Proceedings on Automation in Medical Engineering
Proc AUTOMED, Vol 2, No 1 (2023): Article Ref 722
www.journals.infinite-science.de/automed/article/view/722

Improving sleep through closed-loop autotuning of a robotic bed

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Abstract: Rocking beds that provide vestibular stimulation may be a promising alternative to conventional pharmaceutical treatments that show many side-effects. Past studies have demonstrated that the effectiveness of the vestibular stimulation is influenced by the selected rocking acceleration. Moreover, the movement must be smooth and comfortable to avoid disturbing the user's sleep. Previously, the tuning of the control parameters was done manually, which was time-consuming and did not guarantee an optimal movement of the bed. In this paper we show an efficient and effective way to automatically tune the control parameters of the bed using Gaussian processes while achieving the desired acceleration trajectory and providing a comfortable movement for the user.

I. Introduction

Vestibular stimulation (VS) is known to affect autonomic body functions such as respiration, heart rate, and blood pressure. Moreover, VS induced by a rocking bed has been shown to improve sleep architecture and sleep consolidation, shorten sleep onset time, and generate deeper sleep [1-5]. However, due to the complexity of previous rocking beds, rocking was only applied in lab settings for a few nights only. The Somnomat Casa (developed at the Sensory-Motor Systems Lab, ETH Zurich, Switzerland, Figure 1) is a rocking bed for use in private home settings that provides translational vestibular stimulation in longitudinal direction. The amplitude A of the sinusoidal movement is fixed to 10 cm and the frequencies f can be varied between 0.04 Hz and 0.4 Hz, which corresponds to accelerations a between 0.006 m/s² and 0.63 m/s² according to the relationship $a = (2\pi f)^2 A$. Past studies have shown that frequencies in the range of 0.25 Hz (0.25 m/s²) and 0.3 Hz (0.36 m/s²) provided largest sleep-related benefits [6].

To achieve the desired accelerations on the Somnomat Casa, a feedforward PI velocity controller is used. Moreover, the controller needs to be tuned to provide a smooth and jerk-free movement to avoid disturbing the comfort of the user. Previously, the tuning of the PI and feedforward gains was done manually using known techniques such as Ziegler-Nichols. However, this process is very time-consuming, can only be used to optimize the control variable, and does not guarantee optimality as a large state space of possible gains is never explored. In this paper we introduce a practical, efficient and effective method for automatically adjusting the PI gains of a velocity controller for a robotic bed using Gaussian processes and an arbitrary optimization variable.

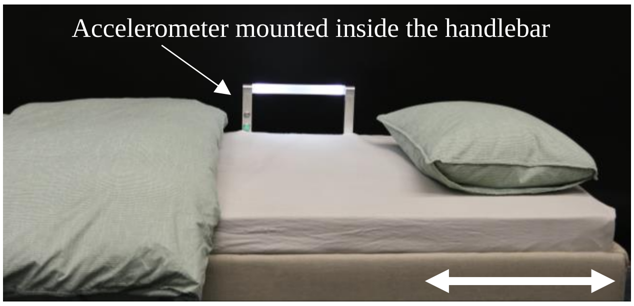

Figure 1: The Somnomat Casa applies translational vestibular stimulation in longitudinal direction. The attached handle has an integrated accelerometer to detect movement on the bed.

II. Material and methods

Autotuning is a technique in control systems to optimize the performance of a system by automatically adjusting its control parameters. Gaussian processes (GP) are an example of stochastic processes that can be used to automatically refine the control parameters θ of a controller based on prior evaluations, current experimental data, and a global control objective [7]. From the desired trajectory of the bed at time t, we can formulate analytically the target motor velocity ω_{des} which is tracked by the PI controller through $u(t)$:

$$u(t) = k_P\big(\omega_{des}(t) - \omega(t)\big) + k_I \int_0^t \omega_{des}(\tau) - \omega(\tau)\, d\tau$$

The acceleration perceived by the user on the bed is optimized through $\theta \coloneqq [k_P, k_I]$ for accurate tracking of the target acceleration. To achieve this, we utilize the acceleration data from the accelerometer located in the handlebar of the bed (c.f. Figure 1 and Figure 2) and calculate a modified mean squared error $e(\theta)$ between the desired and actual acceleration to assess the quality of the controller.

$$e(\theta) := f\sqrt{\int_0^T \left(a_{meas}(\tau,\theta) - a_{target}(\tau)\right)^2 d\tau}$$

where f is the sampling rate of the accelerometer, $a_{meas}(t,\theta) = a(t,\theta) + v, v \sim \mathcal{N}(0,\sigma^2)$, T the length of the experiment, and σ^2 the variance in the measurements.

