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Discrete honey bees mating optimization (DHBMO) for solving environmental optimization problem using single and multi-objectives optimization

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Abstract. One of the recently proposed algorithms in the field of nature-inspired algorithm is the Honey Bees Mating Optimization (HBMO) algorithm by Haddad and Afshar. The HBMO algorithm simulates the marriage behaviour of bees. The solutions are incrementally constructed by the HBMO algorithm. Therefore, the HBMO algorithm is a swarm-based constructive optimization algorithm. However, no study has reported the modification of HBMO for feature selection. Therefore, we try to develop a discrete honey bees mating optimization (DHBMO) as the modification of HBMO for solving discrete optimization problem especially feature selection to improve the performance of machine vision for predicting water stress in plants. We test the algorithm to solve feature selection problem using single and multi-objectives optimization to optimize water usage in plants for environmental sustainability. The results showed DHBMO has better performance compared to the existed nature-inspired optimization algorithms such as genetic algorithms (GA), simulated annealing (SA) and discrete-particle swarm optimization (discrete-PSO).

1. Introduction

Natural systems have been one of the rich sources of inspiration for developing new intelligent systems [1, 2]. In this study, a novel artificial intelligence approaches using nature-inspired algorithm for optimization is proposed. Haddad and Afshar [3] has developed nature-inspired optimization algorithms honey bees mating optimization (HBMMO) that is inspired by a swarming relation in society model assuming a polygynous colony as shown in Figure 1. Each bee performs sequences of actions which accord to genetic, environmental, and social regulation. The result of each action influences the subsequent actions of both a single bee and many drones. The marriage process represents one type of action to construct the optimization algorithm. Genetic algorithm (GA) is search algorithms based on the mechanics of natural selection and natural genetics [4]. Discrete-particle swarm optimization (discrete-PSO) is an evolutionary computation technique inspired in the behaviour of bird flocks which was first introduced by Kennedy and Eberhart [5-9]. Simulated annealing (SA) takes inspiration from the process of shaping hot metals into stable forms through a gradual cooling process whereby the material transits from a disordered, unstable, high-energy state to an order, stable,



low-energy state [10; 11]. The objective of this study was developing discrete honey bees mating optimization (DHBMO) as nature-inspired algorithm for solving single and multi-objective feature selection optimization. The DHBMO is compared with the forefront nature-inspired algorithms i.e. GA, SA and discrete-PSO.

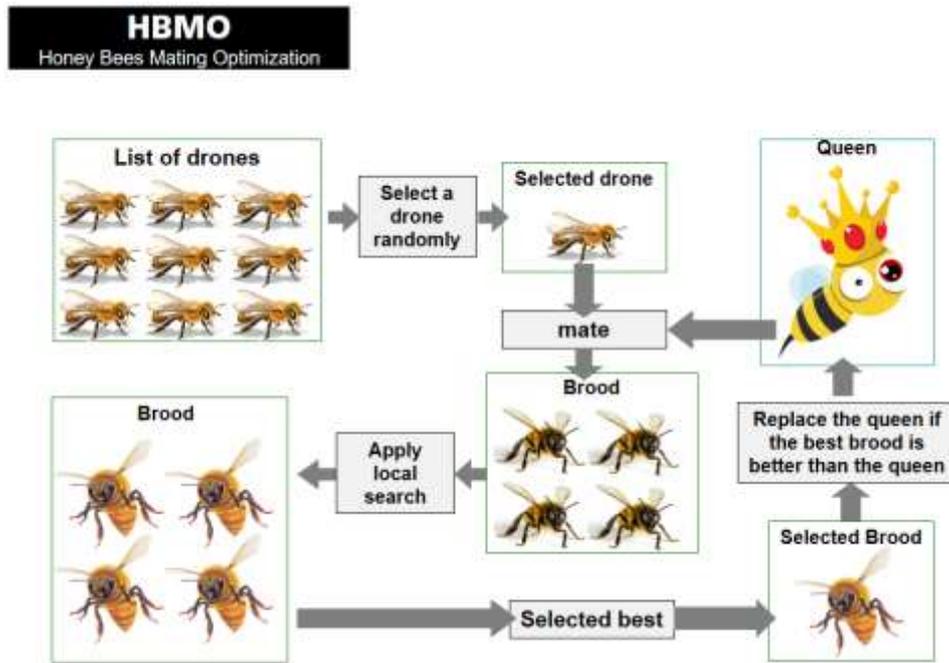


Figure 1. Procedure of honey bees mating optimization (HBMO).

