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Adaptive intermittent control: A computational model explaining motor intermittency observed in human behavior

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1. Introduction

Human sensorimotor system contains many delay/lag elements in the control loop, including sensory processing, neuronal transmittion and muscle activation. It is a fundamental question how our brain achieves real-time motor control with this slow system. Computational theories have pointed out that feed-forward control with internal models is essential for overcoming this problem (Engel & Soechting, 2000; Kawato, 1999; Kawato & Wolpert, 1998; Wolpert & Miall, 1996; Wolpert, Miall, & Kawato, 1998). The validity of feed-forward control has been mainly discussed in the case of ballistic movements such as reaching, presumably because it assumes that motor commands be calculated before the movement onset. Nevertheless, feed-forward control must be indispensable also in continuous, environment-dependent motor tasks (such as target tracking) even though it requires motor planning for every motor action, because ordinary feedback control cannot effectively work with the large delay (Paul, 1981).

In the present study, we propose a hypothetical control model called "adaptive intermittent control" or "segmented control" as a possible mechanism for operating feed-forward control in continuous motor tasks. The principle is that brain divides the time axis into discrete segments and executes feed-forward control in each segment. It is close to the scheme of model predictive control (MPC) proposed in the field of control theory (Maciejowski, 2002).

Most control models for sensorimotor functions (especially for continuous motor tasks) implicitly assume that the control system is stationary: They keep receiving sensory information and producing motor commands in a seamless manner. However, it seems more plausible that the motor control process in our brain is temporally organized: Different computational processes (e.g., model estimation, future prediction and motor planning) work in a temporally non-uniform manner dependent on the internal and external events (Sakaguchi, 2007). One example of control models realizing such a non-stationary control process is "intermittent control," which occasionally updates the control signals at certain sparse points in time (Karniel, 2013). This concept has been proposed in the fields of control theory, biological modeling and nonlinear dynamical system. As a classical work, Craik (1947, 1948) discussed the intermittent nature of the behavior observed in human operators in the control system, and other researchers (Keele, 1968; Keele & Posner, 1968; Navas & Stark, 1968; Pew, 1966; Vince, 1948a, 1948b) have pointed out the intermittent mechanism of human motor control. As an example of recent studies, moreover, Gawthrop, Loram and their colleagues (Gawthrop, 2010; Gawthrop, Loram, Gollee, & Lakie, 2014; Gawthrop, Loram, Lakie, & Gollee, 2011; Gawthrop & Wang, 2006, 2009, 2010, 2011; Gollee, Mamma, Loram, & Gawthrop, 2012; Lakie & Loram, 2006; Loram, Gawthrop, & Lakie, 2006; Loram, Gollee, Lakie, & Gawthrop, 2011; Loram, van de Kamp, Gollee, & Gawthrop, 2012; Ronco, Arsan, &

Gawthrop, 1999; van de Kamp, Gawthrop, Gollee, & Loram, 2013; Vieira, Loram, Muceli, Merletti, & Farina, 2012) have published a series of works proposing the intermittent control model from a viewpoint of control theory, and examined its validity from a viewpoint of biological modeling. Specifically, Gawthrop and Wang (2011) proposed a model based on model predictive control that updated motor commands only intermittently ("i.e., intermittent MPC"). This model has two types of command update rules: Clock-driven and event-driven. In the former type, the motor command is updated with fixed intervals (based on a time clock) while in the latter type, it is updated when the task error exceeds a specific threshold. One merit of intermittent control is to reducing the amount of computation~~al cost~~ because motor planning requires the heaviest calculation (i.e., optimization) in motor control process (see Section 4.4 for a related issue). Another merit is to be able to stabilize the control system with large sensorimotor delay, as we mention below.

In the field of non-linear dynamical system, Minton and his colleagues (Cabrera & Milton, 2002, 2004; Hosaka, Ohira, Luciani, Cabrera, & Milton, 2006; Milton, Cabrera, & Ohira, 2008; Milton, Cabrera, et al., 2009; Milton et al., 2013; Milton, Ohira, et al., 2009; Milton, Townsend, King, & Ohira, 2009) proposed a theoretical control model to discuss the phenomena caused by the interaction between delayed feedback and intrinsic noise. They picked up "stick balancing" as an example of human behavior and showed that their theory could explain the nature of human behavior, especially, the occurrence of "escape" (i.e., the fall of stick). They also showed that given an appropriate threshold for corrective action, the system could avoid escape (Milton et al., 2013).

Therefore, the concept of intermittent control has been already discussed from various viewpoints. Here, we propose an adaptive intermittent control from a viewpoint of "system model of sensorimotor mechanism," aiming to simulate the information processing in our brain. This model could be regarded as an expansion of the conventional intermittent MPC scheme, but includes a novel idea of adaptive determination of the timing of motor updates. As described above, previous intermittent control models update motor commands (or make corrective actions) in a passive manner: Clock-driven controllers update motor plan regularly (i.e., with intervals of a fixed length), and event-driven controllers update when the error exceeds a given threshold. In contrast, the proposed model updates motor plans dependent on the relationship between the prediction error and "reliability" of the prediction.

Motor planning for feed-forward control is inevitably based on the future prediction, but the prediction is not necessarily correct, especially when the environment is not stationary: Motor plan based on wrong prediction might result in a task error. For minimizing the risk of this task error, shorter segment (i.e., more frequent motor update) is preferable. On the other hand, frequent update increases computational cost for motor planning. Coping with this cost/risk trade-off, the proposed model determines the segment length adaptively according to the “reliability” of internal model (Sakaguchi & Takano, 2004), which is measured by the residual error in estimating the internal model (i.e., greater residue brings shorter segment). This adaptive segmentation is a key feature of the proposed model.

With the intermittent control, it is expected that body motion may change discontinuously at segment boundaries because motor commands may sometimes change abruptly. This would be remarkably observed when the motor commands in the previous segment are planned based on erroneous prediction. In concert with this expectation, human motion often shows intermittent discontinuities with variable time intervals in continuous motor tasks (Beppu, Nagaoka, & Tanaka, 1987; Beppu, Suda, & Tanaka, 1984; Miall, Weir, & Stein, 1986, 1993; Sakaguchi, 2013; Wolpert, Miall, Winter, & Stein, 1992). More specifically, when people try to follow a moving target with their hand, the velocity profile of the hand movement shows small humps with variable time intervals even if the target moves smoothly. In the present article, we call this intermittent discontinuity found in movement trajectory “motor intermittency” though other researchers sometimes use this term to represent the discontinuities in the force profile instead of those in the velocity profile (e.g., Asai et al., 2009). Motor intermittency is commonly observed in various tracking tasks and never a measurement artifact. Previous researches have suggested that it originate from the update of motor commands based on visual feedback (Inoue & Sakaguchi, 2014; Miall, Weir, & Stein, 1993; Novak, Miller, & Houk, 2000; Pasalar, Roitman, & Ebner, 2005; Roitman, Massaquoi, Takahashi, & Ebner, 2004), and here we hypothesize that it should be the side effect of the abrupt change in motor commands resulting from intermittent control.

Because the primary aim of the present study is to simulate the human sensorimotor process, replication of motor intermittency is an important issue for evaluating the model’s validity. In contrast, it seems that previous intermittent control models did not pay much attention to this point. Most control theory studies place importance on theoretically demonstrating its advantage as a control mechanism (i.e., to prove its stability or to prove good performance with less computational cost), rather than replicating human behavior. For example, Gawthrop et al. (2011) compared the tracking behaviors of human participants with those of their intermittent MPC controllers (Fig. 11 of their article), but they neither mentioned the motor intermittency observed in human behavior (which can be readily found in panel (a) of Fig. 11) nor tried to replicate it. As an example of dynamical system studies, Minton et al. (Milton et al., 2013) dealt with the stick balancing problem and compared the stochastic properties of occurrence of failure between human participants and mathematical model, but they did not mention intermittent discontinuities observed in the trajectory data (Fig. 3 of their article): Their primary interest seems to be in the nature of non-linear dynamics caused by interaction between delayed feedback and intrinsic noise.

Here, we should note that “intermittent motor update” of the control mechanism and “motor intermittency” of human behavior are different things. The former indicates the internal computational process while the latter means the resultant phenomenon observed from the outside. Actually, the intermittent motor update cannot be necessarily detected as motor intermittency, as we will show in the computer simulation.

In order to validate the proposed model, we performed computation simulation and behavioral experiment using a visuo-manual tracking task. We implemented several other control models as well as the proposed model, and compared their motion profiles with humans. We also analyzed the statistical properties of motor intermittency observed in the profiles.

2. Methods

2.1 Behavioral experiment

We ran behavioral experiments to examine the nature of intermittent discontinuities in human hand movements in a visuo-manual target-tracking task. The experiment was similar to those in the previous studies (e.g., Miall, Weir, & Stein, 1993) but we conducted it in order to obtain detailed data not shown in the published articles.

2.1.1 Participants

Three naive graduate students (male, aged 22–24 yrs) participated in the experiment. All participants received an adequate explanation of the merits and demerits of participation in this research, and we obtained an informed consent form from all participants. They had normal or corrected-to-normal visual acuity and no significant neurological history. They were paid 1000 Japanese Yen (about 10 US dollars) for 1 hour.

This experiment was approved by the University of Electro-Communications Institutional Review Board for Human Subjects Research, and was in accordance with the ethical standards in the Declaration of Helsinki. We obtained a written consent form from all participants.

2.1.2 Apparatus

Participants sat in front of a desk with their heads fixed by a chin rest. They put their index fingers on an air-floating slider (Daedalon, EA-01, Waldoboro, ME, USA), which moved forward and backward in a line with little friction. The slider position was measured by an optical position sensor (Keyence, IL-300, Osaka, Japan) with a sampling rate of 200 Hz. A vertical screen was set in front of the participants (distance of 2.1 m), on which a green laser spot (target) and a red laser spot (cursor) were projected through galvano scanners (GSI, VM500, Bedford, MA, USA). Each moved vertically, with the target position controlled by experimental software and the cursor position determined by the slider position. The ratio of hand (slider) movement to cursor movement was 3:1 (10 cm of hand movement produced 30 cm of cursor movement.) Hand position measured by the position sensor was indicated by the cursor position at delays of less than 5 ms, and could therefore be neglected. More detailed setup has been described elsewhere (Inoue & Sakaguchi, 2014).

2.1.3 Task

The task was to move the slider with the right hand so that the cursor tracked the target as precisely as possible. Various temporal patterns of target movement were used in the experiment, but here we show the results for the two types of target movements. One was a sinusoidal motion with a frequency of 0.3 Hz, and the other was a pseudo-random motion realized by summing four sinusoids with different temporal frequencies (0.073, 0.117, 0.205, and 0.278 Hz) (Miall, Weir, & Stein, 1993). Specifically, target visual position at time t s was given by $y_T(t) = 0.3\cos(2\pi f_0 t)$ (f_0 = 0.3 Hz) in the sinusoidal condition, and, $y_T(t) = 0.1(\cos(2\pi f_1 t) + \cos(2\pi f_2 t) + \cos(2\pi f_3 t) + \cos(2\pi f_4 t))$ ((f_1, f_2, f_3, f_4) = (0.073, 0.117, 0.205, 0.278) Hz) in the peudo-random condition. In a strict sense, the target motion in the pseudo-random condition is deterministic and continuous, and the target behavior could be predicted within a short time span (~ hundreds of milliseconds) because it was rather slow (the frequencies of all components were lower than 0.3 Hz). However, it was difficult (almost impossible) for the participants to predict its future trajectory for a longer time span. This held also in the sinusoidal condition: Though the sinusoidal motion could be completely predicted in a mathematical sense, it was hard for participants to exactly predict its movement (in both spatial and temporal dimensions). The duration of a trial was 60 s, and participants performed the trials in the two conditions alternately for 20 times (10 trials for each condition), with dozens of seconds rest between each. Before starting the main experiment, they performed three trials for familiarization.

2.1.4 Analysis

In evaluating the tracking performance, we used the positional difference between the target and the cursor, together with the difference in their instantaneous phases. Specifically, we applied a Hilbert transform (“hilbert” function of Matlab software) to the target and hand trajectories to calculate their instantaneous phases. In addition, the discontinuous points in the human movement trajectory were extracted automatically using custom-made analysis software written in Matlab software (MathWorks, Natick, MA, USA). It detects the discontinuities by making use of the amplitude and phase information of the complex-valued continuous wavelet analysis, whose details has been presented elsewhere (Inoue & Sakaguchi, 2015). Briefly, this software tried to detect a specific peak position in the jerk profile, making use of the continuous wavelet transform (with a Gaussian derivative kernel) of the velocity profile. A key is to combine the amplitude and phase information of multiple scales of complex-valued wavelet transform to find the singular points. Utilizing the nature of hand movement, moreover, this software stably detects the movement discontinuities without parameter tuning (i.e., parameter-free method). We investigated the temporal positions of the detected discontinuous points and their intervals separately for individual participants. The same analysis method was applied to the trajectory of the control models to compare the model behavior to human behavior.

In showing the trajectory data in the result section, we applied 4th-order Butterworth filter (cut-off frequency: 10 Hz) to the positional data ("filtfilt" function of Matlab). The velocity data was obtained by the numerical differentiation to the filtered positional data.

