Concept of Dynamical Traps in Human Control Theory

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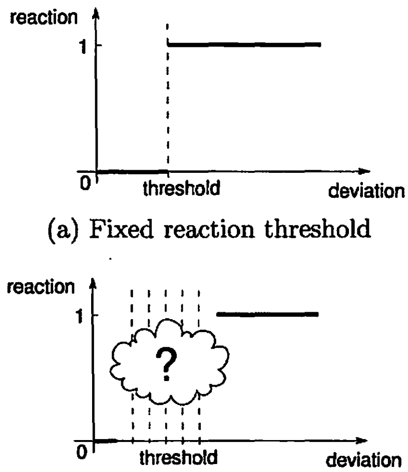
1 Introduction

Stick balancing is an incresingly popular paradigm for studying human control behavior. Theoretical investigations on both virtual and real-world stick balancing, reinforced by experimental evidences, provide useful insights into, e.g., human control over the body vertical position during quiet standing (see, e.g., [1]). It is generally agreed at present that human control of an inverted pendulum is non-trivial and complex process that involves such factors as noise in neuromotor system, perception/reaction delays and prediction. Under these constraints the continous feedback control has been shown to be ineffective; rather, discontinuous or intermittent "drift-and-act" control is implemented by human operators in balancing tasks [2].

The intermittency of human control in many processes is an established fact, however, there is still no consensus on what the mechanism behind this intermittency is. There exist several competing hypotheses (see [3] for a review), one of which assumes that the intermittency is caused by the sensory dead zone: humans do not react to the deviations from the desired system state that are small, and only start controlling the system actively when this deviation exceeds certain threshold (see, e.g., [4, 5]). In the present work we advance the basic idea of this hypothesis by proposing an advanced yet simple model accounting for the intrinsic stochasticity of human reaction threshold. The experimental data on virtual stick balancing in viscous medium [6] give evidence to the fact the assumption of fixed human reaction threshold (Fig. 1a) may be oversimplistic: the observed values of deviation at which the operator starts correcting the stick motion are widely scattered rather than being concentrated in a close proximity of the equilibrium position. The discrepancy between the de facto standard model of fixed reaction threshold and the recent experimental results motivated the current study. Employing the concept of the double well potential widely met in physics, we propose the probabilistic model for human reaction threshold (Fig. 1b). We conduct a preliminary analysis of the model dynamics and compare its results to the previously obtained experimental data on balancing of virtual overdamped stick.



(a) Fixed reaction threshold

(b) Probabilistic reaction threshold

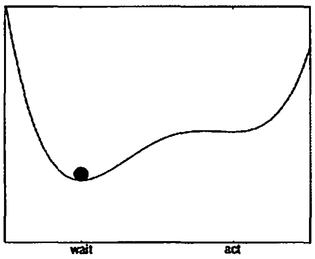
Fig. 1: Two basic models of human reaction threshold

2 Model

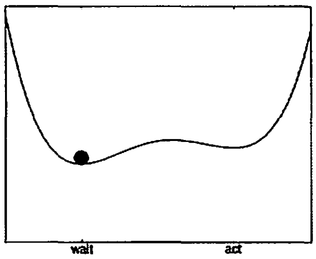
The motion of the stick in viscous medium can be described as follows (after linearization at the origin)

$$\tau_\theta \dot{\theta} = \theta + \frac{\tau_\theta}{l} \upsilon \xi, \tag{1}$$

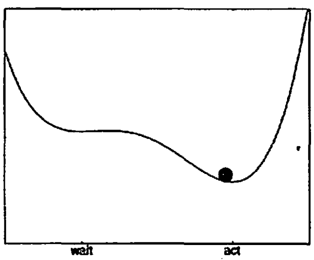
where θ is the deviation of the stick from the vertical position, υ is the control effort applied by the operator at the base of the stick, l is the stick length and τ_θ characterizes the environment properties. In order to describe the dynamics of human control depending on the deviation θ, we introduce the new phase variable ξ describing the mental state of the



