Using Latin Hypercube Hammersley Sampling Method for Algorithm Parameter Tuning: A Case for Differential Ant-Stigmergy Algorithm

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Abstract

Metaheuristic methods have many design parameters, and fine-tuning of that parameters can improve these algorithms performance. In this paper, a sampling based algorithm configuration approach is proposed and applied it to the Differential Ant-Stigmergy Algorithm (DASA)'s five control parameters**.** Performance of a large parameter set of DASA, obtained by Latin Hypercube Hammersley Sampling (LHHS) method, used to solve the Sphere function and compared it with another tuned version. The results of our experiment demonstrated that LHHS method found better performing configurations than the default parameter value of the DASA and also than another proposed tuned version DASA*. And the results demonstrated that three parameter configurations obtained with LHHS found better result than the best configuration obtained with Sobol Sequence Sampling method (DASA*) for function dimension 20, and five parameter configuration for function dimension 40. According to the results, it can be said that usage of LHHS for initialization of other state-of-art algorithm configuration methods instead of other sampling methods is worth investigating.

Keywords
meta heuristics, algorithm configuration, LHHS

1. Introduction

A metaheuristic is defined as "a generic algorithmic template that can be used for finding high quality solutions for hard combinatorial optimization problems" by Birattari and Kacprzyk (2009). However metaheuristic algorithms have specific parameters that affects the algorithm performance significantly. These parameters can be categorical or numerical parameters (Eiben and Smit, 2011a). Although the selection of best performing values for free algorithm parameters is a challenging and tedious task, it can lead effective and good performing version of algorithms for optimization problems. For these reason a number of successful automatic tuning methods developed such as REVAC (Smit and Eiben, 2009) and SPO (Bartz-Beielstein et al., 2005).

In this paper, we used a newly developed sampling method for tuning the Differential Ant-Stigmergy Algorithm (DASA) that can be considered in the scope of the Ant Colony Optimization (ACO) (Šilc et al. 2015). DASA has a tunable parameter set that affects its performance, like other metaheuristics, and fine-tuning these parameters improves its performance. In these study, we used Latin Hypercube Hammersley Sampling (LHHS) (Wang et al., 2004) in order to obtain a parameter set. Afterwards, the target problem is solved with these sampled parameter configurations. And the best performing parameter configuration is selected based on the performance score of these configurations on this problem. Parameter sampling methods like Latin Hypercubes Sampling (LHS) (McKay et al., 1979), and Sobol Sequences Sampling (Joe and Kuo, 2008) has been already used for parameter tuning in the literature. We used a new and hybrid sampling method, LHHS, for parameter tuning task of DASA algorithm and we compared its performance with study of Šilc et al. (2015) which uses Sobol Sequence sampling for parameter tuning.

To summarize the structure of this paper, a brief literature survey about on algorithm configuration problem is given in Section 2, Section 3 is about proposed parameter tuning approach, Section 4 demonstrates the experimental implementation and the results. Lastly, there is a summary of this study and recommendations for further work in Section 5.

2. Literature Review on Algorithm Configuration Problem

Parameter tuning methods suggested in the literature are divided in to two title, offline parameter (parameters values are determined before the execution of algorithm and doesn't change further) and parameter control approaches (parameter values are determined first and changed during execution of algorithm) (Eiben, and Smit, 2011b).

A brief definition of parameter tuning is, for a target algorithm A which is parameterized, a configuration space C, a performance metric that measures the performance of algorithm (i.e., solution quality), a distribution of problem instances I; the goal is to determine the parameter configuration of A that provides an optimal performance of A on I according to the performance measure (Hutter et al., 2011).

There are various taxonomies of offline algorithm configuration techniques in the literature. Eiben and Smit (2011a) divided these techniques into four categories such as;

* **meta-EAs** such as GGA++ (Ansótegui et al., 2015)**,** Revac++ **(**Smit and Eiben, 2009), and Multi-Function Evolutionary Tuning Algorithm (M-FETA) (Smit et al., 2010), ParamILS and Multi- objective ParamILS (Hutter et al., 2007, Blot et al. 2016),

* **Sampling methods** CALIBRA (Adenso-Diaz and Laguna, 2006) and the Empirical Modelling of Genetic Algorithm (Myers and Hancock, 2001) are iterative sampling parameter tuning techniques,

* **Screening methods** such as F-Race (Birattari et al., 2002)

* **Model-based methods** such as SMAC (Hutter et al., 2011), SPO++ (Hutter et al., 2009), Metatuner (Trindade and Felipe, 2019), the irace (Birattari et al., 2010**)**.

