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Daniel Memmert
Deutsche Sporthochschule Köln

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Daniel Memmert [a]; Jürgen Perl [b]
[a] Department of Sport Sciences, University of Heidelberg, Heidelberg [b] Department of Computer Science, University of Mainz, Mainz, Germany

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Game creativity analysis using neural networks

DANIEL MEMMERT[1] & JÜRGEN PERL[2]

[1]*Department of Sport Sciences, University of Heidelberg, Heidelberg and* [2]*Department of Computer Science, University of Mainz, Mainz, Germany*

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Abstract

Experts in ball games are characterized by extraordinary creative behaviour. This article outlines a framework for analysing types of individual development of creative performance based on neural networks. Therefore, two kinds of sport-specific training programme for the learning of game creativity in real field contexts were investigated. Two training groups (soccer, $n = 20$; field hockey, $n = 17$) but not a control group ($n = 18$) improved with respect to three measuring points ($P < 0.001$), although no difference could be established between the two training groups ($P = 0.212$). By using neural networks it is now possible to distinguish between five types of learning behaviour in the development of performance, the most striking ones being what we call "up-down" and "down-up". In the field hockey group in particular, an up-down fluctuation process was identified, whereby creative performance increases initially, but at the end is worse than in the middle of the training programme. The reverse down-up fluctuation process was identified mainly in the soccer group. The results are discussed with regard to recent training explanation models, such as the super-compensation theory, with a view to further development of neural network applications.

Keywords: *Decision making, ecological psychology, cognition, soft-modelling, representative design, pattern recognition*

Introduction

Creative behaviour plays an important role in the performance of sport. It characterizes attentiveness – especially in sport – for the generation of tactical response patterns and for seeking original solution ideas, when a player is also able to perceive objects that appear unexpectedly and incorporate them into the initial game plan. Creative soccer or basketball players, for example, set themselves apart in situations such as the following: although they might intend to pass the ball to player A, they are able to perceive at the last moment that player B is suddenly unmarked and better positioned and pass the ball to him or her instead. In a scientific context, Sternberg and Lubart (1999, p. 3) define creativity as "the ability to produce work that is both novel (i.e. original, unexpected) and appropriate (i.e. useful)". In sport, this means that creativity is players' ability to produce varying, rare, and flexible decisions during competition (Memmert & Roth, 2007).

The analysis of creative thinking is currently of interest (Dietrich, 2004). This is driven by extraordinary modern findings in the field of functional neuroanatomy (Ashby, Valentin, & Turken, 2002; Bekhtereva, Dan'ko, Starchenko, Pakhomov, & Medvedev, 2001; Carlsson, Wendt, & Risberg, 2000; Damasio, 2001). It is generally agreed that distinct brain circuits are involved in specific higher-brain functions (cf. Cabeza & Nyberg, 2000; Damasio, 2001; Duncan & Owen, 2000). These brain functions are responsible for creative performance. To evaluate creativity, quantitative methods tend to be used (Basadur, Wakabayashi, & Graen, 1990; Runco & Sakamoto, 1999; Toplyn & Maguire, 1991; for a review Fink, Benedek, Grabner, Staudt & Neubauer, 2007). Today, it is broadly accepted that creativity is a stochastic combinational process (Dietrich, 2004; Martindale, 1999; Simonton, 2003). This means that creative thinking is characterized by unsystematic drifting and is chaotic, thus permitting the emergence of loosely connected associations.

Accordingly, the question arises: How can neural networks be used to analyse complex processes? One way is to map the learning process to the net to simulate and optimize learning strategies. This way is planned as a second step. It requires experience of dynamic behaviour of networks and therefore needs

Correspondence: D. Memmert, Institute for Theory and Practice of Training and Movement, Ruprecht-Karl-Universität Heidelberg, Im Neuenheimer Feld 700, 69120 Heidelberg, Germany. E-mail: daniel.memmert@urz.uni-heidelberg.de

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the results from the present project. The second way, which is followed here, is to use the network as a tool for detecting influential structures in learning processes and compare them with the properties of artificial adaptation processes.

Therefore, in this paper, we will examine the extent to which neural network-based qualitative analyses can evaluate the development of creative performance. With a re-analysis of data from a structured field-training programme (Memmert & Roth, 2007), we will determine whether neural networks reveal individual learning behaviour of game creativity. The stochastic approach reduces the total recorded data to only a few statistical quantities and checks their influence by means of variance analysis. In contrast, neural networks – considering all available data (e.g. creative performance) to be high-dimensional points that correspond to neurons – can be used to extract specific features and qualitative trends from all original data. Sport is a fruitful area in which to study behaviour in complex situations. In particular, complex situations such as ball games allow the analysis of creative performance in an ecologically valid way, as is recommended by many investigators (Runco & Sakamoto, 1999; Simonton, 2003). Several studies in sports involving more simple skills have demonstrated that it is possible to detect additional notable aspects of neural networks, which are not open to the stochastic approach (McGarry & Perl, 2004; Memmert & Perl, 2005; Perl, 2002a; 2004a; Perl & Weber, 2004; Schöllhorn, Schaper, Kimmeskamp, & Miani, 2002). Neural networks have not been used for the study of creative behaviour in complex field situations such as sports.

