SPECIAL SECTION

Computational Motor Control and Human Factors: Modeling Movements in Real and Possible Environments

Steven A. Jax and **David A. Rosenbaum,** Pennsylvania State University, University Park, Pennsylvania, **Jonathan Vaughan,** Hamilton College, Clinton, New York, and **Ruud G. J. Meulenbroek,** University of Nijmegen, Nijmegen, Netherlands

An aim of human factors research is to have models that allow for the advance design of user-friendly environments. This is still a distant dream because existing models are not yet sufficiently sophisticated. Models in the domain of motor control are a case in point, but recent developments in computational motor control suggest that the gap between the current state of modeling in this area and the desired state is shrinking. To illustrate this point, we review principles of motor control research that any model of motor control must accommodate. Then we describe a model that captures many of the capacities of actors in the everyday world, including the capacity to reach for objects in different ways depending on factors such as the ease with which different joints can rotate, the required speed of movement, and whether obstacles are present. The model relies on the ideas that goal postures are internally specified before movements are generated, that tasks are defined with flexibly ordered constraint hierarchies, and that movements can be shaped according to task demands. Actual or potential applications of this research include designing and testing possible environments where motor components play a key role.

INTRODUCTION

Imagine the great advances the field of human factors could make if there were a perfect computer simulation of all human behavior. With this extraordinary tool, industrial engineers could design a multitude of efficient and comfortable work spaces. In the field of human-computer interaction, software engineers could test many possible graphical user interfaces and implement the one that is easiest to use. All kinds of products could be tested for maximum usability. In essence, any field that relies on interaction between humans and their environments could use the model to select the people and environments that would optimize both short- and long-term performance.

No such model exists, but many researchers have attempted to approximate it by creating computational models that simulate certain aspects of behavior. A complete review of these models is beyond the scope of this article. Interested readers may consult Pew and Mavor (1998) or Ritter et al. (in press).

Tasks simulated by models can be, and commonly are, broken into perceptual, cognitive, and motor components. Although a clear distinction among these categories is questionable and the interactions among them are complex, the divisions can be helpful in simplifying the analysis problem. Most previous models have focused on one of the components while paying less attention to or ignoring the other components. More recent models have been expanded to include all three components, especially in the work on cognitive architectures (for a review, see Byrne, 2002). For example, ACT-rational (ACT-R; Anderson, 1993; Anderson & Lebiere, 1998)

Address correspondence to Steven A. Jax, 429 Moore Bldg., Dept. of Psychology, Pennsylvania State University, University Park, PA 16802; saj151@psu.edu. **HUMAN FACTORS,** Vol. 45, No. 1, Spring 2003, pp. 5–27.

has been expanded with the creation of ACT-R perceptual-motor (ACT-R/PM; Byrne, 2001; Byrne & Anderson, 1998). Even with these expansions, however, the models are still limited to relatively simple perceptual inputs and motor outputs, such as pressing keys, moving and clicking computer mice, generating saccades, or producing terse utterances. Whether these limited abilities are overly restrictive depends on the task being modeled. For example, if one is interested in modeling human-computer interaction tasks, being able to predict the displacements and clicks of computer mice may be sufficient. By contrast, if one is interested in modeling a worker on an assembly line, restricting attention to such limited behaviors would be insufficient.

The focus of the present article is a computational model that strives to account for more complex motor behaviors of the sort carried out on assembly lines. The model to be reviewed is the posture-based (PB) model of Rosenbaum, Engelbrecht, Bushe, and Loukopoulos (1993), Rosenbaum, Loukopoulos, Meulenbroek, Vaughan, and Engelbrecht (1995), and Rosenbaum, Meulenbroek, Vaughan, and Jansen (2001). The model has been designed to account for motor control per se and is not intended as a general model of perception, cognition, and action. The PB model focuses on relatively large-scale limb- and whole-body motor movements. Other models with similar motor abilities have been developed for use in human factors (e.g., Ayoub, Ayoub, & Walvekar, 1974; Badler et al., 1999; Zhang & Chaffin, 2000). A major difference between these models and ours is that our model provides an account of the mental processes involved in planning movements. The other motor-related models developed by human factors researchers have generally been more concerned with simulating executed movements. As we hope to show, understanding movement planning is an important complement to these other approaches. By presenting our work in this special issue, we hope that researchers in all areas of human factors will see that movement planning is a more complex process than is often recognized and that progress can be made toward its understanding.

The article has three parts. First, we review some issues that arise in the study of motor control, focusing primarily on issues related to human factors that may be amenable to modeling. This section is meant to serve a tutorial function but is also meant to establish the desiderata that any successful model of motor performance should satisfy. Second, we review the principal components of the PB model. The review is informal. Technical details are omitted because they can be found in Rosenbaum, Meulenbroek, et al. (2001). In the third section we turn to the fantasy with which this article began – a complete model capable of simulating performance in real and possible environments. We comment in this final section on some ways in which this distant goal might be pursued.

A few disclaimers are needed before we proceed to the main discussion. First, the authors of this article work in a basic rather than an applied research tradition. Our interests have been in fundamental issues in motor control. Consequently, any recommendations we make about human factors research must be treated with caution. Second, the model we present is still in its infancy. Although it can account for a fairly wide range of phenomena in motor control, it is limited in other ways, as will be detailed later. The fact that our model may be one of the most advanced in the field of motor control shows how much further the field has to go. Third, we have not attempted to compare our model with other, more global models of cognition and do not intend to do so here. Presenting our model in this special issue may enable others to take up the challenge of incorporating our ideas into more sweeping theories, or it may lead them to offer feedback to us about ways our model is less different from more global accounts than we may have thought. Either of these outcomes would be healthy.

ISSUES IN MOTOR CONTROL

Four issues are often said to lie at the heart of motor control: (a) the serial order problem, (b) the learning problem, (c) the perceptual-motor integration problem, and (d) the degrees of freedom problem. None of these problems can be treated independently of the others, and none can be said to be more basic than another. Hence, the order in which they are covered is arbitrary. Previous tutorials have been organized around the four issues (Pew & Rosenbaum, 1988; Rosenbaum, 2002), and several textbooks summarize work related to them (Magill, 1989; Rosenbaum, 1991; Schmidt & Lee, 1999). As a result, the issues are reviewed here only briefly.

The Serial Order Problem

The serial order problem was made famous by Lashley (1951) in a paper that was a milestone in cognitive science. Lashley rejected stimulus-response chaining theory as an account of the sequencing of behavior. He argued that not every motor act can be triggered by feedback from the prior motor act. One reason is that successive motor acts can follow each other too rapidly to have been controlled by the feedback loop. Another reason is that behavior offers powerful hints that it is planned and is not merely reactive. Slips of the tongue, for example, reveal that there are long-term plans for forthcoming utterances.

Modern views of behavioral control take planning for granted, making Lashley's (1951) arguments seem quaint today. Still, his influence prompted modern investigators to appreciate that central plans create the conditions that enable sequences of forthcoming motor acts to unfold coherently. This view implies that any model of action, including any that is adopted in human factors contexts, must incorporate plans and planning as an integral component.

Beyond saying that there are plans for forthcoming actions, Lashley (1951) argued that plans are structured hierarchically. This view has remained influential (e.g., Collard & Povel, 1982; see Rosenbaum, 1991, chapter 3, for review). One way in which the hierarchical view of planning has been applied has been through fault analysis (Norman, 1981; Reason, 1990). Errors in industry, transportation, and everyday activities have been ascribed to miscuing of events at different hierarchical levels.

The Learning Problem

Virtually all tasks are performed more ably with practice. A long-held view of motor learning that has gained virtually universal acceptance is that such practice effects are possible in part through chunking (Bryan & Harter, 1897). *Chunking* can be defined as the successive nesting of subroutines. It is fitting that chunking is a likely means of skill learning in view of the importance of hierarchical plans. In other words, if plans are structured hierarchically, it is reasonable to expect that they are built up through chunking, as Bryan and Harter (1897) originally proposed. The speeding of performance with practice can similarly be explained by appealing to the formation of chunks (Newell & Rosenbloom, 1981).

Another long-held view of learning that has gained widespread acceptance is the notion that conditions that facilitate the learning of intellectual skills also facilitate the learning of perceptual-motor skills. For example, spaced learning is superior to massed learning over the long term in both domains. Reviews of such similarities have led psychologists to question the view that the acquisition of intellectual skills and the acquisition of perceptual-motor skills are fundamentally different (Rosenbaum, Carlson, & Gilmore, 2001; Schmidt & Bjork, 1992).

Recent research on the learning of perceptual-motor skills has brought out a number of new ideas, three of which strike us as especially important for emerging models and their applications. One is that during the learning of perceptual-motor tasks, performers become highly reliant on the feedback they receive, provided the feedback is reliable. Proteau, Marteniuk, and Lévesque (1992) showed that people who improve on a visually guided aiming task suffer significant impairments in their aiming if they are deprived of visual feedback late in learning. This finding is surprising, considering the view handed down from Lashley (1951) that skilled performance relies more on central plans as it develops.

A second new idea is that an important component of perceptual-motor skill acquisition occurs off line, after the skill has been practiced. This off-line learning can occur through mental practice (see Schmidt & Lee, 1999) and also through consolidation. Consolidation has recently been shown to have demonstrable neural activity related to the performance of novel tasks and that this persists after people stop actively practicing the tasks. The persisting neural activity appears to promote learning of the tasks (Brashers-Krug, Shadmehr, & Bizzi, 1996).

The third new development in the area of perceptual-motor skill learning is appreciation of the fact that actors form internal models of the environments in which they perform, including their own bodies' capabilities. In an illustrative study (Conditt, Gandolfo, & Mussa-Ivaldi, 1997), participants made point-to-point hand movements in artificial force fields. The participants could adapt to the force fields, as shown by the fact that after adaptation they could stop generating oddly curved hand paths and could return to generating straight hand paths, as occurs normally. Even when the participants had to generate hand translations in new parts of the work space or in new directions, they were able immediately to produce straight movements. This result shows, as Conditt et al. claimed in the title of their article, that "The motor system does not learn the dynamics of the arm by rote memorization of past experience." Instead, the motor system (or the agent possessing a perceptual-motor system) learns functions that can be actively computed as the task requires. Function learning has similarly been demonstrated in higher-level cognitive tasks (Koh & Meyer, 1991).

The Perceptual-Motor Integration Problem

Motor performance never occurs in a functional vacuum. Actions are made in response to stimuli that are present or in anticipation of stimuli that are anticipated. These two kinds of actions are intimately linked. Acting to bring about anticipated effects establishes the cybernetic conditions for evaluating whether those desired changes occur as expected. Said another way, when a plan is established for a forthcoming voluntary act, the plan is generated with reference to what perceptual changes are expected. The subsequent success of the act is judged by whether the perceptual change occurs as planned. The view that action planning relies on anticipations of forthcoming perceptual changes has recently found support in a broad range of behavioral and neurophysiological studies (for review see Hommel, Müsseler, Aschersleben, & Prinz, 2001).

