In: Perspectives on Cognition and Action in Sport
Editors: D. Araújo, H. Ripoll and M. Raab

ISBN: 978-1-60692-390-0

Chapter 5

INCREASING STOCHASTIC PERTURBATIONS ENHANCES ACQUISITION AND LEARNING OF COMPLEX SPORT MOVEMENTS

Wolfgang Schöllhorn[1], Maren Michelbrink[1], Daniela Welminsiki[2] and Keith Davids[3]
[1] University of Mainz, Germany
[2] University of Münster, Germany
[3] Queensland University of Technology, Australia

ABSTRACT

Traditionally, the acquisition of skills and sport movements has been characterized by numerous repetitions of a presumed model movement pattern to be acquired by learners. This approach has been questioned by research identifying the presence of individualized movement patterns and the low probability of occurrence of two identical movements within and between individuals. In contrast, the differential learning approach claims advantages for incurring variability in the learning process by adding stochastic perturbations during practice. These ideas are exemplified by data from a high jump experiment which compared the effectiveness of classical and a differential training approach with a pre-post test design. Results showed clear advantages for the group with additional stochastic perturbations during the acquisition phase in comparison to classically trained athletes. Analogies to similar phenomenological effects in the neurobiological literature are discussed.

INTRODUCTION

Commonalities and differences in traditional motor learning approaches and the question of how to become skilled at everyday actions or sport movements have been addressed by a large variety of theoretical approaches. Traditional motor learning approaches have included the constant repetition of a to-be-learned target movement (Gentile, 1972), progression towards a target skill by performing a methodical series of exercises (Gaulhofer and Streicher, 1924), variability of practice (Schmidt, 1975) and contextual interference learning (Shea and Morgan, 1979). The constant repetition approach is based on the idea that the enhancement of movement skill is only effected by repeating a target movement as often as possible, and learning by means of methodical series of exercise is founded on exercises that have a structural similarity to specific parts of a target movement.

In the variability of practice approach, derived from Schmidt's schema theory (1975), the representation of movement classes is based on invariant programs and variable parameter features. A practical consequence of this assumption is that, if a single invariant is trained in combination with several variable parameters, the program for a specific movement within a given movement class becomes more stable. In spite of this view, it is worth noting that experimental support for the variability of practice hypothesis has mainly been provided from a specific range of movement tasks (Wulf and Shea, 2002) that have primarily required the production of muscular forces, but which have tended to minimize the influence of gravitational forces and moments of inertia (Schneider, Zernicke, Ulrich, Jensen, and Thelen, 1990). Additionally, weaknesses in experimental designs have led to indeterminate evidence in favour of the advantage of variable practice in comparison to constant practice (van Rossum, 1990).

While the variability of practice approach has emphasized investigation of the role in practice of variation of movement elements, the contextual interference (CI) approach maintains a stronger focus on the variation of the practice conditions with respect to the sequential order of different movements. The CI approach, was originally transferred from language learning experiments (Battig, 1966) into movement sciences (Shea et al., 1979). It occurs when at least two types of movements are learned in parallel (Goode and Magill, 1986; Lee and Magill, 1983). The more randomized (high CI) is a sequence of movement tasks during the acquisition period, the greater are expectations that the movements will interfere with each other in comparison to a less randomized (blocked) sequence (low CI). It has been observed that in retention or transfer tests high CI (alternating sequence) groups display smaller decreases in performance than low CI groups (blocked sequence). Meta analyses (e.g., Brady, 2004; Magill and Hall, 1990) have provided evidence for these effects primarily if the learned movements stem from different movement classes with different invariant features (e.g. different relative timing). The effect is assumed not to occur in children (Wulf and Shea, 2002) and less experienced participants (Smith, Gregory, and Davies, 2003), leading to a recommendation that learning new skills should begin with blocked training before random practice follows on a more experienced level (Wulf et al., 2002).

A most intriguing phenomenon was identified when the methodical series approach was interpreted in terms of contextual interference learning (Smith and Davies, 1995). By learning a single movement through different sequences of preparation exercises, facilitation, rather than interference, was predicted during the acquisition period. When movements have been learned in most variable environments, higher rates of improvement have been observed in the acquisition phase when high CI was applied. For instance, in one case water served as variable environment for acquiring a pawlata role in kayaking (Smith and Davies, 1995) while in another case snow texture created a variable environment for learning snowboarding skills (Smith, 2002).

In these traditional motor learning approaches, despite some fundamental distinctions between the contextual-interference, the variability-of-practice, and the repetition approaches, all commonly rely on the implicit assumption of the need for learners to acquire a constant target movement with at least some invariant features. While the repetition approach favours the stability of a movement by simply repeating all parts of the movement as often as possible, the variability of practice approach rather assumes that invariants can be refined in different combinations with variable parameters. Furthermore, the contextual interference approach claims to improve the stability of a target movement by changing the short term (historic) associations for a target movement by preceding it with different movements with different invariants.

