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Behavioral Dynamics of Human Locomotion

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Gibson (1979) argued that "control lies not in the brain, but in the animal-environment system." To make good on this claim, we must show how adaptive behavior emerges from the interactions of an agent with a structured environment guided by occurrent information. Here we attempt to model the behavioral dynamics of human walking and show how locomotor paths emerge "online" from simple laws for steering and obstacle avoidance. Our approach is inspired by Schöner, Dose, and Engels's (1995) control system for mobile robots.

By *behavioral dynamics,* we mean a description of the time evolution of observed behavior. Assume that goal-directed behavior can be described by a few *behavioral variables,* which define a *state space* for the system. Goals correspond to *attractors* in state space to which trajectories converge, whereas states to be avoided correspond to *repellors* from which trajectories diverge. The problem is to formalize a system of differential equations, or *dynamical system,* whose solutions capture the observed behavior.

We take the current heading direction ϕ and turning rate $\dot{\phi}$ as behavioral variables, assuming travel at a constant speed v (see Figure 1). From the agent's current (x, z) position, a goal lies in the direction ψ_g at a distance d_g; an obstacle may also lie in direction ψ_o at a distance d_o. The simplest description of steering toward a goal is for the agent to bring the *heading error* between the current heading direction and the goal direction to zero ($\phi - \psi_g = 0$), which defines an attractor in state space.

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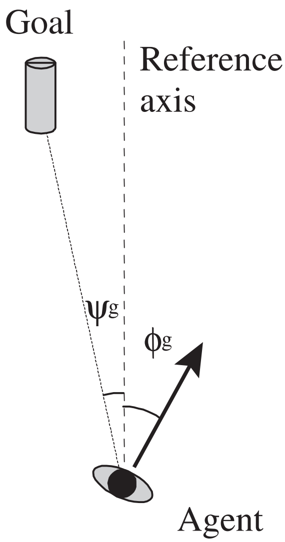

FIGURE 1 Definition of variables.

Conversely, the simplest description of obstacle avoidance is to increase the heading error between the current heading and the obstacle direction ($\phi - \psi_o > 0$), defining a repellor. In addition, nearby obstacles must be avoided before distant ones, so distance (or time to contact) is also likely to influence behavior.

To measure how people walk to a goal and avoid an obstacle, we (Fajen & Warren, 2003) performed a series of experiments in a large virtual environment. We then modeled this behavior and tried to predict the routes that people take in more complex situations. When steering to a stationary goal, participants turn onto a straight path (Figure 2a) and turn more rapidly when the goal is at a greater initial angle or a closer distance. Their angular acceleration increases linearly with goal angle and decreases exponentially with goal distance. The time series of heading error converge to zero from all initial conditions (Figure 2b) such that the goal direction behaves like an attractor of heading.

We modeled this behavior as an angular "mass-spring" system. To get an intuition, imagine that the agent's current heading direction is attached to the goal direction by a damped spring whose stiffness is modulated by the goal distance. Angular acceleration $\ddot{\phi}$ is thus a function of both heading error ($\phi - \psi_g$) and goal distance (d_g):

$$\ddot{\phi} = -b\dot{\phi} - k_g(\phi - \psi_g)(e^{-c_1 d_g} + c_2). \tag{1}$$

The "damping" term b resists turning. The "stiffness" term reflects the finding that angular acceleration increases linearly with heading error, and the k_g parameter determines the slope of this function. Finally, the attractiveness of the goal decreases exponentially with distance, where c_1 determines the rate of decay and c_2 a minimum angular acceleration for distant goals. Least-squares fits to the mean time series yielded $b = 3.25$, $k_g = 7.50$, $c_1 = 0.40$, and $c_2 = 0.40$.

Simulations generate locomotor paths that are very close to the human data (Figure 3a) and time series that converge to zero in a similar manner (Figure 3b). The fits averaged $r^2 = .98$ over all conditions, indicating that the model successfully captures the behavioral dynamics of turning to a goal.