Once feedback is obtained about an ongoing or just-completed action, subsequent corrections may be needed. Early work by Woodworth (1899) suggested that in aiming performance, there is an initial preplanned movement phase that may be followed by one or more corrective phases. A recent review of the large body of work that has been conducted since Woodworth's seminal work supports this hypothesis (Elliott, Helsen, & Chua, 2001).

One elaboration of Woodworth's (1899) model that deserves mention here is by Meyer, Abrams, Kornblum, Wright, and Smith (1988). These investigators showed that initial movements may be chosen with respect to their likelihood of further correction. Assuming that endpoint spatial variability increases as velocity increases, movements may be chosen to minimize the combination of endpoint variability and total movement time. This claim ascribes considerable sophistication to the movement planning system. It says that Fitts's law (Fitts, 1954) – a formula relating movement time to movement amplitude and target width – reflects an optimization strategy. (Fitts's law states that the shortest time, T, needed to cover an amplitude A to arrive within a circular target of width W obeys the relation $T = a + b \log_2 [2A/W]$, in which a and b are nonnegative empirical constants.) As will be seen later, optimization has proven to be an important concept in other motor domains as well.

The Degrees of Freedom Problem

As mentioned earlier, cognitive architectures have mainly focused on simple responses such as key presses or computer mouse movements. These responses are instrumental in the sense that they are performed to satisfy task demands. For many modelers using cognitive architectures, the exact means by which responses are performed is rarely of concern. Nonetheless, from a human factors perspective, the means by which tasks are physically carried out matters greatly. Some tasks can be performed in only one way, in which case it is crucial that the single method be safe and efficient (assuming benevolence on the part of the task designer). Most tasks can be performed in more than one way, however. Moving a finger from one keyboard button to another, for example, can be achieved with different combinations of joint rotations. The time to press one key after the other may be the same or different for these different combinations, and more than one combination may yield the shortest-time solution. Furthermore, the shortest-time solution may not be the most biomechanically efficient.

An effective model of performance should be able to select the means of moving that not only minimizes time (the usual standard adopted) but also maximizes the number of times the task can be performed over the long term (e.g., avoiding carpal tunnel syndrome).

Within the field of motor control, the capacity to achieve a given physical task in more than one way is often discussed under the rubric of the *degrees of freedom problem* (Bernstein, 1967). The term refers to the fact that the typical specification of a task is impoverished relative to the complexity of the options available for its completion. If the task is to press a key on a keyboard, for instance, there are typically many more degrees of freedom in the body than in the ostensive description of the key's location (e.g., its *x*, *y*, and *z* coordinates). Many different postures would place a particular finger on the key, and any finger might be used to press it. When researchers in the field of motor control refer to the degrees of freedom problem, they refer to the problem of determining which of many possible solutions is chosen.

One approach that has been taken to the degrees of freedom problem is to focus on coupling or "synergies" between or among effectors. If limb segments cannot move independently of others, the number of behavioral options is reduced. Bernstein (1967) argued for the synergies approach, as have others (e.g., Turvey, 1990). A reason for the popularity of this approach is that effector coupling is powerful. It is very difficult, for example, to draw a circle with one hand while drawing a square with the other. Human factors recommendations about equipment operation must take such dependencies into account.

As powerful as effector interactions are, however, it is a teleological fallacy to say they exist to reduce the degrees of freedom problem. They may simply increase the probability of successful coordination during ongoing rhythmic performance (e.g., while swimming with the breaststroke). Effector interactions rarely obviate action choices. Thus, although it may be hard to draw a circle with one hand while drawing a square with the other, a person facing such a task still has the possibility of performing it at any of a number of tempos, at any of a number of phase relations, and so on. Coupling is rarely so strong, therefore, that it eliminates the degrees of freedom problem.

An alternative approach to the degrees of freedom problem is cost reduction. Here movement planning is thought to entail a preference for movements that minimize costs defined with respect to one or more criteria. Theorists have suggested different costs for motor control. Flash and Hogan (1985) proposed that the motor system minimizes mean squared jerk (the mean squared third time derivative of position, or the rate of change in acceleration) over the duration of the movement. For Flash and Hogan, *jerk* was defined with respect to extrinsic spatial coordinates. More recent conceptions have allowed *jerk* to be defined with respect to intrinsic, joint-based coordinates (Nakano et al., 1999; Rosenbaum et al., 1995). Another cost that has been proposed is mean squared torque change (Uno, Kawato, & Suzuki, 1989). The latter model takes dynamics into account, whereas the other models do not.

Although the degrees of freedom problem is usefully addressed by postulating cost reduction, relying on a single cost cannot solve the problem fully. This is because movements vary on many dimensions and can be performed in different ways depending on context. Thus some motion paths may be optimal from the point of view of minimizing jerk or torque change, but different paths can be followed at will, as in drawing or reaching around obstacles or, in the case of a violinist, making staccato rather than legato bow strokes. Plainly, a cost-based account of action planning must allow for multiple costs and flexible specification of which costs are important in which contexts. Developing such an account was an aim of the originators of the PB model.

POSTURE-BASED MODEL

The foregoing review provides a list of challenges for any theory in this field. The theory developed in our laboratory was proposed with the primary aim of addressing the degrees of freedom problem, but the theory also includes elements that address the serial order, learning, and perceptual-motor integration problems. The theory has undergone refinement over the years, having been instantiated in three forms, each version being simpler and yet more powerful than its predecessor (Rosenbaum et al., 1993, 1995; Rosenbaum, Meulenbroek, et al., 2001). The version summarized here is the latest one.

To acquaint the reader with the model, we first describe an example task. Then we present a more detailed look at each of the model's components. The main computational steps are presented, but many details are omitted. Interested readers can examine the complete computational description of the model, as well as empirical validation against human performance, in Rosenbaum, Meulenbroek, et al. (2001).

Figure 1 shows an example task. The figure shows a seated stick figure faced with the task of reaching for a target in its work space (Figure 1A). Even when the target's x and y coordinates are given, a unique motor solution is not possible, given that more than one combination of hip, shoulder, and elbow angles enables the hand to occupy the target. There is a degrees of freedom (*df*) problem here: The mapping from the location in space to joint configurations is one to many, owing to the fact that there are three movable joints (3 *df*s) but the target location has only 2 *df*s (its x and y coordinates). Three of the infinite number of combinations of hip, shoulder, and elbow angles that allow the stick figure to reach the target are shown in Figure 1B.

How does the PB model solve this problem? A central property of the PB model is that it is posture based, meaning that movements are planned using an internal coordinate system of joint angles. The term *posture* refers to the set of all joint angles that define the body position at any instant in time. The model performs movements by first selecting a goal posture and then generating a movement to that goal posture. Selection of a goal posture begins by searching through a set of recently adopted postures stored in memory. One stored posture is identified as the most suitable goal posture. After the most suitable stored goal posture is identified, new postures are mentally generated around it to find a potentially more suitable goal posture. The movement trajectory to this most suitable posture is then calculated and the movement is finally performed.

The Goal-Posture-First Idea

As we just intimated, goal postures have special status in the PB model. The model instantiates *backward* planning. That is, it says end states are planned before movements are generated. The alternative would be to say that movements are planned first and final postures happen to emerge when movements terminate (*forward* planning). Others have proposed models that rely on forward planning (Bullock & Grossberg, 1988; Bullock, Grossberg, & Guenther, 1993; Mel, 1991), but we have questioned the validity of those models (Rosenbaum, Meulenbroek, et al., 2001).

Why does the PB model rely on backward planning? One reason is that evidence in the motor-control literature suggests that voluntary

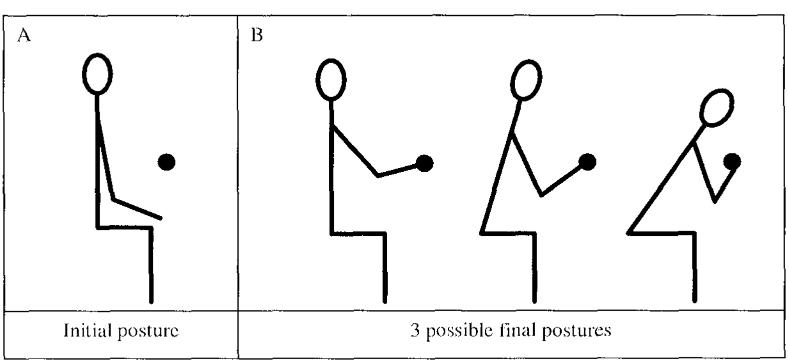

Figure 1. Example of a task the PB model can perform. The task of the seated actor is to move the hand from the initial posture into the black circle (A). Because movements can be made with the hip, shoulder, and elbow, an infinite number of body positions can reach the circle in front of the actor. Three of the possible body positions are shown in panel B.

movements are controlled by establishing desired muscle lengths and forces (called *equilibrium points*) prior to movement onset (Feldman, 1986; Jaric & Latash, 2000). Consistent with this hypothesis, when participants apply forces to maintain the arm in a fixed position against an external, static force and then, as per prior instruction, do not resist the arm's natural movement when the external, static force is released, the arm moves passively to a new position – the putative equilibrium position for the initially held position (Feldman, 1966). Similarly, deafferented monkeys can bring the hand to visually designated locations even when they cannot see, hear, or feel the hand (Polit & Bizzi, 1978). Most remarkably, even if the deafferented monkey's hand is knocked off course on its way to the target, the hand can still reach the target even though no feedback is available about it. Such results suggest that end positions are neurally represented independently of movements (see Dizio & Lackner, 1995; Gomi & Kawato, 1996; Graziano, Taylor, & Moore, 2002).

Data from "motor memory" studies also support the hypothesis that final positions have special status in motor control. These studies show that final positions can be reproduced better than can movement amplitudes (see Smyth, 1984, for a review). If participants are asked to move the hand to some position, they can later bring the hand back to the final position even when the start position for the recalled movement changes and the motion of the hand during the recall phase is momentarily perturbed by the experimenter. By contrast, if participants are asked to move the hand over the *distance* they just did, they do so poorly when they have to move from a different starting position. This dissociation suggests again that final positions are special. Rosenbaum, Meulenbroek, and Vaughan (1999) showed that final positions are coded both as final postures and as final locations in extrapersonal space.

A final source of evidence for the hypothesis that the motor system might first plan goal postures comes from an observation one of the authors made while at a restaurant. The author observed a waiter picking up an upside-down glass and then filling the glass with water. The waiter initially grasped the glass in an awkward position, with the thumb pointing down toward the table. This initially awkward grasp allowed the waiter to hold the glass in a more natural position when the glass was turned right side up. Apparently, the waiter planned his movements with the end position in mind. More formal examinations of this "end-state comfort effect" have yielded similar results and confirmed the primacy of end-state planning (Rosenbaum et al., 1990; Rosenbaum, van Heugten, & Caldwell, 1996).

Goal Posture Selection Using a Constraint Hierarchy

How are goal postures selected in the PB model?

An early approach: Weighted averaging. In early versions of the model (Rosenbaum et al., 1993, 1995), a weighted averaging scheme was used. Postures that were previously adopted were assumed to be stored in memory, and weights were assigned to the stored postures based on their suitability for the task to be performed. The suitability of the stored postures depended on the costs associated with moving to those postures as well as their spatial error costs (how close the hand or other contact point would come to the spatial target). A weighted average of the stored postures was used to arrive at a best candidate goal posture.

