

World-Level Analysis in Top Level Football Analysis and Simulation of Football Specific Group Tactics by Means of Adaptive Neural Networks

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1. Introduction

In modern soccer tactical skills play an important role in all age groups and proficiency levels (Memmert & Harvey, 2010; Memmert & König, 2007). Many experts regard tactics as the factor which gets the least attention in the training process (Greco, Memmert & Morales, 2010; Memmert & Roth, 2007). For that reason, the most potential seems to lie in the tactics area. There are a couple of journal articles in the area of group tactics, however, a systematic overview is not available yet. It is even more crucial that there are no empirically validated differentiations of group tactical requirements in soccer. To be more specific: Of course taxonomies of group tactics occur in books sporadically, but it was not shown yet, whether they are actually relevant in amateur or competitive soccer.

Therefore, Memmert (2006) work on those deficits in order to provide a scientifically based analysis of soccer specific group tactics. Building on pilot studies (second division of German Bundesliga), the coaching philosophy of Hansi Flick (current assistant coach of the German national soccer team) was indirectly examined based on 27 3rd division home games of 1899 Hoffenheim in the seasons 2002/2003 and 2003/2004. During the recorded game, he selected important positive and negative behaviours of different position groups without being aware of the fact that their coaching skills were being evaluated. All in all, 585 match situations were judged and commented on by the coaches. The implicit expert knowledge (video sequences and comments) from the single case analysis was solidified with the help of further qualitative content analyses. The resulting offensive and defensive group tactical skills were allocated to superordinate basic categories by means of inductive categorization. Thus, group tactical challenges were identified, which have to be solved through cooperation of several team members (= position groups). Such position groups are, for instance, strikers or midfielders, but also players in certain areas (e.g. left and right wing) or players from different positions, that move across those areas in a particular moment. Based on the analysis, the following group tactical categories were validated empirically (cf. Table 1.1. & Table 1.2).

| Defense | |
|-------------------------------|---|
| Quick regrouping | <input type="checkbox"/> Group tactical requirement, which demands that position groups prevent their opponent's attacks through quick changes from offense to defense |
| Pressing | <input type="checkbox"/> Group tactical requirement, which demands that position groups disturb the offense actions of their opponent as early as possible |
| Man to man marking | <input type="checkbox"/> Group tactical requirement, which demands that the members of a position groups are aware of the marking of their opponents e.g. during corner kicks or man-marking in general |
| Competing for the second ball | <input type="checkbox"/> Group tactical requirement, which demands that position groups and individual players position themselves adequately in order to win second balls (e.g. after goal-kicks or tacklings) |
| Communication | <input type="checkbox"/> Group tactical requirement, which demands that position groups keep their orientation on the pitch by making adequate use of previously agreed codewords |
| Support play | <input type="checkbox"/> Group tactical requirement, which demands that position groups gain ball possession or avoid shots on goal by an appropriate position play |

Table 1.1. List of 6 defensive group tactics, which result from inductive category formation and further qualitative evaluation steps (Memmert, 2006)

| Offense | |
|--------------------------|---|
| Attacking play | <input type="checkbox"/> Group tactical requirement, which demands that position groups initiate play by systematic actions, e.g. vertical passes |
| Combination play | <input type="checkbox"/> Group tactical requirement, which demands that position groups keep the ball possession through double passes, short passes or triangular passes |
| Switch play | <input type="checkbox"/> Group tactical requirement, which demands that position groups create space by passing the ball from one side of the pitch to the other |
| Creating space | <input type="checkbox"/> Group tactical requirement, which demands that position groups choose adequate paths (e.g. cross-over and dummy runs in order to give each other space |
| Wing play | <input type="checkbox"/> Group tactical requirement, which demands that position groups pose a goal threat on the wings e.g. by through-balls |
| Counter attacks | <input type="checkbox"/> Group tactical requirement, which demands that position groups try to intersect the defense quickly, e.g. by playing through balls |
| Set pieces | <input type="checkbox"/> Group tactical requirement, which demands that position groups create a goal threat through free kicks, corner kicks and throw-ins. |
| Setting up shots on goal | <input type="checkbox"/> Group tactical requirement, which demands that position groups try to pass to their team mates so that they can score a goal from a long or short distance |