2.2 Adaptive Intermittent Control Model: Algorithm and Computer Simulation Experiment

2.2.1 General structure and simulation settings

We implemented the proposed model as in the block diagram shown in Fig. 1. We assumed that the system could continuously observe the position of the target and hand through the visual system. We also assumed that this information contains some fluctuations (i.e., observation noise), and that there is a delay (D_v) between the physical event and its perception. The motor command issued by the central motor system reaches the actuator with a delay (D_m). Here, we do not assume any motor noise because it is not essential for our problem. Visual and motor delays were set D_v = 100 ms and D_m = 50 ms, considering the facts that minimum conduction time between cortical neurons and peripheral sensorimotor organs are about 20 ms, and that delay of motor reaction for visual perturbation was at least 160 ms (Saunders & Knill, 2003). Note that we did not explicitly represent the time for central processing (i.e., motor planning), which were implicitly included in the visual and motor delays. Observation noise obeyed a Gaussian distribution $N(0, 0.0001^2)$ in the computer simulation experiment. Although this noise little affected the overall tracking ability, its randomness modulated the microscopic (i.e., trial-by-trial) behavior of the control system. The forearm system was model with a second-order linear spring-mass-damper system with mass m and damper constant b. The normalized motor command u was translated into the muscle force (or joint torque) with maximum value F through a first-order lag element (time constant τ). In the experiment, we set τ = 50 ms, m = 0.1 Kgm^2, k = 0.1 Nm, b = 0.05 Nms, and F = 30 Nm, referring to the physiological and mechanical properties of muscle activation and the forearm. All simulation experiments were performed with Matlab software.

2.2.2 General flow of the control process

Before going into the detailed mechanism of the proposed model, we briefly outline the flow of information processing.

In the proposed model, the system divides a continuous motor task into discrete segments, and calculates motor commands separately for each segment. The new segment generally starts when the previous segment is finished or when very large prediction error has been detected. When decided to start a new segment, the system first estimates the target motion model (that is, the target motion model is updated at every segment onset). In the computer simulation, this model was implemented as an auto-regressive (AR) model. An important assumption here is that the target motion is never regarded stationary, and the system adaptively updates motor plan according to the change in the target motion. Therefore, the system *updates the target motion model* (instead of *using an identical motion model with updating state variables*), and plans motor commands using the latest motion model. This is an advantage of adaptive intermittent control. In order to make this assumption viable, the AR model is estimated using the sensory data within the limited time range (say, 300 ms) just before the segment onset.

Next to the target motion estimation, the system determines the segment length. Because motor planning spent considerable amount of computational cost, it is preferable to reduce the segment updates or to lengthen the segment length as much as possible. On the other hand, longer segment increases the risk of large tracking error (because motor commands are not modified within a segment) especially when the target motion model was incorrect. In order to make this trade-off, the system determines the segment length according to the “reliability of the target motion model,” which is determined by the sum of residual error when estimating the target motion model. The rationale is that larger residual error, degrading the reliability of the target motion model, means larger risk that the planed motor command might bring extremely large task error. This could happen, for example, when the nature of target motion is changing, when target motion is inherently random, or when the observation noise is large. In every case, it is too risky to plan a motor command over a long time period. Thus, shorter segment length is adopted when a larger residual error is observed.

Once the segmentation length is determined, the system plans motor commands for the segment. In the proposed model, motor planning process is formulated based on an optimal control, that is, command sequence minimizing a loss function during the designated segment is calculated by an optimization algorithm (“lsqlin” function of Matlab). In the present study, the loss function is given by the sum of tracking error (task error) and motor command energy (motor effort).

The following sections explain the details of the above processes.

2.2.3 System description

The system dynamics were described as a discrete-time linear system. Although we could represent both hand and target system as a single dynamical system, here we describe them separately because they were separately implemented in the model. Representing the system state using a state vector $\boldsymbol{x}_H(t)$, the hand system dynamics can be written by

$$\boldsymbol{x}_H(t+\Delta) = A\boldsymbol{x}_H(t) + Bu(t-D_m) \tag{1}$$

Here, A and B are the matrices representing the dynamics of the hand, $u(t)$ is the motor command to the hand that the system should design (satisfying $-1 < u(t) < 1$) at time t, D_m is motor delay, and Δ is the simulation time step (set to 5 ms in the experiment, that is, the sampling rate was 200 Hz).

In the computer simulation, we modeled that the hand system was a second-order linear spring-mass-damper system with mass m and damper constant b, and that motor command u was imposed into this system through a first-order lag element (time constant τ) and amplified. Thus, the state vector $\boldsymbol{x}$ had three components: position, velocity, and acceleration, and the matrices A and B are given by

$$A = \begin{bmatrix} 1 & \Delta & 0 \\ -\frac{k}{m}\Delta & 1-\frac{b}{m}\Delta & \Delta \\ 0 & 0 & 1-\frac{\Delta}{\tau} \end{bmatrix} \text{ and } B = \begin{bmatrix} 0 \\ 0 \\ \frac{F}{m}\Delta \end{bmatrix}. \tag{2}$$

The variables observable by the visual system is described by

$$\boldsymbol{y}_H(t) = C\boldsymbol{x}_H(t), \tag{3}$$

where C is the observation matrix. We assumed that the position and velocity of the hand could be observed, and thus, C was given by

$$C = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \end{bmatrix}. \tag{4}$$

On the other hand, the target position in visual coordinates ($y_T(t)$) was given by $y_T(t) = 0.3\cos(2\pi f_0 t)$ (f_0 = 0.3 Hz) in the sinusoidal condition, and, $y_T(t) = 0.1(\cos(2\pi f_1 t) + \cos(2\pi f_2 t) + \cos(2\pi f_3 t) + \cos(2\pi f_4 t))$ ((f_1, f_2, f_3, f_4) = (0.073, 0.117, 0.205, 0.278) Hz) in the peudo-random condition, just the same as in the behavioral experiment. This target motion was modeled with an autoregressive model for future prediction. Its details will be described in the next section.

When the visual system observed hand and target variables, they suffered from visual delay and observation noise. Thus, observed hand and target signals ($z_H(t)$ and $z_T(t)$, respectively) were given by

$$\boldsymbol{z}_H(t) = \boldsymbol{y}_H(t - D_v) + \begin{bmatrix} \varepsilon_p(t) & 0 \\ 0 & \varepsilon_v(t) \end{bmatrix}, \tag{5}$$

and

$$z_T(t) = y_T(t - D_v) + \varepsilon_p(t), \tag{6}$$

where $\varepsilon_p(t)$ and $\varepsilon_v(t)$ are observation noises of the position and velocity, respectively, and both obeyed Gaussian distribution $N(0, 0.0001^2)$ in the simulation.

2.2.4 Prediction of hand movement

In the present formulation, we assumed that the system had a correct model of hand dynamics and knew the length of sensory and motor delays (D_v and D_m). The hand motion was predicted by the framework of Kalman filter:

$$\boldsymbol{x}_H(t + \Delta) = A\boldsymbol{x}_H(t) + Bu(t - D_m) + Qe_3(t), \tag{7}$$

and

$$\boldsymbol{y}_H(t) = C\boldsymbol{x}_H(t) + Se_2(t), \tag{8}$$

where Q is the diagonal matrix determining amplitude of process noise, S is that determining the amplitude of observation noise, and $e_2(t)$ and $e_3(t)$ are two and three dimensional normalized Gaussian noise, respectively. In the computer simulation, Q = diag(0.0001, 0.0001, 0.0001) and S = diag(0.0001, 0.0001). In order to simplify the explanation, we assumed that the amplitude of process noise Q was enough small compared to the estimation error of target motion model (see below) so that discussion on the uncertainty (or reliability) of prediction was concentrated on the target motion.

2.2.5 Prediction of target movement

The dynamics model of the target motion is estimated using its visual information. We adopted an autoregressive model (AR model) for representing the target motion. Concretely, the visual position of the target $z_T(t)$ was represented by the linear sum of the past n-times positions:

$$z_T(t) = a_1\, z_T(t - \Delta_{\mathrm{AR}}) + a_2\, z_T(t - 2\Delta_{\mathrm{AR}}) + \cdots + a_n\, z_T(t - n\Delta_{\mathrm{AR}}) + \varepsilon(t), \tag{9}$$

where Δ_{AR} is the time step for regression, a_i (i = 1, 2, …, n) are weights, and $\varepsilon(t)$ is the noise obeying the Gaussian distribution. The values of the weights a_i were estimated using the standard method for AR models. We set n = 3 in the computer simulation (it worked also for larger n, but not for n = 2). It is an important question how to choose the visual data for parameter estimation. Assuming that the property of target motion can vary during the task, using data from a longer time range is not always appropriate. Thus, the proposed system uses only the data from the latest limited time period (T_P). Note that because the visual information is perceived with a delay (D_v), the physical time interval used for estimation at time t is given by $(t - (T_P + D_v)),\ t - D_v)$. Because the clock frequency (= 200 Hz) of the computer simulation was too high to represent the target motion, the AR model was applied for the down-sampled (with factor N_D = 5) sensory information (that is, $\Delta_{AR} = 5\Delta = 25$ ms). This means that the system predicted the future target motion from the past 75-ms positions (i.e., 75 ms = 25 ms (AR model time step) × 3 (order of AR model)). In the computer simulation, T_P was set 300 ms, meaning that 10 data was used for estimation because the sampling interval (of sub-sampled data) was 25 ms. We subtracted mean of $z_T(t)$ (i.e., $\overline{z_T(t)}$) in estimating the weights for better modeling. That is, we used in practice the following formula, instead of equation (9):

$$\tilde{z}_T(t) = a_1\,\tilde{z}_T(t-\Delta_{AR}) + a_2\,\tilde{z}_T(t-2\Delta_{AR}) + \cdots + a_n\,\tilde{z}_T(t-n\Delta_{AR}) + \varepsilon(t)\,, \tag{10}$$

where $\tilde{z}_T(t) = z_T(t) - \overline{z_T(t)}$ (averaging is performed over the data used for estimation).

2.2.6 Decision of starting new segment

Before explaining the method used to decide the onset of a new segment, we would like to give a note on the motor planning method of the proposed system. As described above, the proposed system divides the time axis into discrete segments, but this does not mean that all parts of the time axis belong to certain segments; it is possible that some parts do not belong to any segment. The brain does not need to issue motor commands seamlessly throughout the motor task, that is, there can be blank regions for which no motor command is designed.

In a target-tracking task, for example, if the target stays at a fixed position for a while (and the hand stands close enough to the target), there is no need to make a new action and no information useful for future prediction; the best solution is to institute a “moratorium period”, that is, to simply leave the hand there and do nothing until the target starts to move (which brings a clue to future prediction). Considering that the motor planning process occupies some resources in the brain, the brain presumably does not want to start a new motor plan when it is not required or unavailable. This point is essentially different from most engineering control systems in which the controller continuously calculates command signals and sends them to the plant. However, note that the zero motor command produced by a no motor plan (i.e., “do nothing”) cannot be distinguished from the zero command produced by active motor planning (i.e., “put out zero as a result of motor planning”) simply based on the motor command itself.

The algorithm for determining a new segment is as follows. Basically, a new segment starts when the current segment is terminated. However, there are two exceptions. First, as described above, the system does not start a new segment when no sensory cue can be obtained for predicting target movement at the segment offset. When using an AR model for representing target motion, the system does not update the target model (that is, start new segment) until the target prediction error (i.e., the difference between the observed target position $z_T(t)$ and predicted target position $\hat{z}_T(t)$) exceeds a threshold ($\Theta = 0.01$ in the simulation) (though this rarely occurred in the computer simulation because the target kept moving most of the time).

Second, when an unexpectedly large prediction error has been observed, the system starts a new segment even if the current segment is on the way. This “emergent update” is activated when the *target prediction error* exceeds a threshold. More specifically, the system compares the observed target position $z_T(t)$ and target position estimated by the AR model $\hat{z}_T(t)$, and starts a new segment when its absolute value (i.e., $| z_T(t) - \hat{z}_T(t) |$) exceeds the threshold (Θ). Although this mechanism may be superficially similar to the previous error dead-zone method (that is, evoking corrective motor commands only when the *tracking error* (i.e., $| z_H(t) - z_T(t) |$) exceeds a certain threshold), its fundamental concept is essentially different. In contrast to the conventional error dead-zone method that starts the control so as to *compensate for the past tracking error*, the proposed system updates the target model so as to *predict the future target movement exactly*. That is, the proposed method actively tries to detect prediction error so as to avoid the erroneous motor planning. Note that once this emergent update is activated, this mechanism is inhibited for a while. Introducing such a “refractory period (R)” is quite natural because tracking error would not start to decrease because of the motor delay. The length of the refractory period (R) was 100 ms in the computer simulation.

Some may think that predicted tracking error (i.e., $| \hat{z}_H(t) - \hat{z}_T(t) |$) is another possible criterion to detect the unexpected tracking error. Because the system can predict the hand position ($\hat{z}_H(t)$) using the Kalman filter and the target position ($\hat{z}_H(t)$) using the AR model, this error quantity can be obtained free from the visual delay. Actually, this criterion is adopted in another type of intermittent controller (i.e., event-driven intermittent MPC controller, see Sec. 2.3). However, we adopted the above criterion (i.e., $| z_T(t) - \hat{z}_T(t) |$) for the following reason. Quantity $| z_T(t) - \hat{z}_T(t) |$ represents the dissociation between the internal prediction and the external fact. Because the internal model is essential in the feed-forward control system, it is quite important to monitor its validity for managing the system performance, and it is natural to update the motor plan when the system notices that the internal model (i.e., AR model) is no longer correct (i.e., large dissociation between the prediction and external fact). In this sense, quantity $|z_T(t) - \hat{z}_T(t)|$ is closely related to the reliability of internal model. On the other hand, quantity $\hat{z}_H(t) - \hat{z}_T(t)$ simply represents the predicted tracking error, and has no additional meaning for the system maintenance. This point will be further discussed in Sec. 4. 3.