2. Research Methods

The DHBMO algorithm is a swarm intelligence algorithm since it uses a swarm of bees where there are three kinds of bees, the queen, the drones and workers. First, the queen is flying randomly in the air and, based on her speed and her energy, if she meets a drone then there is a possibility to mate with him. Even if the queen mates with the drone, she does not create directly a brood but stores the genotype of the drone in her spermatheca and the brood is created only when the mating flights has been completed. In a hive the role of the workers is simply the brood care. If a brood is better than the queen, then this brood replaces the queen.

The main steps of proposed DHBMO for feature selection are as follows:

1. Initialisation of DHBMO parameters. The maximum iteration is 500. The number of bee's population is 70, the capacity of spermatheca is 50 and the number of *worker* is 40. The initial *speed* and *energy* of the queen are 0.9 and 1, respectively based on the results of preliminary runs.
2. Generate the initial value of worker randomly [0, 1].
3. Generate the initial population of bees randomly (e.g. $bee_i: 0, 1, 1, 0, 0, 0, 0, 1, 0, 0, 1, 0, \dots, f_i$).
4. Evaluate the fitness of bee_i based on the objective function.
5. Compute the individual solution $F(bee_i)$.
6. Based on the individual solution $F(bee_i)$, only in the first iteration, the best member of the initial population of bees is selected as the queen of the hive. The number of queen is one. All, the other members of the population are the drones.
7. Selection of $drone_i$. A drone mates with a queen using annealing function:

$$Prob(D) = e^{\left[\frac{-1 \times |F(bee_i) - F(queen)|}{speed(t)} \right]} \quad (1)$$

Where $Prob(D)$ is the probability of adding the sperm of drone D to the spermatheca of the queen, $|F(bee_i)-F(queen)|$ is the absolute difference between the fitness of D and the fitness of the queen and $speed(t)$ is the speed of the queen at time t .

8. Add sperm of the drone in queen's spermatheca.
9. Update $speed$ and $energy$ of the queen.

$$speed(t+1) = \alpha \times speed(t) \quad (2)$$

$$energy(t+1) = \alpha \times energy(t) \quad (3)$$

Where α is a factor $[0, 1]$ that determines the amount that the speed and the energy will be reduced after each transition and each step.

10. Selection of the worker. $worker$ is randomly selected from the list. Random number: $rnd[0, 1]$ is generated to determine the probability of worker to do crossover function (between the queen genotype and the selected sperm) or mutation function (selected sperm) to the brood. Broods are generated from the cross-over and mutation process.
11. Evaluate the fitness of $brood_i$ based on the objective function.
12. Compute the individual solution $F(brood_i)$.
13. Replace the queen and update the fitness of the queen if the solution of the brood is better than the solution of the current queen.

$$F(queen) \begin{cases} F(brood) & \text{if } q(F_{(brood)}) > q(F_{(queen)}) \\ F(queen) & \text{otherwise} \end{cases} \quad (4)$$

Where function $q(.)$ gives the quality of the solution.

14. Update the total best solution T^{TB} :

$$T^{TB} \begin{cases} T^{TB} & \text{if } q(T^{TB}) \geq q(T^{IB}) \\ T^{IB} & \text{otherwise} \end{cases} \quad (5)$$

15. The search will terminate if the maximum iteration has been reached.

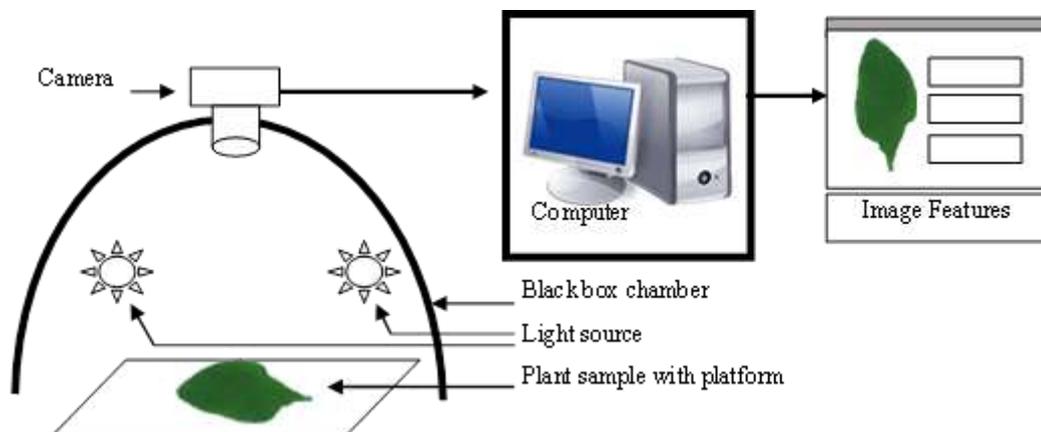


Figure 2. Procedure of image acquisition and image features extraction.

