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Rohan McAdam

Charles Sturt University, mcadam@csu.edu.au

Keith Nesbitt

University of Newcastle, keith.nesbitt@newcastle.edu.au

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Movement-based interfaces for problem solving in dynamics

Rohan McAdam
Centre for Research in Complex Systems
Charles Sturt University
Bathurst
Email: mcadam@csu.edu.au

Keith Nesbitt
School of Design Communication and IT
University of Newcastle
Australia
Email: keith.nesbitt@newcastle.edu.au

Abstract

Humans have a natural ability to cope with the problems of moving in a changing environment. The motivation for our work is to engage our natural ability to move in the understanding of more abstract problems associated with dynamical systems. The question we address is: "Can human movement be coupled to simulations of arbitrary dynamical systems to help understand these more abstract mathematical problems?" In this paper we present a case study where users perform multiple trials to try to find a solution to a well known predator-prey problem by using a simple movement-based interface. Indeed users are able to find a number of different solutions without prior expertise in this domain. While these solutions fall short of being strictly optimal the results provide a convincing proof of concept as well as raising new questions to direct our further enquiries in this area.

Keywords

Human Movement, Dynamical Systems, Natural User Interfaces, Sensory Motor, Continuous Interaction

INTRODUCTION

The term "human computation" has recently been applied to the creation of problem-solving environments that engage human capabilities in the solution of problems that are difficult to solve otherwise (Quinn and Bederson 2009). Examples include image classification problems that utilise human visual processing (von Ahn 2007) and protein folding problems that utilise human spatial awareness (University of Washington 2010). The work described in this paper concerns the application of human sensory-motor abilities to the understanding of movements associated, not with our everyday world, but with more abstract dynamical systems.

Human engagement with the physical world is a continuous process of solving complex problems in dynamics supported by powerful sensory-motor resources in the central nervous system. Every movement action can be considered a problem in the control of a dynamical system, that is, choosing the motor actions (muscle contractions) that act upon the combined body-environment system to achieve a desired sensory outcome (Neilson and Neilson 2005). Running, walking, swimming, riding a bike and driving a car are all complex problems in movement that we can learn to solve with subconscious ease.

Inherent then in human sensory-motor behaviour is the ability to solve difficult problems in dynamics posed by the structure of the human biomechanical system and the environment with which it interacts (Neilson and Neilson 2005). Furthermore, learning new sensory-motor skills means that the mechanisms underlying sensory-motor behaviour need to cope with situations that have never been encountered before (Wolpert et al. 2001). We may not all be able to juggle, but, with enough practice it is a skill that most people can acquire.

However, difficult problems concerning the control of dynamical systems are not peculiar to human movement. The general problem of how to manipulate such systems is relevant to disciplines as diverse as economics, biology, sociology, physics and engineering. Ecologists seek ways to manage fisheries in order to ensure economic viability without endangering ecological sustainability (Kaplan and Smith 2001). Economists investigate how to control production and set prices in order to maximise profits (Kamien and Schwartz, 1991). Is it possible that the natural human abilities used to control movement can also be engaged in the control of these more diverse and abstract problem domains?

This general concept has been described in more detail in other work (McAdam 2010). In this paper we briefly relate this concept in terms of Norman's seven-stage action model (Norman 1988). We also describe further

theoretical work in interactive visualisation and continuous interaction that help underpin the work. The key contribution of this paper is a report on a usability trial designed to measure users' effectiveness in solving a problem concerning the control of a dynamical system. The task involves manipulating a dynamic simulation of a biological population model. Although users' performance is not strictly optimal they do, in general, perform well given no previous experience of the underlying dynamics and the fact that the representation is completely abstracted from the problem domain. A variety of solutions are provided by this approach, all of which satisfy the basic objective of the problem. Some of the solutions are somewhat unexpected. We also discern some distinct patterns of improved performance that may indicate users are learning new patterns of motor control. A number of issues identified in this study provide grounds for further study.