2.2.7 Determination of segment length

Once having decided to start a new segment, the system next has to determine its temporal length. To reduce the computational cost of motor planning (i.e., the frequency of motor update), it is preferable to design as long a segment as possible. However, longer segments give larger risks of producing greater prediction error, which may lead to an emergent update (which will cause additional computati~~on as ~~well as large tracking error). To determine an appropriate segment length, we used “reliability of prediction.” Because the system plans the motor commands so as to follow the predicted target trajectory, there is no need to make a motor plan for a long time span if the predicted trajectory is reliable. To implement this idea, we make use of the residue of the AR model as a measure of reliability (or uncertainty). Specifically, the segment length *H* was given by 1.2 × (threshold error level Θ) / (standard deviation of AR model error) in the computer simulation, where the standard deviation was calculated from the data used for the parameter estimation of AR model. Therefore, the segment is prolonged when the smaller variance (i.e., smaller residue of AR model) is observed in the latest temporal region.

As mentioned above, we only dealt with the reliability of the target motion prediction in the present study. However, it is also possible to consider the reliability of hand motion model, and in such a case, we would determine the segment length dependent on both reliabilities.

2.2.8 Motor Planning

When the system decides to start a new segment, it calculates the motor command by solving an optimization problem. Because the human participants try to minimize the tracking error, that is, the visual displacement between the target and hand, here we think of a loss function given by

$$L[u] = \sum_{s=T_s}^{T_f} (\hat{\boldsymbol{y}}_T(s) - \hat{\boldsymbol{y}}_H(s))^{\mathrm{T}} G(s) (\hat{\boldsymbol{y}}_T(s) - \hat{\boldsymbol{y}}_H(s)) + u^2(s) \quad . \tag{11}$$

where *s* is the time index whose origin is the current time, $G(s)$ is the weight matrix for evaluating the task performance, and T_s and T_f are the time indexes of the start and end of the evaluation region. $\hat{\boldsymbol{y}}_{\mathrm{H}}(\mathrm{t})$ and $\hat{\boldsymbol{y}}_{\mathrm{T}}(\mathrm{t})$ are two dimensional vectors representing the predicted positions and velocities of the hand and target, respectively. Target state was predicted by the system model while the hand state was predicted by the AR model. The system state was estimated by Kalman filter based on the observed hand position and velocity $z_H(t)$. Note that the first term of the loss function (i.e., task error term) was summed up only with an interval of 25 ms because the time step of AR model was down-sampled (with factor $N_D = 5$) as described above. On the other hand, the second term (i.e., command effort term) was summed for every time step (5ms).

Next, we would like to consider the temporal interval for evaluating the loss function (T_s and T_f). Because of the motor delay (D_m) between the central system and the actuator, there is no need to plan the motor command until after this delay at least, and thus, we set $T_s = D_m$. The way T_f is determined has been described in the previous section.

Weight matrix $G(s)$ can be either constant or time dependent. If a considerable amount of tracking error has been already observed at the moment of motor planning, it is not necessarily good to evaluate the tracking error from the first moment of the segment because the error would have increased even more during the motor delay. Instead, it may be preferable to set $G(s)$ as a zero matrix for a certain period and ignore the tracking error at the first part of the segment. The extreme case of this idea is that the tracking error is evaluated only around the segment end, which makes the system just try to catch up with the target at the end of the segment (rather than follow the target movement). Though there are a variety of implementations of this idea, we used the following settings in the computer simulation. Weight matrix $G(s)$ was given by $G(s) = N_D w(s) G_0$ with

$$G_0 = \begin{bmatrix} \lambda_p & 0 \\ 0 & \lambda_v \end{bmatrix}, \tag{12}$$

and

$$w(s) = \begin{Bmatrix} 0 & s < T_s + D \\ 1 & \text{otherwise} \end{Bmatrix}. \tag{13}$$

Here, λ_p and λ_v are the weights for position error and velocity error, respectively, and N_D (= 5) is the down-sampling factor. We can arbitrarily determine these values, and we used $\lambda_p = 5$, $\lambda_v = 0.1$ and $D = 0.05$ s in the computer simulation.

Finally, note that the proposed model does not directly refer to the visual tracking error $z_H(t) - z_T(t)$ in motor planning. The visual target position is used for estimating the target motion model (i.e., AR model), and visual hand position is used for estimating system state (i.e., Kalman filter): The motor command is planned based on predicted hand and target movements.

2.3 Conventional Control Models

To compare the proposed model with other possible control models, we ran simulated experiments using seven control models, in addition to the proposed model: (1) PD and PID controllers with a delay-free sensorimotor system (for reference), (2) PD and PID controllers designed for a delay-free system but operated in a delay-rich system, (3) PD and PID controllers with a Smith predictor, (4) an act-and-wait (AAW) PD and PID control models, (5) intermittent PD and PID controllers with an error dead-zone, (6) a clock-driven intermittent MPC controller, and (7) an event-driven intermittent MPC controller (Fig. 2). In the experiment with controllers (1), the delay element was removed from the system. The parameters of controllers (2) were the same as controllers (1), but the controllers were operated with visual and motor delays. A Smith predictor is an engineering method for compensating for delay elements in the control loop. Miall et al. (1993) proposed that the cerebellum worked as a Smith predictor though later they reported an experiment denying this view (Miall & Jackson, 2006). The parameters of these continuous controllers were determined using the “tunepid” function of Matlab.

The act-and-wait control model (4) (Gawthrop, 2010; T Insperger, 2006, 2011; T. Insperger & Milton, 2014) is a type of intermittent controller (Fig.2, Panel B). This puts motor output in a periodic manner with an interval (T_c), but it issues motor commands only for a limited portion in each interval, and waits (i.e., puts no motor output) for the remained portion. That is, the motor output is gated by the following gating function:

$$g(t) = \begin{cases} 0, & \text{if } 0 \le \mathrm{mod}(t, T_c) < T_w \\ 1, & \text{if } T_w \le \mathrm{mod}(t, T_c) < T_c \end{cases} \tag{14}$$

If the length of the wait portion (T_w) is longer than the feedback delay, the system makes next action after it observes the result of the action of the previous period. As a result, it behaves like a time-discrete control system. Because the feedback delay was 150 ms (=D_v +D_m) in the experimental setting, we set T_c = 200 ms and T_w = 160 ms in the computer simulation. The parameters of PD and PID controllers were the same as for controllers (1).

The intermittent PD/PID controller with the error dead-zone (5) (see Fig.2, Panel C) is a controller whose control signal (i.e., the output of the PD/PID controller) is imposed only when the observed tracking error ($| z_H(t) - z_T(t) |$) exceeds a certain threshold level ($\Theta = 0.02$ for the simulation; see also the results section). Note that the system could detect the tracking error with the visual delay (D_v =100 ms), and the control output suffered from the motor delay (D_m =50 ms). The PID parameter values were the same as for controllers (1).

The intermittent MPC controller designed the motor commands for a certain length of future interval (“horizon”) so as to minimize the tracking error (Fig.2, Panel D). The length of the horizon was set to 1 s. In planning motor commands, the target movement was predicted by an AR model, whose specification was described above (the same as the proposed model). Motor commands were updated with a fixed interval (100 ms) in the clock-driven intermittent controller (6) while in the event-driven controller (7), the commands were updated when the predicted tracking error (i.e., $||\hat{z}_H(t) - \hat{z}_T(t)||$) exceeded a certain threshold ($\Theta = 0.01$). Note that this tracking error was evaluated not by the visual information but by the predicted information, and thus, it did not suffer from the effect of visual delay. Specifically, the hand position ($\hat{z}_H(t)$) was calculated by the Kalman filter and the target position ($\hat{z}_T(t)$) was predicted based on the AR model. In order to refrain from updating the motor commands too frequently, we set the minimum update interval as 100 ms. Parameter values of the AR model were updated when the new motor plan was designed. The weights for loss function in the motor planning process were set as $\lambda_p = 5$ and $\lambda_v = 0.1$, as for the proposed model.

2.4 Determination of Parameter Values

First, the parameter values related to the body dynamics and sensorimotor system were determined considering the physical and physiological situation of visuo-manual tracking task. In addition, the proposed model has several free parameters, including threshold for segmentation (Θ), order of AR model, and weights for loss function (λ_p and λ_v).The values of all these parameters affected the model behavior to some extent: For example, larger weights (λ_p and λ_v) brought steeper change in velocity profile (because the system tries to minimize the tracking error rapidly). Such parameter dependency was observed common to all control models. When we ran the simulated experiments for various combinations of parameter values, however, –the model behavior was kept (at least qualitatively) similar so long as extreme values were not used. Because we cannot show the results of simulations in various conditions in the limited space of this article, we chose specific values of parameters so that we could demonstrate typical behavior of each control model. Unfortunately, we have no objective criterion to evaluate the validity of these parameter settings because we do not know the true values of these parameters. It might be possible to estimate the parameter values in the real human control system by means of searching the values which makes the model behave just like a specific participant, but it is out of scope of the present study. In the result section, we will show the model behavior with different values of parameters as appropriate.

3. Results

3.1 Human behavior during visuo-manual target tracking

First, we show a typical example of the hand trajectory of the target-tracking task (Fig. 3). In general, the participant faithfully tracked the target motion, but his motion profile clearly showed intermittent discontinuities: Small bell-shaped humps are superimposed on the baseline curves in the velocity profile. These results were obtained from one participant, but all three participants showed motor intermittency.

An important feature is that the intervals of the humps were not uniform and that their temporal positions fluctuated trial by trial (and cycle by cycle), implying that the discontinuities did not occur in a regular manner. We should also note that the hand movement often preceded the target movement (more remarkable in the sinusoidal case, but we can see them around 13–15 s in the pseudo-random case) (Ishida & Sawada, 2004).

3.2 Behavior of conventional control models

Before introducing the behavior of the proposed model, we explain the behavior of the conventional control models. Although we do not show concrete data, all continuous feedback control models failed to replicate the human behavior. The ordinary PD and PID controllers achieved faithful tracking in both conditions if the system did not contain delay elements, confirming that this tracking problem is easy to solve with an ordinary feedback controller if the sensorimotor delay does not exist. However, these controllers became unstable if the system had sensory and motor delays, and could not produce stable tracking in either condition. Thanks to the Smith predictor, the system could track the target faithfully and smoothly even with a large delay, but the hand movement was delayed by the amount of visual delay D_v because the Smith predictor compensated only for motor delay. Moreover, the velocity profile was always smooth, different from the human behavior. No clear difference was observed between PD and PID controllers for every control model. Therefore, simple, continuous feedback control models fail to show the motor intermittency observed in human behavior, supporting the validity of feed-forward control as the model of human motor control.

Figures 4 and 5 show the tracking behavior of the intermittent control models for two types of target movements. First, the act-and-wait PD controller (panel A) could track the target almost faithfully. Although small regular ripples can be observed in the velocity profiles, its tracking behavior is generally smooth, apparently different from the human behavior. This was the same for the system with PID controller.

Next, the intermittent PD and PID controllers (panel B) could follow the target movement without the help of any predictor though its tracking error was somewhat large. Its velocity profile showed irregular patterns due to the activation/de-activation of the feedback loop. Furthermore, the general shape of the position and velocity profiles looks greatly different from those of human participants. Moreover, its control behavior much depended on the threshold value (i.e., the size of the error dead-zone) and became unstable with a smaller threshold level (in fact it became unstable when $\Theta = 0.01$ in our experiment, which is why we set $\Theta = 0.02$). This result suggests that “intermittent control" itself is not essential for replicating the human-like motor intermittency, together with indicating that intermittent control and motor intermittency are different things.

The clock-driven intermittent MPC controller (panel C) achieved much more faithful tracking. Its tracking error was always kept around zero and systematic delay was not observed. Generally, the position and velocity profiles of this model are close to those of human participants (see Fig. 3). The velocity profile contained many small humps. We should note that the velocity profile often showed smooth curves in spite that the motor command was updated by every 100 ms in this controller. That is, the intermittency of control mechanism does not correspond to the intermittency of movement discontinuities.

The event-driven intermittent MPC controller (panel D) also achieved a good tracking performance, and its velocity profile showed intermittent discontinuities with variable intervals. This model replicated the features of human motor behavior in these ways though the fluctuation of velocity profiles was a little larger than that of the clock-driven controller. A further analysis revealed that it took 150–200 ms before the tracking error decreased under the threshold level once an over-threshold error was detected, which may be the cause of slowness of error recovery. Therefore, the motor delay (D_m = 50 ms) and slow muscle activation dynamics (τ = 50 ms) had significant effects on its behavior. Note that these phenomena could be moderated if the error detection was based on the future target and hand positions (say, 200 ms from the present time), instead of their current positions. This in turn means that predictive task evaluation is effective for good tracking performance.

3.3 Behavior of proposed model

Figure 6 shows the behavior of the proposed control model, together with the temporal patterns of motor commands $u(t)$.

The system tracked the target almost faithfully, and showed intermittent discontinuities in the velocity profiles. Comparing this figure with Fig. 3, the position and velocity profiles of the proposed model resemble those of participants, as the intermittent MPC controllers.

In the bottom panel, the temporal positions of segment onsets are shown as the vertical gray lines. It clearly illustrates that the intervals of segments varied dynamically even for regular sinusoidal target movement. It can be also seen in the right panel (i.e., pseudo-random condition) that the segment length tended to be increased when the target movement kept its property (i.e., velocity and direction); in other words, the segments were more frequently updated when the target was accelerated or decelerated. These results indicate that the proposed algorithm adaptively determined the segment length.

