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Functions of Learning and the Acquisition of Motor Skills (With Reference to Sport)

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Abstract: In this paper we present theoretical and operational perspectives on the functions of motor learning with reference to sport skills. The data available on this issue are largely from non-sport motor skills but inferences are drawn to the link between processes of learning and their impact on the function for performance outcome over practice time. It is shown that the traditional assumption of the power law as the function of learning is not as well supported as assumed. Furthermore, there are strong tendencies for task properties to influence the functions of learning. This is most strongly revealed in contrasts of tasks that essentially require the task-relevant scaling of an already-learned coordination mode to those that require transitions and the learning of a coordination mode heretofore not produced (as is often the case with learning a sport skill). In our dynamical systems framework to motor learning the multiple time scales of change in task outcomes over time originate from the system's trajectory on an evolving attractor landscape. Different bifurcations between attractor organizations and transient phenomena can lead to a small set of functions including the exponential, power law, or S-shaped learning curves, though we interpret the power law as an idealized function of learning.

Keywords: Learning, functions of learning, sports skills.

FUNCTIONS OF LEARNING AND THE ACQUISITION OF SPORTS SKILLS

There is a more than 100-year history to the study of motor skill acquisition. The centerpiece of the study of motor learning has been and is the change in performance outcome over practice time, although there are many other variables that one could/should consider in the analysis of learning. The plotting of performance outcome over time is the foundation of understanding the dynamics of performance change andis the basis for making inferencesabout the process(es) of learning, in part through determination of the mathematical functions that capture the resultant learning curve or, performance curve as some prefer to call it [1]. This duality in labeling is due to the fact that learning is an inference from the change in performance outcome over time in that it cannot be observed directly – only aspects of performance are directly observable.

There is the long-standing question as to whether the functions of learning are general across all categories of tasks or whether there are some task-particular aspects to the functions of learning in relation to task type. For example, as we consider the learning of sports skills, do we anticipate *a priori* that the principles and practice of the acquisition of sport skills are different than what they are for musical, industrial, military and human factors skills? Furthermore, there have been and are many categorizations of motor skills themselves: including closed and open skills, ballistic and graded skills, gross and fine motor skills, and the more general categories of posture, locomotion and manipulation. Again, do we anticipate a priori that there are different functions of learning for different categories of motor skills? This question of the generality of the function of motor skill learning across motor tasks, and sports skills in particular,is a focus of this paper.

For the moment it is suffice to say that while a task influence on learning has been hinted at many times in several domains of the learning literature,the categorizations of motor skills have not typically and formally led todifferent theories and hypotheses of the functions of learning that are motor skill or task dependent.The net result is that our ideas about the functions of learning sports skills are based as muchor more on the learning curves of motor task categories other than those of sport.We noted in advance that there are actually limited empirical data sets on the functions of learning sports skills.Thus, this analysis by synthesis of the functions of learning in motor skills is driven considerably by theoretical considerations about motor skill learning that have in general been independent of task categorizations.

FUNCTIONS AND STAGES OF MOTOR LEARNING

Through the last century there have been many theoretical frameworks developed for the acquisition of motor skills [2]. A common view of theories or the less formal theorizing about learning has been that there are stages through which learners progress in the acquisition of skill, and there have been several unique expressions of this central idea. The notion of stages in motor skill acquisition is based formally or informally on the assumption that there are changes in a set of processes that, when viewed as a collective, are cap-

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tured by a particular qualitative state. These changes in state provide the basis for qualitative and quantitative changes in the performance dynamics as reflected in the learning curve [3].

The concept of stages is particularly well known in the context of changes that have been associated with development in general including motor development. Piaget's theory [4] of cognitive development is the quintessential example of developmental stages and relates to the developing individual's ability to assimilate and understand information. The stages were defined and labeled: sensori-motor development (birth to 2 years), preoperational (starts to talk to about 7 years), concrete (first grade to early adolescence) and formal operations (adolescence). In this context we need to keep in mind Brainerd's [5] admonition that the concept of stages in development should be reserved for a collective qualitative state based on multiple dimensions rather than a particular qualitative distinction on a single dimension of behavior. Thus, in Brainerd's view a phase transition to a new qualitative movement coordination mode would not constitute the basis for a new stage of development, in spite of the qualitative change. In other words, a true transition in stage would require the collective change of several processes that support a new and more global state.

There have been expositions of the stages of change in the field of motor learning. Two of the most well known and still quoted stage of motor learning frameworks are those of Fitts [6] and Bernstein [7]. There have been several other stage accounts of motor skill acquisition including those of Gentile [8] and Ericsson, Krampe, and Tesch-Romer [9].

