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A Cooperative Honey Bee Mating Algorithm and Its Application in Multi-Threshold Image Segmentation

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***Abstract*—The problems of multi-threshold image segmentation remain great challenges for image compression, target recognition and computer vision. However, most of them are time-consuming. This paper proposes a cooperative honey bee mating-based algorithm (CHBMA) for image segmentation to save computation time while conquer the curse of dimensionality. CHBMA, based on honey bee mating algorithms (HBMA) and the cooperative learning, greatly enhances the search capability of the algorithm. Moreover, we adopt a new population initialization strategy to make the search more efficient, according to the characters of multilevel thresholding in an image arranged from a low gray level to a high one. Extensive experiments have shown that CHBMA can deliver more effective and efficient results to be applied in complex image processing such as automatic target recognition, compared with state-of-the-art population-based thresholding methods.**

Keywords—Image Segmentation; Multilevel Thresholding; Honey Bee Mating Algorithm; Cooperative Learning

I. INTRODUCTION

Image segmentation is considered as an important basic operation for meaningful analysis and interpretation of image acquired. It is useful in separating objects from background, or discriminating an object from objects that have distinct gray-levels. For intensity images, there are four popular approaches: threshold techniques, edge-based methods, region-based techniques, and connectivity-preserving relaxation methods. Image thresholding is widely used in many image processing applications due to its simplicity, robustness and accuracy, such as optical character recognition, automatic visual inspection of defects, detection of video change, moving object segmentation, and medical image applications. The thresholding methods can also be also classified into parametric and nonparametric approaches generally. In the parametric approaches, the gray-level distribution of each class has a probability density function that is generally assumed to obey a Gaussian distribution and attempted to find an estimate of the parameters of distribution that will best fit the given histogram data[1, 2].

Nonparametric approaches find the thresholds in an optimal manner based on some discriminating criteria such as the between class variance, entropy, etc. They are easy to extend to multilevel thresholding as well. However, the amount of thresholding computation significantly increases with this extension. To overcome this problem, some multilevel thresholding techniques based on Intelligent Optimization Algorithms (IOA) have been proposed and obtained good effectiveness in recent years. Among them, Hammouche et al. [3] proposed a fast multilevel thresholding method with a wavelet transform-based technique and Genetic Algorithm (GA) to reduce the time computation. Lai et al. [4] proposed a clustering based approach using a hierarchical evolutionary algorithm for medical image segmentation. Tao et al. [5] proposed a fuzzy entropy method incorporating with ACO. Cuevas et al. [6] used the Artificial Bee Colony (ABC) algorithm to compute threshold selection for image segmentation. Horng [7] proposed a new multilevel thresholding method based on the technology of Honey Bee Mating Algorithm (HBMA), using the maximum entropy criterion. Chander et al. [8] proposed a variant of PSO for image segmentation which makes a new contribution in adapting 'social' and 'momentum' components of the velocity equation for particle move updates. Gao et al. [9] proposed the quantum-behaved PSO (CQPSO) by employing the cooperative method to save computation time and to conquer the curse of dimensionality. Gao et al. [10] presented a PSO algorithm with intermediate disturbance searching strategy (IDPSO), which can enhance the global search ability of particles and increase their convergence rates. The IDPSO

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algorithm is applied to multilevel image segmentation problem for shortening the computational time effectively.

As we know, for PSOs, updating the position of the particle as a whole item has the problem of the curse of dimensionality. Their performance deteriorates as the dimensionality of the search space increases, as described in [11]. This problem also exists in HBMA in which the broods are updated as a whole item. Hence, a new HBMA with the cooperative method (CHBMA) is proposed in this paper for solving this problem. The cooperative method is specifically applied to conquer the "curse of dimensionality" by partitioning the search space of high-dimensional problem into one-dimensional subspaces. Then, the broods in CHBMA make contribution not only as a whole item but also in each dimension. The entropy criterion based measure is employed to evaluate the performance of CHBMA. The experimental results indicate that CHBMA can produce effective, efficient and smoother segmentation results in comparison with several developed methods.