Another important feature common to most traditional motor learning approaches is a generic view of movement variance with respect to the target movements. Variance is considered to occur as a result of erroneous or noisy (Schmidt, 1991) movement planning or execution, requiring error minimization in learners by encouraging them to only practice a movement correctly. From this perspective, variance is accredited with a destructive character and occurs as a result of serendipitous movement errors which passively accompany the learning process. While the repetition approach favours the complete avoidance of errors, the variability of practice and CI approach concede some benefit in some movement errors in the learning process (Magill, 1993, p. 363) since they enhance performer awareness of deviations from a target movement to facilitate conscious corrections for future executions. From this perspective, a certain amount of variance in the target movement is mainly conceived and tolerated as a source of inherent system error. In traditional approaches, variance in the target movement is only considered to play a passive, destructive role because it is included implicitly in the explanation of CI-effects within the Elaboration and Reconstruction hypothesis.

Differential Learning Approach

In contrast to these traditional views, the differential learning approach contains several alternative assumptions based on ideas from dynamical systems theory, artificial neural net research, and stochastic resonance phenomena. Furthermore, differential learning can be explained by focusing on differences between consecutive movements while avoiding movement repetitions to exploit the constructive role of fluctuations during the learning process. In the remainder of this chapter, we outline the differential learning approach in more detail. An important idea in the differential learning approach is the enlargement of differences between subsequent movements in order to produce additional information for the system. This idea is mainly anchored in philosophical approaches to cognition (Heidegger, 1957; Derrida, 1982; Spencer-Brown, 1997), and can be comprehended by understanding how the visual and auditory sensory systems function in the nervous system. In the visual system the difference between an object's image from the left and right eye on the retina provides observers with information on its distance. In the auditory system the difference in the time delay of an acoustic signal received in the left and right ear is perceived as information for the spatial orientation of a signal. Additionally, from a physical point of view, information production is based on a choice between at least two different states (= 1 bit; Shannon, 1948).

The fundamental idea, that movement variability is considered a necessity for adaptive system function, can be traced back to the dynamical systems perspective, where fluctuations are considered as necessary for functional adaptations to changing environmental contexts and the prevention of loss of system complexity as constraints change (Button, Davids, and Schöllhorn, 2006; Kelso, 1995; Schöner and Kelso, 1988). Deviations from an intended movement are not considered as errors but rather as fluctuations and intermittencies in system organization (Tumer and Brainard, 2007). When applied to the study of motor control, fluctuations are particularly important in the adaptive process of switching between stable movement patterns during goal directed behaviour. Fluctuations also seem to govern motor learning processes (Zanone and Kelso, 1992) playing an active role during the acquisition phase.

A similar active and constructive role is ascribed to noise in robotics and artificial neural network (ANN) research. When a robot is confronted (trained) with noisy stimuli within a constantly changing environment during the training or learning phase, much better orientation to different environmental conditions can be observed in the application phase in comparison to a robot that has been trained within a constant environment (Miglino, Lund, and Nolfi, 1995). Training of ANNs with noisy data results in better recognition rates in the application phase as well (Bishop, 1995). A transfer of ANN research to the study of motor learning was undertaken by Horak (1992). In his work, the training phase in ANNs was assigned to the acquisition phase in motor learning and the test phase was aligned with the transfer test. The simulation of different training schedules by Horak (1992) on the basis of three simulated data sets led to a smaller error rate for the blocked condition in an acquisition phase, whereas random and the serial training schedules resulted in smaller error rates for the transfer test. In this context insights into the simulated transfer abilities may be of specific interest for motor learning in humans. Within artificial neural nets the quality of transfer depends highly on the mapping of the transfer task to the nodes' weights, relative to the nodes' weights of the trained tasks. When a transfer task is mapped to an area within the range of the trained area then the ANN will interpolate well, as ANNs are typically quite successful in performing this task. In contrast, a transfer task that is mapped outside the trained area leads to extrapolation which results in larger error rates (Haykin, 1994). Here interpolation corresponds to an estimation towards a region located between two known measurement values, whereas extrapolation is an estimation towards a region that is outside known measurement values.

These characteristics of ANNs are consistent with the idea of the elaboration hypothesis which was developed for explaining phenomena in contextual interference experiments and mainly relies on the assumption of the two processing modes: intra-task and inter-task processing. The elaboration hypothesis proposes that superior retention results during random practice are enhanced due to comparisons of multiple tasks in working memory (Shea and Morgan, 1979). In consequence, during training of ANNs a large neuron space should be covered (by the input data) in order to allow as much interpolation as possible in the transfer phase. From a connectionist point of view it is not only the number of influencing neurons but also the density and distribution of training stimuli that influences the quality of the net in the test phase. Typically, the area of interest should be covered optimally by stimuli that lead to a lattice-like distribution over the ANN neuron space with optimal expansion and influence on the neurons (Hertz, Krogh, and Palmer, 1994; Nguyen and Widrow, 1990). A transfer to neurobiological learning would correspond to an increased variability in content and sequences during the acquisition phase in order to enlarge the neuron space of mesh size of the lattice (Kohonen, 2001).

In a similar way, the differential learning approach (Schöllhorn, 1999) suggests that motor learning could benefit from adding stochastic perturbations in the form of random or variable movement components to a target movement pattern. In this context, stochastic perturbations can be understood as fluctuations which naturally occur during multiple repetitions of the target movement. The term stochastic is used to denote fluctuations in movement repetitions that do not seem to follow any deterministic structure or rule, although they could also be chaotic instead of noisy (Riley and Turvey, 2002). Traditionally, perturbations have been interpreted as the arbitrary execution of erroneous movements whereby the errors are always changing.

