Haptic Preference Learning Using Active Learning and Gaussian Processes

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Abstract

Haptic preference learning (PL) combines user feedback and machine learning to optimise tactile experiences, a critical component of human-computer interaction. This project employs active learning (AL) and Gaussian processes (GP) to iteratively refine a user's preferences in a haptic environment (paddle in our case). The system integrates a feedback loop where users select preferences (e.g., left, right) based on paddle parameters, enabling efficient exploration of high-dimensional parameter spaces. AL ensures minimal user effort by prioritising the most uncertain candidate designs. GP models predict preferences and guide the system towards optimal configurations. Our approach enhances user-centric design by adapting to individual preferences through intelligent sampling and real-time model updates.

Introduction

Haptic systems enable interaction through the sense of touch and are fundamental in advancing human-computer interaction across diverse applications. These systems enhance virtual environments' realism, improving skill acquisition in medical simulations as in Figure 1.

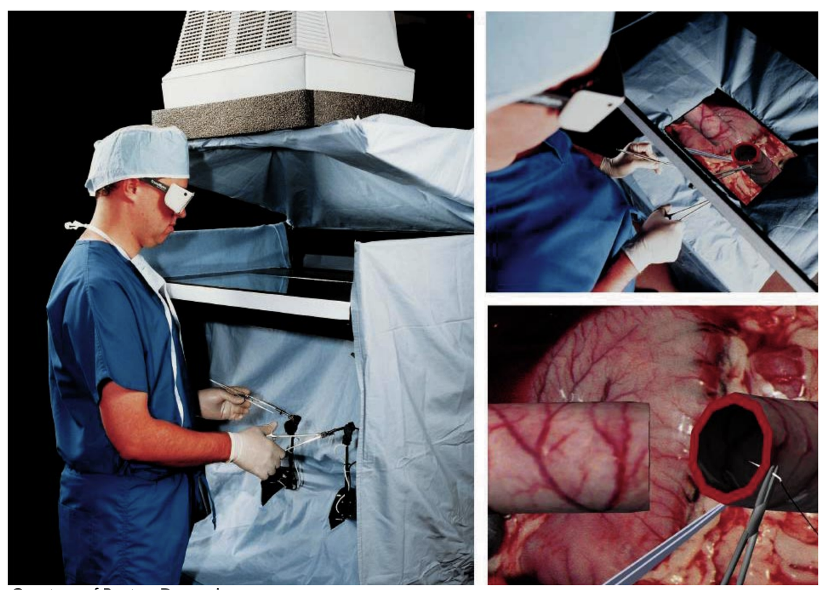

Figure 1: These systems facilitate precision in remote manipulation tasks such as robotic surgery and teleoperation [1, 2].

However, optimising haptic interfaces for individual user preferences remains a significant challenge due to variability in human perception and the complexity of parameter spaces. PL has emerged as a promising solution for addressing this challenge.

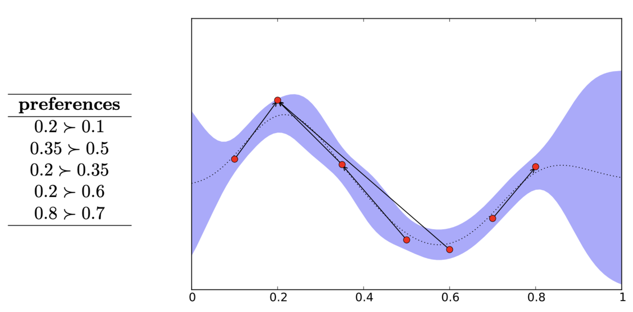

Figure 2: Example of preference relations (left table) used to infer a GP (right plot) on a toy problem taken from [3].

