Falsification of Cyber-Physical Systems Through Multi-Fidelity Stochastic Optimization

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ABSTRACT

This talk will review some recent results on requirements driven search-based testing for Cyber-Physical Systems (CPS). Namely, we will present an extension to a Bayesian optimizer that makes use of models of different complexity (and accuracy) that allow obtaining several approximations of the guiding cost function. The goal of the method is to enable falsification of computationally expensive simulation models through the use of simpler but much faster simulation models.

CCS CONCEPTS

• **Computer systems organization** → **Embedded systems**; **Redundancy**; **Robotics**.

KEYWORDS

optimization, cyber-physical systems, testing, falsification

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1 INTRODUCTION & MOTIVATION

This work is in the field of requirements driven search-based test case generation methods for Cyber-Physical Systems (CPS) [1]. The basic characteristic of search-based testing methods is that the search process is guided by high level requirements captured in formal logic and, in particular, Signal Temporal Logic (STL) [2]. Given a system trajectory, STL specifications can be equipped with quantitative semantics which evaluate to the distance of the given trajectory from violating the requirement. Hence, by searching for trajectories of decreasing value with respect to the specification, a test generation method can be formulated which searches for system behaviors of value 0. Such system behaviors, i.e., trajectories that violate the requirements, are referred to as *falsifying* behaviors. In

addition, signed distance can be utilized when searching for trajectories that maximally violate the specification (negative specification valuations). In this work, we present a novel approach that mixes global and local search for improving finite time performance, i.e., quickly identifying falsification inputs.

2 PROPOSED METHOD

In our preliminary work [4], we have developed a first extension of a Bayesian optimizer that makes use of models of different complexity (and accuracy) that allow to obtain several approximations of the STL robustness function $R_\varphi(\mathbf{x})$ [2, 3]. A multi-fidelity sampler attempts to find the minimizer of the robustness function:

$$\mathbf{x}^* \in \arg \min_{\mathbf{x} \in \mathbb{X}} R_\varphi(\mathbf{x}) \quad (1)$$

where $\mathbb{X}$ represents the input/parameter search for the CPS. In order to solve the general problem in equation (1), we have access to an approximate model of the original system that leads to an inaccurate robustness function. We denote this inaccurate function as $R_\varphi^\ell(\mathbf{x})$ which has a lower associated computational cost when compared to $R_\varphi(\mathbf{x})$. The aim is to use the information obtained from sampling within the low-fidelity space to guide the search towards the global optimum of the high-fidelity function $R_\varphi(\mathbf{x})$. We propose a statistical approach to construct a learning structure link between $R_\varphi^\ell(\mathbf{x})$ and $R_\varphi(\mathbf{x})$. Formally:

$$R_\varphi(\mathbf{x}; \boldsymbol{\theta}_{HF}) = R_\varphi^\ell(M(\mathbf{x}; \boldsymbol{\theta}_M); \boldsymbol{\theta}_{LF}) + B(\mathbf{x}; \boldsymbol{\theta}_B), \mathbf{x} \in X. \quad (2)$$

Under our proposal, R_φ^ℓ and R_φ are both interpreted as realizations of Gaussian processes with $\boldsymbol{\theta}_{LF}$ and $\boldsymbol{\theta}_B$ being the corresponding hyper-parameters [4, 6]. $M(\mathbf{x}; \boldsymbol{\theta}_M)$ represents a general mapping function from the low-fidelity solution space to the high-fidelity solution space that can help in increasing the similarity between low and high-fidelity models with $\boldsymbol{\theta}_M$ being the set of mapping parameters.