The differential learning approach mainly relies on the assumption that each movement trial has to be considered as individual (Schöllhorn and Bauer, 1998; Schöllhorn, Nigg, Stefanyshyn, and Liu, 2002) and unrepeatable (Bernstein 1967; Hatze, 1986). Empirical evidence for the individuality of movement patterns exists in analyses of world class javelin throwers, in which individual throwers could be identified over several years by means of their throwing pattern during the last 200ms of their final throwing phase (Schöllhorn and Bauer, 1998). Furthermore, analysis of several steps of female walkers allowed the recognition of individuals by means of their ground reaction forces and lower limb kinematics (recognition rates > 95%) (Schöllhorn et al., 2002). In order to find an individual's situational optimum, motor learning is not considered as the acquisition and storage process of different movement parameters. Learning is rather characterized as the improvement of internal adaptation processes which is achieved by means of adding stochastic perturbations to a so called "ideal movement" (Schöllhorn, Michelbrink, Beckmann, Trockel, Sechelmann, and Davids, 2006).

There is wide ranging assumption of the existence of 'common optimal movement patterns' in the study of human movement behaviour, which is an example of 'biological determinism' in science, particularly manifesting itself in the cognitive sciences, biomechanics and perceptual-motor disorders (Davids, Bennett, and Newell, 2006). For example, this assumption has been promulgated in the biomechanics optimization literature where a consuming challenge has been to identify optimal techniques for the performance of a wide range of movement activities. The implicit assumption is that identification of optimal patterns for performing specific movements could lead to improvements in sport performance while preventing the occurrence of injuries through dysfunctional movement patterning (e.g., Glazier and Davids, 2009; Hatze, 1986). From this perspective, an "ideal movement" can be understood as a person-independent model of a movement that fulfills momentarily, from the standpoint of science, on average the most effective solution of a given movement task. Typically, an "ideal movement" is defined within relative narrow borders and remains constant over time. In the cognitive sciences, as we noted earlier, increasing expertise has been proposed to lead to movement invariance and the construction of a single motor program, as argued in some traditional theories of motor control.

The misconception of 'common optimal movement patterns' also exists in the motor control literature where theoretically cogent arguments have been proposed as a rationale for studying how individuals satisfy unique interacting task and personal constraints coordination solutions in order to maintain functionality in dynamic environments (Brisson and Alain, 1996; Davids, Bennett, and Newell, 2006). As Latash and Anson (1996) argued, the "phenomena of variability of voluntary movements by themselves indicate that "correct" peripheral motor patterns may form a rather wide spectrum" (p. 65).

In the study of movement disabilities, the implicit 'medical model' or 'disability as tragedy model', used by many clinicians provides a unitary, biologically determined perspective of health and movement behaviour in which variability, viewed as deviation from an 'accepted' norm, is seen as dysfunctional and an index of abnormality (Davids, Shuttleworth, Button, Renshaw, and Glazier, 2003; Latash and Anson, 1996).

The addition of randomly fluctuating movement components to a target skill (such as high jumping) could result in emergent movement solutions changing even after thousands of performance trials because of dynamic performance conditions (Davids et al., 2003; Hatze, 1986; Schöllhorn, 1998). As a consequence of random new elements to movement repetitions, resonance effects might be instrumental in enhancing the ability of performers to adapt to these new elements and engage in a process of performance differentiation through exploring individualized movement solutions (Schöllhorn and Bauer, 1998; Schöllhorn et al., 2002). Resonance effects are typically characterized by an increase in amplitude of oscillations of a signal exposed to an external force. While two anti-phase signals would lead to mutual extinction, two in-phase signals are accompanied by alternate amplification. During differential learning, the fluctuating dynamics of the athlete's performance are assumed to get in resonance with the external force of stochastic perturbations that are provoked by the movement tasks. In this context the finding of the most effective motor learning approach that is operationalized by a maximum learning rate can be assumed as finding the optimum task noise for each individual in each situation.

Historically, the differential training approach is a practical application of the findings of fundamental research on dynamical systems and artificial neural nets research. In both areas the theoretical influence of fluctuations and noise has been described independently from each other. In contrast to dynamical systems research that mainly considers fluctuations as natural and passive characteristics of primarily cyclic movement systems with different amplitudes in stable and instable modes (Haken, Kelso, and Bunz, 1985; Schöner and Kelso, 1988), ANN research has inserted/applied different amplitudes of noise actively for improving the effectiveness of mathematical models of neurons. In combining both aspects, the differential learning approach considers fluctuations as a specific form of noise and applied amplified fluctuations to movement learning in general. Due to the problem of quantifying the frequency content of amplified fluctuations in ballistic movements, these signals have been termed 'stochastic perturbations' in differential learning.

Experimental Evidence for Differential Learning

To investigate these theoretical ideas there is an ongoing program of work to quantitatively examine the effects of the differential learning approach with more traditional approaches to pedagogy in sports such as shot put (Beckmann and Schöllhorn, 2003), football (Schöllhorn et al., 2006), tennis (Humpert and Schöllhorn, 2006) and high jumping. In this chapter we consider research on high jumping to illustrate our arguments. Because high jump includes technical and conditioning elements to training, the effects of differential training on vertical jumping performance were also examined.