This approach was later seen to have problems (Rosenbaum, Meulenbroek, et al., 2001). One problem was that the weighted average posture could be less well suited for the task than were any of the previously adopted, stored postures. This outcome reflects a well-known problem in robotics – the *convex-hull* problem (see Figure 2). The term refers to the fact that one can visualize the set of postures that allow a task to be achieved as a closed region in posture space. A posture found by taking a weighted average of postures in this region may lie outside the region and so may be incapable of achieving the task.

Rosenbaum et al. (1995) developed a technique to circumvent the convex-hull problem. However, Rosenbaum, Meulenbroek, et al. (2001) later identified an even more basic problem with the weighted averaging approach, which even the ad hoc method developed by Rosenbaum et al. (1995) could not circumvent. The problem was related to the fact that in

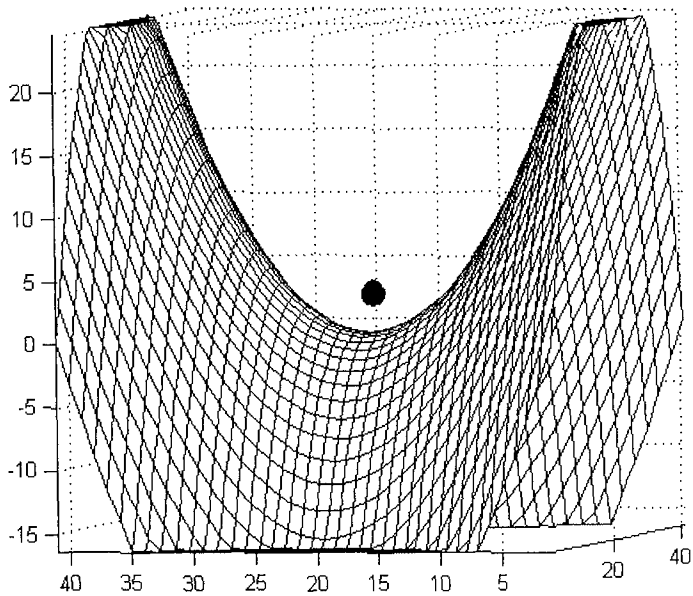

Figure 2. Convex-hull problem. Allowable values (acceptable postures) occupy the saddle-shaped surface. The average of these values (the "marble") lies outside the surface.

weighted averaging, the weights must sum to 1, so it is impossible to assign high weights to more than one constraint at a time. Therefore, it was impossible for the model to seek a goal posture that both minimized the costs associated with moving to that posture *and* that minimized the spatial error cost.

A new approach: Two stages relying on constraint hierarchies and diffusion until a deadline. Recognizing these problems, Rosenbaum, Meulenbroek, et al. (2001) suggested that goal postures are not found through weighted averaging but instead are found through a winner-take-all process. The process occurs in two stages. Stage 1 consists of finding the stored posture that is most suitable for the current task. Stage 2 consists of generating potentially better postures until a deadline is reached.

Stage 1, as just noted, consists of finding the stored posture that is most suitable for the current task. Stored postures are evaluated for their suitability with reference to what Rosenbaum, Meulenbroek, et al. (2001) called a *constraint hierarchy* (see Table 1). A *constraint hierarchy,* as defined by Rosenbaum, Meulenbroek, et al., is a prioritized list of requirements that the actor wishes to satisfy. The most important constraint occupies the highest level, the second most important constraint occupies the second highest level, and so on. The order and identity of constraints defines the task. Thus the constraint hierarchy provides a formal task description.

TABLE 1: Constraint Hierarchies for Two Tasks

Task A:	Reaching for the "off" switch of a rotating electric saw
1.	Don't collide with obstacles
2.	Don't miss the target
3.	Expend little energy
Task B:	Tackling one's football opponent
1.	Do collide with opponents
2.	Don't miss the target (the opponent's knees)
3.	Expend lots of energy

Within the constraint hierarchy, stored postures are evaluated as to how well they satisfy constraints in the hierarchy. Stored postures are evaluated first with respect to how well they satisfy the most important constraint, then with respect to how well they satisfy the second most important constraint, and so on. This procedure amounts to a "weeding out" process, or what Tversky (1972) called *elimination by aspects.* Stored postures that do not satisfy the most important constraint are ruled out first, stored postures that do not satisfy the second most important constraint are ruled out second, and so on. The process continues until only one stored posture is left or until the lowest level is accessed. If more than one stored posture is left when the lowest level is reached, the winner is chosen at random.

This procedure does not ensure that the optimal solution is found. In other words, it is possible that the search does not find the best of all possible solutions. This is an expected and, in some ways, desired feature of our model. Our model, in contrast to others (e.g., Flash & Hogan, 1985; Uno et al., 1989), does not rely on optimization. Instead, it looks for solutions that are merely acceptable. This approach, which Simon (1955) called *satisficing,* is computationally less expensive than is optimizing (Simon, 1989). Computational expense is a major concern in optimization approaches to motor control. For example, no one, to our knowledge, has yet determined how to minimize mean squared torque (Uno et al., 1989) for bodies with more than three limb segments in a row, such as the upper arm, forearm, and hand. Finding a solution that merely affords an acceptable mean squared torque can circumvent this problem.

Satisficing in the PB model occurs with respect to the constraint hierarchy, and different tasks have different constraint hierarchies. A cashier, for example, may set as his or her task scanning items at a checkout counter as quickly as possible. Another cashier may be in less of a hurry. Different constraint hierarchies embody these different priorities, and the different constraint hierarchies in turn give rise to different patterns of movement. (Note that our model does not attempt to say how or why the priority differences arise.)

How do the different movement patterns emerge when there are different constraint hierarchies? To address this question, it is useful to consider some constraints that figure in goal posture selection. One is that the spatial error (how close the hand or other contact point comes to the spatial target) should be acceptably low. Another is that any posture that is adopted when the hand is acceptably close to the target should not result in a collision with an obstacle. It would be unfortunate, for example, if the actor's arm intersected a rotating electric saw when the actor brought his or her finger to the "off" switch. Similarly, when the final posture is adopted, different parts of the body should not occupy the same spatial positions at the same time. It would also be unfortunate if a final posture resulted in one's arm being in the same place as one's leg. As obvious as this point may be, it is worth emphasizing that computational models of motion planning must address such issues.

Another constraint is the cost associated with moving from the starting posture to the potential goal posture. When a movement is made from a starting posture to a goal posture, each joint undergoes some angular displacement (which may be zero for one or more joints). In the PB model, we hypothesize that the cost of moving a joint increases with the angular displacement it undergoes. We also hypothesize that for each joint, the rate at which the cost increases depends on the physical properties of the limb segments (e.g., their masses and the power of their muscles) and also on more subjective properties (e.g., how much it hurts to move the limb because of an injury). Subjective factors related to joint mobility have been largely ignored in motor control research, but we think they are extremely important. We call the rate at which the cost increases with a joint's angular displacement the joint's *expense factor.*

For convenience, we assume that the expense factor is the same no matter what the joint's direction of rotation is and no matter where it is in its range of motion. We also assume for convenience that the expense factor for a joint does not depend on the angles of the other joints. Finally, we assume that the sum of the angular displacements of the joints, weighted by their respective expense factors, predicts the total cost of the movement from the start to the goal posture. We call this total value the *travel cost.* The lower the total travel cost of a candidate goal posture, the more it is preferred as a final posture. Thus when the expense factor of a joint is large, goal postures that incur little rotation of that joint are preferred over goal postures that incur large rotation of that same joint.

The expense factors for all of the joints are free parameters in the PB model and are used to fit the model to human movement data. For example, Vaughan, Rosenbaum, Harp, Loukopoulos, and Engelbrecht (1998) asked university students to bring the right hand into contact with a ball placed at different distances and heights in the midsagittal plane (see Figure 3). The ball was placed in different locations by mounting it on a stiff hook that extended from a large vertical board to the left of, and parallel to, the participant's midsagittal plane. A critical feature of the setup was that no matter where the ball was placed, it could be reached with an infinite number of postures.

Participants were videotaped as they performed the task while remaining seated. Markers on the participants' hip, shoulder, elbow, and hand indicated the x-y positions of these anatomical landmarks and were later

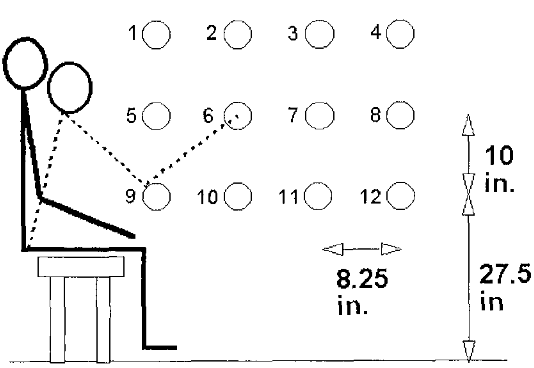

Figure 3. Positioning task used by Vaughan et al. (1998). The hand was held as a gentle fist and the knuckle was brought into contact with the ball positioned at 1 of 12 locations. From Vaughan, Rosenbaum, Harp, Loukopoulos, & Engelbrecht, (1998). Finding final postures. *Journal of Motor Behavior, 30,* 273–284. Reprinted with permission of the Helen Dwight Reid Educational Foundation. Published by Heldref Publications, 1319 18th St., NW, Washington, DC 20036-1802; www.heldref.org/html/jmb.html. Copyright © 1998.

measured, from videotape, at the start and end of each trial. The x-y values were later input to the model along with the x-y position of the center of the ball. The model was used to generate a goal posture given the participant's initial posture and ball position. The participant's initial posture was input to the model for each reach because the model is sensitive to initial positions and the participants' initial postures changed somewhat from trial to trial. The question was how well the model could predict the end postures that participants adopted when the expense factors for the three joints were fitted for each participant. Critically, the expense factors for the three joints of any given participant were not allowed to change over reaching tasks.

As shown in Figure 4, the model did a reasonably good job of predicting participants' postures. The goodness of fit, expressed as the proportion of variance accounted for, exceeded .95 for every participant. Moreover, the ordering of expense factors was consistent over participants. Thus the model predicted the participants' final postures well and in a parametrically consistent fashion. Other examples of using expense factors with the PB model to fit human performance are given in Rosenbaum, Meulenbroek, et al. (2001) and Vaughan, Rosenbaum, and Meulenbroek (2001). Zhang, Kuo, and Chaffin (1998) took a similar approach to data fitting.

In the PB model, the travel cost of a movement does not depend only on the angular displacements that will be required. It also depends on the time a movement takes. In general, the more quickly a movement is performed, the more costly it is. The increase in cost is caused by the increased muscle force required to accelerate and decelerate the limb segments. Rosenbaum et al. (1995) assumed that for each joint there is an optimal time, $T_j^*(\alpha_j)$, for an absolute angular displacement, α_j,

$$T_j^*(\alpha_j) = k_j \ln(\alpha_j + 1), \qquad (1)$$

in which k_j is the nonnegative expense factor for joint j. Expressing $T_j^*(\alpha_j)$ as a logarithmic function of α_j reflects the fact that mean limb velocity is a negatively accelerated function of limb displacement, as observed in many studies; see Rosenbaum and Krist (1996) for review.

