Optimal Input Shaper Tuning Using Constrained Bayesian Optimization in Industrial Robot Systems

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ABSTRACT

1 Introduction

In this article, we propose a data-driven parameter tuning method for industrial robot systems with input shapers. The demand for high-speed and high-acceleration in pick-and-place (PaP) tasks, has made residual vibrations increasingly severe, negatively affecting the working accuracy of industrial robots. The input shaping technique, as an active vibration suppression technology, can effectively mitigate residual vibrations without altering existing control systems or requiring additional materials, making it particularly suitable for commercial industrial robots with unchangeable controllers.

Although input shapers have been proven effective for residual vibration suppression, their performance heavily depends on the dynamic characteristics of robot systems, i.e., natural frequencies and damping ratios. However, accurately determining these dynamic characteristics is nearly impossible, whether through numerical modelling or experiments. Furthermore, the natural frequencies of robot systems are functions of configurations of robots [1], which indicates that simply using the natural frequency of a specific configuration to design an input shaper cannot guarantee optimal performance across motions. While input shapers can reduce residual vibrations, they also lead to trajectory deformation. Although trajectory shape is less critical than positioning accuracy in PaP tasks, trajectory deformation may cause robots to encounter singularities or exceed their workspace limits, especially when the trajectory traverses some sensitive positions [2]. Therefore, designing an optimal input shaper that can not only attenuate residual vibration but also adhere to constraints on trajectory deformation is of significant practical importance.

Compared to designing input shapers by theoretical metrics, data-based metrics provide a more effective and accurate reflection of the real-world performance and conditions of robot systems. These metrics also imply that the optimization objectives are unknown, leading to a black-box optimization problem. Bayesian optimization (BO) is a data-driven, model-free approach that efficiently identifies the globally optimal design variables within relatively few experiments, where the unknown optimization objectives are represented by a surrogate model usually Gaussian process regression (GPR) [3]. BO has been applied in various fields, including controller tuning, hyperparameter optimization, parameter optimization of robots, etc. [4] proposed a sample-efficient joint tuning algorithm for a contour control system using BO, which can enable a trade-off between tracking accuracy, vibration and traversal time. [5] presented a model-free, data-driven parameter tuning method for a PID cascade controller by constrained Bayesian optimization (CBO), where a barrier-like term was introduced into the objective to guarantee safety requirements. BO leverages an acquisition function to determine the next evaluation point, where the acquisition function enables a trade-off between exploitation and exploration [6].

We propose a data-driven parameter tuning approach for input shapers in industrial robot systems performing PaP tasks, aiming to attenuate residual vibrations and improve positioning accuracy. This approach leverages a data-based metric to reflect the actual residual vibrations in the systems. We introduce a constraint to restrict the trajectory deformation. We use GPR to model both the metric and the constraint. We conduct a series of high-fidelity simulations to prove the performance of the proposed auto-tuning method.

2 Main Results

The residual vibration suppression performance of input shapers depends on the design parameters $\theta := [f_n, \xi, k_t]^T \in \Theta \subset \mathbb{R}^3$, where Θ is the feasible set to be predefined,. f_n and ξ denote the natural frequency and damping ratio, respectively. k_t is a parameter related to the time lag of the impulse sequence. These parameters also determine the degree of trajectory deformation. Therefore, we encode an optimization problem with constraints to achieve a trade-off between the residual vibration suppression and trajectory deformation as follows: $\min_{\theta\in\Theta}\ f(\theta)$ and s.t. $g(\theta) \leq q_m$,, where $f(\theta)$ represents the optimization objective that reflects the residual vibration, while $g(\theta)$ is the constraint function that reflects trajectory deformation. q_m is the maximum trajectory deformation defined by users. Data measured by sensors usually contains noise, hence, we assume that the real metric is defined as $f(\theta) = \bar{f}(\theta) + \varepsilon$, where $\varepsilon \sim N(0, \sigma_\varepsilon^2)$ is the measurement noise with zero mean and variance σ_ε^2.

