A Novel Knowledge Space Based on Optimization Hardness

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Abstract. This paper uses exhaustive disturbed particle swarm optimizer(EDPSO) as local search algorithm for memetic algorithm, and improves it by using a novel knowledge space mechanism. The innovative mechanismbased on two key points: 1. using effective high-frequency ratio (EHFR) as a novel indicator for problem features and a control parameters of density and range of disturbance, as same as fitness distance correlation; 2. Using the table of sampling spatial distribution to enhance the effective of disturbance behavior. Then, this paper regards. At last, the result of the comparative analysis between the test results of ant colony optimizer (ACO), differential evolution (DE), and OHBMA indicates that OHBMA shows better performance than ACO and DE.

Introduction

The memetic algorithm[1-3](Memetic Algorithm, MA) is based on the relevant theories of meme, and its biggest feature is the co-evolution of knowledge space and population space, which can be mutually affected through accept function andinfluence function. The evolution in the population space takes other heuristic optimization algorithms such as genetic algorithm and particle swarm algorithm as the basis, which are called as the basic algorithms or local search algorithm in the memetic algorithm. In the knowledge space, there are different types of knowledge corresponding to different receiver functions and influence functions [4, 5]. In the knowledge space, firstly, the accept functionwill extract samples from the population, and then the knowledge updating function will act on the population space through sample creation or knowledge updating and finally the influence function. Figure 1 is the structural diagram of memetic algorithm. It is important to note that, partial literatures [6, 7] disagree with the above descriptions on the structure of memetic algorithm, and take the functions of population space and knowledge space as the local search algorithm and global search algorithm respectively; the local and global search balance can be realized through adjusting these two algorithms.

With respect to the problems existed in the current memetic algorithm, this paper has introduced exhaustive disturbedparticle swarm optimization [8] into the framework of memetic algorithm, which is called as optimization hardness based memetic algorithm (OHBMA). When being compared with other types of knowledge, for knowledge such as OHBMA, there are two advantages. Firstly, the hardness of optimization problem will not be changed in the optimizing process, and for other types of knowledge, generally, the optimal individual in the current population should be tracked, but the optimal individual will be constantly changed during the optimizing process. Therefore, the updating frequency of knowledge based on optimization hardness is not sensitive. Secondly, the adaptation of knowledge based on optimization hardness is strong and suitable for different basic algorithms. Although this paper takes EDPSO as the basic algorithm, the basic algorithm of OHBMA shouldn't be merely limited to the algorithm of EDPSO. The optimization hardness research can also form new knowledge system with various evolutionary algorithms, ant colony optimizer, taboo search and other methods; since the applicable range of search and utilization of balance principle is wide, the research conclusions of the paper should possess stronger universality considering these research results. The work of the paper is not only the application of optimization hardness research achievements in the engineering practices, but also the expansion of the optimization hardness research from numerical function to other optimization problems. The work of the chapter totally has 4 sections, and Section 1.2 will introduce OHBMA; Section 1.3 will apply OHBMA in the real-parameter problems; Section 1.4 will summarize the work of this paper.

Optimization hardness based Knowledge Spaceand OHBMA

During the process of designing the OHBMA, the key step is to construct receiver function, influence function and knowledge updating function. Moreover, two aspects of work should be completed for these three functions; firstly, it is to summarize the relevant conclusions of optimization hardness research; secondly, it is to introduce the control modes of catastrophe strength (P_{Er}), position (L_{Er}) and mode (Mo_{Er}) as well as other parameters, so as to make it adapt to the structure of memetic algorithm.

