Analysis of Tactical Structures in Team Handball by Means of Artificial Neural Networks

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Abstract
In the field of sports games the analysis of the game structure as well as the analysis of the opponent team is of major interest for the training process in order to optimize tactical skills. Based on methodological problems of present game analysis some recent approaches apply artificial neural networks to examine the game structure. With the intention to analyze types of tactical structures in team handball we use a neural network to identify a number of such types which represent play processes with similar tactical structures. Therefore a process oriented observation model of the offensive play was developed on the basis of offensive attempts. 15 matches (12 teams) of the Women's Junior World Championship 2001 were observed. Afterwards a prepared neural network (DyCoN) was trained with 2900 offensive attempts (processes) from all teams to coin offensive attempt patterns. In the contribution it is shown that the neural network can be used in order to identify typical tactics of different teams.

KEY WORDS: NEURAL NETWORK, GAME ANALYSIS, MODELING

Introduction
During many decades research has been investigated in systematic observation of playing performance in sports games. Based on those data, recommendations have been developed in order to analyse and improve tactical behaviour and training processes. Apart from talent scouting and player selection, training science is mainly interested in aspects of sports structure and opponent analysis (condition selection) as well as of training and match control (person’s modification) (Hohmann, 1997, p. 147). The area of condition selection and modification of personal characteristics is of major interest for the training process in order to optimize tactical skills. Therefore conditional and technical elements of individual tactics, group tactics and team tactics are important, which aim at the optimum result and need to be analysed.

Problems in the analysis of sports games
Analysis of literature shows that – based on fast technological development in the area of computers, video etc. – a large number of methods have been developed to analyse the tactical structure of sports games (Winkler & Freibichler, 1991; Loy, 1994, 1995, 1996a, 1996b; Bernwick & Müller, 1995; Müller & Lorenz, 1996; Remmert & Stein-
Most of these game analysis methods use structure oriented observation models. They enable for registering isolated elementary actions of a match, but do not allow for obtaining data about the match process – i.e. about tactical behaviour or concepts (Perl, 2002, p. 92). The elementary actions of a sports game only form the static information basis for the actual play dynamics, which can be monitored and described only by the tactical context and interactions (Hein, 1993, p. 136).

In order to achieve deeper insight into the tactical match structure or the tactics of a team it is necessary to record the substantial tactical actions in a chronological, sequential order. By means of a process oriented model concept the sequence of the structural components (here tactics) - and therefore the tactical behaviour – can be considered (Perl & Uthmann, 1997, p. 54). In a process oriented model the match is characterized by a sequence of events and event-based temporal changes of the system’s state. Play phases or temporal tactical behaviour can define states while events are defined by the player's actions or the team's activities, i.e. by tactical actions. It can be distinguished between two kinds of process oriented models, namely the state-transition-models and the state-event-models. If the analysis focuses on the change of states, a state-transition model can be used without the indication of event data. In sport game research state-transition models are applied to analyse transition probabilities in the course of the match (Lames, 1991, Remmert, 2002, Zhang, 2003, Pfeiffer, 2005).

Regarding the sport games research up to now it turns out that – despite the detailed structural resolution – the process of the play structure can only be represented on a high level of abstraction if transition probabilities are to be used (Perl & Uthmann, 1997, p. 59).

This is due to two reasons: First the complexity of the processes leads to the fact that even with a small number of play states (conditions) the number of the combinable sub processes can quickly become very large (Perl, 1997, p. 82). Connected with this problem of complexity, the structuring of different abstraction levels is also a problem. Conventional methods, usually statistics, are not able to solve these problems. For this reason, some recent approaches apply artificial neural networks to game analysis (Perl, 1997, p. 87). With the help of neural networks even an extreme data complexity can be reduced to a handy size, so that the substantial information from a multiplicity of processes can be compressed into a small number of process types (Perl, 2002, p. 67). In order to analyse tactical structures in handball it would be interesting to identify a number of such types which represent play processes with similar tactical structures. From the point of view of training theory such an approach is interesting for the following reasons:

- For sports game analysis process types with similar tactical structures can be a very meaningful information.
- The findings of quantitative match observation could meet the requests of sport practice much better if they are based on information about individual process types instead about general interrelations only.
- Depending on the frequency of their occurrence in typical game situations, technical-tactical behaviour could represent a priority training goal and thus get into the focus of training practice (Perl & Lames, 2000, p. 211).