The purpose of this paper is to advance understanding by offering a new aspect and therefore a new framework for research and discussion on the analysis of game creativity in sports. Specifically, we: (a) present a net-based computational approach as another method for analysing creativity individually; (b) test kinds of training concept in ball games over longer durations (we used a field hockey training group and a soccer training group, since these sports have similar requirements for tactics and creativity; only the motor skills were varied); and (c) identify special kinds of learning behaviour – such as long-term effect and the super-compensation effect – that have received limited research attention. We will show that dynamically controlled networks can be used for the analysis of adaptive long-term processes. By means of visual inspection of data distribution projected onto the net structure and analysis of inter- and intra-individual correspondences, useful information becomes available, which it is seldom possible to obtain from variance analyses, if at all.

Creativity and neural networks

It has recently been expressed that "any theory on creativity must be consistent and integrated with contemporary understanding of brain function" (Pfenninger & Shubik, 2001, p. 217). Creativity can be explained using psychological, cognitive, and neuroscientific findings (e.g. Cabeza & Nyberg, 2000; Kornhuber, 1993; Pfenninger & Shubik, 2001; Sternberg, 1999; Sternberg & Lubart, 1995; for a review Dietrich, 2004b). However, a systematic study of the neurophysiology of creative processes is still in its initial phases (Dietrich, 2007). For example, Carlsson and colleagues (2000) were able to use local blood-flow analysis to demonstrate that the brain's bilateral frontal lobes are involved in divergent thinking. Substantial evidence has demonstrated that creativity requires cognitive abilities, such as working memory, sustained attention, cognitive flexibility, and judgement of propriety (Ashby et al., 2002; Bekhtereva et al., 2001; Damasio, 2001; Martindale, 1999; Scheibel, 1999). It is evident that the prefrontal cortex is the central structure involved in creative thinking (Dehaene & Naccache, 2001; Fuster, 2002). "A basic assumption of the framework is that neural circuits that process specific information to yield noncreative combinations of that information are the same neural circuits that generate creative or novel combinations of that information" (Dietrich, 2004, p. 1011).

Creativity is a stochastic combinational process (Boden, 2003; Simonton, 2003). Martindale (1995) demonstrated that behavioural and cognitive theories are essentially identical when expressed as a neural network theory. He used a wide range of examples (associative hierarchies, breadth of attention, and arousal) to show that major theories of creativity can be translated into neural networks and modelled with connectionist theories, as the two are almost identical. For example, several behavioural studies have shown that breadth of attention is positively related to creative performance (Kasof, 1997; Mendelsohn, 1976). Breadth of attention is the term used to refer to the number and range of stimuli to which a player attends to at any one time. Mendelsohn (1976) and, more recently, Kasof (1997) argued that because of a narrow breadth of attention, not all stimuli and information that could lead to original and possibly creative solutions in a certain set of circumstances can be admitted and associated with one another. As Martindale (1995, p. 255) pointed out, "in neural network terms, we can divide consciousness into attention (the most activated nodes) and short-term memory (nodes that are activated but less so than those in the focus of attention). Where the division between attention and short-term memory should be drawn is rather arbitrary". For that reason, among others, computational psychology seems to be a suitable way of modelling creative performance without detailed predictions or explanations.

Only limited research in the field of creativity has been conducted in sport (Memmert, 2007; Memmert & Roth, 2007; Raab, Hamsen, Roth, & Greco, 2001). Memmert and Roth (2007) showed that in the first year of a specific training programme (handball training, soccer training), the creative performance of children improved more than that of children following the non-specific concept. During the second year, however, this effect was reversed. Considered together, these results support the widely accepted practical view that, initially, gathering different kinds of game experience is an ideal medium for the creative development of sports players.

To date, only a few psychometric measures of creativity are widely accepted (Plucker & Renzulli, 1999). For example, the test of divergent thinking (Guilford, 1967), Torrance's (1974) test, and the remote associates test (Mednick, 1962) provide valid and reliable measures of originality, flexibility, and fluency. To test the theory of creative thinking, concepts of originality and flexibility identified via factor-analysis by the Guildford research group in 1967 were used and extended to sport-specific contexts.

A new procedure was developed and evaluated to assess the two creativity characteristics. During competition, it is possible to measure creative behaviour – hereinafter referred to as "game creativity" – in a representative manner. Furthermore, Rink's (1996) recommendation that game play should always be judged in specific situations is incorporated through the use of different motor skills. An important point is that it is generally agreed that creative performance characteristics should be analysed individually. Therefore, Simonton's (2003) assertion that creativity is a stochastic combinational process, suggests that analysis using artificial neural networks is appropriate.

Dynamically controlled networks

Dynamically controlled networks are based on the concept of Kohonen feature maps, whereby neurons are trained with data and so build clusters of similar input data, without requiring any additional information. These clusters define *types* of input data and thereby help to recognize and identify test data after the training phase. A given test input is recognized by the net as corresponding to the cluster to which it is most similar and is therefore identified by the type (e.g. name, specification, etc.) of that cluster (Kohonen, 1995). The new idea behind dynamically controlled networks is that each neuron learns and offers information continuously and, more importantly, *individually*.

