Human movement generation based on convergent flow fields: a computational model and a behavioral experiment

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Humans can move a hand smoothly on a straight or curved path towards a target while being able to adjust on-line to a changing goal position. How can we plan and generate such a movement such that we are still able to adapt to a dynamic environment? Next-state planning models have addressed this question by computing the control command from a function of the current state and goal; so far, however, these models have been restricted to straight trajectories (Shadmehr and Wise, 2005). Here, we present a new computational model for generating arbitrary movements that adapts to a new goal with a single parameter. Furthermore, we present a behavioral experiment with switching targets demonstrating that the curves resulting from the switch can be explained by our model. Our work combines ideas from pattern generation with dynamic systems and the observation of convergent force fields that control a frog leg after spinal stimulation.

The discovery of spinal force fields suggests a combined control and planning strategy (Bizzi et al., 1991). The total effect of inverse dynamics and muscle elasticity results in these force fields whose equilibrium points can be controlled by the nervous system. If the brain knows the structure of these fields, it may plan to move a limb on a desired trajectory by appropriately sequencing and superimposing the convergent fields. Indeed, work in the frog provides evidence that the force fields are modulated by time-varying pulse or step functions (Giszter et al., 1993).

For our model, we use acceleration fields instead of force fields. We assume simple linear fields, $\mathbf{K}(\mathbf{c}_i - \mathbf{x}) - \mathbf{D}\mathbf{v}$, where the vectors $\mathbf{x}$ and $\mathbf{v}$ are the current position and velocity of the end-effector, e.g., hand; $\mathbf{c}_i$ are the equilibrium points of the fields; $\mathbf{K}$ is a constant positive-definite matrix, and $\mathbf{D}$ is chosen such that the system is critically damped. Each field is weighted by a Gaussian pulse function ψ_i varying over time; the total field is a superposition of weighted local fields. To guarantee convergence to a goal position $\mathbf{g}$, we add a field around $\mathbf{g}$ and increase its relative weight during the movement. The resulting time-varying acceleration is

$$\dot{\mathbf{v}} = u\,\mathbf{K}\left(\frac{\sum_i \psi_i(u)(\mathbf{c}_i + \mathbf{x}_0)}{\sum_i \psi_i(u)} - \mathbf{x}\right) + (1-u)\mathbf{K}(\mathbf{g} - \mathbf{x}) - \mathbf{D}\mathbf{v} \;, \tag{1}$$

where $\mathbf{x}_0$ is the starting point of the movement; adding $\mathbf{x}_0$ makes the equation translation invariant. Instead of time as explicit variable, this equation is modulated by a phase variable u, as in the dynamic-movement-primitive (DMP) model (Ijspeert et al., 2003). This variable goes from 1 towards 0 with $\dot{u} \propto -u$. Similar to the DMP, the centers $\mathbf{c}_i$ are chosen such that the resulting motion $\mathbf{x}(t)$ is close to a desired trajectory. This minimization can be solved efficiently since finding $\mathbf{c}_i$ is a linear regression problem with non-linear basis functions ψ_i. Once a movement is mastered by finding all $\mathbf{c}_i$, we can adapt to a different goal just by switching the variable $\mathbf{g}$.

Our behavioral experiment studies this adaptation to a new goal $\mathbf{g}$. Three subjects participated (right-handed, male, age 26-30). They were seated in front of a drawing tablet (9x12") and looked at a computer screen (Figure 1). The experiment consists of two phases. First, the subjects practiced tracking a given curve (spiral of half-circle) on the screen. Feedback was given about the pen's position. Second, only start and end point of the curve were shown; and subjects were instructed to quickly move the pen from start to goal along a comfortable curve resembling the previously trained one. In two thirds of trials, randomly, 200 ms after movement onset, the goal switched to a different position. To compare the resulting behavior with the model, the variables $\mathbf{c}_i$ were computed given the mean curve to the original goal. The mean goal-switching curves can be explained by changing, during the movement, the vector $\mathbf{g}$ in (1) to the new goal position (Figure 2).

