Judging Time Intervals Using a Model of Perceptuo-Motor Control

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Abstract

Estimating a time interval and temporally coordinating movements in space are fundamental skills, but the relationships between these different forms of timing, and the neural processes that they incur, are not well understood. While different theories have been proposed to account for time perception, time estimation, and the temporal patterns of coordination, there are no general mechanisms which unify these various timing skills. This study considers whether a model of perceptuo-motor timing, the $\tau_{\text{GUIDE}}$, can also describe how certain judgements of elapsed time are made.

To evaluate this, an equation for determining interval estimates was derived from the $\tau_{\text{GUIDE}}$ model and tested in a task where participants had to throw a ball and estimate when it would hit the floor. The results showed that in accordance with the model, very accurate judgements could be made without vision (mean timing error $\approx 19.24$ msec), and the model was a good predictor of skilled participants’ estimate timing. It was concluded that since the $\tau_{\text{GUIDE}}$ principle provides temporal information in a generic form, it could be a unitary process that links different forms of timing.

INTRODUCTION

Sensing time is an essential survival skill. Without it making sense of the world would be impossible and interacting with ever-changing environments hazardous. Timing is not a single entity though, and because timing abilities take many forms, it is not surprising that a number of different theoretical accounts have been proposed. For example, there are substantial bodies of work on time perception, time estimation, time discrimination, conditioning, circadian rhythms, and the temporal patterns of motor control. The theories and models that have emerged from this work differ not only in the tasks they explain but also in scale, ranging from milliseconds to days. Each has implications for the type of neural structures and mechanisms involved and there are instances within the literature where views on these matters differ radically, or even conflict.

Assessing the extent to which there might be commonality in the neural basis for various timing abilities is not an easy task because many of the models have been developed and tested using specific paradigms. This makes it difficult to create experimental tests that could demonstrate generalization to other timing skills and, consequently, the question of whether there is a common neural mechanism which operates across different time frames or a unitary process that accounts for multiple skills, such as time estimation and the temporal control of movement, has not been fully answered. However, there is one recent model that appears to have the potential to apply to, and be tested on, a range of timing skills. It is called the $\tau_{\text{GUIDE}}$ (Lee, 1998, 2004), and the author’s claim for this model is that it provides a complete description of the temporal control of all actions, and suggests a neural process that is both fundamental to and common to all motor tasks. If this is the case, then it would be interesting to see whether this model can be extended beyond the motor domain to other forms of timing. As an initial test, the current study sets out to evaluate whether the $\tau_{\text{GUIDE}}$ model of action timing could provide an explanation of how the passage of relatively short intervals are estimated. To do this, a mathematical model, which describes how temporal information relating to an action could be used to make an interval judgement, was derived from the original $\tau_{\text{GUIDE}}$ equation. This gave rise to the prediction that when asked to throw a ball in the air without the use of vision, participants would be able to make an accurate estimation of when the ball would hit the ground. This was duly tested along with the extent to which the model predicted performance.

In terms of the neural basis of timing, one of the controversies within the literature is the extent to which neural “clocks” are under the control of central or distributed processes. The idea of a central clock, proposed notably by Treisman (1963), is that there is a neural pacemaker which generates pulses that are

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used for all timing tasks. This central timer has been seen as independent of, and dissociable from, the timing of a motor response (Wing & Kristofferson, 1973), and implies the existence of neurons that are responsible for generating pulses and a counter mechanism which keeps track of the number of pulses emitted. In contrast, more recent research on distributed mechanisms sees timing as an emergent property arising from nonlinear oscillatory processes in both the brain and the motor system. At a neural level, it has been proposed that this could be achieved by different groups of neurons timing different intervals (Ivry & Richardson, 2002), or networks of neurons in which temporal processing is a property of a population as opposed to any single neuron (Buonomano & Karmarkar, 2002).

