Controller Gains of an Inverted Pendulum are Influenced by the Visual Feedback Position

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***Abstract*—In this study we experimentally test and model the control behavior of human participants when controlling inverted pendulums of different dynamic lengths, and with visual feedback of varying congruence to these dynamic lengths. Participants were asked to stabilize the inverted pendulum of $L = 1$ m and $L = 4$ m, with visual feedback shown at various distances along the pendulum. We fit a family of linear models to the control input (cart velocity) applied by participants. We further tested the models by predicting this control input for a pendulum with dynamic length $L = 2$ m and comparing the prediction to the experimental data. We show that the sum of proportional error correction and a term inversely proportional to visual feedback gain can well describe the control in human participants.**

I. Introduction

Humans are regularly exposed to tasks where control of unstable dynamics is required, such as walking, cycling, slicing an apple or balancing a broom on the fingertips [1]. The performance in these tasks improves with learning (i.e. cycling) or deteriorates with suppression of feedback [2, 3]. Many studies have previously looked at learning (or predictive control) in the unstable environments [4, 5], however feedback control in those conditions was investigated much less [6, 7]. While control engineering approaches, such as PD control or LQG, have successfully been applied to model the feedback control of human movement in stable environments with congruent feedback [8, 9], the control with incongruent feedback has not yet been modelled.

The overall importance of visual feedback in human motor learning and control has been broadly investigated. We have previously experimentally shown that the control of a virtual pendulum with variable visual feedback was the most stable when this feedback was congruent with the dynamics of the pendulum [10]. Various hypotheses, such as the limited resources hypothesis, could be used to explain this paradigm qualitatively, but they do not quantify the development of the control stability with a change in visual feedback. Here we suggest a model that may describe the development of control input applied by humans when controlling an inverted pendulum with visual feedback incongruent with the pendulum dynamics. We further use the model to normatively simulate the control input for a novel condition and compare the results with experimentally collected data.

II. Methods

A. Participants

Six right-handed [11], neurologically healthy human participants (1 female, mean age 24.7 years), naïve to the purpose of this study, participated in the experiment. The participants were drawn from a pool of our previous inverted pendulum studies [10, 12], and therefore were familiar with the setup. All participants provided a written informed consent before participating in this study. The study was approved by the Ethics Committee of the Medical Faculty of the Technical University of Munich.

B. Experimental apparatus

Participants performed a balancing task of an inverted pendulum in a robotic manipulandum. Participants were seated in an adjustable chair in front of a robotic rig, with their shoulder movement restrained by a seatbelt. The subject's right arm rested on an airsled and their right hand grasped the handle of the vBOT robotic interface [13]. All hand movements were performed in an x-y plane parallel to the ground. Position and force data was sampled at 1 kHz. Visual feedback was projected via a computer monitor and a mirror system to the plane of the movement in such a way that the direct visual feedback of the hand was prevented.

C. Experimental paradigm

The inverted pendulum was simulated in the x-y plane, with the gravity acting in the negative y direction (towards the participant) and corrective movements executed by participants along the x axis (parallel to participant's chest). Pendulum kinematics and the interface were simulated and presented as described in [12] (Fig. 1A).

Trials were self-paced: participants initiated each trial by moving a cart to the start position, indicated by a grey rectangle (3.0 cm by 1.5 cm) and positioned in the middle of the control channel. The start of the trial was then cued via a short beep, followed by a perturbation of $\dot{\theta} = 0.01$ rad/s on the pendulum 600 ms later. The direction of this perturbation was pseudo-randomised, with equal number of trials for left and right. During each trial participants were instructed to maintain the pendulum upright and with as little of angular movement as possible for 5 seconds. A trial was considered over when the pendulum was successfully maintained for these 5 seconds, or when the angular deviation between the pendulum and the y axis reached 90°. Participants were then