First studies with the Dynamically Controlled Network (DyCoN) developed by Perl (2001) show that in sport games as squash or volleyball this method is able to identify...
types of rallies each of which represents a special tactical behavior. Based on these studies the DyCoN-approach has been used in order to examine the tactical structure in team handball to identify behavioral patterns in the offensive play.

The Model

The starting point for our model was the control of the ball. Therefore the offensive play was modelled on the basis of offensive attempts. An attempt starts when the ball control changes from one team to the other (1), the match is continuing after a referee decision (2), or the attacking team forms up for a new trail (3). In the last case a new offensive attempt is organized. Accordingly, an offensive attempt ends if

- the ball is lost to the opposing team without a referee decision (loss of the ball)
- or
- the referee interrupts the match (e.g. after a technical or rule error) or
- the attack attempt is broken, i.e. the team has to re-organize their offensive play.

Consequently the offensive play of one team is made up of at least one offensive attempt and can also include many subsequent attempts. The offensive play always starts by winning the ball and finishes with the loss of the ball or with a goal.

In order to describe the tactical structure of a handball match the offensive attempts are used as chronologically structuring units, each of which can be characterized by a sequence of states (Figure 1).

Figure 1. Structure model of a handball match

In the following second step of modelling it is necessary to define the states used to analyse the tactical behaviour. The content as well as the structure of the system of states are based on handball-specific concepts and therefore have a theoretical foundation in scientific findings on handball (Czerwinski & Taborsky, 1997; Pfeiffer, 2001, 2002; DHB, 1997). So the process of each offensive attempt is structured by the following states: "offence formation” (general formation of offensive play preceding the first
tactical action), "initiating" (first tactical action), "1st continuing action" (second tactical action), "2nd continuing action" (third tactical action) and "goal throw" (Figure 2). With this model of an offensive attempt a handball match can be described as a process of chronological order with changing states. The state “offence formation” is compulsory for the start of a new offensive attempt, which can turn into one of the next states. Up to the general offence formation an offensive attempt does not inevitably go through all remaining states. The state “1st continuing action” for example is only attainable if a preceding tactical action (initiating) has taken place. In the same way the state “2nd continuing action” requires the preceding state “1st continuing action”.

Figure 2 shows the matrix structure of states and respective selections of possible events the structure model from Figure 1 has been transformed to. It particularly contains virtual "doesn't happen"-events. The reason is that the way we use the neural network (see next chapter) requires constant process length for each attempt. Therefore, if an attempt contains a state in which no tactical actions happens, such a "doesn't happen"-event has to be added for completion.

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Figure 2. Model of an offensive attempt using a sequence of states

As the Figure shows, our model does only include two continuing actions, i.e. a total of three tactics. The reason for this limitation are our findings in preliminary studies that more than 92 % of the offensive attempts are already finished after three tactical actions, i.e. the state “2nd continuing action”. In case of more than three tactical actions in an offensive attempt, our model does not differentiate these attempts further more.

By using the model depicted in Figure 2, the process of each offensive attempt can be described with a five place number (process length), which represents a certain tactical behaviour. In Figure 2 (bottom area) an example is given how to describe an offensive attempt with model symbols. With the sequence of numbers 1 3 1 0 2 an attempt is illustrated, which started in the offence formation “position attack 3:3” (1). Subsequently – as the first tactical action – a transition to the pivot position took place (3), which contained a change of the offence formation from position attack 3:3 to position attack 2:4. The 1st continuing action, i.e. second tactical action, was a feint (1), the offensive at-
tempt finished without a second continuing action (0) by a goal throw from the back position (2).

**DyCoN**

DyCoN – i.e. Dynamically Controlled Network – is a neural network approach, which particularly has been developed for analysis of dynamical adaptation. A DyCoN-network is able to learn and recognize types, frequencies, and distributions as well as time-depending changes of patterns. The pattern itself can be either a static structure of item values (e.g. in case of medical diagnosis or fraud detection) or a dynamic time series of item values (e.g. in case of strategic behavior in sport or in rehabilitation processes). Items primarily mean scalar numeric attributes, but also non-numeric attributes can be used as items.