MOVEMENT IN THE INTERFACE

"Natural User Interfaces" are a recent development in the field of Human Computer Interaction (NUI 2011). Typically these interfaces rely on simple to learn movements or gestures as a basis for controlling software. These emerging styles of interface have been used in applications as diverse as planning story content (Cavazza et al. 2007) and interactive simulations (Mulder et al. 1999). These studies and developments in other fields such as ubiquitous computing, augmented reality and remote operation are underpinned by interactions suggested by Sutherland during the birth of Virtual Reality (Sutherland 1965). At that time, real-world interaction in a virtual world was seen by Sutherland as the "ultimate display" and an obvious progression from the typical point and click interfaces that Sutherland's own work with Sketchbook had pioneered (Sutherland 1963).

Despite much enthusiastic research in this area, most applications still find users interfacing to computers through a screen, keyboard and mouse. This interaction is based largely around tasks such as "select an icon" and "click a button". This style of interface, when well designed, can meet some of the traditional usability criteria, such as memorability, learnability, safety, utility, efficiency, and effectiveness (Preece et al., 2002). A key distinction between our work and these traditional styles of interface is that they tend to involve discrete interactions as opposed to continuous control and feedback. This is typified by the way peripheral devices such as the Sony EyeToy, Nintendo Wii and Microsoft Kinect are used in computer gaming.

Many established HCI approaches for the design and evaluation of user interfaces are still relevant to the study of these emerging styles of interface. Norman's seven-stage model of interaction is a widely used and traditional model used to design and critique user interfaces (Norman 1988). Norman proposed a model of interaction where the user formulates a goal and then with an intention in mind executes an action before evaluating the outcome. This allows systems to be critiqued in terms of any discrepancies between what a user intends to do and the means to do it (gulf of execution) or between what a user needs to know in order to complete a task and what is provided by the system (gulf of evaluation). Although this model is perhaps easy to think about in terms of discrete interaction there is no reason to preclude a more continuous loop of goal formation, execution and evaluation. With our work the focus during execution is on using motor actions to control parameters of the simulation and on techniques, perhaps involving multiple senses, to display the system state. In movement the loops of goal updates, intention formation, execution and evaluation could be expected to be largely subconscious, at least in a skilled operator. The implied use of automated motor patterns as controlled by brain structures such as the basal ganglia, cerebellum and motor cortex are generally under-studied as part of interface design models.

Norman's model focuses on the user side of interaction. It does not explicitly include the system itself. This excludes support for design and evaluation of the system itself. To counter this, Norman's model was extended by Abowd & Beale (1991) to include a dualistic representation of user and system. A similar dualistic model of continuous interaction has emerged from the field of manual control (Massink and Faconti 2002). Massink and Faconti (2002) describe a reference framework that can assist in design of both discrete and continuous interactions. The ability of this model to account for continuous interaction makes it relevant to our own studies of movement-based interfaces.

The Massink and Faconti framework is based on a five-layered model where each layer represents a different layer of abstraction. It is similar in principle to the layered communication model used to describe network communications. At the lowest level it considers the physical exchange of signals, while at higher levels it models information exchange in terms of perceptual, propositional, and conceptual tasks and final group-level exchanges. These representations exist on both the user and system sides of the interface, allowing communication at different layers of the model. As signals move up and down the layers they change between abstract representations and real physical signals.

One distinct benefit of this framework is that existing approaches and models from HCI can be used, where appropriate at each of the layers. For example, at the physical layer, psychophysical principles such as Fitt's law (Fitt 1954) and taxonomies such as Card's Design Space of Input Devices (Card et. al. 1990) can be used. At the perceptual level models such as Barnard's Interacting Cognitive subsystems can be applied. Likewise the GOMS modelling approaches (Kieras and John 1994) and traditional techniques such as Hierarchical Task Analysis

(Annett 2003) are valid at the Conceptual level. The model also allows reasoning about the different time lags involved in multi-sensory tasks. This can be critical in motor tasks where some feedback loops, such as force feedback, operate at refresh rates as high as 1000Hz, while visual and auditory loops have much lower operating frequencies. This framework helps illustrate how many existing approaches in interface design can be leveraged in the attempt to engage continuous human movement in the understanding of dynamical systems.

