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Mechatronical models and tools in human balance and motion control

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Introduction

Manual control of an object is a natural everyday activity for humans. The control process is maintained by an intricate mechanism operated by the central nervous system (CNS) however, the nature and the characteristics of this process are still a subject of debate. Human motor control requires the complex interplay of three main systems: (1) sensory perception of the surrounding environment (i.e., vestibular-, visual-, proprioceptive system); (2) motor command formulation by the CNS (i.e., response planning, strategy selection); (3) movement implementation by the musculoskeletal system (i.e., muscle contraction). The investigation of human manual control is mainly focused on two classes of movements in motor planning and execution. Discrete movements are generally the ballistic type of movement, where there is a pre-planned action at the musculoskeletal level. These types of movements are executed without sensory feedback information (i.e., open-loop control) and have deterministic start and end. Reaching, throwing a basketball, pointing or saccadic eye movements can be mentioned as simple examples. For more complicated systems active feedback is usually necessary for maintaining desired behavior. This manifests in a continuous flow of movements, where ongoing regulations are executed due to the erratic nature of the feedback signal. Simple tracking tasks, driving a car, standing still, or walking are typical examples that require continuous control. Although these suggest that human manual control can be modeled as a servo system, control movements were shown to be a series of discrete movements rather than continuous. Intermittent control is characterized by the continuous perception of sensory information and a series of ballistic type of movements. Depending on the level of skill, humans can execute movements almost continuously, representing a transition between discrete and continuous control. Identification of the decision-making mechanism, in other words, the control law employed by the CNS, is a difficult task since the mechanical model of the human body involves several uncertain elements. There are several concepts in the literature, such as the traditional proportional-derivative (PD) feedback, proportional-derivative-acceleration (PDA) feedback, predictor feedback (PF), intermittent predictive controller or event-driven intermittent controller, to mention a few. Human motor control is constrained by reaction time delay and uncertainties in the process, such as sensory and motor control realization errors. The introduction of a time delay in the feedback loop is generally known as a source of poor performance and instability. Reaction time of human subjects can be readily estimated using reaction time tests. In the stabilization of an unstable system, this reaction time delay has a crucial role. A stabilizing control action should be fast enough to counteract the divergent dynamics.

From a dynamical systems point of view, manual manipulation corresponds to the feedback stabilization of unstable or marginally stable systems. Skill development in novel voluntary tasks requires sensory information and practice. During practice, the variability of the outcome of repetitions mostly decreases as skill increases. Understanding the development of these motor control tasks has important implications in teaching various movement types, for example performing a sudden manoeuvre safely while driving a car or fine motor control during surgical operations.

Different modeling techniques and simplifications usually have a significant effect on the stability of the model. These differences often manifest in a different order, or different degrees of freedom in dynamic systems. By comparing the behavior of different models, conclusions can be drawn w.r.t parameters, control strategy, and the qualitative properties of a sensory system.

The dissertation focuses on human manual control and balance, with a goal to get a slightly better understanding of the strategies during daily

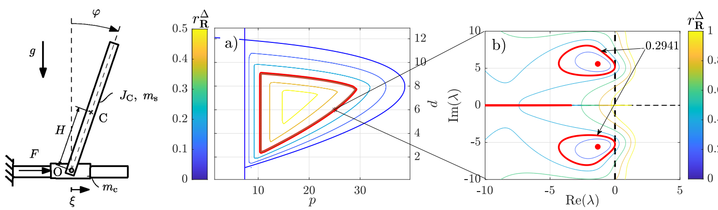

FIGURE 1: Mechanical model of an inverted pendulum, on the right. And on the left: (a) Stability diagram with contours of different stability radii for given system parameter and controller. (b) Pseudo-spectra of the system at the selected parameters.

activities. The main mechanical model is an inverted pendulum that is often used to model human stick balancing or postural sway. The inverted pendulum-cart system is also a conveniently used task to test human manual control. Theoretical investigation and systematic measurements are used to develop knowledge on the uncertainties and skill development. Throughout the dissertation the traditional PDA and a PF controller is investigated to stabilize the pendulum. Although the already known effect of input delay in the controller is well understood, the effect of parameter uncertainties and their limiting factor on time delay is an open question. The framework of real structured robustness analysis was used to analyse stability. The bounded stable region of control gain parameters always had a clear maximum in case of allowed uncertainty, see Figure 1. These maximums were mapped through a range of pendulum length and input delay and the differences between the PDA and PF controllers were analysed. In order to test that these trends are also observable in human manual control, a virtual stick balancing application was developed on a computer. Multiple test were carried out on 51 volunteers in total. The sessions involved reaction time tests and an artificial input delay was added during tests to map out the stabilizability limit of manual control, similarly to the theoretical model before, see Figure 2. The trends of human manual control resembled to that of the theoretical controllers.