Up to now, we have discussed the behavior of human and control models based only on position and velocity profiles. To compare the behaviors of human participants and control models more systematically, we examined the statistical properties of tracking performance and motor intermittency. Here the proposed model and intermittent MPC models were examined because only these models could successfully capture the intermittent nature of human motor behavior. Statistical indices were calculated from the 30 trials (3 participants × 10 trials) data for humans and from the 100 simulation trials data for the control models.

First, Fig. 7 shows the histograms of phase differences between the target and hand movement, where the instantaneous phase was extracted by applying a Hilbert transform to the position data (see Sec. 2.1.4). First, the phase difference in human tracking was distributed around zero irrespective of the types of target movement. The center of the distribution was slightly shifted to the direction that the hand was delayed to the target. Although this fact is reasonable because the hand basically followed the target, it is also important that the hand preceded the target (that is, the phase difference was positive) a considerable proportion of the time. All control models showed similar distributions of phase difference though their details were somewhat different from one another and from human participants. First, the center of the distribution was shifted leftward, that is, to the direction that the hand was delayed to the target commonly for the control models, compared to the human participants. This tendency was more remarkable in the sinusoid conditions. Second, the distribution was narrower for the clock-driven MPC controller, compared to the human participants and the other control models. Anyhow, we did not see any decisive difference among the behaviors of human participants and these control models. That is, all three models comparably replicated human behavior.

For confirmation, we ran a statistical test for the difference in the phase distribution between three control models and human participants (Kruskal-Wallis one-way ANOVA), using down-sampled phase data (i.e., 1 Hz). Different from above qualitative observation, the result showed that these distributions were significantly different for both sinusoidal condition, $\chi(3) = 1733.97$, $p < 0.001$, and pseudo-random condition, $\chi(3) = 91.29$, $p < 0.001$. Post hoc multi-comparison (Dunn-Sidak test) revealed that all pairs were significantly different for the sinusoidal condition (*p*s < 0.001), but difference between the clock-oriented MPC and the proposed model was not significant, $p = 0.843$ (the remaining pairs were all significantly different). Here, it is not fruitful to focus on this detailed difference in *p*-values because they could vary dependent on data sampling. More generally, rather, we should note the result that the order of mean ranks of these models was human > clock-oriented MPC > adaptive intermittent control model > event-oriented MPC in the sinusoidal condition, but human > event-oriented MPC > adaptive intermittent control model ≈ clock-oriented MPC in the pseudo-random condition. Therefore, overall relationship among the models varied dependent on the target motion, implying that no specific model consistently emulated human behavior better than the others, with respect to the phase difference.

Next, we examined the nature of temporal intervals of movement discontinuities. Most previous studies performed frequency analysis (e.g., Fourier transform) to examine the nature of motor intermittency (Miall, 1996; Miall, Weir, & Stein, 1993; Pew, 1966). These studies revealed that frequency components in the range of 0.5–1.8 Hz reflected the motor intermittency. However, as we have seen in the behavioral experiment (Fig. 3) and computer simulation (Figs. 4, 5 and 6), movement discontinuities are observed with variable time intervals, indicating that the nature of motor intermittency is not stationary. This suggests that frequency analysis is not necessarily an appropriate technique to analyze the motor intermittency because it was originally designed for periodic stationary signals. Thus, here we show the raw histograms of the intervals of discontinuous points detected by our custom-name software (Inoue & Sakaguchi, 2015). Figure 8A shows the distributions for human participants and for control models. For human participants, the intervals were distributed in the range 0.1–1.5 s and their profiles were almost the same between two tracking tasks. The distribution profiles for the control models are generally similar to humans, showing that all these models well captured the primary nature of motor intermittency of human behavior. However, the distribution profiles were different in several points. First, the peak position was shorter for the clock-driven MPC controller (0.3 – 0.4 s) and the distribution was more peaky, compared to humans and the other models (0.5 – 0.6 s) for the MPC controllers. Second, the clock-driven MPC controller showed characteristic peaky distribution in the sinusoidal condition, presumably because of the regularity of the sinusoidal motion. Third, the distribution seems bi-modal for the event-driven MPC model while those of humans and the other models are uni-modal (this tendency was observed with other parameter values though we have no idea about its reason). Because the quantitative profile could vary dependent on the parameter values, it is not fruitful to discuss the detailed difference, but peaky distribution of the clock-driven MPC was consistently observed in various conditions, which degrades its validity. Anyhow, here we would like to say that the result from the proposed model matched up nicely with that from the participants, as well as the event-driven MPC model. A statistical test (Kruskal-Wallis test) detected significant difference in the interval distribution for both sinusoidal condition $\chi(3) = 310.9$, $p < 0.001$ and pseudo-random condition, $\chi(3) = 305.76$, $p < 0.001$. In the post hoc multi-comparison (Dunn-Sidak test), significant difference was found between every pair in the sinusoidal condition, ps < 0.05, however, difference between the proposed model and human was not significant, $p = 0.97$ in the pseudo-random condition (the other pairs were significantly different, $ps < 0.001$). The order of the mean ranks was event-oriented MPC > adaptive intermittent control ≈ human > clock-oriented MPC for both tracking conditions, which agrees with the apparent similarity of the distributions in Figure 8A. However, we should be wary of regarding this result as increased support for the proposed model because the result could vary according to the experimental settings.

Figure 8B shows the distributions of segment length for the adaptive intermittent control model and the event-driven intermittent MPC controller (segment length of the clock-driven MPC controller was fixed to 100 ms). Note that this distribution is not available for human participants because we could not observe the computational process inside the brain. Here, we should note that the segment length (determined by the controller) and the interval of discontinuities (detected from the movement trajectory) were completely different quantities. As in Figure 8A, intervals of the discontinuities of the clock-driven MPC controller was distributed over a wide range though it updated motor commands every 100 ms. Segment onsets are not necessarily detected as the movement discontinuities because movement can be smooth if the motor command does not change abruptly at the segment onset. As for the adaptive intermittent control model, nonetheless, the segment length was distributed over the range from 0.1 s to 0.5 s. This wide distribution clearly shows that the proposed model adaptively determined the segment length. The fact that the distribution was different between two target motion conditions also supported the adaptability. To the contrary, the segment length of the event-driven MPC model was concentrated on the minimum limit of the command update (i.e., 100 ms), and longer segments were less observed. This was also true when the minimum limit was set to 200 and 300 ms (Note that the tracking performance was degraded in these conditions). To be more specific, the upper end of the distribution was almost maintained whilst its lower end was shifted rightward with minimum limits of 200 and 300 ms, which resulted in the concentration or shrinkage of the distribution. Therefore, the broad distribution of the segment length is peculiar to the proposed model. As a result, this controller updated the motor commands almost as frequently as the clock-driven MPC controller. There are some possible reasons for this phenomenon. First, the next motor plan was often evoked before the previous tracking error decreased under the threshold level. Second, it may be inappropriate to set the error threshold for the tracking error (i.e., the difference between target and hand positions). Actually, the proposed model set the error threshold for the target prediction error (instead of the tracking error) which is more useful for detecting the wrong target model and correcting motor commands in earlier timings.

In sum, the proposed model achieved the human-like motor behavior with the smallest computational cost (i.e., with the fewest motor updates). This feature presumably stemmed from the feed-forward control and error detecting mechanism and from the adaptive segmentation based on the reliability of prediction.

Before finishing the result section, we would like to show some microscopic features of the movement discontinuities. Figure 9 illustrates some examples of the temporal positions of discontinuities detected by the analysis software for three control models (upper column) and three human participants (lower column). For the participants, the velocity profiles and detected discontinuities are plotted for three different trials for each participant. The precise timings of discontinuities were different among the participants and among different trials of the same participants, indicating that the human behavior varied trial by trial. This is also true for the control models though we do not show the data here. Therefore, it is difficult to compare their behaviors based on the trajectories in individual trials.

Finally, we would like to examine whether or not human participants adaptively determined the segmentation according to the tracking performance. To this end, we analyzed the temporal relationship between the instantaneous tracking error and the segment length (i.e., the interval between consecutive discontinuities): If the participants adjusted segment length according to the latest tracking error (i.e., larger/smaller tracking error produced a shorter/longer segment length,, respectively), temporal profile of the tracking error would somewhat precede that of the temporal change in intervals of extracted discontinuities. To test this prediction, we calculated the cross-correlation function between the absolute tracking error and the *inverse* of intervals. Because the interval of discontinuities cannot be determined for every time step, we generated a continuous function by linearly interpolating the following discrete function defined only at the discontinuous points,

$$\mathrm{inv\_interval}(t) = \frac{1}{(\text{interval to the next discontinuous point})}, \qquad (14)$$

and calculated the cross correlation function of the interpolated function and the low-passed absolute error (cutoff frequency: 4 Hz, “xcorr” function of Matlab)). The maximum temporal lag was set to 5 s.

Figure 10 shows the cumulative cross-correlation functions of ten trials, separately for all combinations of three participants and two target conditions. Though we can see no clear peak in the correlation function, the cumulative cross-correlation functions commonly have the broad peak around −3 – 0 second time-lag, meaning that the tracking error led the segment length.

This result gives a support that human participants adaptively determined the segment length reflecting the latest tracking performance, similar to the proposed model.

4. Discussion

4.1 Summary of present study

We proposed an adaptive intermittent control as a computational model for a human motor control system performing a continuous sensorimotor task. This model essentially operates feed-forward control, but with organizing temporal structure of motor control: It adaptively divides the time axis into discrete segments, designs a motor plan within each segment, and executes it in a feed-forward manner. We also postulated that as a side effect of this temporal organization, the abrupt changes in motor command at segment onsets might cause intermittent discontinuities, a common feature of human motor behavior. The concrete algorithm was given by introducing the idea of reliability of prediction into the theory of model predictive control (MPC), and its behavior was examined using computer simulations of a visuo-manual target tracking task. The proposed model achieved generally faithful tracking with intermittent discontinuities, as is observed for human participants. Previous intermittent MPC controllers also replicated human behavior while feedback controllers (including the intermittent feedback controller) showed behaviors apparently different from those of human participants. This suggests that intermittent feed-forward control is essential for simulating the human motor control process. Among intermittent feed-forward control models, in addition, the proposed performed the target tracking task with less frequent motor updates (i.e., less segmentation), compared to the other models.

Through this study, we first suggest that feed-forward control should play an essential role in the human motor control not only in a discrete motor task (such as reaching) but also in a continuous task (such as target tracking). We examined how different control models behaved in a visuo-manual tracking task with a realistic sensorimotor delay, and illustrated for the first time that feedback control models (including the intermittent feedback controller) did not show human-like motor intermittency, but intermittent feed-forward controllers generally replicated it well. This implies that “intermittent control” itself does not necessarily simulate the human motor control process, but the combination of intermittent control and feed-forward control is essential.

Second, we suggest that intermittent discontinuities should stem from the control algorithm that determines motor commands based on sensory information. Even if the prediction is effective for faithful tracking in most time, it may sometimes cause a large error if the prediction is incorrect. Human control system should keep monitoring whether or not the prediction is correct (i.e., internal model is valid) relying on the sensory information, and once it detects the change, it should modify the prediction and update the motor commands. Because of the sensorimotor delay, however, this update takes effect with some delay, which may be the essential cause of intermittent non-smooth change in the motion profile (i.e., motor intermittency). This is why the motor intermittency was commonly observed in three control models based on MPC schemes.

Moreover, the concept of reliability plays an important role in realizing this adaptability. The reliability is a “subjective measure” representing how much the system relies on its own prediction (Sakaguchi & Takano, 2004). Because we cannot guarantee that the prediction of future target movement is consistently correct, motor planning is necessarily speculative. Thus, the system clips a segment of limited time length and executes feed-forward control within the segment. Our model gives a concrete algorithm to determine the segment length in an adaptive manner. This adaptive mechanism contributed to longer intervals of motor updates, compared to the previous intermittent MPC controllers (Fig. 8). Our computer simulation showed that both event-driven MPC model and our proposed model similarly replicated the human behavior, and thus, these two models are comparable from a viewpoint of replication of human behavior. However, the proposed model performed the tracking task with fewer motor updates (i.e., less computational cost), implying that if human brain adopts the same algorithm, it would achieve the comparable task performance with less computational resource in the brain.

Finally, we think that feed-forward control with adaptive segmentation is a solution that the brain has developed to produce real-time motor control with a slow sensorimotor system in a time-variant environment. Although we believe that the adaptive intermittent control is a promising model of human sensorimotor process, only a qualitative explanation of human motor behavior is not sufficient for its justification. On this point, behavioral experiments are not enough for examining the validity of the model, because multiple models could potentially explain the same behavior, as in our computer simulation. The problem can be essentially resolved by a physiological experiment that reveals the neural events in the brain. We hope that in the near future some neurophysiological data will be reported reflecting the intermittent update process in brain’s motor areas.

4.2 Motor intermittency and intermittent control

As discussed in the introduction section, many researchers have pointed out “motor intermittency” as a feature commonly observed human and monkey motor behavior (Beppu et al., 1987; Beppu et al., 1984; Miall et al., 1986; Miall, Weir, & Stein, 1993; Wolpert et al., 1992). However, the existence of motor intermittency does not directly mean that our control mechanism is operated in an intermittent manner.

Though its underlying mechanism is still controversial, a growing body of evidence supports the view that this phenomenon is not caused by mechanical property of peripheral motor organs but brought by central control mechanism. Novak et al. (2000) proposed that the intermittency was caused not by local oscillations in the peripheral system but by motor programming in the central nervous system, because such discontinuities could be observed only in the awake condition. Roitman et al. and Pasalar et al. (Pasalar et al., 2005; Roitman et al., 2004) analyzed the relationship between the temporal change in tracking error and the motor discontinuities and concluded that the discontinuities were caused by the error correction, and by the brain’s active control rather than a passive cause. Miall et al. (Miall, Weir, & Stein, 1993) found that the intermittency disappeared if the visual cursor represented the hand position, suggesting that the phenomenon stems from the visual feedback of hand motion. These findings together support the contention that the central nervous system is involved in this phenomenon.