Testing is done for optimizing feature selection in machine vision for predicting water stress in plant. Testing procedures includes: first process is image acquisition in a dark chamber as shown in Fig. 2, in which the plant images were captured using digital camera (Nikon Coolpix SQ, Japan) placed at 330 mm perpendicular to the sample surface. The image size was 1024 x 768 pixels. Imaging was done under controlled and well distributed light conditions. Light was provided by two 22W lamps (EFD25N/22, National Corporation, Japan). Light intensity over the moss surface was uniform at $100 \mu\text{mol m}^{-2} \text{s}^{-1}$ PPF (Photometer, Li6400, USA) during image acquisition. For single objective optimization we use total 768 features consist of RGB color space. For multi-objective optimization we use total 212 features consist of color features and textural features from many kind of colour spaces e.g. RGB, Lab, Luv, HIS, HSL, etc. For modelling the relationship between image features and water stress in plant, we use artificial neural network (ANN) with back-propagation neural network (BPNN) learning method. The performance of prediction accuracy is measured with root mean square error (RMSE).

Selection process for selecting relevant image features is done using four alternative nature-inspired approaches *i.e.* DHBMO, GA, discrete-PSO, and SA. Multi objective optimization concerns optimization problems with multiple objectives. The fitness is calculated as follows:

$$function_1 = weight_1 \times RMSE_{(x)} \quad (6)$$

$$function_2 = weight_2 \times \frac{IF_{(x)}}{f_t} \quad (7)$$

$$fitness(x) = function_1 + function_2 \quad (8)$$

Where $RMSE_{(x)}$ is the Root Mean Square Error of validation-set data of BPNN using only the expression values of the selected image features in a subset x , where $IF_{(x)}$ is the number of selected image features in x . f_t is the total number of image features, $weight_1$ and $weight_2$ are two priority weights corresponding to the importance of the accuracy and the number of selected image features, respectively, where $weight_1 \in [0.1, 0.9]$ and $weight_2 = 1 - weight_1$. In this study, the accuracy is more important than the number of selected image features in a feature-subset.

3. Results and Discussion

Figure 3 shows the performance of four bio-inspired intelligent feature selection to improve the performance of machine vision to monitor water stress in plant using single objective function. It shows the superiority of DHBMO, since it achieved better average testing-set RMSE compared with other methods (GA, discrete-PSO and SA). From Figure 3a, we can see that DHBMO has the least average testing-set RMSE followed by GA, discrete-PSO and SA in that order with the average testing-set RMSE of 2.59×10^{-2} , 2.61×10^{-2} , 2.64×10^{-2} , 2.69×10^{-2} , respectively. All feature selection methods indicated small absolute deviations in selecting features and predicting water stress of plant for five trials. Significant levels are less than 0.01, there is a significant difference between the groups with a confidence level of 99%. Figure 3b shows the average number of feature-subset obtained from feature selection models. The result shows that DHBMO was also capable to select smaller quantity of feature-subset, followed GA, SA and discrete-PSO in that order. DHBMO also indicated the highest consistency in the number of feature-subset. One-way ANOVA results explains the significant levels are less than 0.01, there is a significant difference between the groups with a confidence level of 99%. However, based on the original purpose of this study to find the best feature-subset for minimizing the prediction error, we conclude that DHBMO has the best performance for selecting relevant features for optimizing machine vision.