First of all, the best disturbance introduction mode as well as the position and strength of the disturbance are related to the feature of optimization problems. This paper takes EHFR and FDC of the test function participating in the orthogonal test in Literature [8] as the basis, and corresponds results of orthogonal test to EHFR and FDC of the test function, and the obtained matrixEFParam={EHFR, FDC, P_{Er}, L_{Er}, Mo_{Er}}, FDC is from the column vectors in Table 6 of Literature [8], P_{Er}, L_{Er} and Mo_{Er} arefrom the column vectors in Table 7 of Literature [8], and EHFR is the result automatically calculated as per the method stipulated in Literature [9], and elements in the same row of these column vectors correspond to the identical test functions. Secondly, the disturbance mechanism possesses its own issues, for when the dimension of optimization problem is increased, the function of disturbance can be seriously affected, so the occurrence mechanism of disturbance should also be improved to some extent, and this kind of improvement should at least avoid the detection of disturbance behavior in the known area for another time. Therefore, OHBMA divides the search area into several subareas, records the sampling times occurred in each subarea, and then selects the subarea with relatively less accumulated sampling times as the area with disturbance behavior. This kind of disturbance mechanism is relatively complicated, but it can balance the function of local search and global search in the heuristic optimization algorithm. Thus, the knowledge based on the optimization hardness includes the contents in two aspects: firstly, it is the three parameters (P_{Er}, L_{Er} and Mo_{Er}) incurring the disturbance; secondly, it is the table of sampling spatial distribution (TSSD) considering the accumulated sampling times.

Firstly, the accept function (*Afunc*) should include two aspects of work: (1) calculating FDC and EHFR of optimization problems. (2) Recording the position of the current population in TSSD. In case of dividing each dimension for the search domain R of n-dimensional optimization problems into m equal parts, the search domain Rwill be divided into m^n subspaces, and the center point coordinates of these subspaces will be stored inside the coordinate matrix CC located at Row n and Column m^n. The length of TSSD is the vector quantity of m^n, and each element inside will record the sampling times occurred at the corresponding subspaces. The influence of No. $t$generation of population S_t^pon TSSD can be expressed by $TSSD_t$.

$$[TSSD_t, EHFR_t, FDC_t] = Afunc\left(S_t^p, \overline{x_{t-1}}, \overline{f_{t-1}}, CC\right) \tag{1}$$

$$[TSSD_t] = Afunc_1\left(S_t^p, CC\right) \tag{2}$$

$$[EHFR_t] = Afunc_2\left(S_t^p\right) \tag{3}$$

$$[FDC_t] = Afunc_3\left(S_t^p, \overline{x_{t-1}}, \overline{f_{t-1}}\right) \tag{4}$$

Actually, $Afunc_1$refers to the nearest neighbor classification for No. $t$generation of population as per CC, and then the individual amount of each subspace is recorded into $TSSD_t$. In case that the scale for No. $t$generation of population is M_t, the quantity of non-zero elements in $TSSD_t$ must be larger than M_t; $Afunc_2$takes the method put forward in Literature [9]and [10]; $Afunc_3$ takes the method put forward in Literature [10] as the basis. But the sample set required for the calculation of FDC and EHFR is gradually updated along with the iterative process of OHBMA rather than being generated in one time, and in the following part, we will describe the updating step by taking FDC as an example.

After that, the knowledge updating function (*KUfunc*) also includes the functions in two aspects: (1) updating and recording TSSD in each subarea; (2) calculating the disturbance strength P_t, range L_t and the way of introductionMo_t as per FDC_t and $EHFR_t$.

$$[TSSD, P_t, L_t, Mo_t] = KUfunc(TSSD_t, EHFR_t, FDC_t) \tag{5}$$

$$KUfunc_1 : TSSD = TSSD + TSSD_t \tag{6}$$

$$[P_t, L_t, Mo_t] = KUfunc_2(EHFR_t, FDC_t) \tag{7}$$

$$P_t = \frac{KP_{Er}}{K}, L_t = \frac{KL_{Er}}{K}, Mo_t = \left[\frac{KMo_{Er}}{K}\right] \tag{8}$$

Where, the function of $KUfunc_1$ is to accumulate $TSSD_t$into TSSD; the function of $KUfunc_2$can be divided into three steps: (1) respectively using $EHFR_t$ and FDC_t to deduct the first and second columns of matrixEFParam; (2) respectively ranking the absolute values of the results, and then extracting the parameters corresponding to K/2 group (K groups in total) with the smallest absolute value being extracted from EFParam, and forming new vector quantities, including KP_{Er}, KL_{Er}, and KMo_E; (3) As per formula (8), respectively obtain P_t, L_t and Mo_t, butthe average value ofMo_tshould be calculated and rounded to become meaningful.