UNDERSTANDING DYNAMICAL SYSTEMS

One approach to understanding how systems change over time is provided by the notion of a dynamical system. A dynamical system is a system whose behaviour can be described in terms of rules that define how the state of a system changes over time. The rules for continuous dynamical systems take the form of differential equations. Because the rules for a dynamical system typically involve nonlinear relationships they can be difficult to analyse. Dynamical systems are interesting because they are capable of producing rich behaviour from quite simple rules and are valuable tools in the study of a very wide range of phenomena (Alligood et al. 1997) and so there is a general need to develop ways to analyse and understand models in many different domains.

There have been many tools developed to help solve problems concerning the control of dynamical systems. One way in which these tools vary is in the particular user expertise they engage in the problem solving process. Some tools require considerable mathematical expertise. Examples include general-purpose mathematical software such as Matlab and Mathematica for analysing and solving the equations defining the behaviour of a system (MathWorks 2010; Wolfram Research 2010).

Other tools take a particular problem-solving technique and present it in a user-friendly way. For example, Simulink and Vensim provide a building-block approach to constructing simulations of dynamical systems (MathWorks 2010; Ventana 2010). While these tools are still essentially mathematical in nature, much of the mathematical complexity of constructing a simulation is hidden from the user. Even with tools such as these the user may still need considerable mathematical sophistication to ensure that results are valid.

Tools aimed at leveraging domain expertise take hiding mathematical complexity further and allow a user to formulate problems using the concepts and language of the problem domain (Houstis and Rice 2002). One such tool is RAMSES, which is designed for “non-computer scientists” studying environmental systems (ETH 2010). While such tools typically support a somewhat constrained set of problem scenarios they make up for this by allowing users to concentrate on the domain implications of problems and their solutions.

In all of these examples, the human expertise being utilised is high-level and cognitive in nature. A very different, low-level form of human expertise has also been used to solve problems concerning the manipulation of constrained physical systems (Brooks et al. 1990; Witkin et al. 1990) and unstable, rigid body systems (Laszlo et al. 2000). In these cases a user’s intuitive motor-learning and motion-planning skills are used to manipulate a real-time simulation of a system in order to produce results that are difficult to achieve using conventional computational means. In the Masink and Faconti model (2002) these tasks would be modelled at a much lower level, either the physical or perceptual level of their model, compared to the conceptual level tasks required by most of the other tools. Our own work builds on these ideas to produce a problem-solving environment in which human sensory-motor capabilities are used to produce solutions to problems concerning the manipulation of arbitrary dynamical systems, even when those systems have no physical basis whatsoever.

Closely related to the simulation of dynamical systems is a means of visualizing the simulated behaviour of a system. This presents the behaviour of the system in a form that allows visual identification of important features of the system’s behaviour. It is often used as a means of illustrating a result obtained analytically. Beyond this communications role, visualisation can also be used to help identify features of the system that might not be found using analytical techniques (Groller et al. 1996). Visualisation techniques have also been extended to include other sensory modalities such as hearing and touch to enhance the presentation of a dynamical system’s behaviour (Wegenkittl et al. 1997).

Interactive visualisation describes tools that enable users to more rapidly perform simulations, review the results, modify the system and re-run the simulation (Zudilova-Seinstra et al. 2009). Interactive workflows support the process of exploring the behaviour of a system. This interaction is usually discrete in nature and directed at presentation factors such as changing rendering techniques or the user’s point of view. By contrast, *computational steering* (Mulder et al. 1999) allows the user to modify the parameters of a simulation in order to explore the behaviour of a system under different initial conditions or by some form of intervention during the simulation.

A general question in the study of any dynamical system is, given a dynamical system and opportunities for intervening in that system, what are the various ways in which it might be manipulated? With a basic understanding of how a dynamical system can be manipulated, attention can turn to specific problems concerning the manipulation of a system to achieve very particular outcomes. The user trial presented in this paper concerns one such problem.

