Statistical Properties of Human Response Delay: Analysis of Virtual Stick Balancing Experiments

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Abstract

The present work reports the results of our experiments aimed at estimating the distribution of the response delay time in human intermittent control over unstable mechanical systems. A novel experimental paradigm: balancing an overdamped inverted pendulum was used; the over-damping eliminates the effects of inertia and, therefore, reduces the dimensionality of the system. The created simulator of balancing a virtual pendulum by a human operator via computer mouse movement makes the pendulum (stick) invisible when the angle between it and the upward position is less than 5°. It enabled us to measure directly the delay time as the time lag between the moment when the pendulum becomes visible and the moment when a subject starts to move the mouse. Eight persons (male students) were involved in the experiments. The collected experimental data are presented in the form of the delay time histograms. For the analyzed system it is demonstrated, in particular, that (i) the response delay time may be treated as a random variable distributed within a wide interval. Its lower boundary is estimated as less than 50 ms, which corresponds to the limit delay time determined by human physiology. The upper boundary is estimated as 500–600 ms, which is about typical values of the response delay time when a controlled system exhibits complex dynamics. Besides, the obtained results enable us to hypothesize that the response delay in human intermittent control may be determined by cumulative actions of two distinct mechanisms, automatic and international, endowing it with complex nonlinear properties.

1 Introduction

By now there has appeared much evidence in favor of a novel paradigm of human control over unstable mechanical systems which is also applicable to describing physiological processes such as postural balance. It is called human intermittent control [1, 2, 3, 4, 5]. As far as human behavior is concerned, intermittency implies discontinuous control, which repeatedly switches off and on instead of being always active throughout the process. As a result, the actions of a human operator in controlling a mechanical system form a sequence of alternate fragments of phases of his passive and active behavior. According to the current state of the art, this type control being rather efficient on its own is a natural consequence of human physiology (see., e.g., [2]).

The concept of event-driven intermittency is one of the most promising approaches to describing human control. It posits that the control is activated when the discrepancy between the goal and the actual system state exceeds a certain threshold. Models based on the notion of threshold can explain many features of the experimentally observed dynamics [1, 4]. However, much still remains unclear even in the case of relatively simple control tasks, such as real [3, 6, 7] or virtual [2, 8, 9, 10] stick balancing.

Recently, a novel concept of noise-driven control activation has been proposed as a more advanced alternative to the conventional threshold-driven activation [11]. It argues that the control activation in humans may be not threshold-driven, but instead intrinsically stochastic, noise-driven, and stems from stochastic interplay between operators need to keep the controlled system near the goal state, on the one hand, and the tendency to postpone interrupting the system dynamics, on the other hand. To justify the noise-driven activation concept a novel experimental paradigm: balancing an overdamped inverted pendulum was employed [11]. The over-damping eliminates the effects of inertia and, therefore, reduces the dimensionality of the system. Arguably, the fundamental properties and mechanisms of human control are more likely to clearly manifest themselves in such simplified set-ups rather than in more complicated conventional experimental paradigms.

In the frameworks of human intermittent control with noise-driven action the transition from passive to active phases is considered to be probabilistic, which reflects human perception uncertainty and fuzzy evaluation of the current system state before making decision concerning the necessity of correcting the system dynamics. Broadly speaking, during the passive phase the operator accumulates the information about the system state, naturally, this process is not instantaneous but requires some time in addition to the physiological delay in human response. The cumulative effect of the two mechanisms, the accumulation of information about the system state and the physiological delay, can be described by some effective delay time $\tau$. The found stochasticity of human intermittent control in exper-
ments on balancing virtual stick [11] prompts us to expect that this delay time is not a fixed value but a random variable with a relatively wide distribution; this feature is crucial for modeling human intermittent control. To elucidate the probabilistic properties of this cumulative delay in human reaction in controlling unstable mechanical system we have conducted some experiments and the purpose of present work is to report the obtained results.