Because of its ability of identifying patterns and recognizing suspicious features in complex data sets, DyCoN is used for supporting data-based decisions – e.g. in the fields of medicine or sports.

**Scientific background**

DyCoN is based on the concept of Kohonen Feature Maps (KFM), where neurons are trained with information and so build clusters of similar information.

The basic idea of KFMs is that of similarity and inherent correlation: As briefly mentioned above, the single information like a movement pattern is encoded in a vector of attribute values, meaning for instance articulations' positions, angles or speeds. During the iterative training process each neuron develops a correspondence to a specific pattern – i.e. it contains a vector of attribute values, where in any training step the respective input vector is compared to each neuron vector in order to find the most similar one and so identify the winner neuron. This winner neuron and – with decreasing intensity – the neighbored neurons "move" towards the new input – i.e. adapt their attribute vectors to the input vector according to a given learning rule.

One result of this information or pattern training is that similar input patterns build connected areas of neurons or "clusters". Moreover, neighbored clusters normally characterize similar types of patterns. Therefore a high-dimensional space of patterns can be flattened onto a 2-dimensional map with a strong similarity structure. This improves the handling of complex patterns and in particular that of trajectories by far. Note that, different from statistical clustering tools, the cluster distribution has not to be given by the user but is generated by the network.

The second useful result comes from the inherent correlation of the attribute values of patterns, as can easily be seen from the example of movement patterns from above: Supposing the attribute values of articulations' positions, angles or speeds to be independent results in a huge amount of different vectors most of which do not correspond to real movement patterns. Rules for characterizing "correct" movements depend on a lot of context information and therefore are difficult to find. In turn, the network learns from real patterns and therefore implicitly learns the inherent correlation between the values without a need for explicit rules. This on the one hand helps for recognizing "fuzzy" but characteristic types of movements. On the other hand, missing or incorrect attribute values are not a problem (if there number is not too large), because the characteristic information is imbedded in the inherent correlation structure – an effect that is similar to that of holograms, where each single part of it contains nearly the complete information.
A once trained network can easily be used for analyses of similarity or correspondence, where for instance movement patterns of different athletes can be compared inter-individually, or patterns of the same athlete but from different movements or movement types can be compared intra-individually.

A problem with conventional KFMs is the missing learning dynamics. The learning process is controlled by once given external functions that run the network to a final and unchangeable state, which not always is satisfying – in particular if the number of training vectors is too small.

The DyCoN-Approach basically is following the above described concepts of KFMs. The new idea of DyCoN is that each neuron learns and offers information individually and continuously without using external control functions (Perl, 2001, 2002). This way, the network can be trained in different phases, depending on the respective training success, and so can be optimized with regard to available data on the one hand and required precision on the other hand. In particular, besides the original data also synthetic data can be used for net training, if properly generated from the original ones (e.g. by means of Monte Carlo-methods). Using these artificially generated surrogate data the amount of original data necessary for training can be reduced drastically.

Moreover, continuous learning allows DyCoN for continuous completing already learned patterns and trends by new information that was not available during the initial learning phase. This enables for using DyCoN as a tool for the analysis of learning processes. A current project deals with children's learning of creativity in sport games and promises a lot of qualitative information that could not be obtained from quantitative statistical analyses (publication in preparation).

**Application**

As has been mentioned above, DyCoN is a useful tool especially for recognition of behavioral and decision patterns. Two examples from practice presented in the following may give an impression of the broad spectrum of possible DyCoN applications.

*DyCoN as a tool for process analysis in medicine*

A systematic or even statistical analysis of medical processes often fails because of the complexity of the data. For example, in the field of rehabilitation one frequently faces the situation that a large number of status-attributes of the patient (e.g. 10 to 30 attributes per week) contrast to a small number of recorded time intervals (e.g. 5 to 10 weeks).