Now consider how people avoid an obstacle en route to a goal (Fajen & Warren, 2003). Once again, both the initial angle and distance of the obstacle influenced their path (Figure 4a). In this case, the angular acceleration decreased exponentially with both heading error and obstacle distance. The time series of heading error (Figure 4b) shows that the curves diverge from zero in all conditions such that the direction of the obstacle behaves like a repellor.

To model this behavior, we simply added an obstacle component to the previous equation. Imagine that the heading direction is repelled from the obstacle direction by another spring. At any moment, the current heading is the resultant of all spring forces acting on the agent. Angular acceleration is thus a function of the heading error ($\phi - \psi_o$) and obstacle distance (d_o):

$$\ddot{\phi} = -b\dot{\phi} - k_g(\phi - \psi_g)(e^{-c_1 d_g} + c_2) + k_0(\phi - \psi_0)(e^{-c_3|\phi-\psi_0|})(e^{-c_4 d_0}). \qquad (2)$$

The obstacle "stiffness" term reflects the finding that angular acceleration decreases exponentially with a rightward or leftward heading error; the amplitude of this function is determined by the parameter k_o and its decay rate by c_3. The stiffness again decreases exponentially with obstacle distance, where c_4 is the decay rate. We fit the extended model to the mean time series for heading error yielding

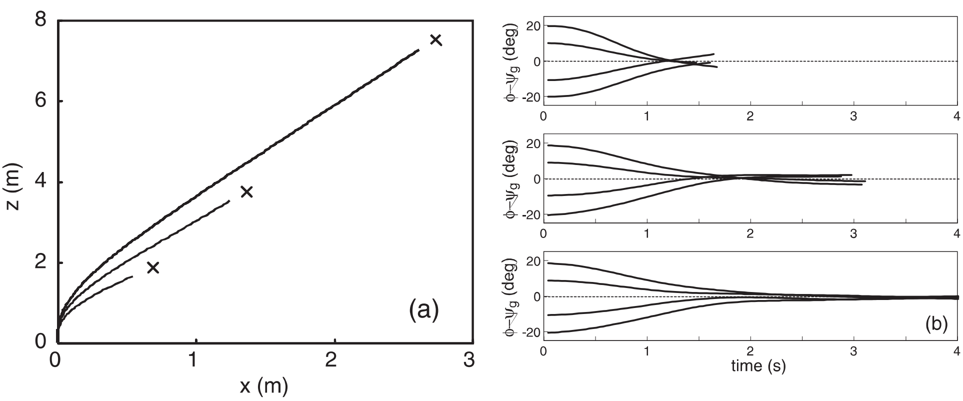

FIGURE 2 Walking to a goal at a distance of 2, 4, or 8 m. (a) Mean paths with an initial goal angle of 20°. (b) Mean time series of goal angle from initial values of ±10° or 20°. s = seconds. From "Behavioral Dynamics of Steering, Obstacle Avoidance, and Route Selection," by B. R. Fajen and W. H. Warren, 2003, *Journal of Experimental Psychology: Human Perception and Performance, 29,* pp. 343–362. Copyright 2003 by the American Psychological Association. Reprinted with permission.