The main contributions of this paper are in the following. (a) We introduce a new bee colony in each generation to avoid higher levels of inbreeding. (b) We also adopt a new population initialization strategy to make the search more efficient and faster. (c) Comparing with previous work, such as HBMA, we delete the brood mutation operator, because we find it is low efficiency by experiments. (d) The cooperative learning method is applied to conquer the "curse of dimensionality".

The remainder of the paper is organized as follows. Section II introduces the related work. Section III presents the proposed algorithm CHBMA. Performance evaluation and experimental analysis are presented in detail in Section IV. Finally, some conclusions are made in Section V.

II. RELATED WORK

A. *Honey Bee Mating Algorithm*

Honey bees are one of the most well studied social insects. HBMA is the algorithm by modeling the marriage behavior of honey-bees and use this model to inspire an optimization search algorithm [12].

Each normal honey bee colony typically consists of one or more egg-laying queens, drones, broods and workers. Queens represent the main reproductive individuals in some types of honey-bees and specialize in eggs laying [13]. A queen bee may live up to 5 or 6 years, whereas worker bee and drones never live more than 6 months. After the mating process, the drones die. The drones are the sires or fathers of colony. They are haploid and act as amplify their mother's genomes without altering their genetic composition expect through mutation. The drones are practically considered as agents that propagate one of their mother's gametes and function to enable females to act genetically as males. Workers specialize in brood care and sometimes lay eggs. Broods arise either from fertilized eggs which represent potential queens or workers or unfertilized ones which represent prospective drones.

In the marriage process, the queens mate during their mating-flight in the air. A mating flight starts with a dance performed by the queens who start a mating flight during which the drones follow the queens and mate with them. In each mating, sperm reaches the spermatheca and accumulates there to form the genetic pool of the colony. Each time a queen lays fertilized eggs and then randomly retrieves a mixture of the sperm accumulated in the spermatheca to fertilize the egg [14].

The mating-flight can be considered as a set of transitions in a state-space (the environment) where the queen moves between the different states in some speed and mates with the drone encountered at each state probabilistically. The queen is initialized with some energy-content at the start of the flight-mating and returns to her nest when the energy is within some threshold or when her spermatheca is full.

In HBMA, the functionality of workers is restrained to brood cares and thus each worker may be regarded as a heuristic which can improve a set of broods. An annealing function [Eq. (1)] is used to describe the probability of a drone (D) that mates with the queen (Q).

$$Prob(Q,D)=\text{Exp}[-|f(Q)-f(D)|/S(t)] \quad (1)$$

Where $|f(Q)-f(D)|$ is the absolute difference of the fitness of D and the fitness of Q, and $S(t)$ is the speed of queen at time t. After each transition of mating, the queen's speed and energy are decayed according to Eq. (2).

$$S(t+1) =\alpha\times S(t),\ \alpha\in[0, 1] \quad (2)$$

where α is the decreasing factor. Workers adopt some heuristic mechanisms such as crossover or mutation to improve the brood's genotype. The process for implementing HBMA [12] is as in Figure 1.

```
Initialize workers, drones and queens
While not stop
{
    For each queen in the queen list
    {
        Initialize energy, speed and position;
        The queen moves between states and probabilistically
        chooses drones
        {
            If (a drone is selected)
                Add its sperm to the queen's spermatheca;
            End If
        }
        Update the queen's internal energy and speed;
    } End For
    Generate broods by crossover and mutation;
    Use workers to improve the broods and update workers'
    fitness;
    If (the best brood is better than the worst queen)
        Replace the queen with the best brood;
    End If
} End While
```

Fig. 1. Pseudocode for HBMA

B. Entropy criterion based measure

Kapur et al. [15] proposed the entropy criterion from information theory for bi-level thresholding. The method can also extend to solve multilevel thresholding problems and it has been widely used in determining the optimal threshold values in image segmentation. The entropic method of thresholding can be described as follows.