Fitts [6] proposed three sequential stages of motor skill acquisition: namely cognitive, associative and autonomous. The cognitive stage is dominated by a high degree of cognitive activity and the development of the basic movement pattern. The associative stage reflects a refinement of the movement pattern, fewer errors and less cognitive and attentional demands. Finally, the autonomous stage has the performance of the movement being virtually automatic, even fewer errors and little cognitive involvement.

For Bernstein [7] motor skill acquisition was essentially an issue of mastering the redundant degrees of freedom of the system. He proposed 3 stages of learning built on this central idea. Stage 1 was that of freezing the degrees of freedom that were emphasized in joint space. Further practice led to stage 2 where there is a progressive release of the frozen joint space degrees of freedom. Finally, in stage 3 the performer learns to exploit the reactive forces that arise from the movement pattern itself.

Ericsson *et al*. [9] characterized the changes in motor skill acquisition with particular emphasis on the nature of what expertise represents in skilled performance. Fig. (**1**) shows their perspective of 3 stages of motor learning. The figure reflects qualitative change in the performance outcome that is driven significantly in their view by the amount of deliberate practice. This account provides a link of the qualitative aspects of stages of motor skill learning to qualitative changes in performance outcome – albeit in a descriptive hypothetical way.

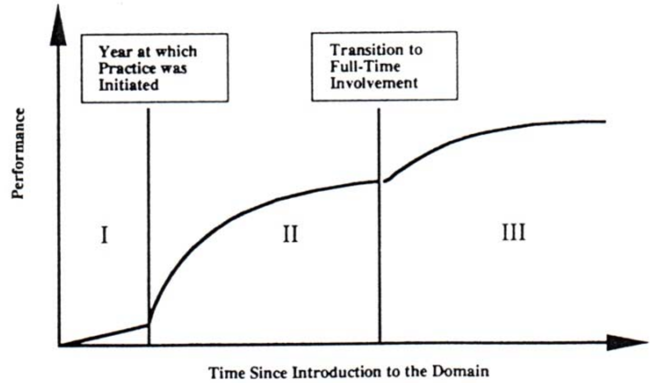

Fig. (1). Three phases of development toward adult expertise (from [9]).

In summary, there has been very little formal linking of these respective stages of learning, and others that have been proposed, to the changes in the function of performance outcome. The stages of learning in the Fitts framework[6]are largely a description of how the behavioral aspects of performance change over practice time.Bernstein's framework is also largely descriptive but on biological dimensions of motor skill acquisition.

The reason for briefly reiterating these established and well-known stage accounts of motor skill learning is that they have implied with varying degrees of explicitness that there will be qualitative changes in the dynamics of performance outcome that can be mapped to the defined stages of learning (as in the Ericsson figure). However, this assumption has not been investigated as few motor learning studies have linked indices of the stages of learning to change in the performance outcome. Indeed, where functions of learning have been assessed, the predominant form of the change in performance outcome is that of a monotonic function, as is often shown in textbook characterizations of the functions of learning.

Fig. (**2**) shows the classic set of hypothetical monotonic functions that have often been taken as candidates for motor skill learning (e.g., [10]). The functions are all monotonic in that they show continuous change over time in the same direction with no qualitative change. Given that they are hypothetical of the learning functions they also do not show any trial-to-trial fluctuation or other processes of change to performance outcome. An implication has been that different tasks can realize these different forms of the learning curve but this task dependent relation for the functions of motor skill acquisition, including those of sport skills, has not been formally developed.

In closing this section it is worth emphasizing that most theoretical perspectives of motor skill acquisition hold that there are qualitative changes to the processes of learning as a function of practice time. The inference is that these changes would be associated with the performance dynamics – thus, leading to the outcome that there would be an associated qualitative change in the performance outcome. Nevertheless, this process-outcome relation has never been formalized very well with the consequence that in a number of cases we have qualitative changes in the processes of motor skill ac-

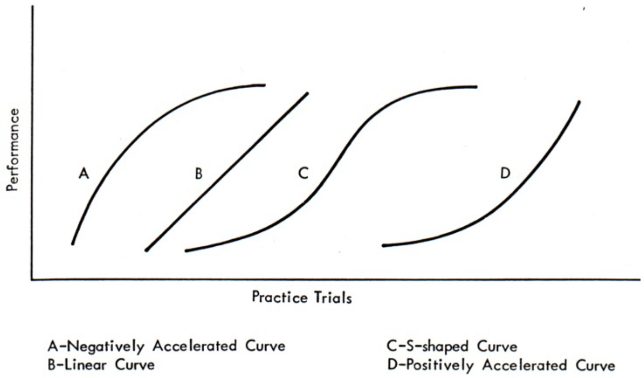

Fig. (2). Typical hypothetical learning curves (from [10]).

quisition reflected in the monotonic change in performance [10]. This leaves the accounts of the functions of motor skill learning largely a descriptive curve fitting exercise with little direct link to and even guidance from theory in motor skill acquisition.This approach to curve fitting in the study of learning is what Thurstone [11] referred to as empirical curve fitting as opposed to thetheoretically driven rational curve fitting.