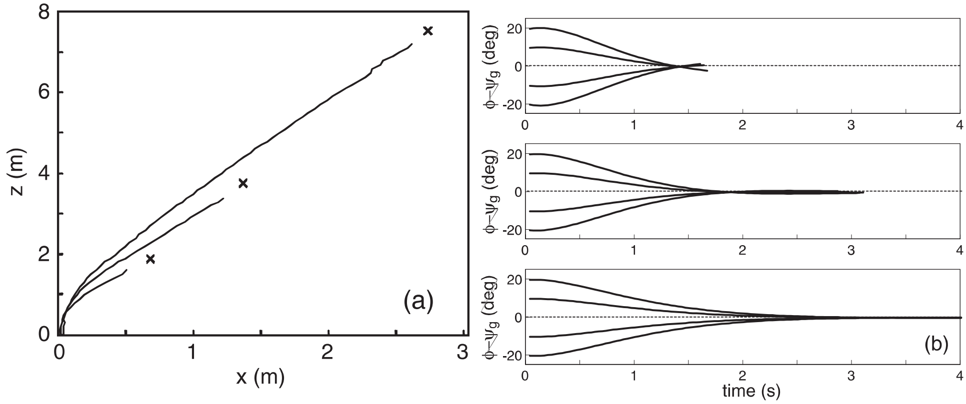

FIGURE 3 Model simulations of walking to a goal at 2, 4, and 8 m. (a) Paths with an initial goal angle of 20°. (b) Time series of goal angle with initial values of ±10° or 20°. s = seconds. From "Behavioral Dynamics of Steering, Obstacle Avoidance, and Route Selection," by B. R. Fajen and W. H. Warren, 2003, *Journal of Experimental Psychology: Human Perception and Performance, 29,* pp. 343–362. Copyright 2003 by the American Psychological Association. Reprinted with permission.

parameter values of $k_o = 198.0$, $c_3 = 6.5$, and $c_4 = 0.8$. Simulations reproduced the human paths (Figure 5a) and time series (Figure 5b) with a mean $r^2 = .975$. The model thus captures the behavioral dynamics of obstacle avoidance.

Now that we have formulated basic goal and obstacle components, can we use them to predict more complex behavior? In the model, routes emerge from the agent's interaction with the environment rather than being explicitly planned in advance. We first tested the simplest case of route selection comparing a direct "inside" path around an obstacle to a goal with a longer "outside" path, depending on the initial conditions. Participants switched from an outside to an inside path when the initial angle between the goal and the obstacle increased to 2° to 4° and as the distance of the goal decreased. The model exhibited a similar pattern of switching but at a somewhat larger angle. Adjusting the "risk" parameter c_4 from 0.8 to 1.6, which allowed a closer approach to the obstacle, induced the switch in the human range.

Such a choice appears as a bifurcation in the model dynamics. If the obstacle is between the agent and the goal, the model is bistable such that both outside and inside heading directions are attractive; the branch selected depends on the agent's initial conditions. As the agent moves around the obstacle, the model exhibits a *tangent bifurcation,* and only one route remains stable. Route selection can thus be understood as a consequence of bifurcations in the system's dynamics.

One advantage of the model is that it scales linearly with the complexity of the scene, simply adding one term for each object. A strong test of this is predicting route selection with large configurations of obstacles (Warren, Fajen, & Belcher, 2001). The model did a reasonable job of reproducing human paths through random arrays of 12 obstacles (e.g., Figure 6). On half of the eight arrays, the model was identical to the most frequent human route; on two arrays, they differed by

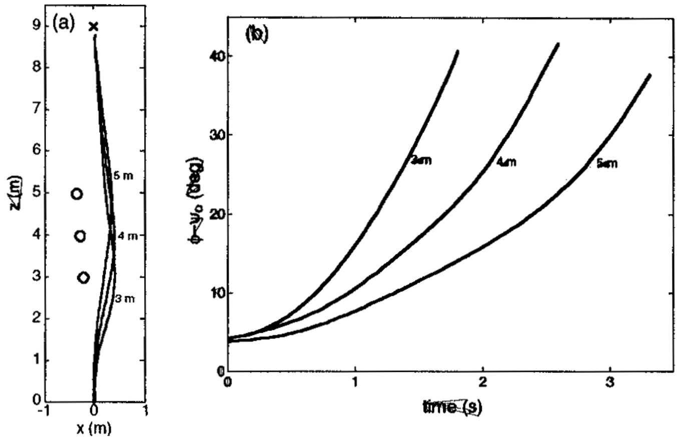

FIGURE 4 Obstacle avoidance with an initial distance of 3, 4, or 5 m and obstacle angle of –4°. (a) Mean paths. (b) Mean time series of obstacle angle. s = seconds. From "Behavioral Dynamics of Steering, Obstacle Avoidance, and Route Selection," by B. R. Fajen and W. H. Warren, 2003, *Journal of Experimental Psychology: Human Perception and Performance, 29,* pp. 343–362. Copyright 2003 by the American Psychological Association. Reprinted with permission.

