CATEGORY: MACHINE LEARNING & AI - ML05

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Parallel Multi-objective Multi-robot coalition formation

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Abstract

This work presents a novel parallel multi-point Pareto Archived Evolutionary Strategy (PAES) algorithm for the multi-objective multi-robot coalition formation problem. The proposed parallel approach is able to generate non-dominated solutions for the given problem when it is scaled to deal with high number of robots.

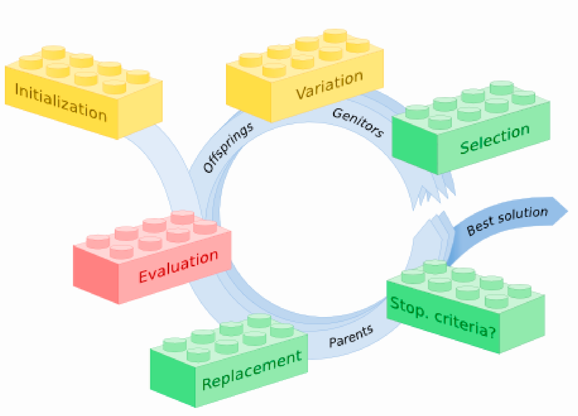
Motivation

Evolutionary approaches have been used for a multi-objective optimization problem due to their capabilities to adapt to the variation in search spaces and still approximate the Pareto optimal set in a single scan. However, these approaches have high computational complexity and thus are unsuitable for time critical robotic applications such as coalition formation. A plausible solution to this problem is to parallelize the evolutionary optimization algorithms. NVIDIA GPU's multi-threaded architecture is very suitable for this kind of scenario due to its Single Instruction Multiple Data (SIMD) model. The proposed parallel multi-point PAES algorithm for the robot coalition formation problem was developed on NVIDIA's Tesla GPU using CUDA framework.

Multi – Robot Coalition Problem

Multi-robot coalition formation problem deals with the formation of best mutually disjoint multi-robot teams, each of which can be assigned to a single task from a given set of tasks for execution. The problem is gaining importance in the robotic community as the complexity of the robotic tasks is increasing day by day. This problem belongs to the NP-hard class of combinatorial optimization problem and brute force techniques fail to generate optimal solution. Moreover, real world scenarios make the problem a case of multi-objective optimization problem as there exists multiple conflicting objectives such as minimization of distance traveled, maximization of resource utilization, minimization of the task completion time, and so on. Therefore, in this work the coalition formation problem has been modeled as a multi-objective optimization problem.

Evolutionary Multi-objective optimization



A problem that has several conflicting objectives, each of which are equally important, falls into the multi-objective optimization problem category. Objective functions that characterize any multi-objective optimization problem constitute a multidimensional space. For a problem with k objective functions namely f_1, f_2, f_3, f_4 and a n-dimensional solution vector represented as $x = (x_1, x_2, \ldots xn)^T \epsilon R^n$,

Corresponding to every solutions vector x there lies a point in the objective space denoted by

$$f(x) = [f_1(x), f_2(x), \ldots f_k(x)]^T$$

Thus, the goal of the multi-objective optimization is to find the vector $x *= (x_1{}^*, x_2{}^*, \ldots . x_n{}^*)^T$ that optimizes the function defined above subject to the following m equality and p inequality constraints :

$$g_t(x^*) = 0; 1 \leq i \ \leq m$$
$$h_t(x^*) = 0; 1 \leq i \ \leq p$$

Most real world problems have multiple conflicting objectives, thus no single solution can serve as the optimal solution with respect to all the objectives concerned and therefore a set of trade-off solutions that are mutually non-dominant is generated. Such an optimized set is known as Pareto optimal set.

