Multiple Time Scale Model of Self Organized Criticality in Human Motor Learning

Gottfried Mayer-Kress[1], Yeou-Teh Liu[2], Karl M. Newell[1]

[1]Department of Kinesiology, Penn State University
[2]Graduate Institute of Exercise and Sports Science, National Taiwan Normal University

Self organized criticality (SOC) has been studied as a universal property of complex adaptive systems. In a series of experiments we could show that principles of SOC also apply to a complex class of motor learning tasks. These tasks (e.g., "Roller ball") are characterized by the fact that they do not only exhibit a simple improvement of score values ("Learning Curves") but also involve a sharp transition from a failure state (not being able to solve the task) to success (being able to perform the task). The system is controlled by two critical parameters, "skill level" and "task difficulty" that can induce the transition from failure to success. The skill parameter thereby plays the role of the sand dropped slowly on the sand pile in the classic demonstration model of SOC. The connection between the two processes is given by the generally accepted assumption/axiom that skill level increases with practice time. In the class of experiments that we try to model the learner has control over a continuous parameter that quantifies the difficulty of the task. Experimental results could confirm a conceptual prediction from the psychology of the flow phenomenon, namely that learners tend to a condition where skill level matches task difficulty. Here it is quantitatively interpreted as difficulty levels for which the expected success rate is close to 50%. In our discrete, stochastic, piece-wise linear map model we further explore conditions for parameters that make this connection between motor learning and models of SOC more explicit and quantitative.

1 Introduction

Learning is a process that continues throughout the lifespan. The change in the performance dynamics of an individual performing a motor task can occur over practice trials, sessions, days, weeks, months and years. The general index of learning is the persistent change in the outcome of the performance toward the task goal. The pathway of change in learning over time is not generally, however, a smooth monotonic function [2], [3] because there are many transitory and adaptive processes that influence a given performance on a given trial or day. Nevertheless, the traditions of the theory of learning have sought a single universal law of learning, as exemplified in the study of learning curves, in spite of the apparently many time scales of change in the performance dynamics.

In this paper the focus of universality in motor learning is shifted away from the search for a common function fit for learning curves on a single dimension at the task level [10] to the universality of the time scales of change in the dynamics of learning ([10], [12], [13]). Here universality is interpreted as quantitative characterization of classes of behavior that do not depend on details of the system; this approach originates in the description of a set of critical phenomena arising in the phase transitions of different systems. It puts the analysis of change with human learning on common ground with current emphases on universal scaling phenomena in physics, economics and biology (cf. [1], [9], [16]). Fractal scaling laws have been widely studied in the spectral distributions of cyclical processes, but there has been no equivalent analysis of the scaling laws in the time domain associated with bifurcations of fixed point attractors associated with learning.

2 Universality and Adaptive Learning

The focus of universality in motor learning is exemplified here in the universality of the transition of success in mastering a difficult motor task. This transition is characterized by a sharp increase in performance score (e.g., in the roller ball task [7], or in juggling [6] often even to the point of defining whether the performer is or is not doing the task) and is interpreted as a (first or second order) phase transition similar to the ones studied for instance in physics (liquid/solid transitions). As noted before, this approach puts the analysis of change within human learning on common ground with current emphases on time scales in physics, economics and biology (cf. [1], [16]).

In our earlier studies [7], we have observed a dramatic increase in fluctuations in the performance score of the roller ball task close to the transition required to learn the task. The roller (or gyro) ball is a commercially available exercise toy, originally designed to exercise hand (wrist) movement (see Figure 1). It consists of a spinning top, whose axis of rotation can move freely in a circular groove inside of a spherical shell that is held and moved in one hand. Angular momentum is transferred by rotating the external shell perpendicular to the axis of the spinning top and also perpendicular to the circular groove. Because of the right hand rule for torques acting on spinning tops the torque produced by the hand will rotate the axis of rotation of the top (precession). The friction between the top axis and groove transfers angular momentum to the top itself. We initiate the ball spin at a prescribed angular velocity (”ball speed”) through an external mechanism (string, motor, etc).

The ball speed determines the degree of force feedback and thereby the level of difficulty of the task. The subject uses the hand (wrist, arm) movement to maintain or increase the ball speed of the top. The general principle is that the angular momentum will only be transferred in special phase relationships between the hand-rotation and the orientation of the axis of rotation of the ball.

In [7] we showed that there were 3 categories of learners in the roller ball task (see Figure 2 below). One group (B) showed a phase transition in the performance dynamics and a discontinuity in the learning curve but was the only group to in effect learn the task (that is operationally they could keep the average acceleration above zero). A second group (C) learned to increase the velocity of the ball but did not produce a phase transition to the task effective coordination mode and, therefore, did not learn the task. A third group (D) showed no improvement in performance dynamics at all in spite of several days of practice. These findings confirm the presence of individual pathways of change in motor learning and importantly that a phase transition occurs in the learning of certain motor tasks. Indeed, in this task, only the group who showed a transition learned the task - a phenomenon that has been masked in the study of most laboratory motor tasks given that they can be characterized dynamically as moving to a fixed point.