A recent computational model of pursuit eye movement shows motor intermittency though it has no intermittent control mechanism (Orban de Xivry, Coppe, Blohm, & Lefèvre, 2013): The velocity profile for a sinusoidally-moving target (Orban de Xivry et al., 2013, Figure 6) shows discontinuities similar to those found in the positional profile of our study, though the authors did not mention it in their paper.

The core idea of their model is to integrate the delayed information from the retina (i.e., retinal information) and non-delayed information calculated from the efference copy and the past memory (i.e., extra-retinal information) in a Bayesian manner. The past memory is a mechanism holding the target trajectory in the previous trial or previous cycle (in a cyclic movement like sinusoids). Here, the weights of Bayesian integration are determined by the covariance matrix of a Kalman filter and updated dynamically during the motor control. Thus, if the covariance matrices are drastically changed (for example, by large prediction error), then the weights are abruptly changed, which may result in the discontinuous motor behavior. To be more specific, the system comes to use the extra-retinal information preferentially when the retinal information becomes less reliable, which causes discontinuous "corrective movements."

Therefore, intermittent discontinuities can be elicited if the system contains some elements causing abrupt change in the motor commands, even if the system is operated in a continuous manner. However, the model by Orban de Xivery et al. has some shortcomings as a model of motor intermittency.

First, their model hardly showed motor intermittency in the velocity-step target. In this condition, the target velocity is kept constant (after the initial step), and thus, it is unlikely the covariance matrix abruptly changes, resulting in few discontinuities. In the manual tracking task, in contrast, motor intermittency can be observed even when the target velocity is kept constant.

Second, the performance of their model is largely owing to the memory mechanism. As mentioned above, their model memorizes the target's velocity trace in the previous trial (or cycle) and uses it to predict target movement on the current trial (or cycle). This mechanism works well in a stationary environment (such as velocity-step and sinusoidal target), but does not work in a non-stationary environment (such as the pseudo-random condition in our experiment). Because discontinuous corrective movements are brought by the accurate target prediction provided by the memory mechanism, the discontinuities would disappear in a non-stationary environment. Therefore, it is unlikely that their model replicates motor intermittency in all situations.

Third, their memory mechanism seems somewhat peculiar because it potentially requires an elaborate management mechanism. In a sinusoidal tracking, for example, it has to detect the onset of every cycle and to update memory representation at the moment. In contrast, the intermittent feed-forward control models introduced in our manuscript (i.e., intermittent MPC controllers and our model) adaptively work for any situation without assuming such a special mechanism.

Therefore, at the present, the control models with intermittent motor update mechanism seem more promising as a computational model of motor intermittency.

4.3 Error dead-zone and active segmentation

As an essential factor in explaining motor intermittency, Wolpert, Miall and their colleagues (Miall, Weir, & Stein, 1993; Wolpert et al., 1992) proposed the concept of an “error dead-zone”, meaning that a control system evokes corrective motor commands only when the tracking error exceeds a certain threshold. In other words, the control system issues no command while the tracking error is within a certain range (i.e., the error dead-zone). This mechanism is believed to be effective for stabilizing the control system in the face of a large feedback delay, and other researchers have adopted this idea for the control of body balance (Asai et al., 2009; Bottaro, Yasutake, Nomura, Casadio, & Morasso, 2008; Loram et al., 2011; Loram et al., 2012; Suzuki, Nomura, Casadio, & Morasso, 2012; van de Kamp et al., 2013). In the proposed model, we also adopted this idea for “emergent correction mechanism” for recovering from unexpectedly large prediction errors.

Therefore, error dead-zone mechanism can be regarded as one of the fundamental mechanisms of brain motor control, but this alone may not explain the brain’s computational principle for realizing real-time motor control because in the computer simulation, the control models with this mechanism (especially in the feedback control scheme) did not well replicate the human behavior. We think that the present study have reinforced this view in the following points. First, while the error dead-zone concept was originally proposed from the viewpoint of feedback control, we introduced it to the feed-forward control. Human motor control is essentially future oriented because our brain seeks to improve motor performance in the future. In contrast, feedback control basically tries to make corrections for past errors, and this contention is also true for conventional error dead-zone view because it tries to *correct* motor commands when the error has exceeded a threshold. Second, the error dead-zone can be defined not only for the tracking error (i.e., task error) but also for the prediction error (i.e., model error). We think that the reliability of prediction is an important factor in motor planning, and error dead-zone should work precisely for the prediction error. Third, the trigger for the abrupt response may not only be the large task error but may also be a clue to the prediction of future target movement.

4.4 Neural implementation of motor planning

In the present study, we formulated the algorithm of the proposed model based on the MPC theory, a kind of optimal control theory. Although most computational models on human motor control/planning are based on similar optimal theories, it is questionable that the real brain determines motor commands by solving such optimization problems in an on-line manner. Actually, a large amount of calculation is required for solving the optimization problem, which would obstruct the real-time control. An antithesis of such “calculation view” is “association view” or “table-lookup view,” meaning that the human brain recalls appropriate commands using associative memory or neural dynamics formed through past experience.

Although our model is based on the optimal control theory, its essence is never contradictory to such association-based implementation. Rather, we prefer that the motor planning in the real brain should be realized by such an associative mapping. The proposed model calculates the motor command based on the internal models of target/hand motion that had been estimated from past experience, and thus, from a general viewpoint, we can regard that the proposed model learns the mapping between the visual input and motor commands and chooses appropriate motor commands using this mapping. The discussion holds also for the determination of the segment length. The computational theory formulates the motor planning process step by step in a logical manner, but the associative method realizes the same function by direct mapping without referring to its underlying computational structure. Considering that visuo-motor mapping for basic motor functions has been consistently experienced since birth, it is natural to think that such mapping has been formed by a long process of trial and error learning and of associative learning. Therefore, we believe that the present control mechanism can be implemented in an association-based manner, which will brings real “real-time control” model of human motor system.

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References

Asai, Y., Tasaka, Y., Nomura, K., Nomura, T., Casadio, M., & Morasso, P. (2009). A model of postural control in quiet standing: robust compensation of delay-induced instability using intermittent activation of feedback control. *PLoS One, 4*(7), e6169. doi: 10.1371/journal.pone.0006169

Beppu, H., Nagaoka, M., & Tanaka, R. (1987). Analysis of cerebellar motor disorders by visually-guided elbow tracking movement. 2. Contribution of the visual cues on slow ramp pursuit. *Brain, 110 (Pt 1)*, 1-18.

Beppu, H., Suda, M., & Tanaka, R. (1984). Analysis of cerebellar motor disorders by visually guided elbow tracking movement. *Brain, 107 (Pt 3)*, 787-809.

Bottaro, A., Yasutake, Y., Nomura, T., Casadio, M., & Morasso, P. (2008). Bounded stability of the quiet standing posture: an intermittent control model. *Hum Mov Sci, 27*(3), 473-495. doi: 10.1016/j.humov.2007.11.005

Cabrera, J., & Milton, J. (2002). On-off intermittency in a human balancing task. *Physical Review Letters, 89*(15). doi: 10.1103/PhysRevLett.89.158702

Cabrera, J., & Milton, J. (2004). Human stick balancing: Tuning Levy flights to improve balance control. *Chaos, 14*(3), 691-698. doi: 10.1063/1.1785453

Craik, K. J. (1947). Theory of the human operator in control systems; the operator as an engineering system. *Br J Psychol Gen Sect, 38*(Pt 2), 56-61.

Craik, K. J. (1948). Theory of the human operator in control systems; man as an element in a control system. *Br J Psychol Gen Sect, 38*(Pt 3), 142-148.

Engel, K. C., & Soechting, J. F. (2000). Manual tracking in two dimensions. *J Neurophysiol, 83*(6), 3483-3496.

Gawthrop, P. (2010). Act-and-Wait and Intermittent Control: Some Comments. *IEEE Transactions on Control Systems Technology, 18*(5), 1195-1198. doi: 10.1109/TCST.2009.2034403

Gawthrop, P., Loram, I., Gollee, H., & Lakie, M. (2014). Intermittent control models of human standing: similarities and differences. *Biol Cybern, 108*(2), 159-168. doi: 10.1007/s00422-014-0587-5

Gawthrop, P., Loram, I., Lakie, M., & Gollee, H. (2011). Intermittent control: a computational theory of human control. *Biological Cybernetics, 104*(1-2), 31-51. doi: 10.1007/s00422-010-0416-4

Gawthrop, P., & Wang, L. (2006). Intermittent predictive control of an inverted pendulum. *Control Engineering Practice, 14*(11), 1347-1356. doi: 10.1016/j.conengprac.2005.09.002

Gawthrop, P., & Wang, L. (2009). Event-driven intermittent control. *International Journal of Control, 82*(12), 2235-2248. doi: 10.1080/00207170902978115

Gawthrop, P., & Wang, L. (2010). Intermittent redesign of continuous controllers. *International Journal of Control, 83*(8), 1581-1594. doi: 10.1080/00207179.2010.483691

Gawthrop, P., & Wang, L. (2011). The system-matched hold and the intermittent control separation principle. *International Journal of Control, 84*(12), 1965-1974. doi: 10.1080/00207179.2011.630759

Gollee, H., Mamma, A., Loram, I., & Gawthrop, P. (2012). Frequency-domain identification of the human controller. *Biol Cybern, 106*(6-7), 359-372. doi: 10.1007/s00422-012-0503-9

Hosaka, T., Ohira, T., Luciani, C., Cabrera, J., & Milton, J. (2006). Balancing with noise and delay. *Progress of Theoretical Physics Supplement*(161), 314-319.

Inoue, Y., & Sakaguchi, Y. (2014). Periodic change in phase relationship between target and hand motion during visuo-manual tracking task: Behavioral evidence for intermittent control. *Hum Mov Sci, 33*, 211-226. doi: 10.1016/j.humov.2013.10.002

Inoue, Y., & Sakaguchi, Y. (2015). A wavelet-based method for extracting intermittent discontinuities observed in human motor behavior. *Neural Netw, 62*, 91-101. doi: 10.1016/j.neunet.2014.05.004

Insperger, T. (2006). Act-and-wait concept for continuous-time control systems with feedback delay. *Ieee Transactions on Control Systems Technology, 14*(5), 974-977. doi: 10.1109/TCST.2006.876938

Insperger, T. (2011). Stick balancing with reflex delay in case of parametric forcing. *Communications in Nonlinear Science and Numerical Simulation, 16*(4), 2160-2168. doi: 10.1016/j.cnsns.2010.07.025

Insperger, T., & Milton, J. (2014). Sensory uncertainty and stick balancing at the fingertip. *Biol Cybern, 108*(1), 85-101. doi: 10.1007/s00422-013-0582-2

Ishida, F., & Sawada, Y. (2004). Human hand moves proactively to the external stimulus: An evolutional strategy for minimizing transient error. *Physical Review Letters, 93*(16). doi: 10.1103/PhysRevLett.93.168105

Karniel, A. (2013). The minimum transition hypothesis for intermittent hierarchical motor control. *Front Comput Neurosci, 7*, 12. doi: 10.3389/fncom.2013.00012

Kawato, M. (1999). Internal models for motor control and trajectory planning. *Curr Opin Neurobiol, 9*(6), 718-727. doi: S0959-4388(99)00028-8 [pii]

Kawato, M., & Wolpert, D. (1998). Internal models for motor control. *Novartis Found Symp, 218*, 291-304; discussion 304-297.

Keele, S. (1968). Movement control in skilled motor performance. *Psychological Bulletin, 70*, 387-403.

Keele, S., & Posner, M. (1968). Processing of visual feedback in rapid movements. *J Exp Psychol, 77*(1), 155-158.

Lakie, M., & Loram, I. (2006). Manually controlled human balancing using visual, vestibular and proprioceptive senses involves a common, low frequency neural process. *J Physiol, 577*(Pt 1), 403-416.

Loram, I., Gawthrop, P., & Lakie, M. (2006). The frequency of human, manual adjustments in balancing an inverted pendulum is constrained by intrinsic physiological factors. *J Physiol, 577*(Pt 1), 417-432.

Loram, I., Gollee, H., Lakie, M., & Gawthrop, P. (2011). Human control of an inverted pendulum: Is continuous control necessary? Is intermittent control effective? Is intermittent control physiological? *Journal of Physiology-London, 589*(2), 307-324. doi: 10.1113/jphysiol.2010.194712

Loram, I., van de Kamp, C., Gollee, H., & Gawthrop, P. (2012). Identification of intermittent control in man and machine. *J R Soc Interface, 9*(74), 2070-2084. doi: 10.1098/rsif.2012.0142

Maciejowski, J. (2002). *Predictive Control with Constraints*: Prentice Hall.

Miall, R. C. (1996). Task-dependent changes in visual feedback control: a frequency analysis of human manual tracking. *J Mot Behav, 28*(2), 125-135.

Miall, R. C., & Jackson, J. K. (2006). Adaptation to visual feedback delays in manual tracking: evidence against the Smith Predictor model of human visually guided action. *Exp Brain Res, 172*(1), 77-84.

Miall, R. C., Weir, D. J., & Stein, J. F. (1986). Manual tracking of visual targets by trained monkeys. *Behav Brain Res, 20*(2), 185-201.

Miall, R. C., Weir, D. J., & Stein, J. F. (1993). Intermittency in human manual tracking tasks. *J Mot Behav, 25*(1), 53-63.