However, before describing our experiments and discussing the obtained results, some comments concerning the research of human response delay are worthwhile. Investigations of response delay in human reactions to various stimuli including visual ones has a relative long history (see, e.g., [12]). Usually in experiments on human visual perception the values of delay time \( \tau \gtrsim 100 \text{ ms} \) are detected and they are unimodally distributed within a wide interval; the gamma or Weibull fits are often used to characterize the found results (see, e.g., [13]). During the last decade there has been accumulated some evidence that mental processes contribute substantially to the response delay and such factors as memory load and required attention are essential in this case (see, e.g., [14, 15] and references therein). Taking into account these facts and the possible existence of two mental systems of information processing (see, e.g., review [16]) we may expect the response delay time distribution to exhibit complex behavior especially in cases when it is related to decision-making in multifactorial processes like human intermittent control.

The physiological control mechanisms employed to balance unstable loads are rather far from being understood well. In particular, it is unclear whether the nervous system has a capacity of planning control activity based on the dynamics of controlled system, whether the control process is highly adaptive or relatively inflexible to the complexity of the system dynamics, whether it is a random process or can be characterized by approximately constant delay time ([17, 18, 10]). These issues are also important for modeling human control of movement under various conditions.

2 Methods

As previously [11], in the reported experiments the paradigm of balancing an overdamped inverted pendulum was employed. It was implemented via balancing a virtual stick whose dynamics is affected by computer mouse movement (Fig. 1). Namely, the stick dynamics is simulated by numerically solving the ordinary differential equation

\[
\tau_\theta \frac{d\theta}{dt} = \sin \theta - \frac{\tau}{I} \dot{\theta} \cos \theta,
\]

where \( \theta \) is the angular deviation of the stick from the vertical position and \( \dot{\theta} \) is the cart velocity. The parameter \( \tau_\theta \) determines the timescale of the stick motion: the higher the \( \tau_\theta \), the faster the stick falls in the absence of human control. The sticks length \( I \) determines the characteristic magnitude of the cart displacements required for keeping the stick upright. The cart position was controlled by the operator via a computer mouse. Following to the technique used previously [11], prior to each screen update, the approximate horizontal mouse cursor velocity was calculated based on five most recent values of cursor position using the second-order low-noise differentiator [19]. The resulting cursor velocity \( \dot{\theta} \) (measured in pixels per millisecond) was then substituted into equation (1) which in turn was integrated using the first-order explicit Euler method to obtain the updated stick angle \( \theta \).

On the computer screen, a subject sees a vertically oriented stick and a moving cart rigidly connected to the base of the stick. The task was to maintain the upright position of the stick by moving the cart horizontally via the computer mouse. The data were collected in the experimental conditions classified previously as the fast motion of the stick, which is the case when \( \tau_\theta = 0.3 \text{ s} \) matching the mean time of stick fall about 1 s in such experiments, provided a subject temporally halts the control [11].

The participants performed the task sitting at the office desk, using the common desktop computer. The distance between the monitor and the subjects eyes was about 70 cm, the stick length on the screen was about 10 cm. The screen update frequency was 60 Hz. The horizontal position of the mouse cursor on the screen was sampled with a frequency of 50 Hz. A commercially available high-precision gaming mouse (Logitech G500) was used in the experiments. A new feature of this balancing simulator is that the stick becomes invisible within the sector \(-5^\circ < \theta < 5^\circ\) (Fig. 1).

The experiments were implemented as a sequence of stick balancing trials. Within one trial the stick is initially placed by the computer inside the sector of invisibility and its further motion is controlled by a subject during the next 5 s or is terminated earlier if the stick has fallen. After the following 3 s designated for subject’s rest the system position is restored, the cart is put in the middle of the screen and the stick is automatically returned into the sector of invisibility. Then, the
The histograms shown in Fig. 3 represent the individual results of six subjects. The left column depicts the data collected by the first group of participants, the right one corresponds to the second group. Histograms in red/blue are constructed based on the data collected within the “One-side”/“Random” set-up. It turned out that in both the groups the histograms of two participants look rather similar, so only one of them is presented in Fig. 3 (the upper row). The obtained histograms change in form for different subjects within one group, therefore to compare the two groups histograms looking similar are placed in one row, if, naturally, this similarity is the case.