A PROBLEM WITH PESTS

Having discussed dynamical systems in more general terms we now introduce a specific example that forms the basis of our usability trial. This case study concerns the management of a soybean crop that is under threat of destruction by soybean caterpillars. The overall goal is to optimise return by maximising crop yield. This requires a strategy for managing the number of caterpillars while also limiting the amount of intervention. A safe level of caterpillars is about 20 caterpillars per square metre. To achieve and then maintain this level there are two types of intervention available, applying a pesticide and introducing a natural predator of the caterpillar, such as the damsel bug (Rafikov and Balthazar 2005).

The dynamics of this problem are non-linear due to the interaction between soybean caterpillars and their predators. The problem can be modelled by a Lotka-Volterra predator-prey model with harvesting (see table 1) by considering the rate at which caterpillar and predator populations grow, the mortality rate of caterpillars due to pesticide and interaction with predators, and so on (Rafikov and Balthazar 2005). The problem of pest control in a soybean crop is then, given an initial starting state, how would you move the system as quickly as possible to a desired state, i.e. a state in which soybean caterpillars can be maintained at a safe level with minimal ongoing intervention? Doing so needs to take into account the natural cycles of population growth and decline in both prey and predator populations. The controls available are the parameters representing the application of pesticide and the introduction of predators.

This problem can be formulated as an optimal control problem in which the objective is to move the system from an initial state to the targeted equilibrium state as quickly as possible and maintain it there (Rafikov and Balthazar 2005). The problem can be solved mathematically in two phases. In the first, the system is driven toward the target state using a control law derived from Pontryagin's minimum principle (Kirk 2004). Once in the region of the target state the system is stabilised using dynamic programming to solve a linearised version of the problem.

In terms of non-linear control problems this is a relatively simple problem, yet finding the solution still requires a considerable degree of mathematical expertise, firstly to formulate the problem in an appropriate way and then to solve it. We instead want to formulate this problem as a task that might be solved by users with no domain expertise using a simple interface that engages their sensory-motor capabilities. The task of driving the non-linear system from an initial state to a suitable final state becomes a 'physical' task to be completed in minimum possible time.

In our movement-based interface the screen displays a ball whose X-Y position represents the current state of the system, i.e. the caterpillar and predator population levels (see Figure 1). The two parameters controlled by the user (application of pesticide and introduction of predators) are manipulated simultaneously using a two-handed Multiplex Cockpit MM controller. This controller has two joysticks, each operated with the user's thumbs, and is a type of device typically associated with remote-control model aircraft. As the system is simulated, the ball on the screen moves to reflect the evolving state of the system in response to its own intrinsic dynamics and the control inputs from the user. The net effect is that by moving their thumbs, users are able to affect the motion of the ball. Visual artefacts such as target boxes can be used to represent desired states to which the system is to be driven.

With this arrangement users are able to interact with an abstract dynamical system in purely sensory-motor terms. In place of chemical and biological controls acting on interacting populations the user experience is one of motor actions and sensory consequences. Clearly, the user will require some effort to learn and master such an arrangement. This is because the current position of the ball depends not only on the two parameters under the user's control but also on the system's intrinsic dynamics. Even if the user provides no input the ball will still move. This is quite unlike the very predictable behaviour of a cursor in response to mouse movements. However, in mastering such a system users will be developing a sensory-motor understanding that allows them to manipulate the system in purposeful ways that can then be interpreted in domain level terms as population management policies.

USER TRIAL

We carried out a user trial and usability test. This was intended as a proof of concept study. We wanted to address the question of how well subjects could solve a simple problem concerning an arbitrary dynamical system when it was presented as a sensory-motor task. Could users with no prior experience in a particular problem domain satisfactorily solve problems concerning the manipulation of an arbitrary dynamical system using only their innate sensory-motor abilities? The arbitrary dynamical system was the Lotka-Volterra pest control problem described previously. The basic problem in dynamical systems terms was to drive the system to a target state in minimal time and maintain it there.

