Motor learning in physical interfaces for computational problem solving

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Abstract
Continuous Interactive Simulation (CIS) maps computational problems concerning the control of dynamical systems to physical tasks in a 3D virtual environment for users to perform. However, deciding on the best mapping for a particular problem is not straightforward. This paper considers how a motor learning perspective can assist when designing such mappings. To examine this issue an experiment was performed to compare an arbitrary mapping with one designed by considering a range of motor learning factors. The particular problem studied was a nonlinear policy setting problem from economics. The results show that choices about how a problem is presented can indeed have a large effect on the ability of users to solve the problem. As a result we recommend the development of guidelines for the application of CIS based on motor learning considerations.

Keywords: virtual reality, simulation, dynamical systems, problem solving, motor learning

1 Introduction
Nonlinear dynamical systems models are used in many fields, from physics to geology, biology, economics, and sociology. Techniques for analyzing and controlling such systems is an active area of research, but there are still many cases where existing techniques either do not apply or, where they do apply, can be difficult for non-specialists to use. Humans, however, are able to understand and manipulate complex nonlinear dynamical systems in the context of physical movement [18]. Continuous Interactive Simulation (CIS) aims to leverage this ability in order to solve problems concerning the control of arbitrary dynamical systems. In essence, CIS presents a dynamical system to users as an object in a virtual 3D environment whose behaviour is driven by a simulation of the system. Users are able to steer the object by manipulating parameters of the system in real time through physical action. Control problems become tasks in which the goal is to steer the object in specified ways. CIS turns what would otherwise be a computational problem requiring specialist knowledge and tools into a physical skill anyone can try their hand at. Previous work has described the basic mechanisms of CIS [9], the exploration of system
properties in a non-linear mechanical system [11], and the solution of a control problem in a nonlinear biological system [10].

There are many decisions to make when presenting a problem to users in a CIS environment. What features of the system should be presented to users? How should those features be presented? How should the participation of users in the problem solving process be organised? How much time do they need to solve a problem? How should that time be organised? Ideally, we would like a set of guidelines that help make these sorts of decisions in a systematic way that improves the likelihood that users will be able to produce useful solutions to a given problem. Since the human ability to learn new physical skills is underpinned by the process of motor learning, it would seem natural to consider a motor learning and performance perspective as a basis on which to develop guidelines for the application of CIS. This paper examines how a motor learning perspective can assist in determining how to map a problem to be solved into a CIS environment.

This paper is organised as follows. Section 2 characterises problem solving in CIS in motor learning terms. Section 3 outlines motor learning factors that may affect the problem solving process. Section 4 introduces a particular problem in economic dynamics used to explore the problem solving process in this paper. Section 5 describes an experiment in which users solve the problem using two different presentations of the problem—a default presentation and a presentation modified according to the motor learning considerations outlined in section 3. Finally, section 6 provides a discussion of the results and their implications for the future development of CIS.
2 Problem solving as motor learning

Consider a continuous dynamical system of the general form

\[ \dot{x} = f(x(t), u(t), t) \]  

(1)

where \( f \) is a function of a vector of variables, \( x \), that represent the state of the system, a vector of control variables, \( u \), and time \( t \). For models of real world systems this function is generally nonlinear and may involve additional complexities such as various forms of constraints, delays, or disturbances.

Many problems concerning such systems involve determining the controls, \( u^*(t) \), that steer a system toward a desired state, \( x^* \), often with additional requirements such as doing so as quickly as possible, as smoothly as possible, or with as little control action as possible. There are a variety of analytic and computational techniques that may be applied to a problem like this, such as feedback control, model-based control, and optimal control, although these techniques often involve assumptions or technical complexities that limit their application. CIS turns such a problem into a physical task by representing the current state of the system, \( x \), with attributes (location, orientation, size, colour, etc) of objects in a 3D virtual environment. As a simulation of the system proceeds, these objects move and change according to the dynamics of the system. Users directly and continuously manipulate the control variables, \( u \), using a continuous input device (haptic pen, gesture tracking etc) in order to influence the motion of the objects and, if possible, steer the system toward the desired state, \( x^* \). If a user is able to steer the system to the desired state their movement actions in doing so constitute a solution to the problem, \( u^*(t) \).

The general arrangement of the particular CIS environment used in this paper is illustrated in fig 1.