3. Proposed Parameter Tuning Approach

Over the past several decades, various sampling techniques have been developed and improved, such as, fractional and full factorial design (Box & Hunter, 1961), Hammersley Sequence Sampling (HSS) (Hammersley, 1960), Monte Carlo sampling (MCS) (Metropolis & Ulam, 1949), Sobol' sequences (Sobol, 1976), Latin Hypercube Sampling (McKay et al., 1979), and Garud et al. (2017) is a recent review in this scope. Wang et al. (2004) suggested a novel sampling method, Latin Hypercube Hammersley Sampling (LHHS) that combines the one-dimensional uniformity of LHS with multidimensional uniformity of HSS. LHHS showed a consistently better performance for various cases than the other sampling methods such as Latin Hypercube Sampling, Median LHS, and Monte Carlo Sampling (Wang et al., 2004).

Sampling methods widely used in algorithm configuration problems and the main advantages of these methods over the full factorial design, is that the size of initial or candidate parameter set (so in other terms total time for tuning process) is decreased (Eiben and Smit, 2011a). Sampling methods can be used as a starting point for model-based tuning methods (i.e., irace method (Birattari et al., 2010) uses a full factorial design (FFD) and random uniform sampling to sample initial and candidate configurations and Wessing et al. (2019) compared four different optimized variants of the LHS method when they are used as a sampling method for the irace method) or can be used as independent parameter tuning methods (such as CALIBRA method) (Eiben and Smit, 2011a).

In these study, we used a newly developed hybrid sampling method, LHHS, for tuning the DASA parameters and we compared its performance with study of Šilc et al. (2015) which uses Sobol Sequence sampling for parameter tuning. In this study the DASA algorithm is considered as a target metaheuristic algorithm; which is based on effective self-organizing behavior of ant colonies resulting from a pheromone-mediated communication (this is the notion of stigmergy) (Bonabeau et al., 1999). And we aimed to tune five parameters of DASA on the Sphere function implementation on Black-Box Optimization Benchmarking (BBOB) 2010 (Hansen et al., 2010).

4. Experimental Evaluation

In this section a practical example and how to use it is described. DASA algorithm has five tunable parameters: and two parameters (m and b) that takes integer values and three real-valued parameters (s+, s-, p). In this study, we aimed to tune these five parameters on the Sphere function implementation on Black-Box Optimization Benchmarking (BBOB) 2010 (Hansen et al., 2010).

The search ranges of these parameter values were defined in the original paper such as:

$4 \leq m \leq 200$,
$0 \leq \rho \leq 1$,
$0 \leq s+ \leq 1$,
$0 \leq s- \leq \rho$, and
$2 \leq b \leq 100$.

Because of the implementation issue, the assessed values for the integer-valued parameters m and b were rounded to the nearest integer value, and the upper bound of s- was limited by the ρ value.

With using LHHS sampling technique, 5000 parameter configurations are created. Then, performance of these parameter configurations on the Sphere function was recorded. Each configuration is executed 15 times on the target function because of stochasticity, and time budget for these execution is determined as 25*D function evaluations (FEs). Subsequently, these parameter configurations were ranked based on their performance in this 15 runs for dimension 20 and 40. We used the same performance criteria with Šilc et. al. (2015), median of function error (the difference between the found and optimal function value) values. The best performing parameter vector is named as t- DASA (tuned DASA).

5. Results

The results of tuning process are discussed in this section. Table 1 demonstrates the parameter settings of, t- DASA and DASA* (tuned values at Šilc et. al. (2015)) and also default values of DASA. The median function error values of best configurations obtained by DASA*, t- DASA and DASA for dimensions 20 and 40, for 25*D function evaluation (FE) values are demonstrated in Table 2.

According to these results t-DASA shows a better performance than DASA* and DASA. And also for dimension 20 there are three parameter vector that solves the problem better than DASA and DASA* and again there are five parameter vector that solves better than others for dimension 40. DASA* algorithm (best parameter configuration obtained by Sobol Sequence Sampling method with parameter values m=5, p=0.324, s+ =0.201, s-= 0.289, b=6) has 2.53 and DASA algorithm (with default parameter values) has 16.7 median function errors value for the Sphere test function and for function dimension D=20. However, three configurations among the obtained 5000 configuration with LHHS method solved the test function with median function errors value less than 2.53 (which is the best parameter configuration obtained with using Sobol Sequence Sampling method).