The initial state in each trial was a population level of 80 caterpillars per square meter and 30 predatory bugs per square meter. The target state was a population level of 20 bugs and 20 caterpillars per square metre. The task presented to users was to “put the ball in a box as quickly as possible and keep it there”. The arrangement of this task in our movement-based interface is shown in Figure 1. The specific details of the user task are provided in Table 1. The system was simulated using a Runge-Kutta 4th order solver with a step size of 0.1 running at 60 Hz. The task lasted for 10 seconds of real time, corresponding to 60 days of simulated population time.

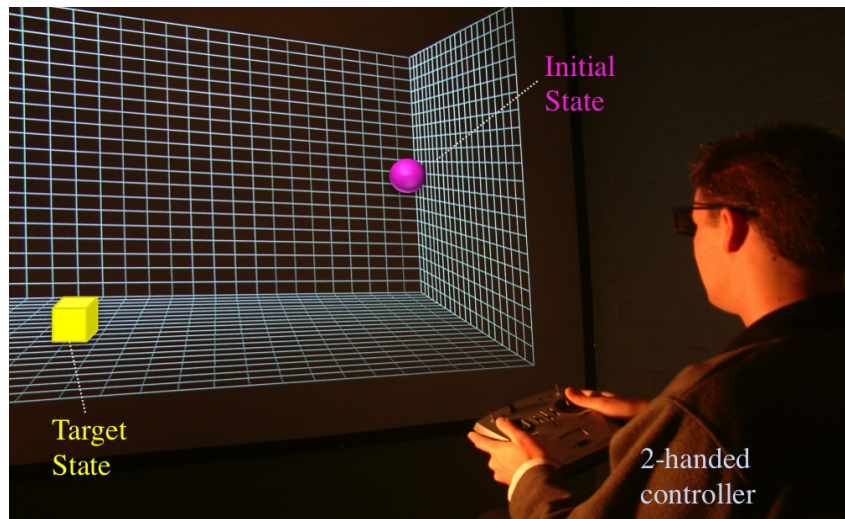


Figure 1: The system setup used in the trial

Table 1. Details of the user task in the trial

System equations	Control parameter mapping	Initial Conditions
$dH/dt = 0.216H - 0.0108HP - h_H$	Right hand joystick : $0 \cdot h_H \cdot 15$	$H = 80$
$dP/dt = 0.0029HP - 0.173P + h_P$	Left hand joystick : $0 \cdot h_P \cdot 15$	$P = 30$
where:	State variable mapping	Target State
H = caterpillar population density	Display X: $0 \cdot H \cdot 100$	$H = 20$
P = predator population density	Display Y: $0 \cdot P \cdot 100$	$P = 20$
h_H = rate of pesticide application		
h_P = rate of introduction of predators		

Five subjects, all male and recruited from computer science staff and PhD students at CSU Bathurst, took part in the trial. None of these users had any knowledge of the study of population dynamics or the study of dynamical systems in general. Each user was given a one-hour training session one week before the trial. During this training they familiarised themselves with the interface and the behaviour of the system in response to their control inputs. Users were allowed to freely explore the behaviour of the system. At the end of the hour they were asked to demonstrate that they had grasped the basic behaviour of the system to ensure that they would have some hope of solving the specific problem presented in this user trial.

After one week users were brought back and given 10 minutes of further training time to reacquaint themselves with the system. At this stage they were told that their task for today was to “put the ball in the box as quickly as possible and keep it there”. They were also told that their performance would be monitored and they were given a score reflecting their performance at the end of each trial. The score was calculated using the time taken to initially reach the target and then the error in subsequently maintaining the target. Lower scores were better.

Each user was given 30 minutes to attempt the task as many times as possible. Each trial lasted for 14 seconds (10 seconds of simulation time following a 4-second count down). Users were responsible for initiating each trial, typically leaving a gap of several seconds between trials. As a result they typically got through about 40 – 50 trials in the allotted 30 minutes (see Table 2).