Lesion and imaging studies point to various cortical networks distributed throughout the brain that are involved in perceptual or motor timing (or both), and while links between neural processes and overt behaviors are increasingly being made (e.g., Meck & Benson, 2002; Harrington & Haaland, 1999; Quintana & Fuster, 1999), there are few instances where a close correspondence between behavioral models and neural mechanisms has been shown. For instance, Ivry and Richardson (2002) proposed a multiple timer model which describes a mechanism that could be used to perceive time intervals and regulate the onset of a movement from which the temporal properties of the action might emerge, but they recognize that evidence at a structural level (such as chronotopic maps in the cerebellum or the coordination of networks of temporally tuned neurons) is currently lacking.

In contrast to these approaches, the generalized \( \tau \) model suggests a very different kind of temporal mechanism for coordinating actions. It has parallels with the theory of population vector coding for directional information (Georgopoulos, Schwartz, & Kettner, 1986) in that just as the weighted directional sum of a neural population determines the direction of movement, the \( \tau \) pattern of firing rates determines the timing of the action (Lee, in press). If this temporal information has a generic form, regardless of the specifics of the action, then the merging of these two basic processes provides a way in which spatial and temporal activity in different brain regions can be multiplexed (Georgopoulos, 2002). Lee and colleagues have provided substantial evidence to show that the \( \tau \) model can account for the temporal control of action at both the behavioral and neural levels (see Lee, in press for a review). The time-to-closure of a physical gap at its current closure rate (referred to as \( \tau \)) forms the basic temporal measure, and the model predicts that the neural code for movement production (the \( \tau \)) corresponds to time-varying changes in neuronal firing patterns that accelerate from a rest level at a constant rate. Studying the activity of a population of neurons in the motor and parietal cortices, Lee and colleagues have shown a high level of correspondence between the model, the “neural power” (defined as the rate of firing at rest divided by the change in firing rate), and the ensuing reaching action. The model also provides a robust description of the temporal evolution of a large range of goal-directed actions, such as striking (Craig, Delay, Grealy, & Lee, 2000), reaching (Lee, Craig, & Grealy, 1999; Lee, Georgopoulos, Clark, Craig, & Port, 2001), and sucking (Craig & Lee, 1999). However, if the \( \tau \) model of motor timing is to account for how judgments of intervals of time are made, then the temporal patterns that the model generates should not only describe the kinematics and strategy behind the action, but should also characterize the temporal representation of other events where there is motion of an object and/or an actor. Perceiving these temporal structures could provide a way of predicting and synchronizing events.

The generalized \( \tau \) model is based on Newtonian equations of motion and assumes a constant gravitational force, although not necessarily set at 1 g. The equation describing the neural activity associated with an action is

\[
\tau = \frac{(\tau_{x,0} + kT)^2}{2(t(\tau_{x,0} + kT) - kT^2)} - kT(1 - \tau_{x,0}T^2) \\
\]

(1)

(see Appendix for derivation), where \( t \) is time running from zero when the \( \tau \) starts, \( \tau_{x,0} \) is the time-to-closure of a gap (\( X \)) when the \( \tau \) is started (e.g., the \( \tau \) of the gap between the ball and the ground at the point of release), \( k \) is a constant, and \( T \) is the duration of the event that is guided. Using this model to predict the total time taken for an event to occur, such as judging when a thrown ball would hit the ground, would require the use of various sources of information to form a temporal representation (\( T \)) for that interval estimate.

To evaluate this, an equation expressing \( T \) was derived from Equation 1 by noting that the velocity of closure of the gap between the ball and the floor was

\[
X = \frac{X_0(1/k)}{(1 + (kT/\tau_{x,0}))(2T/t^2) - (kT/\tau_{x,0})(1/T)} \\
\]

(2)

and that this becomes zero when the ball reaches its zenith, that is

\[
t = T/\{2[1 + (\tau_{x,0}/kT)]\} \\
\]

Rearranging Equation 3, the temporal estimate (\( T \)) can be expressed as

\[
T = t \pm \sqrt{(t^2 + 2t(\tau_{x,0}/k))} \\
\]

Therefore, when parameters associated with the release point of a vertically launched ball are fed into this
equation, it should accurately describe the ball’s temporal trajectory, where \( k = 1 \) under normal gravitational conditions.