LHHS method demonstrated the same success for the dimension D=40. DASA* algorithm (best parameter configuration obtained with using Sobol Sequence Sampling method with parameter values m=7, p=0.388, s+ =0.136, s-= 0.344, b=8) has 9.31 and DASA algorithm (with default parameter values) has 18.3 median function errors value. However, five configurations among the obtained 5000 configuration with LHHS method solved the test function with median function errors value less than 9.31 (which is the best parameter configuration obtained with using Sobol Sequence Sampling method).

Table 3 and 4 demonstrates these parameter configurations which are better than DASA* and DASA**.** The results given in Tables 3 and table 4 indicated that parameter vectors that are successful on solving target function at D = 20, also shows same success for D=40. Figure 1 demonstrates the mean function error values of DASA, DASA*, and five best configuration obtained by LHHS (parameter configurations demonstrated in Table 3) for D=40. Figure 2 demonstrates the mean function error values of DASA, DASA*, and three best configuration obtained by LHHS (parameter configurations demonstrated in Table 4) for D=20. Totally it can be inferred that parameter configuration set created by LHHS is significantly successful than that configuration set created by Sobol Sequence Sampling.

An additional experiment is executed in order to test these five configuration convergence speed. We re-executed these five parameter configuration and three of these parameter configurations (parameter vectors with ID number of 3, 4 and 5 in Table.3) solved target function very close to zero function error value (an error values between E-07 and E-09) for 250*D FE value and solved with zero function error value for 2500*D and 25000*D FE value. This result demonstrate that the convergence speed of the found best parameter vector with LHHS method is also compatible with the convergence speed of the found best parameter vector with Sobol Sequence Sampling method.

Creating a valuable initial configuration set for evaluating algorithm performance is crucial for an algorithm configuration method. And final performance of these algorithm configuration method is depend on the quality of initial configuration set. But these issue does not examined deeply in the existing literature and standard methods like (FFD or LHS) is used by the state of art algorithm configuration methods. The result of these study demonstrated that LHHS can be an effective way of creating an initial or candidate configuration set.

Table 1: Parameter values for, t- DASA, DASA* and DASA.

Algorithm	DASA	DASA*		t-DASA	
Parameter	d = 20,40	d=20	d=40	d= 20	d=40
m	10	5	7	6	4
P	0.2	0.324	0.388	0.3028	0.5067
s+	0.02	0.201	0.136	0.9927	0.4655
s-	0.01	0.289	0.344	0.2006	0.4276
b	10	6	8	5	5

Table 2: Median of function errors values for solving the Sphere function

Algorithm	D = 20	D = 40
DASA	16.7	18.3
DASA*	2.53	9.31
t- DASA	1.9	4.57

Table 3: Successful parameter vectors than DASA and DASA* for D=40 and their median of function error values

ID	Parameter Values (for D=40)					Error Values
	m	p	s+	s-	b	
1	6	0.3028	0.9927	0.2006	5	9
2	5	0.0674	0.7234	0.0219	7	7.76
3	4	0.7559	0.2430	0.2157	33	9.28
4	4	0.5067	0.4655	0.4276	5	4.57
5	4	0.3701	0.3049	0.1504	3	8.56

Table 4: Successful parameter vectors than DASA and DASA* for D=20 and their median of function error values

ID	Parameter Values (for D=20)					Error Values
	m	p	s+	s-	b	
1	6	0.3028	0.9927	0.2006	5	1.9
5	4	0.3701	0.3049	0.1504	3	2.36
4	4	0.5607	0.4655	0.4276	5	2