Table 1.2. List of 8 offensive group tactics, which result from inductive category formation and further qualitative evaluation steps (Memmert, 2006)

These group tactics constitute the theoretical framework for our project in which evaluation tools are developed for the analysis of group tactics. Therefore, international top level soccer matches (world level analysis) are examined on the basis of position data with reference to the effectiveness of group tactical processes. "Considering the influence of the opponent, how do the players have to play together at which point in time in order to be a goal threat?" or to be more specific: "How can group tactical behaviour patterns in soccer be modeled and summarized to characteristic categories? This question is explored in section 2 of the chapter (step 1). By means of an example, potential problems in the process are illustrated and possible solutions are given. In addition, first preliminary results (step 2) are presented which compare the net based position data related procedure with conventional methods (validation study; Section 3). Section 4 of that Chapter illustrates how behaviour patterns can be evaluated, how one can identify creative behaviour and how the simulation can be used for a prognostic evaluation of the effectiveness (step 3).

2. Modelling and typification of group tactical behavior patterns by means of position data (step 1)



Fig. 1. Display of the in-house developed software system for the conventional analysis (a) and position data-supported analysis (b) of team sports (soccer)

At the moment, a variety of team sports (soccer, handball, basketball, volleyball) are analyzed by means of video sequences (conventional analysis, cf. Figure 1a). Current technical improvements however, allow a complete capture of position data of all 22 players and the ball (cf. Figure 1b) so that one can access the xy coordinates of the players and the ball for the entire 90 minutes. With a sampling rate of 25 frames per second, 135.000 xy data per player are produced. Thus, when looking at all players including the ball, one gets the amount of 23×135.000 , i.e. 3.105.000 xy data.

With the software system from Figure 1b, individual match sequences can be allocated to different categories. By means of these categories, according position data can be extracted and used to train neural nets (Memmert & Perl, 2005). This process is illustrated through the following example.

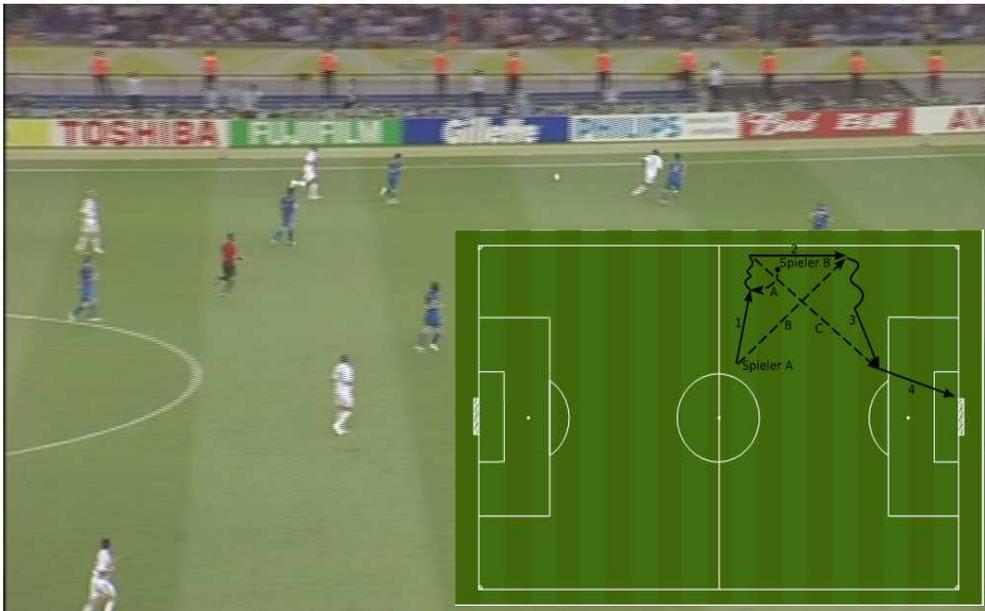


Fig. 2. Display of a video sequence of wing play and the schematic representation as it is usually used to display the actions.

