Psychological Review
2001, Vol. 108, No. 4, 709–734

0033-295X/01/$5.00 DOI: 10.1037//0033-295X.108.4.709

Posture-Based Motion Planning: Applications to Grasping

David A. Rosenbaum
Pennsylvania State University

Ruud J. Meulenbroek
University of Nijmegen

Jonathan Vaughan
Hamilton College

Chris Jansen
University of Nijmegen

This article describes a model of motion planning instantiated for grasping. According to the model, one of the most important aspects of motion planning is establishing a *constraint hierarchy*—a set of prioritized requirements defining the task to be performed. For grasping, constraints include avoiding collisions with to-be-grasped objects and minimizing movement-related effort. These and other constraints are combined with instance retrieval (recall of stored postures) and instance generation (generation of new postures and movements to them) to simulate flexible prehension. Dynamic deadline setting is used to regulate termination of instance generation, and performance of more than one movement at a time with a single effector is used to permit obstacle avoidance. Old and new data are accounted for with the model.

To reach and grasp objects effectively, one must be able to perform actions intelligently. One must be able to reach any point in the work space from any other point with different speeds; one must be able to avoid collisions; one must be able to shape the hand around the object so subsequent manipulations can take place; and if necessary, one must be able to compensate for changes in joint mobility due to accident, disease, or other impediments. The importance of these abilities has been recognized by others (e.g., Hebb, 1949; Lashley, 1942; Raibert, 1977; Wright, 1990), but one of them—the capacity for collision avoidance—has received less attention than we think it deserves. A central point of this article is that obstacle avoidance holds an important key to understanding typical features of human prehension and, by extension, other forms of adaptive movement. The computational solution we have found for the obstacle-avoidance problem may hold interest for researchers in motor control as well as others because the mechanisms we have identified may have general utility across a range of memory retrieval and problem-solving contexts.

The article is organized as follows. In the first major section we review previous theories of motion planning. In the second major section we present a new model and describe its claims. In the third major section we show how this new model applies to grasping in particular. Here we explain how the model accounts for the main findings of previous grasping studies, and we present a new behavioral study involving complex reach-and-grasp motions whose detailed kinematic properties, both of the hand and of the joints, can be accounted for with the model. The final major section concerns the limitations of the model, remaining issues, and implications of our work for motor control and other domains.

Previous Models

Several theories have been developed to account for the abilities mentioned at the start of this article. Those that we consider all concern computational and algorithmic rather than implementation (neural) levels of explanation (Marr, 1982). Furthermore, the theories we review are mainly concerned with the redundancy problem in motor planning—that is, with the question of how particular movements are realized when an infinite number of movements allow a task to be achieved. Having a plethora of movement options is more the norm than the exception in everyday life. In the case of reaching for a point in space, for example, any point within an obstacle-free region of reachable space can usually be reached with an infinite number of final postures, and each of these final postures can usually be arrived at with an infinite number of movements. Thus, the emergence of a particular movement to a particular final posture implicitly represents a

David A. Rosenbaum, Department of Psychology, Pennsylvania State University; Ruud J. Meulenbroek and Chris Jansen, Nijmegen Institute for Cognition and Information, University of Nijmegen, Nijmegen, the Netherlands; Jonathan Vaughan, Department of Psychology, Hamilton College.

This research was supported by National Science Foundation Grants BNS-90-08665 and SBR-94-96290, a grant from the Research and Graduate Studies Office of Pennsylvania State University, National Institutes of Health Research Scientist Development Award K02-MH00977, the Royal Netherlands Academy of Arts and Sciences, the Dutch Organization for Scientific Research (NWO Stimulans Premie), and the Hamilton College Faculty Research Fund. The work benefited from comments by Rinus Aarts, Liana Brown, Richard Carlson, Tom Carr, Marc de Lussanet, Catherine Elsinger, Randall Flanagan, Tamar Flash, Stan Gielen, Daniel Gopher, Jeremy Graham, Carolyn Harp, Steven Jax, Judith Kroll, Mark Latash, Gordon Logan, Esa Rantanen, Jacqueline Shin, Jeroen Smeets, Esther Thelen, and Frank Zaal. We also thank Bert Steenbergen for help with the experiment.

The computer simulation described here is available as an executable, PC-compatible program. It can be downloaded from Ruud J. Meulenbroek's home page (http://www.socsci.kun.nl/~meulenbroek/).

Correspondence concerning this article should be addressed to David A. Rosenbaum, Department of Psychology, Pennsylvania State University, 642 Moore Building, University Park, Pennsylvania 16802. Electronic mail may be sent to dar12@psu.edu.

solution to the problem of finding a unique solution when infinitely many suffice.

The principal means of addressing the redundancy problem has been to suppose that the planning system adds implicit requirements to explicit task requirements. Thus, if the task is to bring the fingertip to a target (an explicit requirement), the planning system may, for example, also require the performed movement to minimize the mean rate of muscle tension change (Dornay, Uno, Kawato, & Suzuki, 1996). The idea that implicit requirements help solve the redundancy problem was recognized long ago in optimal control theory (Bryson & Ho, 1975) and was introduced to the study of motor control by Nelson (1983).

Flash and Hogan's (1985) Minimum Jerk Model

The implicit constraint hypothesis was popularized in motor control by Flash and Hogan (1985), who suggested that aiming movements might obey a "minimum jerk" principle. Here, plotting the speed of the hand as a function of time, one finds that the resulting speed, or "tangential velocity," profile is symmetric and bell-shaped with the ratio of the peak velocity to the mean velocity being about 1.87; see Hogan and Flash (1987) for a review. A function of this form minimizes mean squared jerk (the mean third time derivative of position) over the duration of the movement.

The tangential velocity function that Flash and Hogan (1985) considered was defined with respect to extrinsic spatial coordinates. A prediction of the minimum jerk principle so defined is that hand paths in extrinsic space should be straight. Curved hand paths can be generated, of course, but according to the minimum jerk model, they must be produced by concatenating straight-line segments (Abend, Bizzi, & Morasso, 1982).

Initial evidence for the minimum jerk principle was encouraging. Many speed profiles for manual pointing movements were found to be bell-shaped, and many hand paths were found to be straight (Morasso, 1981). Exceptions were also found, however. Departures from symmetry in tangential velocity profiles were observed (see Bullock & Grossberg, 1988, for a review), and directionally dependent departures from hand path linearity were also detected (Atkeson & Hollerbach, 1985; Haggard & Richardson, 1996; Thiel, Meulenbroek, & Hulstijn, 1998; Uno, Kawato, & Suzuki, 1989). One way of reconciling these findings with the minimum jerk principle is to suggest that departures from linearity might be due to visual misperception (Wolpert, Ghahramani, & Jordan, 1994), but doubt has been cast on this hypothesis (Osu, Uno, Koike, & Kawato, 1997).

Uno, Kawato, and Suzuki's (1989) Minimum Torque Change Model

Another way to explain the effect of movement direction on hand path curvature as well as departures from symmetry in tangential velocity profiles is to allow that movements satisfy a different cost than the one proposed by Flash and Hogan (1985). Uno et al. (1989) hypothesized that movements may satisfy a minimum torque change constraint. They confirmed predictions of this hypothesis in several experiments in which participants moved the hand from place to place on a horizontal surface. Uno et al. (1989) observed directionally dependent changes in hand curvature and asymmetries in tangential velocity profiles consistent with their predictions. They also found further model-consistent changes in performance when movements were resisted by a spring or when movements were made through explicitly designated intermediate or "via" locations. The number of local minima in the tangential velocity profiles changed with the convexity or concavity of the hand path as predicted by the model.

The model of Uno et al. (1989) shifted the focus from optimization with respect to extrinsic coordinates to optimization with respect to intrinsic coordinates. Subsequent discussions of the Uno et al. (1989) model by Kawato (1996a, 1996b) allowed for simultaneous optimization at different levels of control—at the hand path level (where the minimum jerk constraint was assumed) and at the muscle level (where a minimum muscle tension change constraint was assumed as a means of realizing minimum torque change). Kawato (1996a, 1996b) also suggested that the motor system might in addition minimize changes in motor commands. This view implies that there is optimization at the neural and psychological levels as well as at the spatial and muscle levels. The idea that movements satisfy constraints at several levels was an important advance.

The Uno–Kawato (Uno et al., 1989; Kawato, 1996a, 1996b) model had some weaknesses, however. One was that it had no mechanism for changing costs within levels. Such changes are important to allow performance to vary as a function of the task being performed. For example, when a violinist intentionally switches from legato (smooth) to staccato (jerky) bowing, he or she switches from a mode that minimizes torque changes to one that does not. A model of motor control must account for such flexibility.

Another limitation of the Uno–Kawato (Uno et al., 1989; Kawato, 1996a, 1996b) model is that it does not provide a clear means of selecting final postures. This issue was sidestepped in the studies done to test the model because participants moved only the shoulder and elbow to bring the hand to a target location while the wrist was braced. In this arrangement, only one arm posture was associated with each table position. Generally, however, more degrees of freedom exist in the joints than in the geometric description of the location to be reached by the hand within the work space, in which case infinitely many postures allow the location to be reached. The Uno–Kawato model could not say which final posture should be adopted when such redundancy exists. Neither, for that matter, could the model of Flash and Hogan (1985).

A third limitation of the Uno–Kawato (Uno et al., 1989; Kawato, 1996a, 1996b) model was that it, like the Flash–Hogan (1985) model, was mute on the question of how movement times were specified. In both models, movement durations were supplied externally and the models predicted trajectories based on those prescribed times. Everyday actions, however, do not generally have their durations specified externally.

A fourth limitation of the Uno–Kawato (Uno et al., 1989; Kawato, 1996a, 1996b) model was that it did not deal with the problem of obstacle avoidance. Although it provided a means of moving through via locations when such locations were designated, it did not offer a means of indicating how via locations could be found by the actor, as when circuitous movements must be generated to bring the hand from under a table to the tabletop.

Mel's (1990, 1991) Search Model

A model that explicitly addressed the obstacle-avoidance problem was developed by Mel (1990, 1991). He worked with a robot equipped with an arm that moved on a horizontal surface. The robot had a camera that provided an image of the work surface, including the arm. During the robot's "babbling" phase, its arm moved randomly to a large number of configurations, allowing associations to be formed between the visual image of the arm in each configuration and the corresponding joint angles. Later, when the goal was to move the arm to designated targets without hitting obstacles, the robot could do so by first moving the arm "mentally" through a series of tiny submovements generated randomly around each current arm configuration. Each configuration that was reached at the end of each mental submove was evaluated for its ability to bring the arm closer to the target and for its ability to avoid collisions. If both of these criteria were met, the arm was mentally advanced to the newly generated configuration and random submovements were then initiated around the new configuration. If none of the random moves from a current configuration was judged successful, a new submovement from the previous configuration was tried. This "backtracking" process continued all the way back to the beginning of the main movement path if necessary. Ultimately, if a successful movement path was found, it was performed. Otherwise, the robot indicated that the task could not be carried out.

An aim of Mel's (1990, 1991) modeling effort was to avoid endowing the robot with explicit trigonometric equations for predicting limb spatial positions from vectors of joint angles. Instead, Mel sought to have his robot learn to make visually guided arm movements in the way Piaget (1954) argued babies do—by discovering the visual consequences of their own motor acts through trial and error. Mel had his robot recall arm spatial positions given previously adopted joint-angle configurations. This enabled the robot to anticipate the spatial consequences of adopting those joint-angle configurations given the current spatial task. A similar approach was used by Kuperstein (1988).

Mel's (1990, 1991) method had two limitations, however. One was that the memorial backtracking demands of the planning process were onerous and arguably as unnatural as reliance on trigonometric functions. Second, the generated movements were unrealistic. The robot's arm moved jerkily from one position to the next. Mel (1990) acknowledged the latter problem but did not attempt to generate kinematically realistic movement profiles. Conceivably, one could try to smooth the series of submovements generated by a process such as Mel's (1990, 1991) to yield a less jerky composite movement, but this would still rely on the backtracking heuristic. It is also unclear whether movement smoothing could be relied on to avoid collisions.

Rosenbaum et al.'s (1995) Knowledge Model

Whereas the Flash–Hogan (1985) and Uno et al. (1989) models focused on properties of movements to already prescribed final positions in already prescribed times, a model of Rosenbaum, Loukopoulos, Meulenbroek, Vaughan, and Engelbrecht (1995; Rosenbaum, Loukopoulos, Engelbrecht, Meulenbroek, & Vaughan, 1996; Rosenbaum, Meulenbroek, & Vaughan, 1996) focused on the means by which final postures and movement times are chosen. Rosenbaum et al.'s (1995) model—called the *knowledge* model to emphasize the cognitive substrates of motion planning—relied on differential cost emphasis (as in the example of the violinist electing to make legato or staccato bow strokes). The principal aim of Rosenbaum et al.'s (1995) model was to simulate reaching movements in as lifelike a way as possible. The only kinds of movements simulated with the model were sagittal-plane and horizontal-plane pointing movements. Grasping and obstacle avoidance were not addressed.

The main task that Rosenbaum et al. (1995) concentrated on was reaching in the sagittal plane to bring any designated point along the limb-segment chain—a *contact point*—to any designated location in the work space. The model was rendered as a computer-animated stick figure capable of bending at the hip, shoulder, and elbow. The model made four claims about motion planning. The first was that goal postures are selected by making use of stored postures. The second claim was that goal postures are planned prior to movements. The third claim was that it is possible to weight costs differently depending on the task to be performed. The fourth claim was that it is possible to specify movement durations endogenously.

Because these ideas are preserved in the model presented here, it is useful to elaborate on them, especially the most distinctive claims that goal postures are selected by making use of stored postures and that movements are generated on the fly. These notions have at least five sources of justification.

1. Because optimal movements can be generated once initial and final postures are known, as assumed in the Flash–Hogan (1985) and Uno–Kawato (Uno et al., 1989; Kawato, 1996a, 1996b) models, knowing final as well as initial postures can allow for creation of optimal movements.

2. Memory for final positions is better than memory for movements (see Jaric, Corcos, Gottlieb, Ilic, & Latash, 1994, and Smyth, 1984, for reviews). This outcome suggests that final positions are represented at a different level than movements. Recent work indicates that memory for final positions includes memory for final postures, not just memory for final locations (Baud-Bovy & Viviani, 1998; Rosenbaum, Meulenbroek, & Vaughan, 1999).

3. Variability of end positions is generally smaller than variability of movements to those end positions (Desmurget, Prablanc, Rossetti, & Arzi, 1995; Wiesendanger, Kazennikov, Perrig, & Kaluzny, 1996). This outcome is consistent with the view that end positions are not simply the results of movements but instead are goals that movements serve to satisfy. A recent article (Harris & Wolpert, 1998) showed that minimization of end-position variability can account for three of the most important known properties of motor performance: (a) Movements tend to have smooth, roughly symmetrical velocity profiles over a wide range of viscosity and inertia; (b) speed and accuracy of aiming movements tend to trade off in ways captured by Fitts' law (see Meyer, Smith, Kornblum, Abrams, & Wright, 1990, for a review); and (c) the tangential velocity of hand movements decreases as the curvature of the hand path increases (Lacquaniti, Terzuolo, & Viviani, 1983). The fact that these important movement regularities can be ascribed to end point consistency highlights the functional primacy of end point planning.

4. The *end-state comfort effect*, defined as willingness to adopt initially uncomfortable postures for the sake of comfortable final postures (Rosenbaum et al., 1990), is better predicted by ratings of

final-posture comfort than by ratings of movement ease (Rosenbaum, Vaughan, Jorgensen, Barnes, & Stewart, 1993).

5. Considerable evidence exists for the equilibrium point (EP) hypothesis of motor control (see Latash, 1993, for a review). This hypothesis states that the nervous system creates neuromuscular equilibrium positions, which, if different from current equilibrium positions, result in movement. In principle, detailed properties of movements need not be specified when EPs are created. The EP hypothesis is controversial. Questions about it are whether end positions can be reached without sensory feedback, as assumed in one version of the EP hypothesis (Bizzi, Hogan, Mussa-Ivaldi, & Giszter, 1992; Polit & Bizzi, 1978), and whether ongoing movement trajectories can be modified through learning—for example, based on exposure to unusual force fields (Dizio & Lackner, 1995; Gomi & Kawato, 1996; Gottlieb, 1998; Lackner & Dizio, 1994). In our view, the ability to control movements on-line does not vitiate the EP hypothesis because if actors can modify ongoing movements, this does not mean that goal postures were not established in advance. If one drives around a tree that has fallen on the road, this does not imply that one lacked a planned destination.

Detailed Assumptions of Rosenbaum et al.'s (1995) Model

More detailed features of the model of Rosenbaum et al. (1995) are now reviewed because many of them (Equations 1–6 and 11–13) are preserved in the model presented here. Readers wishing to skip the technical details that follow should still be able to understand the subsequent sections.

Suppose an actor is in some initial posture and he or she has decided to reach to a location in the sagittal plane with a specific contact point (typically, the hand). According to the model of Rosenbaum et al. (1995), stored postures (i.e., remembered arrays of joint angles) are weighted according to two task-relevant costs: (a) a spatial error cost and (b) a travel cost. The spatial error cost, S_p, for any posture p is defined as

$$S_p = \sqrt{(x_u - x_v)^2 + (y_u - y_v)^2}, \tag{1}$$

where x and y denote the horizontal and vertical coordinates of the spatial target, u, and of the contact point, v. The values of x_v and y_v are derived through forward kinematics,

$$\begin{aligned} x_j &= x_{j-1} + l_{j-1} \cos \sum_{i=1}^{j-1} \theta_i \\ y_j &= y_{j-1} + l_{j-1} \sin \sum_{i=1}^{j-1} \theta_i \end{aligned}, \tag{2}$$

where the Cartesian location (x_j, y_j) of joint j is determined by computing the horizontal and vertical distances between successive joint locations, from joint $j = 1$ (the toe) anatomically "upward" from the toe to the fingertip to joint $j - 1$, using the length, l_{j-1}, of the limb segment anatomically closer to the toe than the jth joint. As in traditional robotics (Craig, 1986), the joint angle between limb segments i and $i + 1$ is defined as the counterclockwise rotation of segment $i + 1$ with respect to the linear extension of segment i. It is assumed that the Cartesian location of the first joint is known.