Let there be L gray levels in a given image and these gray levels are ranged over [0, L-1]. Let $h(i)$ be the observed frequency of gray-level i; and also let

$$N=h(0)+\cdots+h(i)+\cdots+h(L-1)$$
$$p_i = h(i) / N \tag{3}$$

Assume that there are M thresholds: $\{t_1, t_2, \ldots, t_M\}$, where ($1 \le M \le L-1$), which divide the original image into $M+1$ classes that are represented in the following notations: $C_0 = \{0,1,\ldots, t_1-1\}$, $C_1 = \{t_1, t_1+2, \ldots, t_2-1\}$,…, $C_M = \{t_M, t_M+2, \ldots, L-1\}$. For multilevel thresholding, the formula based on the entropic method is computed as follows:

$$f(t_1,t_2,\cdots,t_M) = E_0 + E_1 + E_2 + \cdots E_M$$

$$\omega_0 = \sum_{i=0}^{t_1-1} p_i, E_0 = -\sum_{i=0}^{t_1-1} \frac{p_i}{\omega_0} \ln \frac{p_i}{\omega_0}$$

$$\omega_1 = \sum_{i=t_1}^{t_2-1} p_i, E_1 = -\sum_{i=t_1}^{t_2-1} \frac{p_i}{\omega_1} \ln \frac{p_i}{\omega_1}$$

$$\omega_2 = \sum_{i=t_2}^{t_3-1} p_i, E_2 = -\sum_{i=t_2}^{t_3-1} \frac{p_i}{\omega_2} \ln \frac{p_i}{\omega_2} \tag{4}$$

$$\vdots$$

$$\omega_M = \sum_{i=t_M}^{L-1} p_i, E_M = -\sum_{i=t_M}^{L-1} \frac{p_i}{\omega_M} \ln \frac{p_i}{\omega_M}$$

In the proposed CHBMA algorithm, we try to obtain these optimum thresholds: $\{t_1, t_2, \ldots, t_M\}$ by maximizing Eq. (4). The objective function is also used to act as the fitness function for CHBMA.

C. Cooperative Learning

The cooperative idea was presented by Potter [16] to apply to GAs successfully, and then van Den Bergh [11] applied Potter's technique to the PSO. The same concept can easily be applied to HBMA to create a cooperative HBMA. First, we introduce the weakness of the HBMA, which also exists in PSO and GA. Then, we present the solution.

Each brood in HBMA represents a potential solution. Each update step is performed on a full c-dimensional particle. This leads to the possibility of some components in the brood having been moved closer to the solution, while others have actually been moved away from the solution. As long as the effect of the improvement outperforms the effect of the components that deteriorated, the HBMA will consider the updated brood as overall improvement but neglect the deteriorated components in the brood. Therefore, it is clear that it is typically significantly harder to find the global optimum of a high-dimensional problem. Hence, we present a new HBMA algorithm with the cooperative learning method for solving this problem.

A simple example that can demonstrate the importance of the cooperative method is given as follows. Consider a three-dimensional vector $\mathbf{X}=[x_1, x_2, x_3]$, and the objective function $f(\mathbf{X}) = (x_1-a_1)^2+(x_2-a_2)^2+(x_3-a_3)^2$, where $\mathbf{A}=(a_1, a_2, a_3)= (10, 20, 30)$. This implies that its global minimum value is 0, where $\mathbf{X}=\mathbf{A}=(10, 20, 30)$. Now, consider a honey bee colony containing two broods X_1 and X_2, and the Queen is (5, 12, 20) at the current time step t. We have:

$$\text{Queen}(t) =(5, 12, 20), f(\text{Queen}(t))=189;$$
$$X_1(t) =(8, 20,42), f(X_1(t))=148;$$
$$X_2(t) =(6, 25, 36), f(X_2(t))=77;$$