Finally, the influence function (*Ifunc*) can generate the individual set of disturbance *D*as per P_t, L_t and Mo_tas well as TSSD and other parameters.

$$[D] = Ifunc(TSSD, P_t, L_t, Mo_t) \tag{9}$$

Of which, the function of *Ifunc* can also be divided into four steps: (1) confirming whether No. *t*generation needs to introduce disturbance, if yes, proceeding with (2), and if no, terminating it; (2) selecting the subspace corresponding to $\min\{TSSD\}$, and then conducting unified and random sampling for one time therein; (3) confirming the quantity of introduced disturbance as per P_t, and repeating Step (2) for $P_t \cdot M_t$times; (4) replacing the corresponding individual in S_t^p as per L_t,, and forming the new population.

The Analysis of Numerical Experimental Results

To evaluate the performance of OHBMA, this paper has introduced ant colony optimizer (ACO) and differential evolution(DE), to conduct performance comparison.

Test function and test conditions

This paper takes CEC05testfunction set as the test object, and selects 2-dimensional and 5-dimensional functions to evaluate the performance of OHBMA. Besides, all of the population scales for these three algorithms are 200, and the maximum generations corresponding to 2-dimensional and 5-dimensional test functions are respectively 50 and 100. Under the aforementioned conditions, each test function will be tested for 500 times under the same condition, to obtain the convergence probability. The aberration rate of DE is 0.6, and the crossbreeding parameter is *0.9*. The inspiring factor of ACOαequals to *1.5*, the expecting factor βequals to *0.5*, the pheromoneevaporation factorρequals to *0.9*, and the intensity of pheromone$Q$equals to *1*. As the parameter setup for the particle swarm algorithm of the basic algorithm of OHBMA, the learning factor C_1equals to C_2as well as*1.4*, and the inertia factor *W*equals to *0.5*.

Analysis of the test results

The test results of OHBMA (be abbreviate to OA), the ant colony optimizer (be abbreviated to ACO) and differential evolution algorithm (be abbreviated to DE) are shown in Table 1. Firstly, analyze the data in Table 1, and with respect to the convergence probability, the performance differences for these three algorithms are different for different types of test function. Functions from F1 to F5 are unimodal functions, and except F3, all of these three algorithms can obtain

100%convergence. Although F3 is the unimodal function, it can exert a strong misleading function in the particle swarm algorithm of dependentgradient information, and in test of the chapter, particle swarm algorithm is the basic algorithm of OHBMA. Functions from F6 to F14 are multimodal functions, and the convergence probabilities of these three algorithms are slightly decreased, but this is not so obvious. Functions from F15 to F22 are composite functions, MA can have a better performance in these composite functions, and considering that these results are obtained under the precondition of few sampling times, it can be seen that the performance of MA is affirmed.

As can be seen from the data of Table 1, due to the increase in the dimension of test problems, all the performances of these three algorithms have been degraded to a certain extent. Under most conditions, results of these three algorithms possess few differences, indicating that the essence for the increase of difficulties in optimization problems due to the increase of dimensions is the increase in the search area of the expected optimization problems, and its relations with the search and utilization balancing adjustment as well as the information utilization mode are not intimate. Therefore, the high-dimensional optimization problem must take the increase of sampling times as the precondition; the search and utilization balance as well as information utilization efficiency and other problems can only be considered on the basis of certain sampling times.

Table 1 Test Results of Three Algorithms for Two and Five Dimension Test Function (Mean Value)

