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RESEARCH NOTE

Extending Fitts' Law to three-dimensional obstacle-avoidance movements: support for the posture-based motion planning model

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Abstract According to Fitts' Law, the time (MT) to move to a target is a linear function of the logarithm of the ratio between the target's distance and width. Although Fitts' Law accurately predicts MTs for direct movements, it does not accurately predict MTs for indirect movements, as when an obstacle intrudes on the direct movement path. To address this limitation, Jax et al. (2007) added an obstacle-intrusion term to Fitts' Law. They accurately predicted MTs around obstacles in two-dimensional (2-D) workspaces, but their model had one more parameter than Fitts' Law did and was merely descriptive. In this study, we addressed these concerns by turning to the mechanistic, posture-based (PB) movement planning model. The PB-based model accounted for almost as much MT variance in a 3-D movement task as the model of Jax et al., with only two parameters, the same number of parameters as in Fitts' Law.

Keywords Fitts' law · Obstacle · Movement time · Motor control · Reaching

Introduction

The time (MT) to move the hand from one target to another can be predicted with considerable accuracy using one of the most robust principles of experimental psychology, Fitts' Law (Fitts 1954; Fitts and Peterson 1964). Conceptually based on the information implicit in the definition of target size and distance moved (Shannon 1948), Fitts' Law describes how movement time is affected both by the distance to be moved and the accuracy required. Qualitatively, Fitts' Law says that movements to far and/or narrow targets take longer than movements to near and/or wide targets.

Most demonstrations of Fitts' Law have been confined to the study of direct movements between targets in two-dimensional (2-D) workspaces, following Fitts' original paradigm. In a representative experiment, Fitts and Peterson (1964) laid out a pair of rectangular targets of varying width (W) and manipulated movement amplitude (A) by varying the separation of the targets. Participants held a metal stylus and moved between the targets, touching them alternately as quickly as possible. Fitts provided a good account of the observed movement times with the formula

$$\mathrm{MT} = a + b\ \mathrm{ID} \qquad (1)$$

where ID is the Index of Difficulty,

$$\mathrm{ID} = \log_2(2\mathrm{A}/\mathrm{W}). \qquad (2)$$

Variants of the foregoing equations, known collectively as Fitts' Law, also account for such data in a variety of situations (see Beamish et al. 2009; Elliot et al. 2001; Meyer et al. 1988). However, we focus on Fitts' original formulation because it is most familiar and because it is adequate for present purposes. Other formulations do not address the main problem we are concerned with here, nor, as far as we know, do they point to solutions of the main problem we consider any better than does Fitts' Law.

In Fitts' experiments, participants could move directly from one target to another along a linear trajectory.

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In everyday life, however, straight-line movements are not always possible. Obstacles intrude, whether they are visible and "cry out" for evasion (e.g., a spinning electric saw at one's workbench) or are invisible but still demand circuitous movements (e.g., one's own head when one touches one's left ear with one's right hand).

In an earlier study, Jax et al. (2007) asked whether MTs could be predicted when obstacles prevented direct movements between targets. Jax et al. had participants perform reaching movements in a 2-D virtual-reality setup. The participants' displacements of a manipulandum (remotely sensed) were reproduced on a video screen, along with representations of the targets to be reached and the obstacles to be avoided. Jax et al. found that Fitts' Law accurately predicted MT between targets when no obstacle was present. However, Fitts' Law did not accurately predict MT when obstacles were in the way. Jax et al. addressed this problem by adding an obstacle-intrusion (OI) term to the formula,

$$\mathrm{MT} = a + b\ \mathrm{ID} + c\ \mathrm{OI}, \tag{3}$$

where a, b, and c were empirical constants, and OI was the extent to which the obstacle intruded into the workspace (i.e., the minimum distance by which the movement trajectory had to diverge from the direct path from the start to the target). Jax et al. found that Eq. 3 provided a much better fit ($R^2 = 0.87$ vs. $R^2 = 0.22$) to the obstacle-present movement-time data because it has one more free parameter, allowing it to address the systematic deviation from the prediction of Eq. 1 caused by the obstacle.

Because Jax et al. dealt with the effect of an obstacle by simply adding a term to Fitts' Law, they did not strive for a mechanistic account of their formula (i.e., an account that explicitly included internal control processes). Neither did they tackle the problem of predicting movement times in 3-D space; their task and model was limited to 2-D (planar) movements.

