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LOCAL SEARCH MANOEUVRES RECRUITMENT IN THE BEES ALGORITHM

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ABSTRACT. Swarm intelligence of honey bees had motivated many bio-inspired based optimisation techniques. The Bees Algorithm (BA) was created specifically by mimicking the foraging behavior of foraging bees in searching for food sources. During the searching, the original BA ignores the possibilities of the recruits being lost during the flying. The BA algorithm can become closer to the nature foraging behavior of bees by taking account of this phenomenon. This paper proposes an enhanced BA which adds a neighbourhood search parameter which we called as the Local Search Manoeuvres (LSM) recruitment factor. The parameter controls the possibilities of a bee extends its neighbourhood searching area in certain direction. The aim of LSM recruitment is to decrease the number of searching iteration in solving optimization problems that have high dimensions. The experiment results on several benchmark functions show that the BA with LSM performs better compared to the one with basic recruitment.

Keywords: Bees algorithm, local search manoeuvres, recruitment strategy, neighbourhood search, benchmark test function

INTRODUCTION

Pham, Ghabarzadeh, et al. (2006) created The Bee Algorithm mimicking the foraging behaviour of honey bees when they are searching for foods around the bee hives. The Bees Algorithm had been used to test the benchmark function optimisation as their first experiment. In the first version of the algorithm, the authors did not mention about the possibility recruits lost during locating the food advertised food source. This paper studies the behaviour of honey bees when she tries to locate the food source after being recruited. The next step is to enhanced The Bees Algorithm basic version mimicking the lost bees. After that, the performance of the proposed enhancement to the optimisation of test function (Pham, Ghanbarzadeh et al. 2009) is proposed and investigating the behaviour of recruits when she try to locate the food source. The study is important for one reason, to examine the recruit's effort locate the food source.

Another interesting behaviour of recruits is when they cannot find the food source as advertised by dancer's bees; she will decide to continue searching or get more information in the hive. During the flight return, recruits sometimes did use the different flight path. This factor motivates the study to investigate the reason of different flight path. Another new motivation factor can be incorporated in optimisation process is recruits will take some times when they failed to locate the food source. Sometimes the duration is up to 20 minutes. Recruits will fly beyond the feeding station if they can't found the food source before return back to the hive. This means they will try harder to locate the food source. The recruit's behaviour will be integrated in an existing Bees Algorithm and try to find another alternative and an option to optimise high dimension problem.

A few experiment benchmark test function are undertaken in this study that is based on (Pham, Ghanbarzadeh et al. 2006). The main contributions of the paper is Enhanced the Bees Algorithm inspired by recruits effort to locate the food source after joined the waggle dance.

The paper is organised as follow; Section 2 explain the behaviour of honey bees during locating the food sources and followed by Section 3, which describe the test for LSM recruitment in the BA to the benchmark test function. Section 4 presents the result and finally section 5 concludes all the sections of the study.

LSM RECRUITMENT

Learning Process of the Bees in the Nature

The study will begin by explaining on how the new idea mutates the natural behaviour of recruits. Seeley (1983) has done an experiment to check the bees behaviour including recruits searching time, recruits cannot find the food source, recruits search beyond the feeding station and recruits return with a different flight path.

Seeley (1983) also discover that food source found by recruits is more profitable and it's worth to return back to that food source compare found by scouts. Most of the recruits did not find food source at their first attempt. Normally they need to be guided by several dances before successfully reach the food source. Recruits also forage for a new food source firstly, but when they know it was failed, they may decide make a return flight to the hive.

Esch and Bastian (1970) had observed 70 honey bees during an experiment. Among these bees, 34 (recruits) were follow the waggle dance and only 14 (recruits) arrived at the food source and left 20 other bees (recruits) did not arrive at the food source. The food source distance between bee hive is a 200-250 meters.