To estimate the time interval \( T \), the parameters that the thrower would need to perceive are the temporal gap between the ball and the floor (ball to floor at release) when the ball is launched, and the time taken for the ball to reach its zenith. \( T \) could be sensed directly by monitoring how the gap between the ball (in the hand) and the feet (on the ground) changes during the throw, or derived by dividing the distance between the hand–ground surface by its instantaneous velocity. The time-to-zenith would also have to be estimated but because this equals the velocity of the hand and ball at release divided by \( g \), sensing the constituent components of \( T \) (the ball’s release velocity and the hand/ball to floor gap), and having an intuitive knowledge of gravity, should be sufficient information to estimate the flight duration \( T \).

Figure 1 shows simulated flight trajectories derived using this model for different values of \( T \). If this model is correct, then sensing the hand’s position relative to the feet and the velocity of the arm movement at the point of ball release should give sufficient information to estimate the ball’s flight time. Because neither of these parameters are dependent on vision, one prediction of this model is that it should be possible to estimate flight duration accurately without vision. To test this, participants were asked to throw a ball with or without vision, and estimate when it would hit the ground. Data from the release point were used to model the ball’s flight duration \( (T) \) and these modeled intervals were compared with the participants’ estimates and actual ball flight times.

**RESULTS**

The \( \tau_{\text{GUIDE}} \) model predicts that accurate estimates of flight duration should have been made without vision, as the information required for this task could be gained proprioceptively. Figure 2 shows that participants were temporally very accurate in both visual conditions and there were no significant differences in mean errors \([t(9) = 0.07, p = .47]\) or absolute errors \([t(9) = 0.68, p = .26]\).

To see whether accuracy levels were consistent across the range of flight times, correlation and regression analyses were carried out. A slight tendency for the participants to conform to Vierordt’s Law was found. This states that shorter events are overestimated and longer events are underestimated. There were significant correlations between timing error and flight duration for both the vision \((r = -.16, p = .02)\) and the no-vision conditions \((r = -.28, p = .01)\), but the regression analyses showed that these relationships only accounted for a very small percentage of variance within the data (with vision \( r^2 = .03 \), without vision \( r^2 = .08 \)). Further inspection of the timing errors showed that they spanned from \(-102\) to \(72\) msec (a range of \(174\) msec) and because ball flight times were in the range of \(331\) msec, it would appear that the participants were not performing stereotypical throws but were using a strategy that allowed them to predict flight times.

Figure 3 shows the relationships between the estimated, modeled and actual flight times for all participants combined. Without vision the model was found to be a good predictor of estimated flight times in that it accounted for \(80\%\) of the variance in the data (Figure 3B). Estimated errors in this prediction were \(\pm 46.5\) msec (with a \(95\%\) confidence level). Not surprisingly, given the high level of accuracy shown, the ball’s actual flight time was also a good predictor of the participants’ estimation of flight time (Figure 3D; \( r^2 = .79 \), estimated error \( \pm 52.5 \) msec). The relationship between the model and the actual ball flight times was similar, accounting for \(79\%\) of the variance, with errors in prediction being estimated at \(\pm 48.0\) msec (Figure 3F).

A comparable picture emerged when the participants completed the task with vision. The model predicted \(86\%\) of the variance in estimated flight times, with the estimated error in this prediction being \(\pm 39.6\) msec (Figure 3A). The relationship between the actual and estimated flight times explained \(84\%\) of the variance, with the estimated error being \(\pm 47.2\) msec (Figure 3C). Finally, the relationship between the modeled and actual flight times was marginally weaker, accounting for \(79\%\) of the variance in the data, with errors in prediction being estimated at \(\pm 52.7\) msec (Figure 3E). Further analysis of the heteroskedastic nature of these

![Figure 1](https://example.com/figure1.png)

*Figure 1.* Modeled ball trajectories for different values of \( T \). Where the amplitude of the gap \((X) = X_0(\pm[1 + (kT/\tau_{X0})(0/T)^2 - (kT/\tau_{X0})(0/T) - 1])^{1/2} \) and the initial gap size and overall duration \((T)\) are set to 1.
relationships (Figure 4) showed no systematic bias. However, other factors, such as sequential effects of how a prior judgment might influence a current response or fatigue effects, were not considered.

