu utilizes the 2-D information of the gray-scale of the pixel and the average gray-scale of the pixels in 3×3 neighborhood windows to set a 2-D threshold. However, all of these algorithms need to search the best threshold in a brute-force manner, and the large search space becomes the limitation for the performance of algorithms.

In recent years, we have witnessed significant theoretical and some encouraging experimental results in the area of utilizing swarm intelligence to improve the performance of image segmentation. For the powerful ability to address distributed problems, these algorithms based on swarm intelligence have good performance and significant improvement. In this section, four existing image thresholding segmentation algorithms based on swarm intelligence are introduced, including fish swarm algorithm, artificial bee colony, bacteria foraging algorithm and particle swarm optimization.

2.1. Fish Swarm Algorithm

Fish swarm algorithm (FSA) [6] is an optimization algorithm which simulates the behaviors of fish swarm. In a pool, fish could always swim towards a position with more food. For every fish agent, its behaviors include:

1) *Foraging*. Fish could swim randomly to the position around its current position and try to find a position with more food.
2) *Clustering*. If the center of its neighborhoods has more food and there are not too many fish clustering around the center, the fish will swim towards the center.
3) *Following*. If some certain neighborhood finds a position with more food and there are not too many fish clustering around the position, the fish will swim following its neighborhood.
4) *Choosing*. According to all the positions of the fish swarm, every fish will have tries the three behaviors above. After trying, every fish will choose the best behavior to swim. And the swarm will evolve.

Image thresholding segmentation algorithm based on FSA [7] considers the search space as the pool and different thresholds as the positions the fish agents may stay in. When FSA finishes evolvement, the best position where the fish swarm has found is the best threshold of an image.

2.2. Bacteria Foraging Algorithm

Bacteria foraging algorithm (BFA) [8] simulates the foraging behaviors of the coli bacillus in human's body. These behaviors include:

1) *Chemotaxis*. Every bacterium could never stop moving forward to the position with more nutrition until it finds a local best position. This behavior makes every bacterium owns the unique ability of continuously searching in a local area.
2) *Reproduction* and *Elimination*. After *chemotaxis*, every bacterium will stay in a local best position. According to the state of the whole swarm, some bacteria with bad state will be eliminated and some bacteria in better position will reproduce. This behavior makes the bacteria swarm obeys the principle "*survival of the fittest*" in the nature.
3) *Dispersal*. In order to avoid the prematurity problem of the swarm, every bacterium may be dispersed into a random position in some certain probability related with the current state of the swarm.

Image thresholding segmentation based on BFA [9] could search the best threshold by iterating 1-3 behaviors to evolve the swarm. When BFA finishes evolvement, the best position where the bacteria swarm has found is the best threshold of an image.

2.3. Artificial Bee Colony

Artificial bee colony (ABC) was proposed to simulate the cooperation of bee foraging in a garden by Karaboga in 2005 [10]. Artificial bee swarm could search the best honey source parallel through the cooperation and communication of *employed bees*, *onlooker bees* and *scout bees*. Then the different behaviors of these three kinds of bees are shown as follows:

1) *Employed bees*. Every employed bee could search a random honey source around. If the new source is better, it will go there to work. Otherwise, the work bee will maintain its position.
2) *Onlooker bees*. The observer bees could share all the information of the employed bees. And they will distribute a new honey source for employed bee in some certain probability related with the information of all the employed bees. Then every employed bee will choose a better one between the new source and the current source.
3) *Scout bees*. If an employed bee has stayed in a same position for several iterations, meanwhile the honey source is just a local best position, and then the employed bee should give up it to try to find a better one. At that time, the scout bee will choose a random position in the garden for the employed bee.

Image thresholding segmentation based in ABC [11] maps the honey sources in the garden to different thresholds. Through the continuous co-work of the three kinds of bees, the bee swarm will find the best honey source in the garden. Similarly, when ABC finishes evolvement, the best honey source where the bee swarm has found is the best threshold of an image.

2.4. Particle Swarm Optimization

Particle swarm optimization (PSO) was designed to simulate the foraging behavior of bird swarm by Kennedy in 1995 [12]. In the evolvement of the particle swarm, every particle could move at some certain speed in the space and adjust its speed according to the state of the whole swarm. The adjustment of every particle depends on two parameters. One is the best position this particle has ever stayed. And the other is the best position the whole swarm has ever found. Through a certain evaluation for these two parameters, every particle will decide how its speed should be changed. At each iteration, every particle will refresh its speed and move forward at the new speed, and then the swarm will evolve until it finds the global best position in the space.

