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 occursent 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 $\phi$ 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 $\psi_g$ at a distance $d_g$; an obstacle may also lie in direction $\psi_o$ 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.
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 ($d_g$):

$$
\ddot{\phi} = -b\dot{\phi} - k_g(\phi - \psi_g)(e^{-c_1d_g} + c_2).
$$

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 success-
fully 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 exponen-
tially 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 di-
rection 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 ($d_o$):

$$\ddot{\phi} = -b\dot{\phi} - k_g(\phi - \psi_g)(e^{-c_1d_o} + c_2) + k_0(\phi - \psi_0)(e^{-c_3|\phi - \psi_0|})(e^{-c_4d_o}). \quad (2)$$

The obstacle “stiffness” term reflects the finding that angular acceleration de-
creases 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 $c_1$. The stiff-
ness 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

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**FIGURE 2** Walking to a goal at a distance of 2, 4, or 8 m. (a) Mean paths with an initial goal an-
gle 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
permission.
parameter values of $k_0 = 198.0$, $c_1 = 6.5$, 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
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.


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.

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