In the video sequence, a wing play is identified (cf. Figure 2, above). The according match sequence is thus allocated to the category “wing play” in the software system and the involved players are inputted. By means of the extracted position data, the wing play can be illustrated schematically on a graphic pitch (cf. Figure 2, down right). Figure 2 shows just one possible realization of a wing play. A couple of variations are schematically depicted in Figure 3. The position data of involved players obtained from several wing plays are then used to train a neural net and memorize the pattern “wing play”. When looking at the wing plays, their capture through a neural net poses a first problem. The number of the involved players varies, down left in Figure 3 there are three players, in the other ones there are just two. Hence, the xy data set from the position data of the players and the ball contains four xy data for the wing play down left and three for the other ones. A neural net however, has a fixed dimension and thus can only process data of a certain length.

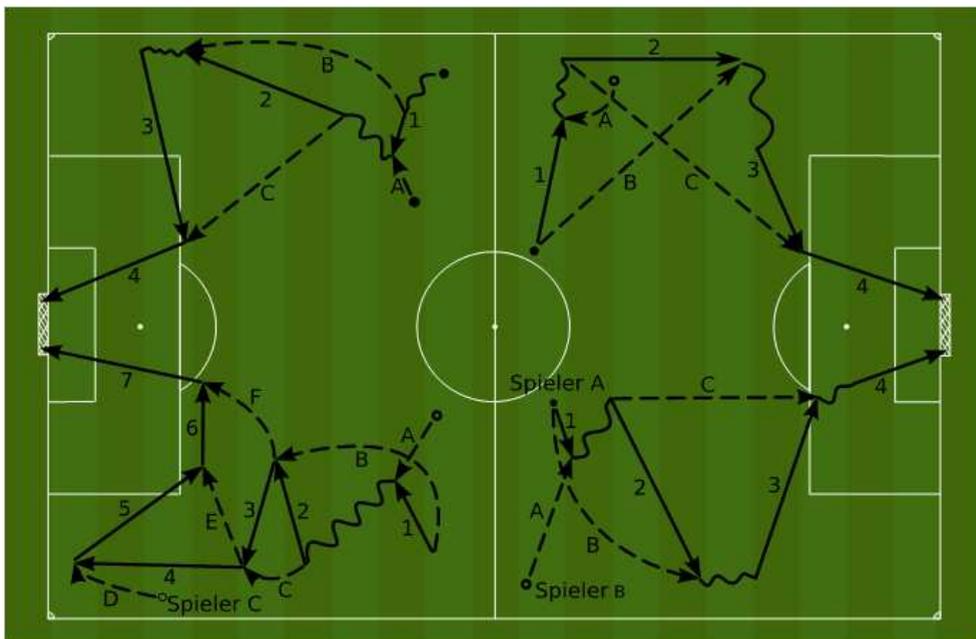


Fig. 3. Display of variations of wing play.

One solution can be to train different nets for different numbers of involved players (which would be one for two players and one for three players with respect to Figure 3). If there are more players involved, further nets would be necessary. A second problem arises due to the fact that areas on neural nets with a lot of information do not have more neurons available than areas with only few information. Thus, the lower information content could be solved