The training of conventional Kohonen feature maps is normally controlled by external functions that guarantee a final state is achieved (McGarry & Perl, 2004). This approach is helpful if the network is used statically as a tool after training. It is of little assistance if the aims are to learn dynamically, adapt to changing situations, and analyse learning processes. Each dynamically controlled network neuron, therefore, contains an individual *learning self-control*, which was originally developed as an autonomous model for physiological adaptation (see Figure 1). In this way, the network is always in a well-defined, non-terminal state. Note, however, that although a dynamically controlled network is able to learn continuously in each test step, it does not necessarily have to do so. Therefore, there are three ways of using a dynamically controlled network: (i) as a static tool, if the application context does not change; (ii) as an adaptive tool, if the application context is changing; and (iii) as an object of analysis, if the learning dynamics of the network is of interest.

The consequences and advantages of this concept are as follows (Perl, 2002a): (i) Training steps and test steps do not have to be separated into phases but can be combined arbitrarily. Temporary states of the network can therefore be monitored during the training process and can be influenced by appropriate training data if necessary. (ii) A training process can be interrupted and continued arbitrarily. Data from time-dependent patterns can be trained repeatedly to increase the quality of *pattern recognition* adaptively. And (iii) in the case of small data volumes, which are normally not sufficient for network training, the network can be *pre-trained* with an unlimited amount of Monte Carlo-generated data, the structure or distribution of which follows that of the original data. The training is then

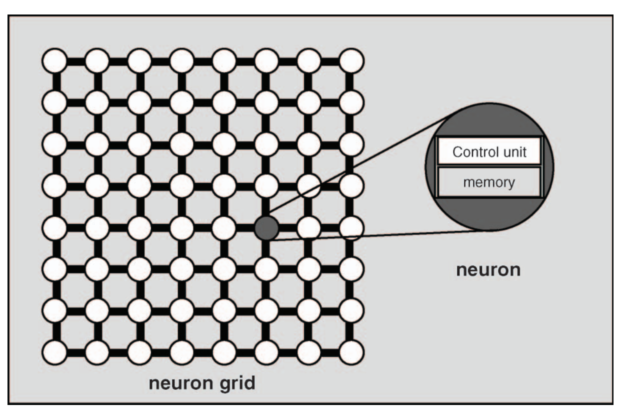

Figure 1. A dynamically controlled network that consists of a grid of neurons, each of which contains an individual memory and an individual control unit, which acts on the memory depending on learning impulses (Perl, 2002b).

completed by a second phase, in which the network is specifically moulded using the original data. This method has been used successfully in several projects in which the structure of the data was well-known, but the amount of original data was too small (Perl & Weber, 2004).

To study interactive learning processes and develop training strategies (e.g. completing learning vs. replacing learning), different patterns can be trained to the same net in different phases. Moreover, there are four explanations that clarify why neural networks should be used and developed to analyse particular aspects of game creativity: (i) Neural networks of the Kohonen feature maps are of importance if data have to be classified without any *a priori information* on the given cluster structure, as is typically the case with data from creative performance. (ii) As has been demonstrated by various projects, dynamically controlled networks are of specific importance if the *data volume* is small and data profiles and/or cluster structures change dynamically in time, as is the case with the available project data, which are recorded from only a modest number of participants over 15 months (see Methods section). (iii) In addition to the advantages mentioned above, neural networks – unlike stochastic methods – allow for *qualitative evaluations*, which can be deduced from spatial (topological cluster representation) or temporal (trajectories) structures of the network.

Six pieces of data are available for creative performance per child (three judgements by experts × two player rotations; see Methods section), which gives an 18-dimensional attribute vector for the three measuring points in time (see Methods section for more detail). In reducing those 18-dimensional original attribute vectors to 2-dimensional vectors of aggregated values – as is necessary in the case of variance analysis – a great deal of useful and necessary information, such as expert-specific evaluation or rotation, is lost. Qualitative aspects of the children's creative development, in particular, become non-transparent.

Neural networks allow qualitative interpretation that complements quantitative evaluations. This means that additional knowledge acquisition is not limited to the recognition of *basic principles*, but that it can be most useful for practical applications. It should be noted that a network cannot recognize semantically relevant structures on its own. A network is used (a) to recognize what type (cluster) an input belongs to and (b) to reduce the high-dimensional input-vector to a two-dimensional neuron position, and so represent processes (i.e. time-dependent input-sequences) by trajectories and therefore analyse and compare those processes easily.

As an initial example, graphical representation demonstrates that the spectrum between very good and less good performances can be represented almost in its entirety. In this way, neural networks can illustrate *mean variations* in the behaviour data. As a second example, neural networks can be used to visualize the *time-dynamic development* of learning processes by means of trajectories and can therefore make these processes accessible for further analyses investigating inter- and intra-individual correspondences.