If solution x_1 dominates x_2

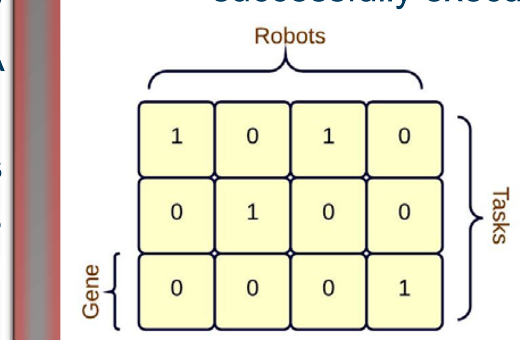
- x_1 is no worse than x_2 in all the objectives.
- x_1 is strictly better than x_2 in at least one of the objectives.

Else the solutions shall be non-dominated

The Coalition Formation Problem Scenario

Consider a system with M robots each having K resource types and N tasks having a vector of K- resource types. A coalition scheme represents a grouping of a given set of robots into disjoint subsets where each subset (coalition) is assigned one task. Thus for N tasks we have N coalition schemes, represented as CS = $\{C_1, C_2, \ldots . C_N\}$, In this problem we have considered the following two conflicting objectives.

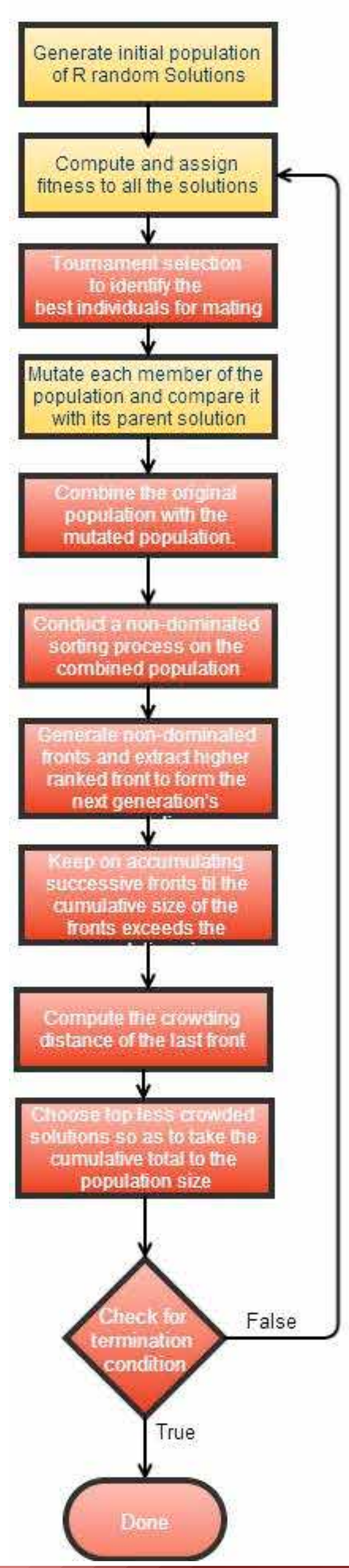
- F^1 : Number of tasks completed (to be maximized)
- F^2 :The sum of distances travelled across all the coalitions that can successfully execute tasks (to be minimized)



The figure on the left presents a sample chromosome wherein each gene has two possible alleles 1 & 0. Value 1(0) denotes the presence (absence) of the earmarked Robot in the coalition represented by the concerned row. It's evident that each column shall have at most single 1 i.e. an individual robot could be part of at most one coalition