In the study of human movement control a task in which the goal is to steer a continuously changing system over a period of time with respect to some reference is known as a continuous tracking task [14]. In fact, the general arrangement shown in fig 1 in which the state of a dynamic system is represented by objects in a computer-based visualization with user interaction via a continuous input device is commonly used in the study of human tracking tasks. The key difference is in the choice of underlying system dynamics and task to be performed. In human tracking studies the dynamics and the details of the task are typically chosen to illuminate particular aspects of human movement behaviour, such as speed versus accuracy tradeoffs. In CIS the dynamics and task are determined by the problem under study.

A movement action with a particular goal is referred to as a skill [8]. In general, humans are not preprogrammed to perform particular skills. Instead, humans have an innate capacity to acquire the ability to perform a skill through the process of motor learning. The key observable characteristic of the motor learning process is systematic improvement in skill performance with repeated practice that persists over time. CIS presents a problem as a skill in which the goal is to manipulate a system in a specified way. As with any novel physical situation users will need to acquire the necessary skill to solve the problem through practice. If a user can learn the necessary skill they can then generate solutions to the problem through performance of the skill. Motor learning is, in effect, the problem solving mechanism in CIS.

\(^1\)CIS is not limited to dynamical systems defined in this way. Any system that can be simulated in discrete time steps can be used.
3 Factors affecting motor learning and performance

There are a great many factors that can affect motor learning and performance. Here we focus on those that relate to a user’s direct experience of a physical situation, such as whether its response to movement action meets their expectations based on experience in other situations, how quickly it responds to movement action, and the effect of human perceptual biases. To begin to explore the relevance of these factors to the application of CIS we focus on the basic decisions to be made when mapping a problem into the CIS environment shown in fig 1. These decisions include the selection, ordering, and scaling of state and control variables, and the rate at which the simulation proceeds in real time. The following is a brief summary of these factors.

1. Selection of state variables – Which of the state variables should be included in the visual representation of the system’s state? All of them or a subset?

2. Ordering of state variables – To which axes in the visual representation should the selected state variables be assigned?

3. Scaling of state variables – What region of the system’s state space should be included in the visual representation?

4. Selection of control variables – Which of the control variables should be mapped onto the haptic pen for user manipulation? All of them or a subset?

5. Ordering of control variables – To which axes of the haptic pen should the selected control variables be assigned?

6. Scaling of control variables – What ranges of the control variables should be assigned to the range of movement of the haptic pen?

7. Simulation time scale – How many time periods, t, should be simulated per real time second?

The decisions made for each of these have a direct bearing on the user’s experience of the system by changing the direction, extent, and speed of motion of the ball and the direction and sensitivity to control input. In motor learning and performance terms these aspects impact on important factors such as stimulus-response compatibility, movement degrees-of-freedom, speed versus accuracy, control stability, perceptual complexity and perceptual biases. The following is a brief summary of these factors and their relation to the decisions that need to be made when presenting a problem in CIS.

1. Stimulus-response compatibility – Stimulus-Response (S-R) compatibility refers to the extent to which the response of a system matches the expectations of a user [13]. When presented with a novel situation a user has no alternative but to base their actions on their experience in similar situations. While a user is unlikely to have encountered the dynamics of an arbitrary dynamical system before, the physical arrangement of the CIS interface of fig 1 is not unfamiliar – an object on a computer screen and an input device with which to manipulate it. In such situations there is a population stereotype that leads users to expect that on-screen objects will move in the same direction as the input device [17]. Users will very likely approach any system presented in this CIS environment with this same expectation. It will be more difficult for users to learn how to manipulate the system if it behaves contrary to this expectation. S-R compatibility in our CIS environment is determined in large part by the order in which variables are assigned to axes in the visual scene and on the input device.
2. *Movement degrees-of-freedom* – The complexity of movement actions has an impact on motor learning and performance. Each control variable assigned to the input device introduces an additional movement degree-of-freedom. Coordinating movement becomes more difficult as the degrees-of-freedom increase requiring additional learning effort [1].

3. *Speed vs accuracy* – There is a well-known tradeoff between speed and accuracy in human movement. Information processing limitations in the central nervous system make it more difficult to perform tasks that require both speed and accuracy [4, 12]. The speed or accuracy required to solve a particular problem is determined by the scaling of state variables and the rate at which the simulation proceeds. Scaling state variables determines the size of target regions. The rate at which the simulation proceeds determines how quickly the system will respond to movement actions and hence the rate at which movement actions need to be made.