In the research program, 36 male and 21 female (22.8 ± 2.2y) novices were categorized into two experimental and one control group according to the results of a high jump pre-test.

A pre-post test design was used with a subsequent retention test conducted 10 days after the posttest. Every test phase included performance of a Fosbury Flop, which has high technical requirements, and a conditioning test related to high jump performance, in the form of a jump-and-reach-test. The Fosbury Flop test was accomplished according to IAAF rules. The jump-and-reach test was carried out standing beside a wall and measured the difference between reach height in a standing position and reach height after a two legged vertical jump (figure 1).

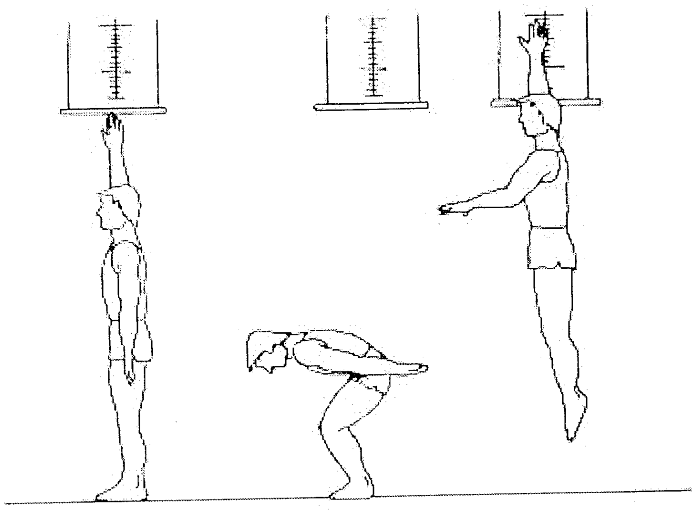

Figure 1. Jump and reach test (Weineck, 2000; p. 322).

The two experimental groups participated in a training intervention program over 4 weeks with 2 training sessions per week. One experimental group (T) was trained in a traditional way according to the IAAF recommendation for high jump (Jonath, Krempel, and Haag, 1995). The other experimental group (D) was trained by differential training principles. The control group (CO) did not participate in a specific jump training during the whole duration of the experiment. Group T was trained with feedback for error correction and performed a high number of repetitions. These training principles were chosen according to classical pedagogic recommendations of encouraging learner progression from easy to hard and from simple to complex exercises. In this approach, every exercise had to be repeated until movement stability was achieved before participants proceeded to the next, more complex exercise. In contrast, group D received no corrective instructions and never repeated a high jump movement twice in the same way, but rather changed their movements after every trial. For this group, different exercises were applied during the approach, take off, flight and clearance of the bar. For instance, the high jump approach could be varied by changes in stiffness at the knees, magnitude of elbow extension or trunk leaning angle. Similarly, the take off could be altered by bending the head to the left or right. All members in the D group adopted the same sequence of differential learning program. Although the exercises for the differential group were selected randomly by the coach, the existence of a latent structure cannot be excluded.

To compare effects of the different intervention methods on high jump performance, results of the two exercises (Fosbury Flop, jump-and-reach test) were analysed statistically with a two-way repeated measures ANOVA. In the case of statistical significant interaction effects of group and test phase, t-tests of pair differences were calculated to detect inter-group differences at each specific test phase. Concerning the jump-and-reach test, paired t-tests were calculated for the two experimental groups separately to evaluate if the intervention had a significant influence on rather conditional factors of high jump performance.

Results showed that the initial average high jump performance of group T amounted to 1.41m (±0.15m). Group D showed an initial performance of 1.40m (±0.16m) height and the control group reached 1.40m (±0.15m). The differences between the three groups were not significant. After 4 weeks of training the athletes of group D improved their high jump performance and reached an average of 1.45m (±0.17m), while group T achieved 1.42m (±0.15m). The performance and variance of the control group did not change. After a break of 10 days, both experimental groups improved high jump performance by 1 cm on average (group T: 1.43m; group D: 1.46), while the control group did not change its performance (see figure 2).

The improvement of high jump performance averaged across the groups was significant between pre and post test (F (2,108) = 11.077; p= .000; η^2 = .170). The test of contrasts of the within-participant factor shows that the significant change happened between pre and post test (F (1,54) = 11.771; p = .001; η^2 = .178). The difference between the group performances averaged across the three test phases as the main factor group was not significant (F (2,54) = .278; p = .758; η^2 = .010). However, the change from one test phase to another was significantly different in at least two groups, as the interaction between the within-participant factor and the main factor group was significant (F (4,108) = 5.885; p = .000; η^2 = .179). Again, contrasts show that improvement differences appeared between the pre and the post test phase which can be seen in figure 2, too. The improvement from pre- to post test between group T and group D was significantly different (t (36) = -2.058; p = .046). Additionally, differences between performance changes of group D and the control group were highly significant (t (36) = 4.082; p < .001). The comparison of performance changes between group T and the control group was not significant (t (36) = 1.748; p = .089). However, these p-values were not alpha-corrected. Concerning the T-tests of pair differences between post and retention test values we did not find any significant results.

