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Automated Tuning of Closed-loop Neuromodulation Control Systems using Bayesian Optimization

Parisa Sarikhani[1], Hao-Lun Hsu[2], and Babak Mahmoudi, Member IEEE[3]

Abstract— **Tuning the parameters of controllers to attain the best performance is a challenging task in designing effective closed-loop neuromodulation systems. In this paper, we present a distributed architecture for automated tuning and adaptation of closed-loop neuromodulation control systems. We use this approach for the automated parameter tuning of a Proportional-Integral (PI) neuromodulation controller using Bayesian optimization. We use a biophysically-grounded mean-field model of neural populations under electrical stimulation as a simulation environment for testing and prototyping the proposed framework and characterizing its performance. Our results demonstrate the feasibility of using Bayesian optimization for performance-based automated tuning of a PI controller in closed-loop set-point neuromodulation control tasks.**

I. INTRODUCTION

Deep Brain Stimulation (DBS) has become an standard approach with remarkable clinical benefits for patients with neurological disorders [1]. Unlike pharmacological interventions that affect the brain and other organs globally, DBS modulates the functionality of the brain circuits locally through delivering electrical, optical or magnetic stimulation to the targeted brain regions to regulate or to induce desired patterns of neural activity. Current DBS systems provides the opportunity of considerable customization of stimulation parameters to achieve the desired effect. Hence, a systematic approach is required for optimal programming of DBS systems. Most of the current neuromodulation experiments and clinical DBS approaches are delivered in an open-loop manner. It has been widely shown that closed-loop neuromodulation approaches provide superior performance [2], however, the complexities of interacting with the nervous system pose challenges for optimal design of closed-loop neuromodulation controllers.

Proportional integral (PI) controller is a common control strategy for closed-loop control. PI controller has a simple structure with easy implementation and low computational complexity which makes it suitable for many real-world applications including process control [3], robotics manipulations [4], and biomedical applications [5] - [7]. PI controllers have been used for adapting DBS parameters in computational models of Parkinson's disease [6] and [7]. Due to their low computational complexities, low latency, and simple architecture, PI controllers are suitable for implantable devices.

While the core concept of PI controller is straightforward, the controller design with optimal parameter settings requires technical expertise and understanding the system under control. To improve the performance of PI controller, various methods has been developed for tuning its parameters. Some of the classical tuning methods include trial and error, Ziegler–Nichols step response method [8], and Ziegler–Nichols frequency response method [9]. However, classical tuning methods are limited to a few classes of plant models. In addition, due to the their underlying assumptions, their performance might degrade with minor changes in the neural dynamics. More intelligent tuning methods like self-tuning PID controllers [10] and tuning of PID controllers using genetic algorithms [11] has emerged. We refer the reader for a comprehensive review of PID controller tuning methods and applications to read [12]. Although these methods have shown successful results in tuning PI controllers, many of these methods require exhaustive open-loop testing or having access to the underlying equations of the plant model, which is not practical in many real-case applications. Moreover, if the system dynamics change the controller parameters need to be re-tuned.

A newer paradigm for tuning the PI controllers is to use machine learning and optimization algorithms. Bayesian optimization has been used for automated tuning of PI controller parameters in a few applications including a high pressure fuel supply system [13] or in an industrial control study [14]. Bayesian optimization is an effective sample-efficient algorithm that is suitable for the situations that the objective function is unknown or expensive to evaluate [15]. Here, we propose a distributed architecture for automated tuning of neuromodulation control systems, where we deploy Bayesian optimization for data-driven and automated tuning of PI controller for DBS. To the best of our knowledge, the proposed framework has not been investigated for applications of automated tuning of DBS control policies. We introduce a distributed architecture which enables integrating the framework in DBS implantable devices, where the PI controller will be implemented on the DBS implantable devices due to its low computational cost. Bayesian optimization will be implemented in a distributed fashion (could be on an external computer, cloud computing resources, or other resources other than the implantable device) to tune the performance of PI controller. We design a performance-based objective function for tuning PI controller using Bayesian optimization. We further employ a biophysically grounded

[1]P. Sarikhani is with the Department of Biomedical Informatic at Emory University, Atlanta, Georgia, 30322, psarikh@emory.edu

[2]H. Hsu is with the Department of Biomedical Engineering and School of Computational Science and Engineering at Georgia Institute of Technology, Atlanta, GA 30332, USA hhsu61@gatech.edu

[3]B. Mahmoudi, is with the Departments of Biomedical Informatics and Biomedical Engineering at Emory University and Georgia Institute of Technology, Atlanta, GA 30322, USA. b.mahmoudi@emory.edu

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mean-field model of neural populations under electrical stimulation [16] to create a closed-loop simulation environment for investigating the performance of PI controller with automated parameter tuning to induce a desired frequency set-point of the neural population oscillatory activities.

