Landscape-Aware Approach for Radar Network Configuration

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1 Background

Real-world optimization problems are often too complex to be analytically described. In order to optimize these kinds of problems, one typically relies on *Black-Box Optimization* where a simulator outputs the value of the fitness function $f(x)$ given a candidate solution x.

Over last decades, many heuristic solvers were developed to solve this sort of problems and continue to be designed, mainly because no algorithm can perform better over all the different problems [7]. Therefore, when facing a new optimization problem, insights on its characteristics can be highly useful to select the appropriate algorithm and a suitable instantiation of its parameters.

The measured structure of an objective function is called its *fitness landscape*. During the last years, many indicators have been developed with the aim of gaining knowledge over the landscapes of objective functions. These numerical indicators are referred as *landscape features* and their design and analysis is the subject of *Exploratory Landscape Analysis (ELA)* [3]. Selecting an algorithm using ELA is referred as *Landscape-Aware Algorithm Selection* [2].

Landscape-aware algorithm selection is at the boundary between black-box optimization and Machine Learning. Its aim is to learn the mapping between the landscape features measures and the performances of algorithms.

If landscape-aware algorithm selection has been already successfully used for both combinatorial [8] and continuous [1] benchmark problems, we investigate in this work this approach on a continuous radar network placement problem.

Figure 1 regroups all the steps needed in order to perform a landscape-aware algorithm selection procedure. It is divided into two distinct parts. A *Learn* part which correspond to the upstream phase where the selector is built and a *Run* part where the selector is actually used to solve an unknown instance of the problem.

2 Contributions

We explain in this work how to perform a landscape-aware approach and actually perform it on a radar network configuration example with a portfolio composed of 15 algorithms: 10 variants of CMA-ES [5], scipy algorithms [6] (version 1.5.4) and a PSO [4].

The approach was tested on a radar network placement problem composed of 4 radars for 153 different Digital Elevation Models (DEM). For each radars, 3 to 4 parameters were involved

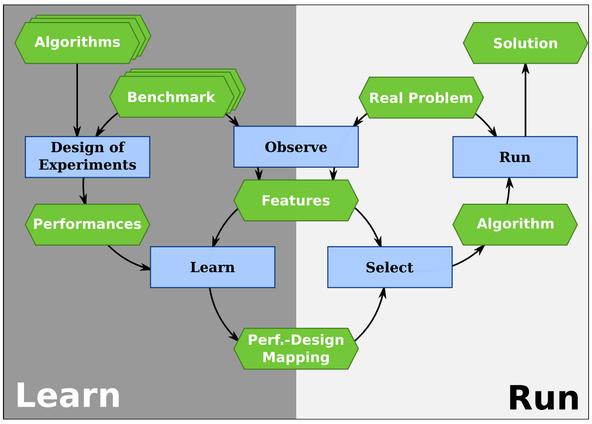

FIG. 1: Landscape-aware algorithm selection pipeline

such as their position x, y, their staring angle and the tilt, i.e. the angle between the horizontal plane and the antenna axis. Hence, the dimension of the problem is $d = 15$.

In this work, we show that landscape features can help distinguish between different instances of the radar network configuration problem even with very low sample budget i.e. $n = 750$ search points in dimension $d = 15$.

Moreover, we show that different algorithms from our portfolio are performing best on different instances, hence a landscape-aware approach to solve this optimization problem seems well suited. Hence a selector is designed using Machine Learning tools to map the information of the features with the best algorithms over the instances. This selector shows promising results compared to a static choice of algorithm.

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