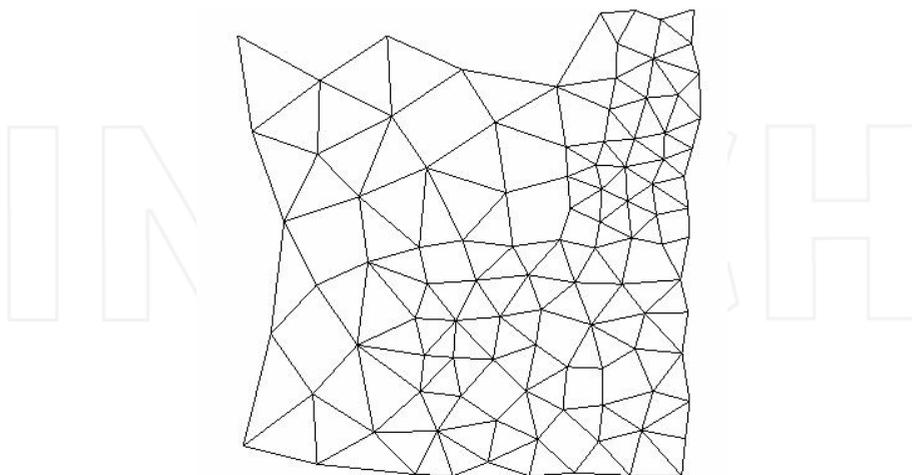


Fig. 4. Exemplary display of a neural net with variable neuron density (Perl, Memmert, Bischof & Gerharz, 2006).

better than the higher information content. With respect to the wing play, for example, this could imply that certain formations of the involved players occur more often than others, and that the more important ones are underrepresented on the net. This problem could, for example be solved with the help of a dynamic generation and administration of nodes. This is illustrated in Figure 4 by means of a two-dimensional neural net: On the left there is an area in which no neurons exist. On the bottom right, on the contrary, one can see a cluster of neurons. Thus, from left to right there is an increase of the neuron density.

When the training of the nets is complete, the movement patterns of individual players, position groups or the whole team can be depicted as trajectories on the net (cf. Figure 5)

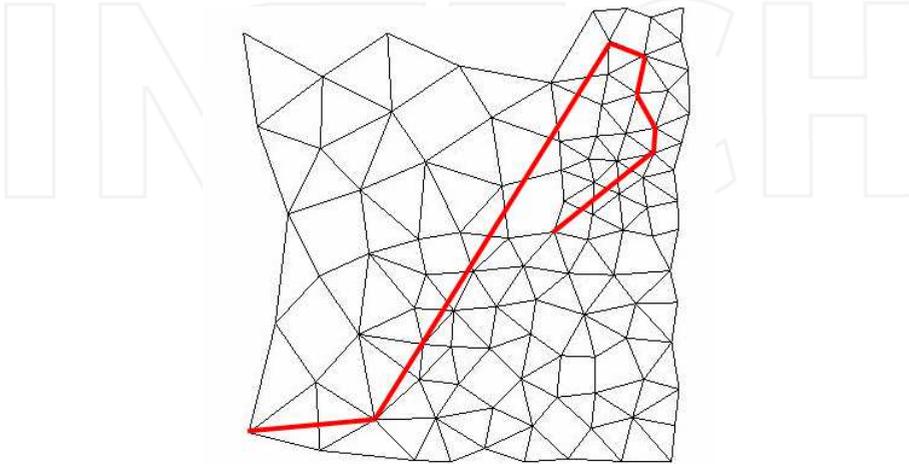


Fig. 5. Exemplary display of a trajectory as an image of a game sequence on a neural net (Perl et al., 2006).