In this study, we sought to approach the latter challenges by building on a model of motion planning developed in our laboratory. This posture-based (PB) motion planning model can generate multi-limb trajectories, including multi-limb trajectories in 2 space and 3 space that are capable of avoiding obstacles. The model is mechanistic in the sense that it predicts outputs from hypothesized internal control processes (Rosenbaum et al. 1995, 2001, 2009; Vaughan et al. 2001, 2006).

The central concept of the PB model is that movements are made to goal postures. These movements are selected to bring required parts of the body or extensions of the body (e.g., hand-held tools) to targets without making unwanted collisions with intervening obstacles. According to the model, the trajectory from the starting posture to the goal posture is, by default, a straight line through joint space. If the resulting trajectory needs to be modified, as in creating a curved paintbrush stroke or avoiding an obstacle, it can be shaped by adding a back-and-forth movement to the main movement. This back-and-forth movement is made from the start posture to a "bounce" posture and back. The reversible movement adds no net displacement to the main movement, and the main movement's shape is determined by which bounce posture is used.

Consider how the foregoing account of movement shaping might lead to predicted MTs. Suppose the amplitude, B, of the bounce movement is the distance between the spatial midpoint of the main movement and the maximum desired deviation from the direct movement.[1] The total distance moved then consists of two terms, A and 2B, where A is the amplitude of the direct movement (as in Fitts' Law) and B is the amplitude of the reversible bounce movement. The accuracy required of the direct movement is W, as in Fitts' Law. Using Fitts' Law, we can then write

$$\mathrm{ID_{PB}} = \log_2(2[\mathrm{A} + 2\mathrm{B}]/\mathrm{W}), \tag{4}$$

$$\mathrm{MT} = a + b\ \mathrm{ID_{PB}}. \tag{5}$$

The number of empirical constants in Eq. 5 is one less than in Eq. 3. This greater parsimony makes the PB-based model preferable to the model of Jax et al. because increasing the number of model parameters always results in a better model fit.

The goal of this study was to test the PB model's predictions about the time to complete both direct and obstacle-avoiding movements, as quantified in Eqs. 4 and 5. To pursue this goal, we asked participants to touch two targets in alternation using a hand-held pointer and recorded the time it took to complete those movements. In separate sets of trials, we varied the movement amplitude (A), the diameter of the targets (W), and the obstacle's intrusion into the movement (B). We asked participants to use a hand-held pointer so the data from this experiment could be compared to data in future studies where the properties of the pointer might be varied (e.g., its length or mass distribution).

Methods

Participants

Eleven participants (5 men and 6 women aged 19–21 years) served after giving informed consent. Two reported being left-handed, but all participants performed with the right hand. All procedures were reviewed and approved by

[1] In the foregoing, B must be at least as large as the distance the obstacle intrudes (OI) into the workspace. For convenience of exposition, we assume that B simply equals OI.

the Hamilton College Institutional Review Board in conformance to the 1964 Declaration of Helsinki.

Apparatus and procedure

Participants sat in front of a bookcase from which two parallel rods, 22 cm long, extended horizontally 91 cm above the floor (see Fig. 1a), separated by a distance, A, of 20, 41, or 81 cm. A pair of targets (either ping-pong balls, whose diameter, W, was 4.0 cm, or tennis balls whose diameter, W, was 6.4 cm) was mounted on the ends of the rods, approximately at the participant's shoulder level.

As shown in Fig. 1b, a vertical pole (diameter 1.2 cm) stood midway between the targets in one of four positions: 18 cm behind the front edge the targets, midway between the targets, 13, or 25 cm in front of the targets. In a fifth condition, there was no obstacle. We included the condition in which the pole stood 18 cm behind the direct path between the targets to see whether the mere presence of the obstacle would serve as a distracter (Tipper et al. 1997).

Participants held a 40-cm baton (an aluminum rod 1 cm in diameter, weighing 195 gm), whose form-fitting handle afforded a unique grip for the hand. A Nest of Birds (Ascension Technology) motion-capture sensor mounted on the baton recorded the tooltip locations at 101 samples/s.

Participants were instructed to start each trial with the tooltip touching one target, move as quickly as possible to the other target in response to a tone, while maintaining accuracy, and then wait with the tool touching that target until the next tone. The tones cued 8 movements per trial, at intervals that varied between 2.5 and 3.5 s, intervals intended to exceed the longest MT. If the participant moved prematurely, the move was repeated. The MT of each move was computed from the instant the tooltip velocity first exceeded 12.9 cm/s (the lowest value that reliably separated all moves) until the tooltip velocity fell below that level, and the median MT of each series of eight moves was computed.