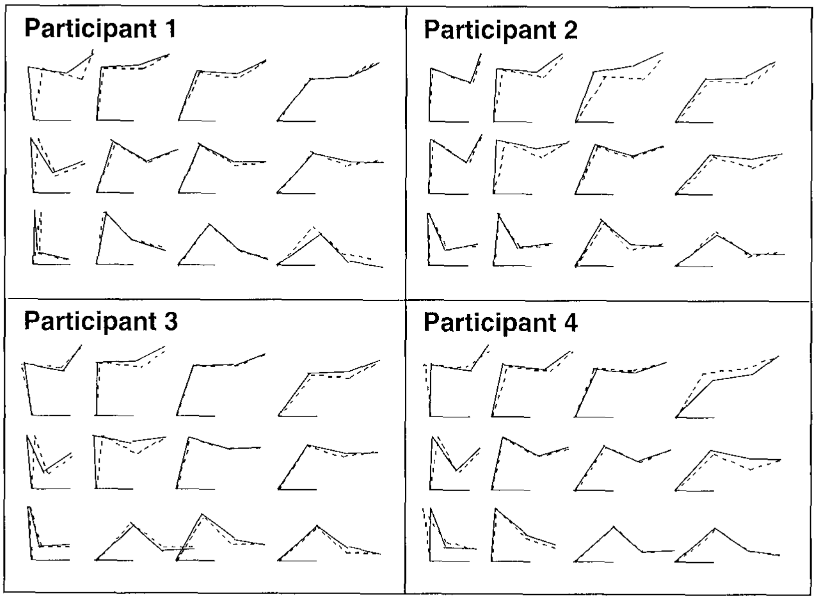

Figure 4. Postures adopted by four participants (solid lines) and postures predicted by the model (dashed lines) for each of the 12 ball locations. From Vaughan, Rosenbaum, Harp, Loukopoulos, & Engelbrecht, (1998). Finding final postures. *Journal of Motor Behavior, 30*, 273–284. Reprinted with permission of the Helen Dwight Reid Educational Foundation. Published by Heldref Publications, 1319 18th St., NW, Washington, DC 20036-1802; www.heldref.org/html/jmb.html. Copyright © 1998.

Equation 1 is a special case of Fitts's law (Fitts, 1954) in that it implicitly sets the tolerance term for spatial accuracy (the denominator, *W*, in Fitts's law) to 1. Another way in which Equation 1 is a special case of Fitts's law is that it is applied to the motion of an individual joint rather than to the motion an entire end effector (e.g., the hand). Because Equation 1 is applied at the single joint level, it may not yield Fitts's law for multijoint movements. More will be said about the PB model's relation to Fitts's law later in this article.

How does the time to move a joint from its start to its goal angle relate to the travel cost for the joint's rotation? The travel cost, V_j, for the *j*th joint to cover an absolute angular displacement α_j in time T_j, is

$$V_j = \left(\frac{k_j \alpha_j}{r}\right)\left(1 + \frac{[T_j - T_j^*(\alpha_j)]^2}{s^2}\right), \qquad (2)$$

in which *r* denotes the unit of absolute angular displacement (in this case, 1°) and *s* denotes the unit of time (in this case, 1 ms). Equation 2 says that the travel cost for a joint's angular displacement grows as the square of the difference between the joint's required movement time, $T_j(\alpha_j)$, and its optimal movement time, $T_j^*(\alpha_j)$, weighted by the product of the joint's expense factor and the angular displacement, α_j, that must be produced.

As the last statement implies, a joint's required movement time need not equal its optimal movement time. Where does the required time for a joint's motion come from? It may come from an experimenter, but more usually it is set by the actor. Rosenbaum et al. (1995) discussed a number of possible methods for endogenous specification of movement time. Among these were (a) allowing each joint to move in its own preferred time while requiring all the joints to end their movements at the same time; (b) allowing each joint to move in its own preferred time while requiring all the joints to start their movements at the same time; and (c) allowing all the joints to have the same optimal common movement time and requiring them to start and stop together. In the third case, the optimal common time, T_p, can be found for all the joints as they move to posture p by determining the value

$$T_p = \frac{\sum_j k_j \alpha_j T_j^*(\alpha_j)}{\sum_j k_j \alpha_j}, \qquad (3)$$

that minimizes the total travel cost, V_p. The optimal common movement time is based on the weighted average of the optimal movement times for the joints to cover their respective angular displacements, in which the weights used for the average are given, as in Equation 2, by the product of the joints' expense factors and their respective angular displacements. Once T_p is found, it replaces T_j in Equation 2 for all joints. The total travel cost, V_p, for a movement to posture p can then be computed by summing the individual travel costs for all j joints using Equation 2.

The foregoing coverage of movement timing shows that the PB model is as much a framework for asking questions about motor control as it is a complete theory. The model makes no commitment yet to a particular method of movement timing. Indeed, nothing in the model precludes different movement-timing methods from being used in different contexts. For convenience in our simulations, we have generally made the joints of our simulated actor start and stop together with an optimal common movement time. An important issue for future research will be to investigate how multijoint movements are actually timed by behaving humans. Kinetic factors (factors related to force production) are likely to play an important role in multijoint movement timing, as would be expected from elementary considerations of the transfer of momentum during tasks such as throwing (Alexander, 1991). This observation suggests that kinetics will probably need to be included in the model to help it predict multijoint movement timing.

Even though the PB model does not include kinetics, it does a reasonably good job of predicting observed changes in the relative contributions of joints for the same task depending on the overall speed of movement (Meulenbroek, Rosenbaum, Thomassen, & Schomaker, 1993; Rosenbaum, Slotta, Vaughan, & Plamondon, 1991; Vaughan et al., 1998). For example, in Rosenbaum et al. (1991), participants oscillated the tip of the right index finger in the horizontal plane using preferred combinations of finger, wrist, and forearm movement. As the speed of oscillation increased, the relative contribution of the finger increased and the relative contribution of the forearm decreased. By contrast, as the speed of oscillation decreased, the opposite changes were observed. Such changes, which were replicated and extended by Vaughan, Rosenbaum, Diedrich, and Moore (1995), are predicted by the PB model provided the finger has a small expense factor and the forearm has a large expense factor. See Rosenbaum et al. (1995) for further discussion.

Generating Novel Postures Using Diffusion Until a Deadline

We have just considered the selection of the most suitable stored posture based on the constraint hierarchy. In the model it is recognized that stored postures alone may be inadequate, however, because actions are performed in an ever-changing environment, so a task may arise for which no previously adopted goal posture will suffice, and even if a previously adopted goal posture might suffice, it may have been forgotten. Rosenbaum, Meulenbroek, et al. (2001) assumed that the last m goal postures are stored. In most of the simulations reported by Rosenbaum, Meulenbroek, et al., m was set to 8.

To allow a potentially better goal posture to be found, a second stage is postulated. This Stage 2 is called *diffusion until a deadline* (see Figure 5). Within posture space (i.e., the axes of which are the mechanical degrees of freedom of the body), postures are considered around the most promising stored posture identified in Stage 1. Consideration of a diffused posture entails evaluating it with respect to the same constraint hierarchy as was used to evaluate stored postures. The locations explored in this second stage occupy ever-widening shells around the most promising stored posture – hence the term *diffusion*.

In the model, diffusion continues until a deadline is reached. The locations in each shell are assumed to be evaluated in parallel at each time step, and the number of time steps, 1, 2,...,d, determines the deadline for the search. The

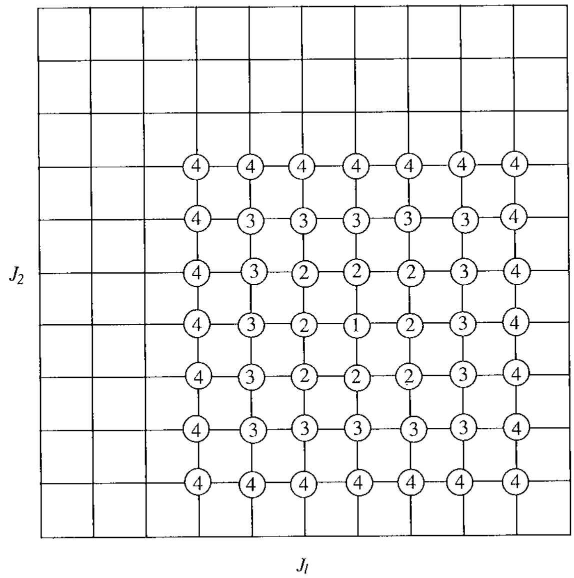

Figure 5. Diffusion until a deadline in posture space for joint angles J_1 and J_2. Copyright © 2001 by the American Psychological Association. Reprinted with permission from Rosenbaum, Meulenbroek, Vaughan, & Jansen, 2001.

evaluation of postures continues until *d* steps occur. When *d* is reached, the evaluation stops and the most suitable of all the evaluated postures is identified as the goal posture.

A potential alternative to this procedure of considering possible postures until *d* search cycles have been completed is to stop searching when a given error tolerance is reached. Why is the latter method not used in the PB model? First, even if a solution is found to be acceptable, there may be an even better solution, in which case it would be advantageous to use it. Second, the deadline method avoids local minima.

How is *d* set? Initially, it is set to a random value between 1 and 2^g, in which *g* is the largest number of subdivisions of any joint axis. In a given trial, if the posture that was identified as the goal posture was found before *d*, *d* is reduced by 1 for the next trial. The rationale for reducing *d* in this case is that more time was spent hunting for the goal posture than was really necessary. Alternatively, if the posture was found in the *d*th cycle, *d* is increased by 1 for the next trial. The rationale for increasing *d* in this case is that an even better posture might have been found if more time had been spent generating and checking candidate goal postures. The deadline is not reduced if *d* reaches a minimum of 1, nor is it increased if *d* reaches a maximum of $g - 1$, in which *g* is the number of subdivisions of any joint axis.

Diffusion until a deadline ensures endogenous specification of planning times. This is important because a model of action planning should predict how long actors spend planning actions. The PB model predicts that the time to plan a goal posture should decrease the more often a spatial region is reached (or, more specifically, how often it is reached within the last *m* reaches). As more goal postures are chosen that permit the hand (or other contact point) to reach a spatial target zone, less time is needed to find a suitable goal posture for that region, so *d* decreases. This prediction holds even if parallel processing is used in the diffusion process, provided one assumes that the processing load increases with an increased number of diffusion cycles, which in turn slows down the process. The diffusion process provides one possible explanation for the observation that people take less time initiating movements to spatial regions toward which they made many recent movements (Requin, Brener, & Ring, 1991).