EMPIRICAL EVIDENCE ON THE FUNCTIONS OF MOTOR SKILL LEARNING

There have been many attempts to characterize the function of motor learning by fitting a mathematical equation to the performance outcome data over time [12,13]. Functions that map to the hypothetical monotonic trends shown in Fig. (**2**) have been well represented. Nevertheless, the two most commonly fitted functions to motor learning data are those of the exponential and the power law. Both of these functions can take on, as shown in a later section of the paper, various expressions that have a different number of parameters [12]. In their most elementary form we have:

Exponential: $y = e^{mt}$ (1)

Power law: $y = At^{m}$ (2)

Where y is the performance score, t is the trial, m is the exponent of change and A is a scaling constant.

It has often been stated that there is not a single learning curve that is representative of the performance dynamics for all individuals learning all tasks. For example, the learning curves that arise can be influenced by characteristics of the individual performer, properties of the task, the conditions of practice, the variable of measurement of performance outcome and whether the data are averaged across individuals or not [10]. The formal contribution of these factors to the function of learning curves has, however, not been forthcoming through investigation.

A. Newell and Rosenbloom [12] reported a synthesis of the published learning functions at that time and concluded based on their interpretation of the data that the power law was the ubiquitous law of learning. Their representative power law was a 3 or 4 parameter version of the more basic power law shown in Equation 2. The power law expression of the change in performance over time was mapped to their information processing based chunking theory of learning.

The A. Newell and Rosenbloom [12] paper analyzed the functions of change in several learning data sets. Nevertheless, there are two data sets from the motor domain that are perhaps the most quoted examples in regard to evidence for a power law function of motor learning. These are the studies of Snoddy [14] and Crossman [15] with the essential learning data from each study shown in Fig. (**3**).

Snoddy [14] reported a study of adults learning a maze drawing task where performance was measured with an amalgamated performance score based on both spatial and temporal dimensions. Fig. (**3A**) shows our re-plotting of the Snoddy data that reflects 20 trials of practice a day over 4 days. A power law function fits the data well except for the early trials, a departure that is often either overlooked or just ignored. It is also the case that the fluctuations of the data points around the function do not appear random. Nevertheless, the Snoddy [14] data have been interpreted as the first and exemplary example of power law motor learning as reflected originally in the plotting of the data on double logarithmic paper.

Crossman [15] reported a study of the performance over time of Cuban factory workers who made cigars. The Fig. (**3B**) shows the task time (time to roll a cigar) as a function of trials of practice. The change in the performance dynamics (reduction in task time) follows well a power law over the initial year of practice trials and appears to only be limited by the constraints of the cigar-rolling machine rather than the limits of the performer. Indeed, the Crossman [15] study, given its large number of practice trials, has often

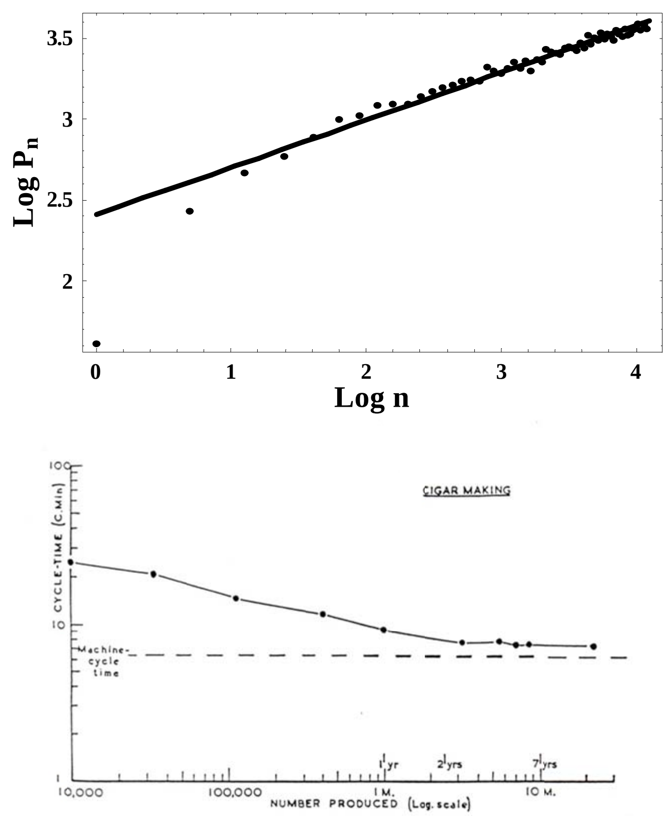

Fig. (3). Two of the most well known demonstrations of power law motor learning. A. from[14]; B from [15].

been used as an example of the notion that there are no limits to human learning.