The travel cost, V_p, for posture p is defined as

$$V_p = \sum_{j=1}^{n} V_j(\alpha_j, T_j), \tag{3}$$

where α_j denotes the absolute angular displacement of the jth joint from its current starting angle to its angle in posture p, and T_j denotes the movement time for that absolute angular displacement.

It was assumed by Rosenbaum et al. (1995) that there is an optimal time, $T_j^*(\alpha_j)$, for absolute angular displacement α_j,

$$T_j^*(\alpha_j) = k_j \ln(\alpha_j + 1), \tag{4}$$

where k_j is a nonnegative real number corresponding to the "expense factor" for joint j.

The travel cost, $Vj(\alpha_j, T_j)$, for the jth joint to cover absolute angular displacement α_j in a time T_j, which can but need not equal $T_j^*(\alpha_j)$, is

$$V_j(\alpha_j, T_j) = \left(\frac{k_j\alpha_j}{r}\right)\left\{1 + \frac{[T_j - T_j^*(\alpha_j)]^2}{s^2}\right\}, \tag{5}$$

where 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 5 says the travel cost for a joint's angular displacement grows as the square of the difference between the joint's required and optimal movement time, weighted by the product of the joint's expense factor and angular displacement that must be produced.

In the model of Rosenbaum et al. (1995) and in the model to be presented here, simulations were restricted to the case of all joints starting and ending their movements together. The way an optimal common time, T_p, was found for all the joints moving to posture p was to find the value of T_p that minimizes V_p. Setting $dV_p/dT_p = 0$, the value of T_p that minimizes V_p,

$$T_p = \frac{\sum_j k_j\alpha_j T_j^*(\alpha_j)}{\sum_j k_j\alpha_j}, \tag{6}$$

is based on the weighted average of the optimal movement times for the joints to cover their respective angular displacements. The weights used for the weighted average are, as in Equation 5, given by the product of the joints' expense factors and their respective angular displacements. Once T_p is found, it replaces T_j in Equation 3 for all joints j.

With the spatial error cost (Equation 1) and the travel cost (Equation 3) for the pth stored posture identified, the two costs are combined to yield a total cost, C_p, for that stored posture,

$$C_p = w_s \frac{(s_p)}{MaxS} + w_v \frac{(v_p)}{MaxV}, \tag{7}$$

where $MaxS$ is the largest spatial error cost and $MaxV$ is the largest travel cost of any stored posture for the current reaching task and where w_s and w_v denote weights given to the spatial error cost and travel cost, respectively. Because w_s and w_v sum to 1, only one of the values has to be specified explicitly.

Once the total cost is obtained for all the stored postures, a single target posture is found by treating each of the $p = 1, 2, \ldots, m$ stored postures as vectors and taking their weighted sum

$$\mathbf{P}^* = \sum_{p=1}^{m} g_p \mathbf{P}_p, \tag{8}$$

where the weight, g_p, of the pth stored posture,

$$g_p = \frac{G(C_p)}{\sum_{p=1}^{m} G(C_p)}, \tag{9}$$

is based on a Gaussian function,

$$G(C_p) = \frac{1}{\sigma\sqrt{2\pi}} \exp\left[-\frac{(C_p - \mu)^2}{2\sigma^2}\right], \tag{10}$$

with $\mu = 0$ and $\sigma = \min(C_p)$. Entering the Gaussian functions into Equation 9 ensures that the weights assigned to the stored postures are inversely related to the stored postures' total costs and that when a stored posture's total cost is zero, it receives a weight of 1.

All the preceding steps allow for identification of a goal posture. After a goal posture is identified, the next step is to generate a movement to it. If one were to assume that movements minimize mean torque change (Uno et al., 1989), one could generate a minimum torque-change trajectory from the starting posture to the goal posture provided one knew the relevant physical parameters of the limb segments. However, because the model of Rosenbaum et al. (1995) was only concerned with kinematics and because the model assumed joint-based control, all joints not already at their goal angles were assumed to move to their goal angles with simple bell-shaped angular velocity profiles based on a prototype function, $v(t)$, relating angular velocity to instantaneous time t relative to total T,

$$v(t) = \frac{1}{2}\left\{1 + \sin\left[\pi\left(\frac{3}{2} + \frac{2t}{T}\right)\right]\right\}, \tag{11}$$

which, after integration to yield a function, $NormA(t)$, relating normalized amplitude to t,

$$NormA(t) = \frac{\int_0^t v(t)dt}{T/2}, \tag{12}$$

was scaled for each joint according to its required angular displacement,

$$A_j(t) = \alpha_j NormA(t). \tag{13}$$

From Equations 11–13, it follows that $A_j(t)$ equals 0 at $t = 0$ and increases sigmoidally to α_j at time $t = T$. Because all moving joints were assumed to obey this principle and to have common starting and ending times, all angle–angle graphs were assumed to be linear. Some observed angle–angle graphs are nonlinear, however, and those departures from linearity have been claimed to be related to dynamics (Flash & Hogan, 1985; Gottlieb, Song, Hong, Almeida, & Corcos, 1996), so the linear angle–angle relations assumed by Rosenbaum et al. (1995), along with the bell-shaped angular velocity profiles, are only first approximations. Linear angle–angle functions have also been assumed by Soechting, Buneo, Herrmann, and Flanders (1995). They are perhaps more reasonable for a purely kinematic model like the model of Rosenbaum et al. (1995) than for a model that includes forces.

Another feature of the Rosenbaum et al. (1995) model was related to the fact that taking a weighted average of stored postures to yield a goal posture can yield a posture for which the spatial position of the contact point falls outside the spatial region occupied by the component postures; this is sometimes called the *convex hull* problem (Craig, 1986). In the model of Rosenbaum et al. (1995) a special process called *feedforward correction* was developed to deal with this problem. After a candidate goal posture was nominated and if its spatial error was found to be unacceptable, a virtual spatial target was created on the opposite side of the original spatial target at half the distance between the target and the contact point of the candidate goal posture. A new goal posture was then derived that was supposed to reach this virtual spatial target. If this new goal posture was able to bring the contact point acceptably close to the actual spatial target, a movement to that goal posture was performed. Otherwise, another virtual spatial target was created, opposite the original spatial target and at half the distance between the target and the last created contact point. This procedure continued until the contact point homed in on the target. The number of cycles needed to get the contact point within the spatial target provided a basis for predicting planning times.

A final feature of the earlier model concerned learning. Whenever the cumulative strength of a stored posture fell below a threshold, it was removed from the posture store and a new randomly chosen posture took its place. The cumulative strength of a stored posture depended on the weight it received in successive reaching tasks regardless of whether it was physically adopted.

Performance of the Rosenbaum et al. (1995) Model

The model of Rosenbaum et al. (1995) yielded simulated movements with many properties of observed movements. Any spatial location in the work space could be reached from any other spatial location in the work space, and this was also the case for any contact point along the limb segment chain, provided it was geometrically possible to bring that contact point to the spatial target. The reason why any contact point whatsoever could be brought to the spatial target was that the spatial error cost could be defined with respect to the particular point along the limb segment chain that was chosen by the actor to be the contact point. The model also permitted compensation for changes in joint mobility. When a joint had a larger than normal expense factor, stored postures that relied on large rotations of that joint were assigned higher than normal total costs. Consequently, the goal posture that was ultimately selected required smaller than normal rotations of that joint. This was an important achievement of the model. No other model that we are aware of permits immediate compensation for changes in joint mobility as quickly or as easily (cf. Mussa-Ivaldi, Morasso, & Zaccaria, 1988).

The model also predicted several outcomes, which are mentioned here only briefly: (a) effects of movement speed on final postures (Fischer, Rosenbaum, & Vaughan, 1997; Meulenbroek, Rosenbaum, Thomassen, & Schomaker, 1993); (b) effects of starting positions on final postures (Fischer, Rosenbaum, & Vaughan, 1997; Soechting et al., 1995); (c) elliptical end point distributions biased toward starting positions (Ghez, Gordon, Ghilardi, & Sainburg, 1990); (d) directional dependence of hand path curvature (Atkeson & Hollerbach, 1985; Haggard & Richardson, 1996; Thiel, Meulenbroek, & Hulstijn, 1998); (e) adverse effects of starting-position uncertainty on movement accuracy (Ghilardi, Gordon, & Ghez, 1995; Prablanc, Echallier, Jeannerod, & Komilis, 1979; Savelsbergh & Whiting, 1988; Sittig, Denier van der Gon, & Gielen, 1987; Smyth & Marriott, 1982); (f) increased efficiency of movement (lower travel cost) with practice (Sparrow & Irizarry-Lopez, 1987); and (g) motor "scotomas," or small regions within the work space that are not reached during blind positioning (Ghez, Gordon, Ghilardi, Christakos, & Cooper, 1990).

When the model was tested against actual behavior, it was found to do a good job of predicting final postures adopted by human participants (Fischer et al., 1997; Vaughan, Rosenbaum, Harp, Loukopoulos, & Engelbrecht, 1998). A novel prediction of the model—that participants should exhibit increased stereotypy in goal postures adopted in successive reaches to the same target ("settling in")—was also confirmed (Fischer et al., 1997).

Limitations of the Rosenbaum et al. (1995) Model

Despite the success of the Rosenbaum et al. (1995) model, it had some limitations. First, for the weighted summing scheme to work, many stored postures were necessary. Second, for weights to be assigned to stored postures, the spatial error weight and effort weight had to sum to 1. This meant that the costs always had to be traded, which meant in turn that there was no way to insist on achievement of several goals simultaneously—for example, to have both high spatial accuracy and high ease of movement. A third limitation of the original model was that although feedforward correction ensured attainment of the spatial target, the procedure was ad hoc. Moreover, feedforward correction was the only way to predict movement planning times. A fourth problem was that it was difficult to use the model to generate reaches when the planning system was not given explicit information about all the spatial targets to be reached by all the relevant contact points. Thus, although the planning system could plan reaches when it was told the coordinates of each spatial target for each contact point, it could not generate reaches when the goal was less explicit (e.g., "Grab the coffee cup."). Similarly, the system could not avoid obstacles or engage in complex tasks such as reaching around one object to grasp another. The principal aim of the model presented here was to tackle these problems.

New Model

The new model preserves several of the assumptions of the earlier model. As before, we assume that goal postures are specified before movements are generated; that forward kinematics (Equations 1–2) is used to determine where contact points will be in extrinsic space; that travel costs are estimated assuming characteristic expense factors for the joints and, for convenience, that there are common movement times for all joint displacements (Equations 3–6); that movements follow bell-shaped angular velocity profiles (Equations 11–13); and that postures can be learned.

The new assumptions are fourfold. First, instead of saying that candidate postures are evaluated with respect to just two costs that must be traded (the spatial error cost and the travel cost), we now allow that candidate postures are evaluated with respect to a prioritized list of requirements, or *constraint hierarchy*. In this approach, it is most important that the goal posture satisfy the highest level constraint, that it next satisfy the second highest level constraint, and so on. The constraint hierarchy defines the task to be performed. Candidate postures are "weeded out" based on how well they satisfy constraints at successively lower levels. This choice method, known as *elimination by aspects* (Tversky, 1972), has proven to be an effective way of modeling flexible decision making with multiple constraints (Janis & Mann, 1996). An advantage of this approach over the one used by Rosenbaum et al. (1995) is that it allows for simultaneous satisfaction of many constraints.

The second new assumption is that instead of identifying goal postures by taking a weighted sum of stored postures (Equations 7–10), goal postures are found through a two-stage process of identifying the stored posture that is most promising for the task to be performed and then generating potentially better postures. In both stages, postures are evaluated with respect to the constraint hierarchy. The two-stage process of first finding a most promising stored posture and then generating a possibly better posture provides a way of accounting for the benefit of learning via instance retrieval on one hand and the capacity for behavioral novelty via instance generation on the other (see Logan, 1988). With the two-stage method, there is also no longer a need for feedforward correction.

The third new assumption concerns the termination of goal-posture planning. In the earlier model, the planning of goal postures stopped when a goal posture was found based on weighted summing of stored postures. If the found goal posture did not satisfy the spatial error requirement, feedforward correction was used until a posture was found that brought the contact point acceptably close to the spatial target. In the new model, because feedforward correction is no longer required and because we use the two-stage process outlined above, we need a way of deciding when posture-identification processes should stop so all possible postures are not always evaluated.

The stopping rule is as follows. Candidate postures are generated around the most promising stored posture until a deadline is reached, at which time the best posture found up to that time (i.e., the one that satisfies the most constraints) is chosen as the goal posture. If the best posture was found *before* the deadline, the deadline is reduced for the next trial unless the deadline is already at its minimum value of 0. If the best posture was found *at* the deadline or if no acceptable posture was found, the deadline is increased for the next trial. The rationale behind this *dynamic deadline setting* procedure is that if the best posture was found when planning had to stop, more planning might have yielded a better goal posture, but if the best posture was found before planning had to stop, more planning was done than necessary. Note that the stopping rule applies to the process of generating new postures around the most promising stored posture, not to the process of evaluating stored postures. In our simulations, all stored postures are evaluated no matter how many stored postures exist.

We call the planning processes outlined above—generating postures around a most promising stored posture until time runs out—*diffusion 'til a deadline.* We use the term *diffusion* because the process of generating postures around a most promising stored posture involves dispersion from a starting point, much as a lump of sugar spreads out when it is dropped into a cup of coffee. To the best of our knowledge, diffusion 'til a deadline is a newly proposed search procedure. It treats stored instances as pointers for search. The most promising pointer is task dependent.

The fourth and final innovation in the new model arose out of our efforts to solve the obstacle avoidance problem. This is a difficult problem that has occupied roboticists (e.g., Haugsjaa, Souccar, Connolly, & Grupen, 1998; Lozano-Perez, 1983) and psychologists (e.g., Dean & Brüwer, 1994; Sabes & Jordan, 1997; Saling, Alberts, Stelmach, & Bloedel, 1998; Schneider, Zernicke, Schmidt, & Hart, 1989; Worringham, 1993) for many years. The solution we have arrived at for this problem is surprisingly simple. We allow more than one movement to be performed at a time even with the same limb segment.

To get a feeling for how this method works, consider the act of bringing the hand from under a table to the top of the table. A direct movement is impossible, of course, so a detour is necessary. The detour can be generated by allowing the hand to move in toward the body and then back out again while the forearm moves up. Said another way, while the arm makes its main upward movement from the starting posture to the goal posture, it simultaneously moves from the starting posture to a via posture and then back to the starting posture. This extra back-and-forth movement adds no net displacement to the main movement but affects the trajectory shape.

This new method is appealing for several reasons. First, the method for specifying the extra back-and-forth movement relies on identification of a via posture, just as the method for specifying primary movements relies on identification of a goal posture. Second, the method comports with other evidence for movement superposition, some of which comes from studies where participants moved the hand to one target and then had to redirect the hand as quickly as possible to another suddenly appearing target (Flash & Henis, 1991; Henis & Flash, 1992). Subjects' hand kinematics suggested that the movement to the first target was not terminated when the movement to the second target began. Instead, the two movements were superposed. The idea that movements can be added can be traced to Fourier's ideas about the composition of continuous waves by the addition of sine waves (see French, 1971). Within the field of motor control, the idea finds expression in models of oscillator-driven movement that rely on summation of underlying waves to create complex movement trajectories (Denier van der Gon & Thuring, 1965; Feldman, 1980; Hollerbach, 1981; Von Holst, 1973).

The third attraction of our obstacle-avoidance method is that the procedure for checking for collisions is posture based. Recall that in the model the default trajectory from the starting posture to the goal posture is a straight-line movement through joint space. Such a movement can result in a collision. To check for possible collisions, we test for spatial overlap between the simulated actor and objects in the environment. We do this by using a subset of the postures that would be adopted during the default movement. Testing for spatial overlap between to-be-assumed postures and objects in the world provides a way of solving the conceptual problem of saying what an obstacle is. An obstacle, whether it is an external object or a part of one's own body, can be defined as one or more postures that would result in unwanted collision. Identifying obstacles in any other way is difficult (Lozano-Perez, 1983). The fact that obstacles and nonobstacles can be defined with reference to postures provides another reason to pursue a posture-based approach to motion planning.

Our aim in the preceding discussion has been to give an overview of the main ideas of the new model. More details are given in the next section. Reviews of previous work that alluded briefly to some ideas in the new model have appeared in Rosenbaum, Meulenbroek, Vaughan, and Jansen (1999); Rosenbaum, Meulenbroek, Vaughan, and Elsinger (1999); and Rosenbaum, Vaughan, Meulenbroek, and Jansen (1999).

Prehension

As mentioned earlier, the model of Rosenbaum et al. (1995) was used to predict behavior in pointing tasks. Such tasks, whether they involve individual pointing motions or cascaded series of pointing motions, are relatively simple because the number of moved joints tends to be small and the spatial requirements of the tasks are generally explicit (i.e., a specified contact point is supposed to go to a designated spatial region). Modeling behavior in prehension (grasping) tasks is more challenging because these tasks usually require coordination of many joints and their objectives tend to be vague. For example, if the task is to "grab the cup," there are no explicit instructions about which contact points should be aligned with which cup locations. The vagueness of the task description increases the modeling challenge.

Another reason why prehension is an attractive target for study is that a great deal of work has been done on it, owing largely to initial observations by Jeannerod (1981, 1984; for reviews, see Jeannerod, 1988; MacKenzie & Iberall, 1994; Rouiller, Hepp-Reymond, & Wiesendanger, 1999; Smeets & Brenner, 1999; Wing, Haggard, & Flanagan, 1996; Zaal, 1995). Many studies of prehension have focused on the task analyzed here—reaching for a circular object in the horizontal plane. The wealth of kinematic data for this task provides benchmarks against which our model can be evaluated.