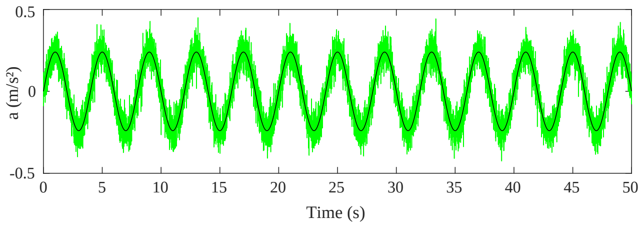

Figure 2: Black shows the desired- and green the actual noisy accelerometer readings. The variance σ^2 reflects the noise of the accelerometer.

We discretize the search space logarithmically using $k_P = 10^{\exp_P}$ and $k_I = 10^{\exp_I}$ where $\exp_P \times \exp_I \in E_P \times E_I := \{0, s_P, 2s_p, \ldots, M_P\} \times \{0, s_I, 2s_I, \ldots, M_I\}$, s_P and s_I denote the stepsizes for the exponentials, and M_P and M_I the maximum exponentials that cover the parameter space. As the evaluation of all parameters is costly, we implement the dynamics of the bed in simulation and compute the optimal solution $\theta^* := \mathrm{argmin}_\theta\, e(\theta)\, \forall\theta$ obtained from simulation. This allows to then compare the computational complexity of a random grid search to the proposed Gaussian autotuning process by defining a set of parameters $\boldsymbol{\theta_\epsilon} := \{\theta \mid |\mathrm{e}(\theta^*) - \mathrm{e}(\theta)| < \epsilon\}$ that contain parameters of ϵ-sufficient quality.

III. Results and discussion

The simulation of the dense parameter space yields an optimal $\theta^* = [10^{5.52},\ 10^{5.76}]$ (Figure 3).

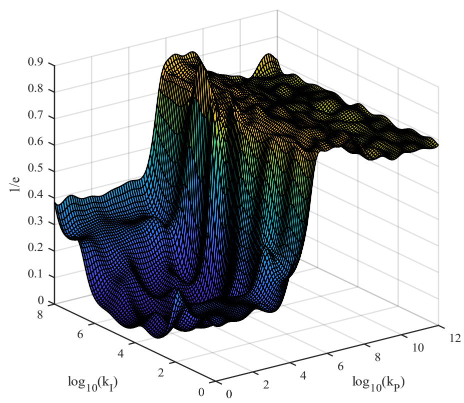

Figure 3: The entire parameter space is discretized and evaluated. The values for k_P and k_I are chosen logarithmically.

When we compare the average number of iterations needed in 100 runs to obtain ϵ-optimality of the parameters for varying grid densities, we observe a quadratic growth for the random search but a constant behavior for the Gaussian process. This demonstrates that excellent controller parameters $\hat{\theta} \in \boldsymbol{\theta_\epsilon}$ can be found using the Gaussian process in constant time, independent of the size of the parameter space. For the random search through the parameter space, we observe a quadratic computational complexity, Fig. 4.

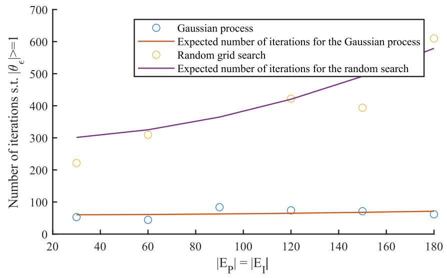

Figure 4: The computational complexity rises quadratically with the size of the search space for the random search but remains constant for the Gaussian process.

Using the same approach as in the simulation, we tune the control parameters on the bed using the Gaussian process. After less than one hour of automated tuning, we have an ϵ-optimal error metric. However, one issue that we observed after tuning the bed was an increase in noise from the motor. Although the motion is smoother than using the manual tuning process from before, the motor is now louder which may pose issues in some sleep-related applications.

IV. Conclusions

In this paper we have demonstrated how Gaussian processes can be used to automatically tune controllers of robotic beds using any desired metric in constant time. In particular, we could demonstrate that the dynamic simulation of the Somnomat Casa is well transferable to the real setup and the Gaussian process led to a more comfortable movement of the bed compared to the previous manual tuning. Future work should include the noise emission of the motor as part of the optimization variable.

Acknowledgments

The authors thank their colleagues at the Sensory-Motor Systems Lab for their valuable contributions, especially Michael Herold Nadig and Paul Schürmann from the electronics lab and Marco Bader from the machine shop. Moreover, Alexander Breuss sincerely thanks the Promedica Foundation for their financial support in conducting this research.

Author's statement

Research funding: This work is partially financed by the Promedica Foundation. Conflict of interest: Authors state no conflict of interest.

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