This implies that $f(X_1(t))$ and $f(X_2(t))$ are even better than the function value of the Queen. If we use HBMA without the cooperative method, Queen(t) will be directly updated with $X_2(t)$ and $X_1(t)$ will be discarded. However, that the second component of $X_1(t)$ has the correct value of 20; it does not make any contribution to the Queen. The cooperative learning method can help the Queen to get the appropriate component by evaluating each component of the broods which are better than the Queen. Figure 2 presents the Pseudo code for cooperative learning method. By applying this method, the Queen is updated as (8, 20, 20) firstly with the help of $X_1(t)$, then updated as (8, 20, 36) with the help of $X_2(t)$. Therefore, in the next time step t+1, the Queen gets more a precise result than HBMA without the cooperative method.

```
% C is the threshold number
% QueenOld is the Queen at the last generation
% fitnessHB() is the fitness function
For ibfit=1:numberBroods % numberBroods is the number of Broods
    If fitnessHB(Broods(ibfit))>queenfitness
        Queen=Broods(ibfit);
        queenfitness=fitnessHB(Broods(ibfit));
        For icoop=1:C           %cooperation Begin
            Queen(icoop)=QueenOld(icoop);
            If fitnessHB(Queen(icoop))>queenfitness
                queenfitness=fitnessHB(Queen(icoop));
            Else
                Queen(icoop)=Broods(ibfit,icoop);
            End If
        End For                 %cooperation End
    End If
End For
```

Fig. 2. The Pseudo code for cooperative learning method

By applying the cooperative method into the thresholding segmentation field, each brood in CHBMA contributes to the population not only as a whole item, but also in each dimension. Therefore, it is not limited to the dimension of optimal thresholds and is particularly suitable for multilevel thresholding. Another benefit from using the cooperative method is that each brood in CHBMA can potentially make a contribution to the optimal thresholds in each dimension; this ensures that the search space is searched more thoroughly and that the algorithm's chances of finding better results is improved.

III. THE PROPOSED ALGORITHM

In this subsection, a cooperative honey bee mating algorithm for image segmentation using multilevel thresholding is developed according to HBMA and its flowchart is given in Figure 3. The specific features of CHBMA are as follows.

In section A of this part, we give the reason that we increase a new bee colony in each generation. In section B, we present the bee colony initialisation strategy of CHBMA. In section C, we illustrate the implementation method of flight mating. In section D, we demonstrate the breeding process. In section E, we present the parameters used in the proposed algorithm.

A. The Introduction of New Species

In the real world, in order to avoid higher levels of inbreeding, the queen would sometimes leave its own colony to mate with the drones from another bee colony. Hence, we imitated this natural phenomenon in our proposed algorithm to keep from generating too many eccentric and homogeneous broods which were one of the important factors causing premature convergence and slow convergence. Our method is that we reduce the initial population size and increase a new bee colony in each generation, the population size of the new bee colony is the same as the initial population size.

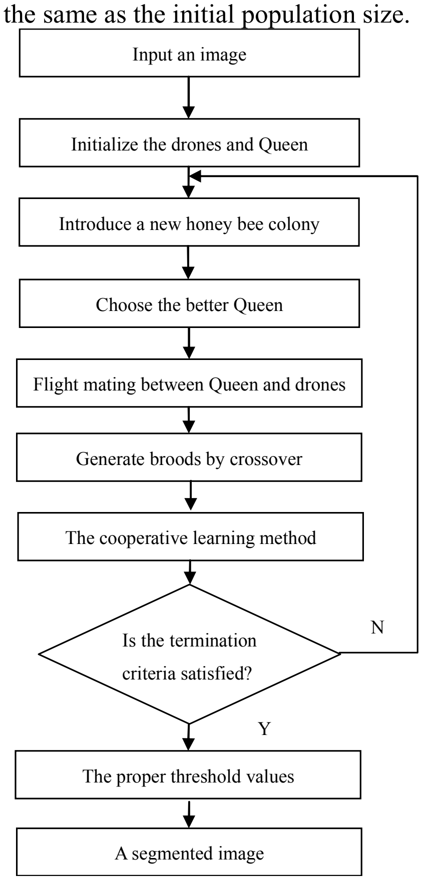

Fig. 3. The flowchart of CHBMA

B. Initialize

The positions of the drones are randomly initialized from the search space. In CHBMA, the dimensionality *D* of a drone is the number of thresholds. Combining with the characters of multilevel thresholding arranged from a low gray level to a high one, the position of an arbitrary drone *i* in d^{th} dimension, i.e. X_{id}, is initialized by uniformly distributed in the interval $[(d\text{-}1)\times\text{floor}(L/D),\ d\times\text{floor}(L/D)]$. This can increase the diversity of the population and improve global searching ability. Among all drones, the drone with the maximum fitness is selected as the queen *Q*.