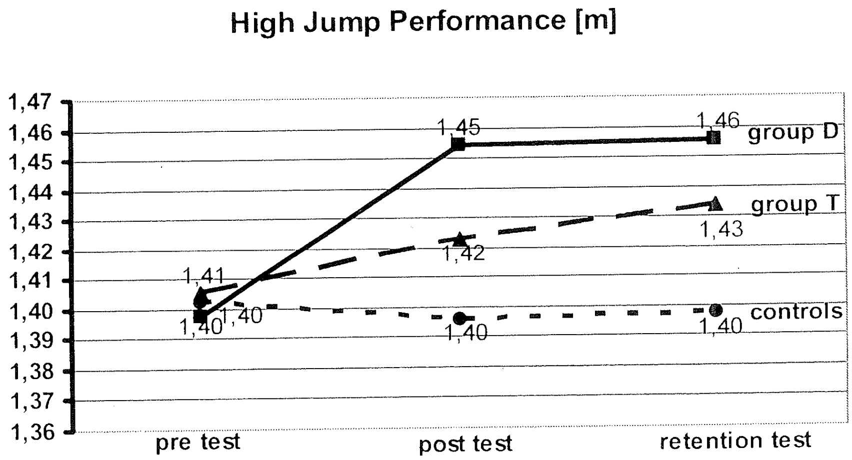

Figure 2. High Jump Performance.

Initial values for the jump-and-reach test averaged between 0.40m (±0.06m) for group T and the control group and 0.41m (±0.05m) for group D. After 4 weeks of intervention, both experimental groups improved their performance in jump-and-reach by about 2 cm, while the controls rested at their starting level on average. After a break of 10 days, group T degraded again to 0.41m while the other groups maintained their performance level (see figure 3).

The improvement of jump-and-reach performance averaged across the groups was significant between pre- and post-test (F (2,108) = 4.591; p = 0.012; η^2 = .078). The test of contrasts of the within-participant factor shows that the significant change happened between pre and post test (F (1,54) = 6.610; p = .013; η^2 = .109). We did not find any difference between the group performances averaged across the three test phases as the main factor group was not significant (F (2,54) = .713; p = .495; η^2 = .026). The change from one test phase to another was not statistically significant different between the groups as the interaction between the inner subject factor and the main factor group was not significant (F (4,108) = 1.227; p = .304; η^2 = .043).

To evaluate, if the experimental groups significantly improved their jump-and-reach performance during the intervention, we applied paired t-tests. Performance changes from pre to post test in group T were not significant (t (18) = -1.458; p = .162 and t (18) = 1.268; p = .221), although the improvement from pre to post test of group D was (t (18) = -2.317; p = .032). As the control group did not change its jump-and-reach performance, there was no significant improvement. Note, these differences do not mean that group D improved its jump-and-reach performance significantly differently from group T as the interaction effect was not significant.

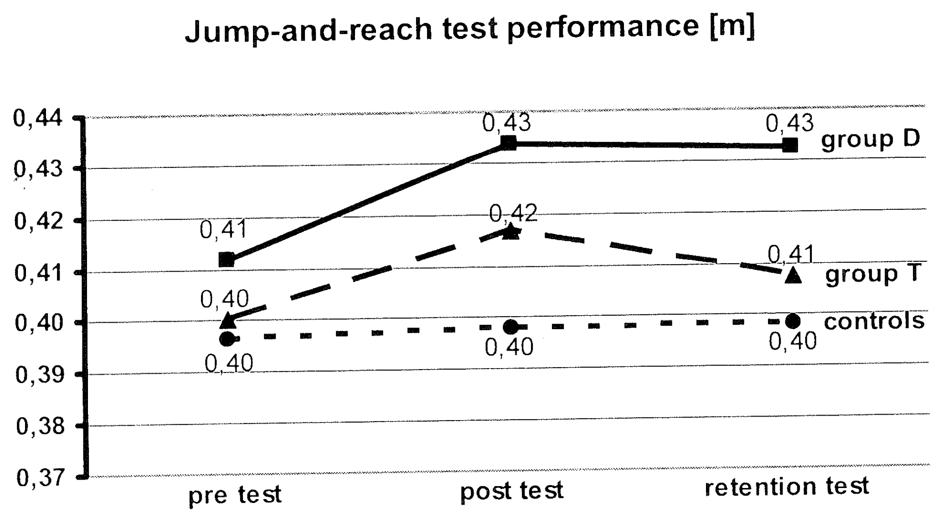

Figure 3. Jump-and-reach performance.

Performances (1.40m-1.60m) and changes in high jump (0.06m) and jump and reach (0.05m) within the training period of 4 weeks were within the range observed in comparable investigations in the literature (Rhea, Peterson, Lunt, and Ayllon, 2008). Both experimental groups were able to improve their fosbury flop performance after 4 weeks of intervention although their training was totally different: The differential learning group D never repeated a movement twice but was characterized by randomly adding stochastic perturbations to the Fosbury Flop technique, while the classical training group was trained by means of error correction and lots of numerous repetitions of perceived correct movements. Most intriguingly, the differential learning group D improved their performance the most during the acquisition phase and was able to maintain its performance advance after the 10-day break. Interactions showed that the improvement rate from pre to post test of group D was significantly different from that of group T and CO. Since it can be assumed that both groups improved their conditioning by a comparable amount during this period, it can also be assumed that the larger performance improvements of the differential learning group were mainly due to technical or coordinative improvements. Here, the interaction of test phase and intervention was not significant.