Methods

Participants

Ninety children (mean age 6.8 years, $s = 0.8$) were recruited for a 15-month field study (for further details, see Memmert & Roth, 2007). Of the children, 65 were boys and 25 were girls. Attrition occurred for several reasons (e.g. move to another town). Also, not all children were available for all three measurement occasions, leaving a total of 55 children who participated in all tests. The co-variables of age during training, time of training, and participation in training had no influence on the presented results.

Groups

The children formed two training groups and a control group (Memmert & Roth, 2007). The children in the two training groups were members of sports clubs. The content of the specific treatments was ascertained after the field study through interviews with the instructors. Both training groups performed two training sessions per week for 15 months (i.e. approximately 120 sessions in total).

Specific training – soccer ($n = 20$). The soccer teams started with non-specific training exercises and played a free soccer game for 30 min at the end of each lesson (7 vs. 7). For the remainder of the time they were taught motor skills, such as passing, stopping, shooting, and dribbling. First, they practised under simple conditions, but later using more complex exercises (e.g. 4 vs. 4). Tactically oriented games were also used to teach "playing together" and "off-the-ball movements". No position-specific exercises or drill training were performed. The children regularly took part in competitive matches.

Specific training – field hockey ($n = 17$). Each training lesson was structured in the same way. The field hockey teams began with coordination exercises and tactical mini games. For the remainder of the time they performed field hockey-specific skills, such as how to handle the stick or the ball. In addition, they learned how to dribble, push-pass, and control the ball. At the end of training sessions, they usually played a field hockey game (6 vs. 6) with modified rules. The children regularly took part in competitive matches.

Control group ($n = 18$). The children in the control group only participated in the regular school sports programme twice a week. No child was a member of a special club.

Instrumentation

"Behaviour turns out to be much more context-dependent and knowledge-dependent than we used to think. What subjects do in cognitive experiments is often not representative of what they would achieve in other, more familiar settings" (Neisser, 1994, p. 227). In accordance with this recommendation from cognitive psychology (Araujo, Davids & Passos, 2007), *competition settings* were constructed as an instrument for data recording. This instrument contains context-dependent real-world representations that provoke ecologically valid creative solutions. In recurring comparable situations, this competition setting evokes creative behaviour in using gaps. In this test, four attackers – two of them in each of two fields – have the task of playing the ball past three defenders in the middle field between the four attackers and below the upper limit into the opposite field. The competition settings involved three kinds of skill (hand, foot, and hockey stick) in a system where the players take turns (two rounds for each person). This means that positions and team players/opponents were varied systematically. Game idea, number of players, rules, and environmental conditions were given. This competitive setting was tested for objectivity, reliability, and validity in several preliminary studies (Memmert, 2007; Memmert & Roth, 2003). For instance, the internal consistency coefficient for creative thinking in the setting is 0.72 and therefore similar to usual measurements of creativity (Hocevar & Bachelor, 1989).

The children's performance in the competitive setting was recorded on videotape and judged using a subsequent *concept-oriented expert rating*. This means that the experts were first given exact observation criteria according to Guilford (1967). The main evaluation criterion as an operational definition of creativity was the originality or unusualness (scale 10 to 1) and the number of unusual solutions they produced (= flexibility; scale 10 to 1). *Originality* denotes the unusualness, innovativeness, or even uniqueness of the children's ideas and decision making. It is defined as the statistical rareness of solutions to the competition settings. *Flexibility* also shows close connections with unusualness, innovativeness, and so on, and characterizes the ease with which someone changes between thought levels, uses other systems of reference, generates different hypotheses, and modifies information. It is defined as the number of solutions to the competitive setting. The experts have to take into consideration both the evaluations of originality and flexibility in their *final assessments*. Second, the experts were trained using special videotapes. Third, the experts underwent a final video-based test to check their expert quality. Only experts showing high reliability as measured against a "gold standard" of ball-games experts were chosen. The children in the game-test situations were each judged by three ball games experts (A, B, and C). Because of the two player rotations, each child received two creative values from each of the three coders. Thirty-nine percent of inter-rater reliability values (intra-class correlation coefficients) determined for rotations 1 and 2 were very high (> 0.95) and 33% were high (> 0.90). The rest were above the crucial limit of 0.80.

Similar satisfactory values would result if one calculated the proportion of agreement (for more details, see Nevill, Lane, Kilgour, Bowes, & Whyte, 2001). Regarding the final assessment, for example, 90% of the differences in judgement between expert A and expert B involved the two rotations, and the three measurement times differed by just ± 1 point.