Another index of the critical point at which universal phenomena may occur is that the distribution of the order parameter for the task would shift from being Gaussian to a distribution with ”fat tails” ([5]). Thus, instead of only measuring performance as a function of practice time we will also analyze statistical properties of the distribution of scores (to be published). The prediction would be that performance score distributions far from the transition point (task is either too difficult or too easy) are Gaussian but close to criticality we observe a distribution with power-law characteristics.

In many natural systems, there is existence of what has become known as self-

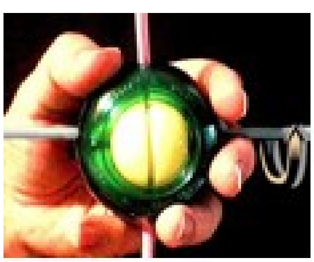

Figure 1: Photo of the roller ball which has a shell over a ball and the task is to move the hand and arm so as to keep the inside ball rolling.

organized criticality, the spontaneous development of systems towards a critical state (e.g., sand-pile model - [1]). Here, the systems naturally gravitate to a state of self-organized criticality, and minor perturbations can lead to qualitative change both large and small, as revealed by the scaling properties of power laws. These scaling properties characterize the distributions of fluctuations that will deviate from Gaussian distributions and exhibit fat tails with characteristic exponents, over a range of living and nonliving phenomena. Since practice time is considered a bifurcation parameter in a learning context, for a single task this transition happens only once during the learning process and it cannot be controlled independently. For instance one cannot move participants back to earlier states of less practice (although phenomena like disease states and warm-up decrement (or other consequences of performance degradation) might seem to have such an effect). It is, therefore, difficult with a fixed task criterion to study universal properties (e.g., measure critical exponents) that are associated with the transition because the fixed criterion of many tasks may not drive sufficiently the full potential of change in the dynamics of the system so as to reveal its universal properties.

One experimental strategy to study these critical phenomena in human learning is to continuously adapt the environmental conditions of the task so as to keep the learner at the critical point ([8], [14]). This manipulation would be a variation of what is known as adaptive learning [15], a strategy that has been used extensively in the human factors context, though not interpreted exactly the same either theoretically or experimentally, as proposed here. In adaptive learning the goal is to match the demands of the training environment with the skill level of the learner. Thus, for example, in the roller ball task where we have shown a phase transition in learning the movement coordination pattern, we can continuously adapt the initial ball speed so as to keep the learner at or near the critical point for the task. The roller-ball task is especially suited for this adaptation study because it has a continuously varying parameter (initial ball speed) that is strongly correlated with task difficulty across participants and skill levels. Thus, the task difficulty can be precisely tuned to an individualized level for each participant so that at the start of the practice session the participant has a probability of success close to zero. But the task difficulty is low enough so that we can increase the probability of success to close to 100%

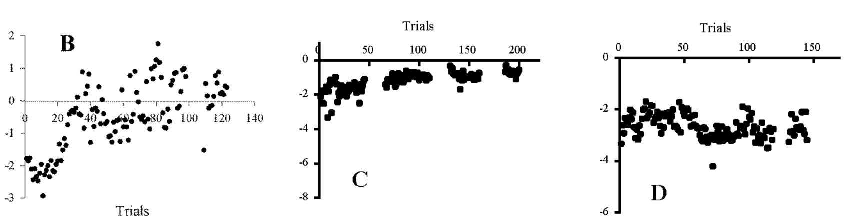

Figure 2: Plots of the average acceleration of the ball over trials for a representative subject from each of the 3 learning strategy groups (B, C, D) identified.

within one or few practice sessions. This specific task also allows us to examine quantitatively the nature of the transition and with a saddle-node bifurcation (1^{st} order transition) we expect hysteresis and bistability.

Based on our theoretical model we can predict which behavioral initial conditions will most likely fail and which ones will succeed: We know that the special behavioral initial condition of keeping the hand still will lead to task failure. One initial condition with a low probability of success therefore will be that of a hand at rest at the beginning of the task. An initial condition with a high probability of success is derived from the concept of adiabatic change: When we keep the system as close to a previously successful state as possible while slowly (adiabatically) changing the difficulty of the task. The concrete instructions for the participant would be to lower the ball speed actively while keeping close to the successful movement pattern until the new task difficulty (ball speed) is reached. The prediction is that with this adiabatic procedure it would be possible to succeed at more difficult tasks (lower ball speeds) than with the start-from-rest initial condition. This adaptive task strategy and associated transfer conditions will allow us to examine the universality of the critical phenomena at or near the phase transition of movement coordination, and provide a dynamical approach to the universality of learning.