Image thresholding segmentation based on PSO [13] utilizes the ability of the communication and self-adjustment of the particle swarm to search the best threshold of an image quickly. When PSO finishes evolvement, the parameter which is the best position the whole swarm has ever found is just the best threshold of an image.

3. EXPERIMENT AND ANALYSIS

In order to analyze and compare the four image thresholding segmentation algorithms based on swarm intelligence, some tests and experiments will be expressed in this section. All the algorithms and tests are coded in *C* language and running in the processor of *Intel Core2 Quad CPU Q6600*. The following tests include the comparisons of the segmentation accuracy, time consumption, convergence and robustness for noise of these four algorithms. And the image benchmarks are the common examples including Lena, Peppers, Camera and Rice as show in *Fig.1*.

Fig.1 The four image benchmarks chosen in the test

In this paper, to make image segmentation more precise and better robust for noise, we choose 2-D Otsu [5] as the original algorithms. *Fig.2* shows the result after 2-D Otsu segmentation. 2-D Otsu would make a brute-force search, consequentially it will find the best threshold. *Tab.1* gives the detail results and time consumption of 2-D Otsu. In this table, the 2-D threshold represents the summation of the gray-scale of the pixel and the average gray-scale of the neighborhood windows of the best result. And the distance means the variance of the target and background after segmentation.

Fig.2 The result images after 2-D Otsu

Tab.1 The result and time consumption of 2-D Otsu

Benchmark	Time(s)	2-D Threshold	Distance
Lena	99.812	261	2883.796

Camera	99.656	206	6894.975
Peppers	99.75	232	4765.596
Rice	99.703	230	2882.172

3.1. Segmentation Accuracy

Image segmentation based on swarm intelligence could find an approximately best threshold. Therefore, the result threshold result will be worse than that of 2-D Otsu. In this section, the segmentation result will be discussed.

Tab.2 illuminates the average segmentation result of all the four image segmentation algorithms based on swarm intelligence for 100 times. In the four algorithms, the size of every swarm is 20 and the time of swarm evolving iterations is 20. In this table, error of a new algorithm is computed by *Eq.(1)*.

$$Error_{new} = \frac{Dis_{2D-Otsu} - Dis_{new}}{Dis_{2D-Otsu}} \tag{1}$$

From the statistical result, it is obvious that AFS and PSO could get the most accurate result, whose average error reach to 0.28% and 0.02% respectively. The results of ABC and BFA are worse and their average errors are 1.61% and 2.46%. It is known that the swarm intelligence will improve its accuracy as the size of the swarm and the time of swarm evolving iteration increase. Therefore, all the four algorithms could make approximately perfect image segmentation.

Tab.2 The average segmentation result of four algorithms based on swarm intelligence for 100 times

		Lena	Camera	Peppers	Rice
2D-Ostu	2-D Threshold	261	206	232	230
	Distance	2883.79597	6894.97501	4765.59569	2882.171815
AFS	2-D Threshold	262.2	217.6	233	226.8
	Distance	2876.503736	6862.05502	4763.74613	2872.605995
	Error	**0.25%**	**0.48%**	**0.04%**	**0.33%**
ABC	2-D Threshold	259	211.6	230	233.4
	Distance	2765.083852	6877.39758	4732.79678	2842.906346
	Error	**4.12%**	**0.25%**	**0.69%**	**1.36%**
PSO	2-D Threshold	261	205.6	232.4	226
	Distance	2883.153104	6894.21462	4764.0451	2881.726728
	Error	**0.02%**	**0.01%**	**0.03%**	**0.02%**
BFA	2-D Threshold	258.6	238.2	195.4	228.2
	Distance	2777.255891	6789.70456	4705.64135	2785.856403
	Error	**3.69%**	**1.53%**	**1.26%**	**3.34%**

3.2. Time Consumption

Since 2-D Otsu needs to search the best threshold in brute-force manner, it will cost much time for image segmentation. One main advantage of the new segmentation algorithms based on swarm intelligence is that they could utilize the communication of the agents in the swarm to search the approximately best and acceptable threshold fast.