Procedure and analysis of data

All children were tested before the study, 6 months into the study, and at the end of the 15-month study. In the tests, they were required to play using hand, foot, and hockey stick. Only the children who completed all three tests were selected. Each child was analysed individually with neural networks and a qualitative analysis was conducted. Figure 2 shows the areas of the network, indicating excellent

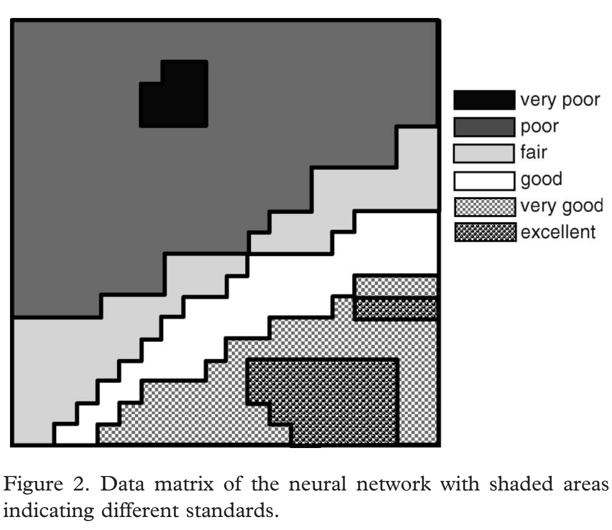

Figure 2. Data matrix of the neural network with shaded areas indicating different standards.

(black structured), very good (grey structured), good (white), fair (light grey), poor (dark grey), and very poor (black) creative performance. Afterwards, scores from the qualitative analysis were compared between the groups using χ^2-statistic procedures for nominally scaled variables. In addition, a quantitative analysis of creativity was carried out using a 3×3 (measurement time $\times$ group) analysis of variance (MANOVA) for repeated measures. Therefore, all judgments from the three experts and two rotations were averaged to calculate the mean. An alpha of 0.05 was pre-selected for all statistical comparisons and the effect sizes recorded.

Results

As can be seen from the increased frequencies in the high-number areas, the network approach indicates an improved formation of game creativity in the case of the soccer- and hockey-specific trained model (see Figure 3, left and right). In contrast, the control group shows a small decrease in creative performance (see Figure 3, middle). A low and stable or even a decreased performance is represented by high frequencies in the low-number areas. Conventional methods showed a pattern of results similar to the one that emerged using the neural network approach. The various types of treatment caused differing increases or decreases in performance ($F_{4,104} = 5.854$; $P < 0.001$, partial $\eta^2 = 0.18$). Furthermore, mean differences in performance were found between the groups that could not be attributed to coincidence alone ($F_{2,52} = 20.103$; $P < 0.001$, partial $\eta^2 = 0.44$). *Post-hoc* analysis revealed that the hockey-trained ($P < 0.001$) and soccer-trained ($P < 0.001$) groups made greater improvements than the control group. No differences occurred between the two training groups ($P = 0.212$).

Graphical representation of the neural networks for the two trained groups and the control group illustrate larger *mean variations* in the 18-dimensional original creative behaviour data (see Figure 3). This can be seen from the distribution of "hits", which build many small centres of low frequency spread over the entire network, apparently representing the spectrum between very good and less good performances almost in its entirety. Notably, the creative development with the "hockey stick" motor function was much more heterogeneous than that with "hand" or "foot", so size and distribution of the neurons together with their correspondences to the clusters provide an idea of the quality of the training results and help to detect striking features, such as specific similarities or differences.

Figure 4 shows trajectories that represent individual training processes. Starting with "black square", the time-steps of the training process move through the areas of the network, indicating from top-left to bottom-right poor, fair, good, and very good creative performance. For the 20 soccer players given in Figure 4, the players' game creativity with

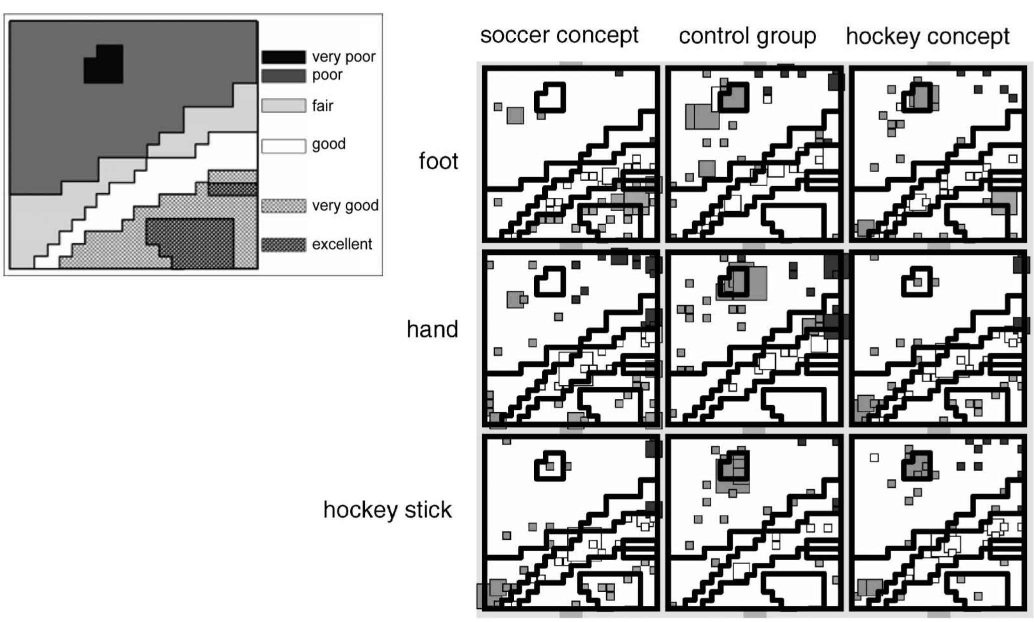

Figure 3. Structure of mappings to the network: "soccer group" (left), "field hockey group" (middle), and "control group" (right). The squares marked on the network represent neurons, which in turn correspond to specific types of information. If an input is tested on the net, the neuron with the information most similar to that of this input is activated. The number of activations – i.e. number of inputs that belong to the neuron – determines the size of the square the neuron is represented by. The landscapes of standards for Figure 3 and Figure 4 correspond to that from Figure 2, as seen in the upper-left corner of Figure 3.