Test function	Two-Dimensions						Five-Dimensions					
	Convergence Rate			Convergence generation			Convergence Rate			Convergence generation		
	OA	ACO	DE	OA	ACO	DE	OA	ACO	DE	OA	ACO	DE
F1	1.00	1.00	1.00	10	15	25	1.00	1.00	1.00	22	80	98
F2	1.00	1.00	1.00	11	15	26	1.00	1.00	1.00	28	93	100
F3	0.28	0.46	1.00	50	49	43	0.00	0.00	1.00	0	0	100
F4	1.00	1.00	1.00	11	16	27	1.00	0.92	1.00	29	99	99
F5	1.00	1.00	1.00	1	1	50	0.50	0.64	0.84	26	10	100
F6	0.92	0.90	1.00	26	31	50	0.54	0.22	0.04	100	100	100
F7	1.00	1.00	1.00	36	40	50	0.96	0.86	1.00	100	100	100
F8	0.68	0.54	0.00	29	34	0	0.00	0.00	0.00	0	0	0
F9	1.00	1.00	1.00	11	32	50	0.90	0.04	0.00	77	100	0
F10	1.00	1.00	1.00	15	42	50	0.08	0.00	0.00	73	0	0
F11	1.00	1.00	1.00	25	47	49	0.58	0.04	0.00	98	100	0
F12	1.00	1.00	1.00	13	47	41	0.88	0.00	0.50	77	0	100
F13	1.00	1.00	1.00	14	12	18	1.00	1.00	1.00	100	100	100
F14	1.00	1.00	0.40	42	44	50	0.80	0.60	0.34	60	100	100
F15	0.90	0.84	0.48	16	47	50	0.36	0.00	0.00	58	0	0
F16	0.98	0.96	1.00	15	48	45	0.00	0.00	0.00	0	0	0
F17	0.96	0.92	1.00	15	48	47	0.00	0.00	0.00	0	0	0
F18	0.48	0.04	0.02	17	38	50	0.34	0.00	0.00	70	0	0
F20	0.54	0.52	0.00	25	50	0	0.10	0.04	0.00	54	100	0
F21	0.42	0.50	0.20	30	40	49	0.00	0.00	0.00	0	0	0
F22	0.50	0.04	0.00	33	33	0	0.00	0.00	0.00	0	0	0

Therefore, with respect to the performance appraisal of OHBMA, the features of the problems should be combined for detailed analysis, and here, we select test functions (F8, F14 and F22) with typical meanings to conduct the analysis. Figure 1, (a), (b) and (c) are respectively the two-dimensional images of the test functions (F8, F14 and F22). Generally speaking, all the convergent probabilities of OHBMA in three functions (including F8) are superior to those of ACO and DE.

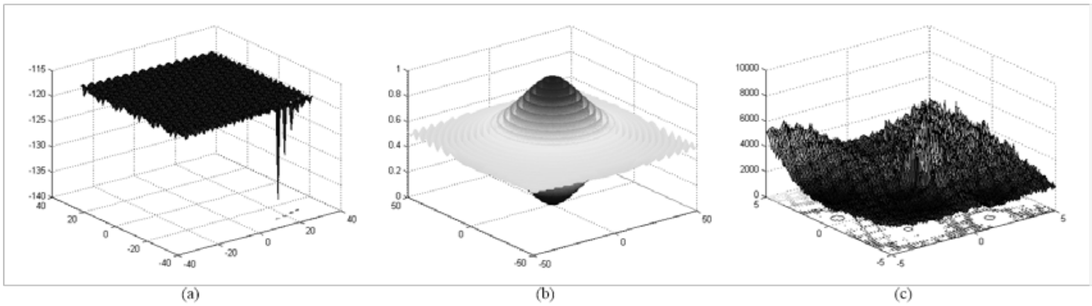

Figure 1 Images of Test Function F8, F14 and F22

As can be seen from the search and utilization balancing theories, the efficiency of searching behavior is subject to the rules of probability, so the efficiency of disturbance will be influenced by the features of optimization problems. As can be seen in Figure 1(a), the global optimum peak of F8 is long and thin, so this can have a relatively bigger negative influence on the efficiency of disturbance behavior, but OHBMA can still obtain the effect superior to ACO and DE, so we can see that the targeted adjustment and adding of disturbance parameter based on the optimization hardness can indeed obtain a better result. The test function F22 is more complicated, so its convergence probability is lower than that for the test function F8, but the convergence probabilitydifferences of MA, ACO and DE are bigger, indicating that the advantages of MA when handling complicated optimization problem features are more obvious. F14 function is a special case, and although the globally optimal solution is also situated at a status of similar isolated point, it can represent a global structure that is very suitable for the particle swarm algorithm, so the effect of particle swarm algorithm is better.

Conclusion and expectations

This paper propose OHBMA as an application of the optimization hardness research, and then tested these three heuristic algorithms including OHBMA on real-parameter problems. On the real-parameterproblems, the performances of OHBMA, ACO and DE possess their own respective advantages, and when the dimension of test problems are lifted, certain performance degradation occurs. On most cases, OHBMA shows better performance than the two other algorithms, this indicates that proper using of optimization hardness related knowledge can enhance the performance of memetic algorithm.

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