There are two factors of recruit behaviour when she cannot locate the food source inspired us to create Local Search Manoeuvres recruitment in neighbourhood search. The first one is the searching space factor where the recruits will search beyond the food source if they unsuccessfully locate the food source. The second factor is a searching direction where recruits will fly with a different direction from normal 90 degree when they cannot find the food source (Seeley 1983) and (Esch and Bastian 1970).

Search beyond the feeding station

The recruits, 20 percent among them search beyond the food source (Seeley 1983). Authors (Riley, Greggers et al. 2005) had made an observation to the honey bees flight path when leaving bee hive. In-hive bees joined the dancer (scouts) during the waggle dance to get the information about the food sources. Then in-hive bees will decide to start foraging or continue joined the waggle dances. If some of the bees (recruits) starts locate the food source, may be several recruits cannot locate the food source. Recruits try may extend the searching beyond the feeding station. Recruits may return to the hive with some nectar or nothing. Figure 1 shows recruits search beyond the feeding station.

Search in different direction

The scout bees can reach up 200 meters when flying looking for food sources. The effort made by recruit's bees can be called as Local Searching Manoeuvre (LSM). Some of recruits return from a different location. For the first 200 meters distance, the mean for flight path direction is average 90 degree. When recruits fly farther, she adjusted the flight direction (Riley, Greggers et al. 2005). Figure 1 shows recruits search in different direction.

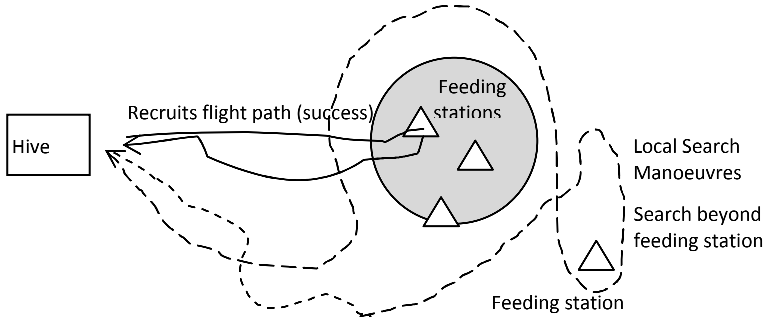

Figure 1. The Foraging Flight Path.

Leaning bees in the basic BA

How does bees learning inside the Bees Algorithm? Initially, groups of scouts, called as *n* will be released randomly to the searching space. The searching space will be called as sites. The scouts will then evaluate the optimisation problem at the searching space and come out with the fitness functions values. The fitness value of every sites then will be compared each other to know which sites are the fittest.

The number of *m* sites will be selected among all evaluated sites. The idea of selection is to increase the searching activities at the promising sites. During the selection, the algorithm will divided into two, first one was best *e* sites and the second one was the *(m-e)* selected sites. After that the number of recruits will be called to search at the selected sites. More recruits will search at the best *e* sites, known as *nep*, and less recruits will search other selected sites (*m-e*), called *nes*. The searching process by recruits (*nep* and *nes*) known as neighbourhood search to aim to exploit the good site quicker and efficiently. Furthermore, the algorithm will evaluate all bees performed the neighbourhood search compare each others. The algorithm then will select the fittest bees from each *e* and *(m-e)* sites.

Finally, in the last process, all fittest bees from all selected sites will combine with new random bees initiate another random search for the whole searching space. The process of searching, evaluating, recruiting and selecting will be repeated until it met certain criteria or at after certain number of evaluation. For example when the fitness values is equal with the answer or less than 0.001 (Pham, Ghanbarzadeh et al. 2006).

Table 1. The Comparison between BA with LSM and Basic BA.

Recruits behaviour	New features in Bees Algorithm	Basic features in Bees Algorithm
Searching exploration (size)	Increase or decrease the size of the neighbourhood	Static neighbourhood size, i.e. *ngh*=0.1 for all iterations. • For all dimension
Searching direction (dimension)	LSM neighbourhood size in random selected dimension.	Did not change dimension in neighbourhood size

Learning lost bees during locating the food source in the BA

In other words mutate a part of the dimension of the searching space. It may be one, or half or any numbers as long as is not all dimension. If mutate all dimension then features will change to shrinking or enlarge.