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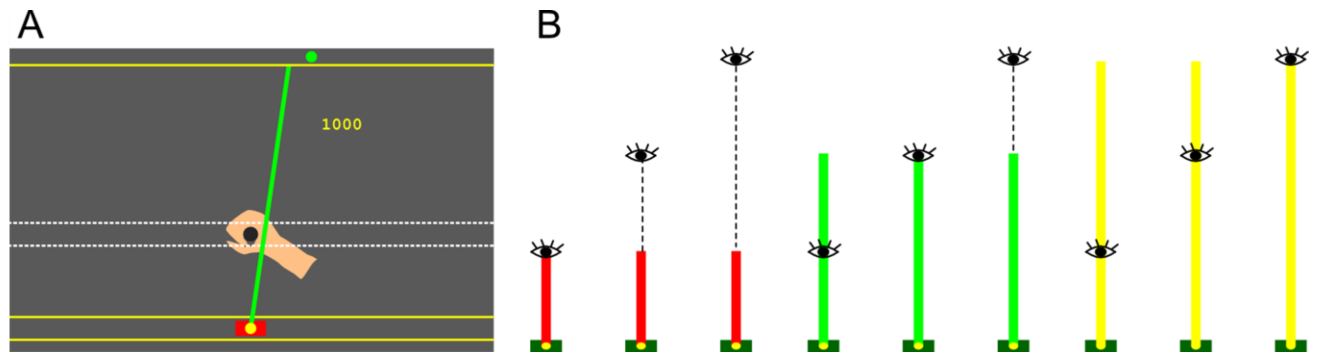

Figure 1. **A.** A sample snapshot of the experimental design. Participants controlled a cart (1.5 cm by 3 cm rectangular red block) directly, by moving the robotic handle along a mechanical channel (white lines and hand, not visible to participants; position dependent force field; stiffness 4000 N/m, damping 2 Ns/m, maximum force of 25 N). This channel constrained participants to move in x-axis only, at a distance approximately 30 cm in front of participant's chest, and was framed in the visual workspace by two yellow lines of 1.0 mm thickness. From participant's perspective, the physical hand location did not match with its visual representation (cart), but was shifted 13.0 cm forward in order to maximize the amount of visual feedback and the range of motion. However, the x-coordinate of the cart always matched the x-coordinate of the hand. **B.** Experimental paradigm schematic. Participants were introduced to pendulums of two different dynamic lengths (1 m, red and 4 m, yellow), and had previously participated in a similar experiment of a different dynamic length (2 m, green). Participants were provided with visual feedback at different locations. These locations were the same for all three dynamic conditions. As the horizontal displacement of the visual feedback point at the same pendulum angle is proportional to the visual feedback distance, this distance can be treated as the visual feedback gain.

provided with their score, indicating their task success [12], and were free to initiate the next trial.

Participants were required to control two different pendulums of dynamic length L = 1 m and L = 4 m. Each of the lengths was presented in a blocked fashion, with three participants starting with L = 1 m and then L = 4 m, and three participants with this order reversed. For each of the dynamic lengths participants were provided visual feedback equivalent to nine different visual distances from the cart: L_v=[0.25 m, 0.5 m, 0.75 m, 1 m, 1.5 m, 2 m, 4 m, 6 m, 8 m]. Each length was also presented in a blocked fashion, with 20 trials in each block and block order randomized (Fig. 1B). Each of these blocks was repeated twice, so that every pendulum condition was repeated for 40 trials in total, resulting in 720 trials per participant. Short breaks (5 s) were provided after every block, indicating participants that the condition would change.

D. *Data analysis*

Data collected in this experiment was analyzed and compared to the data of [10]. We used MATLAB 2017b for the data analysis. Kinematic time series were low-pass filtered with a zero-phase-lag, fifth-order Butterworth filter with 40 Hz cutoff frequency. Linear acceleration was obtained by differentiating the velocity data online and filtering it with eight-order low-pass Butterworth filter (40 Hz cutoff)

E. *Modelling*

Previously we have suggested a theoretical proportional feedback control model that could explain the development of the pendulum control input (cart velocity) [10]. In this study we test our theoretical model, as well as compare this model with alternative models. In order to quantify our model performance, we fit the model coefficients on the dynamic pendulum lengths L = 1 m and L = 4 m, and test the model by calculating the residual sum of squares (RSS) between the normative prediction of dynamic length L = 2 m and the respective data, collected in our previous study [10].