RESULTS

At the completion of their trials, all users had managed to produce solutions that satisfied the basic requirement to “put the ball in the box and keep it there”. The solutions produced varied in two main ways – the particular control strategy adopted and the actual time taken to initially acquire the target (recall that the task presented was to put the ball in the box as quickly as possible and keep it there). The results of the user trial are summarized in Table 2. User performance in the first phase of the task, initially acquiring the target state, is compared with a solution generated by an implementation of an optimal control algorithm, DIDO (Ross and Fahroo 2002).

Table 2. Results comparing user performance against an algorithmic solution

User	Number of trials	Best Score	Optimality*	Strategy
1	45	3.99	0.969	2 handed
2	47	5.29	0.732	2 handed
3	37	8.71	0.444	1 handed
4	42	9.1	0.425	1 handed
5	40	4.12	0.939	2 handed
DIDO	n/a	3.87	1.0	2 handed

* optimality is calculated by DIDO solution / user's best score

Given the two controls available (rate of pesticide application and rate of predator introduction), the optimal solution is to use a mixture of pesticide and introduced predators to quickly bring caterpillars under control and keep them at the required population level (Rafikov and Balthazar 2005). From a user’s perspective this strategy involves using both hands. Three out of the five users adopted a two-handed control strategy. However, two users also discovered that it is possible to effectively control caterpillars using introduced predators alone, i.e. using just their left hand. One-handed solutions took about twice as long as two-handed solutions to initially acquire the target state. While these solutions are a long way from being optimal, the existence of a solution that does not involve pesticide may be valuable for environmental reasons even if it is slower to act. The state variable trajectory of the system for one- and two-handed user solutions and the DIDO solution are shown in Figure 2. Time series plots of state variables and control parameters for the best solution discovered by User 1 and the DIDO solution are shown in Figure 3.

While this solution was not quite as good as the optimal solution found using DIDO it had essentially the same form as the DIDO solution. There is a slight overshoot in the caterpillar population density and a slight undershoot followed by an overshoot in the predator population density. These deviations from the target state may be partly explained by the relatively large size of the target box and the fact that users were told that the ball was “in the box” if the centre of the ball was inside the box. This allowed the users to move the ball half a diameter in the X and Y directions and still be “in the box”.

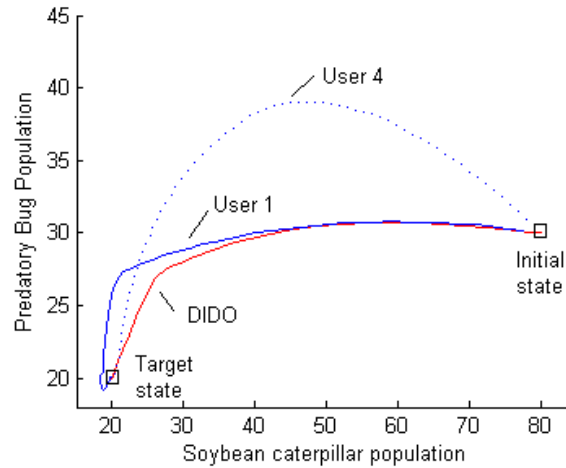


Figure 2: System trajectories for one-handed and two-handed user solutions and a solution generated using the DIDO optimal control algorithm