II. Methods

A graphical overview of the proposed distributed adaptive closed-loop neuromodulation framework is shown in Fig. 1, where PI controller is used for performing the neuromodulation task in the inner loop and Bayesian optimization is used for automated tuning of the PI controller parameters based on its performance in the outer loop. More detailed explanations of each module is provided in the following.

A. Biophysically-grounded mean-field model of neural populations under electrical stimulation

Authors in [16] presented a biophysically grounded mean-field model of neural populations under electrical stimulation which is a reduced mean-field model of excitatory and inhibitory adaptive exponential integrate-and-fire (AdEx) neurons and can be used to efficiently study the effects of electrical stimulation on large neural populations.

In [16], authors varied the amplitude and frequency of external electrical stimuli to study the frequency-dependent response of the interactions between the stimulus and the endogenous oscillations of the excitatory-inhibitory system. It has been shown that for weak fields with field strengths in the order of 1.5 V/m, the external stimulus entrains the ongoing oscillation in a range around endogenous frequency of the system. However, slightly stronger oscillatory input currents can entrain the ongoing oscillations for a considerably wider range of frequencies including the external frequency, its harmonics and subharmonics, and its interactions with the endogenous frequency of the neural population.

This model provides a safe and resource-efficient simulation environment for designing and prototyping control algorithms in a closed-loop neuromodulation system. This mean-field model has been shown to simulate neural population activities/dynamics that are compatible with in-vivo/vitro experimental studies which supports the translatability of this in-silico environment to in-vivo experimental setups. We employed the model of neural population activity under electrical stimulation to evaluate the performance of PI controller in modulating a set-point oscillatory frequency in neural population activity. We fixed the stimulation amplitude to a strong input current, i.e. $100pA$ and let the PI controller to tune the frequency of external stimuli with the goal of entraining the ongoing oscillation to a set-point frequency. We filtered the output signal of the model in response to the external stimuli with a highpass filter to remove the DC component and the transient effects of stimuli and then applied Fast Fourier Transform (FFT) on the filtered signal to calculate its spectrum and detect the dominant frequency of oscillations which is the frequency at which the signal has the highest power.

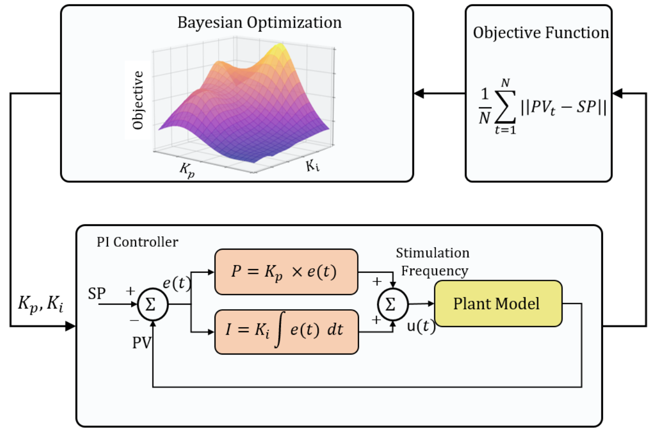

Fig. 1: Overview of the distributed closed-loop neuromodulation framework with automated tuning of the PI controller using Bayesian optimization.

B. PI Controller

The PI controller is a feedback control system which is widely used due to its simple structure and easy implementation. The PI controller is described by:

$$u(t) = K(e(t) + \frac{1}{T_i}\int_0^t e(t)\, dt) = K_p e(t) + K_i \int_0^t e(t)\, dt, \quad (1)$$

where $u(t)$ is the control signal, $y(t)$ is the measured variable also called the process variable (PV), $r(t)$ is the reference variable, also called set-point (SP), $e(t)$ is the control error ($e(t) = r(t) - y(t)$), and T_i is the integral time constant. K_p and K_i are the controller parameters which can be tuned to get optimized control actions. PI controller can be represented with two gains, where the proportional gain is $K_p = K$ and the integral gain is $K_i = \frac{K}{T_i}$. The control signal is the sum of two control terms which is the input to a plant. A plant is a system or a environment which is controlled by a controller. Running a negative feedback system via a PI controller can adjust the current process variable to meet the value of set point. The proportional gain K_p determines the ratio of control signal to the error. In pure proportional control with $T_i = \infty$, the error can be decreased with increasing K_p, indicating increasing the speed of the control response. However, the current process variable often deviates from its set point, which can be avoided by adding the integral action. Since the integral component sums the error over time, the integral response will continually increase unless the steady state error is zero.