Each session had 2 blocks of 30 trials each (3 distances $\times$ 2 target diameters $\times$ 5 obstacle locations), giving 480 total moves. Target sphere diameter and distance were counterbalanced within each block; obstacle locations were randomized for each target and distance combination. Participants began all trials of one block on the left target, and those of the other on the right, with order counterbalanced across participants.

Results

Movement times

The mean MT across all conditions was 511 ms (range 258–720 ms). Figure 2a shows the observed MT between the large targets and between the small targets for the three distances and five obstacle conditions. MTs between the small spheres were longer than MTs between the large spheres, $F(1, 10) = 10.44$, $p < 0.01$, consistent with the hypothesis that movements requiring more accuracy are executed more slowly than movements requiring less accuracy. Similarly, larger-amplitude moves took longer than smaller-amplitude moves, $F(2, 20) = 460.15$, $p < 0.001$. Finally, the larger the obstacle intrusion on the direct path, the longer the MTs, $F(4, 40) = 388.51$, $p < 0.001$. When the obstacle was not in the path of movement, the [−18] intrusion condition, MTs were not different from the control condition, $t(10) = 0.32$, *ns*. This outcome indicates that the mere presence of the obstacle did not affect performance. All other pairwise comparisons defined with respect to obstacle position were statistically significant, all $t(10)$'s > 7.00, all $p < 0.001$. There was a significant interaction of distance and obstacle condition,

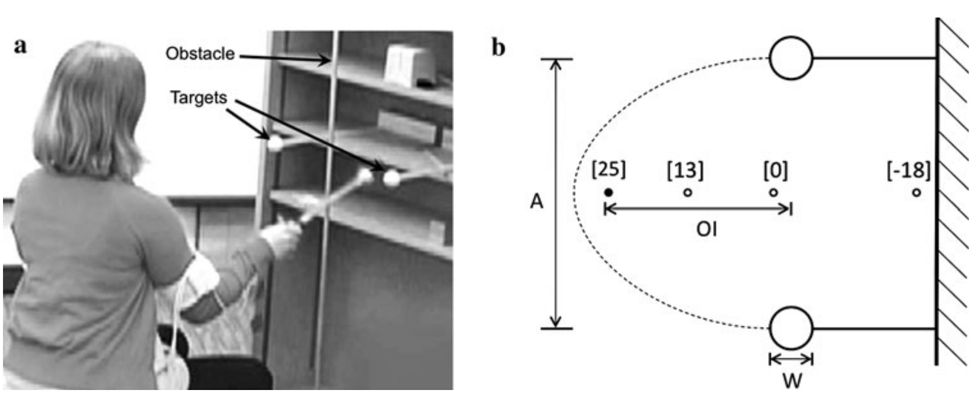

Fig. 1 Experimental setup. **a** A participant performing the task. **b** *Top view* of the workspace showing the width (*W*) of one type of target (tennis balls), the distance (*A*) between the target centers, and four values of obstacle intrusion (*OI*) achieved by placing a vertical pole midway between the targets in each of four positions. In a control condition, no pole was present. The *dotted line* shows an idealized tool tip trajectory from one target to the other

$F(8, 80) = 37.01$, $p < 0.001$, reflecting the greater effect of obstacle intrusion on MTs at the shorter inter-target distances than at the longer inter-target distances.

Modeling

In the no-obstacle [control] or non-intruding obstacle [−18] intrusion conditions, the traditional Fitts' Law equation (Eq. 1) was an adequate predictor of MT: $\text{MT} = -58 + 117 \times \text{ID}$, $R^2 = 0.94$. However, when all the obstacle conditions were included, this equation fit the data much less well: $\text{MT} = 248.5 + 90.5 \times \text{ID}$, $R^2 = 0.31$. By contrast, the modified OI model advanced by Jax et al. (2007; Eq. 3) fit the data of all obstacle conditions with significantly greater precision than did the traditional Fitts' Law equation

$$(z(29) = 4.27, p < .001) : \text{MT} = 143.6 + 90.5 \times \text{ID} + 21.8 \times \text{OI}, R^2 = 0.90.$$

The most critical question was how well the PB model (Eq. 5) fit the MT data. The PB model fit the data of all obstacle conditions: $\text{MT} = -131 + 141 \times \text{ID}_{\text{PB}}$, $R^2 = 0.87$ (Fig. 2b). This fit was significantly better than the fit of the unelaborated Fitts' Law equation, $z(29) = 3.76$, $p < 0.001$. Most importantly, the fit of the PB model was not significantly worse than the modified OI model, using a partial F test to take account of the additional free parameter of the modified OI model, $F(1, 26) = 0.87$, *ns*.