In this process, every data set of a match sequence activates a neuron in the net. Consecutively connected, all activated neurons result in a trajectory. With a superior neural net, groups of similar match sequence patterns shall then be allocated to a mutual neuron or a cluster of adjacent neurons. For instance, all realizations of a wing play shall be identified by a neuron or neuron cluster "wing play". For this purpose, the net must have been trained with a multiplicity of different wing play patterns in advance. From this follows a third problem: For being extracted from recorded matches, there are usually only a limited number of realizations of a pattern available. Thus, it could, for example, happen that there are no position data available for some of the variations of a wing play. One solution could be to schematically draw the variations of a movement pattern onto a graphic display of a pitch, in order to let the software calculate the position data for the training with the help of a Monte Carlo simulation. This approach may seem a bit odd, but it turned out to be remarkably successful and effective due to the special training model (Perl, 2004). When processing the trajectories, the above mentioned problems occur: On the one hand, trajectories can be too long so that high dimensional nets are generated. On the other hand, trajectories can differ in length. When looking at the schematic displays in Figure 3, one can recognize that the distance covered by the involved players and the ball, varies in each example. Consequently, due to the length of the match sequence, longer trajectories are generated if the distance in longer movement patterns is not covered faster. As mentioned before, training specific nets with different lengths is not viable. With the systematic

removal of redundant vectors, trajectories which are too long, can be shortened to a standard length. However, this approach is problematic for implicitly accelerating the speed of the actions. A practicable solution is the “sliding window method”: from sequences of different lengths, sequences with a constant length are cut out.

3. Validation study (step 2)

For the validation of the trained nets, the results of the traditional game analysis (“golden standard”) and the results of the net based position data based procedure have to be compared. Pre-studies showed that almost 80 % of the traditionally identified group tactical match events from Table 1 like playmaking, set pieces (further differentiated into throw-ins, free kicks and corner kicks) and shots on goal were also identified by our nets. At the moment we are working on a further optimization in order to obtain matching rates of more than 90 %.

4. Evaluation, creativity and simulation (step 3)

With the help of trained nets, it is possible to automatically display all match sequences of the above mentioned categories – even for yet uncategorized matches. For example, one wants to have an overview of all wing plays in a soccer match, view all sequences on video and capture them in a database for a comprehensive analysis. For example, the action patterns, which were obtained through the net based typification, can be analyzed statistically. This way, the frequency can be determined, with which a certain pattern occurs, as well as frequency of the transition from one pattern to the other.

Therefore, in a study analyzing the individual creativity (see for a definition: Memmert, 2010) of soccer players, nets were developed and validated in pre-studies, which were able to represent the individual training processes of soccer players including creative behavior (cf. Memmert & Perl, 2009b). Beginning with a red and ending with a yellow square, Figure 6 depicts the particular time steps of the respective process as red edges on all of the individual net representations. In the three steps of the process, the trajectory runs through the colored quality areas (from light green (excellent) to dark violet (poor)). The results (Figure 6) show a very unequal creativity development of 20 soccer players over the time period of 15 training months: In 5 of 20 cases (25%) the performance increased in the beginning, but turned out to be worse than in the middle of the training process eventually (up-down fluctuation process). The opposite results came up for 30 % of the test persons (down-up fluctuation process). In 25 % of the cases the performance increased monotonically, whereas it decreased monotonically in 10 % of the cases. In 10 % of the cases the performance remained (almost) entirely the same.

For the qualitative classification of actions and action types, a rating is required, which normally is not just the result of a team’s actions, but rather the result of the interaction with the opponent team. The net based solution for this problem consists of the usage of team specific nets for the actions, which enable the identification and analysis of the interaction types through a hierarchically super-ordinate net. This way, actions and action types can be rated in the context of the respective interaction.

Figure 7 illustrates the used methodology: The sequence of the offense actions of Team A is illustrated in the according offense net (top left) in colored sub-sequence representations, so called phases (phase diagram offense, top), which correspond with the according defense phases of Team B (phase diagram defense, bottom). The corresponding phase sequences are transferred to the interaction net where they deliver the data for interaction and movement analyses.