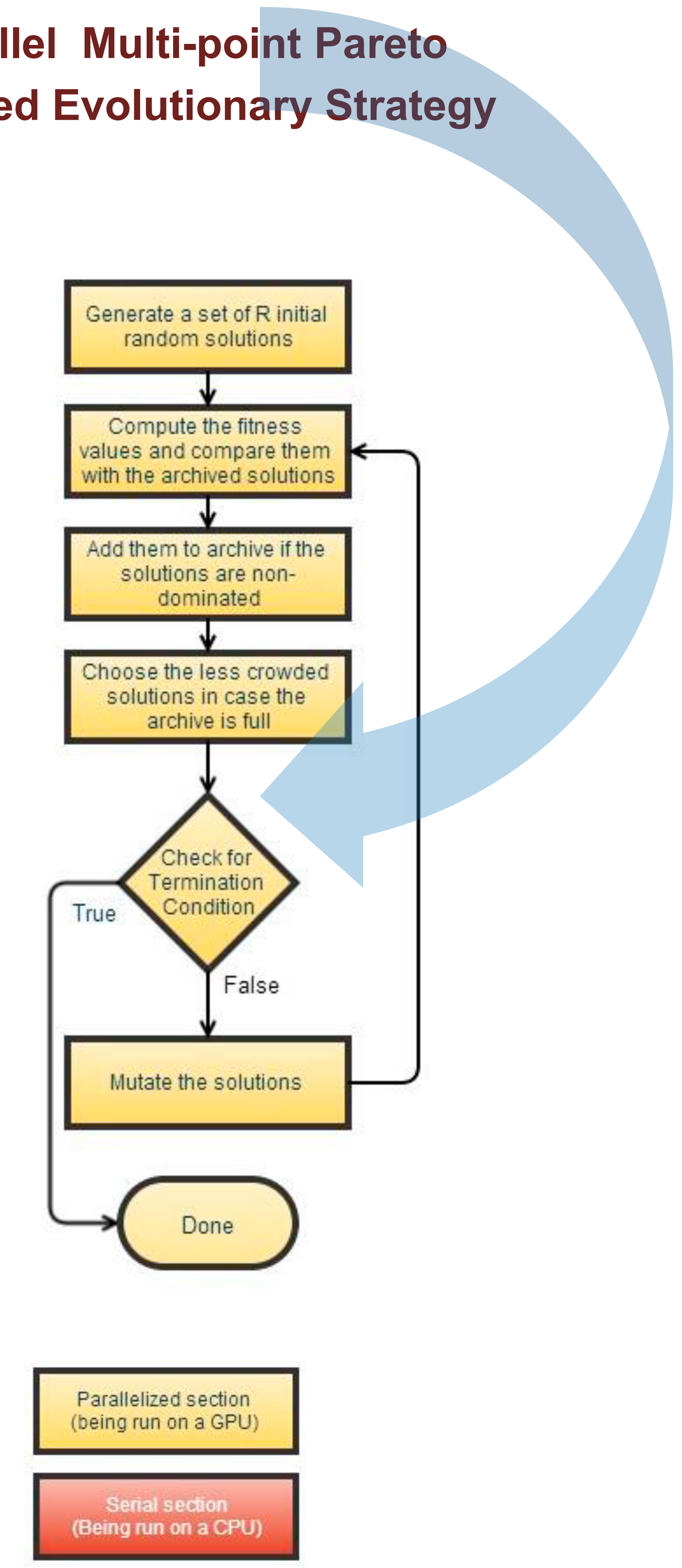
Parallel Multi point Pareto Archived Evolutionary Strategy & Parallel Non-Dominated Sorting Genetic Algorithm || (NSGA)