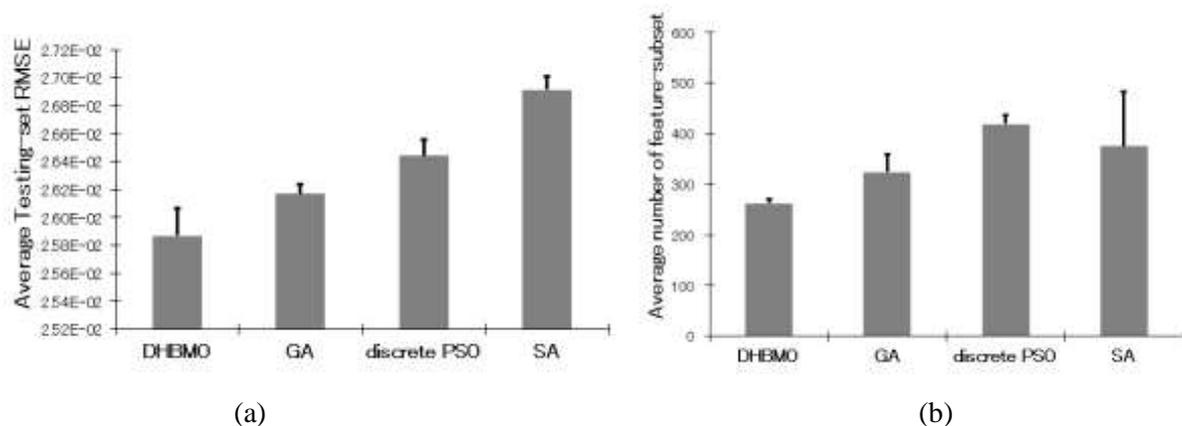


Figure 3. Performance of feature selection algorithms for single objective optimization based on: (a) average testing-set RMSE of BPNN; (b) average feature-subset.

The best fitness plots of the iteration of each feature selection methods are displayed in Fig. 4 to highlight the search process in each feature selection method. The best DHBMO's fitness function converged with the lowest validation-set RMSE of 2.56×10^{-2} when using 266 features. The best GA's fitness function converged with the lowest validation-set RMSE of 2.61×10^{-2} when using 320 features. The best discrete-PSO's fitness function converged with the lowest validation-set RMSE of 2.63×10^{-2} when using 346 features. The best SA's fitness function converged with the lowest validation-set RMSE of 2.68×10^{-2} when using 371 features. From Figure 4, we can see that the validation-set RMSE changed and it is getting better through all the iterations. It indicates that the performances of DHBMO, GA, discrete-PSO and SA are effective. In all of the iterations, the validation-set RMSE of all feature selection methods changed most in the first few iterations.

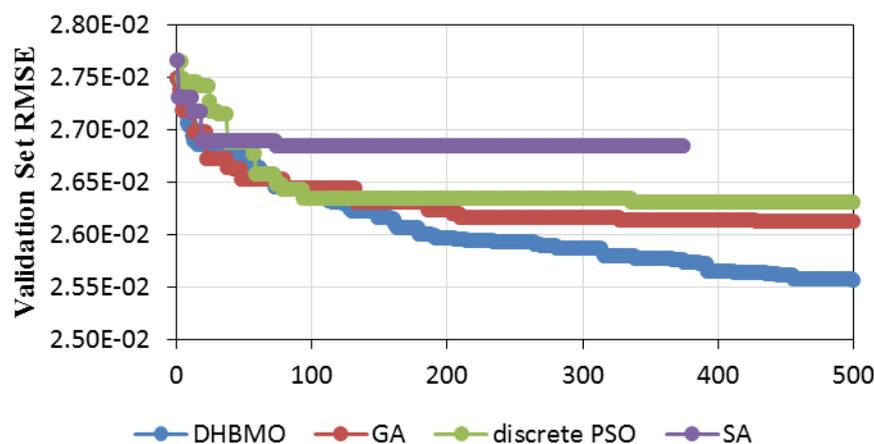


Figure 4. Plot of best fitness values using: (a) GA; (b) discrete-PSO; (c) DHBMO; (d) N-SA.

DHBMO has also been tested using multi-objectives optimization problem to predict water stress in plant using machine vision [9]. The plots of best fitness values of multi-objectives optimization using all optimization methods are displayed in Figure 5 to highlight the search process in each optimization method. At the beginning of the iteration, all optimization methods (DHBMO, GA, SA, and discrete-PSO) were given the same optimization problem, which is defined as the initial condition. The fitness value obtained from the initial condition and then normalized by the value of 1.00. During the multi-objectives optimization process, the fitness value continues to decrease, searching for the most

minimum fitness value. Using the same *weight* parameter ($weight_1 = 0.9$ and $weight_2 = 0.1$), it shows that DHBMO has the best performance to minimize the fitness value (normalized fitness value = 0.66), followed by GA (normalized fitness value = 0.67), SA (normalized fitness value = 0.81) and discrete-PSO (normalized fitness value = 0.84) in that order, respectively. Most of all optimization methods can quickly minimize the fitness value at the beginning of 50 iterations, but based on the comparison analysis on the performance of all optimization methods, it shows the superiority of DHBMO to minimize the fitness value in early iterations, followed by GA, SA, and discrete-PSO, respectively. From the results, we can see that, DHBMO is quicker in locating the optimal solution. DHBMO has the ability to converge quickly. It has strong search capability in the problem space and can efficiently find optimum solution for multi-objectives optimization.