C. Flight Mating Between the Drones and Q

In this Stage, we select the set of better drones to mate with the queen *Q* by using the simulated annealing method. The best drone D_i in the drone set *D* is first selected as the object of mating with *Q*. After the flight mating, the queen's speed and energy will be decayed according to Eq. (2). The flight mating continues until the number of sperms in the queen's spermatheca is more than the threshold N_{sp}. The value of N_{sp} is generally preset by user and less than the number of the drones. An sperm can be described by $SP_i=(X_i^1, X_i^2, \ldots, X_i^3)$, where SP_i is the i^{th} individual in the queen's spermatheca.

D. Generate Broods by Breeding Operator

Broods will be generated in this stage based on flight mating between the queen and the drones stored in the queen's spermatheca. In the breeding process, the j^{th} individual of the spermatheca is selected to breed if its corresponding random number is less than a user-defined breeding ratio P_c. The breeding process transfers the genes of drones and the queen to the j^{th} individual based on the Eq. (5).

$$Brood_j=Q\pm rand(1)\times \text{abs}(SP_j - Q) \qquad (5)$$

The parameter *rand*(1) is in the interval [0,1] randomly generated with uniform distribution during each generation.

The + and - sign occurs with equal probability. If we only use + sign or – sign in Eq. (5), the values of genes of broods will always keep increasing or decreasing.

E. The Parameters Used in CHBMA

Through a lot of experiments, the parameters used in the proposed algorithm are shown in Table 1.

TABLE I THE PARAMETERS USED IN CHBMA

Parameter	Description	Value
Q	The number of queens	2
NumberOfDrones	The number of drones	50
M	The number of threshold value	3,4,5,6
L	The grayscale of image	0~255
α	The decreasing factor	0.98
N_{sp}	The capacity of spermatheca	20
$S(0)$	The initial speed of mating flight	1.0
P_c	The breeding ratio	0.8
Gen	The generation numbers	80

IV. EXPERIMENTAL ANALYSIS

We present a set of experiments that shows goodness of our algorithm. We have done our experiments under a personal computer with 2.40 GHz CPU, 2 GB RAM with window 7 system and we have coded with MATLAB 7.2 software.

The performance of CHBMA is evaluated by comparing its results with some other algorithms developed in the literature so far: the quantum-behaved PSO employing the cooperative method (CQPSO) [9]; the hybrid cooperative-comprehensive learning PSO algorithm (HCPSO) [17]; the maximum entropy-based honey bee mating optimization thresholding (HBMA) method [7]. We have implemented them on a wide variety of images provided by the Berkeley segmentation data set (www.eecs.berkeley.edu). Figure 4 presents these six original images. The parameters of CHBMA are in Section 4 and the parameters of other algorithms are set as described in their own papers, except that the generation number is set to 100.

In our experiments, when two thresholds satisfy that the absolute value of their difference is less than 6, we will unify them. So, the threshold number obtained through the experiments may be less than the initial threshold number in the algorithms.

