Bayesian optimization to enhance coverage performance of a swarm of UAV with chaotic dynamics

Emmanuel Kieffer[1], Martin Rosalie[1], Grégoire Danoy[2], and Pascal Bouvry[2]

[1] Interdisciplinary Centre for Security, Reliability, and Trust, University of Luxembourg
6, Avenue de la Fonte, L-4364 Esch-sur-Alzette
emmanuel.kieffer@uni.lu,martin.rosalie@uni.lu
[2] CSC Research Unit, University of Luxembourg
6, Avenue de la Fonte, L-4364 Esch-sur-Alzette
gregoire.danoy@uni.lu, pascal.bouvry@uni.lu

1 Introduction

We recently propose a mobility model of a swarm of UAVs whose purpose is to cover an unknown area: CACOC (Chaotic Ant Colony Optimization to Coverage) [3]. Our algorithm is based on Ant Colony Optimization where chaotic dynamics are used to enhance the exploration part of the algorithm. CACOC mobility model uses repulsive pheromones to guide the UAVs over the area they have to cover. The UAVs share a map of virtual pheromones that indicates recently visited areas when high pheromone concentrations are present. The UAVs then have a higher probability to move to the least recently visited areas. When there is no pheromone to guide the UAVs, the introduction of chaotic dynamics permits to obtain an efficient exploration of the unknown area. Since the chaotic dynamics are obtained from a three differential equations system with parameters, we can tune one parameter to obtain another chaotic dynamic. The aim of this work consists in discovering a chaotic dynamic leading to the best coverage which can be only computed after a CACOC simulation. For this purpose, we consider Bayesian Optimization which has been originally designed for time-consuming black-box optimization. Indeed in order to evaluate the chaotic dynamic for a specific parameter, a full simulation should be realized. S Global optimization techniques (e.g. population-based heuristics) could be very time-consuming contrary to a surrogate model which would minimize the number of simulations to perform to determine the best parameter of the chaotic system. The next section will first introduce the Rossler system and its chaotic system. Section 3 describes how the chaotic system of CACOC has been optimized using Bayesian Optimization. Finally, we will conclude and discuss future works.

2 Chaotic dynamics of the Rössler system

We used the Rössler system [4] with a parametrization of its parameters [5]

$$\begin{cases} \dot{x} = -y - z \\ \dot{y} = x + ay \\ \dot{z} = b + z(x - c)\ , \end{cases} \quad \text{where} \quad \begin{cases} a = 0.2 + 0.09\alpha \\ b = 0.2 - 0.06\alpha \\ c = 5.7 - 1.18\alpha\ . \end{cases} \tag{1}$$

We already provide a detailed analysis of the chaotic dynamics that can be obtained by varying the parameter α [6]. As a chaotic dynamic is a solution of a deterministic process, the periodic orbits of attractors are used to describe the topological structure of chaotic attractors. We used these periodic orbits to obtain recurrent pattern in our exploratory movement. In our original method [3], we found three patterns: straight lines (period 1 orbit), large turns (period 2 orbit) and serpentine patterns (period 4 orbit) when $\alpha = -0.25$.

For $\alpha \in [-0.8; 0.4]$ we know that the global dynamic is only composed by an increasing branch followed by a decreasing branch. However, when α varies, the orbits are not the same. For instance, this can lead to the apparition of a new orbit of period four, itself leading to a pattern with very large turn. This can be instead of the serpentine pattern or in addition. As it is fastidious to explore all the periodic orbits changes when α varies for this range of values, we choose to use Bayesian optimization to find out the best α for CACOC. We used a metric developed to evaluate CACOC: the slope of coverage. It permits to evaluate how the 10 UAVs spread on the area and then, how they manage to visit unvisited area. For a given simulation, the percentage of covered area is ploted against the number of steps, the slope of coverage is the linear regression of this percentage over the number of step: the higher the value, the best it is.

3 Bayesian optimization

Bayesian optimization belongs to surrogate-based optimization algorithms. It has been originally designed to tackle black-box optimization problems where the evaluation of a solution could be very time-consuming. Indeed, many optimization problems do not have a formal mathematical expression because it is either unknown or difficult to obtain. To cope with such issues and minimize the number of evaluations, a surrogate model based on Gaussian processes [2] is created to approximate the unknown objective function. Bayesian optimization samples promising zones in the feasible region by computing a distribution of the objective function. This distribution give us a prior knowledge on location of the optimal solution. Bayesian optimization is thus characterized by a probability measure on F describing our prior beliefs on F as well as an acquisition function which allows to gain information on the location of the minimum value of the objective function. It has been succesfulluy used to tackle bi-level optimization problems (cite Manu) to reduce dramatically the number of evaluation of the objective function while providing accurate solution values. In this work, the objective function, i.e. coverage cannot be formally described and a simulation has to be run to measure the influence of the α parameter on the chaotic dynamic. Therefore, we attempt to create a surrogate model using Gaussian process which will be refined until no improving $alpha$ can be obtained. Due to the non-linearity of the problem, we consider the Matern32 kernel to define the covariance matrix of the Gaussian processes. Promising area are sample using the optimization of the Lower Confidence Bounds acquisition function.

4 Conclusion

In this work, we introduced the optimization of CACOC through Bayesian Optimization. CACOC is based on a chaotic system, i.e. Rossler system whose behavior can be modified by tuning the α parameter. In order to evaluate the performance of CACOC for different value of α, the coverage metric has to be evaluated after simulation. The latter is time-consuming. Therefore, a surrogate-based optimization, i.e. Bayesian Optimization has been privilegied to tackle this issue. Experiments have been conducted on the High Performance Computing (HPC) platform of the university of Luxembourg [7]. An analysis of the chaotic system with the obtained α value has been performed to compare the periodic orbits and their associated patterns. Numerical results show that the best α value avoid a waste of time in periodic region of the bifurcation diagram. Future works will focus on more complex chaotic system as well as new application domain of the optimized CACOC approach.

References

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