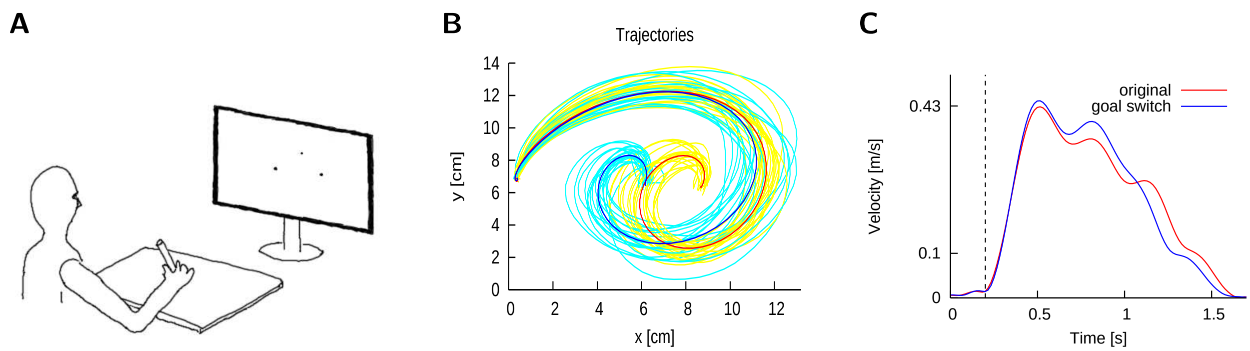

Figure 1: Experimental setup and task. (A) Subjects sit with a drawing tablet in front of a screen. After practicing a target movement, they see start and end-point (goal) of the movement. Visual feedback is given of the current position of the pen. (B) Raw trajectories and their mean values for one subject shown for two conditions: no goal switch (red) and goal switch (blue). (C) Mean tangential velocities corresponding to data in B. The dashed line marks the time of goal switching (200 ms after movement onset).

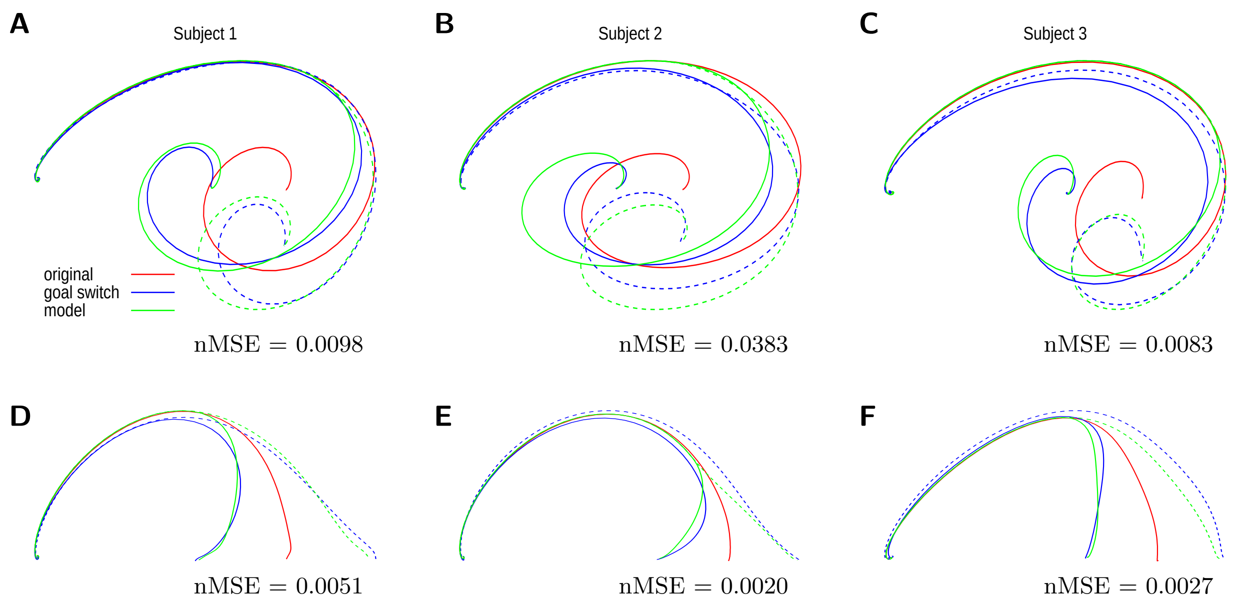

Figure 2: Mean trajectories (red and blue) for three subjects compared with our new computational model (green). For each target curve, the goal switched to either of two different positions; depending on these positions, the resulting curves are solid or dashed. The green curves are obtained just by switching the variable **g** at a computed switch-time that results in the minimal normalized mean square error (nMSE) between model and observed goal-switch curve. For all subjects and curves, the optimal switch time was between 390 and 610 ms after the goal switch.

References

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