Computing Through Movement

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Abstract

One human capability that seems to have received little attention from researchers in human computation so far is our ability to understand and manipulate the complex dynamics of physical movement. This research investigates the use of human motor learning as a mechanism for exploration and problem solving for nonlinear dynamical systems. This paper illustrates the approach with an example from the study of sustainable economic growth.

Introduction

Human motor learning and control is, essentially, a problem in understanding and manipulating dynamical systems. The human sensory-motor system must interact with a wide variety of environmental dynamics in order to produce desired movement outcomes. Doing so requires the solution of difficult problems such as prediction, optimisation, and control in the face of delayed and incomplete sensory information, time varying nonlinear dynamics, and constant disturbance (Wolpert, Ghahramani, and Flanagan 2001). In a very real sense we are all natural born dynamicists.

Nonlinear dynamical systems can be difficult to understand and control. Existing analytic techniques, where they exist, involve many assumptions and require significant expertise to apply. This research investigates a form of human computation that uses of human motor learning to explore the behaviour and control of nonlinear dynamical systems. The approach allows human participants to interact with a physical realization of a dynamical system. Participants can explore the behavior of a system and learn to manipulate it through continuous real-time physical interaction with the parameters of the system. Problems concerning the control of a system can then be presented to participants as a physical skill to learn and master.

Engaging motor learning mechanisms

A dynamical system of the form

$$\dot{\mathbf{x}} = \mathbf{f}\left(\mathbf{x}(t), \mathbf{u}(t), t\right) \qquad (1)$$

Figure 1: A physical representation of an arbitrary dynamical system.

can be presented as an object such as a ball in a virtual environment whose attributes (location, orientation, etc) represent the state variables, $\mathbf{x}$. As a simulation of the system proceeds the object moves and changes. The user can continuously manipulate the control variables, $\mathbf{u}$, using a haptic pen in order to explore the effect of control variables on the motion of the object. The user experiences the system as a physical situation to be explored and mastered. A problem in the control of the system can be expressed as a physical task such as "put the ball in the box" (see fig 1).

Case study

In order to illustrate the use of human motor learning and control as a means of solving computational problems we turn to a dyamical system model that relates economic, demographic, and environmental systems known as Wonderland (Sanderson 1994) and defined as follows:

$$x(t+1) = x(t)\left[1 + b\Big(y(t), z(t)\Big) - d\Big(y(t), z(t)\Big)\right], \; (2)$$

$$y(t+1) = y(t)\left(1 + \gamma - (\gamma + \eta)\Big[1 - z(t)\Big]^{\lambda} - \gamma_0 \frac{\tau}{1-\tau}\right) \qquad (3)$$
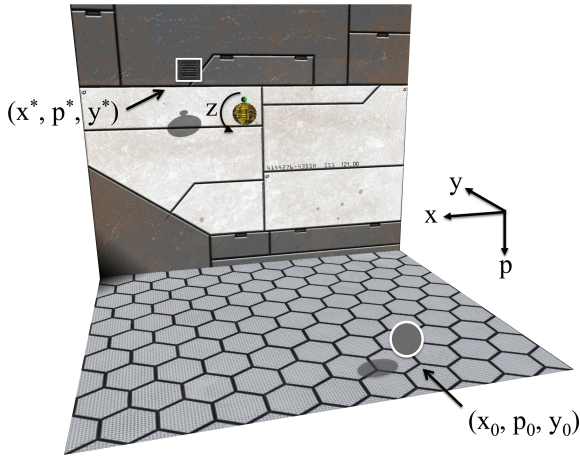
Figure 2: User's view of the Wonderland system. The x, p, and y variables of the system are represented by the location of an "orb" in X, Y, Z display coordinates respectively. The z variable is represented by the angular displacement of the orb about the Z-axis of the display. The orb starts at the initial condition (x_0, p_0, y_0). A target state (x^*, p^*, y^*) is represented as an air vent on the back wall of the scene.

$$z(t+1) = \frac{g\Big(x(t), y(t), z(t), p(t)\Big)}{1 + g\Big(x(t), y(t), z(t), p(t)\Big)}, \qquad (4)$$

$$p(t+1) = p(t)\left(1 - \chi - \chi_0 \frac{\tau}{1+\tau}\right), \qquad (5)$$

where

$$b(y,z) = \beta_0\left[\beta_1 - \left(\frac{e^{\beta y}}{1 + e^{\beta y}}\right)\right], \qquad (6)$$

$$d(y,z) = \alpha_0\left[\alpha_1 - \left(\frac{e^{\alpha y}}{1 + e^{\alpha y}}\right)\right]\left[1 + \alpha_2(1-z)^{\theta}\right], \quad (7)$$

$$g(x,y,z,p) = \frac{z}{1-z} e^{\delta z^{\rho} - \omega f(x,y,p)}, \qquad (8)$$

and

$$f(x,y,p) = xyp. \qquad (9)$$

The state variables $x(t)$, $y(t)$, $z(t)$, and $p(t)$ represent the population, per capita output, stock of natural capital, and pollution flow per unit of output respectively. Under certain conditions the system exhibits a " Horror Scenario" in which a period of economic growth is followed by precipitous environmental collapse. The problem is to discover strategies for achieving continued economic growth under this scenario without environmental collapse through manipulation of tax policy (Kohring 2006). To do this users were presented with the physical representation of the system shown in fig 2 and asked to explore ways of steering the system to a target state of economic activity and environmentatl sustainability (represented by an air vent on the back wall) by moving a haptic pen bound to parameters representing tax policy in the model, τ and χ_0.
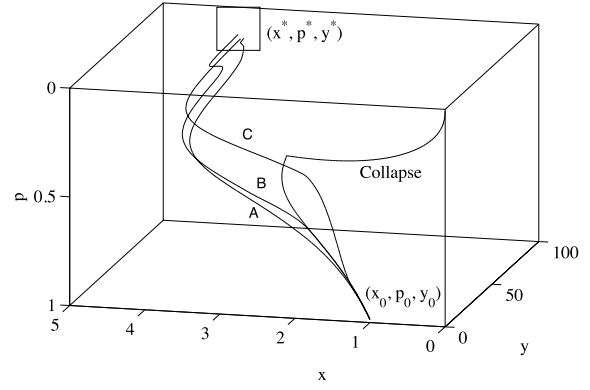

Figure 3: A user discovered control strategies A, B, and C that maintain economic growth while avoiding environmental collapse. Each strategy represets a distinct tax policy using different combinations of tax policy parameters.

Results and discussion

Users were able to discover a variety of strategies for maintaining economic growth while avoiding environmental collapse through active control of parameters representing tax policy with only a few minutes of exploration. The system trajectories for strategies discovered by one user are illustrated in fig 3. The results demonstrate that it is possible to use human movement based interaction as a means of exploring the behavior of nontrivial nonlinear dynamical systems that have no basis in the physical environment in which movement normally occurs. Extending the approach further, the results of this *strategy discovery* exercise can form the basis of a *strategy refinement* exercise in which users refine a particular strategy with respect to specified criteria, e.g. refine strategy A in fig 3 so that the system reaches the target state as quickly as possible.

This case study is part of a larger effort to systematize the application of human motor learning and control to the study of dynamical systems. The approach provides a relatively assumption free way to explore dynamical systems using innate human abilities. It is hoped that the approach can be developed to the point that can it becomes a useful addition to the canon of human computation techniques.

References

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