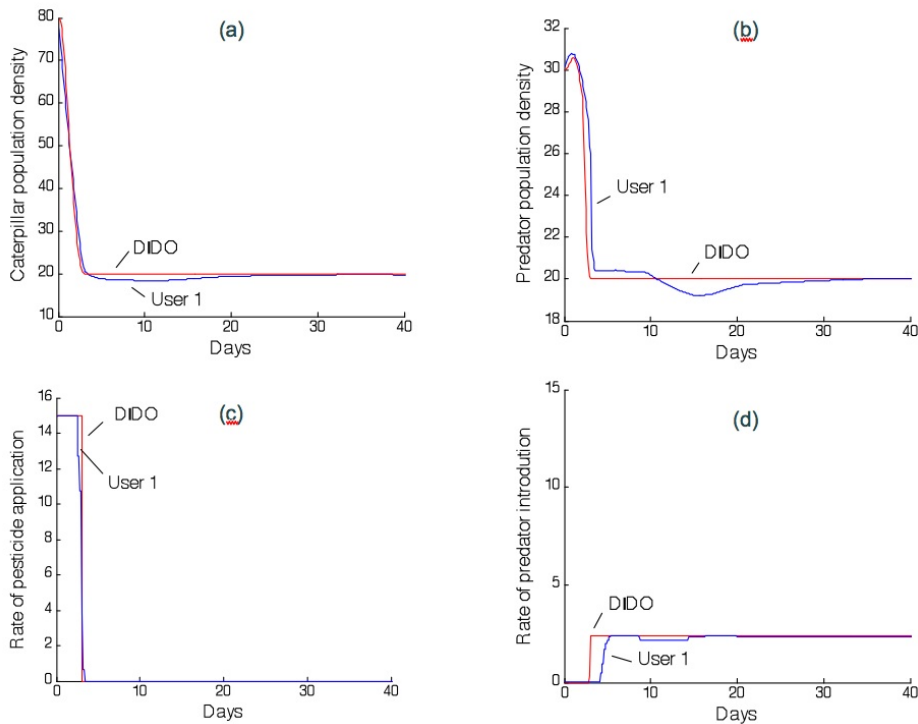


Figure 3: (a) Caterpillar population density over time (b) Predator population density (c) Rate of application of pesticide (d) Rate of introduction of predators

The main difference between control strategies used by User 1 and DIDO is in the timing of the control actions. In the application of pesticide, DIDO applied pesticide at the maximum rate for slightly longer than User 1. There was also a delay in the introduction of predators by User 1 when compared with the DIDO solution. Another difference between these solutions was the rate at which the control variables were changed. Control variable changes in the DIDO solution were close to instantaneous, while control variable changes in the solution from User 1 were more gradual, reflecting the time required for users to physically move their thumbs.

Interpreting User 1's solution in domain level terms we find that the best strategy discovered was to initially apply pesticide for a period of about 4 days at a rate sufficient to kill 15 caterpillars per square metre per day to quickly reduce the caterpillar population density, after which it is stabilised at the desired level of 20 caterpillars per square metre through the introduction of predatory bugs alone at a constant rate of 2.32 bugs per square metre per day.

For a particular control strategy (one or two-handed), there was considerable variation in the solutions generated with respect to the time taken for the system to arrive at the target state. The time taken to arrive at the target state varied considerably both between users and across trials for the same user. The task presented to users was, in essence, to learn a new physical skill in which the speed at which they could perform the task was a performance characteristic (Magill 2007). As such, we might expect that a user's performance would improve with practice and, indeed, this appears to be the case. Figure 4 illustrates the performance of User 4 over 42 trials. This data suggests that the mechanisms of sensory-motor learning were engaged in developing a new physical skill specific to the dynamics of the Lotka-Volterra population system. Furthermore, it suggests that further improvements in performance may have been possible with more practice.