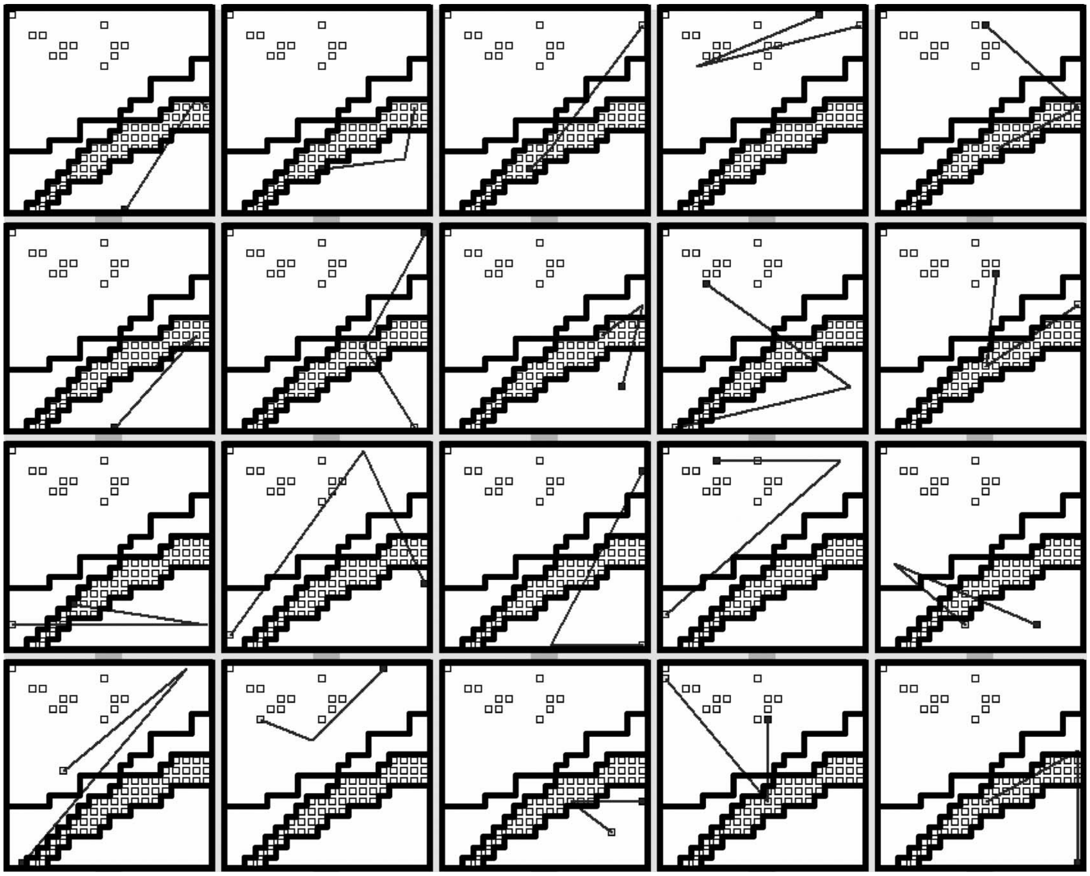

Figure 4. Representation of the trajectories of the participants specifically trained in field hockey. The learning process starts with a "black square" and ends with a "white square". The shadings of the neurons correspond to those in Figure 2.

the "hand" motor function shows different types of development over the 15 months. In 5 of 20 cases (25%), creative performance increases initially, but at the end, at the "white square" step, it is worse than in the middle of the training session (up-down fluctuation process). The reverse development was identified in 30% of the children (down-up fluctuation process). In 25% the performance increases and in 10% it decreases. Only in a few cases does no development occur (10%).

The examples from Figure 4 have been chosen to demonstrate differences in obtained learning profiles – instead of increasing monotonously, as might have been anticipated. If, however, the learning trajectories are clustered under the aspect of similarity, this results in five clearly distinguishable types, as shown schematically in Table I.

Table I presents the overall results from the two trained groups and the control group, and also from the three motor functions. Notably, the field hockey group shows a different pattern of results from the soccer group, independent of the motor functions. A comparison of the two fluctuation processes' chi-squared statistic shows an effect between the field hockey and the soccer groups ($\chi^2_{(1)} = 18.942$; $P < 0.001$, $n = 52$). The children in the field hockey trained group showed a stronger up-down fluctuation than the soccer group, and vice versa. No marked differences were observed in the other three learning behaviours – stable, increase or decrease in game creativity – between the three groups.