In the following subsections, we describe the procedures used to simulate prehension. Then we show how our simulation results compared with previously observed findings. The last part of this section presents a new behavioral study that was designed to confront our model with kinematic data. The data to be fit were time-varying spatial position data for the fingertips as well as time-varying joint position data for the shoulder and elbow. As described below, the model did as well predicting the behavior of individual participants as other participants did, although there were versions of the model (i.e., some parameter combinations) that caused it to predict individual participant data more poorly than any other participant. These results indicate that the behavioral data were not so variable that they allowed any model to fit them nor that the model is so powerful it could never be rejected.

Modeling Prehension

The prehension task we modeled was grabbing an object with the tips of the index finger and thumb (the so-called precision grip). The joints whose motions we simulated were the right arm's shoulder, elbow, wrist, two joints of the thumb, and three joints of the index finger. The joint motions permitted movement of the arm, hand, and fingers in the horizontal plane (see Figure 1).

Because in our model any task must be defined with a constraint hierarchy, we first established a constraint hierarchy for the prehension task. The constraint hierarchy is given below, with the constraints listed in order of decreasing importance. Note that constraints for the hand come before constraints for the arm.

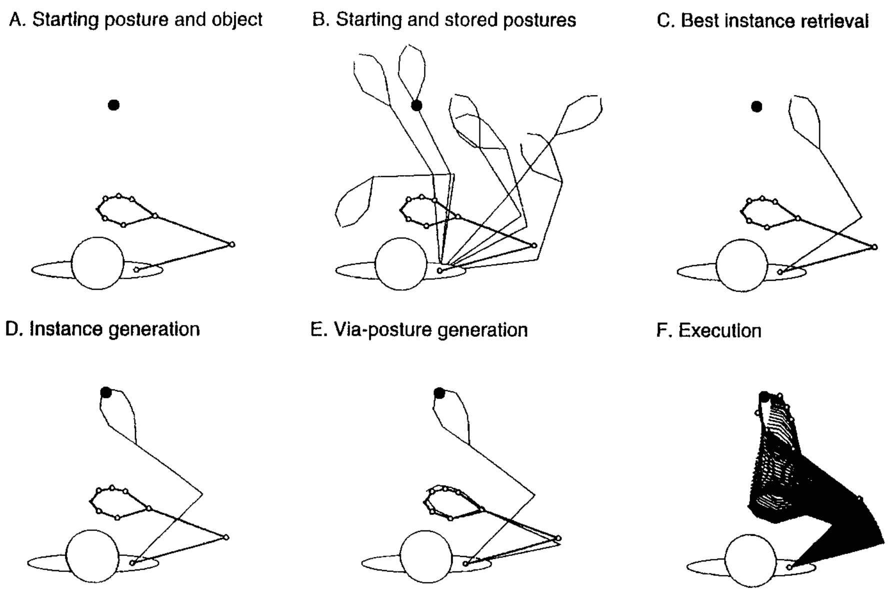

Figure 1. Overview of the grasping model. A: Stick figure with nine movable joints and object to be grasped (closed circle). B: Starting posture as in first panel plus seven stored postures. C: Best retrieved instance (most suitable stored posture) for current task. D: New posture identified through instance generation. E: Via posture (posture near original starting posture) that permits most effective collision-free movement. F: Execution (movement).

1. When the hand is in its goal position, it should not collide with (spatially overlap) an obstacle or the object to be grasped.
2. When the hand is in its goal position, it should contact the object to be grasped such that the distance between the index finger and thumb equals the diameter of the object.
3. The travel costs incurred by the index finger and thumb during their angular displacements from their starting angles should be as small as possible for the movements considered.
4. When the arm is in its goal position, it should not collide with (spatially overlap) an obstacle.
5. When the arm is in its goal position the distance of the wrist from the center of the object should allow the hand to adopt the shape necessitated by Constraints 1 and 2.
6. The travel costs incurred by the shoulder, elbow, and wrist should be as small as possible for the movements considered.
7. The movement to the goal postures of the hand and arm should avoid collisions.

Note that in the preceding list, Constraints 1–3 applied to the fingers; Constraints 4–6 applied to the shoulder, elbow, and wrist; and Constraint 7 applied to all the joints. Because the finger constraints (1–3) were considered before the arm constraints (4–6), the model identified a goal posture for the fingers before identifying a goal posture for the arm. We found it easier to simulate grasping this way than by considering entire hand–arm postures throughout planning, although we do not wish to claim that hand-posture planning must precede combined hand–arm posture planning. Evidence that hand postures are neurally represented separately from arm postures has been reported (Rizzolatti, 1987; Rizzolatti et al., 1988), evidence that hand postures are specified before arm postures has also appeared (Klatzky, Fikes, & Pellegrino, 1995), and it has been inferred from kinematic and reaction time data that hand as well as arm postures are mentally represented before prehension movements begin (Jeannerod & Biguer, 1982; Pellegrino, Klatzky, & McCloskey, 1989; Rosenbaum, Vaughan, Barnes, & Jorgensen, 1992).

Figure 1 gives a graphical overview of the steps leading to prehension performance in our model. As can be seen in Figure 1A, the simulation used a stick figure with nine movable joints and a circular target object. The parameters used in the simulation are listed in Table 1.

Figure 1B illustrates the first step in searching for a goal posture. In this case, the stick figure has eight stored postures. The number of possible stored postures, m, can be as small as 1 (just the last goal posture adopted) or as large as g^n, where g is the number of subdivisions of a mechanical degree of freedom (a joint axis) and n is the number of degrees of freedom. We call $1/g$ the grain of the system. For convenience, we assign the same grain to all degrees of freedom. The learning rule is that the last m goal postures are stored. The stored postures are evaluated serially with respect to the constraint hierarchy, but in principle all the stored postures can be evaluated in parallel. For each stored posture, the constraints in the constraint hierarchy are checked from top (most important) to bottom (least important) in a self-terminating fashion. The more constraints a stored posture satisfies, the better its judged suitability for the task. Checks for collision are achieved with forward kinematics. Travel costs are evaluated using Equations 3–6.

The outcome of the evaluation of stored postures is identification of the most promising stored posture, an example of which is shown in Figure 1C. Here we refer to the most suitable stored posture as the result of "best instance retrieval" to emphasize that this stage (and the preceding one) entail past-instance retrieval. Note that the hand and arm postures are represented together as a single posture even though they are planned sequentially in our simulations.

The most suitable instance of past performance may not permit task achievement, as is the case in Figure 1C. Figure 1D shows our

Table 1
Simulation Parameters

Joint	Length of distal limb segment (cm)	Minimum angle (degrees)	Maximum angle (degrees)	Possible expense factors (arbitrary units)
Shoulder	30	−60	110	0.5, 1.0, 1.5
Elbow	25	0	160	0.5, 1.0, 1.5
Wrist to finger	10	−60	60	0.5, 1.0, 1.5
Wrist to thumb	9	15	50	1.0
Metacarpophalangeal joint	4	0	35	1.0
Proximal joint of index finger	4	0	40	1.0
Distal joint of index finger	4	0	45	1.0
Proximal joint of thumb	6	−40	0	1.0
Distal joint of thumb	4	−45	0	1.0

Note. Additional parameters were grain (.01); maximum number, *m*, of postures in memory (200); deadline (15 search cycles); and instructed movement time (100).

solution to this problem. This figure shows the result of *instance generation.* Here, postures are generated around the most suitable stored posture and are evaluated with respect to the constraint hierarchy in the same way that stored postures are. Posture generation works via diffusion 'til a deadline (see Figure 2). The process starts at the point in posture space corresponding to the most promising stored posture; points around it are visited in ever widening shells until the deadline, *d,* is reached. The shells are farther and farther from the most promising stored posture by a distance, $1/g$, of each joint's range of motion. Every point that is considered corresponds to a combination of joint angles defining a possible posture, and each of these possible postures is evaluated with respect to the constraint hierarchy. If a generated posture

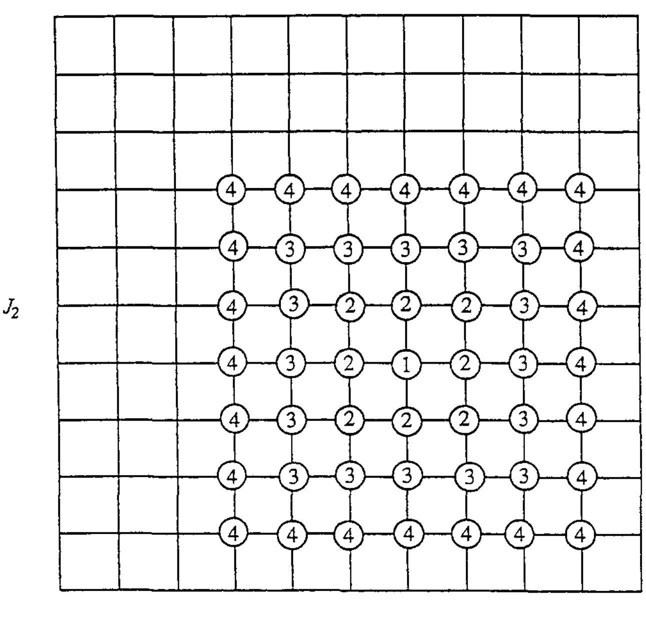

Figure 2. Diffusion 'til a deadline. The most promising stored posture is available in the first cycle (1). Numbers denote search cycles in which other postures are evaluated. The search continues until a deadline is reached. Here the deadline is four search cycles. The axes correspond to degrees of freedom for two joints, J_1 and J_2.

happens to be a stored posture, it is evaluated again. This inefficiency of computation is justified only by simplification of bookkeeping. When more points must be tested, planning time grows, but this is not a significant problem because our simulations are not time critical (i.e., they are used for basic research) and our serial evaluation of postures within a search cycle reflects the fact that we perform our simulations on a serial computer. In principle, the evaluation of postures within a cycle could all occur in parallel.

Once the deadline is reached (i.e., once all the candidate postures in the *d*th shell have been evaluated), the best found posture is defined as the goal posture. If there is a tie for best posture, the tie is broken randomly. If the best posture was found in a search cycle less than *d* (i.e., before the deadline), the deadline for the next trial is reduced by 1, provided the deadline is not at 0. If the best posture was found in the *d*th search cycle (i.e., at the deadline), the deadline for the next trial is increased by 1, provided the deadline is not at the maximum allowable value of *g*.

Figure 1E shows the next step—via-posture generation. In the case shown here, the via posture is not dramatically different from the starting posture, but this is desirable. The role of the via posture is to serve as a posture that one can move to from the starting posture and then move back from while the main movement is performed so the compound movement is collision free (Constraint 7). A lower level constraint for the via posture is that it should require as easy a back-and-forth movement as possible. Hence, via postures should be as close as possible to starting postures, and they should be especially close along axes of posture space whose joint rotations have high expense factors.

Identification of the via posture relies on the same basic machinery as identification of the goal posture. The only difference is that it uses a different constraint hierarchy for the requirements just mentioned. Identification of the via posture is achieved by generating candidate via postures around the most promising via posture in ever-widening shells in posture space until the deadline, *d.* For each candidate via posture, a compound movement is internally simulated, consisting of the main movement from the starting posture to the goal posture plus the movement from the starting posture to the via posture and back. To generate this compound movement, each joint slated to move from its starting posture to a via posture and back uses the same common movement time as the main movement; the common movement time is based on the method outlined earlier for the Rosenbaum et al. (1995) model. As shown in Figure 3, any joint that makes a via movement proceeds from its starting angle to its via angle with a bell-shaped angular velocity and then moves from its via angle back to its starting angle with a bell-shaped angular velocity. Mathematically, the angular velocity, v_v, of any such joint as a function of normalized time, t, for $0 < t < \pi$, is

$$v_v(t) = \sin(t) \times \sin(2t). \tag{14}$$

The angular velocity, v_m, of the same joint making its main movement from its starting angle to its goal angle is

$$v_m(t) = \sin(t) \times \sin(t). \tag{15}$$

Note that Equation 15 comprises a simplification of the procedure used in the model of Rosenbaum et al. (1995) to generate a bell-shaped angular velocity profile; see Equations 11–13.

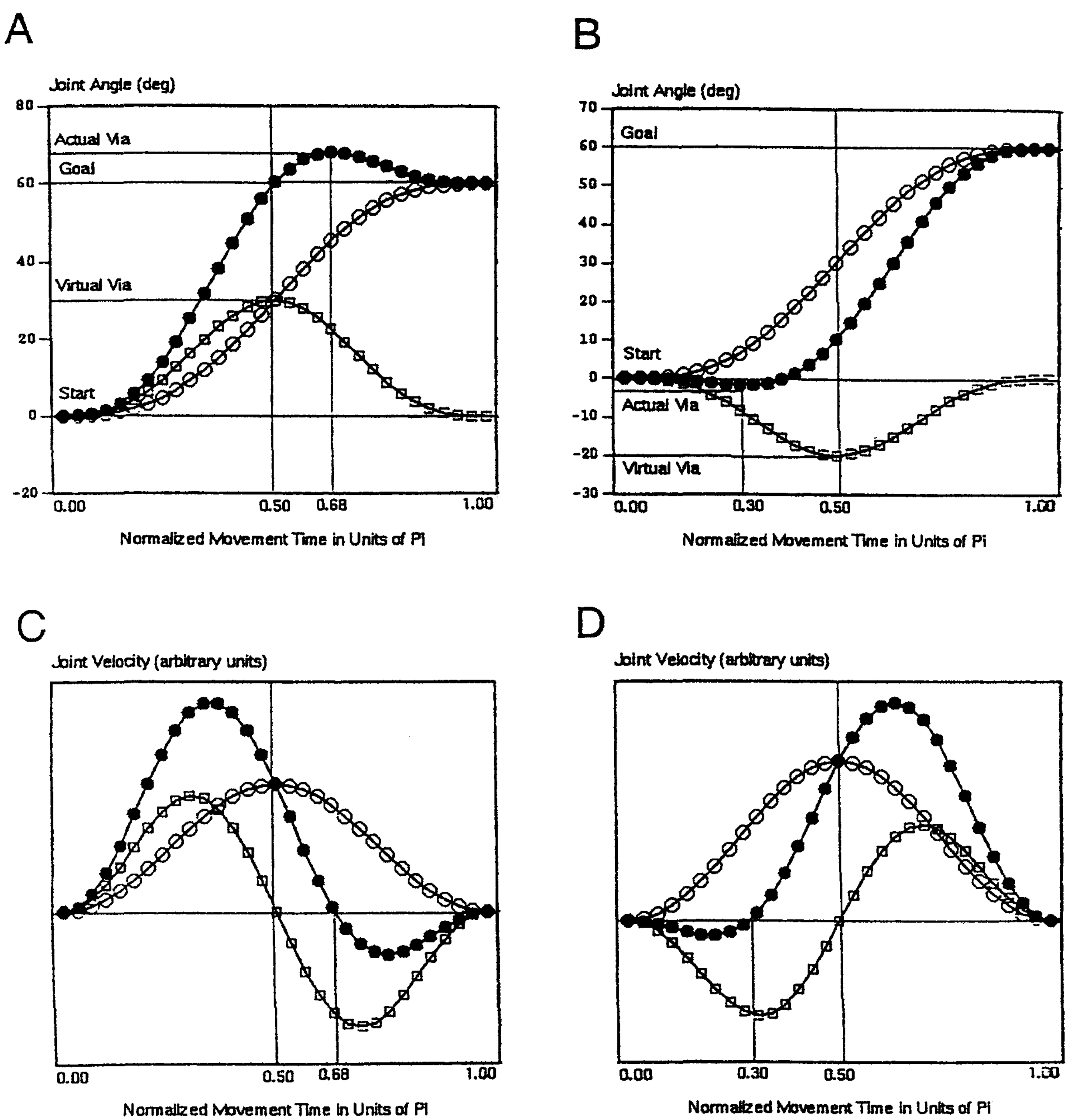

Figure 3. Superposition of angular velocity profiles (C and D) and their corresponding angular position profiles (A corresponding to C and B corresponding to D). Curves with open circles correspond to main movements. Curves with squares correspond to movements toward and away from via angles. Curves with filled circles are sums of the component functions. A and C are for a movement whose via angle lies between the start angle and goal angle. B and D are for a movement whose via angle lies on the starting-angle side, away from the goal angle. Joint velocities begin at 0. deg = degrees; Pi = units of π.

Given the compound movement, $v_c(t)$, that is internally simulated,

$$v_c(t) = v_v(t) + v_m(t), \tag{16}$$

postures that would be adopted at g evenly spaced moments in the total time of the compound movement are checked for collision using forward kinematics.

The last thing our model does is actually carry out a movement. Figure 1F shows a time-lapse image of this behavior. The static image does not do justice to the verisimilitude of the computer simulation viewed in real time (see the Author Note section for information about how to obtain a running version of the program). The fingers open and then close in on the object in a way that looks lifelike.

Simulations of Prehension

Figure 4A shows a typical reach-and-grasp movement performed by the model. The parameters used in this and the following simulations appear in Table 1. As can be seen in Figure 4C, aperture size varies with time in a manner reported in the literature. The fingers spread apart gradually and reach a maximum separation that exceeds the separation that will ultimately be adopted. The reason the model overspreads its fingers is that this ensures avoidance of collision with the object before the fingers extend enough to begin closing in. To avoid such collisions, the fingers and arm not only make a main movement from their starting angles to their goal angles; they also move from their starting posture to the via posture and back again to the starting posture. For the simulated reach-and-grasp movement shown in Figure 4, the maximum aperture occurs during the second half of the movement, at 62% of the movement time. This value comes close to the one typically observed in human reaching—between 65% and 90% of total movement time (Castiello, 1996; Jeannerod, 1981, 1984; Wallace & Weeks, 1988). As shown in Figure 4C, as the fingers spread apart, the arm speeds up and then slows down, taking less time for speeding up than for slowing down. This is also what generally happens in human prehension (Castiello, 1996; Jeannerod, 1981, 1984; Wallace & Weeks, 1988).

