Dynamic Regional Harmony Search with Opposition and Local Learning

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ABSTRACT
Harmony search (HS), mimicking the musician's improvisation behavior, has demonstrated strong efficacy in optimization. To deal with the deficiencies in the original HS, a dynamic regional harmony search (DRHS) algorithm with opposition and local learning is proposed. DRHS utilizes opposition-based initialization, and performs independent harmony searches with respect to multiple groups created by periodically regrouping the harmony memory. An opposition-based harmony creation scheme is used in DRHS to update each group memory. Any prematurely converged group is restarted with its size being doubled to enhance exploration. Local search is periodically applied to exploit promising regions around top-ranked candidate solutions. DRHS consistently outperforms HS on 12 numerical test problems from the CEC2005 benchmark at both 10D and 30D.

Categories and Subject Descriptors
I.2.8 [**Artificial Intelligence**]: Problem Solving, Control Methods, and Search – *heuristic methods*; G.1.6 [**Numerical Analysis**]: Optimization – *global optimization*

General Terms
Algorithms, Experimentation, Performance

1. INTRODUCTION
Harmony search (HS) [1], as an emerging metaheuristic algorithm, has succeeded in various applications. However, it suffers from some deficiencies. HS excessively relies on the harmony memory (HM) to exploit the solution space. The random selection operator can merely provide limited exploration beyond the HM. Therefore, the good performance of HS relies on a careful HM initialization that should extensively cover the solution space. On the other hand, a new harmony is always generated using the entire HM, which may degrade the efficacy of HS in solving multimodal problems. This is because too many harmonies scattering away from global optima may hamper the HM to evolve towards global optima. Moreover, the HM is prone to prematurely converging at undesirable local optima owing to the greedy replacement based HM updating scheme. Furthermore, a limited HM capacity may result in stagnation during the searching unless the random selection operator takes considerable efforts to resume the evolution. To address these issues, we propose a dynamic regional harmony search (DRHS) algorithm.

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2. HS
HS [1] represents candidate solutions of an optimization problem by musical harmonies. The quality of candidate solutions corresponds to the euphoniousness of musical harmonies. By simulating how a group of musicians keep enriching their experiences to collaboratively seek for the most euphonious harmony in the improvising procedure, HS searches for global optima using three harmony improvisation operators (i.e., HM consideration operator, random selection operator and pitch adjustment operator) as well as the greedy replacement based HM updating scheme to iteratively evolve the HM that consists of promising candidate solutions.

3. DRHS
Major deficiencies in HS, as mentioned in Section 1, are listed below, followed by the strategies used in DRHS to address them.

- The good performance of HS relies on the HM initialization.

DRHS strategies: DRHS initializes one half of the HM randomly within the solution space with another half obtained using opposition-based learning [2] with respect to the solution space. This can make candidate solutions to better cover the entire solution space.

- The new harmony is always generated using the entire HM.

DRHS strategies: DRHS splits the HM into multiple groups and forces each group to independently exploit different sub-regions of the solution space. This can make promising sub-regions of the solution space to be efficiently exploited by certain groups. To prevent premature convergence, the HM is periodically and randomly regrouped. Moreover, an opposition-based restarting is invoked to reactive any converged group. Meanwhile, the size of any restarted group is doubled to enhance its exploration ability.

- The HM is prone to prematurely converging.

DRHS strategies: For each group, besides a new harmony generated by the original HS operators, DRHS also creates an opposite harmony by applying opposition-based learning to that new harmony with respect to the corresponding group. Among these two newly generated harmonies, the one with better quality is used to update the group memory. This opposition-based harmony creation as well as the group based memory updating can reduce the risk of premature convergence.

- The limited HM capacity may lead to stagnation.

DRHS strategies: The above periodical HM regrouping, group restarting with doubled size and opposition-based harmony creation schemes can reduce the risk of stagnation.

DRHS periodically applies local search on several top-ranked group best harmonies to exploit promising regions around them. Furthermore, DRHS reserves the final few numbers of function evaluations for local search to fully exploit the region around the best harmony in the HM. DRHS is detailed in [3].

4. EXPERIMENTS

Performances of DRHS and HS are compared on 12 numerical test functions taken from the CEC2005 benchmark [4]:

F_1: Shifted Sphere Function; F_2: Shifted Schwefel's Problem 1.2; F_3: Shifted Rotated High Conditioned Elliptic Function; F_4: Shifted Schwefel's Problem 1.2 with Noise in Fitness; F_5: Schwefel's Problem 2.6 with Global Optimum on Bounds; F_6: Shifted Rosenbrock's Function; F_7: Shifted Rotated Ackley's Function with Global Optimal on Bounds; F_8: Shifted Rastrigin's Function; F_9: Shifted Rotated Rastrigin's Function; F_{10}: Schwefel's Problem 2.13; F_{11}: Expended Extended Griewank's plus Rosenbrock's Function (F8F2); F_{12}: Shifted Rotated Expended Scaffer's F6.