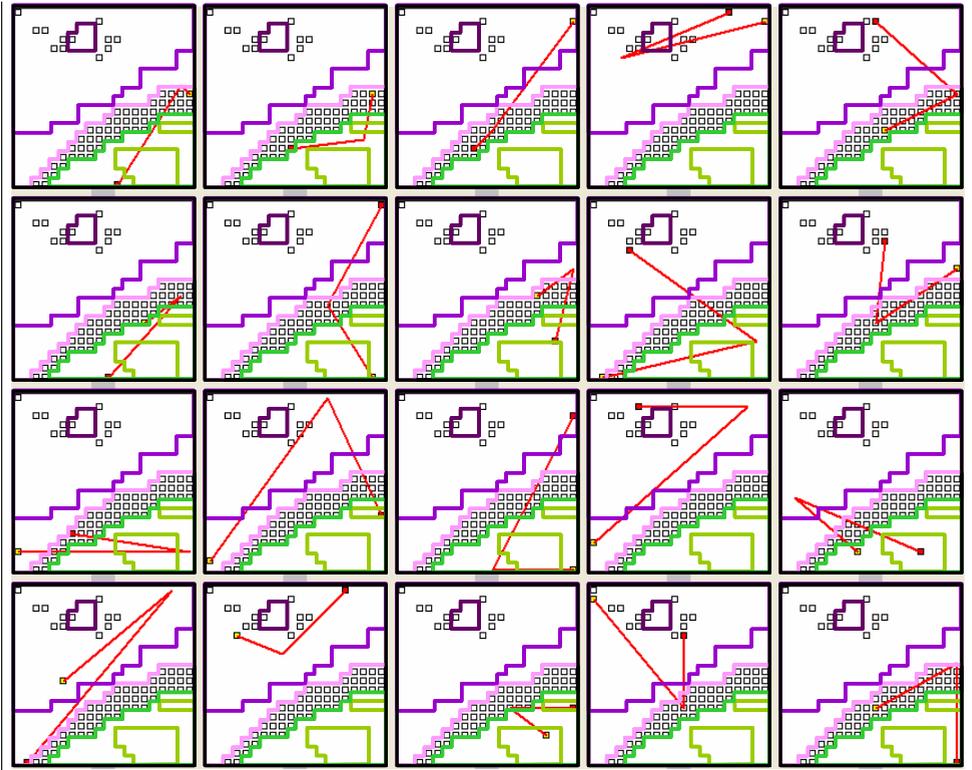


Fig. 6. Representation of intra-individual trajectories of a soccer training. The learning process begins in the red square and ends in the yellow square (cf. Memmert & Perl, 2009b).

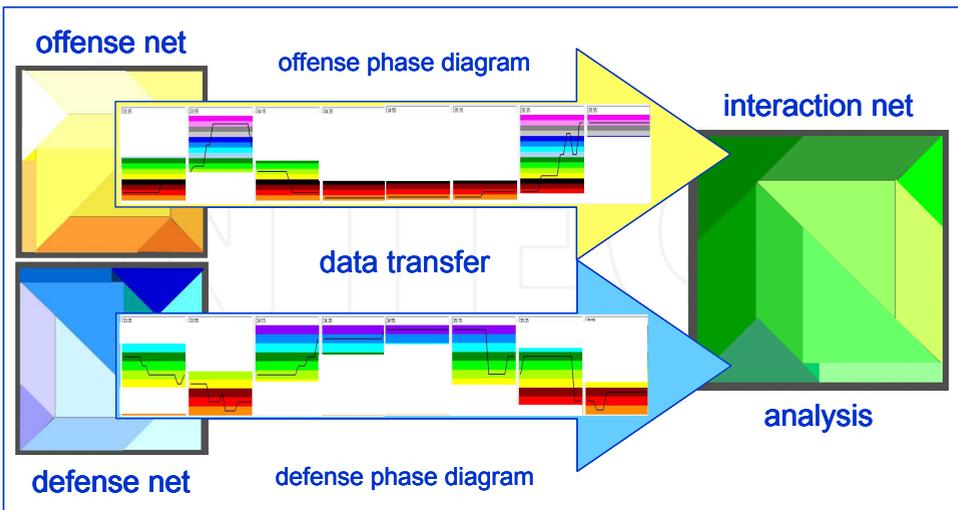


Fig. 7. Hierarchical interaction - and evaluation analysis (Grunz, Memmert & Perl, 2009)

