Human intermittent control: concept of noise-driven control activation

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Abstract

Recent progress in motor control suggests that in controlling unstable systems humans switch intermittently between the passive and active behavior instead of controlling the system in a continuous manner. Traditionally, the models of intermittent control employ the notion of threshold to mimic control switching mechanisms in humans. The notion of noise-driven control activation developed here provides a richer alternative to the conventional threshold-based models of intermittent motor control. We show that the model implementing noise-driven activation matches the experimental data on human balancing of virtual overdamped stick. Our results suggest that the stochasticity of the control activation mechanism is a fundamental property and may play an important role in the dynamics of human-controlled systems.

1 Introduction

Control of unstable systems underlies many critical procedures performed by human operators, as well as numerous routines that all of us face in daily life. Eliciting and modeling the basic mechanisms of human control can help us to understand the nature of such processes, and in the end, hopefully, to reduce the risks associated with human error [1, 2].

Intermittency has long been attributed to human control processes [3]. Nonetheless, despite being recognized for decades, it is still far from being completely understood. In recent years it has been studied mainly in the context of two relatively simple human balancing tasks: quiet standing and stick balancing (Fig. 1). Besides their simplicity, these two tasks have much in common, and are often discussed in relation to each other [2]. In both tasks intermittent control is more robust, energy-efficient, and, importantly, more natural for humans than continuous control [4]. Still, even within such a basic setup the particular mechanisms behind intermittent human control remain unclear.

Among the explanations of human control intermittency proposed so far are: the interplay between noise and delays in sensorimotor system [5], the clock-driven (see, e.g., [6]) and the event-driven control. The latter hypothesis has become the most widely employed recently (see review in [7]). Event-driven models build up on the fact that human operators cannot detect small deviations of the controlled system from the goal state. Therefore, the control is switched off as long as the deviation remains below a certain threshold value,

$$\text{control} = \begin{cases} 
\text{off} & \text{if } \theta \leq \theta_{th}, \\
\text{on} & \text{if } \theta > \theta_{th}, 
\end{cases} \quad (1)$$

where $\theta$ is the controlled variable and $\theta_{th}$ denotes the threshold value. Some studies hypothesize that human operators may also exploit the dynamical properties of the controlled system. For instance, in quiet standing humans may ignore the large angular deviation of the body if the body already moves towards the upright position due to inertia [8]. Even so, the latter mechanism is assumed to operate not on its own, but jointly with the threshold-based control.

The importance of the control activation mechanism in human control models is widely acknowledged. Still, virtually all current models of event-driven human control utilize the very basic, threshold-driven activation mechanism. In essence, they presume that the control is triggered at the very moment the deviation of the controlled system from the goal state crosses the fixed, precise boundary of the sensory deadzone (Eq. (1)). Additive or multiplicative noise is often used to introduce some variance (i.e., to “blur” threshold). However,
Fig. 2: Action points observed in human balancing of overdamped stick. Solid lines represent the trajectory of the 5-second balancing trial without stick falls. Circle markers denote action points.

the experimental findings reveal that the threshold-based mechanism may be inadequate in capturing the patterns of control activation observed in humans [9]. The purpose of the present paper is to outline the new approach to modeling control activation in humans, namely, the noise-driven control activation.

2 Background

Stimuli of small magnitude cannot be sensed by humans due to bounded capabilities of our perception. Consequently, in controlling an unstable object humans cannot compensate for small deviations of the system from the goal just because they cannot detect these deviations. In addition, many factors other than the magnitude of deviation can affect human response. For instance, if the control process lasts for a relatively long time, the mental expenses for staying perfectly aware of the tiniest deviations may be unbearable for the operator. In this case, even the deviation that otherwise can be clearly perceived may be neglected due to energy considerations. Another relevant factor is the limited ability of the operator to precisely manipulate the unstable system. Even a highly skilled operator cannot accurately compensate for small, barely detectable deviations. In order not to destabilize the system by the imprecise interruption, the operator may prefer to wait until the deviation becomes large enough. As a result, the corrective movements need not be thoroughly planned and implemented.

All these factors lead to emergence of two phases in human-controlled processes, active and passive [9]. The moments corresponding to the transitions from passive to active phase are called action points (Fig. 2). Understanding the physics of transitions from passive to active phase is a key issue in modeling dynamics of human-controlled systems. Traditional, threshold-based transition (1) necessarily yields normal distribution of action points centered at the hypothetical threshold value. However, it has been demonstrated that in overdamped stick balancing the distribution of action points in humans is substantially non-Gaussian (Fig. 3), and thus cannot be explained by threshold-driven activation.