Miall, R. C., Weir, D. J., Wolpert, D. M., & Stein, J. F. (1993). Is the cerebellum a smith predictor? *J Mot Behav, 25*(3), 203-216. doi: 10.1080/00222895.1993.9942050

Milton, J., Cabrera, J., & Ohira, T. (2008). Unstable dynamical systems: Delays, noise and control. *Epl, 83*(4). doi: 10.1209/0295-5075/83/48001

Milton, J., Cabrera, J., Ohira, T., Tajima, S., Tonosaki, Y., Eurich, C., & Campbell, S. (2009). The time-delayed inverted pendulum: implications for human balance control. *Chaos, 19*(2), 026110.

Milton, J., Fuerte, A., Belair, C., Lippai, J., Kamimura, A., & Ohira, T. (2013). Delayed pursuit-escape as a model for virtual stick balancing. *Nonlinear Theory and Its Applications, IEICE, 4*(2), 129-137.

Milton, J., Ohira, T., Cabrera, J., Fraiser, R., Gyorffy, J., Ruiz, F., . . . Alexander, J. (2009). Balancing with vibration: a prelude for "drift and act" balance control. *PLoS One, 4*(10), e7427.

Milton, J., Townsend, J., King, M., & Ohira, T. (2009). Balancing with positive feedback: the case for discontinuous control. *Philosophical Transactions of the Royal Society a-Mathematical Physical and Engineering Sciences, 367*(1891), 1181-1193. doi: 10.1098/rsta.2008.0257

Navas, F., & Stark, L. (1968). Sampling or intermittency in hand control system dynamics. *Biophys J, 8*(2), 252-302. doi: 10.1016/S0006-3495(68)86488-4

Novak, K. E., Miller, L. E., & Houk, J. C. (2000). Kinematic properties of rapid hand movements in a knob turning task. *Exp Brain Res, 132*(4), 419-433.

Orban de Xivry, J. J., Coppe, S., Blohm, G., & Lefèvre, P. (2013). Kalman filtering naturally accounts for visually guided and predictive smooth pursuit dynamics. *J Neurosci, 33*(44), 17301-17313. doi: 10.1523/JNEUROSCI.2321-13.2013

Pasalar, S., Roitman, A. V., & Ebner, T. J. (2005). Effects of speeds and force fields on submovements during circular manual tracking in humans. *Exp Brain Res, 163*(2), 214-225. doi: 10.1007/s00221-004-2169-6

Paul, R. P. (1981). *Robot Manipulators: Mathematics, Programming, and Control*. Cambridge, Massachusetts: MIT press.

Pew, R. W. (1966). Acquisition of hierarchical control over the temporal organization of a skill. *J Exp Psychol, 71*(5), 764-771.

Roitman, A. V., Massaquoi, S. G., Takahashi, K., & Ebner, T. J. (2004). Kinematic analysis of manual tracking in monkeys: characterization of movement intermittencies during a circular tracking task. *J Neurophysiol, 91*(2), 901-911. doi: 10.1152/jn.00261.2003

Ronco, E., Arsan, T., & Gawthrop, P. (1999). Open-loop intermittent feedback control: Practical continuous-time GPC. *IEE Proceedings-Control Theory and Applications, 146*(5), 426-434. doi: 10.1049/ip-cta:19990504

Sakaguchi, Y. (2007). *A system model for real-time sensorimotor processing in brain.* Paper presented at the 14th International Conference on Neural Information Processing (ICONIP), Kita-Kyushu.

Sakaguchi, Y. (2013). *Intermittent brain motor control observed in continuous tracking task*. Paper presented at the Advances in Cognitive Neurodynamics (III).

Sakaguchi, Y., & Takano, M. (2004). Reliability of internal prediction/estimation and its application. I. Adaptive action selection reflecting reliability of value function. *Neural Networks*, 935-952. doi: DOI 10.1016/j.neunet.2004.05.004

Saunders, J. A., & Knill, D. C. (2003). Humans use continuous visual feedback from the hand to control fast reaching movements. *Exp Brain Res, 152*(3), 341-352. doi: 10.1007/s00221-003-1525-2

Suzuki, Y., Nomura, T., Casadio, M., & Morasso, P. (2012). Intermittent control with ankle, hip, and mixed strategies during quiet standing: A theoretical proposal based on a double inverted pendulum model. *J Theor Biol, 310C*, 55-79. doi: 10.1016/j.jtbi.2012.06.019

van de Kamp, C., Gawthrop, P., Gollee, H., & Loram, I. (2013). Refractoriness in sustained visuo-manual control: is the refractory duration intrinsic or does it depend on external system properties? *PLoS Comput Biol, 9*(1), e1002843. doi: 10.1371/journal.pcbi.1002843

Vieira, T., Loram, I., Muceli, S., Merletti, R., & Farina, D. (2012). Recruitment of motor units in the medial gastrocnemius muscle during human quiet standing: is recruitment intermittent? What triggers recruitment? *J Neurophysiol, 107*(2), 666-676. doi: 10.1152/jn.00659.2011

Vince, M. A. (1948a). Corrective movements in a pursuit task. *Q J Exp Physiol Cogn Med Sci, 1*(Pt. 2), 85-103.

Vince, M. A. (1948b). The intermittency of control movements and the psychological refractory period. *Br J Psychol Gen Sect, 38*(Pt 3), 149-157.

Wolpert, D. M., & Miall, R. C. (1996). Forward Models for Physiological Motor Control. *Neural Netw, 9*(8), 1265-1279.

Wolpert, D. M., Miall, R. C., & Kawato, M. (1998). Internal models in the cerebellum. *Trends Cogn Sci, 2*(9), 338-347. doi: S1364-6613(98)01221-2 [pii]

Wolpert, D. M., Miall, R. C., Winter, J. L., & Stein, J. F. (1992). Evidence for an error deadzone in compensatory tracking. *J Mot Behav, 24*(4), 299-308.

Figure Captions

Figure 1 General diagram of segmented control model

General structure of the proposed control model is depicted. We assumed a visual target-tracking task where the system tries to follow the target movement whose position is given by visual information. The proposed control model is a feed-forward control system, in which the command planning module designs motor commands using the internal model of the arm system. The target position is observed through the visual system where an information processing delay (D_v) is imposed. To overcome this delay, the system predicts the target movement trajectory using a target motion model, and this information is also conveyed to the command planning module. The planning module designs a motor command whose resultant hand trajectory exactly tracks the predicted target trajectory. The task segmentation module divides the continuous time axis into discrete segments and tells the planning module the segment length, that is, the temporal duration during which the motor commands should be designed. Once the motor commands are determined for a specified segment, they are sent to the arm system with a motor delay (D_m).

Figure 2 Conventional control models examined in this study

We picked up several conventional control models to examine how they behave in the visuo-manual tracking task with large sensorimotor delays and whether or not they show the intermittency observed in human motor behavior. (A) PD/PID controller in a basic feedback control scheme (B) PD/PID controller with a Smith predictor, (C) PD/PID controller with an act-and-wait (AAW) control scheme, (D) intermittent PD/PID controller with an error dead-zone, (E) clock-driven or event-driven intermittent MPC controller. Note that observation noise is not depicted in the figure.

Figure 3 Motor Intermittency observed in human visuo-manual tracking

Typical behaviors observed in the visuo-manual tracking task are shown. This figure shows typical position and velocity profiles for the target movement (broken curves) and hand movement (solid curves) for two types of target movements: sinusoidal movement with a frequency of 0.3 Hz (left panel) and peudo-random movement that was created by the linear sum of four sinusoids with different temporal frequencies (right panel). Small humps are clearly observed on the velocity profiles, that is, motor intermittency.

Figure 4 Behavior of conventional control models (sinusoidal condition)

To examine the behavior of the conventional control models in the visuo-manual tracking task, we ran a series of computer simulations in the situation resembling the behavioral experiments whose results are shown in Fig. 3. Four panels show the behaviors of an act-and-wait (AAW) control model (A), intermittent PD controller with an error dead-zone (B), a clock-driven intermittent MPC controller (C), and an event-driven intermittent MPC controller (D). In each panel, solid and broken curves represent hand and target movements, respectively. Only intermittent MPC controllers successfully replicated both generally faithful tracking and motor intermittency found in human movement trajectories. See Results for details.

Figure 5 Behavior of conventional control models (pseudo-random condition)

Four panels show the behavior of the four different control models, respectively, in visuo-manual tracking for pseudo-random targets. Again, only intermittent MPC controllers successfully replicated faithful tracking and intermittent discontinuities. See Results for details.

Figure 6 Behavior of ~~adaptive~~ intermittent control model

The behaviors of the proposed control model are shown. Vertical thin lines indicate the timing of segment onsets. The representation is the same as in Figs. 4 and 5, but temporal motor command patterns are also shown. Adaptive intermittent control model successfully replicated both faithful tracking and intermittent discontinuities. See Results for details.

Figure 7 Phase relationship between target and hand

The phase relationship between the target and hand was calculated by applying a Hilbert transform to the target and hand position data from the human participants and control models. Phase difference was distributed around zero but slightly shifted to the hand-delayed direction for both humans and segmented control model while it was shifted to the opposite direction for intermittent MPC controllers. It is important that the hand preceded the target (that is, phase difference was positive) a considerable proportion of the time, supporting the contention that the humans performed the tracking task in a predictive manner.

Figure 8 Statistical properties of motor intermittency and control segment

Panel A shows the normalized histograms of the intervals of discontinuous points for human participants and three feed-forward control models. The intervals were distributed in the range 0.1–1.5 s for both human participants and the control models though their shapes and peak positions were different. As for the present result, the proposed model best captured the characteristic features of motor intermittency observed in human participants though the model behavior potentially could vary dependent on parameter values. Panel B shows the distribution of the segment length for the proposed model and event-driven MPC controller. For the proposed model, segment length was distributed over a wide range, implying that the segmentation structure was determined adaptively. To the contrary, the distribution was concentrated onto the minimum limitation time (0.1 s) for the event-driven MPC controller. This shows that the proposed model achieves the human-like motor behavior with a smaller computational cost (i.e., fewer motor updates).

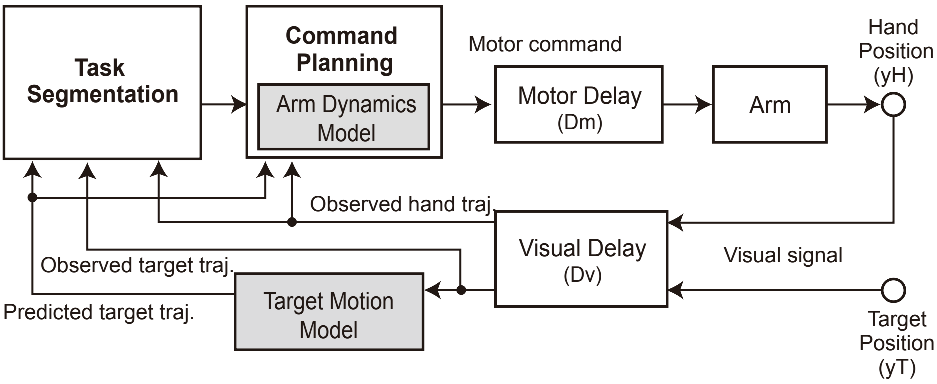
Figure 9 Microscopic characteristics of movement discontinuities

This figure shows the temporal positions of discontinuities extracted by the software, for both control models (upper column) and human participants (lower column). Vertical lines indicate the detected discontinuities. For human participants, the velocity profiles and detected discontinuities are plotted for three different trials for each participant. The precise timings of discontinuities were different among the participants and among different trials of the same participants, which clearly indicates that the human behavior varied trial by trial.