Such a process-oriented presentation of the results might help to detect problems and find explanations. In this particular example, this could be because the whole training process was underlined by different

Table I. Summary of the results of all trajectories of the three treatment groups.

		Field hockey group	Soccer group	Control group
$a = b = c$		3 (1/0/2)	5 (2/3/0)	4 (1/3/0)
$a \leq b \leq c$		10 (1/5/4)	11 (5/2/4)	11 (7/2/2)
$a \geq b \geq c$		12 (5/4/3)	8 (2/1/5)	17 (4/6/7)
$a < b > c$		24 (9/7/8)	11 (5/0/6)	11 (4/4/3)
$a > b < c$		1 (1/0/0)	17 (6/9/2)	6 (2/3/1)

Note: The five types of learning behaviour are presented. The number for each learning behaviour in the three motor functions (hand, foot, hockey stick) is given in brackets.

kinds of learning behaviour according to the training groups. Possible explanations for down-up and up-down fluctuation processes are discussed next.

Discussion

The aim of this study was to determine whether and how – as indicated by individual learning behaviours – game creativity could be improved by a structured field-training programme. A secondary aim was to evaluate neural networks by studying creative performance. The soccer and the field hockey groups improved their creative performances considerably over time. In contrast, no improvement in performance was evident for participants in the control group over the three measuring points ($P = 0.52$). It was surprising to discover that five main types of learning behaviour existed, depending on the training group. Only two of them showed a consistent profile with constant or improved performance over time, as expected (see Table I, first and second rows), while a third type shows a continuous deterioration (Table I, row 3) and two types – down-up and up-down fluctuation processes – show strange behaviour with alternately increasing and decreasing performance (Table I, rows 4 and 5). Thus, a practice-oriented training programme can lead to markedly different kinds of learning performance.

We analysed this phenomenon by means of the Performance Potential Metamodel (Perl, 2004b), which was originally developed to analyse physiological adaptation processes. The use of the Performance Potential Metamodel here is based on the idea that creative behaviour can also be understood as a dynamic adaptation process (e.g. Boden, 2003; Simonton, 2003). Typical results of a Performance Potential Metamodel analysis are the delay values Delay in Strain and Delay in Response, which characterize the way the organism's performance is adapted to the training load stimulus. If Delay in Strain is smaller than Delay in Response, the strain becomes effective first, causing a reduction in performance (up-down fluctuation process), which is later compensated by the delayed response (supercompensation effect). If Delay in Response is smaller than Delay in Strain, then the response becomes effective first (down-up fluctuation process), causing an initial improvement, which can later be stabilized or reduced, depending on the delayed impact of strain.

Figure 5 shows the five types of learning behaviour observed compared with Performance Potential Metamodel simulated profiles. It transpires that, on the one hand, all five types of learning can be simulated using proper delay values of Delay in Strain and Delay in Response, as demonstrated in Table II with the "strange" cases of learning behaviour highlighted. In contrast, the results from Figure 5 show that adaptation is not a smooth, continuous process and that at least two or three additional measurement times are required if a deeper understanding is to be gained. One main question could be: Are there individual learning types, characterized for instance by particular ratios of delays, that can be recognized and then used to optimize individual learning strategies?

Summary and directions for future research

Recently, there has been an increasing demand for interdisciplinary projects to investigate phenomena. This tendency is based on the anticipation that new results, even in individual disciplines, depend increasingly on a fruitful *transfer of knowledge*. In well-structured and successfully run research paradigms, additional potential will be available from interdisciplinary collaboration – particularly from a creative exchange of methods.

The neural network paradigm revealed five types of learning behaviour, depending on the training group (down-up and up-down fluctuation processes of creative performance) that are particularly important. In this way, networks demonstrate the advantages of qualitative analysis in addition to quantitative stochastic approaches. The stochastic approach reduces the totality of recorded data to a few measures that are not necessarily data-specific. Variance analysis can, however, be used to assess the statistical significance of changes in the data. In contrast, network-based analysis allows mapping of the 18-dimensional time-dependent process structure to 2-dimensional trajectories without destroying topological and qualitative structures such as *similarity* and *connectivity*. In this way, clusters together with *trajectories* can help to recognize qualitative features and analyse process dynamics. Also, this allows interpretable representations of time-dependent learning processes, as well as improved visual judgement of distributions. Such mapping of the complete data set to the structure of the network allows recognition of specific data structures and striking features, which can also be helpful in developing new ideas and theories.