The relationship between the approximate and exact robustness function allows to exchange information between the search in low and high fidelity. In particular, we proceed iterating using the low accuracy model which sequentially proposes low accuracy candidates, $\mathbf{x}_k^{\ell,*} \in \arg \min_{\mathbf{x} \in \mathbb{X}^\ell} R_\varphi^\ell(\mathbf{x})$. It is important to highlight that using low fidelity information is convenient in sampling since the low fidelity model may be “easier to optimize” and to sample. As an example, we may use random projections and convexification to generate low accuracy representations for the robustness function and quickly produce low accuracy proposals of the type in Eq. (2). But how long can we run the algorithm using $R_\varphi^\ell(\mathbf{x})$? We devised a

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statistical certificate of the relationship between the low and high-fidelity models.

For the candidate point at iteration k , $\mathbf{x}_k^*$, we want to certify the validity of our model in Eq. (2) representing the relationship we constructed between low and high-fidelity models. A statistical test can be constructed of the form:

$$H_0 : \hat{R}_\varphi^\ell(\mathbf{x}_k^*) \sim \mathcal{N}(\mu_\ell(\mathbf{x}_k^*), \sigma_\ell(\mathbf{x}_k^*)) \quad (3)$$

$$Q \equiv \frac{R^\ell(\mathbf{x}_k^*) - \mu_\ell(\mathbf{x}_k^*)}{\sigma_\ell(\mathbf{x}_k^*)} \quad (4)$$

where $\mu_\ell(\mathbf{x}_k^*)$ is obtained using the high fidelity information. Intuitively, the test statistics in equation (4) uses the conditional density of the low fidelity function predicted by the high accuracy robustness to detect whether there has been a change in the assumed model parameters. If the test fails, it means we need to perform expensive high accuracy iterations. In our first empirical evaluation, we observed that calls to the high-fidelity oracle are most likely to happen at the beginning of the procedure and they reduce as the algorithm progresses.

3 PRELIMINARY RESULTS

To demonstrate the performance of the approach, we considered the cost functions from [7], with $\mathbf{x}_i \in (0, 1)$:

$$R_\varphi(\mathbf{x}) = -2.5 \prod_{i=1}^d \sin(\pi x_i) - \prod_{i=1}^d \sin(5\pi x_i), \quad (5)$$

$$R_\varphi^\ell(\mathbf{x}) = -2 \prod_{i=1}^d \sin(\pi(x_i - b)/a_i) \quad (6)$$

To evaluate the performance of the proposed method, we considered problems with $d = 3, 6, 9, 12$ decision variables and $i = 1, 2, \dots, 5$ different randomly generated values for a_i and b_i . For each combination of problem size and mapping parameters, 50 macro replications each with a different seed was conducted. The same set of seed values was used to run Efficient Global Optimization (EGO) [5] and the proposed algorithm. The objective is to compare the performance of the algorithm with that of EGO [5] – a state of the art Bayesian optimizer – and to compare the optimality gap achieved upon termination of the algorithm, i.e., $\frac{|\hat{R}_\varphi^* - R_\varphi^*|}{|R_\varphi^*|}$ where R_φ^* is the global optimum of the high-fidelity objective and $\hat{R}_\varphi^*$ is the solution reported by the algorithm upon completion.

Figures 1a-1b show the average optimality gap estimated across 50 macro-replications of the algorithm as a function of the number of high-fidelity estimations performed by the procedure, for the cases in 9 and 12 dimensions. The approach is very promising and, especially for low number of iterations, our approach is orders of magnitude better than the benchmark EGO.

4 CONCLUSIONS AND DEVELOPMENTS

Using low fidelity information to guide the search towards the optimum of an expensive high-fidelity model in a multi-fidelity optimization framework is an issue that recently has

(a) $d = 9$

(b) $d = 12$

Figure 1: Analysis of Average optimality gap for different dimensions (1a-1b)

attracted much interest in the verification community. In this paper, we introduce a sampler that uses a cheap low fidelity model and uses space mapping to reconcile the information from the low and high fidelity model. We are working on the extension of the framework to different mappings and to enable the automatic generation of low fidelity models.

5 ACKNOWLEDGMENTS

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