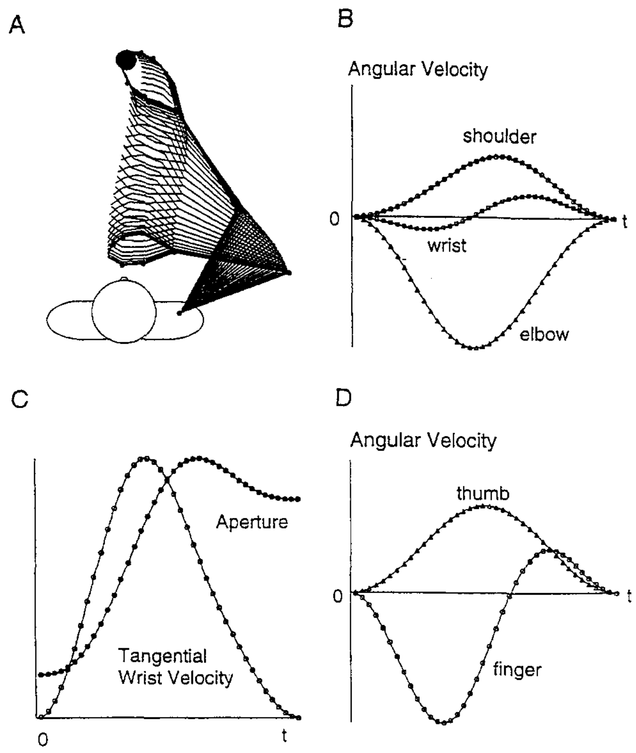

Figure 4. Simulated reach-and-grasp movement. A: Cartoon of the movement. B: Angular velocities of the shoulder, elbow, and wrist as a function of time. C: Tangential wrist velocity (wrist speed) and aperture (distance between tip of the thumb and tip of the index finger) as a function of time. D: Angular velocities of the proximal phalanx of the index finger and the interphalangeal joint of the thumb as a function of time. t = time.

Another important property of the reach-and-grasp movement shown in Figure 4B is that the angular velocity profiles for the elbow and shoulder are bell-shaped. The shoulder reaches its peak angular velocity (see Figure 4B) near the time when the finger joint reverses direction (see Figure 4D). Note as well that the angular velocity profiles for the wrist and finger are biphasic and that the wrist reverses direction before the finger does. Complex timing relations like these have been observed in behavioral studies and have been taken to connote functional linkages between the effectors (Bootsma & Van Wieringen, 1992; Jeannerod, 1981, 1984, 1988; Paulignan, MacKenzie, Marteniuk, & Jeannerod, 1990). Our model provides a way of understanding how these functional linkages originate.

A final noteworthy feature of the kinematics shown in Figure 4 concerns the difference between the movements of the thumb and index finger. The thumb does not reverse direction, but the finger does (see Figure 4D). This outcome corresponds to the observation that in grasping the thumb is usually relatively stable compared with the other fingers (Wing & Fraser, 1983; Wing, Turton, & Fraser, 1986). Our model provides a way of understanding why this difference is observed. For most reach-and-grasp tasks, the fingers need to move more than the thumb to avoid collisions with objects being grasped.

Effects of Object Size on the Size and Time of Maximum Aperture

Figure 5 shows two more grasping movements—one to a small object (Figure 5A) and one to a larger object (Figure 5B). The starting postures are the same in the two simulations as are the centers of the objects and all other parameters. The corresponding aperture–time functions are shown on the right side of Figure 5, where it can be seen that maximum finger aperture is larger for the large object than for the small object. This outcome makes sense from the perspective of obstacle avoidance and obstacle enclosure. The larger the object to be grasped, the more the fingers need to spread out to avoid premature collision.

It has been reported in many studies that maximum finger aperture increases with the size of the object to be grasped and that the rate of increase of the maximum aperture is lower than the rate of increase of the object size. For example, Marteniuk, Leavitt, Mackenzie, and Athenes (1990) reported a 0.77 cm increase of maximum finger aperture for each added centimeter of object size. According to Marteniuk et al., the slope is less than 1 because participants visually underestimate the size of the object to be

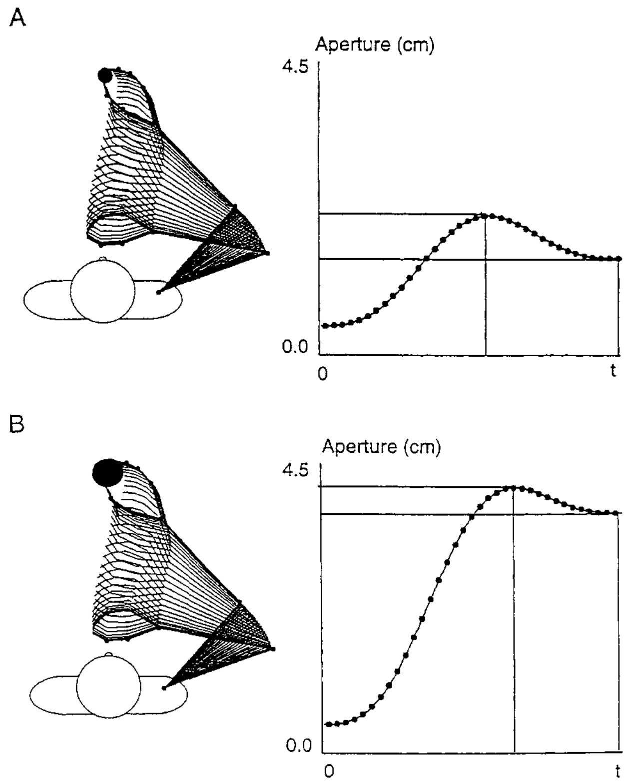

Figure 5. Simulated reach-and-grasp movements to a small object (A) and to a large object (B). Left: Cartoons of the movements. Right: Relation of aperture size to time (t). The starting postures and locations of the targets are the same in the two simulations.

grasped. Our model shows that the lower than unity slope need not be explained by appealing to visual misperception, which does not imply that misperception cannot be the source of the effect (see also Smeets & Brenner, 1999).

Figure 6 provides more information about the basis for the relation between maximum aperture size and object size. This figure shows theoretical angular displacement functions corresponding to aperture movements to a small object (Figure 6A) and to a large object (Figure 6B). The change in magnitude of the main movement causes a larger aperture overshoot for the small object than for the large object.

The latter outcome is expanded in Table 2, where we show the results of 1,800 simulated reach-and-grasp movements. The size of the object was varied at random from 2.5 to 10 cm, and the object was randomly positioned within a rectangular region (38 × 10 cm) of the work space at 20 cm in front of the stick figure's body midline. In three simulation runs of 600 movements each, g, the number of subdivisions for any joint's range of motion, was set to 100, 20, or 10 (i.e., grain, $1/g$, of .01, .05, or .10). As can be seen in Table 2, maximum aperture size was highly correlated with the size of the object to be grasped. Moreover, the slopes of the best fitting curves were less than 1.0 as reported by Marteniuk et al. (1990). The extent to which the slopes of the best fitting curves fell short of 1.0 depended on $1/g$. The less fastidious the planning (the larger the value of $1/g$), the more the slope fell below 1.0. By determining how the slope varied as a function of grain, slope = 1.0078 − 1.1713 ($1/g$), R^2 = .993, the slope of .77 reported by Marteniuk et al. can be obtained when $1/g$ equals .202. When $1/g$ is set to .10, the slope comes close to the value reported in a number of other studies (Bootsma, Marteniuk, Mackenzie, & Zaal, 1994; Chiefi & Gentilucci, 1993; Goodale, Jakobson, & Keillor, 1994; Paulignan, Jeannerod, Mackenzie, & Marteniuk, 1991; Servos, Goodale, & Jakobson, 1992; Smeets & Brenner, 1999; Zaal & Bootsma, 1993).

Besides showing that maximum finger aperture is larger for a large than for a small object, the simulations shown in Figures 5 and 6 demonstrate that the maximum aperture comes at a later time for the larger object. In general, the model predicts that with identical starting postures, maximum aperture size should come later in the movement as the size of the object to be grasped becomes larger. Several studies have reported such a relation (Gentilucci, Castiello, Corradini, Scarpa, Umilta, & Rizzolatti, 1991; Hofsten & Ronnqvist, 1993; Marteniuk et al., 1990). Our model predicts this finding because of the interaction between the main movement and the back-and-forth movement (see Figure 4).

Figure 7 presents more information about this outcome. This graph shows the results of simulations involving 600 grasping movements, all of which began with the same starting posture (and so the same initial aperture). What varied in these simulations was the size and position of the object to be grasped. For the majority of grasps, the moment of maximum aperture occurred later as the object size increased, as observed in the studies just cited.

Influence of Distance To Be Covered on the Manipulation Component

Figure 8 shows two more grasping movements—one to an object close to the starting positions of the fingers (Figure 8A) and the other to an object far from the starting positions of the fingers (Figure 8B). The corresponding aperture–time functions appear on the right side of the figure. No observable differences emerge between the aperture–time functions in these two examples. In general, the model predicts no systematic relation between maximum aperture time and distance to the object being grasped. In the literature, although we know of one study that reported a maximum aperture increase for larger distances (Jakobson & Goodale, 1991), most studies have found no systematic relationship between these two variables (Bootsma et al., 1994; Chiefi & Gentilucci, 1993; Paulignan et al., 1991; Zaal & Bootsma, 1993). Hence, the model again yields an outcome similar to what is observed.

Influence of Movement Speed on Maximum Aperture Size

Wing, Turton, and Fraser (1986) reported that maximum aperture increases with reaching speed. They interpreted this to mean that increased movement speed results in increased uncertainty about hand position. Participants opened the hand more, according to Wing et al. (1986), to compensate for this higher uncertainty. Wallace and Weeks (1988) replicated this relation and came to a similar conclusion.

Our model can account for greater hand opening with higher speed without appealing to compensation for uncertainty (see Figure 9). The reason is that joints for small effectors (finger joints) can be assumed to prefer quicker movements than joints for large effectors (elbow and shoulder joints; for supporting evidence,

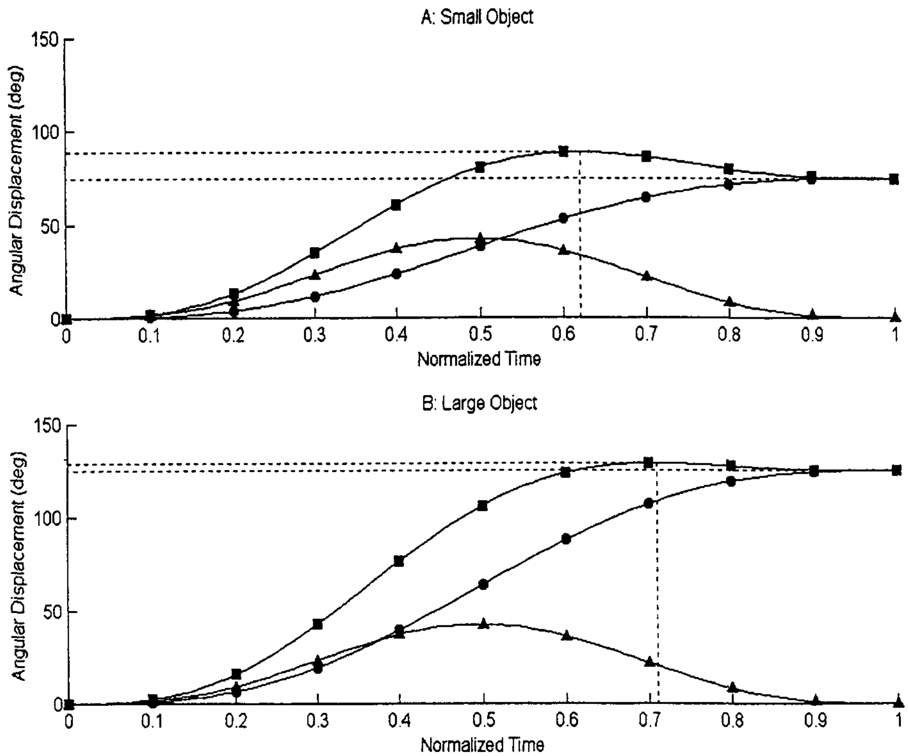

Figure 6. Theoretical basis for expecting maximum finger aperture to increase at a lower rate than size of the object being grasped. A: Reach to a small object. B: Reach to a large object. Circles, triangles, and squares correspond to main movements, via movements, and main plus via movements, respectively. The via movement is the same in the two cases. The distance between the two dashed horizontal lines, representing the degree of angular (aperture) overshoot, is larger for the small object than for the large object. Dashed vertical lines indicate moments of maximum aperture. deg = degrees.

see Hatsopoulos & Warren, 1996; Rosenbaum, Slotta, Vaughan, & Plamondon, 1991; Vaughan, Rosenbaum, Diedrich, & Moore, 1995). If rapid movements are required, the system relies more on finger joints and less on arm joints if possible, but if slower movements are required, the system relies more on arm joints and less on finger joints if possible. This explanation is not meant to exclude the possibility that uncertainty can affect finger aperture. Wing et al. (1986) observed increases of maximum aperture when participants closed their eyes, so there is reason to allow for an uncertainty effect. Our simulations merely show that greater finger widening at higher speeds may also stem from other sources.

Table 2
Relation Between Maximum Aperture (y) and Object Size (x) Indexed by Proportion of Variance Accounted For

Grain (1/*g*)	Best fitting regression line	R^2
.01	$y = 0.999x + 0.009$	1.000
.05	$y = 0.944x + 0.994$	.902
.10	$y = 0.893x + 2.188$	.809

Note. Table values are based on 1,800 simulated reach-and-grasp movements (600 simulated movements using each of three grains). g = the number of subdivisions for any joint's range of motion.

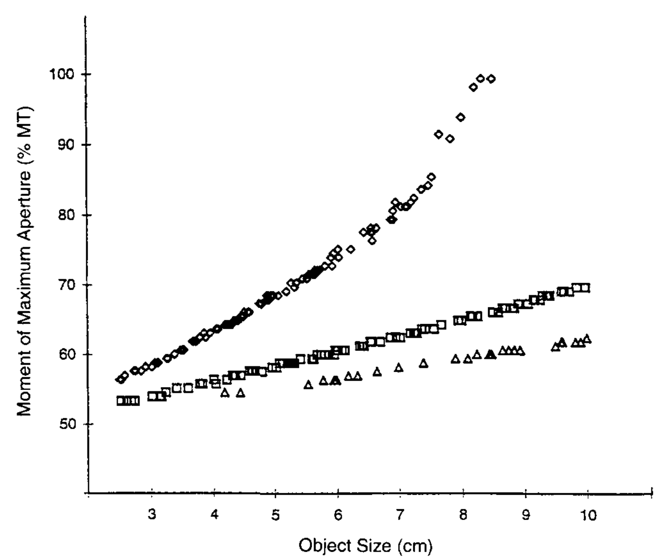

Figure 7. Moment of maximum aperture (expressed as a percentage of movement time; MT) as a function of object size. The data points are distinguished on the basis of an aperture overshoot index, obtained by summing the distances between the via angles and starting angles of the index finger and thumb joints. As the aperture overshoot index increased (diamonds → squares → triangles), the moment of maximum overshoot occurred earlier. In all cases, however, the moment of maximum aperture increased with object size.

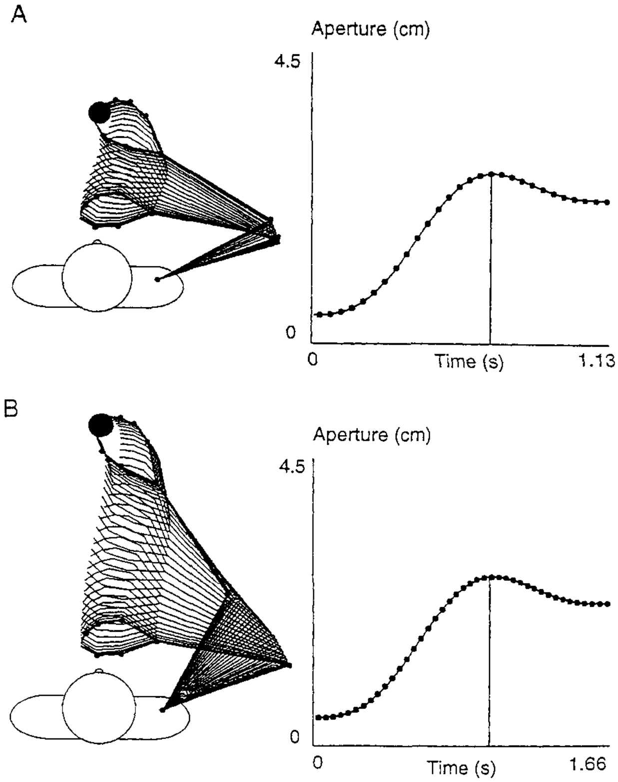

Figure 8. Reach-and-grasp movements to a near target (A) and to a far target (B). Corresponding aperture-versus-time functions appear on the right. The scale of the ordinate is linear and identical in the two cases.