The Crossman [15] study with its power law representation of learning has received notoriety because of the very large number of practice trials – some 10 million trials over 7 ½ years. The sufficiency of the number of practice trials has long been a limitation of motor learning experiments and this study has been seen as an unique and important example of the dynamics of performance that arise from very long-term practice. However, it is often overlooked that each data point in Fig. (**3b**) represents the performance of a different participant and also that the information compression is considerable with the large degree of data averaging and the non-reporting of performance on the majority of days over the years. A cross-sectional approach to the study of motor learning has its place but the failure to have a within-participant set of performance dynamics tends to undermine the veracity of the power law interpretation usually afforded this study.

Nevertheless, A. Newell and Rosenbloom [12] concluded that the power law is the ubiquitous law of learning but, as we note here, the evidence from at least two of the key power law learning studies is not as compelling as advocated. Furthermore, many papers subsequently endorsed the centrality of the power law in learning (e.g., [16-19]) that in turn provided further support to the universality interpretation of the power law for learning. It took another 20 years or so for challenges to the idea of the power law as the universal law of learning [20,21,3]. There are a number of different aspects to the challenge on the appropriateness of the power law for motor learning.

In many studies of motor learning the function is determined by a best fitting criterion of the percent of variance accounted for without consideration of theory. The problem is that the differences in the fit of functions are small and often of the order of around 1% [12,13]. This challenge in distinguishing small quantitative differences in percent of variance in function fitting opens the consideration of using qualitative criteria that relate to each function as a means to distinguish between them [22]. For example, a distinguishing feature of an exponential is that it has a single time scale of proportional change whereby the change from trial to trial is proportional to the initial level of performance. This qualitative property provides a straightforward way to test and interpret the qualitative aspects of the performance dynamics unlike the percent of variance accounted for. Another significant criticism of the power law interpretation of learning is based on the fact that averaging data can mask the actual change in the performance dynamics of individuals that make up the averaged group function, a challenge that is most relevant given that averaged data have typically been used in the assessment of the function of learning.

INDIVIDUAL VS AVERAGED FUNCTIONS

It has long been advocated that averaging learning data can change the determination of the function of learning [23]. Nevertheless, it would appear that most evaluations of the function of learning are based on averaged data. Indeed, in the A. Newell and Rosenbloom [12] paper the function fitting is predominantly on group averaged data.We have not been able to find published motor learning data from individual performers where a power law function is shown to be a better fit when formally contrasted with other function fits. Indeed, most function fitting in learning data has been of the demonstration kind rather than the investigation kind.

Motor learning data can be averaged in two ways. One is to average the data over participants. The other is to average the data over trial blocks as opposed to analyzing the individual trial data. In most experimental studies of motor learning both forms of averaging are used simultaneously in the analysis of data. These averaging procedures can combine to mask the determination of the actual time scale of change of each individual learner.

In [3] we showed through simulation that averaging a group of exponential functions with different exponents leads to the average curve approximating a power law. This is because the different exponents of each exponential are bringing into the averaged data different time scales so that the average in principle more closely approximates a power law that has infinite time scales over the range studied. Thus, in this simulation case the averaging of the data over participants led to the determination of a group learning function that did not represent the qualitative properties of learning of any single individual. Furthermore, the inference is that the more people over whom the averaging is done in this example, the more closely a power law will be approximated because more time scales are being brought into the average.

The averaging of trials is performed with regularity in the motor learning domain but there do not appear to be any guiding principles to the technical assumptions of this procedure. The primary goal inthe smoothing of the data is to take away the trial-to-trial fluctuations through the averaging procedure. This approach seems to fit well with the expression of idealized hypothetical functions of learning that are shown in Fig. (**2**). On the other hand the information in the trial-to-trial fluctuations is lost in part or all together with the progressive masking of the time scale of change by increasing the trial block size in the averaging.

A final point here is on the time scales of motor learning [3] which is beyond the focus of this paper for full treatment. It is that the appropriate time scale of the abscissa in motor learning studies is not entirely clear because it has not been sufficiently investigated. Performance data from each trial are usually plotted on the basis of trials leading to equal intervals between trials and then also the samegap over the days of no practice between sessions, in spite of the fact that the time between trials is different within a session from that between session. However, the data could be plotted on the basis of real clock time to investigate the functions of learning but they rarely are. The more general theoretical question is a determination of the appropriate time-related dimension on which to investigate the function of learning.