Taking the velocity of the hand and the gap between the hand and the floor at the point of release, the GUIDE model was able to predict the participants’ estimate of flight duration to within ±46.5 msec and the actual flight duration to within ±52.5 msec. This level of accuracy was similar in magnitude to that shown by the participants whose overall absolute mean timing error was 27.7 msec when performing without vision. This suggests that the precision level of the model matched that of the humans.

Although the participants were not using a stereotypical action during the experiment, it should be noted that they were well practiced at the task. It could be that by only looking at highly skilled performances, the degree to which the GUIDE model truly reflects a basic temporal neural process is exaggerated. To assess this, a second experiment was carried out where a different group of participants were asked to perform the same task without prior practice or feedback being given during the trials. Additionally, to evaluate whether the findings were specific to the use of a particular object or limb, participants were asked to throw two balls of differing weights and use their preferred and nonpreferred hand (see Methods for details).

**Performance without Practice or Feedback**

While increases in timing errors were noted under the conditions of no practice or feedback, the participants still showed great temporal accuracy in both visual conditions. With vision the overall mean timing error increased from −19.47 msec with practice to −78.29 msec without, and from −19.24 to −40.32 msec in the no-vision condition. Surprisingly, when practice and feedback were denied, the overall mean error without vision (−40.32 msec) was significantly smaller than that with vision (−78.29 msec) \[ t(6) = 2.71, p = .03, ES = 0.71 \].

To test for differences in temporal accuracy between the visual conditions, the two ball weights and the hand used to throw the ball, a three-way repeated-measures ANOVA was conducted on mean timing errors. This revealed no significant differences in accuracy for performances with or without vision \[ F(1,6) = 0.40, p = .55 \], or when participants used their preferred or nonpreferred hand \[ F(1,6) = 1.67, p = .24 \]. There was a trend towards significance with the two ball weights \[ F(1,6) = 4.90, p = .07 \], with more accurate responses being given when the heavier ball was used.

Regression analyses were carried out for each participant separately to assess the relationships between the modeled, estimated, and actual flight times. The data (Table 1) clearly indicate that the model fitted the
behavior of some participants better than others, with the percentage of variance in the estimation data the model accounted for ranging from 2% to 74%. However, an analysis of the relationship between timing errors and the predictive power of the model (Figure 5) revealed that those participants who were poor at making estimate judgments under these conditions also showed the model to be a poor predictor of their estimation.

**DISCUSSION**

Georgopoulos (2002) argues that the cognitive control of action requires the merging of separate processes that share common general principles for extracting information in space and executing tasks in time. The $\tau_{\text{GUIDE}}$ model is offered as one such general principle. Until now this has been seen as a temporal measure that defines the evolving time course of an action at both neural and behavioral levels. The results of this study suggest that the same process could be used for judging short time intervals associated with the consequences of an action.

With practiced performers, the regression equations describing the relationship between the $\tau_{\text{GUIDE}}$ model and estimates of flight duration accounted for 80% (no vision) and 86% (vision) of the variance in the data.
The model also predicted that participants would be able to make very accurate estimates of flight time without the use of visual information. The overall mean timing error of −19.24 msec confirmed this. However, without the benefits of practice or feedback, the model’s ability to predict estimated flight times revealed considerable variations between individuals, but these differences were mirrored in the participants’ ability to make accurate responses. Those whose temporal accuracy was acute for making interval judgments showed a good correspondence between the model, their temporal estimates and actual flight times, and for those who were less accurate the strength of these relationships declined. However, consistent patterns in ac-

**Figure 4.** Plots of standardized residuals against the standardized model for the relationship between the estimated versus modeled durations (A and B), estimated and actual durations (C and D), and modeled and actual flight times (E and F). Left panels show performances with vision and the right panels without vision. The lack of a linear trend in residuals shows no heteroskedasticity.
Accuracy were seen when using the dominant and non-dominant hand and the two different ball weights, suggesting that the results reflect a general ability for performance of this skill. The fact that some of the participants were better than others at this task, which is not one which is performed routinely in everyday life, could reflect the sensitivity of this task to reveal differences in the ability to use perceptual information in making timing judgments. This was not confined to the use of proprioceptive information since when they were allowed to see the upper part of the ball’s flight (including when it reached its zenith) the participants’ accuracy did not improve—in fact the overall mean timing error increased.