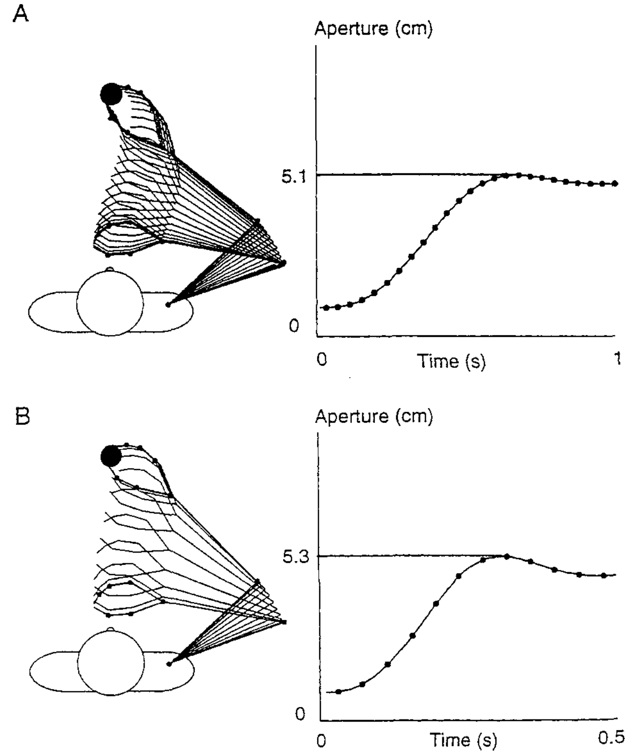

Figure 9. Reach-and-grasp movements to a fixed target from a fixed starting posture at a slow speed (A) and at a fast speed (B). Corresponding aperture-versus-time functions appear on the right. The faster movement yields a larger maximum aperture.

Evanescence of the Low-Velocity Phase of the Transport Component

Woodworth (1899) noted that simple pointing movements usually have two phases, a large-distance ballistic phase followed by a smaller distance homing-in phase. Jeannerod (1981, 1984) likewise identified a ballistic phase followed by a low-velocity phase in the tangential velocity profile of the wrist during prehension. Jeannerod (1981, 1984) also observed that the onset of the low-velocity phase usually coincides with the start of closure of the hand, which he suggested might be due to some mechanism that synchronizes the manipulation and transport components. Some authors (Wallace & Weeks, 1988) have failed to find a low-velocity phase, however, and have argued that it may not be an essential feature of prehension. This raises the question of why the low-velocity phase appears in some situations but not in others.

Figure 10 shows two reach-and-grasp movements in which the low-velocity phase is present. Recall that in Figure 4 no low-velocity phase appeared. The difference in outcomes provides a hint about why the low-velocity phase appears in some reaches but not in others. For the cases shown in Figure 10 the hand would have collided with the object had it not made a detour. To achieve such a detour, the shoulder and elbow joints had to follow a curved path in joint space, resulting in zero crossings in their angular velocity profiles, which in turn gave rise to a low-velocity phase for the tangential velocity of the wrist. By contrast, in Figure 4, the hand would not collide with the object if the shoulder and elbow

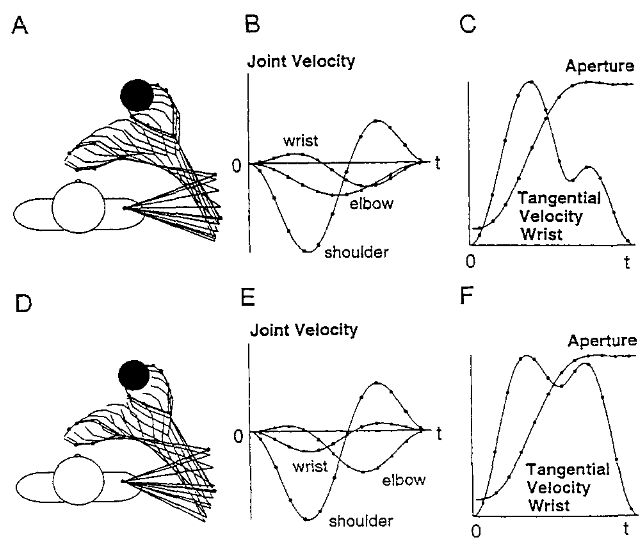

Figure 10. Examples of two grasping movements with low-velocity phases. A and D: Cartoons of the movements. B and E: Corresponding angular velocity functions of the shoulder, elbow, and wrist. C and F: Corresponding aperture–time and tangential wrist velocity functions. The ratio of proximal to distal joint expense factors was 4:1 for the upper panels and 1:1 for the lower panels. t = time.

followed straight-line trajectories through joint space, so there was no need for either joint to slow down and then speed up during the motion. No low-velocity phase was seen for this movement as a result. Together, these observations suggest that the collision-avoidance requirements of prehension tasks can account for the presence or absence of the low-velocity phase.

Timing of Maximum Aperture Size

For reach-and-grasp movements that have a low-velocity transport phase, the moment of maximum aperture of the fingers is likely to occur near the start of the low-velocity phase of the transport component (Jeannerod, 1981, 1984). Our model can yield this effect, as shown in Figure 10C and Figure 10F.

Grasping After Circumventing Intermediate Obstacles

Figure 11 shows that the stick figure is capable of grasping an object even when there is more than one object in the environment and when only one of the objects should be grasped. As shown in Figure 11, the stick figure can avoid obstacles on the way to a final grasp. This figure shows the culmination of what our model can achieve.

Fitting the Model to New Prehension Data

It is one thing to say one's model can yield results like those from previous studies. It is another to show that it can account quantitatively for new data. We turn now to this challenge by reporting a behavioral study of grasping that let us evaluate the goodness of fit of the model to trajectories of the hand and fingers in extrinsic space as well as rotations of the shoulder and elbow in intrinsic space.

Method

Four right-handed participants volunteered. Three were male and one was female. Their ages ranged from 24 to 32 years. Although 4 is a small number of participants, this number is common in studies such as this one where immense amounts of data are obtained for each participant.

Each participant was asked to move the hand from a starting position to grasp a cylindrical object as shown in Figure 12. The participant sat at a table raised to shoulder height so all movements could be made with just the shoulder, elbow, wrist, and fingers in the horizontal plane. At the start of each trial the participant's right arm rested comfortably on the surface, with the hand positioned 20 cm in front of the body midline and with the palm perpendicular to the table surface and facing the participant (i.e., the thumb was up and the little finger was in contact with the table). A cylinder, 3 cm wide and 9 cm high, was positioned at each of nine locations corresponding to distances of 20, 30, or 40 cm from the hand at angles of 45°, 90°, or 135° relative to the near edge of the table from the participant's perspective. Each experimental condition was tested twice, but only the second grasp was analyzed. The participant was asked to grasp the cylinder quickly and accurately, using a single, smooth gesture.

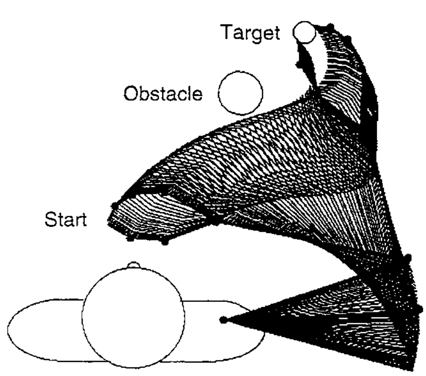

Figure 11. Example of a simulated reach-and-grasp movement performed in the presence of an intermediate obstacle.

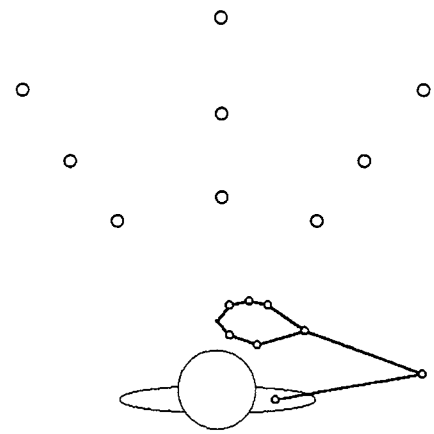

Figure 12. Top view of experimental setup. Circles indicate target locations.

Movements were recorded with an OPTOTRAK 3020 motion-tracking system (Northern Digital Corporation, Waterloo, Ontario, Canada). Five infrared emitting diodes (IREDs) were fixed to the participant's right shoulder, elbow, wrist, proximal lateral corner of the index fingernail, and proximal medial corner of the thumbnail. The xyz positions of the IREDs were sampled at a rate of 200 Hz with a spatial accuracy of better than 0.2 mm in each spatial dimension. IRED displacement data were filtered off-line with a third-order, zero phase lag, low-pass Butterworth filter (cutoff frequency = 8 Hz). The tangential wrist velocity and aperture time functions were derived to determine the start and end of the grasping movements. These were found by identifying the appropriate local velocity minima in these functions.

We focused both on the finger–thumb paths in extrinsic space and on the shoulder–elbow paths in intrinsic (joint) space. The finger and thumb paths were given by the displacements of the IREDs on the finger- and thumbnails. The angular displacement of the shoulder was derived by determining for each sample the angle between the line connecting the IREDs on the shoulder and elbow with the positive x-axis running parallel to the near edge of the table. The angular displacement of the elbow was derived by determining the angle between the line connecting the IREDs on the shoulder and elbow and the line connecting the IREDs on the elbow and wrist.

Results

The results presented here first concern the finger–thumb paths in extrinsic space and then concern the shoulder–elbow paths in intrinsic space. For the intrinsic space analysis, we focus only on the shoulder and elbow, omitting the wrist, because the shoulder and elbow were the prime movers for the task. Moreover, once the fingertip locations (in extrinsic space) and the shoulder and elbow angles (in intrinsic space) were known, no additional information was conveyed by the wrist.

Observed and modeled finger–thumb trajectories in extrinsic space. The finger and thumb trajectories of the 4 participants are shown in Figure 13. Each trajectory was time normalized to 100 data points by means of spline-function interpolation to facilitate comparison of the observed trajectories with the model-based trajectories and to facilitate comparison of the observed trajectories from the different participants. Our strategy for model evaluation was to compute mean square errors (MSEs) between every participant's trajectory and every other participant's trajectory to see how well each participant's data could predict the data of every other participant. We also computed the MSEs between model-based trajectories and every participant's trajectory to see whether the model could do as well as other participants in accounting for each participant's data.

After time normalization, the movements were modeled using the parameters listed in Table 1. The simulations were performed by giving the model the average initial posture of the participants and, for each task, a spatial description of the object to be grasped (i.e., its position and size). The model's task was the same as the participant's—to grasp the object. We allowed the model to perform each task with each of 27 combinations of expense factors for the shoulder, elbow, and wrist given by setting the expense factor of each of these three joints to 0.5, 1.0, or 1.5 times the expense factors of the finger joints, which were set arbitrarily to 1 (see the right-hand column in Table 1). Each model trajectory consisted of 100 x–y pairs corresponding to an instructed movement duration of 100 time units. Because each participant contributed 100 x–y pairs for each of nine targets, each time the model was fitted to the data, there were just three free parameters for 900 data points.

An example of modeled finger–thumb paths is shown in Figure 14. These paths were obtained with expense factors of the shoulder, elbow, and wrist set at 0.5, 0.5, and 1.5, respectively.

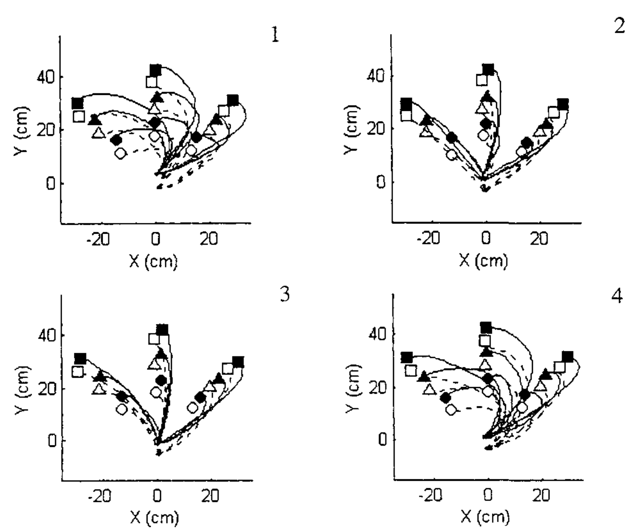

Figure 13. Observed finger paths (solid lines and closed markers) and thumb paths (dashed lines and open markers) of Participants 1–4. Circles, triangles, and squares correspond to the 20-, 30-, and 40-cm object distances, respectively.

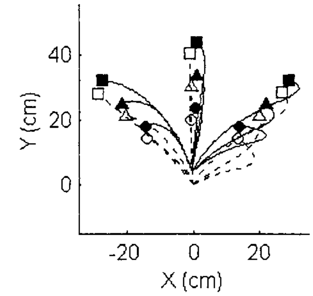

Figure 14. Modeled finger paths (solid lines and closed markers) and modeled thumb paths (dashed lines and open markers) from a simulation in which the expense factors for the shoulder, elbow, and wrist were, respectively, 0.5, 0.5, and 1.5 times the expense factor of the finger joints, which were all set arbitrarily to 1. Circles, triangles, and squares correspond to the 20-, 30-, and 40-cm object distances, respectively.

We compared the modeled and observed finger trajectories as well as the modeled and observed thumb trajectories in the following way. First we normalized the two trajectories with respect to their initial position by linearly shifting them to (0, 0). Next, we squared the distance between the trajectory samples at corresponding times for the corresponding tasks. Finally, we summed the squared deviations and divided the sum by 100 (i.e., the number of data points), yielding a mean sum squared error (MSE in squared centimeters), reflecting the dissimilarity between the two compared trajectories for each task. These MSEs were computed between every model-based trajectory and every participant's trajectory to see how well the model could predict each participant's data. We also computed the MSEs between every participant's trajectory and every other participant's trajectory to see how well each participant's data could be predicted by the data of every other participant.

Figure 15 shows the squared deviations for the finger trajectories as a function of normalized time. The squared deviations for the thumb trajectories are not shown but were very similar. As illustrated in Figure 15, the squared deviation functions were nonmonotonic. The squared deviations between model-generated and human-generated finger positions increased and then decreased as a function of time. Thus, any participant's finger position was usually better predicted by another participant's finger position at the end of the movement than during the course of the movement. The fact that the error for intermediate positions was generally as high for participant–participant comparisons as for model–participant comparisons suggests that the model may have done about as well as it could have when fitted to the participant's movement paths.

Observed and modeled shoulder–elbow trajectories in intrinsic space. The results just described pertained to the finger's and thumb's movements in extrinsic space. Complementary analyses pertained to the model's fits to the shoulder and elbow's movements in intrinsic (joint) space. These were important to consider because the model relates intrinsic planning to extrinsic performance, making it important to check that the model could account as well for joint-space movement paths as for extrinsic-space movement paths.

Figure 16 shows shoulder–elbow trajectories of the 4 participants. Note that these trajectories are for the same reaches as in

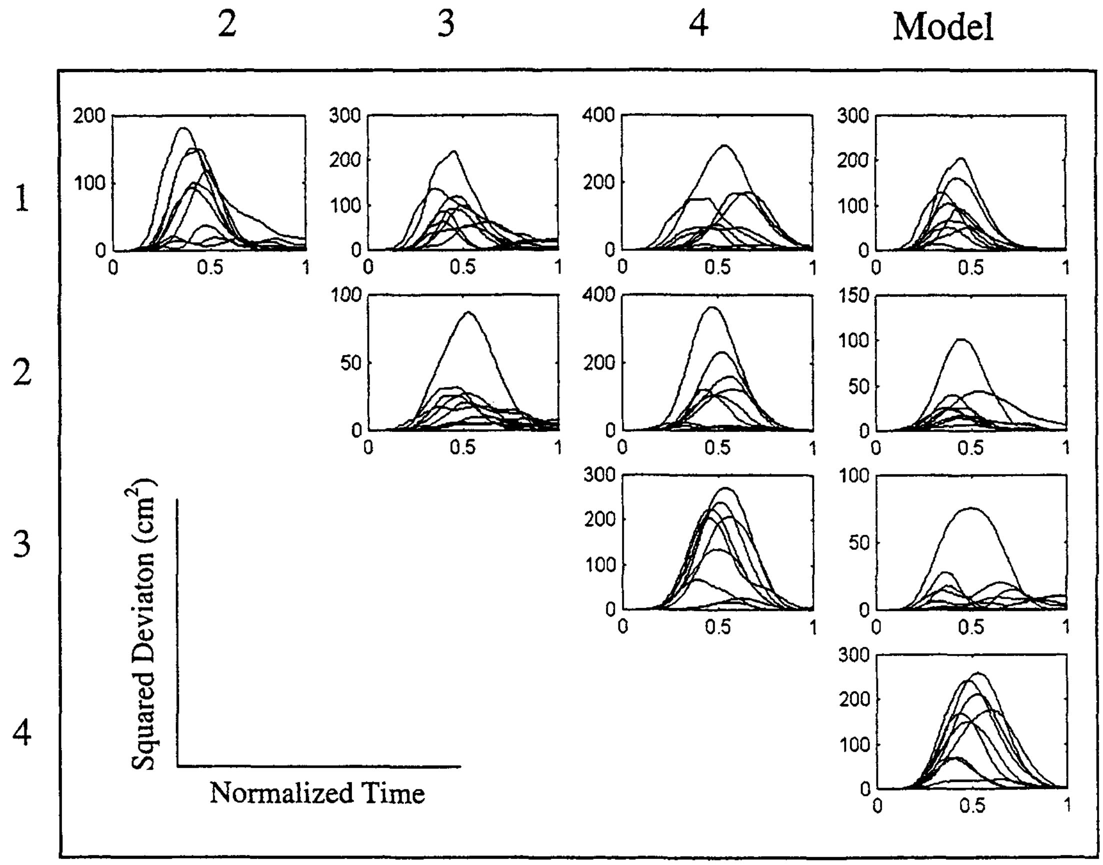

Figure 15. Squared deviations of finger–finger work-space trajectory comparisons as a function of normalized time. Each panel shows the results of trajectory comparisons for reaches to each of the nine targets. The four rows correspond to Participants 1–4. The four columns correspond to Participants 2–4 and one version of the model (whose shoulder, elbow, and wrist expense factors were set, respectively, to 0.5, 0.5, and 1.5 times the finger expense factors). The top left panel shows the squared deviations between Participant 2 and Participant 1, the top right panel shows the squared deviations between the model and Participant 1, and so on. Different ordinate scales are used to reveal the shapes of all the squared deviation functions. Other simulations yielded similar time-varying errors.