(a) Small deviation



(b) Intemediate deviation



(c) Large deviation

Fig. 2: Double well potential of human mental state during a control process

operator. Value of ξ equal to zero corresponds to the operator feeling that the current value of deviation can be neglected. In contrast, $\xi = 1$ reflects that the operator is actively controlling the system. The dynamics of ξ is intrinsically stochastic: the larger the deviation, the higher the probability that ξ takes value unity. Such behavior can be naturally captured by model of random walk in a double well potential (see Fig. 1), where the energy landscape dynamically changes depending on the current value of the stick deviation:

$$\begin{aligned} \tau_\xi \dot{\xi} &= -\frac{\partial H}{\partial \xi} + \epsilon H \zeta, \\ H(\xi, \theta) &= \frac{\xi^4}{4} - \frac{\xi^3}{3}(1+a) + \frac{\xi^2}{2} + \frac{1-a}{12}, \\ a &= \frac{\theta_{\text{th}}^2}{\theta_{\text{th}}^2 + \theta^2}. \end{aligned} \tag{2}$$

Term $\epsilon H \zeta$ is a multiplicative white noise, parameter ϵ determines the noise intensity, τ_ξ defines the time scale of human mental state dynamics, quantity $a = a(\theta)$ characterizes the deviation from the vertical position with respect to operator sensory threshold θ_{th}. The operator, first, aims at eliminating the deviation θ and, second, realizes in some sense open-loop control — the larger the current control effort value, the higher the tendency to halt the control:

$$\dot{v} = -(\theta + \sigma v), \tag{3}$$

where σ is a constant parameter.

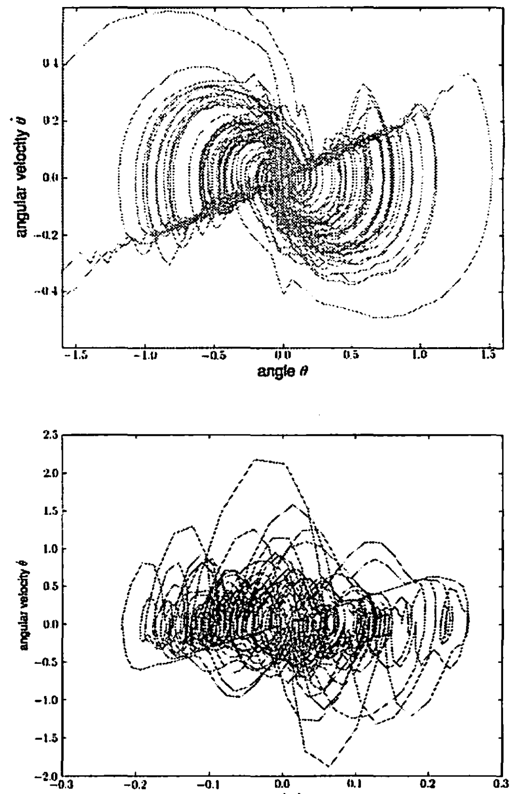


Fig. 3: Phase portraits of stick motion generated by model (1–3) (top frame) and human operator (bottom frame, adapted from [6]). Values of parameters used for simulations are: $\tau_\theta = 3, l = 1, \tau_\xi = 0.05, \epsilon = 0.7, \theta_{\text{th}} = 0.2$.

3 Simulation results

Here we report some preliminary results of the analysis of the model (1–3) and confront the model with the previously obtained experimental data. Indeed, the proposed model still requires the detailed