4. *Control stability* – The user and the dynamical system they are controlling form a coupled control system. The stability of this coupled system depends on matching the response of the dynamical system to the characteristics of the human motor control system. Instabilities such as user induced oscillations can arise when the system responds too quickly to user control input making the system harder to control [7].

5. *Complexity of the visual scene* – The complexity of a visual scene has an impact on both the mental effort required to process the scene [16] and the ability of a subject to attend to the specific features in the scene that are relevant to solving the problem at hand [19]. The primary source of this complexity in our simple CIS environment is the number of state variables selected for inclusion in the visual scene. Each additional state variable adds an extra dimension to the motion of the ball. It may be possible to exclude certain state variables if they do not provide information that is relevant to solving a particular problem.

6. *Perceptual biases* – Human visual perception is a complex phenomenon and there are a number of biases that affect perception of motion in space. Of particular relevance here are biases concerning perception of motion along the $z$ axis. In general, perception of motion along the $x$ and $y$ axes is less prone to bias and state variables should be assigned to these in preference to the $z$ axis [16].

This is, of course, a scant outline of a complex subject and there are numerous other factors that affect motor learning, but it is sufficient to get a sense for the sorts of factors brought to light by taking a motor learning perspective on problem solving in CIS. If the motor learning perspective is an appropriate foundation on which to base guidelines for the application of CIS we would expect that the ability of users to solve a problem would be enhanced by presenting the problem in a way that takes factors such as these into account. The following sections outline an experiment to investigate the relevance of motor learning considerations to the practical application of CIS to the solution of a problem in the control of a non-trivial nonlinear dynamical system.

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2Selecting a subset of state variables would be required in cases where the number of state variables exceeds the number of dimensions provided by the CIS environment, which is three in our simple example CIS environment.
4 Getting to grips with economics

In order to investigate the problem solving process in CIS we chose a non-trivial non-linear dynamical system from economics – a dynamic IS-LM model with delayed collection of tax revenues [2]. The dynamical system is defined using the following system of delay differential equations

\[
\begin{align*}
\dot{Y}(t) &= \alpha \left[ A^{Y(t)} + g - s[(1 - (1 - \epsilon)\tau)Y(t) - \epsilon\tau Y(t - \theta)] - \tau[(1 - \epsilon)Y(t) + \epsilon Y(t - \theta)]\right], \\
\dot{r}(t) &= \beta \left[ \gamma Y(t) + \frac{\lambda}{r(t)-\tau} - M(t)\right], \\
\dot{M}(t) &= g - \tau[(1 - \epsilon)Y(t) + \epsilon Y(t - \theta)]. 
\end{align*}
\]

(2)

The state of the system, \(x\), is defined by the vector [\(Y, r, M\)] whose elements represent investment, interest rates, and money supply respectively. The parameters \(\alpha, a, b, g, s, \beta, \gamma, \lambda, \hat{r}\) represent various economic features. The parameters \(\tau, \epsilon, \) and \(\theta\) represent tax policy – tax rate, the proportion of tax revenues affected by delayed collection, and the delay in collection respectively. Under the economic settings shown in table 1 (Policy A) the system settles into a stable equilibrium at \(x^* = [8.3351, 0.2403, 4.5954]\) from an initial condition of \(x = [5.0, 5.0, 2.0]\).

If, under a new policy (Policy B), the time delay in collecting tax revenues, \(\theta\), is increased from 5 to 20 time periods the behaviour of the system changes and the previously stable equilibrium becomes an unstable equilibrium [2]. The problem we investigate here is, under this new policy, achieve the same economic outcome that would have been achieved under Policy A. Since the system is unstable under Policy B this will only be possible through active control of, in this case, the tax rate. In other words, we want to stabilize the system at \(x^*\) through manipulation of the parameter \(\tau\), where \(0.03 \leq \tau \leq 0.09\). We add an additional requirement that we want the system stabilized as quickly as possible. This problem can be stated mathematically as finding a tax policy, \(\tau^*(t)\), that minimizes the error of the system from the desired state, i.e., minimize

\[
\int_0^T |x^* - x(t)|dt
\]

(3)

over the time period \(T\).