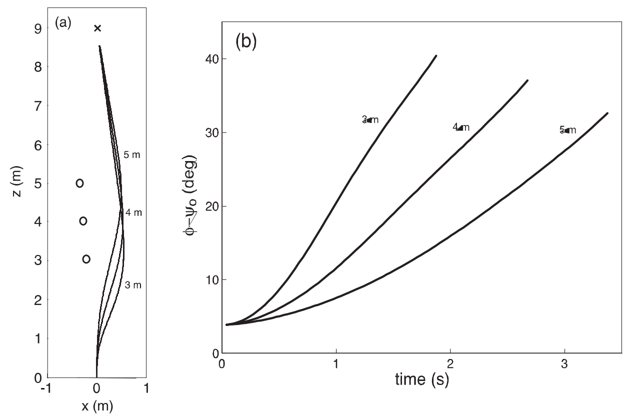

FIGURE 5 Model simulations of obstacle avoidance with an initial distance of 3, 4, or 5 m and obstacle angle of –4°. (a) Paths. (b) Time series of obstacle angle. s = seconds. From "Behavioral Dynamics of Steering, Obstacle Avoidance, and Route Selection," by B. R. Fajen and W. H. Warren, 2003, *Journal of Experimental Psychology: Human Perception and Performance, 29,* pp. 343–362. Copyright 2003 by the American Psychological Association. Reprinted with permission.

only 1 obstacle; and on one array each, they differed by 2 and 4 obstacles. Of course, there was some variability in human routes across trials and individuals due to the number of bifurcation points in such a configuration that could send the participant down different paths. We have recently found that the distribution of human paths can be approximated by adding Gaussian noise to the initial values of the model parameters and perceptual variables.

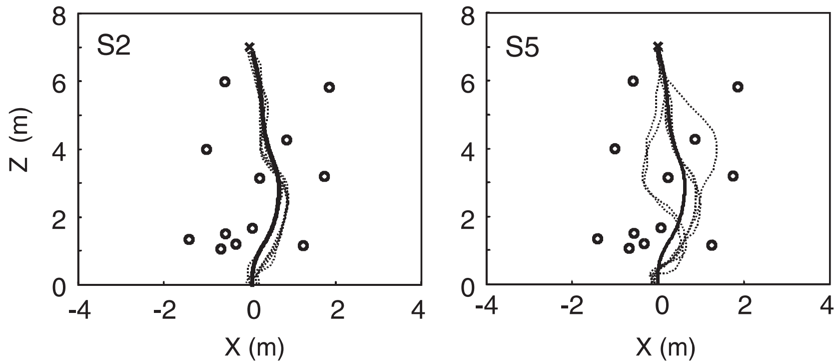

FIGURE 6 Routes to a goal (X) through an array of 12 obstacles (O) for 2 participants (S2 and S5). Dotted curves represent 6 trials from each participant; solid curves represent the model simulation. Starting point is at (0,0).

In sum, human route selection can be understood as a form of emergent behavior, which unfolds as an agent with certain steering dynamics interacts with a structured environment, making explicit path planning unnecessary. The ultimate aim of this research program is to characterize the behavioral dynamics of locomotion in a complex dynamic environment. We plan to model steering to stationary and moving goals (Fajen & Warren, in press) and avoidance of stationary and moving obstacles. Once these basic locomotor "rules" for an individual agent are understood, we can model interactions among multiple agents such as pedestrian traffic flow and crowd behavior in particular environments. Locomotion thus offers a comparatively simple model system for understanding how adaptive human behavior emerges from information and dynamics.

ACKNOWLEDGMENTS

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