Further research is necessary to improve the process-oriented learning dynamics of neural networks, which has been achieved by combining the advantages of the growing neural gas concept (Fritzke, 1997) with those of dynamically controlled networks (Perl, 2004a). The resulting dynamically controlled neural gas can generate new neurons dynamically like a growing neural gas, can control the neurons' information dynamically like a dynamically controlled network, and therefore can recognize

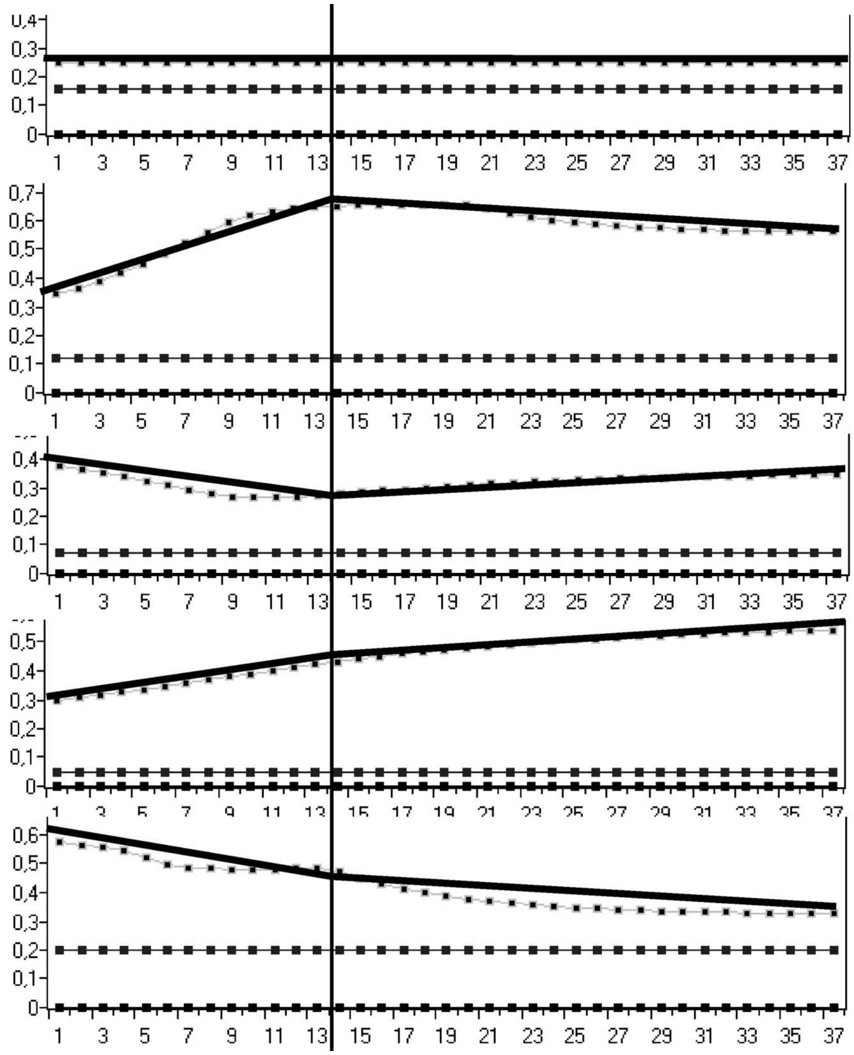

Figure 5. Five types of observed learning behaviour (bold black lines) compared with the corresponding PerPot-simulated performance profiles (upper dotted lines; lower dotted lines: constant load input).

Table II. Five types of observed learning behaviour compared with the corresponding delay values taken from the Performance Potential Metamodel simulation.

Type	Profile	Delay in Strain delay of unlearning	Delay in Response delay of learning
1 a = b = c		1.5	**1.2**
2 a ≤ b ≤ c		7.0	**3.5**
3 a ≥ b ≥ c		**4.7**	7.5
4 a < b > c		10.5	**6.5**
5 a > b < c		**3.3**	3.5

Note: The delay values of the "strange" types of behaviour demonstrate the change of delay ratio: if the delay of learning (Delay in Response) is smaller than the delay of unlearning (Delay in Strain), the learning progress is faster at the start of the learning process (profiles 1, 2, 4) but can be dominated by unlearning at the end (profile type 4). In contrast, if the Delay in Strain is smaller than the Delay in Response, the process starts with unlearning (profile types 3, 5), which can be followed by a dominating learning phase (profile 5).

if a neuron contains information that is relevant for an information theoretical understanding – for example, regarding new or rare events like creative activities. Furthermore, the current evolution of dynamically controlled neural gas offers associative clusters and bridging neurons and therefore simulates learning processes with embedded creative events. The creative learning model of dynamically controlled neural gas is currently being tested using data from a field-based study (Memmert & Perl, in press). Implicit and explicit teaching concepts are compared, dealing for example with the game creativity of about 60 children from eight measurement times (Perl, Memmert, Bischof, & Gerharz, 2006).

Finally, further research should address the latest discussion on intuition (Lieberman, 2000; Plessner, Betsch & Betsch, 2008), which is closely linked to the discussion of creativity. Lieberman (2000) proposed that implicit learning processes are the cognitive substrate of social intuition. He supports this connection through conceptual correspondence between implicit learning and social intuition, as well as by relevant neuropsychological, neuroimaging, neurophysiological, and neuroanatomical data: "Applied broadly, this approach will interactively allow the real world phenomena studied by social psychologists to inform the hypotheses formed by neuroscientists regarding the processing mechanisms in the brain, as well as allow the growing knowledge of the computational properties of neuroanatomical regions and their interactions to refine and clarify our understanding of social psychological phenomena" (Lieberman, 2000, p. 128).

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