This problem was mapped into the CIS environment shown in fig 1 in which the position of the ball in space represented the state of the system. The ball was initially placed at the initial condition, \(x_0\). Once the simulation was started the ball moved according to the evolving dynamics of the system. The simulation was performed using a Runge-Kutta 4th order solver with delayed variables. The position of the haptic pen was mapped to the value of the taxation rate, \(\tau\). As the user moved the pen, the taxation rate changed altering the evolving dynamics of the system. A box was placed at the target state, \(x^*\). The task for the user was to “put the ball in the box as quickly as possible and keep it there”. The specific details of how the problem was mapped into the CIS environment was the subject of the experiment described below.

| Parameter | Value |
|-----------|-------|
| Policy A (stable) | 0.03 1.03 0.60 0.05 1 0.001 1 0.08 1 0.9 5 0.06 |

Table 1: Parameters of the dynamic IS-LM system.
5 Experiment

In order to explore the relevance of motor learning considerations to problem solving in CIS an experiment was conducted in which users were presented with one of two presentations of the problem. In the first, users were presented with a default presentation of the problem in which somewhat arbitrary choices were made for each of the decisions described in section 3. In the second, these decisions were made by taking the relevant motor learning considerations into account.

5.1 Default problem presentation

In the default presentation of the problem decisions on variable selection, ordering and scaling, and the time scale of the simulation were made as simply as possible. All state and control variables were included. State variables were mapped to the \( x, y, \) and \( z \) axes of the visual representation in the order in which they appear in equation 2. The state variables were scaled so that the region surrounding the initial condition and the equilibrium state filled the visual scene. The range of control variable, \( \tau \), was mapped to the full range of movement of the \( x \) axis of the haptic pen and the pen was constrained with force feedback to move only in the \( x \) direction. The time scale of the simulation was set so that 20 time periods were simulated in 1 second of real time, which allowed the stable version of the system (Policy A) to settle into equilibrium in 10 seconds of real time – a reasonable period for a task users would need to repeatedly practise. The ball was placed initially at \( x_0 \) and the target box was placed at \( x^* \). The instruction to the subjects was to “put the ball in the box as quickly as possible and keep it there”. The task ended if a subject managed to stabilize the system (kept the center of the ball inside the box) for 40 consecutive simulated time periods or terminated automatically if the subject failed to stabilize the system after 200 simulated time periods (2 seconds and 10 seconds of real time, respectively). This default presentation of the system is summarised in table 2 and illustrated in fig 2.

5.2 Modified problem presentation

The default presentation was modified according to the considerations outlined in section 3 based on observations during a small pilot study in which two subjects attempted to solve the problem using the default presentation.

In the region of the unstable equilibrium the system maintains an approximately constant value of \( r \), regardless of changes in the tax rate, \( \tau \). For this reason, the variable \( r \) was dropped from the presentation of the system, which then became two-dimensional in the variables \( Y \) and \( M \), with \( Y \) mapped to the \( x \)-axis of the display and \( M \) mapped to the \( y \)-axis. This simplification was useful for three reasons. Firstly, it reduced the complexity of the visual scene making it easier for subjects to attend to the information relevant to solving the problem at hand. Secondly, the motion of the ball was now entirely in the \( x-y \) plane avoiding any perceptual biases associated with the \( z \)-axis. Finally, it helped with the biggest concern expressed by the pilot subjects – a significant degree of S-R incompatibility in the response of the system.

Subjects, naturally, first approach the IS-LM system with the basic expectation that moving the pen will cause the ball to respond in the same direction. The default presentation of the system violates this basic expectation in two ways. Firstly, the pen only moves in one dimension (left-right), but the ball that it controls moves in three dimensions. Subjects initially assumed that to control a ball moving in three dimensions they would need to be able to move the pen in three dimensions. Reducing the presentation from three to two dimensions lessens this concern.
State variables

| Selection  | \( Y, r, M \) |
|------------|----------------|
| Ordering   | \( Y \Rightarrow x, r \Rightarrow y, M \Rightarrow z \) |
| Scaling    | \( 0 \leq Y \leq 10, 0 \leq r \leq 10, \) |
|            | \( 0 \leq M \leq 10 \) |

Control variables

| Selection  | \( \tau \) |
|------------|-------------|
| Ordering   | \( \tau \Rightarrow x \) |
| Scaling    | \( 0.03 \leq \tau \leq 0.09 \) |
| Time scale | 1 real time second = 20\( \ell \) |

Table 2: Default problem presentation

Figure 2: Subject’s view of the default problem presentation. Labels and freeze frame reconstruction of system trajectory under the stable Policy A shown for illustration.