An alternative explanation for the diversity of results could come from differences in our intuitive knowledge of gravitational forces. An assumption of the model is that we can accurately sense and take into account gravity. Although this seems reasonable given that gravity is the fundamental characteristic that the earth’s environment affords to all organisms, it might not be the case. The effect that changing gravity has on the control of movements has been well documented (Fisk, Lackner, & Dizio, 1993; Bock, Howard, Money, & Arnold, 1992), and considerable adaptation of the neuromuscular system has been shown which suggests that we do have an intuitive knowledge of gravitational forces (Avela, Santos, Kyrolainen, & Komi, 1994). The ability to visually perceive gravitational accelerations has also been demonstrated by Stappers and Waller (1993) and Watson, Banks, von Hofsten, and Royden (1992), who argued that gravity could be used as a monocular cue for the perception of absolute distance or size. However, our sensitivity to this has been questioned by Hecht, Kaiser, and Banks (1996), who showed that observers were more sensitive to the average velocity than to the gravitational acceleration pattern of a simulated ball throw.

McIntyre, Zago, Berthoz, and Lacquaniti (2001) have also suggested that a knowledge of gravity is used to make temporal judgments. They studied behaviors in altered gravitational states and were able to show how perceptual estimates of distance, velocity, and the acceleration of an object, along with a knowledge of gravity, could be used in an internal model to make temporal

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Table 1. Summaries of Individual Regression Analyses for the Relationships between Modeled and Estimated Flight Durations

![Figure 5](123456789.png)

Figure 5. Relationships between the percentage of variance accounted for by the regression equation relating modeled and estimated flight times as a function of timing accuracy.
judgments for the time of arrival of a dropped ball. However, if the ball is initially thrown upwards and visual information is not available, as in the present study, then using this model to make temporal estimates would be quite demanding. It would first require making an approximation of the distance the ball travels from release to its zenith (which in turn requires an estimate of the time taken for the ball to get there), and then using this to calculate the overall flight time. An internal timing system for judging when this interval has elapsed would also be required to allow for an appropriate response to be made. Additionally, while this model can account for how some temporal estimates are made, it cannot account for the temporal control of actions.

In contrast to the work which suggests we have an intuitive knowledge of gravity there are reports that our conceptual and perceptual knowledge of projectile motion is sometimes quite poor. Hecht and Bertamini (2000) reported poor judgments of the maximal velocity of a thrown ball. Half of their adult sample (n = 176) erroneously believed that the ball would continue to accelerate after it had left the hand, and 31% thought, again erroneously, that the ball would speed up then slow down. Furthermore, Krist, Fieberg, and Wilkening (1993) showed a dissociation between perceptuo-motor and judgmental abilities in children aged 5–6 years. While their actions showed an understanding of gravitational forces, their ratings of speed were poor compared with older children and adults. Therefore, it is possible that a conceptual misunderstanding of gravity could explain why some of the participants performed poorly when they were not given the opportunity to learn how to perform the task. However, in the visual condition of the second experiment, they could track the ball for at least half of its trajectory and this did not improve performance, which suggests that a more likely explanation is that some of the participants simply had a poor sense of timing.

Apart from an understanding of gravity, a further requirement of the \( \tau_{\text{GUIDE}} \) model is its use of intervals of time, notably the parameter \( t \) in Equation 1. Lee and colleagues (see Lee, in press) have shown how this mechanism could be represented by the “neural power” of neuronal firing rates, a solution which negates the need for a centralized clock or specialized interval units. They argue that if the pattern of neural firing rates take a \( \tau_{\text{GUIDE}} \) form, this in itself provides a neural chronometer for each action or imagined event. Modulations in firing rates that could occur through priming, or changing synaptic thresholds, suggest a means by which “internal timing” (the parameter \( t \)) could be modified. This highlights the disparity between this model and models such as Wing and Kristoffersen’s in that the \( \tau_{\text{GUIDE}} \) does not rely on a central pacemaker that provides regular beats nor is it dissociable from the timing of a motor response, rather it links neural and behavioral events through a common process.