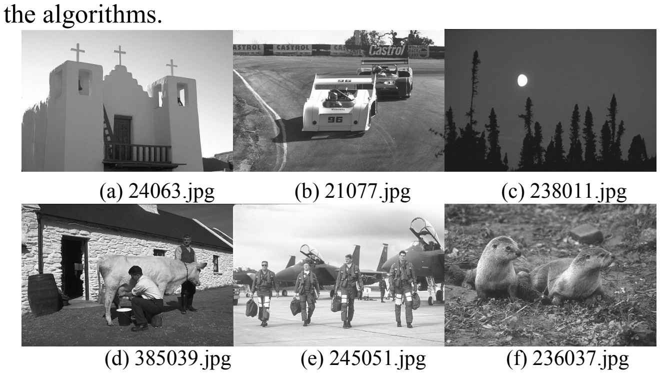

Fig. 4. The six original images

A. *The Comparison of Segmentation Results, with M=4*

For a visual interpretation of the segmentation results, we present the segmented images with M=4 in Figure 5. It can be easily seen that the quality of segmentation of CHBMA is better in general, especially the images of a1, b1, c1, d1 and e1. When we enlarged the segmented images and enhanced image information in Figure 5, the following observations could be made: (1) our method yielded the clearer result of images (a), (b) and (c) with only 3 or 4 thresholds than those of the other methods; (2) our segmented result of image (d) was absolutely clear, except that some part of the horse' body was too white. In most cases, the CHBMA segmentation results are better than those of HBMA. For example, there is often only the moon but no trees in the HBMA results of image (c); (3) The CQPSO method obtained even worse results than the other methods, and sometimes the CQPSO results was too vague, especially the images (d) and (f); and (4) the HCPSO results were also pretty good; however, it is time-consuming due to its the complicated process.

B. *The Comparison of Threshold Values, PSNR, Computation Time*

The quality of segmented images can be evaluated through the peak signal to noise ratio ($PSNR$), which is used to compare the segmentation results by using the multilevel image threshold techniques [7, 18, 19] as follows.

$$PSNR = 20 \times \log_{10}(255/RMSE) \qquad (6)$$

, where $RMSE$ is the root mean-squared error defined as:

$$RMSE = \sqrt{\sum_{i=1}^{m} \sum_{j=1}^{n} (I(i,j) - I'(i,j)) \Big/ (m \times n)} \qquad (7)$$

, where I and I' are the original and segmented images of size $m \times n$; respectively. A larger value of $PSNR$ means the quality of the segmented image is better. Furthermore, as the threshold number increases, the $PSNR$ tends to be larger. The results from the four methods over the testing images are summarized in Table II. From the table, we can make the following observations. HCPSO was the slowest of the four methods. CHBMA was faster than other algorithms and its computation time was insensitive to the number of thresholds. The $PSNR$ of images (a), (b), (c), (d) and (e) (M=4, as shown in Figure 5) were the largest among the four methods. Generally, the $PSNR$ values obtained by CHBMA were the best or were close to the best in different threshold number. Moreover, CHBMA could obtain a clearer and more complete segmentation image for video image compression.

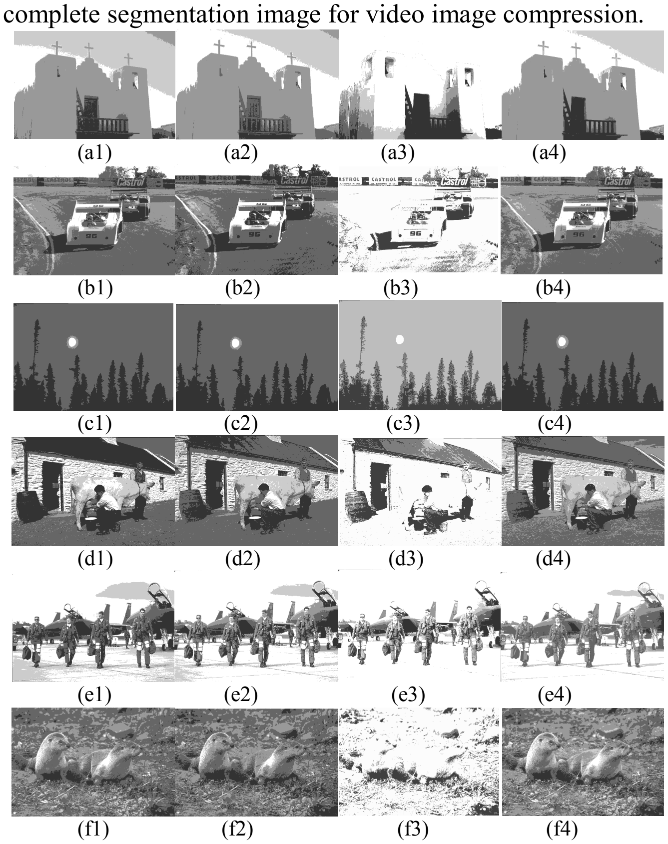

Fig. 5. The comparison of segmentation results: (a1)-(f1) the segmentation results of our method CHBMA, (a2-f2) the segmentation results of HBMA, (a3-f3) the segmentation results of CQPSO, and (a4-f4) the segmentation results of HCPSO.