Figure 15. Figure 16 shows that for objects located behind the dorsum of the hand at the hand's start position (the 45° object-angle condition), the movements yielded highly curved joint-space paths. By contrast, for objects located in front of the hand at the hand's start position (the 135° object angle condition), the joint-space paths were more linear. These results were expected in view of the fact that when the object was initially behind the hand, circuitous movements were needed to avoid colliding with the object prior to grasping it. In contrast, when the object was initially in front of the hand, such circuitous movements were unnecessary. (To the best of our knowledge, this is the first study of prehension movements directed to objects located initially behind the hand.)

An example of modeled shoulder–elbow paths using the parameters listed in Table 1 is shown in Figure 17. These paths resulted from a simulation in which the expense factors of the shoulder, elbow, and wrist were 0.5, 0.5, and 1.5, respectively. The simulated shoulder–elbow paths shown in Figure 17 are comparable to those shown in Figure 16.

We evaluated the goodness of fit of these theoretical paths to the observed paths by computing the errors in joint space (MSEs in degrees squared) between the two paths, using the same procedure as for the observed and modeled finger–thumb trajectories. We also computed the MSEs between the joint-space paths of each pair of participants to see whether the model did as well in predicting participants' movements through joint space as other participants did.

The quality of the joint-space fits as a function of time appears in Figure 18, where it can be seen that the errors between the predicted and observed joint-space paths increased and then decreased, as was the case for the finger paths in extrinsic space (Figure 15). This nonmonotonic trend was evident regardless of whether the errors derived from fits of the model to any given participant's data or from fits of a participant's data to any other participant's data. Thus, the capacity of the model to predict the movements of the joints was about as good as the capacity of other participants to predict those movements.

The next figure, Figure 19, shows something we did not show for the fingertip data, although the outcome is similar. Figure 19 shows how the goodness of fit depended on the parameters used. The most important message to take from this figure is that the

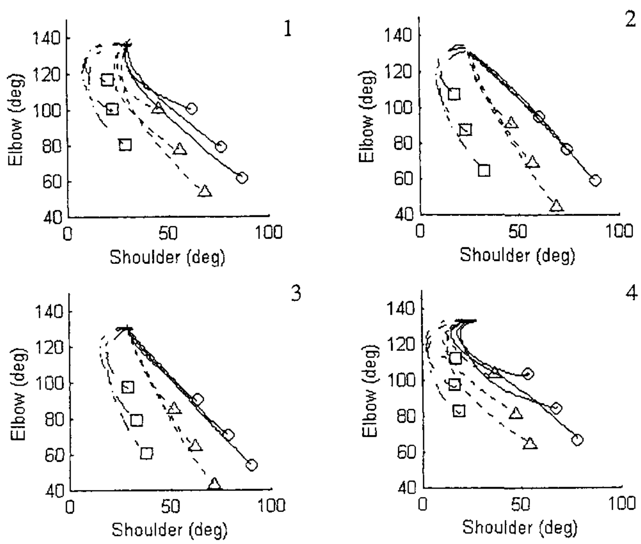

Figure 16. Observed shoulder–elbow paths for Participants 1–4. Squares, triangles, and circles correspond to the 45°, 90°, and 135° object angles, respectively. deg = degrees.

model-to-participant fitting errors were generally of the same magnitude as the participant-to-participant fitting errors. The fact that the model could generally predict participants' data as well as other participants could was not just a reflection of high noise in the data, because the fitting errors were only 2%, or 100 degrees squared, relative to the squared mean joint-space trajectory length of 4,900 degrees squared. (For the fingertip displacement data, the fitting errors were 1.5%, or 25 cm^2, relative to the squared mean fingertip trajectory length of 1,600 cm^2.) Moreover, the model was not equally predictive of participants' performance no matter what parameters were used. As shown in Figure 19, there were some parameter values for which the model failed to predict participants' data as well as other participants' data did. This means that the model was rejectable.

Visual inspection of Figure 19 suggests that variations in the model's parameters had consistent effects over participants. This impression was confirmed in an analysis of variance that evaluated the effects of shoulder, elbow, and wrist parameter values on mean squared deviations, with participants as the random factor. There were three values for each joint: 0.5, 1.0, or 1.5 times the finger expense factor, which, as mentioned earlier, was arbitrarily set to 1. The three-way interaction of Shoulder × Elbow × Wrist was highly significant, $F(8, 24) = 6.56, p < .0001$, consistent with the hypothesis that variation of the parameters had reliable effects on the goodness of fit to the shoulder–elbow trajectories of individual participants. Globally, the best fit was achieved with shoulder, elbow, and wrist expense factors of 0.5, 0.5, and 1.5, respectively.

Final Remarks About Prehension

The foregoing section has shown that the model can account quantitatively as well as qualitatively for detailed features of the coordination of the effectors in reaching and grasping. Qualitatively, the model captures most of the observed kinematic effects observed in previous studies of prehension. Quantitatively, it accounts for new prehension data for finger and thumb motions in extrinsic space and for shoulder and elbow rotations in intrinsic space. Unlike previous prehension theories, which have focused on the positions of the wrist and fingertips without regard to the activity of more proximal effectors (e.g., Hoff & Arbib, 1993), the present model provides a way of generating movements that involve all the needed joints. Because the present model can produce complex reach-and-grasp movements, such as reaches for objects behind the hand, it takes the study of prehension a step forward.

A few items deserve mention before we leave the topic of prehension. First, we have not reported the consequences of dynamic deadline setting in the generation of possible goal and via postures. Our simulations have shown, as expected, that when similar reaches are required in successive trials, the deadline for planning decreases. The system becomes an expert for similar reaching tasks tested in succession because, as more and more trials require similar reaches, there is less benefit of generating new postures. Previously stored postures are available for the reaches, so the planning deadline decreases. In addition, the movements have lower travel costs, in keeping with observed practice-related increases in movement efficiency (Sparrow & Irizarry-Lopez, 1987).

The second item that deserves mention concerns the independence of joint motions assumed in the model. We have treated all the joints as autonomous, primarily for convenience (see Table 1). However, it is well-known that there are linkages between effectors (Turvey, 1990). As some of our simulations have shown (see the earlier discussion surrounding Figure 4), our model yields behaviors that have been ascribed to functional linkages, though in our simulations no linkages were built in. From this outcome, we do not mean to suggest that linkages are unimportant. On the contrary, treating all the joints as autonomous has allowed us to see where functional linkages, whether real or merely apparent, may originate. Interestingly, the simulation program ran more quickly when we coupled the proximal and distal joints of the index finger, reflecting the high correlations between those joints, and when we coupled the proximal and distal joints of the thumb, also reflecting the high correlations between those joints. Speeding up a program on a serial computer by using coupling does not constitute proof that coupling is computationally useful for the highly parallel nervous system. Still, our experience suggests that even if functional linkages are not strictly necessary, they are helpful.

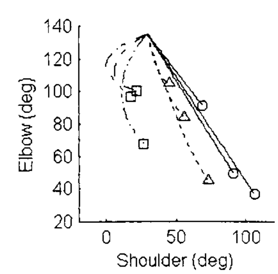

Figure 17. Modeled shoulder–elbow paths from a simulation in which the expense factors for the shoulder, elbow, and wrist were, respectively, 0.5, 0.5, and 1.5 times the expense factor of the finger joints, all of which were arbitrarily set to 1. Squares, triangles, and circles correspond to the 45°, 90°, and 135° object angles, respectively. deg = degrees.

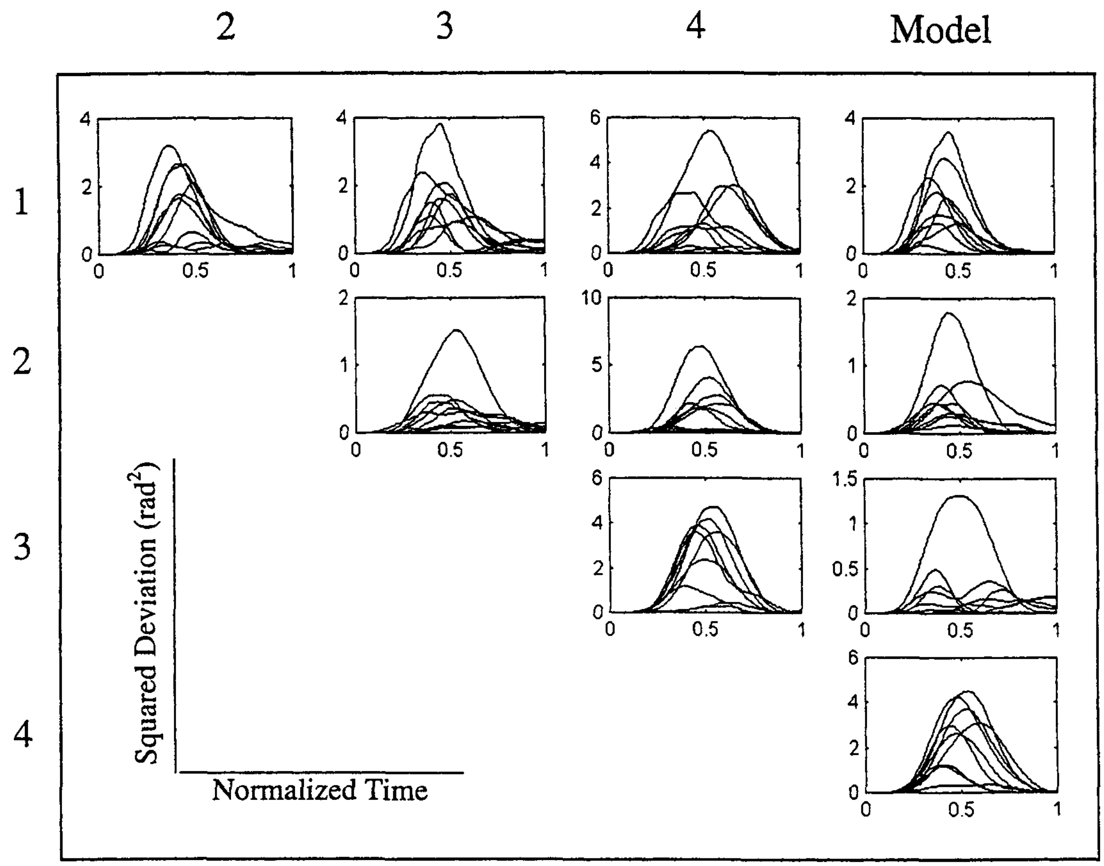

Figure 18. Squared deviations of shoulder–elbow joint-space trajectory comparisons as a function of normalized time. Each panel shows the results of trajectory comparisons for reaches to each of the nine targets. The four rows correspond to Participants 1–4. The four columns correspond to Participants 2–4 and one version of the model (whose shoulder, elbow, and wrist expense factors were set, respectively, to 0.5, 0.5, and 1.5 times the finger expense factors). The top left panel shows the squared deviations between Participant 2 and Participant 1, the top right panel shows the squared deviations between the model and Participant 1, and so on. Different ordinate scales are used to reveal the shapes of all the squared deviation functions. Other simulations yielded similar time-varying errors.

A third item pertains to precedents for the ideas behind our prehension simulations. The idea of a functional distinction between planning hand and arm activity was promoted by Arbib, Iberall, and Lyons (1985); Hoff and Arbib (1993); MacKenzie and Iberall (1994); Iberall and Fagg (1996); and Uno, Fukumura, Suzuki, and Kawato (1993). The idea that different hand and arm postures are selected on the basis of demands of the task to be performed follows not only from our own general line of theorizing but also from work of Klatzky and her colleagues (Klatzky, Pellegrino, McCloskey, & Lederman, 1993) showing that a small set of basic manual activities can be hypothesized for haptic tasks. A central idea from Klatzky et al. (1993) is that different postures are adopted depending on the fit of possible movements to the demands of the task to be performed. The choice of whether to pinch, poke, pat, or clench, for example, depends on the chance that each of these activities can achieve the necessary physical transformations for the task at hand. Our notion of selecting candidate hand and arm postures according to a constraint hierarchy is similar.

A final remark about reaching and grasping is that, although the preceding discussion has focused on the coordination of the arm, hand, and fingers, the mechanisms adduced here may also apply to other forms of prehension. Specifically, the model may also apply to tasks that involve grasping without prototypical grasping effectors (see Flanagan & Tresilian, 1993). Sometimes actors grasp objects with two hands rather than with the fingers of one hand, or they use the upper arm and torso (e.g., when holding a newspaper under one's arm), or they may use the torso alone (e.g., when pushing an object against the wall with one's chest while using both hands to make a ceiling repair). These capabilities illustrate the great flexibility—indeed the great creativity—that is brought to bear in everyday physical activity. The present model provides one account of how this creativity may emerge. Although we have not explicitly modeled grasping with effectors other than the finger and thumb, it would be straightforward to do so. Postures would be evaluated according to their capacity for satisfying the current grasping task, and the postures that would be promoted would be

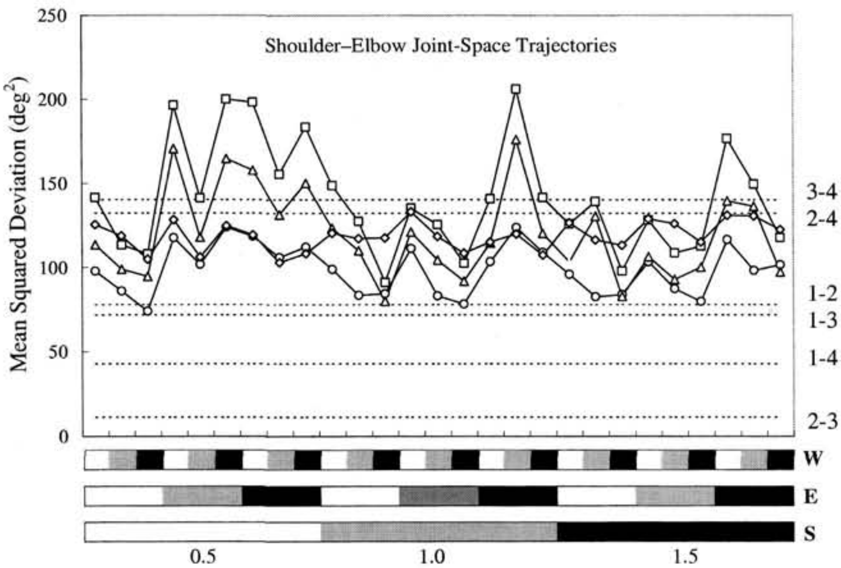

Figure 19. Mean sum of squared deviations between modeled and observed shoulder–elbow joint-space trajectories. Each horizontal dashed line corresponds to a participant–participant comparison (participant numbers are given on the right) for reaches over 100 time values to the nine targets. The plotted points are the mean squared deviations between the shoulder–elbow joint-space trajectories of the model and of Participant 1 (circles), Participant 2 (triangles), Participant 3 (squares), and Participant 4 (diamonds). Twenty-seven versions of the model were tested. These had expense factors of 0.5 (white horizontal bars), 1.0 (gray horizontal bars), and 1.5 (black horizontal bars) for the shoulder (S), elbow (E), and wrist (W). Points above the top horizontal dashed line correspond to parameter combinations for which the model predicted participants' data more poorly than any participant did. All other points correspond to parameter combinations for which the model predicted participants' data about as well as other participants did. deg = degrees.

ones that are physically possible given whatever limits are imposed on the effectors normally used for grasping.

General Discussion

This article has presented a model of motor planning that updates an earlier model (Rosenbaum et al., 1995). Whereas the earlier model relied on weighted averaging of stored postures to identify a goal posture, the new model relies on a two-stage process of selecting a most promising stored posture and then generating a possibly better posture to serve as the goal posture. Evaluation of the stored and generated postures is done with reference to a constraint hierarchy that defines the task to be performed. The model relies on internal simulation (forward modeling) of possible movements to the goal posture from the starting posture to test for collisions with obstacles. Collision-free movements are generated by searching for via postures that allow for acceptable movements composed of movements made to and from the via posture while a movement is made from the start posture to the goal posture. As was shown here, this approach makes it possible to provide qualitative accounts of a broad range of kinematic phenomena from previous prehension studies and to fit the kinematics of complex reach-and-grasp movements both in intrinsic and extrinsic space.

In the remainder of the article we undertake two final aims. First, we consider similarities and differences between our claims and those of others. Second, we discuss remaining challenges.

Our Claims and Those of Others

Claims of Guenther, Hampson, and Johnson (1998)

One approach we did not discuss before was advanced by Guenther, Hampson, and Johnson (1998). These authors were concerned with the control of speech, although they indicated that their perspective could also extend to manual control.

Guenther et al. (1998) argued against motor planning models that emphasize final-posture planning. Their main arguments were twofold. First, they said that physical actions are rarely performed for the sake of achieving goal postures. Second, they suggested that a source of evidence for final-posture planning, achievement of invariant final postures, is misleading. Guenther and Micci Barreca (1997) challenged the earliest version of the posture-based model (Rosenbaum, Englebrecht, Bushe, & Loukopoulos, 1993) on these grounds.

We consider each of these points in turn to see how and whether they vitiate our approach. First, in connection with the argument that physical actions are rarely performed for the sake of achieving goal postures, although we understand this claim, we fail to see why it indicates that final postures are not planned. In the case of speech, the normal aim may indeed be to generate invariant acoustic targets, and for manual pointing and manual prehension the normal aim may be to achieve invariant spatial targets. Indeed, in our constraint hierarchies, achieving spatial targets (or more precisely bringing specified contact points acceptably close to spatial targets) generally takes priority over finding final postures or movements to those final postures. Saying that there are higher purposes than achieving final postures does not obviate the need for finding motoric means to achieve those higher purposes.