Finally, it is postulated that self-organized criticality explains why in unsupervised (self-discovery) skill learning (e.g., kids learning roller skating or video games) the task is often continuously modified by the individual(s) to become more difficult as soon as a given skill level is reached. A consequence of the self-organized criticality condition one observes the fastest rates of performance improvement or in other words the highest probability to experience a transition from failure to success in the task. Physiologically one would expect that this is precisely the condition for activating pleasure centers in the brain (natural high, flow [4]) which would provide an experimentally testable mechanism for why participants seek this self-organized critical state of matched skill level and task difficulty.

3 An example of learning the dynamics (phasing) of the roller ball under adaptive task conditions [8])

The focus of this experiment was on the re-organization of the dynamical state space and its influence on the time scales of change in the learning function under adaptive task conditions ([8]). The experimental strategy was to study critical phenomena in human learning by continuously adapting the environmental conditions of the task so as to keep the learner at the critical point of the coordination transition. This manipulation would be a variation of what is known as adaptive learning [15], where the goal is to match the demands of the training environment with the skill level of the learner. Thus, for example, in the roller ball task where we have shown a phase transition in learning the movement coordination pattern [7], we can continuously adapt (in this case slow) the initial ball speed so as to keep the learner at or slightly below the critical point for the task in the sense that the task difficulty is just high enough so that the participant will experience a transition to success within relatively few practice trials. This adaptive task strategy and associated transfer conditions allowed us to examine the universality of the critical phenomena close to the phase transition of movement coordination, and investigate a dynamical approach to the universality of learning.

Most studies of motor learning have shown gradual or apparent continuous improvements of the performance outcome. There are tasks, however, such as bicycle riding, juggling, whose outcome is either "success" or "failure". The performance of these tasks is rarely used in the analysis of motor learning and is not accommodated by motor learning theory. From the dynamical system perspective, the learner's movement dynamical landscape determines the performance potential and each movement practice re-shapes a small piece of the movement dynamical landscape. When the movement dynamical landscape contains the basin of attraction that belongs to the goal movement, the performer is capable of performing the goal movement through a continuous change in the movement pattern along a path of steepest descent, i.e. each new movement pattern leads to a slightly improved performance. Examination of the movement patterns is a very important part of this experimental series, and we will use a "minimum distance" or Cauchy method to discern patterns. We have shown previously that only the participants that learned the task showed a bifurcation in coordination mode that was preceded by enhanced performance variability (critical fluctuations).

As mentioned aboe, if the hand movement of the roller ball task is not in proper relation with the precession of the top within a short period of time, the top will come to rest within about 10 s depending on the initial ball speed. With the help of a small fiber-optic tachometer, the roller ball speed (relevant performance variable) was recorded. A 3-D accelerometer was placed on the cover of the ball to obtain the 3-dimensional ball kinematics. The 3 wrist rotational angles with respect to an external reference axis were recorded as a trajectory in a three-dimensional space of polar coordinates. No translational degrees of freedom are involved and, therefore, the rotational degrees of freedom can be efficiently analyzed in a compact polar coordinate representation.

There were two independent learning groups of subjects (n = 10). The restricted self-organized criticality (RSOC) group had the choice of increasing the difficulty by 10% of the initial ball speed or stay at the current difficulty after a successful trial, and could choose to decrease the difficulty by 10% or stay at the current level after a failure trial. The progressively increasing difficulty (PID) group was required to increase difficulty by 10% only after 8 successes out of 10 consecutive trials. All the subjects practice 50 trials a day for 5 days.

We expected that within a characteristic time interval the participants will undergo a transition to successful movement patterns. These time-scales will change according to characteristic parameters of the individuals (skill) and also as a function of task difficulty (i.e. they will become longer as we continue reducing the initial ball speed). We predicted that the transition curves (with rescaled skill and difficulty parameters) will exhibit universal properties (i.e. the rescaled curves will cluster in tight universality classes. In the simplest case there will only be one universality class and all curves will fall on top of each other. At a critical point in practice time performance will fluctuate (critical fluctuations) and we will test whether the distribution of performance values at each adaptive critical point shows power law behavior (fat tails) and contrast it to the distributional properties that precede and follow the behavior at the critical point.

The results showed that the daily success rates between the two groups were significantly different, $t(17) = 1.9, p < 0.05$, and the one sample t test results also demonstrated that the average success rate of the RSOC group was not different from 50%, which supported the original hypothesis. The mean success rate for the RSOC group was 50% and for the PID group 39%. The analysis of the coefficient of variations of the daily success rate also showed a significantly more stable rate for the RSOC group compared to the PID group, $t(17) = 2.5, p < 0.05$. The average improvement rates also showed a small advantage to the RSOC group at $p < 0.10$ level, which provides evidence for the theoretical claim that a 50% success rate is optimal for learning the roller ball.

4 Closing Comments

In this paper we could show that general concepts of the theory of self organized criticality can be applied to the area of human motor learning. Besides providing a coherent theoretical framework for adaptive learning it also leads to predictions that could be confirmed experimentally. Among those are a convergence of a task difficulty level that leads to a 50% rate of success.

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