Our previously proposed model follows the mathematical expression:

$$M_0 : v_x = A \cdot \frac{1}{L_v} + B \cdot e_x, \quad (1)$$

where v_x is the average cart velocity applied by participant, e_x is the visual feedback error, and A and B are model constants. However, in this study we examine a family of models of the general form

$$M : v_x = A \cdot \frac{1}{(L_v - C)} + B \cdot e_x + D, \quad (2)$$

where C and D are also model constants. Model constants may be dependent on the dynamic length, in which case they will be denoted with the subscript L (eg. A_L). We will further refer to separate models by these model constants *[A, B, C, D]*.

III. Results

A. *Experimental data*

Performance of six participants was compared across three different pendulum lengths in a balancing task. In order to test the effect of the dynamic length (L) and the visual feedback length (L_v) on the stability of the control, we performed a two-way repeated-measures ANOVA on the balance score as the dependent variable, with dynamic length (3 levels) and visual feedback length (9 levels) as within-subject independent factors. The analysis showed a significant main effect in both factors and their interactions (L: $F_{2,10}$=51.94, p<0.001; L_v: $F_{8,40}$=32.11, p<0.001; L*L_v: $F_{16,80}$=12.28, p<0.001). Post-hoc analysis (Holm-Bonferroni) revealed significant pairwise differences across all three dynamic lengths, with L = 4 m being most stable, and L = 1 m being the least stable, indicating an increase in stability for each increasing dynamic pendulum length (Fig. 2, top).

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In order to better understand the interaction effects we also performed three one-way repeated-measures ANOVAs with visual feedback lengths (L_v) as factors (9 levels), and where dynamic pendulum length (L) was constant. For each of the dynamic lengths we found significant main effects in visual feedback length (L=1 m: $F_{8,40}$ = 17.32, p<0.001; L=2 m: $F_{8,40}$ = 13.74, p<0.001; L=4 m: $F_{8,40}$ = 53.77, p<0.001). Moreover, for each pendulum, participants exhibited the most stable control when presented with a visual feedback length matching its dynamic length (Fig. 2, middle), with decay in controllability away from this point. Such a result is consistent with our previous findings [10], as well as with optimal feedback control models of an inverted pendulum where the observer and the plant have conflicting dynamic models.

B. Modelling

We fit a family of linear models (2) to our experimental data and evaluated their performance by comparing the model predictions for dynamic length $L = 2$ m to our previously collected data [10]. Here we present two best-fit models and compare them to the baseline models.

The two baseline models were chosen of the form *[A, 0, C, D]* and *[0, B, 0, D]*. The former model represents the control strategy where only the visual feedback location (L_v) influences the controller input. The best fit model of this form showed RSS_{fit} = 1899.2 and RSS_{test} = 862.6. The latter model represents the control strategy where only the visual endpoint error (Fig. 2, bottom) is corrected, with no estimate of the pendulum dynamics based on visual feedback location. The best fit model of this form showed RSS_{fit} = 1491.4 and RSS_{test} = 873.0. These both models show only a marginal improvement over the constant model *[0,0,0,D]*, with RSS_{fit} = 2040.5, and RSS_{test} = 1034.9, suggesting that neither of the two mechanisms are enough to represent the control system in our human participants.

Our two best-fit models were of the form *[A,B,C,0]* and *[A_L,B,C,0]*. The former model represents the control strategy where both inverse term and visual error are combined in a linear manner (Fig. 3, left). The best fit model of this form showed RSS_{fit} = 800.7 and RSS_{test} = 494.6, a significant improvement over any of the baseline models. The latter model assumes additional modulation of the inverse term with dynamic pendulum length. The best fit model of the latter form showed RSS_{fit} = 726.1, RSS_{test} = 489.7, a significant improvement (Fig. 3, right). Although more complex, the model *[A_L,B,C,0]* better describes our experimental data, and therefore is selected as a best-fit model.