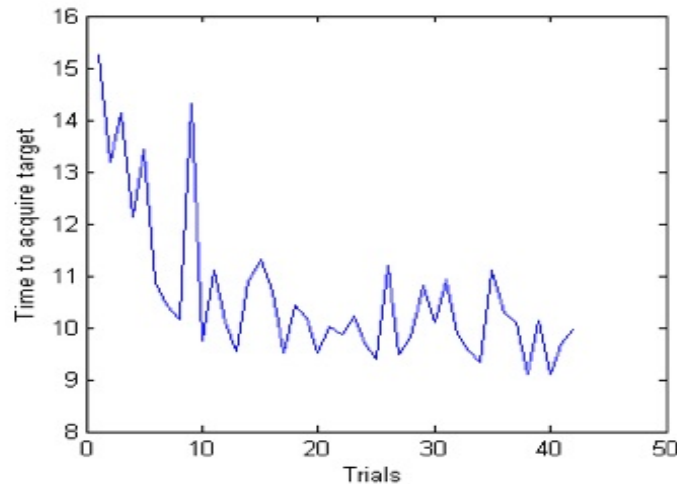


Figure 4: Time to acquire target over 42 trials for User 4

DISCUSSION

This trial was designed as a proof of concept to demonstrate that it is possible to map an arbitrary dynamical system to a simple movement-based interface. Indeed, users can complete a typical task from the domain without any domain expertise. They did so consistently, reaching a terminal solution to the problem on each of the over 40 trials they undertook. Some of the solutions produced by users were close to optimal, especially in the two-handed strategy adopted by users 1, 2, and 5. The other two users explored non-optimal and somewhat unexpected one-handed control strategies. In trying to assess the results of this user trial and to frame further research it is useful to apply Norman's interaction model to the simple movement-based interface presented in this paper. In particular, we can consider the interface in terms of gulfs of execution and evaluation.

Gulfs of execution occur where the users' intentions, planned actions or executed acts at the interface are not allowed for by the system. Identifying and removing any such discrepancies leads to interfaces that are more intuitive and easier to use. There are a range of factors in the movement-based interface described that could be addressed in this fashion, such as the effects of sensory-motor reaction times, variability in performance, and performance ceilings that may affect a user's ability to produce useful solutions. However, it is also important to note that the approach suggested in this paper of utilising human sensory-motor capabilities as a problem-solving mechanism relies on an essential gulf of execution – the unknown relationship between control action and system response. When first confronted with a task such as "put the ball in the box as quickly as possible" a user does not know, nor can the system tell them, what actions are required to achieve the goal. This gulf of execution is the problem to be solved and the idea is to leverage human sensory-motor learning as the means of bridging the gulf. An important point to note is that the particular movement strategies needed to solve this problem depend entirely on the dynamics of the system under study and the way the system is presented to users. Systems with different dynamics will require users to develop different sensory-motor skills

Gulfs of evaluation occur when the information provided by a system falls short of the information need by a user to complete a task. Sensory-motor engagement with a system relies on an adequate sensory representation of the evolving state of the system. The design of our interface was simple. More complex visual, auditory or haptic feedback could be provided to try to assist in presentation of the system state. This is a general issue in all interface design, particular the design of multi-sensory displays of such abstract data. In particular, these issues apply to the scaling of the sensory representation in space and time. For example, the visual distance between the initial state and the target, and the size of the ball and target box, affect the user's ability to accurately acquire the target. Similarly, the rate at which the dynamics of a system play out in real time may have a large affect on a user's ability to manipulate a system. For example, while the task in the user trial lasted for 10

seconds, all of the control actions required to acquire the target took place within about 1 second of real time. Had the simulation run at a slower rate, users may have been able to produce better results in the time available.

CONCLUSION

This paper has reported on a usability trial designed to test the concept of using human movement in the solving of problems related to non-linear dynamics. Five users each performed over 40 trials the task was to move a simulated dynamical system from an initial state to a target state as quickly as possible. While this problem is relatively easy to solve using conventional techniques, there are many more problems of this general form that are much more difficult to solve such as problems with more state and control variables, constraints on state and control variables, stochastic disturbances, and so on. We believe that movement-based interfaces may provide a means of engaging human dynamics problem solving capabilities in solving these more complex problems, particularly when those problems come from domains in which human movement skills are not normally considered relevant, such as economics, sociology, biology, and so on. However, much further work needs to happen if these interfaces of the future are to become a reality. It is our intention to look further at the issues we have uncovered in this exploratory study. These include multi-sensory representations critical for the user to evaluate the system state and issues related to the user's execution of intentions, such as how movement patterns are acquired, the variations that occur in individual skill and general strategies employed in solving movement problems.

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