Another prediction of the model is that as planning deadlines decrease, so do travel costs for goal postures selected for repeated reaches to the same spatial region. This prediction stems from the fact that in the model, searching for a goal posture always entails searching for the best possible goal posture, given the limited planning time set by *d*. By using the stored goal posture from the previous reach to the same spatial location, the diffusion process can begin in a region of posture space already near the spatial location of the target. This affords a higher likelihood of finding a goal posture with an even lower travel cost before the deadline occurs. Lower travel costs are predicted by the model as a result, and repeated movements to a spatial target region do in fact become more efficient with practice (Fischer, Rosenbaum, & Vaughan, 1997; Sparrow & Newell, 1998).

Generating Movements with or without Via Movements

Once the goal posture has been selected, how is the movement to it generated? Not surprisingly, given the model's reliance on internal computation to select goal postures, it also relies on internal computation to select movements to goal postures. Such internal computation is necessary to ensure that movements have appropriate forms. The default form can be altered to create other forms as needed.

It is assumed in the PB model that the default movement from the start posture to the goal posture is a straight line through posture space (see bottom panel of Figure 6). For a movement through posture space to be linear, all the joints must start and end their movements simultaneously. This amounts to the common movement time option discussed earlier. The assumption that joints start and end their motions simultaneously is often made in motor control research (e.g., Soechting, Buneo, Herrmann, & Flanders, 1995).

In the model, as in observed studies, each joint's motion speeds up and slows down in a bell-shaped fashion. The function governing how the angular velocity, v_m, of the joint changes as it makes its main movement, *m*, to its goal position in normalized time, *t*, for $0 < t < \pi$, is

$$v_m(t) = \sin(t) \times \sin(t). \qquad (4)$$

Figure 6 shows this angular velocity function, the corresponding angular position function, and the way one joint's position changes as a function of another's when Equation 4 holds for both joints and the two joints move simultaneously.

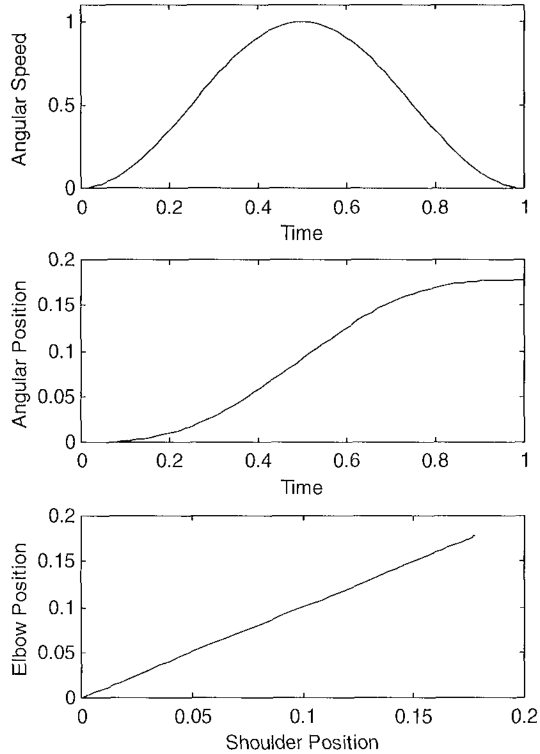

Figure 6. Movement in the PB model. Top: Angular velocity of one joint as a function of time. Middle: Corresponding angular position function. Bottom: Angular position of one joint as a function of angular position of another joint that moves the same way. When both joints begin and end their movements at the same time and follow the angular velocity profile in the top panel, a straight-line movement through posture space is observed.

A straight-line motion through posture space may result in a collision with an obstacle. It is important to be able to detect potential collisions and to shape the forthcoming movement accordingly. Collisions are anticipated in the PB model by mentally simulating a movement to the goal posture, assuming the angular velocity profile given by Equation 4. The simulation uses forward kinematics (trigonometry) to determine where sample points along the limb segment chain will be in successively adopted postures. If it is anticipated that those sample points will occupy spatial regions occupied by obstacles, a collision is expected. If no collision is expected, or if an anticipated collision is desired, the movement is carried out. Alternatively, if an anticipated collision is unwanted, the movement to the goal posture must be shaped to permit a movement around the obstacle.

Movement shaping is achieved in the PB model by superimposing a back-and-forth movement to and from a via posture onto a movement made directly to a goal posture. The process is illustrated in Figure 7. Figure 7A illustrates the model's task – moving the hand into the open circle while avoiding a collision with an obstacle (the filled black circle). To perform this movement, the goal posture shown in Figure 7B is first selected. Next, a movement to this goal posture is simulated. In this illustration an unwanted collision is anticipated, so the model searches for a second, back-and-forth movement (Figure 7C), which, when executed at the same time as the movement to the goal posture, would result in a curved path around the obstacle (Figure 7D). In the PB model, this back-and-forth movement is called the *via movement.* The turn-around point of the movement is called the *via posture.*

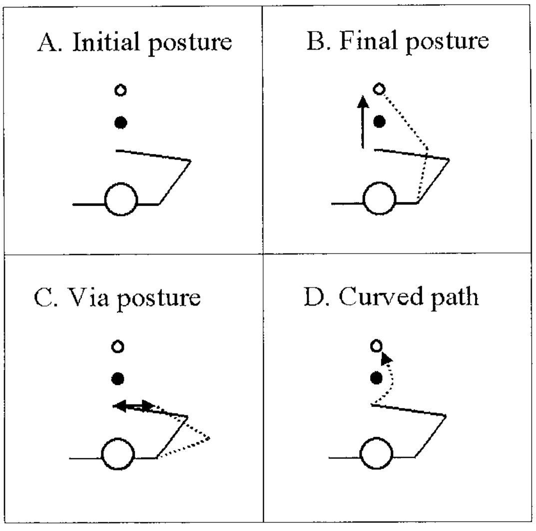

Figure 7. Formation of a curved movement by addition of two movements: (A) Posture initially adopted. (B) A final posture and the direct movement that will be made to it. (C) A via posture to which a movement will be made from the starting posture and then from which a movement will be made back to the starting posture. (D) The curved path that results from combining the movement shown in panel B with the movement shown in panel C.

It is important to understand that when the via movement is made while the direct movement is made to the goal posture, the via movement adds no net displacement to the overall translation. The via movement affects only how the hand reaches its final position.

How is the via movement selected? Consistent with the planning of the goal posture, planning for the via movement first entails finding a suitable via posture. The search proceeds in essentially the same way as the search for a suitable goal posture. The model searches through the same set of recently adopted stored postures that were used in the goal posture search. The suitability of the stored postures for use as a via posture is evaluated with a constraint hierarchy defined for obstacle avoidance. Because it may be possible to find an even better via posture than was found by searching stored postures only, new potential via postures are generated around the most suitable via posture candidate using diffusion until a deadline. Of all the candidate via postures that were evaluated by the deadline, the one that is found to be the most suitable is defined as the via posture. Once the via posture is selected, movement execution occurs. A movement from the start posture to the via posture and back to the start posture is combined with the direct movement to the goal posture to yield a more circuitous movement than would occur if only the direct movement were carried out.

This method of shaping movements in the context of obstacles differs from others. For example, it differs from staggering of joint motions to achieve different movement paths (Hollerbach & Atkeson, 1986). A limitation of the staggering method is that it yields only monotonic angular position functions, whereas reversals of joint motion are often observed in obstacle avoidance. The PB model also differs from the trial-and-error search method of Mel (1991). A limitation the trial-and-error search method is that it can place extraordinary demands on memory updating (keeping track of paths that were explored versus paths that were not explored). Finally, the PB model differs from potential-landscape methods (Haugsjaa, Souccar, Connolly, & Grupen, 1998), which treat obstacles as repellors ("hills"), goals as attractors ("dales"), and the current state of the system as a moving point in the landscape (a "rolling marble"). The difficulty we have with this approach is that it does not make specific predictions.

Some further remarks befit the PB model's approach to obstacle avoidance. First, the PB model says that if a joint must move to and from a via angle (i.e., its angle in the via posture) while it also moves to its goal angle, the via movement proceeds from the starting angle to the via angle with a bell-shaped angular velocity and then moves from the via angle back to the starting angle with a bell-shaped angular velocity. Such a trajectory, shown in the top panel of Figure 8, can be captured by the following equation relating angular velocity, v_v, to normalized movement time, t, for $0 < t < \pi$,

$$v_v(t) = \sin(t) \times \sin(2t). \quad (5)$$

When Equation 5 is summed with Equation 4, the composite movement, $v_c(t)$,

$$v_c(t) = v_v(t) + v_m(t), \quad (6)$$

can be nonmonotonic, as shown in the middle panel of Figure 8. Correspondingly, the angle-angle graph for two joints can be highly nonlinear, as shown in the bottom panel of Figure 8. In this example, one joint has a nonmonotonic movement path, whereas the other joint has a monotonic movement path. Such motions, when rendered as stick-figure animations (Figure 9), can achieve obstacle avoidance. The motions appear realistic and, when fitted to actual obstacle-avoidance behavior, yield reasonably good fits (Dean & Brüwer, 1994, 1997; Vaughan et al., 2001).

The second remark about the PB model's approach to obstacle avoidance is that it relies heavily on internal simulations to judge the likelihood of collisions. It evaluates the suitability of each candidate via posture, in effect, by imagining what series of postures would be adopted if the combined direct and via movement were made to it. This method is computationally intensive, but a great deal of evidence has shown that motor imagery is surprisingly rich and accurate (Jeannerod, 1984; Johnson, 2000).

A third remark about the obstacle avoidance method used in the PB model is that the via posture is not a via *location* (see Bullock, Bongers, Lankhorst, & Beek, 1999). The reason for planning with respect to via postures rather than via locations is to make planning at this stage consistent with planning goal postures. Focusing on postures for the planning of obstacle avoidance also helps establish what an obstacle is. An obstacle can be represented as a posture or set of postures that, if adopted, would spatially overlap an object in the environment (Lozano-Pérez, 1983).

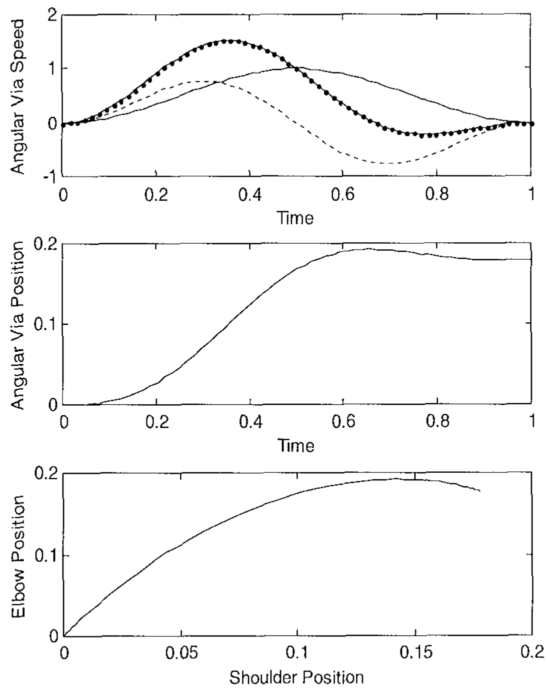

Figure 8. Movement shaping in the PB model. Top: Angular velocity of one joint in its main movement to its goal-posture value (solid line), angular velocity of the same joint to and then from its via-posture angle (dashed line), and the sum of these two angular velocity functions (dotted line). Middle: Angular position function corresponding to the combined main and via movement. Bottom: Angular position of one joint as a function of angular position of another joint where one joint moves to and from a via angle and the other joint does not. With the addition of the via movement, a curved movement through posture space is observed.