In interpreting these results two explanations can be considered. The first explanation is related to the performance of errors during the realization of the traditional approach and is thus a question of intervention accomplishment. Note, this explanation has got a negative nuance. The second one is oriented towards feasible advantages of an alternative approach and is rather a question of principle concerning the intervention method. This explanation tends to be more positive. In the first case, it can be argued that the ideal technique proposed to the traditional training group T was not correct. This explanation can be rejected, because all the students of this group were informed in advance about the technique by means of photographs of world class high jumpers. Furthermore, all error corrections were given according to the IAAF recommended literature that are based on world class athletes as well and therefore are oriented on the same model (Jonath, Krempel, and Haag, 1995). The possibility that the corrections were given with the wrong instructions e.g. body related or metaphorically (Schmidt and Wulf, 1997), can be excluded because both groups received the same amount of body and metaphorically oriented instructions.

The consequence of the second explanation is to question the traditional understanding of model learning. Model learning is based on the assumption of a performer-independent ideal technique and thereby neglects individual sources of variance. Alternatively, the differential learning approach offers a systems dynamic model for the explanation of the observed phenomena that has been tested analytically in artificial neural nets (Horak, 1992). Similarly to successfully trained ANNs, it seems that the athlete has to be confronted by "noisy" data during the acquisition process in order to optimize not only the next movement but also subsequent movement trials for solving movement problems. The noise that is applied in an ANN corresponds to randomly adding stochastic perturbations to the model movement of high jump in the differential training group. In the differential training group athletes were confronted with all kinds of additional tasks that forced them to adapt consistently to new tasks. Therefore, athletes not only experienced a broader area of possible solutions, but they also seemed to learn to adapt to new situations more individually and more quickly. Within this explanation the results of the traditional group can also be interpreted. The variations that can be observed within the repetitions of the traditional group seemed to be too small to allow the system to follow performance changes over time, consequently leading to less rapid performance improvement.

Fundamental differences exist between these models at the level of learning principles, based on the phenomenon that consecutive movement repetitions will always be unequal (Bernstein, 1967). According to the assumptions of the differential learning approach no movement repetition will be identical (Bernstein, 1967). Despite the clustering of movement classes by means of hypothetical generalized motor programs, their small variations (Heuer, 1988a,b; Heuer and Schmidt, 1988) still lead to an infinite number of combinations of muscle activation patterns and joint momentums. The implicit assumption of such motor program structures is that similar movement outcomes are the result of the same motor program with added noise in the periphery. This assumption can be associated with the principle of strong causality. Strong causality is typically associated with similar effects that follow similar causes. With respect to boundary conditions this understanding of causality demands much more than the understanding of weak causality where only similar causes lead to similar effects. Mathematically it needs more boundary conditions in order to fulfill this strong causality which is actually associated with much more parameters to control (Cramer, 1980). Overall it seems to be neither the most adequate model for describing the variation or noise phenomena or to provide the basis for learning recommendations. However, over a longer time scale the 'repetition without repetitions' approach is associated with a change in the movement system, underpinned by reactions at the cellular level. When the movement system, in this case the athlete, is changing all the time, it seems plausible to provide a training regime that allows the athlete to cope with the same problem under changed conditions as well (Schöllhorn, Mayer-Kress, Newell, and Michelbrink, in press).

Due to the abstract and general level of the underlying theory of fluctuations, with its emphasis on system stability and instability, there is significant potential for understanding how stochastic perturbations function at different levels of description (Verejken, Chapter 6). The application of stochastic perturbations to the acquisition of catching movements is particularly interesting, because in this case the interaction of several fluctuating sub-systems like the visual perception system, the oculo-motor system, and the limb system used for catching, have to be scaled to each other (Savelsbergh and van der Kamp, Chapter 2). Similarly, investigations have revealed that the influence of coupled fluctuations between several athletes for tactical behaviour can also be considered (see Hristovski, Davids, and Araújo, Chapter 4, and Passos, Araújo, Davids, Gouveia, Milho, and Serpa, Chapter 3).

CONCLUSION

To summarise, we have described some data from a program of work that has verified other results on differential learning, where adding stochastic perturbations to a to-be-learned movement led to higher improvement rates than traditional learning approaches. In combination with findings of other investigations on differential learning (e.g., Beckmann and Schöllhorn, 2003; Humpert and Schöllhorn, 2006) all traditional learning approaches exemplify levels of stochastic perturbation which merely differ in amplitude and frequency. Accordingly, the search for a most effective learning approach can be considered as the search for optimum noise since a decrease in learning rate can be observed when too much noise is put into the system. With the same argument, the findings of Wulf and Shea (2002) can be explained whereby children show better learning rates with low contextual interference while adults are more successful with higher levels of contextual interference. It is probable that movement repetitions of children have a larger level of variability or noise that would lead to a detrimental effect when additional noise is applied to the learning experience. On the other hand more advanced athletes have reduced the levels of variability within their movement repetitions leading only to suboptimal learning progress and therefore requiring the combination of additional noise. In principle, the results implied that pedagogists should think about the typical model oriented understanding of learning, since the addition of random stochastic perturbations led to at least the same learning progress as in the highly systematic traditional approach. Future research should be aimed at examining the size and number of stochastic perturbations during the acquisition phase and according to Frank et al. (2008) to the noise during the retention phase as well.