Based on the obtained results we can draw the following conclusions.

(i) The human response delay time recorded in these experiments is practically a random variable distributed inside a wide interval. The lower boundary $\tau_l$ of this interval can be less than 50 ms (within the obtained accuracy); its upper boundary $\tau_u$ is about 500–600 ms. This estimate of $\tau_l$ is rather close to the limit response time determined by human physiology (for a resent review see, e.g. [20] and the following discussion), whereas the found value of $\tau_u$ is typical for human response delay during complex balancing tasks (see, e.g., [10]). Moreover, as demonstrated [10], in complex balancing tasks human response may indicate flexible, variable delay and intentional mechanisms associated with central processing.

Moreover, appealing to the presented data we see that the response delay time can vary widely during a balancing processes, so in modeling, at least, human control over unstable systems the delay time cannot be regarded as a certain constant value.

(ii) For different subjects the histograms can exhibit a strong as well as weak dependence on the predictability of the stick motion, namely, the side on which the stick appears for the first time after the initial system position having been restored. Two subjects, whose diagrams are shown in the lower row in Fig. 3, demonstrated a strong dependence on this factor. Their histograms in the case of the “One-side” set-up are remarkably wider than in the case of the “Random” set-up due to the considerable contribution of the region of small values less than 200 ms. This region of rather short response delay may be related to the automatic mechanism of human reaction [10]. It is interesting that this region practically does not contribute to the histograms shown in the upper row or their contribution is substantial in histograms placed in the middle row independently on the experimental set-up.

The number of subjects (8 students) involved in the experiments is not enough to draw statistically proved conclusions, so the obtained results have to be categorized as preliminary ones. Nevertheless they allow...
Fig. 3: Histograms of response delay time obtained based on the conducted experiments for six subjects. Blue lines represent the results of the “Random” set-up, red lines match the “One-side” set-up. The group of histograms in the left column presents the results obtained within the arrangement where the “One-side” setup preceded the “Random” step; the right column corresponds to the opposite order.
us to hypothesize that in human intermittent control both the automatic and intentional mechanisms contribute simultaneously to human response and are in a continuous interplay with each other. During the last decades there have been ongoing debates about the existence of two types of cognitive processes that are fast, automatic, and unconscious and those that are slow, deliberative, and conscious. Moreover they may be assumed to occur from two architecturally (and evolutionarily) distinct cognitive systems. Correspondingly one of these systems must be reflexive, automatic, fast, affective, associative, and primitive, and the second one should be deliberative, controlled, slow, cognitive, propositional, and more uniquely human. Besides, there are accounts assuming the dual-processes to arise parallel and compete with each other, however, there are also arguments against the dual system of decision-making; for a review and discussion of the evidence supporting both sides of the debate a reader may be referred to Refs. [16, 21, 22, 23]. The found dependence of the constructed histograms on subject’s individuality argue for the fact that the two cognitive systems are comparable in influence on response delay in human intermittent control. Therefore the response delay must be actually a certain rather complex function of the human state affected by the current situation.

In addition, the obtained results may be regarded as certain arguments for the concept of dual-system of cognitive processes (see for a review [16]). It assumes the existence of two distinctive systems of information processing; one of them is automatic and fast, the second is slow and deliberative. As should be expected in the case of several mechanisms governing human response, the found distributions of the delay time significantly deviate from the gamma, Weibull, or Gaussian forms.

(iii) The histograms obtained within both the set-up arrangements are rather similar, at least, the variations of their form within one group due to subject’s individuality are stronger than these variations in comparing the histograms within the rows separately. It allows us to assume that subject’s learning during the balancing process may have no considerable effect on the human response delay or is characterized by relatively short time scales. In the latter case the notion of adaption seems to be more appropriate for characterizing the human behavior in control processes.

The found results are essential for constructing mathematical models of human intermittent control that operate directly with the human response delay and have to treat it as a certain complex nonlinear and, maybe, stochastic function. Besides, these models should allow for the substantial role of mental processes in evaluating the current state of system dynamics by human operators.

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References