In connection with Guenther et al.'s (1998) second argument—that achievement of invariant final postures is a misleading source of evidence for final posture planning—Guenther et al. granted that some studies have shown relative invariance of final arm postures even when considerable variation was physically possible (e.g., Cruse, Brüwer, & Dean, 1993). However, Guenther et al. did not find these results persuasive. Quoting from an earlier report by Guenther and Micci Barreca (1997), they suggested that

> the only invariant target for a reaching movement is a spatial target of the hand and . . . movement trajectories are planned in spatial coordinates, but . . . the mapping from planned spatial trajectories to the muscle contractions needed to carry them out contains biases that favor certain arm postures over others. (p. 612)

In the Guenther et al. article about speech motor control, the authors made an analogous claim, arguing that just as one can be misled into thinking that final-posture planning is primary for manual control, one can be misled into thinking that articulatory or constrictive targets are primary for speech. What a final-posture or articulatory target cannot explain, according to Guenther et al., is that speakers can immediately adapt to bite blocks and other perturbations to produce desired utterances. Furthermore, even without perturbations, different oral configurations allow for production of the same phoneme.

The suggestions made by Guenther et al. (1998) raise an interesting challenge to the view that the planning of final postures is primary. However, our model does not say that final-posture planning is primary, nor does it rely on invariance of adopted postures. Our model predicts that different final postures will be adopted depending on initial positions. It says this because final postures are planned partly with respect to travel costs from starting postures. Final postures have been found to depend on initial postures (Desmurget, Gréa, & Prablanc, 1998; Soechting et al., 1995), and the way they do accords with what our model predicts (Fischer et al., 1997). Furthermore, our notion of the constraint hierarchy allows, and indeed in most cases of reaching to spatial targets requires, that spatial constraints take priority over postural ones. Thus, our model is consistent with the claim that spatial targeting is more important than postural targeting. In fact, a recent adaptation study (Rogosky & Rosenbaum, 2000) explicitly tested the hypothesis that posture targeting is subordinated to spatial targeting. That study yielded positive conclusions about this hypothesis and its fit with the posture-based model.

With regard to speech, although our model does not address speaking per se, it would place the adoption of final vocal tract postures (or constrictions) secondary to the achievement of desired sounds, just as it places the adoption of final limb and trunk postures secondary to the achievement of desired hand (or contact point) locations. A strength of our model is that it allows for the fact that there are some tasks for which postures (manual or oral) do come first, such as gesturing or making faces, and others for which they do not, such as hitting a desired elevator button. Collectively, these observations lead us to conclude that it is misleading to say, as Guenther et al. (1998) did, that goal postures are not planned. In our view goal postures are planned but with different priorities depending on the task.

Claims About Obstacle Avoidance

Now we turn to the relation of our model's claims about obstacle avoidance to others' claims about this topic. Our approach shares features with other psychologically oriented approaches to obstacle avoidance. Like Mel (1990, 1991), we invoke internal simulation as a basis for collision checking. The notion that actors can mentally simulate movements has gained considerable support from both behavioral and physiological studies (see Jeannerod, 1994, for a review). Our claim that movements must be withheld if they are expected to result in collision is reminiscent of the idea that successful obstacle-avoidance behavior requires inhibition of initial movement impulses. This form of inhibition may be lacking in babies (Diamond & Gilbert, 1989; Lockman, 1990; Lockman & Thelen, 1993).

Claims About Cost Containment Rather Than Optimization

One way our model differs from others in the motor control field is that it does not rely on optimization. A great deal of research, mainly stimulated by Flash and Hogan's (1985) proposal that the motor system minimizes mean squared jerk, has relied on the idea that one or more cost might be minimized in movement production (e.g., Kawato, 1996a, 1996b; Soechting et al., 1995). Our approach differs from this one in that it relies on cost containment rather than minimization. By selecting goal and via postures that allow for acceptable performance, we *satisfice* (Simon, 1955) rather than optimize.

Claims About Elimination by Aspects

The way satisficing is achieved in our model has implications for research on decision making and search. Goal postures and via postures are identified in our model through a weeding out procedure known as elimination by aspects (Tversky, 1972). Research on decision making has shown that elimination by aspects is more powerful than other choice methods in complex problem situations (Janis & Mann, 1996). That it has proven useful here attests to the power of the elimination-by-aspects approach. Moreover, to the extent that our model is an accurate depiction of biological motor planning, our application of elimination by aspects to motor planning extends the domain of that method to a lower level of decision making (the perceptual-motor level) than it has occupied before. This outcome might be taken as an indirect source of support for the view that the computational substrates of perceptual-motor functioning and intellectual functioning are fundamentally similar (e.g., Calvin, 1994; Piaget, 1952; Rosenbaum, Carlson, & Gilmore, 2001).

Remaining Challenges

Our model still faces challenges. One is to enable it to generate the same written or drawn output with any effectors. This example of "motor equivalence" is a core challenge for any model of motor control. The model of Rosenbaum et al. (1995) was extended to achieve handwriting with different effectors (Meulenbroek, Rosenbaum, Thomassen, Loukopoulos, & Vaughan, 1996), and the new model can presumably be extended this way as well. The principal means used by Meulenbroek et al. (1996) to produce connected strokes in writing and drawing was cascading of discrete movements directed to target locations (points of maximum curvature in the required graphic output) through different via locations (points of minimum curvature in the required graphic output). Cascading of movements to ensure smoothly connected strokes has been used in other writing models (Bullock, Grossberg, & Mannes, 1993; Edelman & Flash, 1987; Morasso & Mussa-Ivaldi, 1982; Morasso, Mussa-Ivaldi, & Ruggiero, 1983), and continuity of performance in other domains (e.g., speech) might be similarly achieved by allowing planning of future movements to occur while earlier movements are under way.

A second challenge facing the model is to extend it from two spatial dimensions to three. More specifically, there is a need to extend the model so that, instead of merely generating movements in a plane, it can also generate movements in a volume. So far, the model has only generated movements in one plane at a time—the sagittal plane for pointing and the horizontal place for reaching and grasping. Extending the model to three spatial dimensions should be straightforward, however. This fact actually provides another, previously unmentioned, reason to embrace a posture-based approach to motion planning.

A great deal of discussion has occurred recently in motor-control circles about the noncommutativity of joint rotations. The term *noncommutativity* refers to the fact that the order in which joints are rotated in three orthogonal dimensions affects the final position of the limb (Gielen, Vrijenhoek, & Flash, 1997). To gain familiarity with this problem, consider a spatial coordinate frame centered on your right shoulder such that the x-, y-, and z-axes correspond to the right–left, in–out, and up–down dimensions, respectively. While standing, perform the following two series of shoulder rotations. Series A should be performed as follows.

A1. Begin with your right arm dangling by your side with the palm facing in.

A2. Raise your extended arm 90° about the x-axis. Your arm will be straight out in front of you, and your palm will face left.

A3. Rotate your extended arm 90° about the y-axis. Your arm will now be straight out in front of you, and your palm will face down.

A4. Finally, rotate your extended arm 90° about the z-axis. Your arm will now be directed to your right, and your palm will still face down.

Next, perform Series B.

B1. As before, begin with your right arm dangling by your side with the palm facing in.

B2. Rotate your extended arm 90° about the z-axis. Your arm will be by your side, and your palm will face forward.

B3. Raise your extended arm 90° about the x-axis. Now your arm will be straight out in front of you, and your palm will face up.

B4. Finally, rotate your extended arm 90° about the y-axis. Your arm will be in front of you, and your palm will face left.

The final position in Series B is different from the final position in Series A, though the rotations in the three spatial coordinates were the same; only their order differed. If joint rotations were commutative, final positions would not depend on rotation order, as is the case, for example, in addition, where it does not matter whether one adds 1 to 2 or 2 to 1.

Noncommutativity of joint rotations is a problem for motion-based approaches to motion planning because, unless joints are rotated in a fixed order, there is no guarantee that the same final posture will be reached on different occasions, even given the same starting posture. Because one rarely has the luxury of always moving from the same starting posture, the unpredictability of final positions is compounded if one takes a motion-based approach. By contrast, in a posture-based motion planning system, these problems disappear. Moving from a starting posture to an already identified goal posture via interpolation through joint space, as assumed in our model, circumvents the noncommutativity problem because the goal position is defined ahead of time, not a posteriori based on the movement that is attempted. This implies that the extension of our approach to movement in three spatial dimensions is simpler than it would be if we used a motion-based planning system. (We thank C. C. A. M. Gielen, personal communication, January 2000, and J. Smeets, personal communication, April 2000, for confirming this point.)

A third challenge for the model is to extend it to dynamics—that is, to have it generate forces (muscle tensions) as well as joint angles and be sensitive to gravitational and other forces. This challenge was mentioned at the end of the Rosenbaum et al. (1995) article, but we felt that basic computational issues, principally concerning search, had to be dealt with first. In principle, the constraint hierarchy can include requirements concerning forces, in which case the approach developed here should extend to kinetics. The computations involved in inverse dynamics are formidable, however, which is one reason why we have confined ourselves so far to kinematics.

A fourth challenge for the model is to account for variability in movement (see Meyer, Smith, Kornblum, Abrams, & Wright, 1990; Wing, 1993). Currently, the only source of noise in the model is randomness of initially stored postures, which we have used in some simulations (not reported here). Adding variability to the processes assumed in the model could allow us to evaluate the model in interesting ways. For example, if obstacle-avoidance movements were composed of two independent movement paths, the variability of those movements might be similarly decomposed. (We thank R. Flanagan, personal communication, May 1998, for pointing this out.)

A fifth challenge for the model is to cast it in a neural network as others working in this area have already done (e.g., Bullock, Grossberg, & Guenther, 1993; Kawato, 1996a; Mel, 1990, 1991; Morasso & Sanguineti, 1995; Mussa-Ivaldi, Morasso, & Zaccaria, 1988; Sporns & Edelman, 1993). Apart from the fact that a model should have neural or quasi-neural elements to be brainlike, a neural-network style of representation may make it easier to achieve something our model allows but does not yet achieve—bidirectional communication between levels of control. Specifically, our computer simulation does not yet have a means of altering a goal posture if subsequent movement planning indicates that a movement to the initially chosen goal posture will be very costly. In principle, we could build this into our current architecture so a new goal posture is sought after an unwieldy movement turns out to be the only means of reaching it, after which a new movement to that second goal posture could be chosen, and so on. The problem with this approach is that if the second goal posture and associated movement were no better than the first, or if the third goal posture and associated movement were no better than the first or second, there could be a serious backtracking problem like the one noted earlier in connection with Mel's (1990, 1991) model. A neural-network model, or more specifically, a model that allows for bidirectional communication during planning, might be able to avoid this problem as Kawato's (1996a, 1996b) neural-network model; which explicitly allows for bidirectional cross talk, already does.

A sixth challenge for the model is to address more fully the issue of movement learnability. Our model relies on stored or learned postures. The strongest form of our model would say that movements cannot be learned. A weaker form would say that they can be. If the weaker form of the model were adopted, the learning of movements could entail learning parameters of trajectories given some trajectory prototype, or learning different movement cost functions in different contexts, or both. If movements were learned, they could either be linked to stored goal posture or not. A number of investigators have explicitly modeled memory for movement (e.g., Bullock, Grossberg, & Guenther, 1993; Houk, Buckingham, & Barto, 1996; Jordan, Flash, & Arnon, 1994; Lukashin, Wilcox, & Georgopoulos, 1994). It makes sense that information about movements could be learned, for how else could a violinist, say, recall the timing and manner of his or her bow strokes for a particular piece? Some motor activities may not be based on representations of final postures. For example, although saccadic eye movements are elicited by position error signals, pursuit eye movements are elicited by retinal velocity error signals. Given these considerations, it would be unwise to make the strong claim that goal postures can be learned but movements cannot be. On the other hand, the fact that final positions are better remembered than movements raises the question of why that outcome has been obtained so often.

A speculative answer to this question is that physically arriving at a final position is generally a higher level goal than physically moving toward a final position (e.g., pushing an elevator button depends more on how the finger comes in contact with the button than on how it arrives at the contact point). This may be why it is so natural to use the term *end* synonymously with *purpose.*

It is useful here to make an analogy to language, where it is almost universally accepted that there are different levels of language production. The semantic level is higher than the movement (utterance) level, for example (Dell, 1986; Fromkin, 1971). It is well-known that in recalling sentences, the information that is preserved the longest corresponds to the highest level (Sachs, 1967). Thus, surface forms are forgotten quickly, whereas sentence meanings are retained longer. This analogy suggests that goal postures might be specified before movements, as assumed in our model, because goal postures occupy a higher functional level than movements do. Furthermore, just as there are different ways to verbally express the same idea, there are different ways to move to the same goal posture. Identifying different ways of expressing an idea might rely on retrieval of stored utterances or on generating utterances through rule or rulelike systems. Similarly, identifying different ways of moving to a goal posture might rely on retrieval of stored movements or on generating movements de novo using rules or cost functions like the ones we have discussed. The model we have developed does not resolve this issue, but may help stimulate future research on it.

References

Abend, W., Bizzi, E., & Morasso, P. (1982). Human arm trajectory formation. *Brain, 105,* 331–348.

Arbib, M. A., Iberall, T., & Lyons, D. (1985). Coordinated control programs for movements of the hand. In A. W. Goodwin & I. Darian-Smith (Eds.), *Hand function and the neocortex* (pp. 111–129). Berlin, Germany: Springer-Verlag.

Atkeson, C. G., & Hollerbach, J. M. (1985). Kinematic features of unrestrained arm movements. *The Journal of Neuroscience, 5,* 2318–2330.

Baud-Bovy, G., & Viviani, P. (1998). Pointing to kinesthetic targets in space. *The Journal of Neuroscience, 18,* 1528–1545.

Bizzi, E., Hogan, N., Mussa-Ivaldi, F. A., & Giszter, S. (1992). Does the nervous system use equilibrium-point control to guide single and multiple joint movements? *Behavioral and Brain Sciences, 15,* 603–613.

Bootsma, R. J., Marteniuk, R. G., Mackenzie, C. L., & Zaal, F. T. J. M. (1994). The speed–accuracy trade-off in manual prehension: Effects of amplitude, object size and object width on kinematic characteristics. *Experimental Brain Research, 98,* 535–541.

Bootsma, R. J., & Van Wieringen, P. C. (1992). Spatio–temporal organisation of natural prehension. *Human Movement Science, 11,* 205–215.

Bryson, A. E., & Ho, Y. C. (1975). *Applied optimal control.* New York: Hempshire.

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.

Bullock, D., Grossberg, S., & Mannes, C. (1993). A neural network model for cursive script production. *Biological Cybernetics, 70,* 15–28.

Calvin, W. H. (1994, April). The emergence of intelligence. *Scientific American, 271,* 101–107.

Castiello, U. (1996). Grasping fruit: Selection for action. *Journal of Experimental Psychology: Human Perception and Performance, 22,* 582–603.

Chiefi, S., & Gentilucci, M. (1993). Coordination between the transport and grasp component during prehension movements. *Experimental Brain Research, 94,* 471–477.

Craig, J. J. (1986). *Introduction to robotics.* Reading, MA: Addison-Wesley.

Cruse, H., Brüwer, M., & Dean, J. (1993). Control of three- and four-joint arm movement: Strategies for a manipulator with redundant degrees of freedom. *Journal of Motor Behavior, 25,* 131–139.

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.

Dell, G. S. (1986). A spreading activation theory of retrieval in language production. *Psychological Review, 93,* 222–233.

Denier van der Gon, J. J., & Thuring, J. P. (1965). The guiding of human writing movements. *Kybernetik, 2,* 145–148.

Desmurget, M., Gréa, H., & Prablanc, C. (1998). Final posture of the upper limb depends on the initial position of the hand during prehension movements. *Experimental Brain Research, 119,* 511–516.

Desmurget, M., Prablanc, C., Rossetti, Y., & Arzi, M. (1995). Postural and synergic control for three-dimensional movements of reaching and grasping. *Journal of Neurophysiology, 74,* 905–910.

Diamond, A., & Gilbert, J. (1989). Development as progressive inhibitory control of action: Retrieval of a contiguous object. *Cognitive Development, 4,* 223–249.

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.

Dornay, M., Uno, Y., Kawato, M., & Suzuki, R. (1996). Minimum muscle-tension change trajectories predicted by using a 17-muscle model of the monkey's arm. *Journal of Motor Behavior, 2,* 83–100.

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

Feldman, A. G. (1980). Superposition of motor programs: I. Rhythmic forearm movements in man. *Neuroscience, 5,* 81–90.

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.

Flanagan, J. R., & Tresilian, J. R. (1993). Grip-load force coupling: A general control strategy for transporting objects. *Journal of Experimental Psychology: Human Perception and Performance, 20,* 944–957.

Flash, T., & Henis, E. (1991). Arm trajectory modification during reaching towards visual targets. *Journal of Cognitive Neuroscience, 3,* 220–230.

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

French, A. P. (1971). *Vibrations and waves.* New York: Norton.

Fromkin, V. A. (1971). The non-anomalous nature of anomalous utterances. *Language, 47,* 27–52.

Gentilucci, M., Castiello, U., Corradini, M. L., Scarpa, M., Umilta, C., & Rizzolatti, G. (1991). Influence of different types of grasping on the transport component of prehension movements. *Neuropsychologia, 29,* 361–378.

Ghez, C., Gordon, J., Ghilardi, M. F., Christakos, C. N., & Cooper, S. E. (1990). Roles of proprioceptive input in the programming of arm trajectories. *Cold Spring Harbor Symposia on Quantitative Biology, 55,* 837–847.

Ghez, C., Gordon, J., Ghilardi, M. F., & Sainburg, R. (1990). Contributions of vision and proprioception to accuracy in limb movements. In M. S. Gazzaniga (Ed.), *The cognitive neurosciences* (pp. 549–564). Cambridge, MA: MIT Press.

Ghilardi, M. F., Gordon, J., & Ghez, C. (1995). Learning a visuomotor transformation in a local area of work space produces directional biases in other areas. *Journal of Neurophysiology, 73,* 2535–2539.

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, April 5). Equilibrium-point control hypothesis examined by measured arm stiffness during multijoint movement. *Science, 272,* 117–120.