In such a situation the DyCoN-approach first of all provides the advantage of taking Monte Carlo-generated data for net training, which allows for compensating the deficit of original data. On the basis of a pre-trained net, the DyCoN approach allows for evaluating a rehabilitation process in its time-depending development – thereby enabling recognition of critical situations in time. DyCoN has been applied in a number of interdisciplinary projects with medicine in the areas of "weaning" (i.e. conversion from artificial to natural breathing) and rehabilitation (in particular: post-operative treatment of knee-injuries (Rebel, 2004)) as well as in psychological post-operative treatment of high-risk patients (not yet published).

*DyCoN as a tool for process analysis in sports*

The analysis of processes in sports, e.g. biomechanical motion processes (Perl, 2004) or strategic processes in sports games (Perl, 2002), contrasts to the situation in rehabilita-
tion processes at least in one main point: While rehabilitation processes offer small numbers of imprecise data, processes in sport often provide a huge amount of data of high precision.

In such a situation the net-approach helps for filtering the relevant information out of the vast set of complex data and making them available for further evaluation and decision processes. This way, patterns of motion or behavior can be recognized in order to evaluate their effectiveness. The obtained information can be fed back to the training process. During the last years about 20 projects with national and international partners have been run in a broad spectrum of disciplines. A current project funded by the German Federal Institute of Sport Science deals with transferring some phenomena of creativity as well as of associative thinking and operating to the DyCoN-approach in order to compare net-behavior with the behavior of players in sport games.

Data

In the context of a performance diagnostic investigation 15 matches (12 teams) participating in the Women's Junior World Championship 2001 were observed (Pfeiffer, in print). The instrumental consistency of the observation system (objectivity) was examined by the inter-observer agreement of two observers (inter observer agreement). The Cohen’s Kappa values of the observation categories were found to be between 0.75 and 0.92, which according to Robson (2002) represents an "excellent" classification (> 0.75). The data of the systematic game observation were reorganized according to our model of an offensive attempt. In the following training process a prepared neural network was trained with 2900 offensive attempts (processes) from all teams to coin offensive attempt patterns. Based on the specific form and the position of these patterns of behavior conclusions can be drawn on the tactical structures of the offensive play (Perl, 2002, p. 257). For technical reasons offensive attempts without tactical actions and without goal throws, i.e. attempts with the coding "10000" and "20000", were not included into our analysis.

Results

Some selected results are presented below to indicate the kind of conclusions about the tactical structure in team handball which can be provided by DyCoN. Figure 3 illustrates the trained network, where the marked surfaces represent those patterns of offensive attempts, which exhibit a similar tactical structure.
In the upper left corner of the network offensive attempts are identified, which are formed in fast attacks (solid dashed line). Those attempts in the position attack with the system 4:2 are classified by the network on the top within the middle area (striped area). The remaining network represents attempts in the position attack 3:3. Within these larger network area clusters of neighbouring neurons are identified, which are connected by lines (called edges) where an edge indicates that similarity exceeds a given minimum.

In a next step the neurons and clusters identified by the network architecture can be specified and analyzed w. r. t. the tactical behaviour (figure 3). In the diagonal from the top right to the bottom left attempts with none or only one individual or group tactic actions were located (bold line). Here obviously simple tactical concepts were used or further tactical actions were prevented by the opposing team. Also note the large area in the lower middle range of the network area, where attempts with only one individual tactic (feint) are illustrated. Offensive attempts consisting of two tactical actions (initiating and 1st continuing action) were assigned (with one exception) to the right network area (bold dashed line). Finally the left as well as the lower edge of the network represent attempts with more complex tactical structures. In these offensive attempts at least three individual or group tactics were accomplished (cross-hatched area).

By using neural networks, which classify attempts according to the similarity of their tactical structure, different teams can be examined w. r. t. the similarity in their tactical behaviour. As an example the offensive attempts of the three best teams were isolated from the training data and tested afterwards with the network. A network-pattern for each team, in which the quantity of an offensive attempt type is represented by the circle diameter, is shown in Figure 4. For a better illustration the frequently occupied areas, i.e. dominant types of attempts, are marked grey in Figure 4.