Nevertheless, many questions about the \( \tau_{\text{GUIDE}} \) model remain. For example, there is the issue of how simplicity at one level can be integrated with complexity at another. Kerr and Worringham (2002) discuss the complexity of perceiving the hand’s velocity from proprioceptors that are distributed within muscles, tendons, joints, and the skin, and it is not clear how this information could be amalgamated and used in a fashion similar to that described by Equation 4. Consideration also needs to be given as to how, within this framework, information from different sensory systems is temporally integrated and how actions are synchronized to events so as to give a perception of simultaneity (Aschersleben & Prinz, 1995; Mates, Müller, Radil, & Pöppel, 1994; Pöppel, Schill, & von Steinbuchel, 1990). Additionally, if this model is an accurate descriptor of an estimate timing process, then two other interesting findings that emerged from this study also need to be considered. The first is that the participants’ estimates did not improve with vision, that is, having a visual cue as to when to stop “timing” did not improve performance. This would imply that the use of proprioceptive information gained at the point of release allowed participants to make extremely accurate judgments about the consequences of the throwing action. However, the extent to which the model’s utility is dependent on proprioceptive information or a sense of agency needs to be addressed.

The second is that the degree of accuracy remained fairly constant over the range of time intervals studied (see Figure 4C and D), whereas it might be expected that the variance in estimates would increase as the judgement length increased. Although it could be argued that the range of intervals studied was relatively small, if this is found to be the case over a larger range then this would suggest that the process associated with making these judgments is dissimilar to the pacemaker or accumulator mechanisms that have previously been proposed (e.g., Gibbon, Malapani, Dale, & Gallistel, 1997). If a lack of scalar variance is found, then there are two ways in which this model could operate. Participants could either use information gained at the point of release to define the initial parameters for flight and then mentally track the trajectory visualizing the ball’s temporal path following a \( \tau_{\text{GUIDE}} \) like form, or they could calculate the flight duration using equations of motion or Equation 4. From these data, it is not possible to say which of these methods might have to be used. One speculation though is that being able to imagine the motion of an object during the interval to be estimated, that is, having an internal representation of the ball’s temporal trajectory, could reduce the likelihood of systematic errors such as scalar variance. However, although further work is needed to address these issues, it would seem that in trying to answer the question of whether there is a single mechanism which forms a unitary process for different timing abilities,
the $\tau_{\text{GUIDE}}$ model (or a variant of it) could help provide the solution.

**METHODS**

**Experiment 1**

*Participants*

Nine women and one man (mean age 26.2 years, $SD = 4.5$ years) participated. All gave informed consent and local ethical approval was granted in line with the Declaration of Helsinki.

*Procedure*

Participants stood in front of two pressure-sensitive mats and were instructed to throw a lacrosse ball upwards with their dominant hand so that it landed on one mat. Their throwing arm was splinted so that there was no flexion at the wrist and a cup with a pressure sensitive switch was attached to the palm of their hand. The ball was placed in this cup and when it was thrown the switch was released starting two millisecond timers. One timer was stopped when the ball hit the mat, while the other was stopped by the participant tapping the other mat with a stick which they held in their nondominant hand. Participants were asked to use the stick to indicate when they thought the ball would hit the ground. They were told to hold it in a stationary position above the mat during the throwing action and to make a single downward movement so that it struck the mat at the same time as when the ball hit the other mat. Participants were allowed to practice until they felt they were making accurate judgments and then performed 12 trials with vision and 12 trials wearing a blindfold, presented in a random order.

A Flock of Birds motion analysis system (Ascension Technology, North America) was used to record the throwing action and the movement of the stick. On the throwing arm sensors were placed on the shoulder and elbow joints and on the underside of the hand below the switch. A fourth sensor was placed on the top of the stick that was held in the nondominant hand. Trials were recorded at 120 Hz, and digitally filtered using a gaussian filter with a cutoff of 8 Hz.