REFERENCE

Battig, W. F. (1966). Facilitation and Interference. In E.A. Bilodeau (Ed.), *Acquisition of skill* (pp. 215-244). New York: Academic Press.

Beckmann, H., and Schöllhorn, W.I. (2003). Differential Learning in Shot Put. In W. I. Schöllhorn, C. Bohn, J. M. Jäger, H. Schaper and M. Alichmann (Eds.), *Mechanics, Physiology, Psychology - Conference Proceedings of the 1st European Workshop on Movement Science* (pp. 68-69). Köln: Sport and Buch Strauß.

Bernstein, N.A. (1967). *The Coordination and Regulation of Movements*. London: Pergamon Press.

Bishop, C.M. (1995). *Neural Networks for Pattern Recognition*. Oxford: Oxford University Press.

Brady, F. (2004). Contextual interference: a meta-analytic study. *Perceptual and Motor Skills, 99*, 116-126.

Brisson T.A., and Alain, C. (1996). Should common optimal movement patterns be identified as the criterion to be achieved? *Journal of Motor Behavior 28*, 211-223.

Button, C., Davids, K., and Schöllhorn, W.I. (2006). Coordination profiling of movement systems. In K. Davids, S. Bennett, and K.M. Newell (Eds.), *Variability in Movement Systems* (pp. 133-152). Champaign; Ill.: Human Kinetics.

Cramer, J.G. (1980). Generalized absorber theory and the Einstein-Podolsky-Rosen paradox. *Physics Review D, 22*(2), 362-376.

Davids, K., Bennett, S.J. and Newell, K.M. (Eds.) (2006). *Variability in Movement Systems*. Champaign; Ill.: Human Kinetics.

Davids, K., Shuttleworth, R., Button, C., Renshaw, I., and Glazier, P. (2003). "Essential noise"-enhancing variability of informational constraints benefits movement control: a comment on Waddington and Adams. *British Journal of Sports Medicine, 38*, 601-605.

Derrida, J. (1982). Differance. In J. Derrida (Ed.), *Margins of Philosophy*, pp. 3-27. Chicago: The University of Chicago Press.

Frank, T.D., Michelbrink, M., Beckmann, H., and Schöllhorn, W.I. (2008). A quantitative dynamical systems approach to differential learning: self-organization principle and order parameter equations. *Biological Cybernetics, 98*, 19-31.

Gaulhofer, K. and Streicher, M. (1924). Grundzüge des österreichischen Schulturnens. Fundamentals of austrian school gymnastics. Wien.

Gentile, A.M. (1972). A working model of skill acquisition with application to teaching. *Quest, 17*, 3-23.

Glazier, P., and Davids, K. (2009). Constraints on the complete optimization of human motion. *Sports Medicine* 39, 15-28 .

Goode, S., and Magill, R. A. (1986). Contextual Interference Effects in Learning Three Badminton Serves. *Research Quarterly for Exercise and Sport, 57*, 308-314.

Haken, H., Kelso, J.A.S. and Bunz, H. (1985). A Theoretical Model of Phase Transitions in Human Hand Movements, *Biological Cybernetics*, *51*, 347–356.

Hatze, H. (1986). Motion Variability – its Definition, Quantification, and Origin. *Journal of Motor Behavior, 18*, 5-16.

Haykin, S. (1994). *Neural Networks*. New York: Macmillan College Publishing Company.

Heidegger, M. (1957). *Identität und Differenz* (Bd. 10). Stuttgart: Neske.

Hertz, J., Krogh, A., and Palmer, R. G. (1994). *Introduction to the theory of neural computation*. (9th ed., Vol. 1) Reading: Addison-Wesley Publishing Company.

Heuer, H. (1988a). Adjustment and readjustment of the relative timing of a motor pattern. *Psychological Research, 50*, 83-93.

Heuer, H. (1988b). Testing the invariance of relative timing: Comments on Gentner (1987). *Psychological Review, 95*, 552-557.

Heuer, H., and Schmidt, R.A. (1988). Transfer of learning among motor patterns with different relative timing. *Journal of Experimental Psychology: Human Perception and Performance, 14*, 241-252.

Horak, M. (1992). The utility of connectionism for motor learning: A Reinterpretation of contextual interference in movement science. *Journal of Motor Behavior, 24*, 58-66.

Humpert, V., and Schöllhorn, W.I. (2006). Vergleich von Techniktrainingsansätzen zum Tennisaufschlag. In Ferrauti,A. and Remmert,H. (Eds.), *Trainingswissenschaft im Freizeitsport - Symposium der dvs-Sektion Trainingswissenschaft* (pp. 121-124). Hamburg: Czwalina.

Jonath, U., Krempel, R., and Haag, E. (1995). *Leichtathletik: Springen (Track and field: Jumping)*: Vol. 2. Reinbek bei Hamburg: Rowohlt.

Kelso, J.A.S. (1995). Dynamic patterns - The Self-Organization of Brain and Behavior. Cambridge: MIT Press.

Kohonen, T. (2001). *Self-Organizing Maps*. (3rd ed., Vol. 30) Berlin: Springer.