Figure 10 Temporal relationship between tracking error and segment length

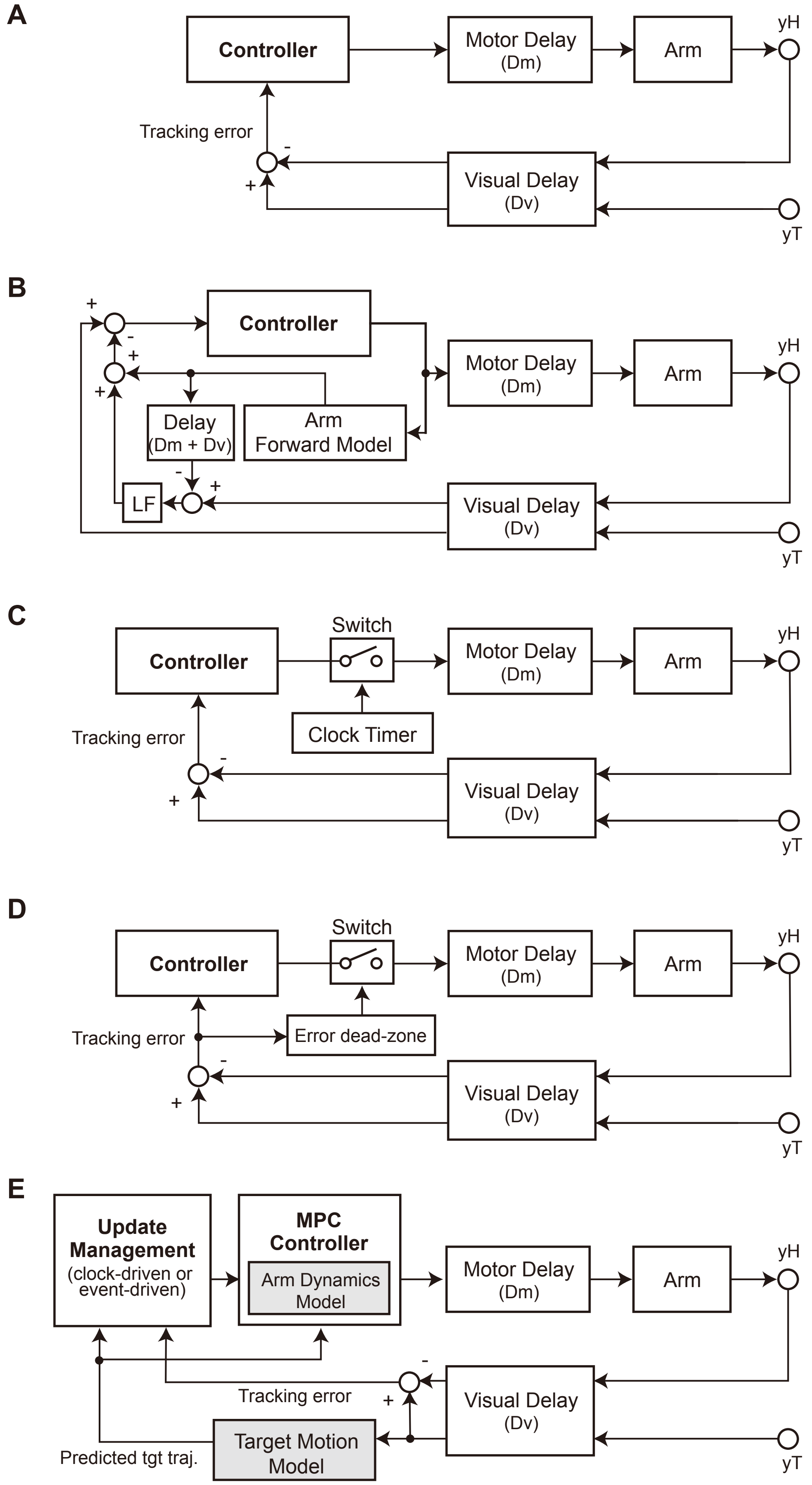
This figure shows cross-correlation function between the tracking error and the inverse of the segment length (i.e., the interval of consecutive discontinuities extracted by the analysis software) for every combination of three subjects and two target conditions. Cross-correlation functions are accumulated for ten trials. Common to all panels, the cross correlation have a broad peak around the around −3 – 0 s time-lag, indicating that the change in the tracking error preceded that in the segment length. This result is consistent with the view that human participants adaptively adjusted the segmentation according to the latest tracking performance (i.e., a larger/smaller tracking error brings shorter/longer segments, respectively).

Figure 1



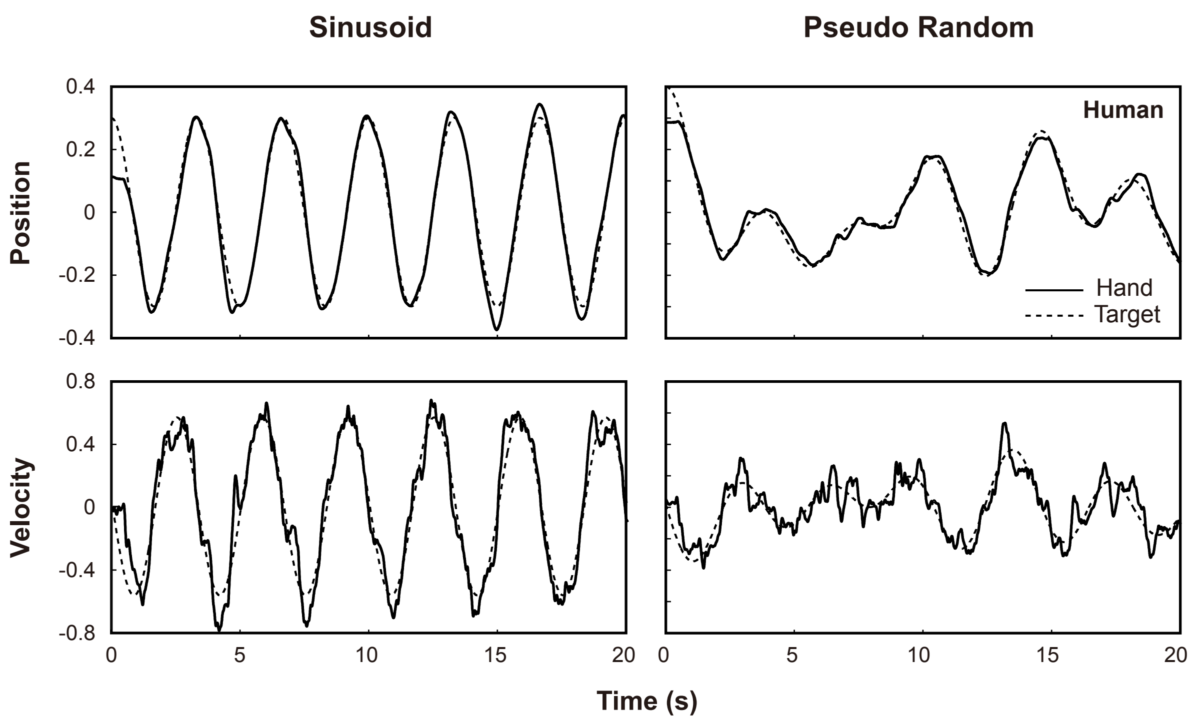
Task Segmentation
Command Planning
Arm Dynamics Model
Motor command
Motor Delay (Dm)
Arm
Hand Position (yH)
Observed hand traj.
Visual Delay (Dv)
Visual signal
Observed target traj.
Predicted target traj.
Target Motion Model
Target Position (yT)

Figure 2



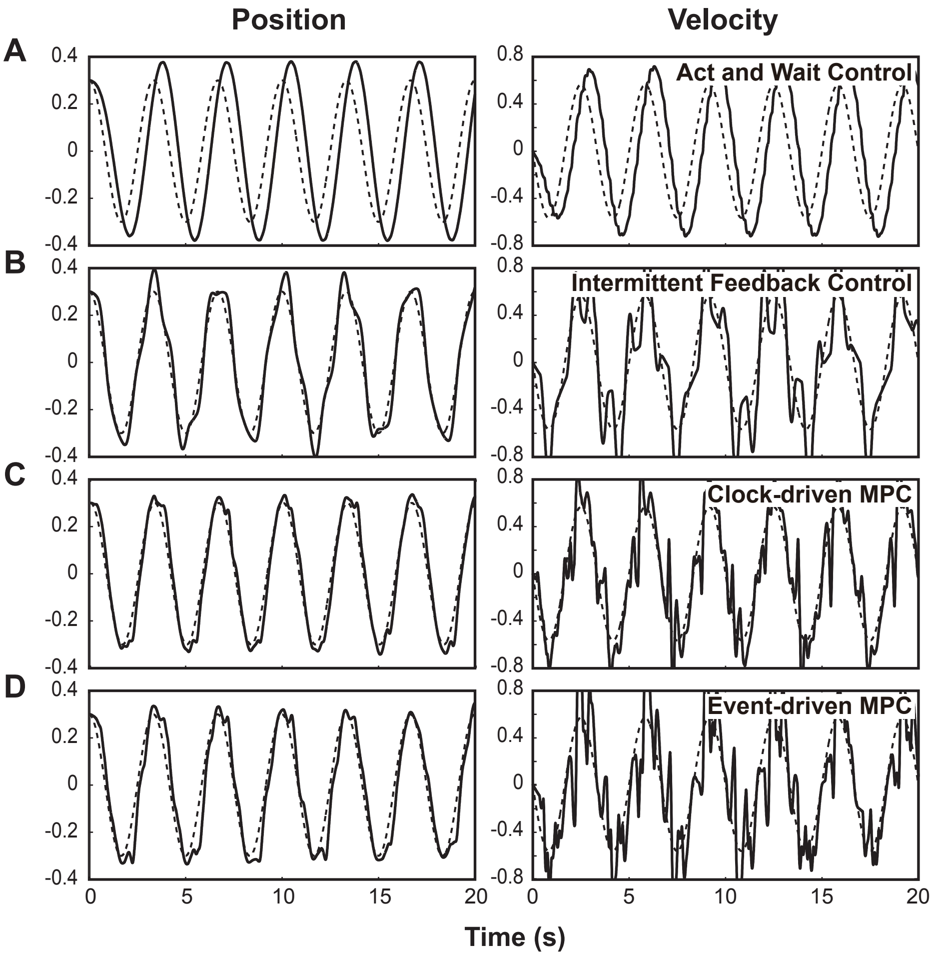
A
Controller
Motor Delay
(Dm)
Arm
yH
Tracking error
-
+
Visual Delay
(Dv)
yT
B
+
Controller
-
+
+
Motor Delay
(Dm)
Arm
yH
Delay
(Dm + Dv)
Arm
Forward Model
-
+
LF
Visual Delay
(Dv)
yT
C
Switch
Controller
Motor Delay
(Dm)
Arm
yH
Clock Timer
Tracking error
-
+
Visual Delay
(Dv)
yT
D
Switch
Controller
Motor Delay
(Dm)
Arm
yH
Tracking error
Error dead-zone
-
+
Visual Delay
(Dv)
yT
E
Update
Management
(clock-driven or
event-driven)
MPC
Controller
Arm Dynamics
Model
Motor Delay
(Dm)
Arm
yH
-
Tracking error
+
Visual Delay
(Dv)
Predicted tgt traj.
Target Motion
Model
yT

Figure 3



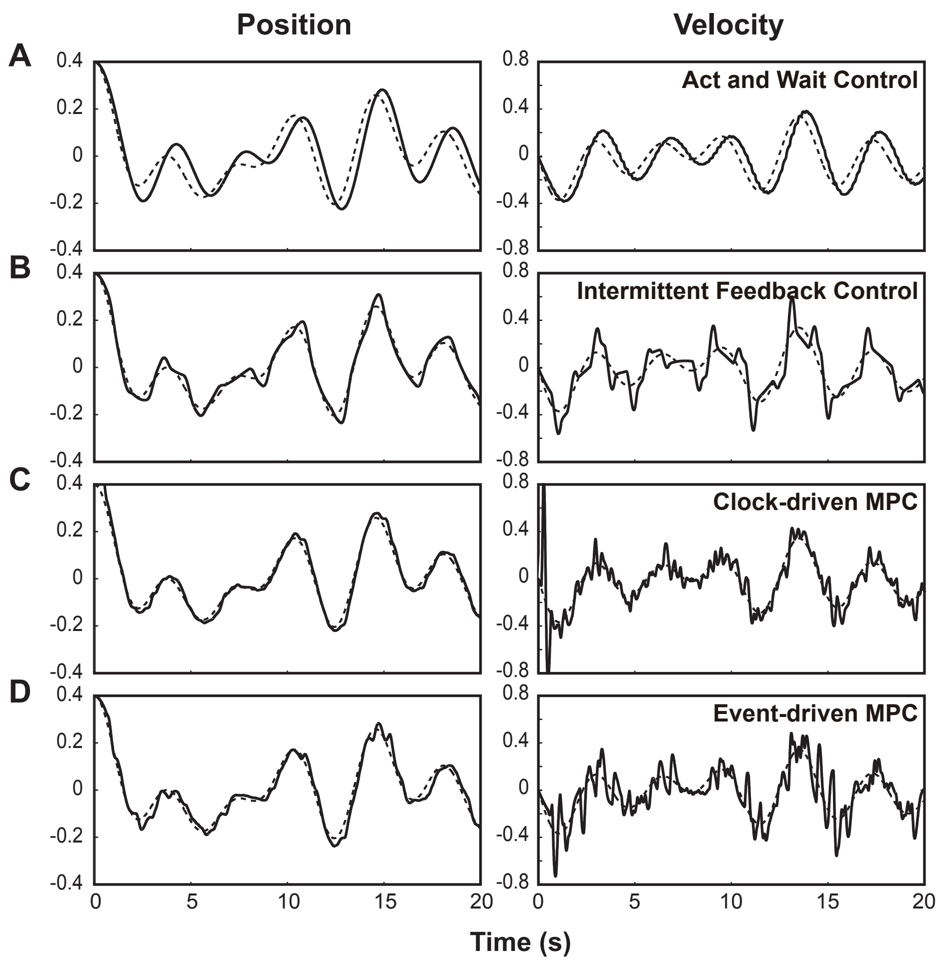
Sinusoid
Pseudo Random
Human
Position
Velocity
Hand
Target
Time (s)
0.4
0.2
0
-0.2
-0.4
0.8
0.4
0
-0.4
-0.8
0
5
10
15
20