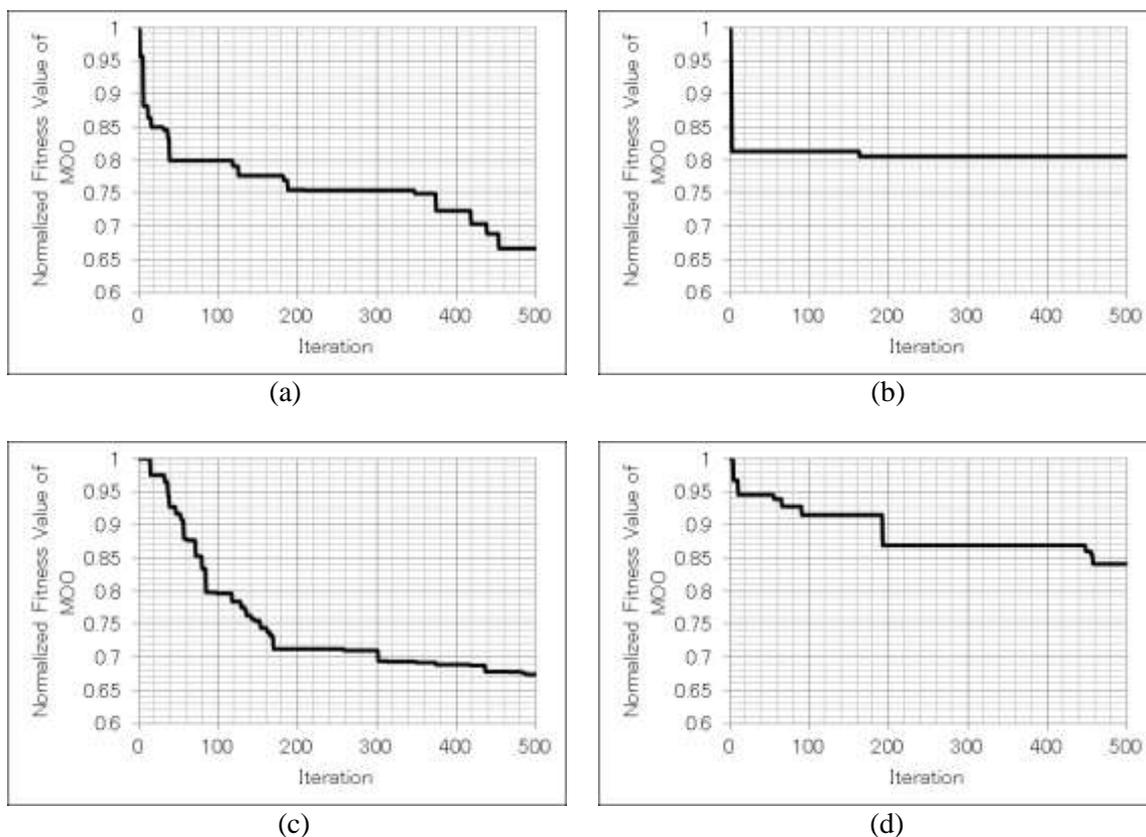


Figure 5. Performance of multi objectives discrete-optimization (a) DHBMO; (b) SA; (c) GA; (d) discrete-PSO.

4. Conclusion

Comparative analysis showed the superiority of Discrete-Honey Bees Mating Optimization (DHBMO) compared with other feature selection methods such as Genetic Algorithm (GA), Discrete Particle Swarm Optimization (discrete-PSO) and Simulated Annealing (SA) in solving single objective optimization, since they achieved better prediction performance. The average testing-set Root Mean Square Error (RMSE) of DHBMO was 2.61×10^{-2} . The best DHBMO's fitness function converged with the lowest validation-set RMSE of 2.56×10^{-2} . Based on the optimization performance, DHBMO has the best performance for optimizing the fitness function of multi-objective optimization problem, followed by GA, SA, and discrete-PSO in that order, respectively. With this optimization method, the

system can detect water stress in plants, so that it can optimize water usage in plants for environmental sustainability.

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