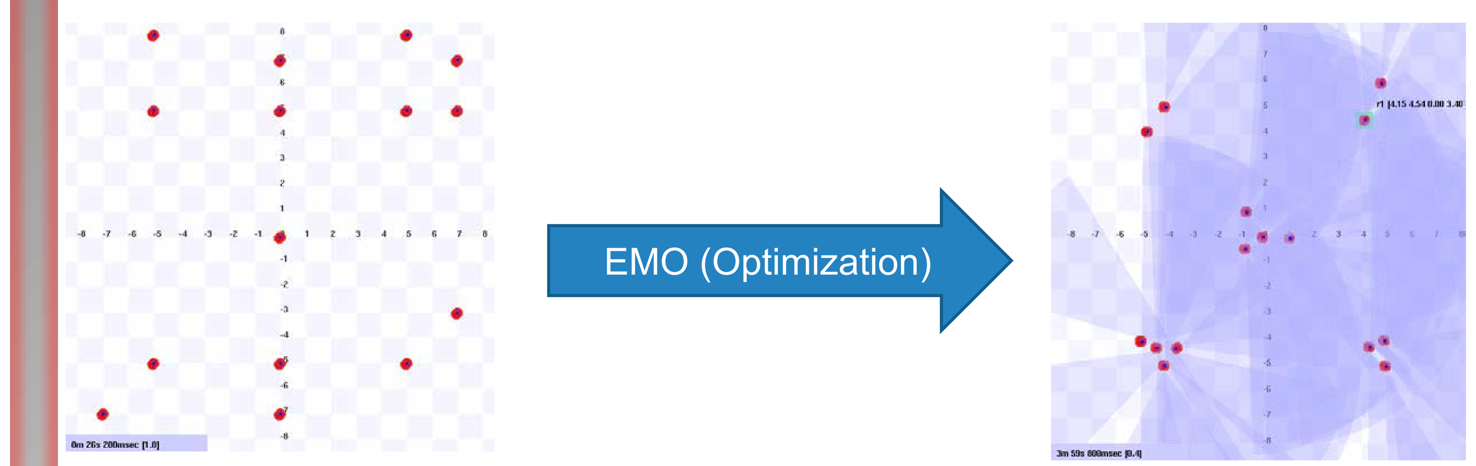
Evolutionary algorithms typically starts with a random population which is then evaluated for its fitness post checking for any violation of assumptions and making necessary correction. In every iteration a mutation is induced into the population and optimal solutions are stored in an external population. Pareto Archived Evolutionary Strategy (PAES) & NSGA II belong to this very class of algorithms. Here we present parallelized implementation of NSGA II & a novel variant of PAES (named multi-point PAES). Their corresponding algorithms are portrayed as under.



Parallel Non-Dominated Sorting Generic Algorithm-II

Parallel Multi-point Pareto Archived Evolutionary Strategy





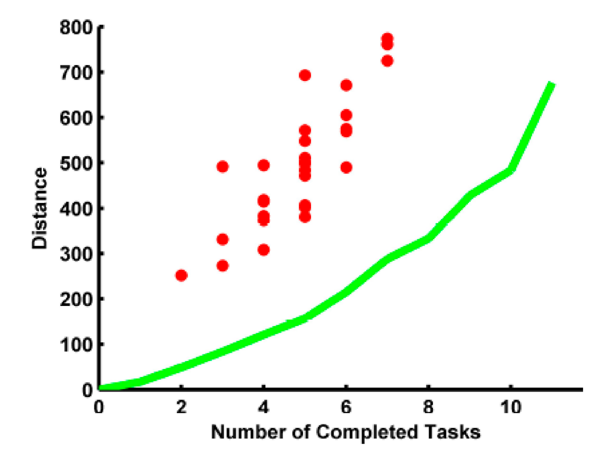
Initial Scenario

Optimized Scenario

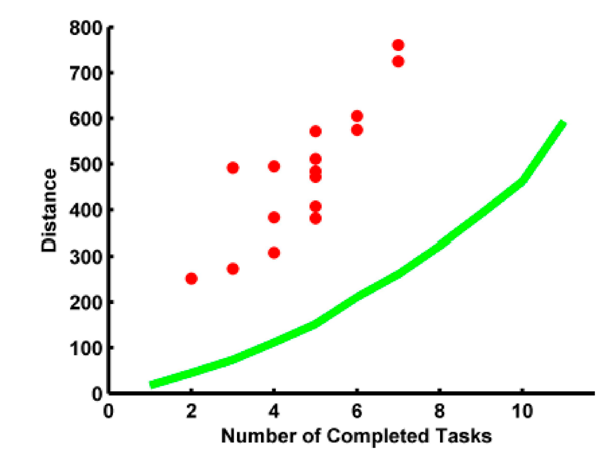
A multi-objective multi-robot coalition formation optimization scenario for 15 robots and 5 tasks placed on a 2-dimensional grid