Figure 4



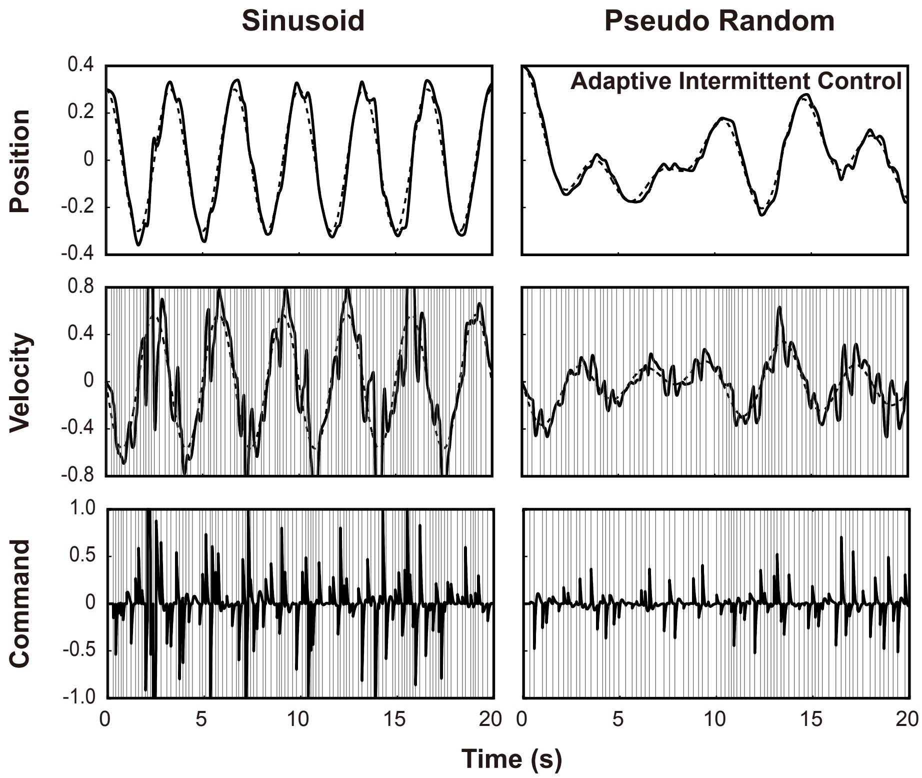
Position
Velocity
A
B
C
D
Act and Wait Control
Intermittent Feedback Control
Clock-driven MPC
Event-driven MPC
0.4
0.2
0
-0.2
-0.4
0.8
0.4
0
-0.4
-0.8
0
5
10
15
20
Time (s)

Figure 5



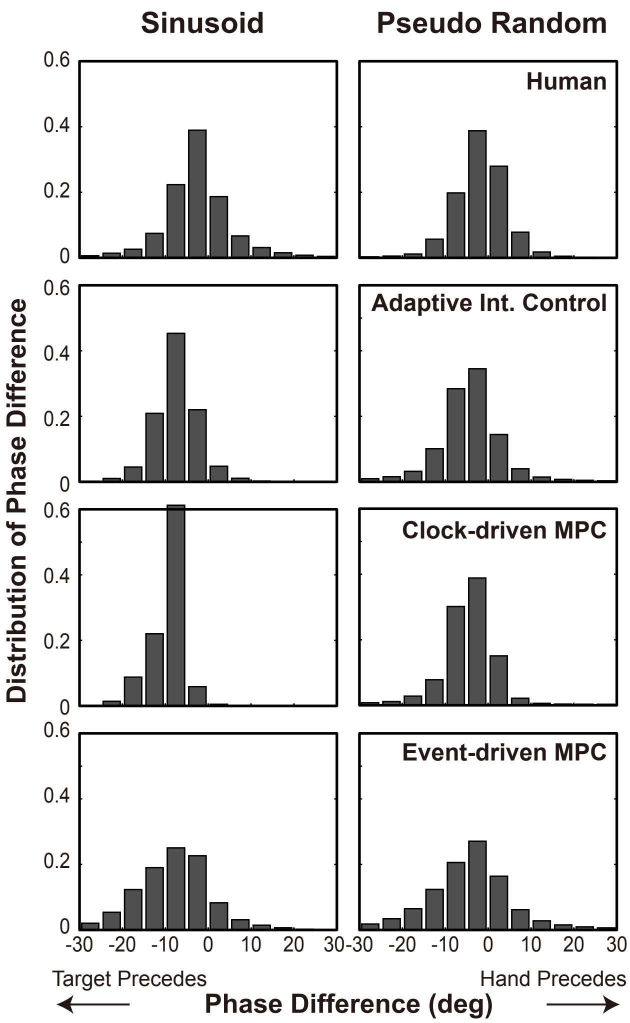
Position
Velocity
A
B
C
D
Act and Wait Control
Intermittent Feedback Control
Clock-driven MPC
Event-driven MPC
0.4
0.2
0
-0.2
-0.4
0.8
0.4
0
-0.4
-0.8
0
5
10
15
20
Time (s)

Figure 6



Sinusoid
Pseudo Random
Adaptive Intermittent Control
Position
Velocity
Command
0.4
0.2
0
-0.2
-0.4
0.8
0.4
0
-0.4
-0.8
1.0
0.5
0
-0.5
-1.0
0
5
10
15
20
Time (s)

Figure 7



Sinusoid
Pseudo Random
Human
Adaptive Int. Control
Clock-driven MPC
Event-driven MPC
Distribution of Phase Difference
0.6
0.4
0.2
0
-30 -20 -10 0 10 20 30
Target Precedes
Hand Precedes
Phase Difference (deg)

Figure 8

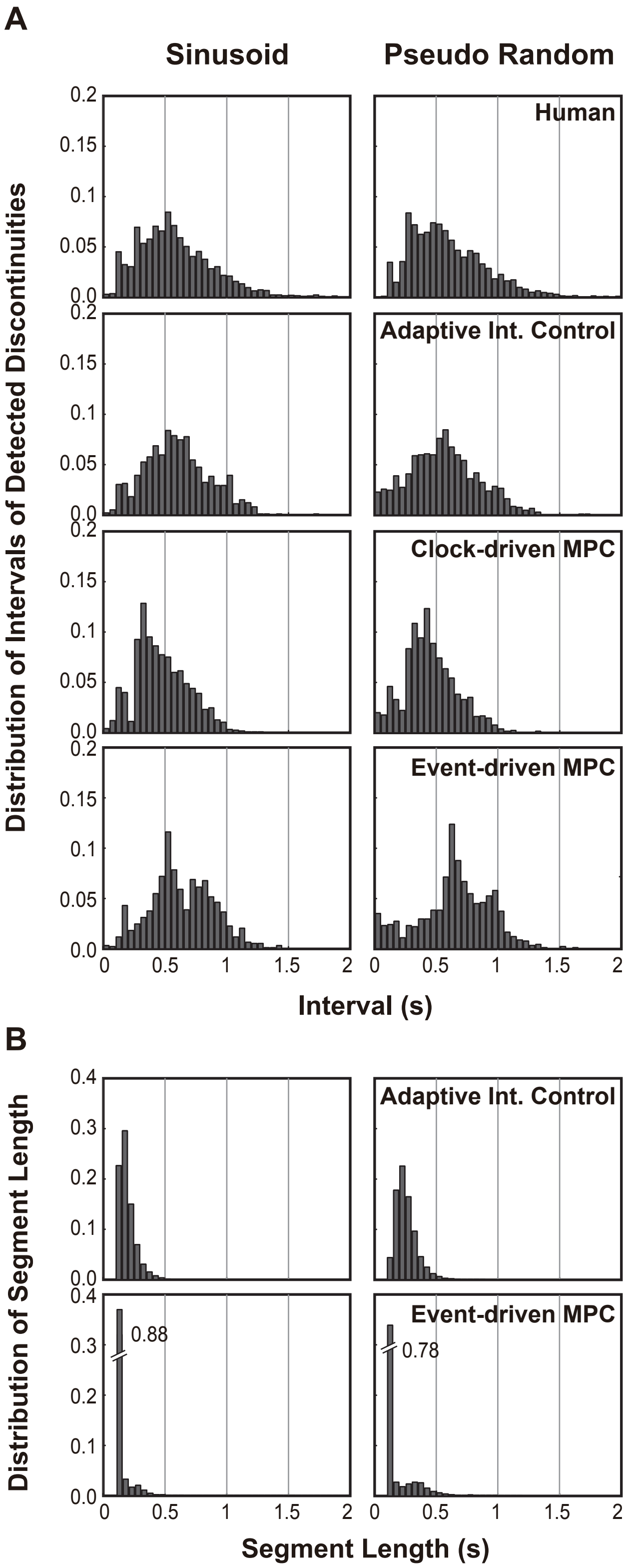

A
Sinusoid
Pseudo Random
Human
Adaptive Int. Control
Clock-driven MPC
Event-driven MPC
Distribution of Intervals of Detected Discontinuities
0.2
0.15
0.1
0.05
0.0
0
0.5
1
1.5
2
Interval (s)
B
Adaptive Int. Control
Event-driven MPC
Distribution of Segment Length
0.4
0.3
0.2
0.1
0.0
0.88
0.78
Segment Length (s)

Figure 9

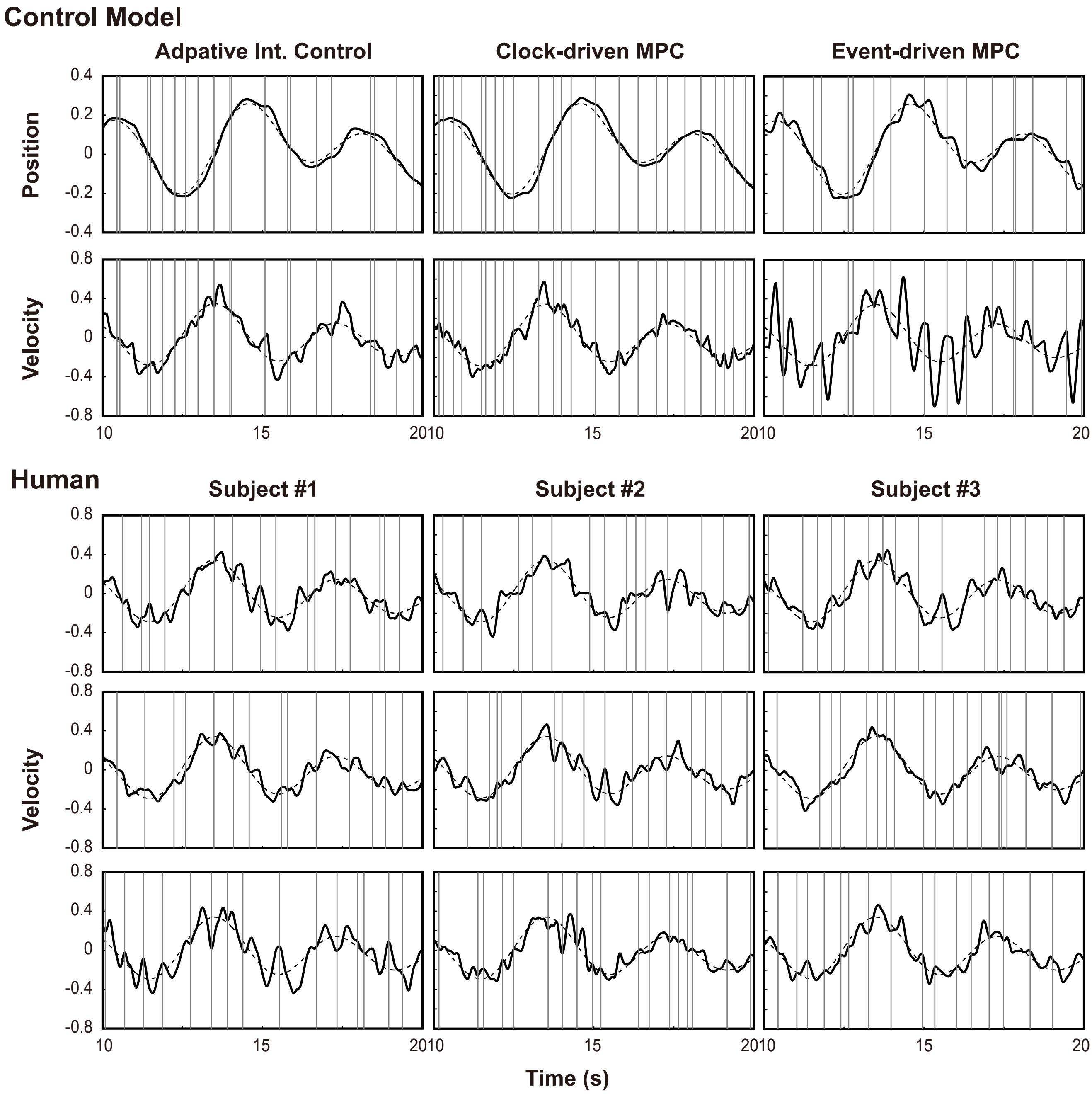
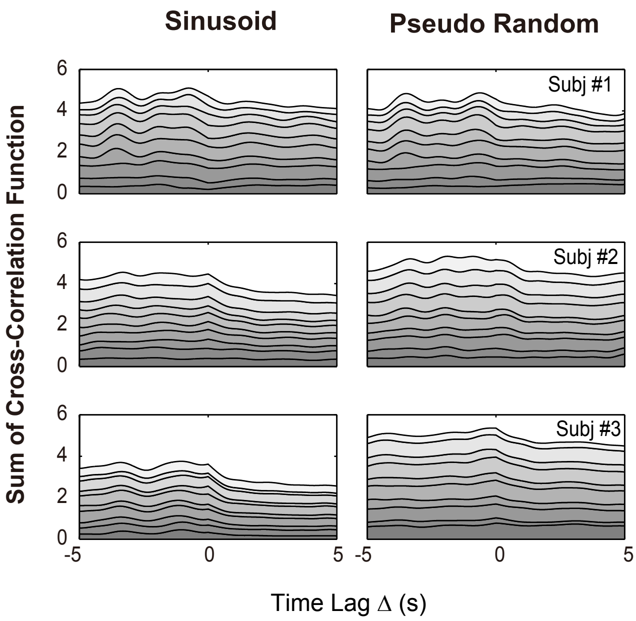

Control Model
Adpative Int. Control
Clock-driven MPC
Event-driven MPC
Position
Velocity
0.4
0.2
0
-0.2
-0.4
0.8
0.4
0
-0.4
-0.8
10
15
20
Human
Subject #1
Subject #2
Subject #3
Velocity
Time (s)

Figure10


Sinusoid
Pseudo Random
Subj #1
Subj #2
Subj #3
Sum of Cross-Correlation Function
Time Lag Δ (s)
6
4
2
0
-5
0
5