Secondly, moving the pen to the right caused the ball to accelerate toward the left, and vice versa, the opposite of what users were expecting. Reversing the sign of the mapping of the input variable, \( \tau \), to the \( x \)-axis input device addressed this concern\(^3\).

Finally, under the default simulation time scale the pilot subjects tended to overshoot and undershoot the target position in a series of oscillations that were difficult to eliminate. Under the modified presentation the time scale of the simulation was reduced so that 1 second of real time corresponded to 10 periods of simulated time in order to slow the response of the system to subject input and reduce the likelihood of subject induced oscillations in the motion of the ball.

Again, the instruction to the subjects was to “put the ball in the box as quickly as possible and keep it there”. If they managed to stabilise the system for a period of four seconds the task terminated. The task terminated automatically after 20 seconds. These longer time periods were to ensure the same simulated time periods under the modified time scale. This modified presentation of the system is summarised in table 3 and illustrated in fig 3.

### 5.3 Method

The experiment employed a standard motor learning retention test methodology in which subject performance was recorded over an initial series of skill acquisition trials and then again 24 hours later in a series of retention trials [14]. 28 subjects were recruited from a population of office workers aged between 25 and 50. 25 subjects were male and 3 female. All subjects but 2 were right handed. All subjects had normal stereoscopic vision. The subjects were randomly assigned to either the default or the modified presentation with 14 subjects in each group.

Each subject was asked to perform the task of “putting the ball in the box as quickly as possible

\(^3\) A similar result could also have been achieved by changing the signs of the state variable ordering.
possible” 80 times in the initial acquisition session. The 80 acquisition trials were performed in four blocks of 20 trials with a 60 second break between blocks. Subjects were then asked to return 24 hours later to perform an additional 20 retention trials. There were no pre-practice trials – subjects were exposed to their assigned presentation from the very first trial. Subject performance on each trial was calculated using equation 3. Subjects were not given any information about the nature of the underlying system. None of the subjects had any background in economics or non-linear systems analysis.

5.4 Statistical analysis

Individual subject performance was recorded on every trial and averaged over each block of trials. Motor learning was assessed within each presentation using a repeated measures analysis of variance (ANOVA with Greenhouse Geisser correction) with trial block as the repeated measure [6]. Additonal pair-wise comparisons of block means were made with Bonferroni adjustment for multiple comparisons. The alpha level for all statistical tests was 0.05.

5.5 Results

Of the 14 subjects assigned to the default presentation 11 could be said to have learned to solve the problem in that they were able to steer the ball toward the target box and keep it either in the box or in its general vicinity without the ball escaping from the region of the unstable equilibrium. Fig 4a shows the median performance on the 80th trial for the default presentation. Three subjects were unable to effectively control the ball at all, even after 80 trials of practice. The results of these three subjects were excluded from the results. The performance of the remaining 11 subjects over the 5 blocks of trials is summarized in fig 4b. Mean performance improved over the 5 blocks of trials, F(2.7, 27.0) = 34.7, P < 0.001. This improvement in performance persisted into the retention trials. Indeed, performance improved continued to improve in the retention trials with the mean error in Block 5 (M=240.59, SD=106.87) less than Block 4 (M=303.42, SD=136.99), P = 0.036.
Of the 14 subjects assigned to the modified presentation 11 were able to readily solve the problem after a relatively short number of practice trials with a high degree of reliability. Fig 5a shows the median performance on the 80th trial for the default presentation. One subject was unable to learn how to control the ball at all. One subject withdrew from the trial due to ill health and one subject failed to return for the retention trials. The results of these three subjects were excluded from the results. The performance of the remaining 11 subjects over the 5 blocks of trials is summarized in fig 5b. In this case there is a very marked and rapid improvement in performance over Blocks 1 to 3 both in terms of average performance and variance. Analysis over blocks 3 to 5 shows no further improvement during the acquisition trials nor deterioration into the retention trials, F(1.368, 13.68) = 3.3, P = 0.0816.

Comparison of performance at the end of the acquisition trials (Block 4) between the default presentation (M=303.42, SD=136.99) and modified presentation (M=95.07, SD=9.32) reveals a significantly better final performance with the modified presentation (Welsch-t = 16.73, p < 0.001).