CHARACTERISTIC TIME SCALES OF MOTOR LEARNING

Our approach to understanding learning curves has been through the principles of an epigenetic landscape for considering the role of characteristic time scales of learning. The approach also offers a system identification strategy for decomposing the processes of learning curves. In this account, the change of performance over time is the product of a superposition of characteristic exponential time scales that reflect the influence of different processes. Our approach can also produce the power law of practice but we have hypothesized that this function may prove to be an idealized case of motor learning rather than that of a ubiquitous law [3,24-26].

Time Scales

The phrase time scales has been increasingly used of late in the study of many aspects of behavioral change over time. The use is typically descriptive in the sense of capturing the time duration of an event or process to unfold for an action. There is, however, a more rigorous approach based in the physics of motion that provides a dynamical set of principles to the determination of a time scale and a basis for our approach to the dynamics of motor learning.

Briefly, in dynamical systems there are two types of idealized motions that lead to the fundamental concept of time scales. These motions have either periodic oscillations [27] or growth/decay at a constant rate [28]. In oscillatory systems the intrinsic time scale is the period or inverse of frequency. In growth/decay systems the intrinsic time scale is the inverse of the growth/decay rate. These two classes of behavior and combinations thereof are in linear dynamical systems the only forms of movement observed and thus are the basis for the characteristic time scales of change.

The oscillatory and growth/decay processes are fundamental to describing behavior close to a fixed point – the concept that is associated with equilibrium regions of the dynamics. For example, fixed points correspond to the absence of motion as in a pendulum at rest. An important principle is that the motion close to a fixed point can be approximated so as to be described by linear dynamical systems. This means that the motion of the trajectory can be characterized by the exponential function of Equation 1 or the real part of a complex exponential function [3]. The time scale within a growth or decay process to a fixed point is characterized by the time for the dynamics to double/half the distance to the fixed point. Thus, in our approach a time scale is not simply the duration of an event but importantly the characteristic time duration of an event that arises from a periodic or growth/decay dynamical process.

These assumptions about fixed points and attractor dynamics provide the theoretical basis for the assessment of the characteristic time scales of change in motor learning and development. We interpret the multiple time scales of change in task outcome over time to originate from the system's trajectory on an evolving attractor landscape. Different bifurcations between attractor organizations and transient phenomena can lead to exponential, power law or s-shaped learning curves, among other pathways of change. In this view there is not a single law (function) of learning as has been traditionally sought in behavioral science but rather a coherent set of dynamical principles that can lead to a small set of different functions of change in task outcome and limb trajectories [3,24,25].

Landscape Model of Characteristic Time Scales

The approach of mapping a single function of learning to the performance dynamics is grounded in the theoretical proposition of a single process organizing learning and the persistent change in performance over time. In this view, the performance outcome is typically taken to reflect the construct of memory largely on the basis of the positive influence of the degree practice and the negative influence of the increasing time between practice. Thus, the single and central construct of memory strength is the foundation for learning, retention and transfer as reflected in the properties of performance score changes in learning curves.

However, there is a long history to the idea that the performance dynamics of learning curves is the product of multiple processes that, in addition to memory strength, include constructs such as warm-up, inhibition, noise and fatigue [1,29,30] Schmidt & Lee, 2005; [31]. The theoretical perspective of multiple processes to learning provides a rational basis for multiple characteristic time scales in the performance dynamics together with the theoretical and practical need in motor learning for system identification strategies to tease out the contribution of these processes to the performance dynamics. This is a more focused challenge than that presented in the introduction of the paper in regard to the relation between the notion of stages of learning and changes in the performance dynamics as reflected in learning curves.

A central assumption of our approach is that the different processes that contribute to the performance dynamics of acquiring motor skills, including sports skills, have different time scales. For example, learning is typically interpreted as a long-term relatively persistent change, whereas the influences of warm-up and fatigue on performance are more short term and, interestingly, are reversible through rest. Indeed, the physically demanding whole body actions of many sports skills may increase the relative contribution of these transient processes to the performance dynamics. In general, our approach holds that the persistent processes of learning can be distinguished from the more short term and transient influence processes on performance.

In our theoretical perspective one can model the data through determining the contributions of characteristic time scales to the performance dynamics. An essential feature is the identification of behavioral patterns as locations in a landscape and the performance values as elevation levels with this landscape [3,24,25]. The goal of the task is assigned the lowest elevation in the landscape and in dynamical terms this is seen as the point attractor. The axes of the landscape are the time scales of the exponentials that are derived from the superimposed exponential fit to the data.