Here, we use the mean-field model of neural population under electrical stimulation as the plant model, where the process variable is the dominant ongoing frequency of oscillations, as described in the previous section, and the control signal is a Sinusoidal signal defined with a fixed amplitude and a frequency determined by the PI controller. Set-point is the desired dominant frequency of neural population activity. PI controller interacts with the plant model by adjusting the frequency of external stimuli to modulate the set-point frequency in neural population activity. We used Bayesian optimization for automated tuning of the PI controller parameters described in the following section.

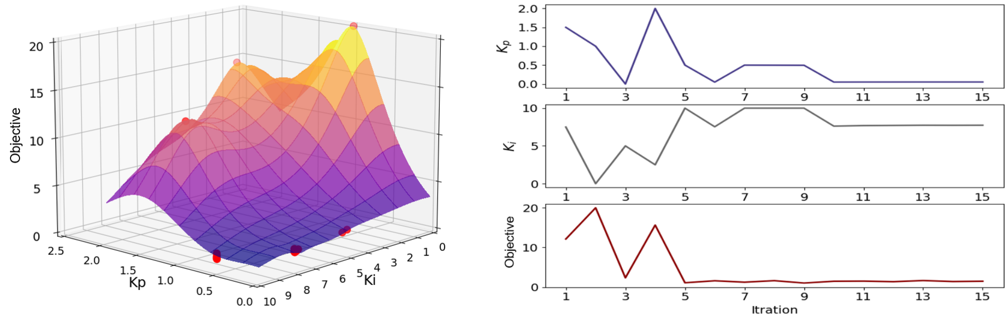

Fig. 2: Performance of Bayesian optimization in automated tuning of PI controller. The figure on the left shows the mean surface of the surrogate GP model showing the objective of Bayesian optimization for different values of K_p and K_i parameters. The red circles shows the collected samples proposed by Bayesian optimization. The Right figure shows the trajectory of selected parameters and the objective value of Bayesian optimization for 15 iterations.

C. Bayesian Optimization for automated tuning of PI controller parameters

Bayesian optimization is a global optimization algorithm, which is a well-known algorithm for optimizing objective functions that are unknown or expensive to evaluate. Bayesian optimization is a sequential algorithm that searches for the optima in a two-step process. First, it builds a surrogate model based on the collected data. Second, it suggests the next candidate points to be evaluated by optimizing an underlying acquisition function. We used Gaussian process (GP) model with matern kernel as the surrogate model [17]. GPs have been widely used as an efficient surrogate model for Bayesian optimization as they are considerably data-efficient and take the uncertainty of the observations into account. We deployed the popular Upper Confidence Bound (UCB) acquisition function to suggest the next best set of (K_p, K_i) parameters. UCB has the following form

$$\alpha_{GP-UCB} = \mu(x) + \beta\sigma(x), \tag{2}$$

where $\mu(x)$ is the mean, $\sigma(x)$ is the covariance function of the surrogate GP model, and β is used to trade off exploration against exploitation and is a tuning parameter. Algorithm 1 describes the pseudocode for Bayesian optimization.

Algorithm 1 Bayesian optimization

Collect initial measurements $D_0 = \{(x_i, y_i), i = 1, ..., n_0\}$.
for $n = n_0 + 1, ..., n$ **do**
  Update the surrogate GP model.
  Select the next point $x_n + 1$ by optimizing the surrogate-dependent acquisition function α:

$$x_{n+1} = argmax_x \alpha(x; D_n)$$

  Query the objective function to evaluate y_{n+1}.
  Augment data $D_{n+1} = \{D_n, (x_{n+1}, y_{n+1})\}$.
end

We employed Bayesian optimization to automatically tune the PI controller's parameters. We used the following objective function to tune the PI controller parameters over a time horizon N

$$f(K_p, K_i) = \frac{1}{N}\sum_{t=1}^{N} \|PV_t - SP\|, \tag{3}$$

where PV_t is the process variable, i.e. the dominant ongoing frequency in the model's output and SP is the set-point frequency. PI controller starts with randomly selected parameters, i.e. K_p and K_i, to control the dominant ongoing frequency of the neural population for N time steps. Then we calculate the objective function as in equation 3 and use Bayesian optimization to suggest the next best set of (K_p, K_i) parameters to tune the PI controllers' performance.