Application Areas and Benefits

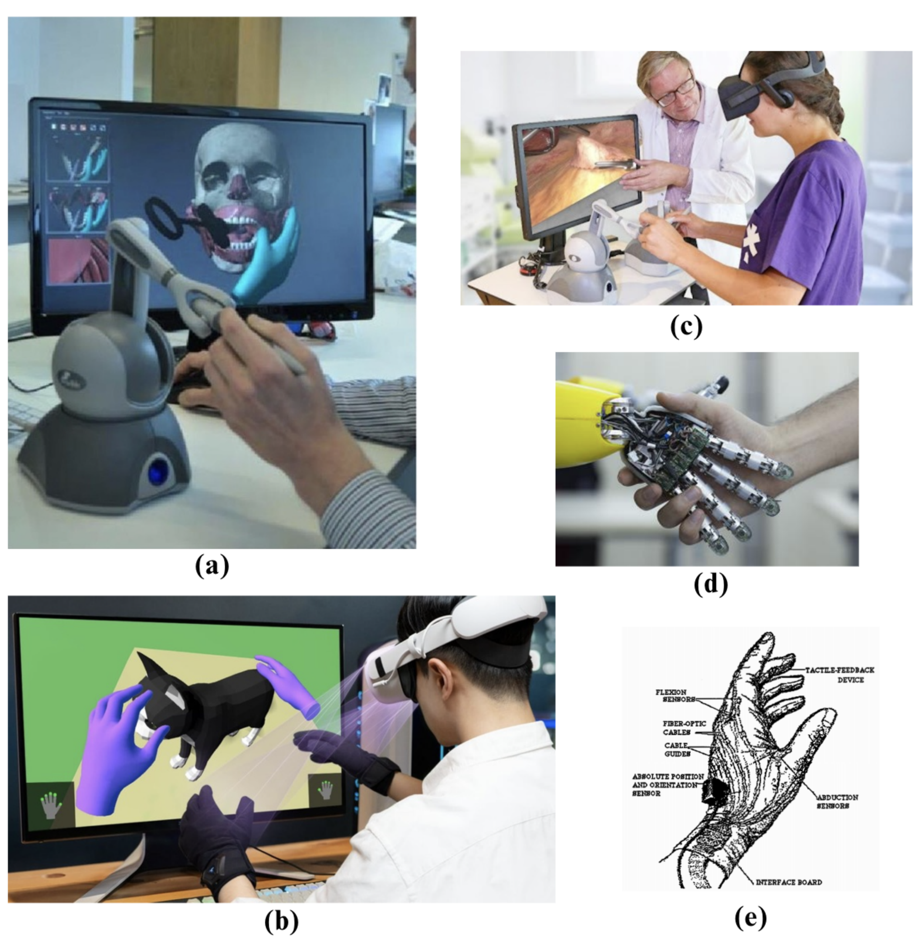

Figure 3: Demonstration of haptic technology on health, gaming and VR, education, robotics. (a) is taken from [4], (b) is taken from Bhaptics, (c) is taken from ARVRSol, (d) is taken from Slate, (e) is taken from NASA.

Figure 4: The benefits of PL with GPs and AL paradigms

The approach minimises user effort while accelerating system optimisation, adapts to individual preferences to enhance satisfaction, and ensures reliable performance by handling variability and noise in feedback. Its versatility extends to various fields, including health, gaming, education, robotics, and virtual reality.

Paddle-Based Haptic Environment

Our system centres around a paddle-based haptic environment (see Figure 5) that integrates AL and GP into the PL framework to overcome these limitations. AL optimises learning by targeting the most uncertain configurations, minimising data collection needs. GPs offer a probabilistic approach to modelling preferences, ensuring powerful predictions with limited data [5, 6].