The prototypical example of this approach to modeling the characteristic time scales of performance over time may be understood in our reanalysis of the original Snoddy [14] data shown in Fig. (**3A**). Fig. (**4**) shows a landscape with two distinct time scales reconstructed from these same learning data of [14]. The relatively fast time scale captures the performance dynamics at the beginning of each practice session while the relatively slow time scale captures the persistent change in the performance dynamics over the days of practice. Fig. (**5**) shows the same data plotted in a more typical learning curve frame of reference with the power law superimposed for comparison. Clearly, the two time scale model fits the Snoddy [14] data better than the power law and reveals the dominant contribution of two characteristic time scales to the performance outcome over days.

We have conducted more formal investigations of the two time scale model in the [14] data set and in other motor

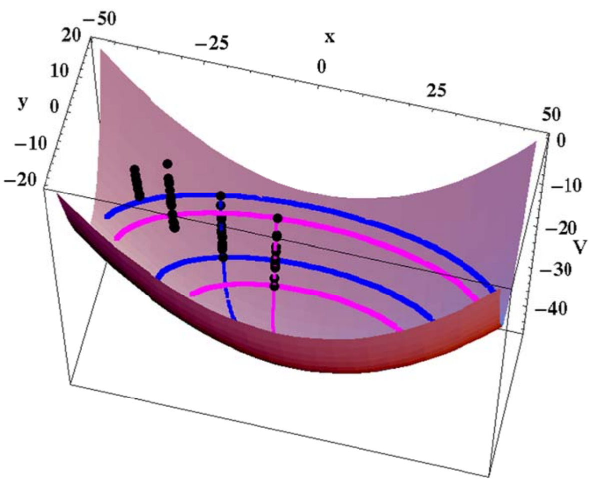

Fig. (4). Landscape associated with Snoddy's score data (black dots) as elevation levels. The four clusters correspond to the four training sessions. The x-behavioral variable corresponds to the slow time-scale (shallow dimension) whereas the y-variable corresponds to the fast time-scale (steep dimension). For sessions 3 and 4 we plot the contour lines of the first and most successful trials. Note, that each contour line illustrates the degree of behavioral degeneracy (redundancy) for the given performance score (reproduced with permission from [25]).

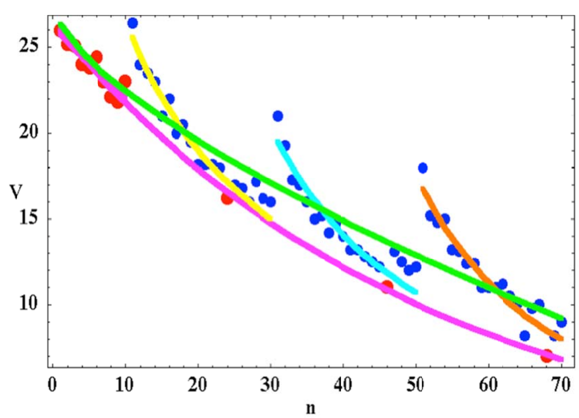

Fig. (5). Performance data $V_n$vs trial number n from Fig. (**4**) of [14]. Main figure shows distance to asymptotic score Va = 46 in linear scale. Magenta curve: exponential regression through first ten scores and best score of each session. Yellow, Cyan, Orange: Exponential fit to each of the practice sessions. Green: Power law fit through all data points. Note that the ten first points are not included in the main regression whereas in our model all data points can be accounted for by the model (reproduced with permission from [25]).

learning data sets [32]. Equations 3 and 4 capture the performance dynamics for the two time scale model. The envelope function in the model is represented as an exponential decay that occurs across all trials, while the fast time-scale changes as the function of the trials within each practice session, *j*. The two time scale model has been compared to other standard models of learning data though Akaike information criterion evaluations [33] and a rigorous theoretical assessment of the exponents and asymptotic values of the equations. The two time scale model was shown to consistently fit the performance dynamics as well or better in both individual and group averaged learning data sets.

Slow time scale:

$$y_{en}(n) = y_{inf} + a_{en}\, e^{-\cdot\cdot_{en}\, n} \qquad (3)$$

Slow and Fast time scale:

$$y_j(n) = y_{inf} + a_{en}\, e^{-\cdot\cdot_{en}\, n} + a_j\, e^{-\cdot\cdot_j (n-n_j)} \qquad (4)$$

The model describes how a performance related variable y(n) converges to an asymptotic target value y_{inf} as time n – measured in units of trial numbers – increases. a_{en} is the initial distance to the performance goal y_{inf} and - $\cdot\cdot_{en}$the exponent for the envelope slow time scale function whereas a_j determines the amount of warm-up decrement at the beginning of session *j*, starting with trial number n_j. The exponentfor the respective practice session *j=1,…,4*is given by- $\cdot\cdot^{j}$. The model holds that the exponents for the fast time scale are the same on each day anassumption of invariance that reduces the number of parameters in the model.