Based on information from the lost bees, the nature behaviour of these bees will be applied to the existing basic Bees Algorithm. We add the new features Local Search Manoeuvres factor neighbourhood search. This feature is aims to reduce the number of function evaluation of searching the optimum value and tackle the high dimension problem. Figure 2 shows the pseudo-code with the LSM at the neighbourhood search. The LSM will increase or decrease the neighbourhood size in different dimensions. Table 1 show the comparison between the basic BA and LSM enhanced BA.

1. Begin the optimisation
2. Release scouts in searching space, *n*
3. Calculate the fitness value of every scouts
4. Decide best sites, *m*
5. Choose elite sites *e* among the best sites *m*
6. Send many recruits to elite sites, *ne*
7. Send fewer recruits to *m* sites, *nm*
8. Perform neighbourhood (*ngh*) search: increase/decrease *ngh* size for selected dimension, (1 < dimension < maximum dimension)
9. Choose the best sites between neighbourhood search
10. New population of scouts: best each sites + (*n-m*) scouts
11. Repeat no. 3

Figure 2. The Bees Algorithm with LSM Pseudo-code.

The LSM Operation on Neighbourhood Size

The first Local Search Manoeuvres operation was to increase the neighbourhood size of The Bees Algorithm. To get a new position in neighbourhood search basic BA approach, new position = random number between (selected position – *ngh*, selected position + *ngh*). In an enhanced version of the BA, we increased the neighbourhood size with Local Search Manoeuvres and use random selected dimension (dim) with condition, 1< *lsm* dim < max dim: New position = random number between (selected position – (*ngh* * *lsm*), selected position + (*ngh* * *lsm*)). Table 2 shows how to increase the *ngh* size.

Table 2. Increase Neighbourhood Size.

Initial *ngh*	0.1	
lsm >1	1.94149	
	without *lsm*	with *lsm*
start	0.1	0.005851
End	0.3	0.394149
original point	0.2	0.2
new range	***0.2***	***0.388298***
new rand()	***0.2551137***	***0.178707598***

The second Local Search Manoeuvres operation was to decrease the neighbourhood size of the Bees Algorithm. The operation started with select the number of dimension to be decreased and the condition of the dimension, 1< *lsm* dim < max dim. Then the new position = random number between (selected position – (*ngh* * *lsm*), selected position + (*ngh* * *lsm*)). Table 3 shows how to decrease the *ngh* size.

Table 3. Decreased Neighbourhood Size.

Initial *ngh*	0.1	
Lsm	0.5	
	without *lsm*	with *lsm*
start	0.1	0.15
end	0.3	0.25
Selected point	0.2	0.2
new range	0.2	0.1
new rand()	0.2330907	0.205542

Table 4. LSM Experiment Result with Benchmark Test Function.

	Test Function	n	m	e	nm	ne	ngh	lsm	Mean without LSM	Mean with LSM	% mean improve
1	De Jong 2d	10	3	1	2	4	0.1	0.52	1860.51	1614.48	13.22
2	Goldstein & Price 2d	20	3	1	1	13	0.1	0.01	11488.72	713.98	93.79
3	Branin	30	5	1	2	3	0.5	0.0095	15909.39	1355.63	91.48
4	Martin & Gaddy 2d	20	3	1	1	10	0.5	0.0095	885.88	590.61	33.33
5a	Rosenbrock 2d	10	3	1	2	4	0.1	0.52	1580.42	1288.39	18.48
5b	Rosenbrock 2d b	6	3	1	1	4	0.5	0.25	12072.27	4758.92	60.58
6	Rosenbrock 4d	20	6	1	5	8	0.0015	0.35	43727.99	42798.65	2.13
7	Hypersphere 6d	8	3	1	1	2	0.3	0.05	59472.39	2361.17	96.03
8	Grienwangk 10d	50	5	2	10	20	5	5	1314.46	487.18	62.94
										average %	52.44