Discussion

This study extends Fitts' Law to obstacle-avoidance movements in a 3-D workspace. Participants moved a hand-held baton back and forth between pairs of targets of different sizes, separated by different distances, and with an obstacle at various distances in front of the targets. We focused on the timing of the contacts on the targets by the participant's hand-held tool.

As expected from Fitts' Law, we found that MT was larger for small targets than for large targets, and larger for large movements than for small movements. We also found that the greater the intrusion of the obstacle into the direct path between the targets, the longer the movement time. The latter result is broadly consistent with Fitts' Law, which says that longer movement paths should lead to longer MT. However, Fitts' Law does not explicitly say anything about the lengths of actual movement paths, only the lengths of the straight-line distances between targets. Significantly, Fitts' Law is expressed solely in terms of extrinsic variables, though its predictive focus is on the time to complete body movements. At the same time, given the conceptual origin of Fitts' Law in information theory, it is consistent to frame the increased movement time in terms of the greater information needed to move to a goal around an obstacle than to move directly to the goal. To summarize, we asked how the timing of body movements in the Fitts reciprocal movement task is affected by the presence of an obstacle standing midway and with varying degrees of intrusiveness between the targets to be touched. The model we tested was one that explicitly focuses on the planning of body movements, the posture-based motion planning (PB) model of Rosenbaum et al. (1995, 2001, 2009) and Vaughan et al. (2001, 2006). In the present obstacle-avoiding task, we found that this model accurately predicted MTs, doing as well in accounting for MTs as a model we previously considered that had one more parameter, the model of Jax et al. (2007).

Several issues remain. One is how well the PB model accounts for the movement times in a 2-D workspace previously reported by and modeled by Jax et al. (2007). If

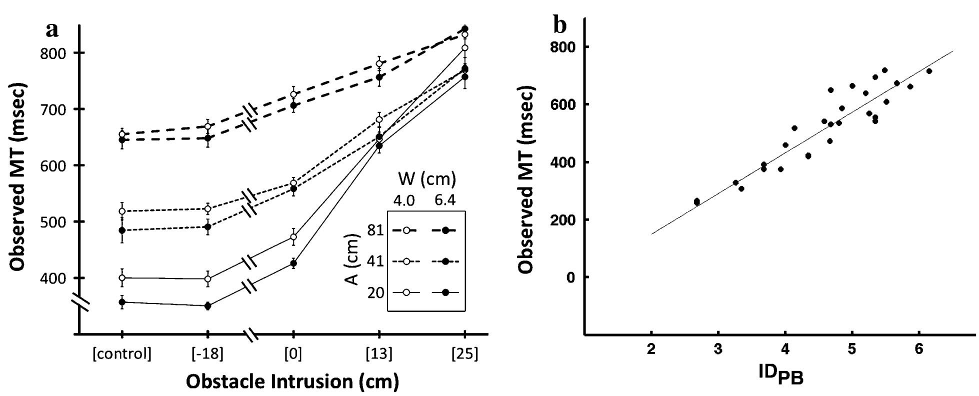

Fig. 2 Observed and predicted data. **a** Mean observed movement time (±1 SE) as a function of target size (*W*), movement amplitude (*A*), and obstacle intrusion (*OI*). Obstacles in the (*0*), (*13*), and (*25*) conditions impeded direct movement to the target. **b** Mean observed movement time as a function of the Index of Difficulty ($\text{ID}_{\text{PB}} = \log_2(2[A + 2B]/W)$, where A is movement amplitude, B is obstacle intrusion, and W is target width

the PB model accounts for MTs of obstacle-avoidance behavior in a 3-D workspace, as shown here, it should also account for MT of obstacle-avoidance behavior in the 2-D workspace. We fitted the PB model to the data of Jax et al. and found that it fit the data quite well: $\mathrm{MT} = -43.6 + 266.5 \times \mathrm{ID_{PB}}$, $R^2 = 0.82$. This R^2 value is comparable to the R^2 value of the model of Jax et al. ($R^2 = 0.89$), even though the PB model has one fewer parameter.