The epigenetic landscape framework supplemented with the system identification approach to decomposing the performance dynamics clearly shows in the group averaged data of [14] that the two time scale model fits the data qualitatively and quantitatively better than the power law and other models of learning. As we have stated previously, however, this does not mean that all performance dynamics will fit the two characteristic time scale model. It is our postulation that this model will be most relevant when there are no bifurcations in the performance dynamics, that is, when the task requires merely the rescaling of an already established coordination mode to the task outcome [34].

A question to be pursued in the analysis of learning curves is what further processes could be decomposed from the performance dynamics beyond the characteristic time scale of the warm-up decrement adaptation phase and that of the relatively permanent change over all trials and days. We have mentioned the short-term fast time scale and the reversible influences of motivation, attention and fatigue that would be particularly influential in sport skills.

In [32] we modeled learning data from a star tracing task [35] with a 3 characteristic time scale model that included the negative influence of fatigue. In this demonstration of extending the model to 3 time scales we showed that it provided a better fit to the performance dynamics but importantly in a way that was motivated by theory. In general, we estimate that additional processes will be difficult to tease out of the performance dynamics and this modeling effort may need to use other ways to analyze the performance data. For example, a consideration of the best score achieved in a learning session to define the dynamics may prove useful, but this just reflects a broader need to go beyond the standard analysis strategy of single function curve fitting to all the performance data.

And, in closing this section, we would propose that this approach to the system identification of performance dynamics holds promise for a new approach to the analysis of the effects of practice distributions on motor learning, including sport skills. This is a topic that has lost impetus since Hull's theoretical formations [30,36] regarding reactive inhibition and learning that were investigated primarily on continuous laboratory tasks, such as the pursuit rotor. The distinguishing of the transient adaptive and persistent learning effects on practice schedules should provide new ways to consider such old problems as oblivescence and reminiscence [37], massed /distributed practice schedules [1], and practice condition effects more generally.

LEARNING CURVES FOR TASKS WITH COORDINATION MODE TRANSITIONS

The multiple characteristic superimposed exponential time scale model of learning is restricted to tasks that have fixed point dynamics. In practice these are tasks that require largely the rescaling in space, time or force of an already established coordination mode to be learned [34]. The acquisition of many sports skills requires the transition of coordination modes to occur and thus arenot in general in the rescaling category of skills, although there are elements of this process through the processes of coordination mode changes. Thus, sport skills will often require the acquisition of coordination modes that are more specific than those of the fundamental movement skills that are formed in infancy and early childhood. There has been considerably less study of the learning of motor tasks that require a transition of coordination to realize the task goal and this is why the monotonic learning functions of movement scaling tasks are less relevant to sport, even though they have dominated the study of motor learning in laboratory tasks.

We show here one example of motor learning that requires a coordination transition to accomplish the task with the net result that the learning curve becomes rather different from those emphasized in fixed point dynamics and, moreover, different learners have different patterns to their change in performance outcome over time that is related to different patterns of change in the movement coordination dynamics. [38,39] have studied the performance dynamics of learning the roller ball task. In this task, the outer shell of a ball-like object is held in the hand and needs to be rotated so as to preserve or even increase the velocity of a ball that is held within the outer shell. This condition can only be realized by finding the appropriate spatial phase relation of the motion of the inner ball to that of the outer shell.

Fig. (**6**) is taken from [38] and shows in effect 3 types of learners over the 3 days of practice. One group rescales the ball velocity and makes the task relevant spatial phase transition of ball motions. A second group succeeds in improving the scaling of inner ball velocity but never realizes the phase transition necessary to keep the ball rolling. Finally, a third group of learners shows no change within or over the practice sessions. These patterns of change in the performance dynamics are very different from those of the rescaling tasks emphasized so far in this paper. We would claim, however, that they are much more relevant to the kinds of dynamics to be found in the learning of many sports skills or motor tasks more generally where a new pattern of coordination is required (including infant motor development).

The transition points in the performance dynamics were also characterized by the increased variability in ball velocity a feature that is a classic hallmark property of a phase transi-