3 Model

To capture the experimentally observed stochasticity of the control activation mechanism, we employ the approach of phase space extension [10]. In addition to the set of phase variables describing the physics of the controlled system, we introduce additional phase variable corresponding to the control effort of human operator,

\[ \dot{u} = \Omega(u)F(x, u) + f(t), \]

where \( u \) is the control variable, \( x \) is the state vector of the controlled system, \( F(x, u) \) describes the system behavior in the active control phase, \( f(t) \) is the random force of small amplitude, and \( \Omega \) is a function of \( u \) such that \( \Omega \approx 0 \) if \( u \approx 0 \), and \( \Omega \approx 1 \) otherwise.

In Eq. (2) the cofactor \( \Omega \) introduces the “trapping” region around the status quo state of the human operator, \( u = 0 \). However, the random cofactor \( f(t) \) allows the system to escape from this region; in this way the transition from passive to active phase is implemented.

In what follows we exemplify the general model (2) using the simple task of overdamped stick balancing. We also wish to underline that this model can be easily adapted also to high-dimensional human control processes, e.g., car following.

Hypothetically, the dynamics of the overdamped stick under human control can be described by the dimensionless dynamical system (see [11, 12] for details)

\[ \dot{\theta} = \theta - \nu, \]

where \( \theta \) is the stick tilt angle, if only the cart velocity \( \nu \) is specified as a function of \( \theta \) or time \( t \). However,
\[ \dot{v} = \gamma \theta - \sigma \nu, \]  

where \( \gamma \) and \( \sigma \) are non-negative constant parameters.

The pivot point of the present model is that the operator’s decision when to react is determined by the noise-mediated interplay between two stimuli. On the one hand, the operator is averse to actively controlling the stick; the zero value of the cart velocity, \( \nu = 0 \), is thus attractive to the operator (according to the above speculations). On the other hand, the ultimate goal, to maintain the stick upwards, inclines the operator to act, and the other one resulting in resistance to moving the cart, are assumed to compete stochastically. The dynamics of their interplay can be captured by modifying Eq. (4) in the following way (cf. Eq. (2))

\[ \dot{\nu} = \Omega(\nu)[\gamma \theta - \sigma \nu] + \epsilon \xi, \]  

where \( \xi \) is white Gaussian noise, \( \epsilon \ll 1 \) is the noise amplitude, and \( \Omega(\nu) = \nu^2/(\nu^2 + 1) \). We wish to underline that the random force \( \epsilon \xi \) does not represent the sensorimotor noise, but instead serves to mimic the stochasticity of the operator’s decision when to react.

4 Results

We found that the model reproduces well the experimentally observed behavior reported in Refs. [11, 12]. Typical phase trajectory exhibited by the model is represented in Fig. 4a. The initially perturbed system moves along the \( \theta \)-axis with the cart velocity \( \nu \) close to zero, so that \( \dot{\theta} \approx \theta \). This motion regime represents the passive control phase. As the angle \( \theta \) increases, the system may escape from the vicinity of the manifold \( \nu = 0 \) due to the random force \( \epsilon \xi \). Small fluctuations of the system moving along the axis \( \nu = 0 \) result, sooner or later, in the situation when the trapping effect of cofactor \( \Omega \) is suppressed by the growing magnitude of the cofactor \( [\gamma \theta - \sigma \nu] \). This triggers the sharp transition from \( \dot{\nu} \approx 0 \) to \( \dot{\nu} \approx \gamma \theta - \sigma \nu \), i.e., the transition from the passive to the active control phase. However, in case the random force is absent, \( \epsilon = 0 \), the system steadily moves away from the equilibrium along the \( \theta \)-axis. The switching from the passive to the active phase is thus driven solely by noise.

Most notably, the distribution of action points (i.e., values of stick angle corresponding to moments when the control switches on) produced by the model decays exponentially, following the experimentally obtained distributions (Fig. 4b). This prompts that the suggested model captures the essence of the control activation mechanism employed by human subjects.

5 Conclusion

In controlling unstable systems humans often switch intermittently between the passive and active behavior instead of controlling the system in a continuous manner. The present paper argues that some intricate properties of intermittent control activation can be explained using the notion of noise-driven control activation. Appealing to modern understanding of human intermittent control, we propose to distinguish between the passive and active phases of operator’s behavior. We then describe the repeated switching between active and passive behavior by a phenomenological model capturing the interplay between two stimuli, one inclining the operator to act, and the other one resulting in resistance to change the cart position. The dynamics of this interplay is stochastic; we capture this stochasticity by the additive noise mimicking the uncertainty in oper-
Fig. 4: (a) Typical phase trajectory of the model (3),(5). Arrowed lines represent the force field of the corresponding linearized system; (b) Action point distribution exhibited by the model (3),(5) compared to the experimental distributions.

ator’s perception. We demonstrate that the key characteristic of human control activation in simple stick balancing task, that is, the exponentially decaying action point distribution, is reproduced by the model. We conclude that the proposed model is a physically plausible approach to modeling control activation in tasks where humans exhibit intermittent control behavior.

**References**