Latash, M.L., and Anson, J.G. (1996). What are "normal movements" in atypical populations? *Behavioural and Brain Sciences, 19*, 55-106.

Lee, T.D. and Magill, R.A. (1983). The Locus of Contextual Interference in Motor-Skill Acquisition. *Journal of Experimental Psychology: Learning, Memory, and Cognition, 9*, 730-746.

Magill, R.A. (1993). *Motor learning - concepts and applications*. Dubuque, IA: Brown Communications.

Magill, R.A., and Hall, K.G. (1990). A review of the contextual interference effect in motor skill acquisition. *Human Movement Science, 9*, 241-289.

Miglino, O., Lund, H.H., and Nolfi, S. (1995). Evolving mobile robots in simulated and real environments. *Artificial Life, 2*, 417-434.

Nguyen, D. and Widrow, B. (1990). Neural Networks for Self-Learning Control Systems. IEEE *Control Systems Magazine*, *10*(3), 18-23.

Rhea, M.R. Peterson, M.D. Lunt, K.T. and Ayllon, F.N. (2008). The effectiveness of resisted jump training on the VertiMax in high school athletes. *Journal of Strength and Conditioning Research*, *22*(3), 731-4.

Riley, M., and Turvey, M. (2002). Variability and determinism in motor behavior. *Journal of Motor Behavior, 34*(2), 99-125.

Schmidt, R.A. (1975). A schema theory of discrete motor skill learning. *Psychological Review, 82*, 225-260.

Schmidt, R.A. (1991). *Motor learning and performance*. Champaign, IL: Human Kinetics.

Schmidt, R.A., and Wulf, G. (1997). Continuous concurrent feedback degrades skill learning: implications for training and simulation. *Human Factors, 39*, 509-525.

Schneider, K., Zernicke, R.F., Ulrich, B.D., Jensen, J. L., and Thelen, E. (1990). Understanding movement control in infants through the analysis of intersegmental dynamics. *Journal of Motor Behavior, 22*, 493-520.

Schöllhorn, W.I. (1998). Systemdynamische Betrachtung komplexer Bewegungsmuster im Lernprozess. Frankfurt: Peter Lang.

Schöllhorn, W.I. (1999) Individualität - ein vernachlässigter Parameter? *Leistungssport, 2*, 5-11.

Schöllhorn, W.I. and Bauer, H.-U. (1998). Identifying individual movement styles in high performance sports by means of self-organizing Kohonen maps. In H.J. Riehle and M. Vieten (Eds.), *Proceedings of the XVI Congress of the ISBS 1998.* (pp. 574-577). Konstanz University Press.

Schöllhorn WI, Mayer-Kress G, Newell KM, Michelbrink M. (in press). Time scales of adaptive behavior and motor learning in the presence of stochastic perturbations. Human Movement Science. 2008 Dec 3. [Epub ahead of print]

Schöllhorn, W.I., Michelbrink, M., Beckmann, H., Trockel, M., Sechelmann, M., and Davids, K. (2006). Does noise provide a basis for the unification of motor learning theories? *International Journal of Sport Psychology, 37*, 186-206.

Schöllhorn, W.I., Nigg, B.M., Stefanyshyn, D., and Liu, W. (2002). Identification of individual walking patterns using time discrete and time continuous data sets. *Gait and Posture, 15*, 180-186.

Schöner, G. and Kelso, J.A.S. (1988). A Dynamic pattern theory of behavioral change. *Journal of Theoretical Biology, 135*, 501-524.

Shannon, C.E. (1948) A Mathematical Theory of Communication. *The Bell System Technical Journal, 27*, 379-423, 623-656.

Shea, J.B., and Morgan, R.L. (1979). Contextual Interference Effects on the Acquisition, Retention, and Transfer of a Motor Skill. *Journal of Experimental Psychology: Human Learning and Memory, 5*, 179-187.

Smith, P.J.K. (2002). Applying contextual interference to snowboarding skills. *Perceptual Motor Skills, 95*, 999-1005.

Smith, P.J.K., and Davies, M. (1995). Applying contextual interference to the Pawlata roll. *Journal of Sports Sciences, 13*, 455-462.

Smith, P.J.K., Gregory, S.K., and Davies, M. (2003). Alternating versus blocked practice in learning a cartwheel. *Perceptual and Motor Skills, 96*, 1255-1264.

Spencer-Brown, G. (1997) *Laws of form*. Lübeck: Bohmeier.

Tumer, E.C., and Brainard, M.S. (2007). Performance variability enables adaptive plasticity of 'crystallized' adult birdsong. *Nature, 450*(7173), 1240-4.

van Rossum, J.H.A. (1990). Schmidt's Schema theory: the empirical base of the variability of practice hypothesis. *Human Movement Science, 9*, 387-435.

Weineck, J. (2000). *Bewegung und Sport - wozu?* Editio Zenk.

Wulf, G. and Shea, C.B. (2002). Principles derived from the study of simple skills do not generalize to complex skill learning. *Psychonomic Bulletin and Review, 9*, 185-211.

Zanone, P.G. and Kelso, J.A.S. (1992). Learning and transfer as dynamical paradigms for behavioral change. In G.E. Stelmach and J. Requin (Eds.), *Tutorials in motor behavior II* (pp. 563-582). Amsterdam: North Holland.