Another focus of my research focused on a different balancing task, that can be used to model human standing for example. The mechanical model in this case was a pinned inverted pendulum, equipped with an

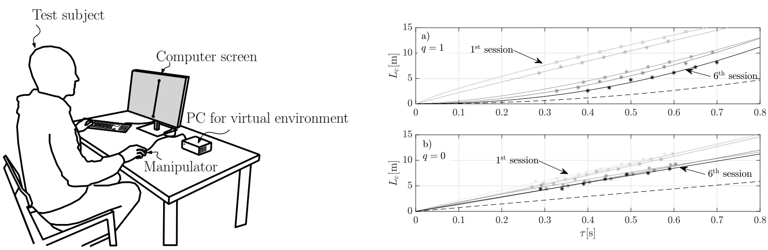

FIGURE 2: Schematic of the virtual stick balancing system on the right. The change of the critical length over the 6 balancing sessions as function of the overall delay for a selected subject. The fitted curves are shown by thin solid lines, while dashed lines indicate the theoretical critical lengths.

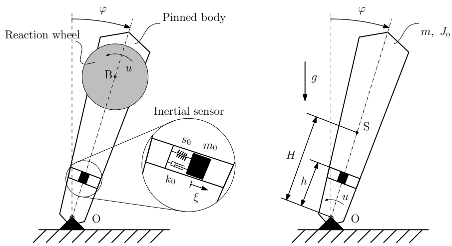

FIGURE 3: Mechanical model: the pinned body, the inertial sensor and the reaction wheel.

accelerometer as sensor to measure the state of the object, see Figure 3. Four mechanical models were investigated based on the model simplification. These four models were tested with four different control strategies, some of which involved input delay, and sampling. Based on the modal parameters of the sensor and its distance from the pivot point, the stabilizability of the inverted pendulum can be determined and a suitable controller can be designed to achieve vertical balance.

Ultimately, the main goal of my research was to identify parameters in human manual control and balance that are critical for achieving a good performance during the task. The robust framework of the parameter uncertainties let me construct a formula, that was useful to assess the balancing skill development and balancing performance of the test subjects. Different models and techniques were used throughout the research and a few interesting observations can be concluded.

Main results

Results of Chapter 3.

The dynamics of the inverted pendulum subject to predictor feedback (PF) in the presence of static uncertainties in the control gains is described by

$$\begin{aligned}\dot{\mathbf{x}}(t) &= \mathbf{A}\mathbf{x}(t) + \mathbf{B}u(t-\tau)\\ u(t) &= \mathbf{K}_1\left(\mathrm{e}^{\mathbf{A}\tilde{\tau}}\mathbf{x}(t) + \int\limits_{-\tilde{\tau}}^{0}\mathrm{e}^{-\mathbf{A}s}\mathbf{B}u(t+s)\mathrm{d}s\right) + \mathbf{K}_2\dot{\mathbf{x}}(t).\end{aligned}$$

where

$$\mathbf{x} = \begin{bmatrix}\varphi\\ \dot{\varphi}\end{bmatrix},\ \mathbf{A} = \begin{bmatrix}0 & 1\\ b & 0\end{bmatrix},\ \mathbf{B} = \begin{bmatrix}0\\ 1\end{bmatrix},\ \begin{matrix}\mathbf{K}_1 = [p+\delta p, d+\delta d]\\ \mathbf{K}_2 = [0, a+\delta a]\end{matrix},$$

$b > 0$ is the system parameter, (p, d, a) and $(\delta p, \delta d, \delta a)$ are the control gain parameters and the corresponding static uncertainties, τ is the input delay and $\tilde{\tau}$ is the estimated delay in the internal model. In case of $\tilde{\tau} = 0$ the controller acts as a proportional-derivative-acceleration (PDA) feedback control. Based on the stability analysis of the model the following two statements can be made.

1. **Main contribution**

   The pendulum can be stabilized if its length is longer than a critical length

   $$L_{\text{crit}} = c(\mathbf{\Delta}, \tilde{\tau})\tau^2,$$

   where $c(\mathbf{\Delta}, \tilde{\tau})$ is the regression coefficient, that depends on the structure of the parameter perturbation $\mathbf{\Delta} = [\delta a/\varepsilon_a, \delta d/\varepsilon_d, \delta p/\varepsilon_p]^T$ and ε_p, ε_d, ε_a are the corresponding weights.

The stabilizability of an inverted pendulum in terms of critical length L_{crit} either by delayed proportional-derivative (PD) feedback or by predictor feedback (PF) is more sensitive to changes in the input delay than to changes in control gain parameters. In the case of PD feedback with delay $\tau = 200$ms (which is typical to human reaction time), 25% relative increment in the delay results in 56.25% change in L_{crit}, while the same relative change in the stability radius (i.e. in the control gains) results in 18.7% change in L_{crit}. In the case of PF with delay $\tau = 200$ms and with 10% delay mismatch, 25% relative increment in the delay results in 56.25% change in L_{crit}, while the same relative change in the stability radius (i.e. in the control gains) results in 10.7% change in L_{crit}.