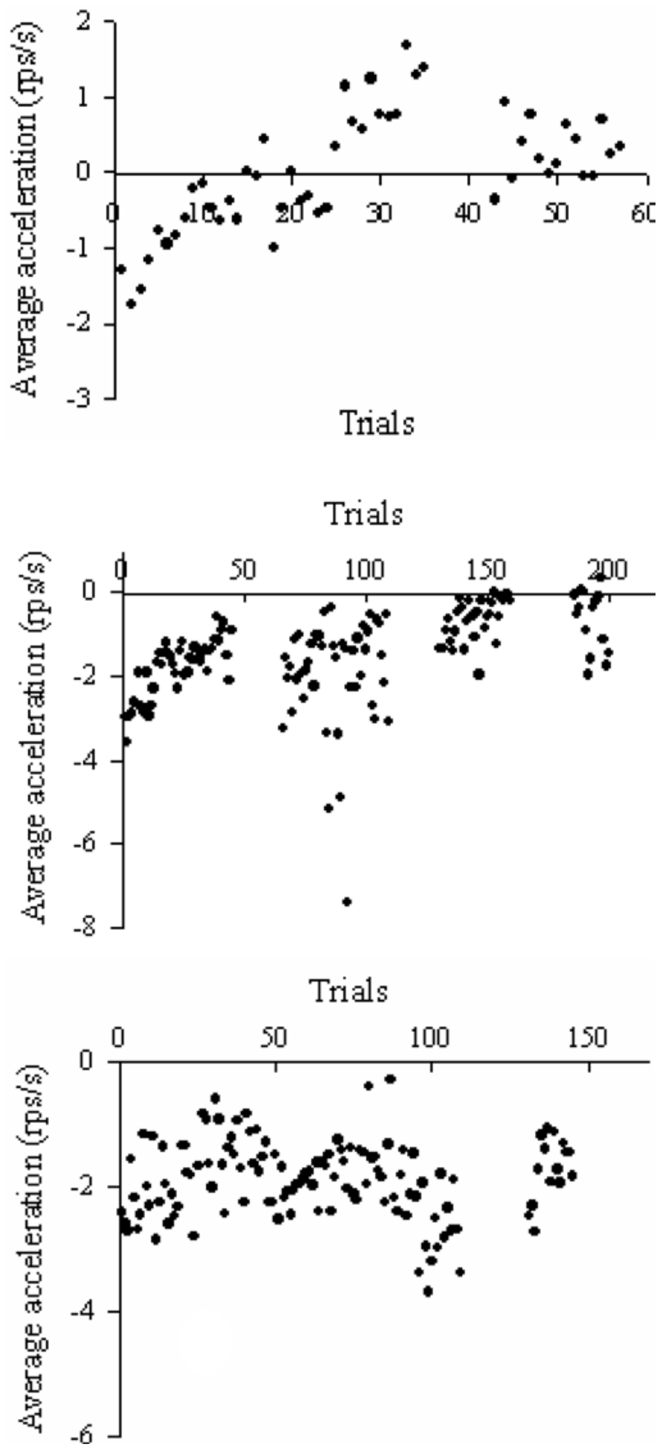

Fig. (6). Performance data of 3 classes of learner over days of learning the roller ball task (reproduced with permission from [26]).

tion [40]. In a subsequent rollerball study [39] bi-stability and hysteresis in the coordination mode were revealed as a manifestation of dependence on the initial conditions. It was shown that the transition from failure to success in the roller ball task as a function of practice time can be modeled as a saddle-node bifurcation corresponding to a first order phase transition. This bifurcation would support an S-shaped learning curve in the outcome score but it would only be realized with a fuller data set than provided in Fig. (**6**). In this task it was also proposed that task difficulty acts as a control parameter that is a dual to skill level (that is, increased skill level is equivalent to reduced task difficulty and vice-versa) and that also effectively compensates for practice time [39].We would project that the learning of sports skills would channel the succession of a number of phase transitions but as implied earlier there are little or no data that speak directly to this issue.

Thus, the learning of motor tasks that require directly or indirectly a coordination mode transition are likely to have very different patterns to the performance outcome dynamics than are shown in what we have called movement rescaling tasks. In themotor tasks with a coordination mode transition the performance outcome would seem to not necessarily be an instance of a monotonic function. The tasks with transition invoke additional time scales to performance dynamics that the field is only beginning to investigate.

CONCLUDING COMMENTS

In this paper we have presented theoretical and operational perspectives to the functions of learning motor skills with particular reference to sport skills. It was shown that the traditional assumption of the power law as the function of learning is not as well supported as assumed. Furthermore, there are strong tendencies of task influence on the functions of learning that are revealed in contrasts of tasks that essentially require the task-relevant scaling of an already-learned coordination mode to those that require transitions and the learning of a coordination mode here to for not produced (as is often the case with a sport skill). This distinction also reflects the differences in the dynamics of performance outcome as a function of their associated changes to the movement pattern. In our view, the multiple time scales of change in task outcome over time are interpreted to originate from the system's trajectory on an evolving attractor landscape. Different bifurcations between attractor organizations and transient phenomena can lead to exponential, power law, or S-shaped learning curves, though we see the power law as an idealized function of learning.

CONFLICT OF INTEREST

The authors confirm that this article content has no conflicts of interest.

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