EXPERIMENTS AND RESULTS

To evaluate the effectiveness of enhanced algorithm with the basic bees algorithm, the Local Search Manoeuvres will be applied to the eight benchmark test function as in (Pham, Ghanbarzadeh et al. 2006). Table 4 shows the number of parameters used in the benchmark test function. These parameters were initial population *n*, number of selected sites *m*, number of elites sites *e*, number of recruited bees in elites sites *ne*, number of selected bees around other selected sites *nm*, neighbourhood size *ngh* and Local Search Manoeuvres *lsm.* In test function 1, 2, 3, 4, 5a and 5b, only one dimension will be used for Local Search Manoeuvres. In test function six Rosenbrock four dimensions, test function seven Hypershere six dimensions and test function eight Griewank ten dimensions, the number of dimension for Local Search Manoeuvres should be selected for more than one dimension and not greater than the maximum dimension. In the first De Jong two dimensions test function, Local Search Manoeuvres improved by 13.22 percent compare to calculation using basic Bees Algorithm. The second function was Goldstein and Price with two dimensions test function show the improvement with 93.79 percent. The next test function was Branin two dimensions and it shown an improvement with a high percentage 91.48 percent. Martin and Gaddy two dimensions test function improved about 33.33 percent. There were two Ronsenbrock test function with a different range where 5(a) with a small range [-1.2, 1.2] and 5(b) with a bigger range [-10, 10]. The Bees Algorithm with Local Search Manoeuvres recruitment also can improve the performance of the Rosenbrock (5a) with 18.48 percent and success to reduce the number of function evaluation for Rosenbrock (5b) by 60.58 percent.

The next three test function was a high dimension. First were Rosenbrock four dimension, Hypersphere six dimension and Griewangk ten dimension test functions. The results show an improvement using Local Search Manoeuvres with 2.13 percent for Rosenbrock, 96.03 percent for Hypersphere and Griewangk test function with a 62.94 percent improvement. The average improvement for eight benchmark test function was 52.44 percent.

CONCLUSION

The Local Search Manoeuvres recruitment in the Bees Algorithm mimicking lost recruits bees when locating the advertise food source able to increase or decrease the neighbourhood size, thus give a chance to find the optimum solution faster. As general the Bees Algorithm with LSM recruitment performs better compared to the one with basic recruitment especially for benchmark test functions with high dimensions. The LSM recruitment can perform well with benchmark test function optimisation problem stated that the parameters need to be selected properly for the Bees Algorithm. The Bees Algorithm had been applied with benchmark test function consists of low, medium and high dimension problems. The future works should implement and test the performance of the Bees Algorithm with Local Search Manoeuvres with the different type of optimisation problem such as the constrained engineering optimisation problems.

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REFERENCES

Esch, H. and J. A. Bastian (1970). "How do newly recruited honey bees approach a food site?" Journal of Comparative Physiology A: Neuroethology, Sensory, Neural, and Behavioral Physiology **68**(2): 175-181.

Pham, D., A. Ghanbarzadeh, et al. (2006). The bees algorithm–a novel tool for complex optimisation problems.

Pham, D., A. Ghanbarzadeh, et al. (2009). "Optimal design of mechanical components using the Bees Algorithm." Proceedings of the Institution of Mechanical Engineers, Part C: Journal of Mechanical Engineering Science **223**(5): 1051-1056.

Riley, J. R., U. Greggers, et al. (2005). "The flight paths of honeybees recruited by the waggle dance." Nature **435**(7039): 205-207.

Seeley, T. D. (1983). "Division of labor between scouts and recruits in honeybee foraging." Behavioral ecology and sociobiology **12**(3): 253-259.