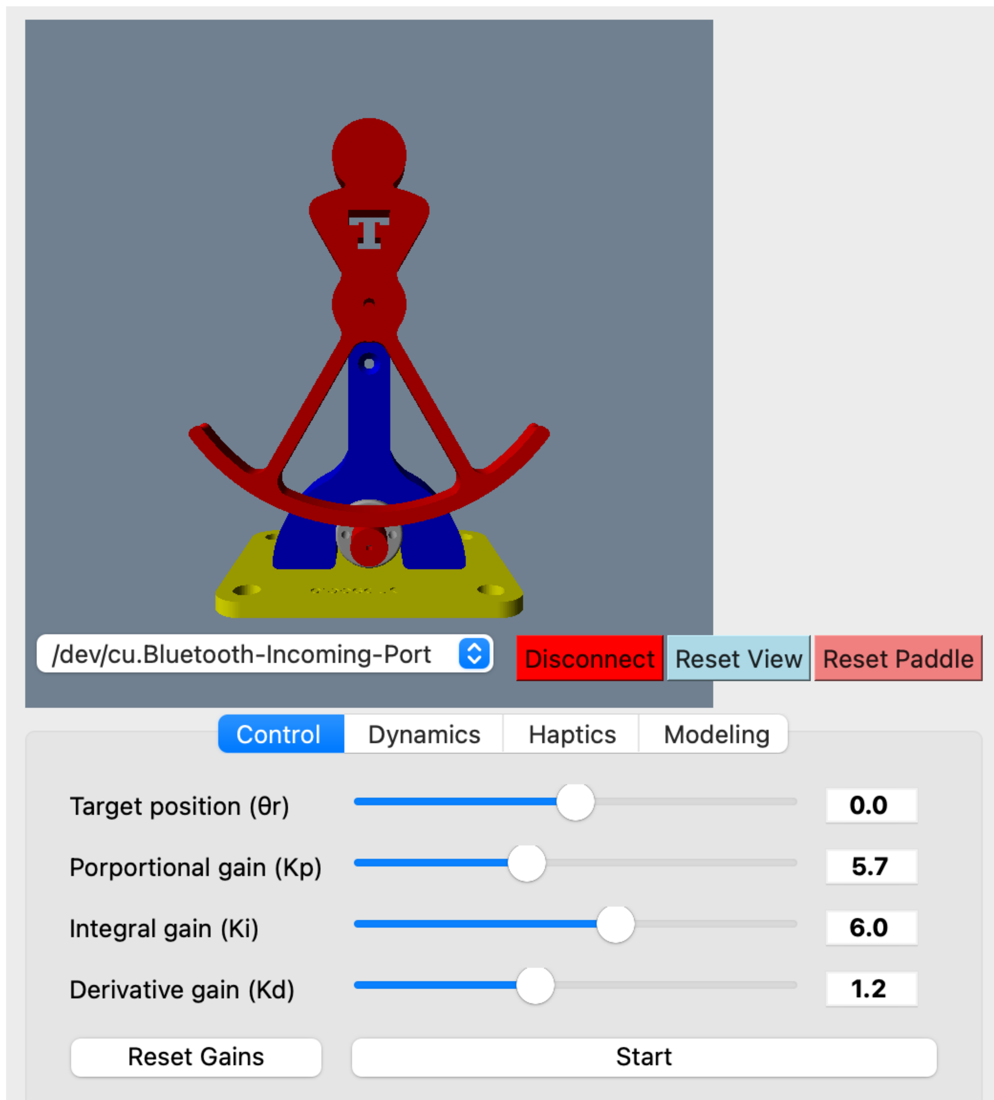

Figure 5: Paddle GUI with different settings

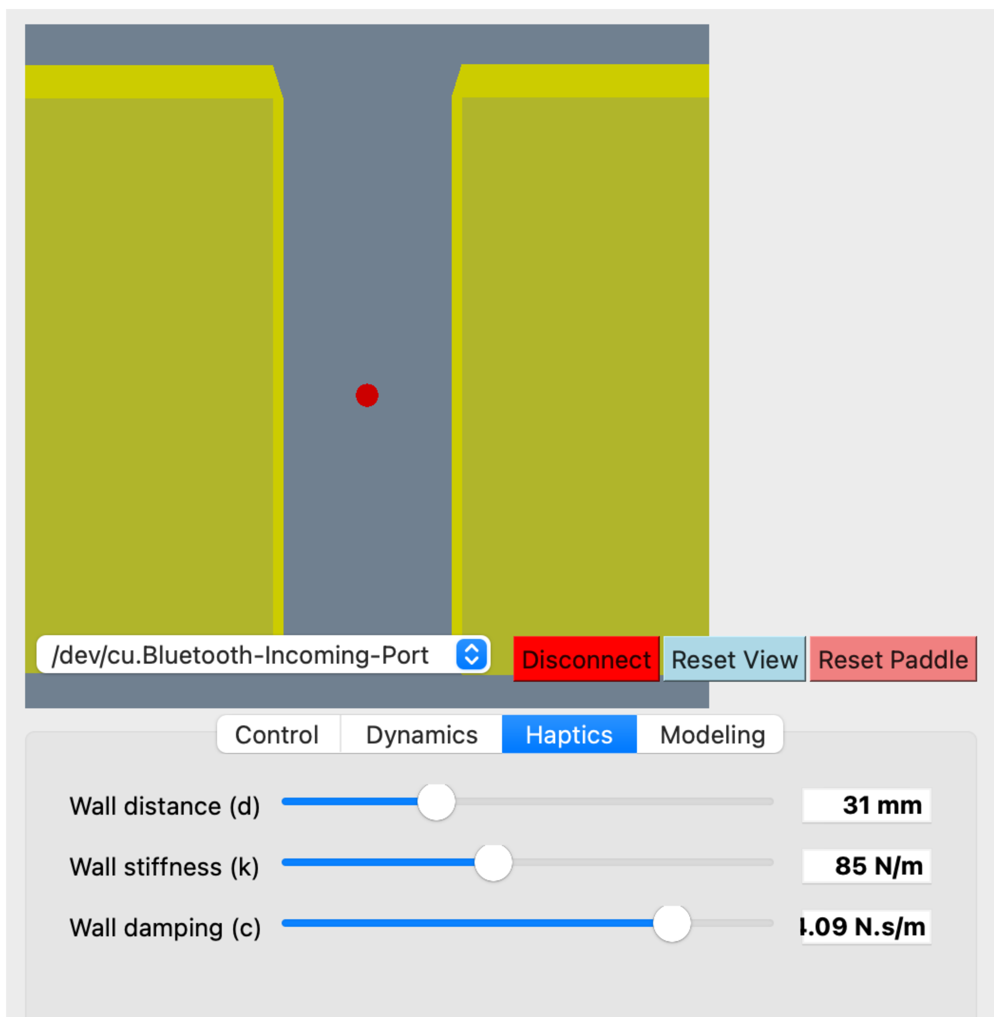

Figure 6: Original paddle settings, showing paddle centre and walls. Parameters can be controlled.

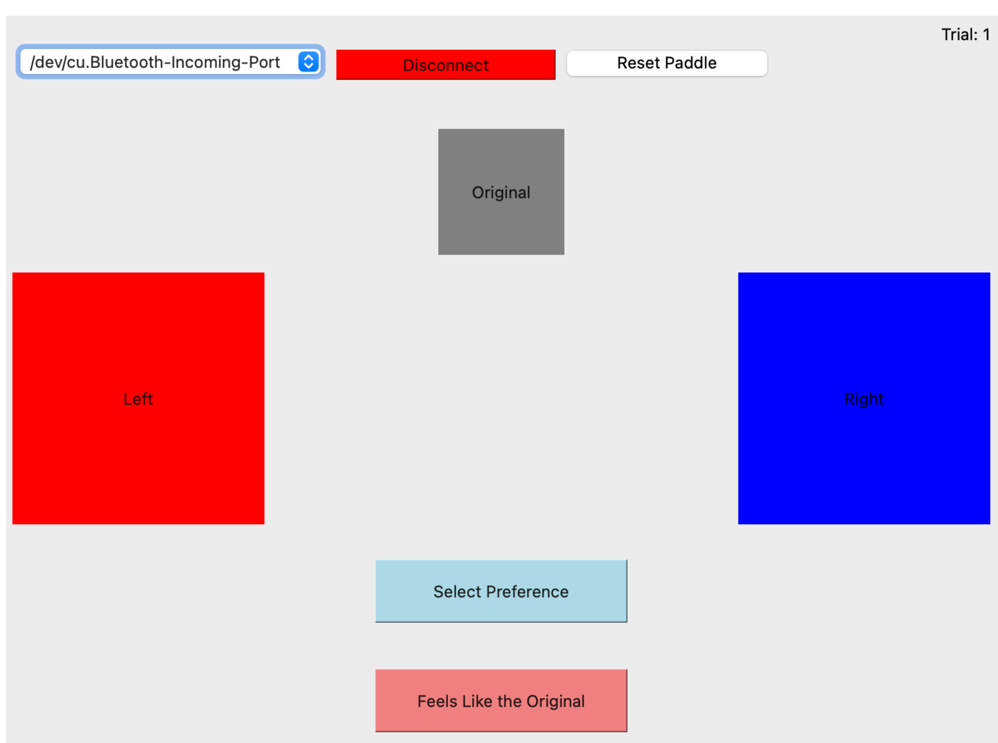

Figure 7: Experiment setting

The system is equipped with the following key components:

Haptic Paddle: A mechanical interface that users can manipulate along three positions: L, O, and R, as in Figure 7.

Parameter Control: The paddle's configurations, defined by parameters like wall distance, stiffness, and damping, enable exploring diverse feedback settings.

Feedback Loop: Users provide feedback (e.g., prefer left over right) based on their experience, guiding preference model training.

Data Collection and Logging: Each interaction log paddle parameters, the chosen position (left or right), and distances from the original configuration for comparison.

AL Framework: The system uses AL to minimise interactions by selecting paddle configurations that maximise model uncertainty, efficiently exploring the parameter space based on user feedback.