Then we will discuss the performance of all the four algorithms based on swarm intelligence. *Fig.3* demonstrates the time consumption of the four swarm intelligence-based algorithms with the same size of swarm 50 and with different iteration times for Lena image. It is found that the time consumption approximately increases linearly as the increase of iteration times. PSO is the fastest algorithms, and the average time consumption is about 1.39 second. From the introduction in *Section 2*, it is easy to understand that for the high performance are liable the peculiar properties of that the behavior of PSO is the most simple and efficient. AFS and ABS have a similar increasing trend of the time consumption, and their average time consumptions are 10.46 seconds and 9.98 seconds respectively. Compared with them, BFA is the slowest one with the average time consumption of 44.93 seconds. Even worse, when the iteration time reaches to 50, the time consumption of BFA is above 100 seconds which is more than that of 2-D Otsu, 99.812 seconds. It means BFA will be inefficacious and nonsense. Since every bacterium must continue moving forward to a better position until finding a local best position, this procedure would cost lots of time, and it is the main reason that BFA is the slowest algorithm.

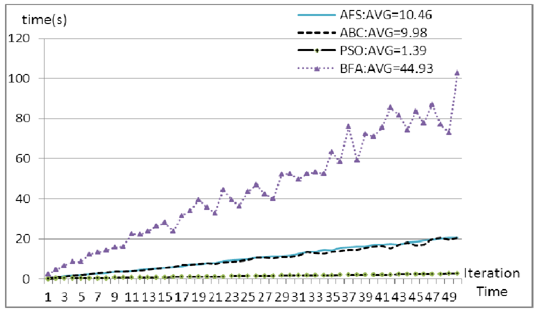

Fig.3 The time consumption of the four swarm intelligence-based algorithms with the same size of swarm 50 and with different iteration times for Lena image.

3.3. Convergence

Convergence is an important measurement, which depends on the increasing trend of the accuracy of swarm intelligence-based algorithms as the increase of the size of swarm and the iteration time. And convergence is crucial to not only the speed of finding the best threshold, but also the ability of every agent in the swarm to get rid of the local best position to find the global best one.

Fig.4 and *Fig.5* represent the average distance of image segmentations based on swarm intelligence for Lena benchmark for several times with different size of swarm and with different iteration times respectively.

From *Fig.4*, it is shown that when the iteration time is constant 10, all the four algorithms could find better threshold as the size of swarm increases. Among the four algorithms, ABC has the best convergence. Even if the swarm size is only10, ABC could find an acceptable good threshold.

From *Fig.5*, the accuracies of PSO, AFS and ABC improve and their results are very near to the global best threshold as the increase of the iteration time when the size of swarm is constant 20. However, the convergence of BFA is bad, compared with the other algorithms. The main reason is that every bacterium stays in a local best position during the evolvement of the swarm. Although the principle "*survival of the fittest*" may make a few bacteria search in the global space, most of the swarm will stay in its position. Compared with other swarms, BFA is deficient to the ability of getting rid of local best position so that the convergence of BFA is the worst of all.

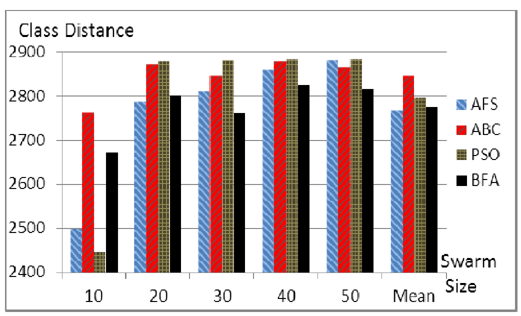

Fig.4 The average distance of image segmentations based on swarm intelligence for Lena benchmark for several times with different size of swarm (the iteration time is constant 10)

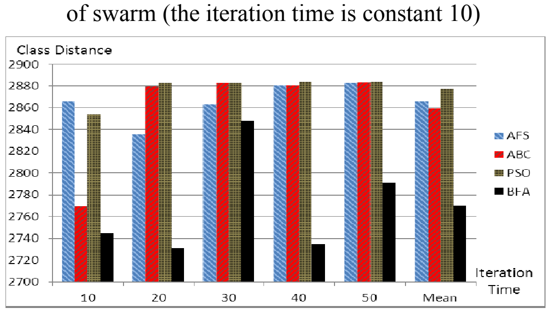

Fig.5 The average distance of image segmentations based on swarm intelligence for Lena benchmark for several times with different iteration times (the size of swarm is constant 20)

3.4. Noise Robustness

The actual image is always disturbed by noise. The common noises include: Salt&Pepper noise, Gaussian noise, Pulse noise and Poisson noise. Noise will cause error of image thresholding segmentation. Therefore, noise robustness is remarkable for the algorithms based on swarm intelligence. In this section, we will mainly discuss the influences of Salt&Pepper noise and Gaussian zero-mean noise.