IV. Discussion

In this study we tested and modelled a control behavior of human participants when controlling inverted pendulums of different mechanical properties under different visual feedback conditions. Our participants showed increasingly stable control behavior the closer visual feedback location was to the dynamic center of the pendulum, a result matching our previous study [10]. In addition to replicating this result for two new dynamic lengths (L = 1 m and L = 4 m), we also tested our previously proposed model of the control behavior.

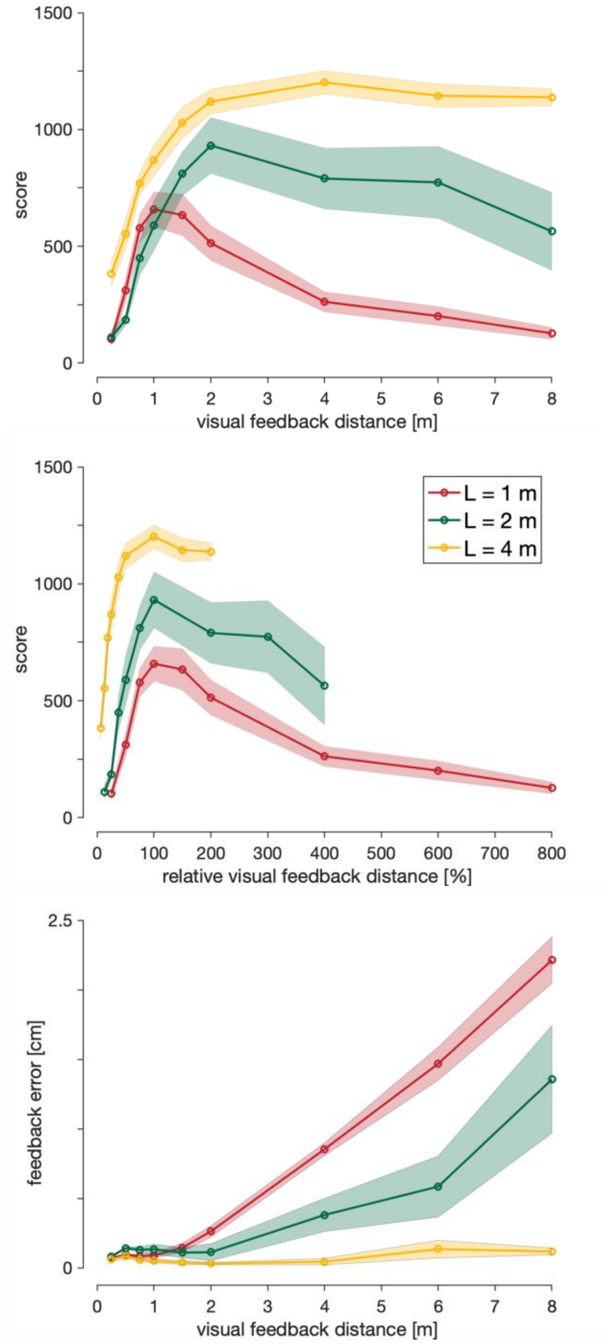

Figure 2. **Top.** Mean score across participants for different dynamic conditions and visual feedback distances. **Middle.** Score across all participants, as a function of visual feedback distance normalised by the dynamic pendulum length. Participants show the highest stability when controlling a pendulum with visual feedback congruent to the dynamic length. **Bottom**. Visual feedback point errors with respect to cart position. Participants successfully mitigate errors for visual feedback distances shorter than the dynamic lengths, but errors increase proportionally at longer than dynamic visual feedback lengths.

Our normative prediction of this control behavior generated results comparable to those recorded in human participants, with the model predictions within 1SEM from the human data (Fig. 3).