III. Results

We evaluated the performance of PI controller in frequency modulation to entrain the dominant frequency of neural oscillations to a specific set-point. Performance of PI controller heavily depends on the proportional and integral gains, i.e. K_p and K_i. Tuning these parameters is a difficult task especially in real-word scenarios as it requires exhaustive open-loop testing or having access to the underlying equations of the plant model which is not possible in many cases. We investigated the utility of Bayesian optimization for automated tuning of the PI controller parameters as the controller interacts with a mean-field model of the neural populations and demonstrate the feasibility of incorporating this framework in controlling the ongoing neural oscillations frequency using electrical stimulation.

PI controller starts with five sets of randomly selected parameters, i.e. (K_p, K_i) over the horizon $N = 100$. The performance of PI controller is then calculated for each set of parameters using the objective function defined in equation 2. The pairs of parameter and objective values are then fed into Bayesian optimization to suggest the next set of parameters. Fig. 2 shows the results of applying Bayesian optimization, where the right subfigure shows the trajectory of sampled K_p and K_i values suggested by Bayesian optimization as well as the objective we want to minimize for 15 iterations. The left sub-figure in Fig. 2 shows the mean surface of the surrogate GP model and red circles are the sampled parameters.

Fig. 3 shows a sample response of the PI controller with the optimized parameters determined by Bayesian optimization in a set-point tracking task. The dashed red line in Fig. 3 shows the reference trajectory of set points, where we evaluated the PI controller performance for four different set point values. The blue traces show the dominant ongoing frequency of the neural population under electrical stimulation at each iteration. The tuned PI controller is able to modulate the desired frequency of oscillations in a few iterations.

IV. Discussion

This study demonstrates the utility of our proposed framework for automated tuning of closed-loop neuromodulation control systems. We used the proposed framework for designing a PI-based set-point controller and automatically tuning the controller parameters using Bayesian optimization, as the controller interacts with the neural system. PI controllers represent a class of simple and computationally efficient algorithms that are suitable for implementation in implantable devices. However, tuning its parameters is a challenging task and may require a lot of fine-tuning for different applications or subjects. Bayesian optimization is a powerful sample-efficient global optimization algorithm. Our results show that Bayesian optimization is able to automatically tune PI controller in a few number of trials which is suitable for many real-world experiments where the objective function is unknown or expensive to evaluate. However, the downside is that it is computationally expensive. The proposed framework has a distributed architecture, where PI controller could be implemented on the DBS implantable devices and Bayesian optimization could be trained outside of the loop to tune the performance of the PI controller. We evaluated the feasibility of the proposed closed-loop neuromodulation framework using a biophysically-grounded mean field model of neural populations for a set-point control task, where the PI controller controls the dominant oscillatory activity of population of neurons. The framework is generalizable to other neuromodulation tasks. Moreover, the objective function for Bayesian optimization could be further developed to consider various design constraints such as safety and energy efficiency.

V. Conclusion

Developing automated and data-driven control strategies are crucial for designing intelligent closed-loop neuromodulation systems and improving the efficacy of neuromodulation therapies. Since the governing equations of the underlying neural dynamics in most neuromodulation control design problems are unknown, classical control design strategies may not be applicable. In this study, we presented a distributed closed-loop neuromodulation architecture for automated tuning of PI controllers for DBS using Bayesian optimization. We employed a mean-field model of neural populations under electrical stimulation to develop a simulation environment and demonstrated the feasibility of tuning a closed-loop PI controller to induce a desired neural oscillation rhythm using the proposed framework.

VI. Acknowledgment

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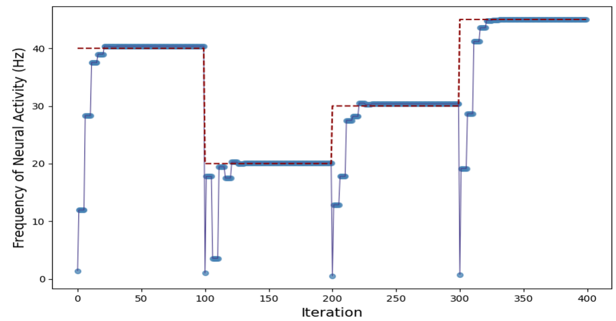

Fig. 3: Performance of set-point tracking using PI controller with the optimized parameters determined by Bayesian optimization. The blue circles show the dominant ongoing frequency of the neural population under electrical stimulation and the dashed red line shows the reference set-points.

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