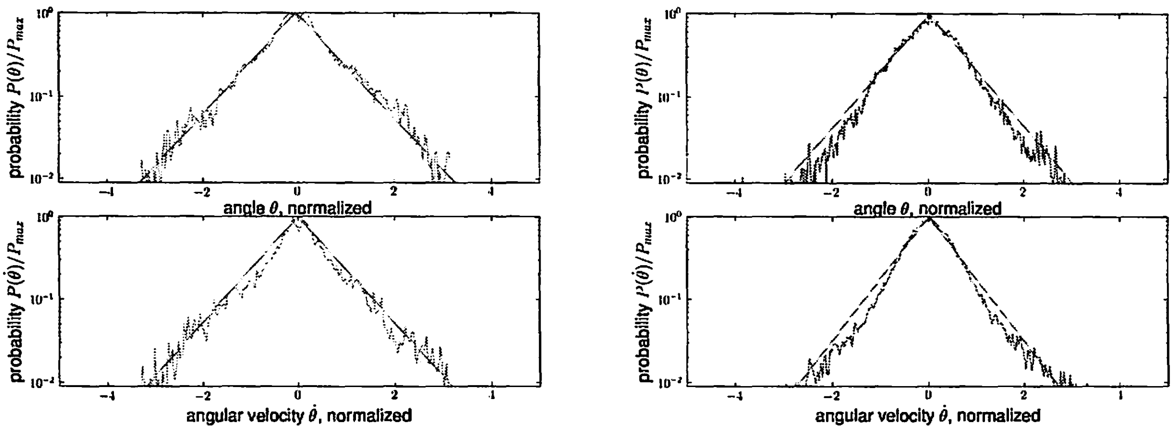


Fig. 4: Angle and angular velocity distributions of stick motion generated by model (1–3) (left frame) and human operator (right frame, adapted from [6]). Values of parameters used for simulations are: $\tau_\theta = 3, l = 1, \tau_\xi = 0.05, \epsilon = 0.7, \theta_{\text{th}} = 0.2$. The angle and angular velocity values are normalized with respect to their standard deviations: $\theta \to \theta/\text{std}(\theta)$, $\dot{\theta} \to \dot{\theta}/\text{std}(\dot{\theta})$. All four distributions are best fit with the Laplace distribution represented by thin purple lines.

scrutiny, as well as thorough comparison to the data from human subjects; these analyses will be reported elsewhere.

We analyze numerically the basic properties of the system (1–3) by simulating its dynamics using the second-order stochastic Runge-Kutta algorithm [7]. The values of system parameters used in simulations are: $\tau_\theta = 3$, $l = 1, \tau_\xi = 0.05$, $\epsilon = 0.7, \theta_{\text{th}} = 0.2$.

Fig. 3 represents the phase portraits of the stick balanced during 50-second trial by a human subject [6] compared to the phase portrait of the system (1–3) obtained by numerically simulating the system dynamics (simulation period of 1000 time units). One may easily see that both phase portraits have several similarities in their structure. First, there is a noticable straight line passing through the origin in both trajectories; this line corresponds to the uncontrolled motion of the pendulum, when $\xi \approx 0$ in Eq. (1) so that $\tau_\theta \dot{\theta} = \theta$. Second, the shape of the system (1–3) trajectory fragments corresponding to the active control of the operator ($\xi = 1$) is very similar to the one-step corrective movements of the human subjects. The control is activated when the stick angle becomes large enough; the control effort returns the system to some vicinity of the origin, where the control is turned off again. Indeed, one may argue that the bottom frame of Fig. 3 represents several patterns of the corrective movements other than the simple single-step control. For instance, the human subjects often perform several corrections of the initially implemented control actions, thus causing the complex structure of the stick phase portrait. The proposed model is not able to capture these most probably important features of human control. However, as we demonstrate further, the presence or absence of such complex control patterns practically does not affect the statistical properties of the controlled system.

We compare the distributions of the phase variables (θ and $\dot{\theta}$) of the stick balancing by human subject during 10 minutes and the corresponding distributions produced by system (1–3) in a numerical simulation with duration of 10000 time steps. Fig. 4 illustrates the high degree of similarity of the distribution functions. Both stick angle and angular velocity distributions of the human-controlled stick are, first, well fit by the Laplace distribution, and, second, well captured by the model (1–3).

4 Discussion

The anomalous, non-Gaussian distributions of the stick angle and angular velocity indicate that the mechanisms of human control are highly non-linear and cannot be described by the standard linear feedback model. The proposed model takes into account that the human operators react to the system deviations from the desired state in a fuzzy manner. In our model whether or not certain angle value triggers the reaction or not is determined not only by the particular value of the angle, but also by random factors. The similar models based on random walks are widely employed in cognitive science to describe the stochastic information accumulation during decision making (see [8] for a review).

In the present paper we argue that the human cognitive mechanism responsible for the control of dynamical systems may be decomposed into two major subsystems or mechanisms: the first one is responsible for recognizing the critical state of the system that requires the corrective actions (i.e., when to react), while the second one determines the particular values of the control effort in response to the stimulus (i.e., how to react). The currently available models of human control focus mainly on the latter mechanism, either ignoring the former one or treating it as trivial (fixed reaction threshold model). Up to our knowledge, the present model is the first attempt to describe the probabilistic nature of the human reaction to dynamical stimulus.

We propose the rather general stochastic model for human control behavior. Using the stick balancing as an example of human-controlled system, we provide the experimental evidences for the validity of the model. Although the model captures only the simplest type of human corrective actions, it is proven to be enough for capturing the basic statistical properties of the virtual stick under human control. We strongly believe that the proposed probabilistic approach captures the intrinsic properties of human control and may be considered as a more advanced alternative to the standard fixed reaction threshold concept when modeling human control in a wide class of real-world systems.

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