Because we contrast the present task from the task used by Jax et al. (2007) in terms of 3-D versus 2-D, it is germane to consider the importance of describing a task as 2-D or 3-D (see also Murata and Iwase 2001). The task of Jax et al. (2007) was 2-D in the sense that the targets were circles occupying a single plane and the virtual manipulandum moved in that same plane. By contrast, in this experiment, the task was 3-D in the sense that the targets were spheres and the manipulandum was a tool whose 6 positional degrees of freedom could vary freely.[2]

Despite these seeming differences between the 2-D and 3-D tasks just discussed, there is an important sense in which almost no perceptual-motor tasks are really linear and, just as importantly, almost no perceptual-motor tasks really escape obstacle-avoidance requirements. For example, the participants in Fitts' original experiments (Fitts 1954) used a metal stylus to contact each target. They had to make manual arcing movements to bring the stylus in contact with each target, which was a metal conductive plate. If the participants in the 1954 study had simply slid the stylus directly between the target plates, the stylus would have touched an "undershoot" detection plate before touching the target plate. Thus, even in the original experiments of Fitts, 3-D displacements of the stylus were required to prevent collision with obstacles.[3]

This last point bears on a final issue, concerning the role of intrinsic versus extrinsic variables in account of human motor control. We observed above that Fitts' Law is expressed in extrinsic terms even though its main focus is the time to complete body movements. The fact that Fitts' Law works as well as it does—indeed, the fact that it is called a *Law*—attests to the fact that it predicts MTs very well, notwithstanding its inability, shown here and in the Jax et al. (2007) study, to account for MTs when obstacle-avoidance behavior is a major or explicit challenge rather than a minor or implicit challenge, as in the original reciprocal tapping experiments of Fitts (1954) and Fitts and Peterson (1964).

One might ask whether the model offered here is actually "more intrinsic" than Fitts' Law. After all, we expressed the extra displacement required by obstacle avoidance not in terms of what the arm must do but rather in terms of where the obstacle was located. The clearance around the obstacle might have differed if the non-preferred hand had been used (Worringham 1993) and the postures adopted might have changed over the course of successive reaches (Fischer et al. 1997). We did not analyze those features of performance for this report, however, though in principle we could have done so. It is always possible to investigate performance in greater and greater detail, as there are always sources of uncontrolled variation in actual performance. Even Fitts (1954) could have analyzed other movement properties (e.g., exact position of the stylus on each target, the angle of the stylus as it contacted each target, the angles of the arm joints at the moments of contact) but found impressive regularity of performance, summarized in his famous Law, by taking into account only the effector tip.

Our strategy was similar. Our justification for the choice of model we made, apart from the fact that it employs one fewer parameter than the model our group pursued before (Jax et al. 2007), is that it is important in applied contexts to predict how performance will be shaped by features of the external environment. Thus, the input to the model can be expressed in extrinsic terms, though the model should be able to accommodate performer characteristics. The PB model can accommodate such features, as discussed in detail in its earlier presentations (Rosenbaum et al. 1995, 2001, 2009; Vaughan et al. 2001, 2006). A model that represents the interface of the external environment to the capabilities of the body accounts not only for data of the kind studied here, but may also be useful for a variety of practical purposes—for enabling robots to generate efficient movements, for optimizing performance in human–computer interaction, for helping designers create safe habitats, and so on.

Future research can focus on movement timing *and* body kinematics together. This study suggests that the PB model may hold promise in this regard. So do other models of obstacle avoidance that were not considered here, principally because no other model that we are aware of predicts body positions rather than just end-effector positions in manual obstacle-avoidance tasks (but see Cruse et al. 1993). Our decision to focus on the PB model was based on the idea that the PB model is the most complete model of manual obstacle-avoidance behavior that we know of. We do not mean to suggest that other models that posit via-point specification as a means of obstacle

[2] The six positional degrees of freedom of a rigid object are the *x*, *y*, and *z* values of a reference point within the object such as its center of gravity, and the object's pitch, roll, and yaw.

[3] It is not unusual for a target to be an obstacle. When reaching for a glass, for example, the glass is an obstacle vis à vis the dorsal side of the hand and fingers. This is why the hand must move around the glass before closing in on it. The PB model was designed to generate such behaviors and simulates them accurately (Rosenbaum et al. 2001).

circumvention (Bullock et al. 1999) or that focus on resistance to inertial perturbations (Sabes et al. 1998), for example, could not account for the MT reported here as well as the PB model does. These and other models, operating at somewhat different levels of analysis, have the common goal of understanding movement timing processes, for which no single approach is so powerful that it excludes others.

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