\[\text{pa} = \text{position attack, } \text{w} = \text{goal throw wing, } \text{p} = \text{goal throw pivot, } \text{jeb} = \text{jump shot back court, } \text{wot} = \text{without goal throw, } \text{stb} = \text{straight shot back court, } \text{wt} = \text{with goal throw}\]
Considering the upper left corner of the pattern, which represents attempts organized in the formation “fast attack”, it becomes evident that Hungary turned fast attacks 1 to a similar degree into actions with and without goal throw. In contrast to this the Russian team more frequently terminates fast attacks 1 with a goal throw, which at least opens up the possibility to score. For the German team the relation between fast attack 1 with and without goal throw was unfavourable, i.e. more attempts are finished without a goal throw. However the German fast attacks are characterised by the fact that in the fast attack 2 the attempts with goal throws were dominating. If we look at the offensive attempts organized in the formation “position attack”, the type-pattern of the Hungarian team is dominated by the formation 3:3 and individual tactical concepts. In contrast for Russia three areas of activity could be identified. As in the Hungary tactical concepts individual actions are used, but also transitions and other actions (predominantly barriers) are applied as the first tactical action. The Russian team (as the only of the three teams under consideration) more frequently organized the position attack in a 2:4 formation. Contrary to Russia and Hungary, ranking first and second in the championship, we could hardly identify dominating tactical types in the position attack in the type-pattern of the German team. Rather the offensive attempts are distributed over the entire network area, indicating a diversified tactical behaviour. In comparison to the Hungarian pattern it is striking that attempts without tactical actions predominantly terminated with a straight shot.

In a second analysis we separately tested the successful attempts of the three teams, (i.e. those attempts finished with a goal). As figure 5 shows, the network also identifies different type-patterns for the three teams. While the Hungarian team is more successfully in the fast attack 1 (upper, left area), the Russian team scores with both variants of fast attack and the Germans act predominantly successful with the fast attack 2 (figure 5).
The Hungarian team does not only use individual tactic concepts frequently (figure 4), they also scored frequently by using this tactics (Figure 5). They were frequently successful by initiating with a feint without accomplishing continuing actions (dotted line). The Russian team acts partly in the same way, but three further areas of successful attempts can be identified by the network. Offensive attempts in the position attack 2:4 are to be emphasized. In comparison to the network pattern of the teams from Hungary and Russia up to the fast attacks we could not found dominant cluster of successful attempts by the Germans. Successful offensive attempts are distributed over large areas of the network (bold line) shows that the Germans scored with a variety of different tactical concepts.

For the interpretation it must be considered that the defensive system of the opponents is not included in the present model of an offensive attempt. From a handball-specific point of view, however, there is an evident connection between the defensive system and the tactics of the offensive play. Therefore additional information’s about the behaviour were registered as attributes next to the tactical characteristics, e.g. the defensive system. Hungary organise their offensive attempts too over 60% more frequently against offensive (18%) or half-offensive (44%) systems than the other two teams (RUS = 41% and GER = 37%). That could be a reason for the individual tactic concept of the Hungarian team.

**Discussion**

The aim of the contribution was to show that the method of neural network can be usefully applied to analyze the complex tactical structures in the field of sports games. In particular, the method provides a way to investigate the run of the match which is conceived as a detailed process with high structural resolution. In the presented application a model of an offensive attempt was taken as structural unit in order to identify typical tactics of three teams aggregated over several plays. It is to be noted that the presented approach is not restricted to the use of the offensive attempt as structural unit: By defining other appropriate structural units (depending on the particular aim of investigation) different methods of game structure analysis can be implemented. But even if we restrict to the presented structural unit, the application can be helpful for tackling a variety of further questions:

If it is of interest to detect the change of tactical concepts within one match, several play phases may be considered separately by comparing the distribution of each phase on the
same specifically coined network. Another way to investigate the evolution of the tactics within a match could be to classify the attempts in their chronological order obtaining trajectories over the network.

The structural analysis relies on information, which represents the reality of the respective play only in an incomplete and selective way. The representation of the play in the model implies that, of course, not all relevant information can be contained in the data recorded according to this model. It is possible, however, to add potentially relevant information using additional attributes, which can provide important hints useful for the interpretation of results.

Finally, analysis could be restricted to those attack attempts, which are comparable under the view of corresponding play ideas or play contexts.

Finally, testing only those attack attempts, which - based on the respective play idea - can be meaningfully compared with each other could be interesting. Moreover, this analysis could be further restricted to those attack attempts, which were accomplished against similar defense systems.

References

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