The simulation is conducted by Simscape. The Delta robot is required to operate a PaP trajectory, where the total time of the reference trajectory is 0.8s and the total time of the simulation is set to be 1.2 s. The sampling time is chosen as $dt = 0.001$s. The performance metric is defined as follows $\bar{f}(\theta) = \sqrt{\frac{1}{m}\sum_{i=1}^{m}||a_{rv,i}||^2}$, where $a_{rv,i} \in \mathbb{R}^3$, $i = 1, 2, \cdots, m$ denotes the acceleration vector of residual vibrations at sampling time $t = idt$ after the trajectory is finished. The standard deviation is selected as $\sigma_\varepsilon = 0.001$. m is set to be 100 in this article. The constraint is defined as the difference between the reference trajectory and the trajectory after the input shaper, i.e., $g(\theta) = \sqrt{\frac{1}{\varpi}\sum_{i=1}^{\varpi}||q_{s,i} - q_{r,i}||^2}$, where ϖ denotes the total number of sampling points. $q_{r,i}$ and $q_{s,i}$ are the original reference trajectory and the trajectory after input shapers at ith sampling point, respectively.

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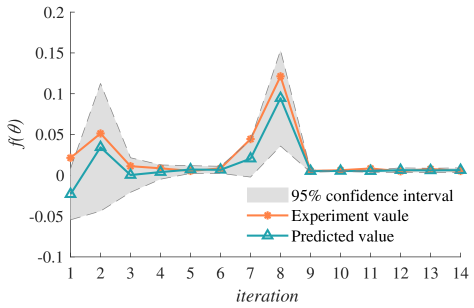

Figure 1: The predicted mean and experimental values over iterations.

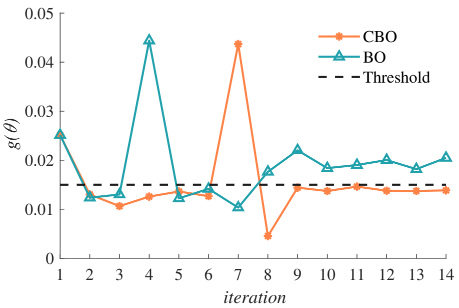

Figure 2: Constraints over iterations for two methods.

We use the constrained *Expected Improvement* (EI) acquisition function to determine the next point to be evaluated [4]. In order to stop the iteration timely, a stopping criterion is necessary during the real experiment. In addition to setting a fixed number of iterations, motivated by [5], we introduce the following criterion $a_{CEI,i} \leq \eta \max_{i \leq \kappa-1} a_{CEI,i} \quad i = \kappa, \kappa+1, \kappa+2$, where $\kappa \geq 2$ denotes κth iteration, and η is a positive threshold. The above inequality implies that once consecutive three expected improvements cannot improve the performance metric effectively compared to all previous iterations, we terminate the optimization process timely. We use consecutive three iterations instead of one to prevent premature termination before finding the optimal value due to a single error. Here, we select η as $\eta = 0.02$.

Fig. 1 illustrates the convergence of the CBO algorithm and the variance of the constrained EI maximum at each iteration. In this case, we set the initial data set to contain 5 experiments. The variance is relatively large at the beginning, because GPR lacks sufficient information for accurate predictions with high confidence. This also explains why the initial prediction is less than zero, which is obviously unreasonable. As the tuning process converges, the predicted mean closely aligns with the experiment value, which demonstrates the accuracy and effectiveness of the GPR model after accumulating enough information. The experiment value increases and decreases twice during the entire optimization process, and then converges to the optimum from 9th iteration. The optimal parameters that can minimize the performance metric and not violate the constraints are found at 12th iteration. At the same time, starting from 12th iteration, the following three consecutive constrained EIs meet the stopping criterion. Although the constrained EI also satisfies the threshold at 10th iteration as well, the optimization process continues thanks to the stopping criterion. The experiment value at 8th iteration deviates from the optimum to a large degree, likely because the constrained EI adopts a set of parameters with more exploration information.

The change in constraints $g(\theta)$ throughout the tuning process is illustrated in Fig. 2, where the results of normal BO with EI are introduced for comparison. It can be found that although we use the constrained EI as acquisition function, the constraint is not always satisfied during the tuning process. Note that the principle of constrained EI is to increase the expected improvement in regions where the constraint has a high probability of being satisfied, and reduce the expected improvement in the other regions, which means it is affected by performance of the GPR model for constraints. As the tuning process converges, the results of CBO are close to the boundary of the constraint without exceeding it. On the contrary, standard BO with EI fails to meet the constraint requirements.

Acknowledgments

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