C. The Stability of Our Proposed Methods, with M=3, 4, 5, 6

Because the four population-based methods in this paper are stochastic and random searching algorithms, the results of experiments are not absolutely the same in each run, which is influenced by the initial population. We analyze the stability by calculating the standard deviation (*STD*) of the queen fitness recorded in each independent run. In the same situation, the bigger value of *STD* proves that the result of experiment is unstable. The standard deviation values for 100 runs of CHBMA and HBMA (with *M*=3, 4, 5, 6) are presented in Table III. From the results, we can see that CHBMA is more stable than the HBMA algorithms on each image. One reason is that a new bee colony is introduced in each generation to avoid premature convergence and slow convergence. The other is that the cooperative method helps CHBMA search in the feasible solution space more thoroughly. Therefore, CHBMA has a more powerful global searching ability, which ensures that it gets more stable results in limited time.

TABLE II THE COMPARISON OF THRESHOLD VALUES, UNIFORMITY, COMPUTATION TIME

TABLE II (A) *M*=4

	Method	*M*	Threshold values	PSNR	CPU(s)
24063.jpg	CHBMA	4	0-52-97-171-228-255	**20.601**	**1.2962**
	HBMA	4	0-42-95-165-207-255	18.869	1.6593
	CQPSO	4	0-99-108-115-123-255	10.602	1.3962
	HCPSO	4	0-61-94-146-199-255	18.706	2.4356
21077.jpg	CHBMA	4	0-62-125-178-234-255	**25.022**	1.4498
	HBMA	4	0-81-138-169-210-255	24.561	1.5901
	CQPSO	4	0-61-83-89-255	7.293	**1.3881**
	HCPSO	4	0-62-117-173-218-255	23.973	2.0944
238011.jpg	CHBMA	4	0-59-93-136-229-255	**20.617**	**1.2297**
	HBMA	4	0-49-94-138-236-255	20.381	1.4722
	CQPSO	4	0-27-58-137-255	8.124	1.3702
	HCPSO	4	0 -55- 92-128-234-255	20.512	2.2889
385039.jpg	CHBMA	4	0-62-103-148-200-255	**20.152**	**1.0489**
	HBMA	4	0-48-119-162-214-255	19.573	1.6467
	CQPSO	4	0-45-52-61-255	6.620	1.3751
	HCPSO	4	0-43-88-164-217-255	17.282	2.1748
245051.jpg	CHBMA	4	0-91-146-179-217-255	**22.016**	**1.3455**
	HBMA	4	0-85-114-173-206-255	20.690	1.5447
	CQPSO	4	0-79-98-120-142-255	15.951	1.3888
	HCPSO	4	0-61-107-156-195-255	19.100	2.0171
236037.jpg	CHBMA	4	0-61-119-167-207-255	22.805	**1.0805**
	HBMA	4	0-69-120-186-217-255	**24.052**	1.5828
	CQPSO	4	0-63-73-84-255	6.650	1.3974
	HCPSO	4	0-62-106-155-200-255	20.172	2.4873