4.1 Experimental Setup

Parameter settings of HS and DRHS are specified in [3]. For each test problem, each of DRHS and HS is executed 25 times starting from different random seeds while both algorithms share the same random seed for any individual run. Two stopping criteria are applied: (1) the maximum number of function evaluations (*maxFEvals*) is reached. Here, the *maxFEvals* is set to 10^4 times the problem dimension. (2) The difference of objective function values between the best solution found so far and the global optimal solution (i.e., error function value (**EFV**)) is smaller than 10^{-8}. In such a case, the EFV is negligible and set to zero.

The optimization performance is measured using (1) the mean value and standard deviation of the best EFVs achieved when an algorithm terminates over 25 runs and (2) the success rate (**SR**) over 25 runs. Success means an algorithm achieves an EFV smaller than the pre-specified accuracy level. According to [4], the accuracy level is set to 10^{-6} for F_1 to F_5 and 10^{-2} for F_6 to F_{12}.

4.2 Results

Table 1 reports, with respect to each of 12 test problems at 10D and 30D, the performances of HS and DRHS in terms of the mean value and standard deviation (*italic* below the mean value) of the best EFVs over 25 runs as well as the SR under the pre-specified accuracy level over 25 runs. For each function, bold fonts show the largest SR (if not zero) and the optimal best EFVs (i.e., with the smallest mean value) as well as those best EFVs indiscernible from the optimal based on the Wilcoxon's signed-rank test [5] at the significance level of 0.05. In comparison, DRHS consistently outperforms HS on all test problems at both 10D and 30D.

Table 1. Performance comparison of HS and DRHS

		10D		30D	
		HS	**DRHS**	**HS**	**DRHS**
F_1	**Best EFV**	3.039E-09 *5.737E-09*	**0.000E+00** ***0.000E+00***	2.997E-05 *4.643E-06*	**0.000E+00** ***0.000E+00***
	SR (10^{-6})	**1.00**	**1.00**	0.00	**1.00**
F_2	**Best EFV**	1.701E+02 *1.092E+02*	**7.419E-09** ***1.577E-08***	1.409E+03 *6.133E+02*	**5.626E-08** ***1.201E-07***
	SR (10^{-6})	0.00	**0.92**	0.00	**0.16**
F_3	**Best EFV**	1.008E+06 *7.527E+05*	**4.329E+00** ***1.178E+01***	7.513E+06 *3.227E+06*	**2.014E+03** ***1.708E+03***
	SR (10^{-6})	0.00	0.00	0.00	0.00
F_4	**Best EFV**	9.370E+02 *7.260E+02*	**9.453E+01** ***9.328E+01***	9.981E+03 *2.996E+03*	**1.277E+03** ***7.172E+02***
	SR (10^{-6})	0.00	0.00	0.00	0.00
F_5	**Best EFV**	1.804E+03 *1.185E+03*	**2.688E+02** ***2.450E+02***	5.766E+03 *9.979E+02*	**3.364E+03** ***6.620E+02***
	SR (10^{-6})	0.00	0.00	0.00	0.00
F_6	**Best EFV**	1.384E+03 *2.976E+03*	**4.784E-01** ***1.322E+00***	6.180E+02 *2.476E+03*	**4.377E+01** ***6.848E+01***
	SR (10^{-2})	0.00	**0.88**	0.00	0.00
F_7	**Best EFV**	2.036E+01 *6.917E-02*	**2.000E+01** ***8.164E-05***	2.094E+01 *5.513E-02*	**2.000E+01** ***1.130E-06***
	SR (10^{-2})	0.00	0.00	0.00	0.00
F_8	**Best EFV**	8.933E-07 *5.492E-07*	**0.000E+00** ***0.000E+00***	5.581E-03 *1.267E-03*	**0.000E+00** ***0.000E+00***
	SR (10^{-2})	**1.00**	**1.00**	**1.00**	**1.00**
F_9	**Best EFV**	1.230E+01 *6.492E+00*	**3.423E+00** ***9.561E-01***	5.125E+01 *3.932E+01*	**2.436E+01** ***5.131E+00***
	SR (10^{-2})	0.00	0.00	0.00	0.00
F_{10}	**Best EFV**	1.774E+02 *4.350E+02*	**3.145E+00** ***6.774E+00***	3.626E+03 *3.419E+03*	**1.208E+03** ***2.065E+03***
	SR (10^{-2})	0.00	**0.04**	0.00	0.00
F_{11}	**Best EFV**	4.319E-01 *1.330E-01*	**4.082E-01** ***1.338E-01***	1.962E+00 *2.796E-01*	**1.516E+00** ***2.929E-01***
	SR (10^{-2})	0.00	0.00	0.00	0.00
F_{12}	**Best EFV**	2.941E+00 *4.499E-01*	**2.412E+00** ***5.805E-01***	1.300E+01 *3.029E-01*	**1.255E+01** ***2.861E-01***
	SR (10^{-2})	0.00	0.00	0.00	0.00

5. CONCLUSIONS

We present a DRHS algorithm with opposition and local learning to address the deficiencies in the original HS such as premature convergence and stagnation. Experiments on 12 numerical test problems taken from CEC2005 benchmark at both 10D and 30 consistently demonstrate the superiority of DRHS over HS.

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7. REFERENCES

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