The accuracy of the participant’s estimate was calculated by noting the difference between the two millisecond timers. Mean (signed) and absolute (nonsigned) errors were calculated for each condition. The parameter $\tau_{(\text{ball to floor at release})}$, which was required to model the flight time $T$ (Equation 4), was gained from kinematic parameters at the time of ball release. Using the ball’s flight time as recorded by the millisecond timer, and noting the difference between the actual and estimated times, the time of release was calculated.

**Experiment 2**

*Participants*

Five men and two women (mean age 26 years) who had not taken part in Experiment 1 participated. All gave informed consent and local ethical approval was granted in line with the Declaration of Helsinki.

*Procedure*

Participants were instructed to throw a ball in the air and predict as accurately as possible when it would hit a foam platform on the floor ($1 \times 0.5$ m) beside them. They did this with vision and without vision, with their preferred and nonpreferred hand and with a heavy ($400$ g) and a light ($150$ g) ball. In the “with vision” condition, a horizontal screen was placed around the participant’s neck so that they could see the ball arriving at its zenith and starting its descent to the landing pit. In the “no vision” condition, participants wore a blindfold.

The 15 trials in each condition were randomized, giving a total of 120 per participant. To eliminate learning effects from auditory feedback, participants wore a headset through which white noise was played. The ball’s flight time and the kinematics of the arm movement were measured using an Elite passive motion capture system (BTS, North America) sampling at 100 Hz. Markers were placed on the elbow and wrist joints and both balls were completely covered in reflective tape. Participants’ predictions about the ball’s arrival time were made using a switch held in their nonthrowing hand, and this was sampled at 500 Hz via the Elite system. The gap between the ball in the hand and the floor, and the velocity of this gap derived using finite differences, were used to model the flight duration $T$ (Equation 4).

**APPENDIX: DERIVATION OF THE FORMULA OF THE $\tau_{\text{GUIDE}}$**

At any point during its closure a physical a gap ($X$) can be described as

$$X = (ut + 0.5at^2) - (uT + 0.5aT^2)$$  \hspace{1cm} (A1)

where $u$ is the initial velocity, $a$ is acceleration, $t$ is time starting from zero, and $T$ is the total duration for the closure. Because the velocity of closure at time $t$

$$\dot{X} = u + at$$  \hspace{1cm} (A2)
the time to closure, or \( \tau_{\text{GUIDE}} \) is

\[
\tau_{\text{GUIDE}} = \frac{(ut + 0.5at^2) - (ut + 0.5at^2)}{|u + at|} \quad (A3)
\]

Dividing numerator and denominator by \( u \), and simplifying:

\[
\tau_{\text{GUIDE}} = \frac{[(t - T) + 0.5(a/u)(t^2 - T^2)]/[1 + (a/u)t]}{u} \quad (A4)
\]

Thus when \( t = 0 \),

\[
\tau_{\text{GUIDE},0} = [-T - 0.5(a/u)T^2] \quad (A5)
\]

Because \( \tau_{\text{GUIDE},0} = (1/k)\tau_{X,0} \) (see Lee, 1998 for details), substituting \( (1/k)\tau_{X,0} \) for \( \tau_{\text{GUIDE},0} \) in Equation A5 and solving for \( a/u \)

\[
a/u = -2[\tau_{X,0} + kT]/[kT^2] \quad (A6)
\]

Substituting for \( a/u \) from Equation A6 in Equation A4,

\[
\tau_{\text{GUIDE}} = \frac{[k(t - T) + 0.5\{-2[\tau_{X,0} + kT]/T^2\}]}{[k + \{-2[\tau_{X,0} + kT]/T^2\}t]} \quad (A7)
\]

Simplifying

\[
\tau_{\text{GUIDE}} = \frac{[\tau_{X,0} + kT]T^2 - kT^2t - \tau_{X,0}T^2}/[2(\tau_{X,0} + kT) - kT^2] \quad (A8)
\]

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