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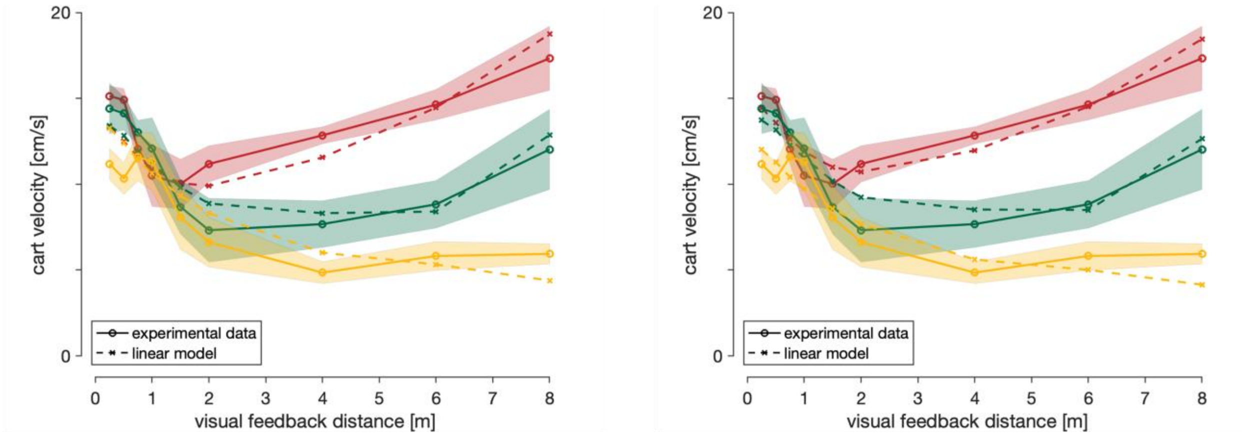

Figure 3. Two best-fit cart velocity models (solid lines), overlaid with the experimental data (dashed lines). Shaded areas represent 1SEM across participants. Both models capably represent our experimental data, with model predictions within 1SEM from the experimental data. **Left**. Model *[A,B,C,0]* (2nd best model). **Right.** Model $[A_L,B,C,0]$ (best-fit model).

Our proposed model qualitatively captures the human control behavior of an inverted pendulum by combining mechanisms of proportional error correction and a term inversely proportional to visual feedback length. While the idea of error correction is widely accepted in human motor control, the purpose of a hyperbolic term is yet unclear and could have multiple explanations. One explanation for the presence of this term could be that humans experience an illusionary effect of reduced inertia of the pendulum with increasing visual length. Assuming a prior of Newton's 2nd law, the inertia of the pendulum would be estimated by a ratio between applied force and the acceleration of the visual feedback point. However, as the acceleration of this point scales with L_v, the perceived inertia would scale inversely. As a result, conditions with short visual feedback would feel "heavy" and would invoke stronger corrective responses, while the opposite is true for the long visual feedback locations.

Our participants exhibited significantly better stability when controlling a pendulum of a dynamic length $L = 4$ m, compared to $L = 2$ m and $L = 1$ m, at a visual feedback length $L_v = L$, while stability *of* $L = 2$ m was not different from $L = 1$ m in the same conditions. Previously we [12] have shown that virtual pendulums of L = 4 m and $L = 2$ m, simulated in a similar environment as in our experiment, were significantly more stable than a pendulum of $L = 1$ m. We believe that this difference stems from learning effects – all of our participants started with dynamic length $L = 2$ m, followed by the other two conditions in a balanced order, while in the previous study all three lengths were presented in a random order. Therefore, our participants managed to significantly improve their stability by performing the control task on different conditions. As a result, this may mean that the control strategies observed in our study have not yet converged to the optimal control. Further studies may compare how the controller changes with experience within this inverted pendulum environment.

In this article, we proposed a normative model of how humans may try to stabilize an inverted pendulum. More importantly, we showed the importance of a controller modality in which the control gains are inversely proportional to the visual feedback gains, suggesting that similar processing may occur in humans when controlling an unstable system. This result may allow us to better understand what control strategies or cost functions are used by humans, leading to a better understanding of human brain as well as a possibility to develop more efficient control algorithms by mimicking it.

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