Other Phenomena Explained by the PB Model

Besides accounting for obstacle avoidance, the PB model provides a possible explanation of some other phenomena of everyday motor performance.

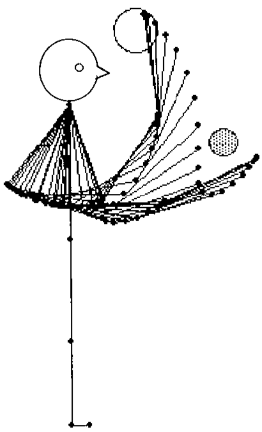

Figure 9. Obstacle avoidance performed by a standing stick figure. The obstacle is the shaded circle. The target is the empty circle. The stick-figure's task was to bring its "hand" anywhere within the target, avoiding a collision with the obstacle on the way.

Aiming with a tool or nonterminal end effector. Because the PB model relies on forward kinematics to predict where any point along the limb segment chain will be at any given time, it lets one predict where an extension of the anatomical limb segment chain will be at that time. The model predicts that the temporal dynamics of aiming with the tip of a hand-held tool should be the same as the temporal dynamics of aiming with the tip of the finger. This prediction is supported by research on visually guided aiming (Elliott et al., 2001).

The model also provides a way of accounting for the fact that one can aim for a point in external space with a point along the limb segment chain that is *proximal* to the end effector. For example, one can aim for a location with one's elbow, as when one nudges a neighbor during a talk, or one can aim for a spatial target with the shoulder, as when one turns on the light switch with a shrug rather than a finger flick when one comes home carrying shopping bags. To explain such phenomena, the constraint hierarchy is changed so that the contact point for aiming is shifted from the hand to the elbow or shoulder. Forward kinematics is used to predict where the contact point will be with respect to the spatial target.

Aiming for moving targets. The PB model allows for interception of moving targets. This capacity emerges from the computational power of the model. Given an inferred space-time trajectory of a projectile, one can determine which combination of spatial location, body-movement time, and goal posture will be most likely to ensure projectile interception. See Rosenbaum et al. (1995) for further discussion.

Writing and drawing with different effectors. One phenomenon that illustrates the adaptive flexibility of the motor system is its capacity to generate essentially the same graphic output with different effectors in different planes and with different size scales. Individual writing styles are preserved regardless of whether one is writing with the preferred hand, nonpreferred hand, one's foot, or even with one's mouth. Explaining how such equivalence is achieved has long occupied researchers in the field of motor control, who have called this the problem of *motor equivalence.*

The PB model provides a possible solution to the problem of motor equivalence by building on work in visuospatial cognition (see Meulenbroek, Rosenbaum, Thomassen, Loukopoulos, & Vaughan, 1996). The model allows that when people intend to write a series of letters, they have an internal representation of what those letters should look like. In effect, the desired appearance of the letters is "projected onto" the writing surface, oriented as the writing surface is orientated and scaled according to the desired size of the graphic output. People's ability to make such projections is taken for granted in research on visual imagery (Kosslyn, 1980).

With these assumed capabilities, the problem for the writer is to generate movements that enable the pen tip to produce the shapes that are projected onto the writing surface. The problem can be solved by using the method outlined earlier for directing a point to a target through a controlled shape. Simulations are given in Rosenbaum et al. (1995), building on earlier work by Edelman and Flash (1987). The simulations are reproduced in Figure 10. In creating them, the pen was aimed for spatial targets corresponding to points of maximum curvature in the to-be-produced script.

Prehension. Another domain of manual performance to which the model has been applied is reaching and grasping. This kind of behavior has been studied in considerable detail since

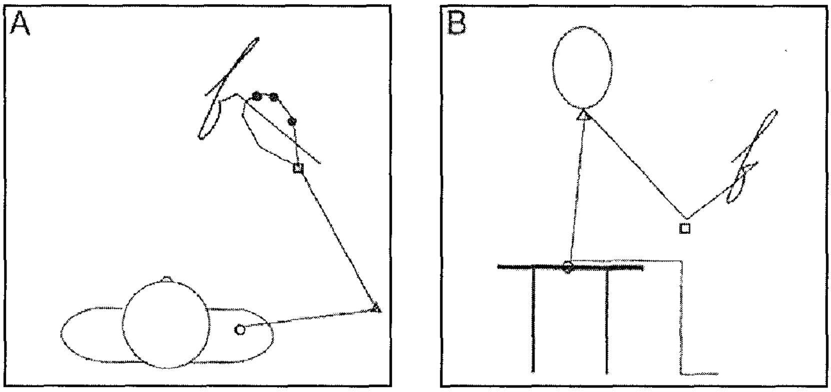

Figure 10. Example of the model's ability to write with different effectors and in different spatial planes. Reprinted with permission from Meulenbroek, Rosenbaum, Thomassen, Loukopoulos, & Vaughan (1996). Adaptation of a reaching model to handwriting: How different effectors can produce the same written output, and other results. *Psychological Research,* Vol. 59, p. 71, Figure 5, © 1996 Springer-Verlag GmbH & Co. All rights reserved.

early observations by Jeannerod (1981, 1984) of the coordination of the arm, hand, and fingers during prehension. An aim of the PB model is to account for the key kinematic features of prehension that have emerged from these and related studies (see Rosenbaum, Meulenbroek, et al., 2001).

The PB model accounts for virtually all of the previously reported phenomena related to prehension kinematics. In a typical prehension simulation (Figure 11), the fingers open and then close on the to-be-grasped object, much as occurs in biological grasping. Figure 12 shows that it is even possible to get the simulated hand to move around an obstacle on its way to an object that will be grasped. Rosenbaum, Meulenbroek, et al. (2001) showed that the PB model provided good fits both to old data from prehension studies and also to new behavioral data that were collected to challenge the model.

Remaining Challenges for the PB Model

The foregoing discussion was meant to show that the PB model holds promise as a model of motor control. A number of assumptions were necessary to get the model to perform at the level we wanted, however, and the theory is still limited in a number of ways. The following competencies have not yet been verified or built into the model. Each will have to be included if the model is to be taken seriously in applied contexts.

Movement times. As discussed, the current version of the model allows for a wide range of multijoint timing options. The one we have relied on the most in our simulations calculates an optimal common movement time that minimizes the travel cost of the movement across all joints. The equations used to predict this optimal common movement time (Equations 1–3) have yet to be verified empirically.

Fitts's law. Another limitation of the model is that it does not yet predict Fitts's law (Fitts, 1954). Meyer et al. (1988) showed that Fitts's law can be accounted for if movements are chosen to minimize endpoint variability in combination with total movement time, assuming that endpoint variability is proportional to velocity. This model depends on the ability to make corrective movements after the main movement has been launched. In its current instantiation, the PB model is ballistic (i.e., once planned, the movement is launched without further modification), and so it has no obvious means of predicting Fitts's law. It will be important in the future to see how and whether the inclusion of stochastic elements may enable the model to predict Fitts's law in addition to other phenomena of movement variability.

Series of actions. An important challenge for the future will be to extend the model to series of actions. We gave one example here of a series of simulated actions – those involved in producing a series of writing strokes. It will be

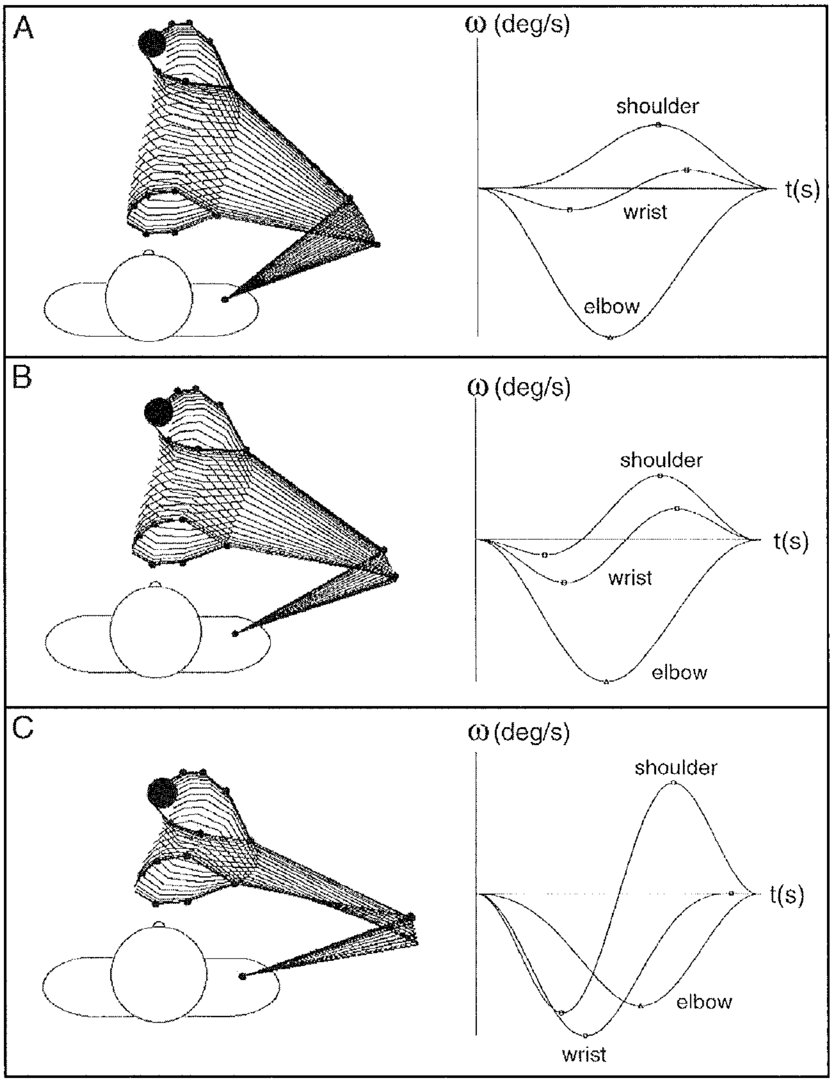

Figure 11. Reaching for an object at three distances from the hand's starting position and corresponding angular velocity profiles for the shoulder, elbow, and wrist.

important to simulate other series of ongoing motor acts, primarily to study the planning of future acts while ongoing acts are being performed. Corrective movements are often initiated so quickly that they are presumably planned before errors are manifest. It may be possible to simulate such cascaded planning and execution in the PB model.