From this approach result two important applications: First, by means of a simulation, the effectiveness of behavior processes can be evaluated prognostically. For that purpose, the game is stopped, and instead of the next action type, another type with a higher rating is chosen for the examined team. Afterwards, the game proceeds and a target performance analysis is conducted in order to determine a possible advantage of the simulated action. This way, tactical options can be tested in simulations and dropped if necessary. Second, creative actions in the sense of relevance (surprising, rare) and adequacy (successful in a particular situation) can be identified and inserted into the simulative analysis process.

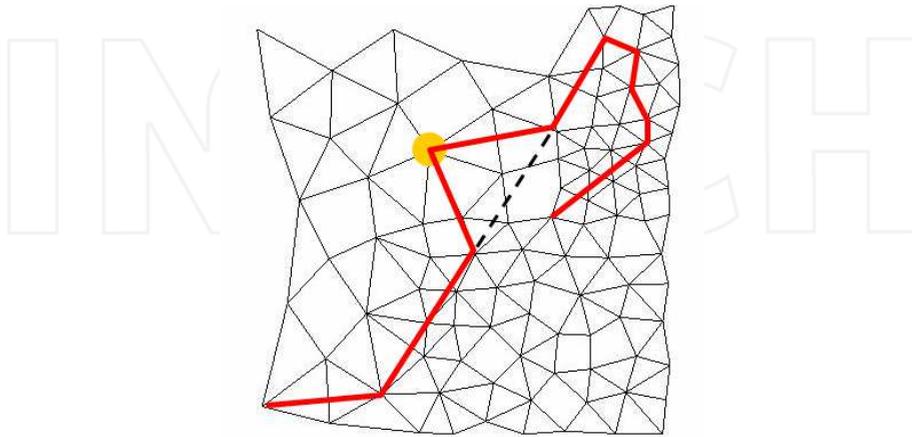


Fig. 8. Exemplary display of creative behavior in the frame of a neural net (cf. figure 5)

Figure 8, as opposed to figure 5, is a schematic depiction of a behavioral process with a new, creative aspect. The progression of the trajectory taken from figure 5 is illustrated by the dashed line. Due to the creative action, a neuron is activated and hence the trajectory deviates from the expected progression. In a longitudinal study, Memmert and Perl (2009a,b) could validate neural nets that are able to identify creative actions. Therefore, special neural nets were constructed, which combined DyCoN's (Dynamically Controlled Networks, see Perl, 2004) and neural gas elements. With their help, it was possible to select not only rare, but also tactically relevant behaviours from a multiplicity of behavior patterns. By the means of these preliminary works (Memmert & Perl, 2009a,b), in a third research episode, it is looked for rare but successful actions in the frame of different group tactics. To be concrete, the important question for practical application is explored, whether there are unusual actions in the set of wing play situations that pose a goal threat.

5. Summary and practical applications in competitive soccer

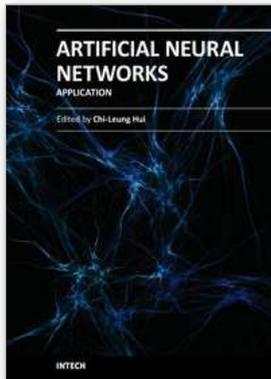
The developed nets allow a comparison of match scenes of one or more games in order to find out which tactical formations lead to which results on the pitch. The goal is to make the selection of soccer match scenes easier so that it does not have to be done manually (conventional analysis) but automatically with the help of neural nets. Thus, it is made possible to classify extensive data volume according to differences and similarities within a short time period. The analysis system based on neural nets can arrange match situations according to success or failure within seconds and hence find out whether a 4-2-3-1 formation is superior to an opponent's 4-4-2 formation under certain circumstances. With the aid of simulations, the question is followed whether changes in offense and defense