Performance Evaluation

Hardware Specification
GPU : NVIDIA Tesla S2050
CPU: Intel Pentium 4, 3Ghz

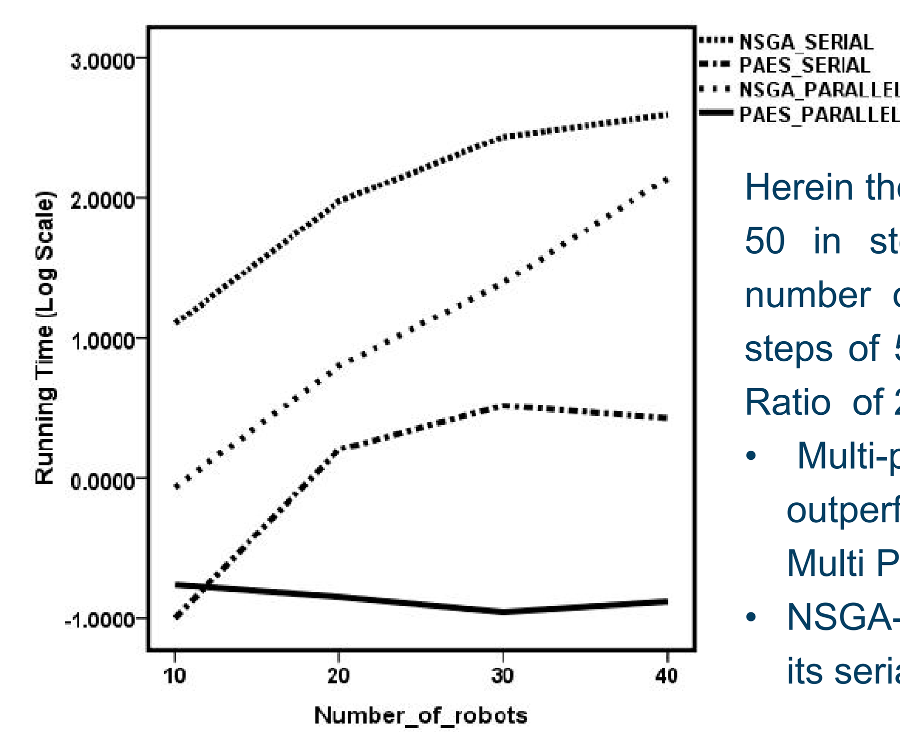


NSGA II Parallel



Multi Point PAES Parallel

A Comparative study of spread obtained by Multi – point PAES Parallel & NSGA –II Parallel on the bi-objective coalition formation problem for 30 robots and 15 tasks.



Variation of time with problem size

Herein the number of Robot are varied from 10 to 50 in steps of 10 while their corresponding number of tasks were varied from 5 to 25 in steps of 5 maintaining a constant Robot to Task Ratio of 2:1

- Multi-point PAES Parallel run on GPU outperforms NSGA – II , NSGA-II parallel & Multi Point PAES
- NSGA-II Parallel is comparatively faster than its serial counterpart

Conclusion & Future Work

- Parallelized novel variant of PAES, Multi –point PAES performs significantly faster on a GPU in comparison to its serial counterpart on CPU with a speed up varying from 1.36 time to 134.56 times
- NSGA II owing to its heavy computing overhead was outperformed even by PAES Serial, nevertheless it was faster than its serial counterpart
- Solution multi-point PAES algorithm exhibited greater diversity than all the other algorithms

Future Work involves development of fully distributed , fault tolerant version of the algorithm for the multi-objective robot coalition formation problem

References

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- J. D. Knowles and D. W. Corne. The Pareto archived evolution strategy: A new baseline algorithm for Pareto multiobjective optimization. In *Congress on Evolutionary Computation (CEC99)*, volume 1, pages 98{105, Piscataway, NJ, 1999. IEEE Press.