GP Modelling: A GP models user preferences probabilistically, predicting unexplored configurations and updating iteratively with new feedback as in Figure 8

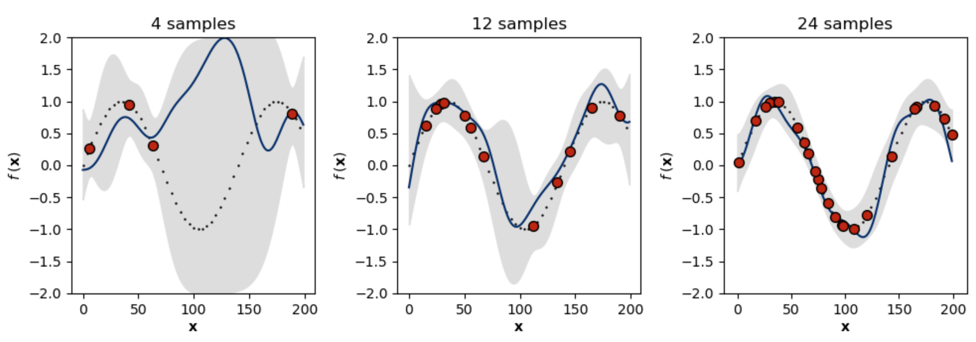

Figure 8: A visualisation of a GP fit taken from [7]

User Interaction Workflow

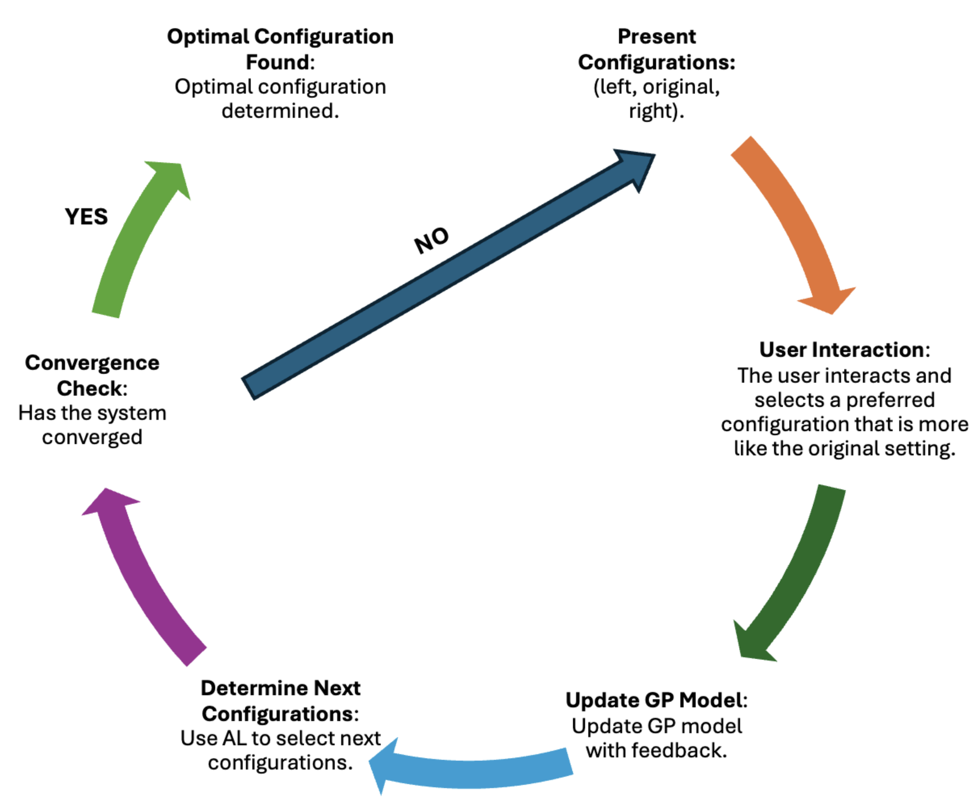

Figure 9: Interaction loop

Expectations and Future Work

The project is under development, with plans to refine the GP model through user feedback and validation via user experiments. Optimising the AL algorithm will reduce user effort while enhancing accuracy and uncertainty estimation. The system will dynamically adapt to individual preferences, enabling custom interactions. Applications include medical training, gaming, virtual reality, and assistive devices. The final goal is to publish this work as an open-source framework to encourage collaboration in haptic systems and preference modelling.

References

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