Goodale, M. A., Jakobson, L. S., & Keillor, J. M. (1994). Differences in the visual control of pantomized and natural grasping movements. *Neuropsychologia, 10,* 1159–1178.

Gottlieb, G. L. (1998). Rejecting the equilibrium-point hypothesis. *Motor Control, 2,* 10–12.

Gottlieb, G. L., Song, Q., Hong, D. A., Almeida, G. L., & Corcos, D. (1996). Coordinating movement at two joints: A principle of linear covariance. *Journal of Neurophysiology, 75,* 1760–1764.

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.

Haggard, P., & Richardson, J. (1996). Spatial patterns in the control of human arm movements. *Journal of Experimental Psychology: Human Perception and Performance, 22,* 42–62.

Harris, C. M., & Wolpert, D. M. (1998). Signal-dependent noise determines motor planning. *Nature, 394,* 780–784.

Hatsopoulos, N. G., & Warren, W. H. (1996). Resonance tuning in rhythmic arm movements. *Journal of Motor Behavior, 28,* 3–14.

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.

Hebb, D. O. (1949). *The organization of behavior: A neuropsychological theory.* New York: Wiley.

Henis, E. A., & Flash, T. (1992). A computational mechanism to account for averaged modified hand trajectories. In J. E. Moody, S. J. Hansen, & R. P. Lippmann (Eds.), *Neural information processing systems* (Vol. 4, pp. 619–626). San Mateo, CA: Morgan Kaufman.

Hoff, B., & Arbib, M. A. (1993). Models of trajectory formation and temporal interaction of reach and grasp. *Journal of Motor Behavior, 25,* 175–192.

Hofsten, C. von, & Ronnqvist, L. (1993). The structuring of neonatal arm movements. *Child Development, 64,* 1046–1057.

Hogan, N., & Flash, T. (1987). Moving gracefully: Quantitative theories of motor coordination. *Trends in the Neurosciences, 10,* 170–174.

Hollerbach, J. M. (1981). An oscillation theory of handwriting. *Biological Cybernetics, 39,* 139–156.

Houk, J. C., Buckingham, J. T., & Barto, A. G. (1996). Models of the cerebellum and motor learning. *Behavioral and Brain Sciences, 19,* 368–383.

Iberall, T., & Fagg, A. H. (1996). Neural network models for selecting hand shapes. In A. M. Wing, P. Haggard, & R. Flanagan (Eds.), *Hand and brain: Neurophysiology and psychology of hand movement* (pp. 243–264). San Diego, CA: Academic Press.

Jakobson, L. S., & Goodale, M. A. (1991). Factors affecting higher-order movement planning: A kinematic analysis of human prehension. *Experimental Brain Research, 86,* 199–208.

Janis, I., & Mann, L. (1996). Satisficing. In J. Billsberry (Ed.), *The effective manager: Perspectives and illustrations* (pp. 157–159). London: Sage.

Jaric, S., Corcos, D. M., Gottlieb, G. L., Ilic, D. B., & Latash, M. L. (1994). The effects of practice on movement distance and final position reproduction: Implications for the equilibrium-point control of movements. *Experimental Brain Research, 100,* 353–359.

Jeannerod, M. (1981). Intersegmental coordination during reaching at natural objects. In J. Long & A. Baddeley (Eds.), *Attention and performance* (Vol. 9, pp. 153–169). Hillsdale, NJ: Erlbaum.

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

Jeannerod, M. (1988). *The neural and behavioral organization of goal-directed movements.* Oxford, England: Oxford University Press.

Jeannerod, M. (1994). The representing brain: Neural correlates of motor intention and imagery. *Brain and Behavioral Science, 17,* 187–245.

Jeannerod, M., & Biguer, B. (1982). Visuomotor mechanisms in reaching within extrapersonal space. In D. J. Ingle, M. A. Goodale, & R. J. Mansfield (Eds.), *Analysis of visual behavior* (pp. 387–409). Cambridge, MA: MIT Press.

Jordan, M. I., Flash, T., & Arnon, Y. (1994). A model of the learning of arm trajectories from spatial deviations. *Journal of Cognitive Neuroscience, 6,* 359–376.

Kawato, M. (1996a). Bidirectional theory approach to integration. In T. Inui & J. L. McClelland (Eds.), *Attention and performance: Vol. 16. Information integration* (pp. 335–367). Cambridge, MA: MIT Press.

Kawato, M. (1996b). Trajectory formation in arm movements: Minimization principles and procedures. In H. N. Zelaznik (Ed.), *Advances in motor learning and control* (pp. 225–259). Champaign, IL: Human Kinetics.

Klatzky, R. L., Fikes, T. G., & Pellegrino, J. W. (1995). Planning for hand shape and arm transport when reaching for objects. *Acta Psychologica, 88,* 209–232.

Klatzky, R. L., Pellegrino, J., McCloskey, B., & Lederman, S. J. (1993). Cognitive representations of functional interactions with objects. *Memory & Cognition, 21,* 294–303.

Kuperstein, M. (1988, March 11). Neural model of adaptive hand–eye coordination for single postures. *Science, 239,* 1308–1311.

Lackner, J. R., & DiZio, P. (1994). Rapid adaptation to Coriolis force perturbations of arm trajectory. *Journal of Neurophysiology, 72,* 299–313.

Lacquaniti, F., Terzuolo, C., & Viviani, P. (1983). The law relating the kinematic and figural aspects of drawing movements. *Acta Psychologica, 54,* 115–130.

Lashley, K. S. (1942). The problem of cerebral organization in vision. *Biological Symposia, 7,* 301–322.

Latash, M. L. (1993). *Control of human movement.* Champaign, IL: Human Kinetics.

Lockman, J. J. (1990). Perceptuo-motor coordination in infancy. In C.-A. Hauert (Ed.), *Developmental psychology: Cognitive, perceptuo-motor and neuropsychological perspectives. Advances in psychology* (Vol. 64, pp. 85–111). Amsterdam: North-Holland.

Lockman, J. J., & Thelen, E. (1993). Developmental biodynamics: Brain, body, behavior connections. *Child Development, 64,* 953–959.

Logan, G. D. (1988). Toward an instance theory of automatization. *Psychological Review, 95,* 492–527.

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

Lukashin, A. V., Wilcox, G. L., & Georgopoulos, A. P. (1994). Overlapping neural networks for multiple motor engrams. *Proceedings of the National Academy of Sciences, 91,* 8651–8654.

MacKenzie, C. L., & Iberall, T. (1994). *The grasping hand.* Amsterdam: North-Holland.

Marr, D. (1982). *Vision: A computational investigation into the human representation and processing of visual information.* New York: Freeman.

Marteniuk, R. G., Leavitt, J. L., MacKenzie, C. L., & Athenes, S. (1990). Functional relationships between grasp and transport components in a prehension task. *Human Movement Science, 9,* 149–176.

Mel, B. W. (1990). *Connectionist robot motion planning.* San Diego, CA: Academic Press.

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., Smith, J. E. K., Kornblum, S., Abrams, R. A., & Wright, C. E. (1990). Speed–accuracy tradeoffs in aimed movements: Toward a theory of rapid voluntary action. In M. Jeannerod (Ed.), *Attention and performance XIII: Motor representation and control* (pp. 173–226). Hillsdale, NJ: Erlbaum.

Morasso, P. (1981). Spatial control of arm movements. *Experimental Brain Research, 42,* 223–227.

Morasso, P., & Mussa-Ivaldi, F. A. (1982). Trajectory formation and handwriting: A computational model. *Biological Cybernetics, 45,* 131–142.

Morasso, P., Mussa-Ivaldi, F. A., & Ruggiero, C. (1983). How a discontinuous mechanism can produce continuous movement in trajectory formation and handwriting. *Acta Psychologica, 54,* 83–98.

Morasso, P., & Sanguineti, V. (1995). Self-organizing body schema for motor planning. *Journal of Motor Behavior, 27,* 52–66.

Mussa-Ivaldi, F. A., Morasso, P., & Zaccaria, R. (1988). Kinematic networks: A distributed model for representing and regularizing motor redundancy. *Biological Cybernetics, 60,* 1–16.

Nelson, W. L. (1983). Physical principles for economies of skilled movements. *Biological Cybernetics, 46,* 135–147.

Osu, R., Uno, Y., Koike, Y., & Kawato, M. (1997). Possible explanations for trajectory curvature in multijoint arm movements. *Journal of Experimental Psychology: Human Perception and Performance, 23,* 890–913.

Paulignan, Y., Jeannerod, M., Mackenzie, C., & Marteniuk, R. (1991). Selective perturbation of visual input during prehension movements: II. The effects of changing object size. *Experimental Brain Research, 87,* 407–420.

Paulignan, Y., MacKenzie, C., Marteniuk, R., & Jeannerod, M. (1990). The coupling of arm and finger movements during prehension. *Experimental Brain Research, 79,* 431–435.

Pellegrino, J. W., Klatzky, R. L., & McCloskey, B. P. (1989). Time course of preshaping for functional responses to objects. *Journal of Motor Behavior, 21,* 307–316.

Piaget, J. (1952). *The origins of intelligence in children* (2nd ed.; M. Cook, Trans.). New York: International Universities Press.

Piaget, J. (1954). *The construction of reality in the child.* New York: Basic Books.

Polit, A., & Bizzi, E. (1978, September 29). Processes controlling arm movements in monkeys. *Science, 201,* 1235–1237.

Prablanc, C., Echallier, J. E., Jeannerod, M., & Komilis, E. (1979). Optimal response of eye and hand motor systems in pointing at a visual target: II. Static and dynamic cues in the control of hand movement. *Biological Cybernetics, 35,* 183–187.

Raibert, M. H. (1977). *Motor control and learning by the state-space model* (Tech. Rep. No. AI-TR-439). Cambridge: Massachusetts Institute of Technology, Artificial Intelligence Laboratory.

Rizzolatti, G. (1987). Functional organization of Inferior Area 6. *Ciba Foundation Symposium, 132,* 171–186.

Rizzolatti, G., Camarda, R., Fogassi, L., Gentilucci, M., Luppino, G., & Matelli, M. (1988). Functional organization of Inferior Area 6 in the macaque monkey: II. Area F5 and the control of distal movements. *Experimental Brain Research, 71,* 491–507.

Rogosky, B. J., & Rosenbaum, D. A. (2000). Frames of reference for human perceptual-motor coordination: Space-based versus joint-based adaptation. *Journal of Motor Behavior, 32,* 297–304.

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., Loukopoulos, L. D., Engelbrecht, S. E., Meulenbroek, R. G. J., & Vaughan, J. (1996). Integration of extrinsic space and motor space. In T. Inui & J. L. McClelland (Eds.), *Attention and performance: Vol. 16. Information integration in perception and communication* (pp. 315–333). Cambridge, MA: MIT Press.

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* (Vol. 13, pp. 321–342). Hillsdale, NJ: Erlbaum.

Rosenbaum, D. A., Meulenbroek, R. G. J., & Vaughan, J. (1996). Three approaches to the degrees of freedom problem in reaching. In A. M. Wing, P. Haggard, & R. Flanagan (Eds.), *Hand and brain: Neurophysiology and psychology of hand movement* (pp. 169–185). San Diego, CA: Academic Press.

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., Vaughan, J., & Elsinger, C. (1999). Approaching grasping from different perspectives. *Motor Control, 3,* 289–297.

Rosenbaum, D. A., Meulenbroek, R. G. J., Vaughan, J., & Jansen, C.

(1999). Coordination of reaching and grasping by capitalizing on obstacle avoidance and other constraints. *Experimental Brain Research, 128,* 92–100.

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

Rosenbaum, D. A., Vaughan, J., Barnes, H. J., & Jorgensen, M. J. (1992). Time course of movement planning: Selection of hand grips for object manipulation. *Journal of Experimental Psychology: Learning, Memory, and Cognition, 18,* 1058–1073.

Rosenbaum, D. A., Vaughan, J., Jorgensen, M. J., Barnes, H. J., & Stewart, E. (1993). Plans for object manipulation. In D. E. Meyer & S. Kornblum (Eds.), *Attention and performance: Vol. 14. A silver jubilee: Synergies in experimental psychology, artificial intelligence and cognitive neuroscience* (pp. 803–820). Cambridge, MA: MIT Press.

Rosenbaum, D. A., Vaughan, J., Meulenbroek, R. G. J., & Jansen, C. (1999). Cognitive psychological modelling of movement planning. *Cognitive Studies: Bulletin of the Japanese Cognitive Science Society, 6,* 274–289.

Rouiller, E. M., Hepp-Reymond, M. C., & Wiesendanger, M. (Eds.). (1999). Neural basis of hand dexterity [Special issue]. *Experimental Brain Research, 128*(1–2).

Sabes, P. N., & Jordan, M. I. (1997). Obstacle avoidance and a perturbation sensitivity model for motor planning. *The Journal of Neuroscience, 15,* 7119–7128.

Sachs, J. (1967). Recognition memory for syntactic and semantic aspects of a connected discourse. *Perception & Psychophysics, 2,* 437–442.

Saling, M., Alberts, J., Stelmach, G., & Bloedel, J. R. (1998). Reach-to-grasp movements during obstacle avoidance movements. *Experimental Brain Research, 118,* 251–258.

Savelsbergh, G. J. P., & Whiting, H. T. A. (1988). The effect of skill level, external frame of reference and environmental changes in one-handed catching. *Ergonomics, 31,* 1655–1663.

Schneider, K., Zernicke, R. F., Schmidt, R. A., & Hart, T. J. (1989). Changes in limb dynamics during the practice of rapid arm movements. *Journal of Biomechanics, 22,* 805–817.

Servos, P., Goodale, M. A., & Jakobson, L. S. (1992). The role of binocular vision in prehension: A kinematic study. *Vision Research, 32,* 1513–1521.

Simon, H. (1955). A behavioral model of rational choice. *Quarterly Journal of Economics, 69,* 99–118.

Sittig, A. C., Denier van der Gon, J. J., & Gielen, C. C. A. M. (1987). The contribution of afferent information on position and velocity to the control of slow and fast human forearm movements. *Experimental Brain Research, 67,* 33–40.

Smeets, J. B. J., & Brenner, E. (1999). A new view on grasping. *Motor Control, 3,* 237–271.

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 Press.

Smyth, M. M., & Marriott, A. M. (1982). Vision and proprioception in simple catching. *Journal of Motor Behavior, 14,* 143–152.

Soechting, J. F., Buneo, C. A., Herrmann, U., & Flanders, M. (1995). Moving effortlessly in three dimensions: Does Donders' law apply to arm movement? *The Journal of Neuroscience, 15,* 6271–6280.

Sparrow, W. A., & Irizarry-Lopez, V. M. (1987). Mechanical efficiency and metabolic cost as measures of learning a novel gross motor task. *Journal of Motor Behavior, 19,* 240–264.

Sporns, O., & Edelman, G. (1993). Solving Bernstein's problem: A proposal for the development of coordinated movement by selection. *Child Development, 64,* 960–981.

Thiel, E. van, Meulenbroek, R. G. J., & Hulstijn, W. (1998). Path curvature in workspace and in joint space: Evidence for coexisting coordinative rules in aiming. *Motor Control, 2,* 331–351.

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., Fukumura, N., Suzuki, R., & Kawato, M. (1993). Integration of visual and somatosensory information for preshaping hand in grasping movements. *Advances in Neural Information Processing Systems, 5,* 311–318.

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.

Von Holst, E. (1973). *The behavioral physiology of man and animals.* Coral Gables, FL: University of Miami Press.

Wallace, S. A., & Weeks, D. L. (1988). Temporal constraints in the control of prehensile movement. *Journal of Motor Behavior, 20,* 81–105.

Wiesendanger, M., Kazennikov, O., Perrig, S., & Kaluzny, P. (1996). Two hands—One action: The problem of bimanual coordination. In A. M. Wing, P. Haggard, & R. Flanagan (Eds.), *Hand and brain: Neurophysiology and psychology of hand movement* (pp. 283–300). San Diego, CA: Academic Press.

Wing, A. M. (1993). The uncertain motor system: Perspectives on the variability of movement. In D. E. Meyer & S. Kornblum (Eds.), *Attention and performance: Vol. 14. Synergies in experimental psychology, artificial intelligence, and cognitive neuroscience* (pp. 709–744). Cambridge, MA: MIT Press.

Wing, A. M., & Fraser, C. (1983). The contribution of the thumb to reaching movements. *Quarterly Journal of Experimental Psychology: Human Experimental Psychology, 35A,* 297–309.

Wing, A. M., Haggard, P., & Flanagan, R. (Eds.). (1996). *Hand and brain: Neurophysiology and psychology of hand movement.* San Diego, CA: Academic Press.

Wing, A. M., Turton, A., & Fraser, C. (1986). Grasp size and accuracy of approach in reaching. *Journal of Motor Behavior, 18,* 245–260.

Wolpert, D. M., Ghahramani, Z., & Jordan, M. I. (1994). Perceptual distortion contributes to the curvature of human reaching movements. *Experimental Brain Research, 98,* 153–156.

Woodworth, R. S. (1899). The accuracy of voluntary movement. *Psychological Monographs, 3,* 1–114.

Worringham, C. J. (1993). Predicting motor performance from variability measures. In K. M. Newell & D. M. Corcos (Eds.), *Variability and motor control* (pp. 53–63). Champaign, IL: Human Kinetics.

Wright, C. E. (1990). Generalized motor programs: Reexamining claims of effector independence in writing. In M. Jeannerod (Ed.), *Attention and performance* (Vol. 13, pp. 294–320). Hillsdale, NJ: Erlbaum.

Zaal, F. T. J. M. (1995). *On prehension: Toward a dynamical account of reaching and grasping movements.* Unpublished doctoral dissertation, Free University Amsterdam.

Zaal, F. T. J. M., & Bootsma, R. J. (1993). Accuracy demands in natural prehension. *Human Movement Science, 12,* 339–345.

Received November 24, 1996
Revision received April 27, 2000
Accepted July 13, 2000 ■