Fig.6 displays the Lena image disturbed by Salt&Pepper noise with density from 0.01 to 0.05 (a) and disturbed by Gaussian zero-mean noise with variance from 0.01 to 0.05 (b). As the increase of noise intensity, the change of the image data is more obvious.

In order to test the noise robustness, the images in *Fig.6* are utilized to be segmented by all the algorithms. To be fair, in the four algorithms based on swarm intelligence, the sizes of all the swarm are 20 and the iteration times are 50. *Fig.7* gives the result comparison of all image segmentation algorithms for Lena images with Salt&Pepper noise with density 0.05 and disturbed by Gaussian zero-mean noise with variance 0.05. Compared with the result image in *Fig.2*, it is obvious that the two kinds of noise could disturb image segmentation seriously.

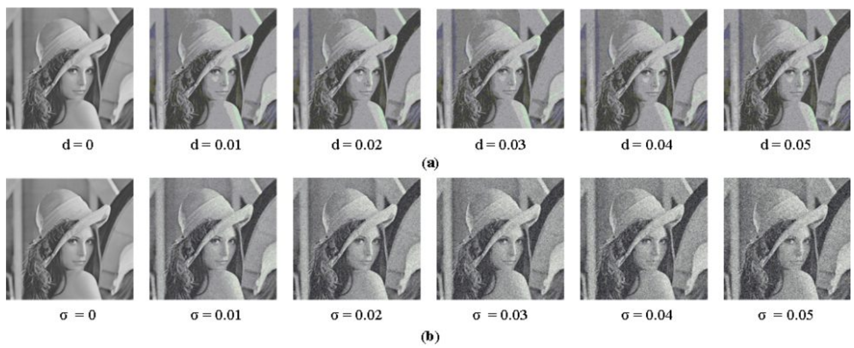

Fig.6 (a) The Lena image disturbed by Salt&Pepper noise with density from 0.01 to 0.05 (b) the Lena image disturbed by Gaussian zero-mean noise with variance from 0.01 to 0.05

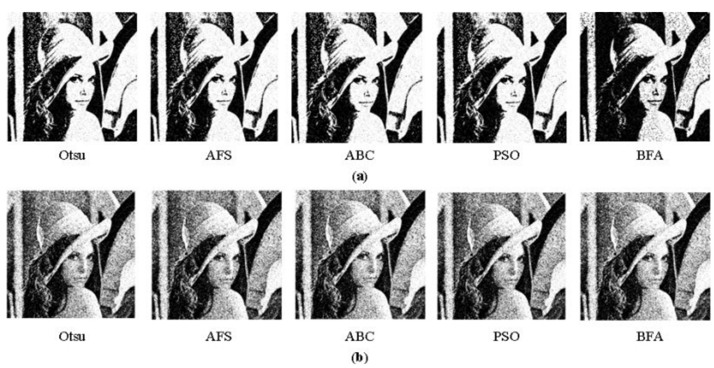

Fig.7 (a) The comparison result of all image segmentation algorithms for Lena images with Salt&Pepper noise with density 0.05 (b) The comparison result for Lena images with Gaussian zero-mean noise with variance 0.05

Fig.8 demonstrates the average distances of all image segmentation algorithms for Lena image disturbed by Salt&Pepper noise with density from 0.01 to 0.05. We see that AFS and ABC could find an approximately best threshold near to that of 2-D Otsu, and it means both of them have good robustness for Salt&Pepper noise. Meanwhile, when the density of noise is small, PSO shows good accuracy. However, as the increase of the density of noise, PSO could not find an approximately best threshold. BFA has the worst robustness for Salt&Pepper noise. Owing to noise, BFA could not search good threshold effectively and its result is far from the best result of 2-D Otsu.