6 Discussion

In terms of the problem subjects were asked to solve the results of the experiment show that is indeed possible to stabilise the unstable economic system described in section 4 by manipulating the taxation rate. This non-trivial problem in non-linear economic dynamics was solved through physical interaction, with a subject’s movement actions providing the solution to the problem, i.e., a tax policy, $\tau(t)$. Further examination and interpretation of the solutions produced is not dealt with here. Nor do we attempt to compare the solutions produced by subjects with solutions produced using other techniques\(^4\). Instead, we focus on the process by which subjects came to be able to solve the problem.

First and foremost, the results illustrate the importance of practice in improving the solutions produced by subjects. Subjects progressed from having basically no ability to solve

\(^4\)Such a comparison was performed in [10].
the problem to being able to solve the problem with some reliability. The rate of improvement and ultimate quality of solution varied between presentations, but in both cases solutions improved systematically with more practice. This improvement is consistent with the characteristics of human motor learning for continuous tracking tasks – power law-like improvement in performance with practice, and strong retention of skill over time [5].

The results of the experiment clearly demonstrate that the details of how a problem is presented can have a very large impact on the ability of subjects to solve the problem. The subjects using the modified presentation produced better solutions with less practice than the subjects using the default presentation. The modified presentation included a number of changes to the presentation of the problem, but the results of the experiment do not allow us to discriminate the individual effects of these changes. They were, however, all motivated by motor learning and performance considerations, which suggests that the application of CIS would benefit from the development of systematic guidelines based on these sorts of considerations.

The results also showed that while the modified presentation clearly produced better solutions more quickly, the solutions produced by subjects using the default presentation did improve over time and continued to improve into the retention trials. Perhaps with more practice the solutions produced by these subjects may have approached those of the subjects using the modified presentation. Indeed, the best performance on the final acquisition trial using the default presentation (87.2) compares favourably with the median performance on the final acquisition trial using the modified presentation (88.3). This shows that good performance is possible with the default presentation. We might expect that other subjects would also attain this level of skill with more practice. This is an important result as more complex problems will result in more complex tasks for subjects to perform, even with the most careful design. In such problems we would expect subjects to require more time to learn the required skills. Monitoring subject performance during this process may provide an indication of whether further improvement may be possible. For example, the performance of subjects using the modified presentation plateaued in Block 3 with no further improvement through to Block 5 suggesting that further practice would be unlikely to produce better solutions. It should also be acknowledged that a small number of subjects never “got the hang” of controlling the ball and were
unable to produce any useful solutions, even with the modified presentation. There is no guarantee that an individual subject will be able to solve a problem and using a group of subjects will improve the chances of getting useful results.

The key role that practice plays in solving problems in CIS raises two important issues. The first concerns the conditions of practice – the extent and form of instruction, the amount and quality of practice, feedback on performance. The second concerns how to recruit and retain the users whose motor learning efforts provide the means of solving problems. A user’s involvement may require a significant commitment of time and effort and there is the obvious question of what is in it for them. The subjects’ response to the problem solving experience in this experiment varied significantly. There were a number who expressed frustration at the difficulty of the task, particularly with the default presentation, but there were also a significant number who seemed to enjoy the challenge of learning a new skill. The current popularity of physical skill-based computer games suggests that CIS could use gamification as a way of engaging users in the problem solving process. The skills needed to solve problems in CIS are likely to be more challenging than those needed for a game designed purely for entertainment and may require more motivation and on the part of the user. User motivation may be helped by informing them of the nature and importance of the skill they are trying to learn [14]. A good example of this “serious gaming” approach is the online game FoldIt [15] around which a community of skilled participants has developed that attempt to solve protein folding problems using their skills of spatial reasoning. This approach has yielded some important results that have eluded conventional computational techniques [3].

7 Conclusion

CIS enables a form of problem solving that is qualitatively different to more conventional computational techniques having at its disposal the considerable resources of the mechanisms underlying human motor learning. While it would be a stretch to say that the subjects in this study learned anything explicit about economics, the experimental data suggests that they did acquire the knowledge of system dynamics required to solve this particular problem in economic management. That knowledge has its expression in movement action.

Getting the most out of CIS as a problem solving tool will require careful attention to the factors that facilitate and enhance the process of developing the physical skill required to solve a problem. Further research aims to develop a more comprehensive set of guidelines based on motor learning and performance considerations to help maximize the likelihood that subjects will be able to solve a given problem.

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