2. **Main contribution**

   In case of delayed PD control of an inverted pendulum, the sensitivity of the controller to changes in the time delay is stronger by a factor of 3 than to changes in the controller gains. In case of PF controller, the sensitivity to changes in the time delay is stronger by a factor of 5 than to changes in the controller gains. The PF controller is shown to be superior to PD in the sense that L_{crit} for PF is smaller than the half of L_{crit} for PD, if the input delay $\tau < 500ms$ and the stability radius $r_{\mathbb{R}}^{\mathbf{\Delta}} < 0.8$.

Related publications: [1, 2]

Results of Chapter 4.

Considering the manipulation of objects with complex behaviour, human subjects are mostly limited by their sensorimotor uncertainties and their reaction delay. Using the result of the previous chapters and the developed virtual balancing environment, two groups of people were tested to investigate the similarities to the theoretical PD feedback. Two main contributions can be stated on the control strategy of human manual control based on the measurement results. Based on virtual stick balancing trials by 27 human subjects the following observation is stated.

3. **Main contribution**

   After systematic series of virtual balancing tests with artificially added reaction delays, the relation between the critical length L_{crit} *(the length of the shortest stick that human subject can balance) and the overall reaction delay* τ *can be well described by* $L_{\text{crit}} = c\tau^2$ *with an average coefficient of determination* $R^2 = 0.82$*. The regression coefficient c reflects the robustness to uncertainties in sensory and motor control. Relating the human performance to the theoretical model implies that the allowed static uncertainty in the perception of angular position is* 14.1% *on average, while the allowed perturbation in the velocity feedback is* 40.3%*.*

Virtual stick balancing trials were performed by 24 subjects with artificially added reaction delays, such that the dynamics were second-order for half of the subjects (Group 1.) and it was first-order for the other half (Group 2.). The relation between the reaction delay (τ) and the critical length (L_{crit}, the length of the shortest stick that a human subject can balance) can be well described by $L_{\text{crit}} = c\tau^{\kappa}$, where c is the control efficiency parameter. Based on the theoretical model, the exponent $\kappa = 1$ for first-order dynamics and $\kappa = 2$ for the second-order dynamics. The fitted exponent during the initial sessions was $\kappa \approx 1$ independently of the order of the dynamics. The fitted exponent κ converged to 1.5 for Group 1, and it was $\kappa \approx 1$ for Group 2 over the first 6 sessions. In the 7^{th} session, both groups performed the session with a dynamics order different from the one they were training on, and the fitted exponent was $\kappa \approx 1$ for both groups. Based on the measurements the following observation is stated.

4. **Main contribution**

   After systematic series of 6+1 *virtual balancing sessions with overnight consolidation, skill development of subjects trained on second-order dynamics was more pronounced, than for the subjects trained on first-order dynamics in terms of critical length. On the* 7^{th} *session the subjects trained on second-order dynamics, showed good performance in first-order dynamic tests. The subjects trained on first-order dynamics, showed that they have to re-adapt to the more complex second-order task. This suggests that human subjects can readily adapt to first-order dynamics, while accommodation to second-order dynamics requires more practice.*

Related publications: [3, 4, 2, 5]

Results of Chapter 5.

Consider an object that is balanced around a fixed pivot point with a single inertial sensor and feedback delay. The mathematical model is written in the following form

$$\ddot{\varphi}(t) - b\varphi(t) + \gamma\left(h(\epsilon\ddot{\varphi}(t) + \varphi(t)) + \epsilon\ddot{\xi}(t) - \xi(t)\right) = \frac{1}{J_{\mathrm{o}}}u(t),$$
$$\ddot{\xi}(t) + 2D_0\alpha_0\dot{\xi}(t) + \alpha_0^2\xi(t) = g(\varphi(t) - \epsilon\ddot{\varphi}(t)),$$
$$u(t) = -k_p\xi(t-\tau) - k_d\dot{\xi}(t-\tau),$$

where $b = \frac{gHm}{J_{\mathrm{o}}}$ is the system parameter, $\gamma = \frac{m_0 g}{J_{\mathrm{o}}}$, $\epsilon = \frac{h}{g}$ is the parameter related to the position of the sensor on the rod, $\alpha_0 = \sqrt{\frac{s_0}{m_0}}$ the natural angular frequency, $D_0 = \frac{k_0}{2\sqrt{s_0 m_0}}$ is the relative damping coefficient of the inertial sensor, k_p, k_d are the feedback gains, τ is the continuous feedback delay in the closed-loop system and J_{o}, H, m, s_0, m_0, k_0, h are the physical parameters of the balanced object. Based on the stability analysis of the model the following statement can be made.

5. **Main contribution**

   Stable balancing is possible, if and only if, the distance h between the location of the sensor and the pivot point is less than the critical distance

   $$h_{\mathrm{crit}} = \frac{2D_0}{\alpha_0\tau}\frac{J_{\mathrm{o}}}{Hm},$$

   When a digital controller is employed, then h_{crit} gives a larger bound for the critical distance, and if the sampling frequency is increased then it approaches the critical distance obtained for the continuous case.

Related publications: [6]

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