Fig.9 depicts the average distances of all image segmentation algorithms for Lena image disturbed by Gaussian zero-mean noise with variance from 0.01 to 0.05. Compared with the result in *Tab.2*, it is found that the results of all the image segmentation algorithms changes greatly. This great change is also shown in *Fig.7*. However, all of the four algorithms based on swarm intelligence could find approximate and acceptable result near to the best result of 2-D Otsu. Thus, it is asserted that the robustness for Gaussian noise of 2-D Otsu is bad. However, the swarm intelligence-based algorithms could be well tolerant with Gaussian noise.

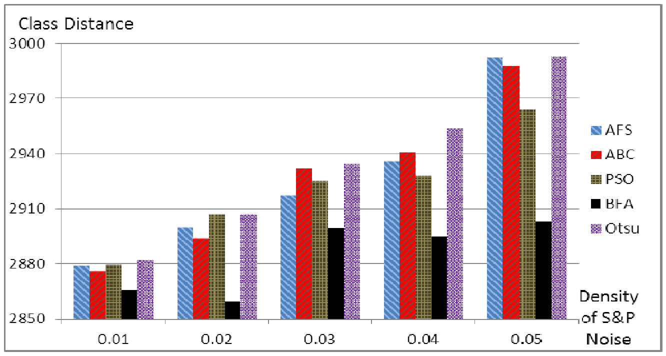

Fig.8 The average distances of all image segmentation algorithms for Lena image disturbed by Salt&Pepper noise with density from 0.01 to 0.05

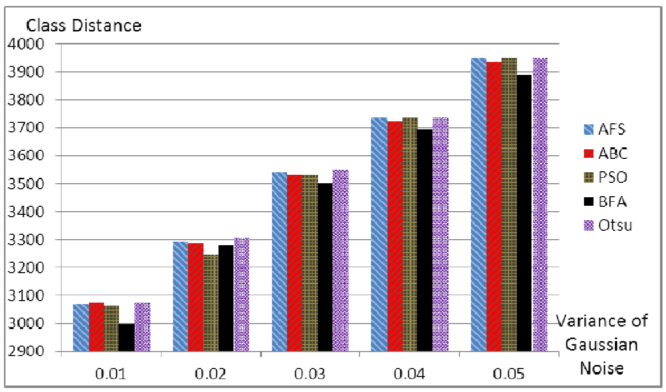

Fig.9 The average distances of all image segmentation algorithms for Lena image disturbed by Gaussian zero-mean noise with variance from 0.01 to 0.05

4. CONCLUSION AND FRONTIER

Through the experiments and analyses of the four algorithms based on swarm intelligence in *Section 3*, some important conclusions have been discovered by extensive empirical study as follows:

1. The accuracies of all the four algorithms are good and all of them could make perfect image segmentation, especially AFS and PSO.
2. In the aspect of performance, PSO is the fastest algorithm of all, AFS and ABC are modest. On the contrary, BFS is the slowest one.
3. ABC has the best convergence as the increase of the size of swarm. And BFS has the worst convergence as the increase of the iteration times.
4. AFS and ABC have good robustness for Salt&Pepper noise, yet BFS has bad robustness. Meanwhile, all the four algorithms have perfect robustness for Gaussian noise, but the great change of image segmentation results from the bad robustness of 2-D Otsu.

Certainly, for the different applications, these algorithms based on swarm intelligence may express some changes of performance and efficiency which may result in some slight change of these conclusions. However, compared with the traditional image threshold segmentation algorithms, the swarm intelligence-based algorithms could find an approximately best and acceptable result much faster. Hence, they have more outstanding availability and usability for the actual image segmentation.

In the field of swarm intelligence, there are many novel researches emerging according to the regular behavior of the swarms in the nature. These novel ideas motivate researchers to improve the effect of the swarm intelligence algorithms for the actual applications. Recently, a trend of combining quantum computation with swarm intelligence has proved to be very fruitful [14]-[16]. For example, [14] introduces some conceptions in quantum mechanism into swarm intelligence, such as probability amplitude, the entanglement state, Von Neumann entropy and so on. A novel quantum particle swarm optimization for image processing is designed which is named GQPM. Compared with PSO, GQPM shows better convergence and robustness for noise. Hence, the swarm intelligence algorithms based on quantum computing will be a new trend and a hot issue for image processing in the near future.

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