More effectors. So far the only effectors that have been simulated with the PB model are the arm, hand, and fingers. Not all of the fingers have been modeled, however, and we have so far modeled one arm rather than two. Because the PB model was designed to reflect general claims about motor planning, it should be extendable to more than one arm and to other motor subsystems, such as those involved in walking, speaking, and making facial expressions. Speaking and walking have already received some attention from us. In response to criticisms of the PB model by Guenther, Hampson, and Johnson (1998) and Guenther and Micci Barreca (1997) pertaining to the applicability of the PB model's claims to speech production, Rosenbaum, Meulenbroek, et al. (2001) defended the PB approach for speech. In regard

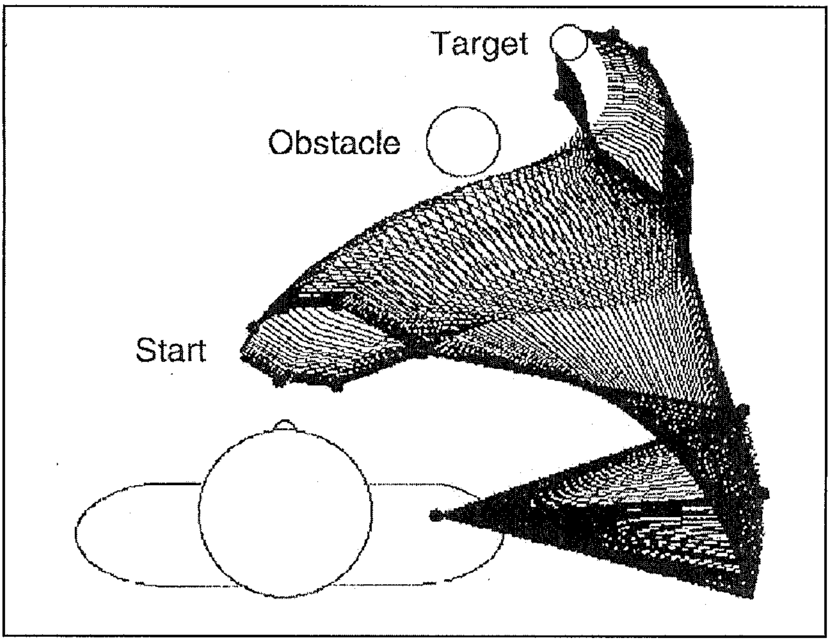

Figure 12. Reaching for an object that first requires the hand to circumnavigate an obstacle. Copyright © 2001 by the American Psychological Association. Reprinted with permission from Rosenbaum, Meulenbroek, Vaughan, & Jansen, 2001.

to walking, Rosenbaum et al. (1995) described an informal simulation of walking that reduced the problem of locomotion to shifting from one whole-body posture to another.

Moving in three spatial dimensions. All the simulations discussed here entailed movement in one spatial plane at a time. An important challenge will be to extend the model to three spatial dimensions. This problem is nontrivial (Hollerbach, 1990). One reason is that joint rotations in three spatial dimensions are noncommutative. Where one's arm ends up depends on the order in which the shoulder rotates about its three axes of rotation (Gielen, Vrijenhoek, & Flash, 1997). This may be less of a problem for the PB model than for other approaches to motor planning, however, because, as emphasized, in the PB model movements are viewed as interpolations between starting postures and goal postures. Interpolation does not run into the commutativity problem, which is another argument for the PB approach.

Kinetics. Another limitation of the PB model is that it has been restricted to the consideration of positions (kinematics) without regard to the forces or torques that give rise to them (kinetics). We elected to proceed in this way because full consideration of kinetics can be daunting. Even in advanced biomechanics, there is no straightforward way yet of conceptualizing, or even computing, all the interaction forces and torques that exist about multiple limb segments (Hollerbach, 1990). Clearly, a realistic model of motor control must take forces and torques into account because the nervous system is able to do so. Addressing this issue will be an important priority for future work, as we acknowledged earlier in connection with multijoint movement timing.

FROM FANTASY TO REALITY

We began this article by engaging in fantasy. "Imagine the great advances the field of human factors could make if there were a perfect computer simulation of all human behavior," we said. "With this extraordinary tool," we continued, "industrial engineers could design a multitude of efficient and comfortable work spaces." When we offered these opening remarks, we were referring to the ultimate aim of all of human factors research – to design environments so that people behaving in them can perform safely and efficiently. With a fully developed computer simulation of human behavior, one could design a factory or office in advance, being sure that the way the work space is arranged, the tasks to be performed, and the people doing the tasks are well matched.

This state of affairs is still years away, but advances such as the ones outlined here provide some hope that the dream may one day turn to reality. Two things will have to happen for models like ours to be used in designing possible environments. First, the models will have to be made more complete. The PB model will have to be extended along the lines summarized in the last section. Similarly, other models of perception, cognition, and action will have to become more sophisticated. An emerging challenge will be to link the models so that expertise in one complements expertise in another.

Second, the models will have to be validated against real rather than possible environments. In the case of the PB model, a sensible approach will be to fit the model to tasks that are more realistic than the tasks to which it already has been applied. It will not suffice to have the model reach out to touch a ball (Vaughan et al., 1998), reach around an obstacle (Vaughan et al., 2001), or grab a dowel (Rosenbaum, Meulenbroek, et al., 2001). The model will need to tackle the kinds of complex tasks that people perform in the real world, such as ringing up sale items at supermarket checkout counters – a task one of us has already begun to investigate (Lehman, Psihogios, & Meulenbroek, 2001). When the model is enhanced to the point where it can successfully simulate this sort of behavior, we will be one step closer to predicting human factors in both existing and possible environments.

ACKNOWLEDGMENTS

This work was supported by National Science Foundation grants to the second author, National Institutes of Health Grant 1 R15 NS41887-01 to the third author, and grants to the fourth author from the Dutch National Science Foundation.

REFERENCES

Alexander, R. M. (1991). Optimum timing of muscle activation for simple models of throwing. *Journal of Theoretical Biology, 150*, 349–372.

Anderson, J. R. (1993). *Rules of the mind.* Hillsdale, NJ: Erlbaum.

Anderson, J. R., & Lebiere, C. (1998). *The atomic components of thought.* Mahwah, NJ: Erlbaum.

Ayoub, M. A., Ayoub, M. M., & Walvekar, A. G. (1974). A biomechanical model for the upper extremity using optimization techniques. *Human Factors, 16*, 585–594.

Badler, N., Bindiganavale, R., Bourne, J., Allbeck, J., Shi, J., & Palmer, M. (1999, April). *Real time virtual humans.* Presented at the International Conference on Digital Media Futures, Bradford, UK.

Bernstein, N. (1967). *The coordination and regulation of movements.* London: Pergamon.

Brashers-Krug, T., Shadmehr, R., & Bizzi, E. (1996). Consolidation in human motor memory. *Nature, 382*, 252–255.

Bryan, W. L., & Harter, N. (1897). Studies in the physiology and psychology of the telegraphic language. *Psychological Review, 4*, 27–53.

Bullock, D., Bongers, R. M., Lankhorst, M., & Beek, P. J. (1999). A vector-integration-to-endpoint model for performance of via-point movements. *Neural Networks, 12*, 1–29.

Bullock, D., & Grossberg, S. (1988). Neural dynamics of planned arm movements: Emergent invariants and speed-accuracy properties during trajectory formation. *Psychological Review, 95*, 49–90.

Bullock, D., Grossberg, S., & Guenther, F. (1993). A self-organizing neural model of motor equivalent reaching and tool use by a multi-joint arm. *Journal of Cognitive Neuroscience*, 5, 408–435.

Byrne, M. D. (2001). ACT-R/PM and menu selection: Applying a cognitive architecture to HCI. *International Journal of Human-Computer Studies*, 55, 41–84.

Byrne, M. D. (2002). Cognitive architecture. In J. Jacko & A. Sears (Eds.), *The human-computer interaction handbook: Fundamentals, evolving technologies, and emerging applications* (pp. 97–117). Hillsdale, NJ: Erlbaum.

Byrne, M. D., & Anderson, J. R. (1998). Perception and action. In J. R. Anderson & C. Lebiere (Eds.), *The atomic components of thought* (pp. 167–200). Hillsdale, NJ: Erlbaum.

Collard, R., & Povel, D.-J. (1982). Theory of serial pattern production: Tree traversals. *Psychological Review, 85*, 693–707.

Conditt, M. A., Gandolfo, F., & Mussa-Ivaldi, F. A. (1997). The motor system does not learn the dynamics of the arm by rote memorization of past experience. *Journal of Neurophysiology, 78*, 554–560.

Dean, J., & Brüwer, M. (1994). Control of human arm movements in two dimensions: Paths and joint control in avoiding simple linear obstacles. *Experimental Brain Research*, 97, 497–514.

Dean, J., & Brüwer, M. (1997). Control of human arm movements in two dimensions: Influence of pointer length on obstacle avoidance. *Journal of Motor Behavior, 29*, 47–63.

Dizio, P., & Lackner, J. R. (1995). Motor adaptation to coriolis force perturbations of reaching movements: Endpoint but not trajectory adaptation transfers to the nonexposed arm. *Journal of Neurophysiology, 74*, 1787–1792.

Edelman, S., & Flash, T. (1987). A model of handwriting. *Biological Cybernetics, 57*, 25–36.

Elliott, D., Helsen, W. F., & Chua, R. (2001). A century later: Woodworth's (1899) two-component model of goal-directed aiming. *Psychological Bulletin, 127*, 342–357.

Feldman, A. G. (1966). Functional tuning of the nervous system with control of movement or maintenance of a steady posture: II. Controllable parameters of the muscles. *Biophysics, 11*, 565–578.

Feldman, A. G. (1986). Once more on the equilibrium point hypothesis (λ model) for motor control. *Journal of Motor Behavior, 18*, 17–54.

Fischer, M. H., Rosenbaum, D. A., & Vaughan, J. (1997). Speed and sequential effects in reaching. *Journal of Experimental Psychology: Human Perception and Performance, 23*, 404–428.

Fitts, P. M. (1954). The information capacity of the human motor system in controlling the amplitude of movement. *Journal of Experimental Psychology, 47*, 381–391.

Flash, T., & Hogan, N. (1985). The coordination of arm movements: An experimentally confirmed mathematical model. *Journal of Neuroscience, 5,* 1688–1703.

Gielen, C. C. A. M., Vrijenhoek, E. J., & Flash, T. (1997). Principles for the control of kinematically redundant limbs. In M. Fetter, H. Misslisch, & D. Tweed (Eds.), *Three-dimensional kinematics of eye-, head-, and limb-movements* (pp. 285–297). Chur, Switzerland: Harwood Academic.

Gomi, H., & Kawato, M. (1996). Equilibrium-point control hypothesis examined by measured arm stiffness during multijoint movement. *Science, 272,* 117–120.

Graziano, M. S. A., Taylor, C. S. R., & Moore, T. (2002). Complex movements evoked by microstimulation of precentral cortex. *Neuron, 34,* 841–851.

Guenther, F. H., Hampson, M., & Johnson, D. (1998). A theoretical investigation of reference frames for the planning of speech movements. *Psychological Review, 105,* 611–633.

Guenther, F. H., & Micci Barreca, D. (1997). Neural models for flexible control of redundant systems. In P. Morasso & V. Sanguineti (Eds), *Self-organization, computational maps and motor control* (pp. 383–421). Amsterdam: North-Holland.