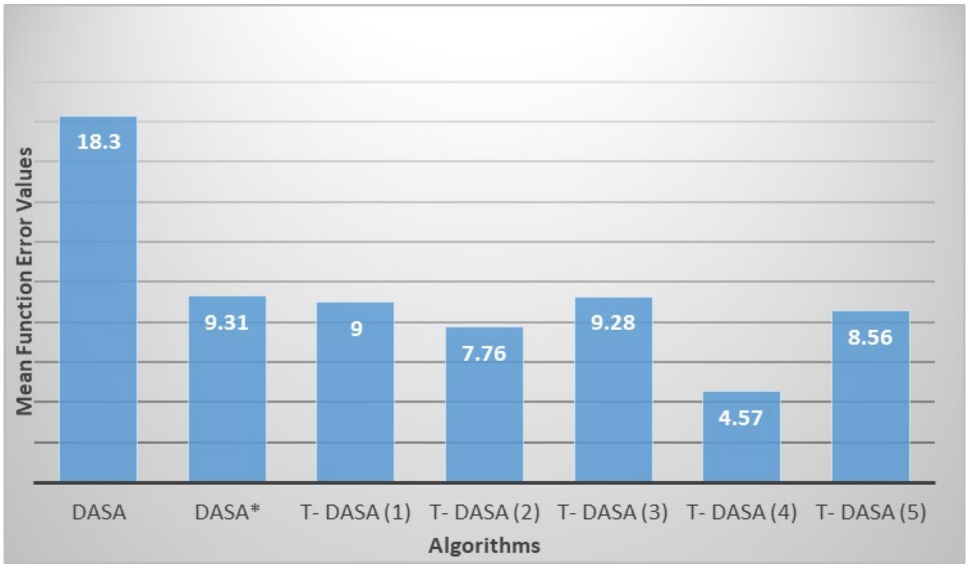

Figure 1: The mean function error values of DASA, DASA*, and five best configuration obtained by LHHS.

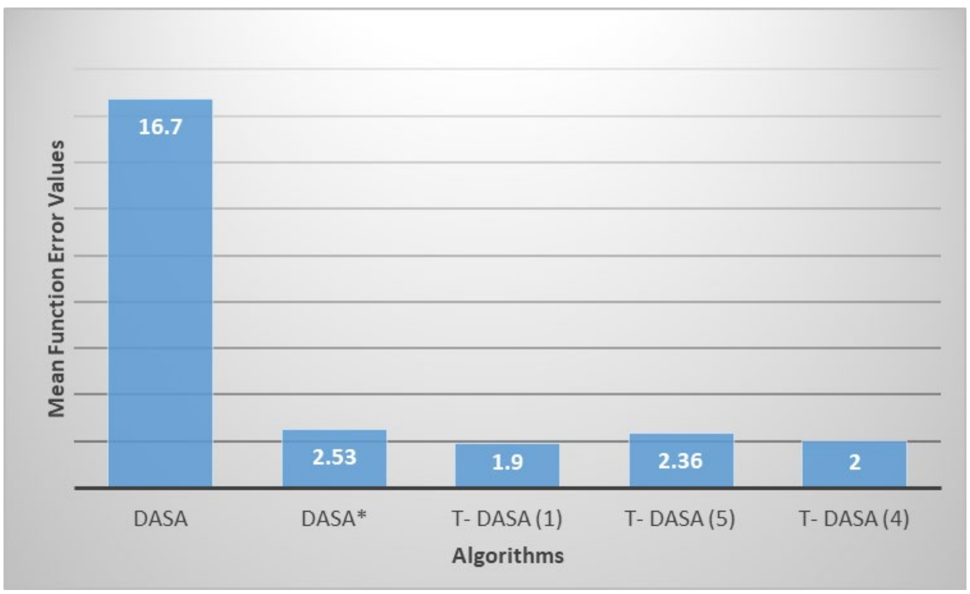

Figure 2: The mean function error values of DASA, DASA*, and three best configuration obtained by LHHS.

6. Conclusion and Discussion

Fine- tuning of metaheuristic algorithms parameter values can improve its ability to solve the optimization problem. For this purpose we focused on the problem of tuning the Differential Ant-Stigmergy Algorithm's (five) control parameters. In our study, we evaluated DASA algorithm performance tuned with LHHS method for the Sphere function on two problem dimensions (20 and 40). In this study we compared the performance of LHHS sampled parameter set and Sobol sampled parameter set for tuning the parameters of DASA algorithm.

The results of experiment demonstrated the success of LHHS method over Sobol Sequence Sampling method. According to these results, t-DASA (DASA algorithm tuned with LHHS method) demonstrated a better performance than DASA* and DASA. For function dimension 20 there are three parameter vector that solves the problem better than DASA and DASA* and again there are five parameter vector that solves better than others for dimension 40.

Another advantage of using this method for parameter tuning task is, it has no specific parameters like other well used parameter tuning methods, i.e., SPO and Revac. Although these methods shows very impressive performance, they have own specific parameters that directly affects their search behavior. And also they need an intensive user experience and time to understand and use these methods. LHHS based tuning method is simple to use when comparing other methods.

Creating a valuable initial configuration set for evaluating algorithm performance is crucial for and final performance of an algorithm configuration method is depend on the quality of initial configuration set. But these issue does not examined deeply in the existing literature and standard methods like (FFD or LHS) is used by the state of art algorithm configuration methods. For future tasks, novel parameter tuning methods can be developed by integrating LHHS method with any parameter configuration selection method (i.e. racing methods).

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