TABLE II (B) *M*=5

	Method	*M*	Threshold values	PSNR	CPU (s)
24063.jpg	CHBMA	5	0-41-93-143-176-218-255	24.042	**1.1235**
	HBMA	5	0-70-117-154-200-225-255	**25.020**	1.6998
	CQPSO	5	0-99-109-118-124-255	10.831	1.7656
	HCPSO	5	0-39-97-146-177-217-255	23.941	2.4032
21077.jpg	CHBMA	5	0-49-100-144-180-229-255	**25.580**	**1.0675**
	HBMA	5	0-82-138-183-217-241-255	19.816	1.6389
	CQPSO	5	0-55-77-86-93-255	7.380	1.7829
	HCPSO	5	0-50-79-135-180-223-255	21.564	2.1048
238011.jpg	CHBMA	5	0-50-95-118-165-223-255	**28.060**	**1.0496**
	HBMA	5	0-45-92-112-161-216-255	27.606	1.4965
	CQPSO	5	0-27-38-112-163-255	11.225	1.7734
	HCPSO	5	0-48-97-135-201-244-255	27.944	2.1375
385039.jpg	CHBMA	5	0-42-97-139-177-218-255	**22.284**	**1.1339**
	HBMA	5	0-35-69-114-180-206-255	17.621	1.8418
	CQPSO	5	0-27-56-126-190-255	12.687	1.7571
	HCPSO	5	0-26-69-106-158-202-255	16.739	2.2914
245051.jpg	CHBMA	5	0-50-95-140-187-222-255	**24.875**	**1.1389**
	HBMA	5	0-92-117-152-211-230-255	22.167	1.5759
	CQPSO	5	0-75-88-105-120-139-255	15.942	1.7544
	HCPSO	5	0-113-139-159-197-234-255	20.081	2.1618
236037.jpg	CHBMA	5	0-50-88-134-175-221-255	**22.595**	**1.1321**
	HBMA	5	0-67-128-154-199-226-255	22.341	1.6504
	CQPSO	5	0-62-72-78-85-247-255	9.987	1.7534
	HCPSO	5	0-49-90-128-167-211-255	21.782	2.3152

D. The Ability to Conquer "The Curse of Dimensionality", with M= 5, 9, 12, 16

For verifying the searching ability of our proposed method on a high dimension, we also test it on each image, with *M*=5, 9, 12, 16. Table IV shows the mean computation time (seconds) for 100 runs. The other parameters of CHBMA are in section E of Section III, which can make our method achieve a good segmentation effect. Therefore, we can say that CHBMA is effective and efficient, and it has a powerful ability to conquer "the curse of dimensionality".

V. CONCLUSION

In this paper, we have described a cooperative honey bee mating algorithm for image segmentation based on the cooperative learning method and HBMA, which has a powerful ability to conquer "the curse of dimensionality". Furthermore, except for being evaluated by the benchmark images shown in this paper, the proposed method is also tested on a wide variety of images provided by the Berkeley segmentation data set. The results prove that the proposed method could generally produce better results than several well known methods. The future work is on how to integrate other popular image segmentation methods to improve the segmentation results and then apply it to medical image segmentation and complex image processing.

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TABLE III THE STABILITY OF CHBMA WITH *M*=3, 4, 5, 6 (*STD*)

M		**24063.jpg**	**21077.jpg**	**238011.jpg**	**385039.jpg**	**245051.jpg**	**236037.jpg**
3	CHBMA	**0.0158**	**0.0084**	**0.0234**	**0.0042**	**0.0187**	**0.0087**
	HBMA	0.0550	0.0288	0.0664	0.0198	0.0467	0.0257
4	CHBMA	**0.0359**	**0.0346**	**0.0363**	**0.0095**	**0.0416**	**0.0202**
	HBMA	0.1039	0.0711	0.1195	0.0582	0.0670	0.0627
5	CHBMA	**0.0351**	**0.0247**	**0.0536**	**0.0250**	**0.0387**	**0.0381**
	HBMA	0.1324	0.1240	0.1379	0.0873	0.1171	0.0978
6	CHBMA	**0.0474**	**0.0424**	**0.0828**	**0.0271**	**0.0727**	**0.0260**
	HBMA	0.1613	0.1765	0.2033	0.1118	0.1712	0.1419

TABLE IV THE COMPUTATION TIME WITH *M*=5, 9, 12, 16

M	**24063.jpg**	**21077.jpg**	**238011.jpg**	**385039.jpg**	**245051.jpg**	**236037.jpg**
6	1.1385	1.0760	0.9945	1.0960	1.0381	1.0770
9	1.1623	1.1416	1.0683	1.1779	1.1156	1.1453
12	1.2612	1.2214	1.1582	1.2451	1.1855	1.2203
16	1.3344	1.3261	1.2388	1.3445	1.2979	1.3174

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