(change of formation or replacements of players) have an influence on the probability of success of certain tactical moves. Furthermore, the net based approach helps not only to identify standard match sequences, but also rare and surprising sequences, and evaluates those with respect to success and adequacy in their specific contexts. Often, extraordinary actions or rare goals are discounted as coincidence, which can be identified as spontaneous, creative and non-accidental processes after a closer analysis. This could be extremely helpful for the evaluation of sport-specific training concepts to improve creative behavior (Memmert, 2007; Memmert, Baker & Bertsch, 2010).

Of course, neural nets will still never be able to replace experts. However, they offer the opportunity of an interactive communication (high speed and online) with coaches and provide them with specific data and information that they can interpret and make use of. This way, results are provided in a quick and convenient manner. These results are helpful to study an opponent and they give information about which game formations are more likely to be successful against a certain team with a certain tactic and a certain formation.

6. References

- Greco, P.; Memmert, D. & Morales, J. C. P. (2010). The effect of deliberate play on tactical performance in basketball. *Perceptual & Motor Skills*, 110, 849-856. [0.30]
- Grunz, A.; Memmert, D. & Perl, J. (2009). Analysis and Simulation of Actions in Games by Means of Special Self-Organizing Maps. *International Journal of Computer Science in Sport*, 8, 22-37.
- Memmert, D. (2006). *Optimales Taktiktraining im Leistungsfußball [Optimal Training of Group Tactics in Top Level Soccer]*. Balingen: Spitta Verlag.
- Memmert, D. (2007). Can creativity be improved by an attention-broadening training program? - An Exploratory Study Focusing on Team Sports. *Creativity Research Journal*, 19, 281-292. [0.81]
- Memmert, D. (2010, in press). Sports and Creativity. M. Runco & S. Pritzker, *Encyclopedia of Creativity*, 2nd Edition. Elsevier.
- Memmert, D. & Harvey, S. (2010, in press). Identification of Non-Specific Tactical Problems in Invasion Games. *Physical Education and Sport Pedagogy*.
- Memmert, D. & König, S. (2007). Teaching Games at Elementary Schools. *International Journal of Physical Education*, 44, 54-67.
- Memmert, D. & Perl, J. (2005). Game Intelligence Analysis by Means of a Combination of Variance-Analysis and Neural Networks. *International Journal of Computer Science in Sport*, 4, 29-38.
- Memmert, D. & Perl, J. (2009a). Analysis and Simulation of Creativity Learning by Means of Artificial Neural Networks. *Human Movement Science*, 28, 263-282.
- Memmert, D. & Perl, J. (2009b). Game Creativity Analysis by Means of Neural Networks. *Journal of Sport Science*, 27, 139-149.
- Memmert, D. & Roth, K. (2007). The Effects of Non-Specific and Specific Concepts on Tactical Creativity in Team Ball Sports. *Journal of Sport Science*, 25, 1423-1432. [1.80]
- Memmert, D.; Baker, J. & Bertsch, C. (2010). Play and Practice in the Development of Sport-Specific Creativity in Team Ball Sports. *High Ability Studies*, 21, 3-18.
- Perl, J. (2004). A Neural Network approach to movement pattern analysis. *Human Movement Science*, 23, 605-620.
- Perl, J.; Memmert, D.; Bischof, J. & Gerharz, Ch.(2006). On a First Attempt to Modelling Creativity Learning by Means of Artificial Neural Networks. *International Journal of Computer Science in Sport*, 5, 33-38.



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This book covers 27 articles in the applications of artificial neural networks (ANN) in various disciplines which includes business, chemical technology, computing, engineering, environmental science, science and nanotechnology. They modeled the ANN with verification in different areas. They demonstrated that the ANN is very useful model and the ANN could be applied in problem solving and machine learning. This book is suitable for all professionals and scientists in understanding how ANN is applied in various areas.

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