Haugsjaa, K. A., Souccar, K., Connolly, C. I., & Grupen, R. A. (1998). A computational model for repetitive motion. In D. A. Rosenbaum & C. Collyer (Eds.), *Timing of behavior: Neural, computational, and psychological perspectives* (pp. 345–367). Cambridge, MA: MIT Press.

Hollerbach, J. M. (1990). Planning of arm movements. In D. N. Osherson, S. M. Kosslyn, & J. M. Hollerbach (Eds.), *An invitation to cognitive science: Vol. 2. Visual cognition and action* (pp. 183–211). Cambridge, MA: MIT Press.

Hollerbach, J. M., & Atkeson, C. G. (1986). Characterization of joint-interpolated arm movements. In H. Heuer & C. Fromm (Eds.), *Generation and modulation of action patterns* (pp. 41–54). Berlin: Springer-Verlag.

Hommel, B., Müsseler, J., Aschersleben, G., & Prinz, W. (2001). The theory of event coding (TEC): A framework for perception and action planning. *Behavioral and Brain Sciences, 24,* 849.

Jaric, S., & Latash, M. L. (2000). The equilibrium-point hypothesis is still doing fine. *Human Movement Science, 19,* 933–938.

Jeannerod, M. (1981). Intersegmental coordination during reaching at natural objects. In J. Long & A. Baddeley (Eds.), *Attention and performance IX* (pp. 153–169). Hillsdale, NJ: Erlbaum.

Jeannerod, M. (1984). The timing of natural prehension movement. *Journal of Motor Behavior, 26,* 235–254.

Johnson, S. H. (2000). Thinking ahead: The case for motor imagery in prospective judgments of prehension. *Cognition, 74,* 33–70.

Koh, K., & Meyer, D. E. (1991). Induction of continuous stimulus-response associations for perceptual-motor performance. *Journal of Experimental Psychology: Learning, Memory, and Cognition, 17,* 811–836.

Kosslyn, S. (1980). *Image and mind.* Cambridge, MA: Harvard University Press.

Lashley, K. S. (1951). The problem of serial order in behavior. In L. A. Jeffress (Ed.), *Cerebral mechanisms in behavior* (pp. 112–131). New York: Wiley.

Lehman, K. R., Psihogios, J. P., & Meulenbroek, R. G. J. (2001). The effects of sitting vs. standing and scanner type on cashiers. *Ergonomics, 44,* 719–738.

Lozano-Pérez, T. (1983). Spatial planning: A configuration space approach. *IEEE Transactions on Computers, C-32*(2), 108–120.

Magill, R. A. (1989). *Motor learning* (3rd ed.). Dubuque, IA: Brown.

Mel, B. W. (1991). A connectionist model may shed light on neural mechanisms for visually guided reaching. *Journal of Cognitive Neuroscience, 3,* 273–292.

Meulenbroek, R. G. J., Rosenbaum, D. A., Thomassen, A. J. W. M., Loukopoulos, L. D., & Vaughan, J. (1996). Adaptation of a reaching model to handwriting: How different effectors can produce the same written output, and other results. *Psychological Research, 59,* 64–74.

Meulenbroek, R. G., Rosenbaum, D. A., Thomassen, A. J., & Schomaker, L. R. (1993). Limb-segment selection in drawing behavior. *Quarterly Journal of Experimental Psychology, 46A,* 273–299.

Meyer, D. E., Abrams, R. A., Kornblum, S., Wright, C. E., & Smith, J. E. K. (1988). Optimality in human motor performance: Ideal control of rapid aimed movements. *Psychological Review, 95,* 340–370.

Nakano, E., Imamizu, H., Osu, R., Uno, Y., Gomi, H., Yoshioka, T., & Kawato, M. (1999). Quantitative examinations of internal representations for arm trajectory planning: Minimum commanded torque change model. *Journal of Neurophysiology, 81,* 2140–2155.

Newell, A. M., & Rosenbloom, P. S. (1981). Mechanisms of skill acquisition and the law of practice. In J. R. Anderson (Ed.), *Cognitive skills and their acquisition* (pp. 1–55). Hillsdale, NJ: Erlbaum.

Norman, D. A. (1981). Categorization of action slips. *Psychological Review, 88,* 1–15.

Pew, R. W., & Mavor, A. S. (Eds.). (1998). *Modeling human and organizational behavior: Applications to military simulations.* Washington, DC: National Academy.

Pew, R. W., & Rosenbaum, D. A. (1988). Human motor performance: Computation, representation, and implementation. In R. C. Atkinson, R. J. Herrnstein, G. Lindzey, & R. D. Luce (Eds.), *Stevens' handbook of experimental psychology* (2nd ed., pp. 473–509). New York: Wiley.

Polit, A., & Bizzi, E. (1978). Processes controlling arm movements in monkeys. *Science, 201,* 1235–1237.

Proteau, L., Marteniuk, R. G., & Lévesque, L. (1992). A sensorimotor basis for motor learning: Evidence indicating specificity of practice. *Quarterly Journal of Experimental Psychology, 44A,* 557–575.

Reason, J. (1990). *Human error.* Cambridge, UK: Cambridge University Press.

Requin, J., Brener, J., & Ring, C. (1991). Preparation for action. In J. R. Jennings & M. G. H. Coles (Eds.), *Handbook of cognitive psychophysiology: Central and autonomic nervous system approaches* (pp. 357–448). New York: Wiley.

Ritter, F. E., Shadbolt, N. R., Elliman, D., Young, R., Gobet, F., & Baxter, G. D. (in press). *Techniques for modeling human and organizational behavior in synthetic environments: A supplementary review.* Wright-Patterson Air Force Base, OH: Human Systems Information Analysis Center.

Rosenbaum, D. A. (1991). *Human motor control.* San Diego, CA: Academic.

Rosenbaum, D. A. (2002). Motor control. In H. Pashler (Series Ed.) & S. Yantis (Vol. Ed.), *Stevens' handbook of experimental psychology: Vol. 1. Sensation and perception* (3rd ed., pp. 315–339). New York: Wiley.

Rosenbaum, D. A., Carlson, R. A., & Gilmore, R. O. (2001). Acquisition of intellectual and perceptual-motor skills. *Annual Review of Psychology, 52,* 453–470.

Rosenbaum, D. A., Engelbrecht, S. E., Bushe, M. M., & Loukopoulos, L. D. (1993). Knowledge model for selecting and producing reaching movements. *Journal of Motor Behavior, 25,* 217–227.

Rosenbaum, D. A. & Krist, H. (1996). Antecedents of action. In H. Heuer & S. W. Keele (Eds.), *Handbook of perception and action* (Vol. 2, pp. 3–69). London: Academic.

Rosenbaum, D. A., Loukopoulos, L. D., Meulenbroek, R. G. M., Vaughan, J., & Engelbrecht, S. E. (1995). Planning reaches by evaluating stored postures. *Psychological Review, 102,* 28–67.

Rosenbaum, D. A., Marchak, F., Barnes, H. J., Vaughan, J., Slotta, J., & Jorgensen, M. (1990). Constraints for action selection: Overhand versus underhand grips. In M. Jeannerod (Ed.), *Attention and performance XIII* (pp. 321–342). Hillsdale, NJ: Earlbaum.

Rosenbaum, D. A., Meulenbroek, R. G., & Vaughan, J. (1999). Remembered positions: Stored locations or stored postures? *Experimental Brain Research, 124,* 503–512.

Rosenbaum, D. A., Meulenbroek, R. G., Vaughan, J., & Jansen, C. (2001). Posture-based motion planning: Applications to grasping. *Psychological Review, 108,* 709–734.

Rosenbaum, D. A., Slotta, J. D., Vaughan, J., & Plamondon, R. J. (1991). Optimal movement selection. *Psychological Science, 2,* 86–91.

Rosenbaum, D. A., van Heugten, C. M., & Caldwell, G. E. (1996). From cognition to biomechanics and back: The end-state comfort

effect and the middle-is-faster effect. *Acta Psychologica, 94,* 59–85.
Schmidt, R. A., & Bjork, R. A. (1992). New conceptualizations of practice: Common principles in three paradigms suggest new concepts for training. *Psychological Science, 3,* 207–214.
Schmidt, R. A., & Lee, T. D. (1999). *Motor control and learning – A behavioral emphasis* (3rd ed.). Champaign, IL: Human Kinetics.
Simon, H. (1955). A behavioral model of rational choice. *Quarterly Journal of Economics, 69,* 99–118.
Simon, H. (1989). *Models of thought.* New Haven, CT: Yale University Press.
Smyth, M. M. (1984). Memory for movements. In M. M. Smyth & A. M. Wing (Eds.), *The psychology of human movement* (pp. 83–117). London: Academic.
Soechting, J. F., Buneo, C. A., Herrmann, U., & Flanders, M. (1995). Moving effortlessly in three dimensions: Does Donders' law apply to arm movement? *Journal of Neuroscience, 15,* 6271–6280.
Sparrow, W. A. & Newell, K. M. (1998). Metabolic energy expenditure and the regulation of movement economy. *Psychonomic Bulletin and Review,* 5, 173–196.
Turvey, M. T. (1990). Coordination. *American Psychologist, 45,* 938–953.
Tversky, A. (1972). Elimination by aspects: A theory of choice. *Psychological Review, 79,* 281–299.
Uno, Y., Kawato, M., & Suzuki, R. (1989). Formation and control of optimal trajectory in human multijoint arm movement: Minimum torque-change model. *Biological Cybernetics, 61,* 89–101.
Vaughan, J., Rosenbaum, D. A., Diedrich, F., & Moore, C. (1995). Cooperative selection of movements: The optimal selection model. *Psychological Research, 58,* 254–273.
Vaughan, J., Rosenbaum, D. A., Harp, C. J., Loukopoulos, L. D., & Engelbrecht, S. E. (1998). Finding final postures. *Journal of Motor Behavior, 30,* 273–284.
Vaughan, J. Rosenbaum, D. A., & Meulenbroek, R. G. J. (2001). Planning reaching and grasping movements: The problem of obstacle avoidance. *Motor Control,* 5, 116–135.
Woodworth, R. S. (1899). The accuracy of voluntary movement. *Psychological Review Monograph Supplements,* 3(3), n.p.
Zhang, X., & Chaffin, D. B. (2000). A three-dimensional dynamic posture prediction model for simulating in-vehicle seated reaching movements: development and validation. *Ergonomics, 43,* 1314–1330.
Zhang, X., Kuo, A. D., & Chaffin, D. B. (1998). Optimization-based differential kinematic modeling exhibits a velocity-control strategy for dynamic posture determination in seated reaching movements. *Journal of Biomechanics, 31,* 1035–1042.

Steven A. Jax is a graduate student of psychology at Pennsylvania State University, where he received his M.S. in psychology in 2002.

David A. Rosenbaum is professor of Psychology at Pennsylvania State University. He received his Ph.D. in psychology in 1977 from Stanford University.

Jonathan Vaughan is a professor of psychology at Hamilton College. He received his Ph.D. in experimental psychology from Brown University in 1970.

Ruud G. J. Meulenbroek is an associate professor in the Department of Psychology at the University of Nijmegen, Netherlands, where he received his Ph.D. in psychology in 1989.

Date received: November 29, 2001
Date accepted: April 16, 2002