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NEURAL NETWORKS FOR ANALYSING SPORTS GAMES

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Summary

Two interlinked challenging tasks characterize the problem of analysing sports games: recording complex process game data and transforming them into useful information. These days, a significant part of the first task can be carried out using automatic position recording, thus placing increased emphasis on the second task; tracking a soccer game at 25 frames per second results in about 135,000 frames per game, which sums to about 6 million x-y coordinate data per game. Nevertheless, an experienced coach can filter significant information from these data and recognize patterns of player constellations in the playing processes. Neural networks using self-organizing maps (SOMs; see Kohonen, 1995) can recognize patterns in large data sets too and hence net-based data analysis can support the coach’s work. The first ideas of net-based analysis of sports games date back a few years, with recent advances in automatic position recording lending increased attention to complex games like soccer, handball, or basketball. Following a brief introduction to net-based game analysis, the chapter introduces the basics of net-based handling of process data and reports three instances detailing conceptual and methodical approaches of current research projects investigating handball, basketball, and soccer, respectively.

Introduction

The complexity of game processes is a challenging aspect of game analysis and conventional methods make it difficult to produce more than simple results, like frequencies of actions for comparison purposes. Even automatic position recordings are used typically for calculation of kinematic data, such as position distributions of players, distances covered, and work rate (e.g. time spent walking, jogging, running, and sprinting). In contrast, self-organizing neural networks, like the dynamically controlled network DyCoN (Perl, 2001), are useful for game analysis by recognizing movement patterns, including the behavioural processes of tactical groups like offence or defence. First approaches of net-based game analysis began in the late 1990s with the idea of using pattern recognition abilities of SOMs for identifying static patterns (e.g.
constellations of volleyball players: Perl and Lames, 2000; Jäger et al., 2007) and dynamic patterns (e.g. position sequences of squash players: Perl, 2001; McGarry and Perl, 2004).

While studies in volleyball (Perl and Lames, 2000; Jäger et al., 2007) and handball (Pfeiffer and Perl, 2006) focussed on pattern frequencies and distributions as statistical characterizations of a game or a team, the squash study and later some volleyball studies started to analyse the dynamic process patterns of the players and teams under the aspect of technical or tactical behaviour. Problems recording position data, until recent times, restricted these investigations to games with relatively small numbers of players. In 2005, first approaches in automatic position recording yielded accessible data for dynamic analysis of volleyball. In soccer, a first research project dealing with net-based constellation analyses was conducted successfully (Leser, 2006), encouraging development for increasing research activities in this field. Since 2006 then, a specific focus of net-based game analysis has been on soccer (Perl, 2008; Grunz et al., 2009; Memmert and Perl, 2009a, 2009b; Grunz et al., 2012), although other complex team games, such as handball and basketball, have also been the subject of net-based process analyses.

In the following sections, research approaches are introduced, dealing with handball, basketball, and soccer, thereby offering different aspects of data recording technologies, data preprocessing, pattern recognition and analysis, as well as data post-processing. The next section presents a brief introduction of concepts and methods of net-based pattern analysis with particular attention on aspects of data reduction and the transfer of data to information.

The general approach: net-based constellation analysis

To optimize the abilities of a pattern-recognizing neural network, the data must be reduced to pattern-containing fragments. In case of position data, this means that constellations of players on the playground (i.e. field of play) are usable for situational patterns. However, there are a huge number of constellations during a game, making it necessary to map them to formations by separating their centroid (i.e. the ‘centre of gravity’ of the players’ positions). If the same constellation of players appears on different positions on the playground, it is mapped to the same formation, storing the centroid information for position-oriented analyses. This reduces the huge number of constellations to a small number of formations, which can easily be learned and, again, reduced to characteristic types by a network. The automatically generated game protocol for each point in time contains the formation, the formation type, and the centroid. Together with manually added information about activities and success, it enables a wide range of analyses, from process animation to tactical concepts, to statistical analysis.

In Figure 19.1, a trained network is presented as a matrix of coloured (presented white through black) squares, where each colour stands for a formation type. Different neurons of equal colour represent variant formations of the same type. Representing those variants by just one characteristic type reduces the number of significantly different items to about ten, which has the advantage of enabling statistical analyses on reasonable distributions. On a more dynamical level of analysis, sequences of position data can be fed to the trained network. In so doing, each data set marks its corresponding neuron, mapping the original process to a neuron-trajectory of the time-depending formation series.

Figure 19.1 shows how it works. The position data sets of the game activate corresponding neurons of the network, starting with the one with the black mark. The process then runs through some light grey neurons followed by some middle grey and some dark grey ones, and so on. Reduced to the significant types represented by the corresponding colours, the trajectories become much simpler in representing the specific behaviours of the corresponding tactical group (see the small embedded graphic on top left). By switching from formations to forma-
Neural networks for analysing sports games

In a second step, those patterns of processes like the embedded one of Figure 19.1 can be used for training a second-level network, the input of which are vectors of formation-type numbers derived from the type trajectories. This method has already proved successful in several cases of motion analysis. As one example for handling game processes, the trajectory from Figure 19.1 represents the type sequence 5,5,5,5,5,3,3,3,3,2,2,2,2,2,3,3,3,3,3,3, which, for example, could characterize a particular tactical manoeuvre, like preparing an attack phase (note that this same sequence can be represented in condensed phase sequence as 5,3,2,3). As described in more detail in the following section, the second-level network would find those tactical patterns and compare their frequencies and distributions with those of opposing teams. Even infrequent and possibly creative patterns can be found using advanced network approaches (Memmert and Perl, 2009a, 2009b).

Handball: movement and action sequence analysis

Notational analysis of complex sport games like soccer, basketball, or team handball has gained a lot of interest in the last few decades. Scientific challenges remaining in the analysis of such complex sports games are: (1) identifying team tactics; (2) discriminating between successful and unsuccessful player/team behaviours; (3) anticipating player/team behaviours; and (4)
determining the physical demands on players/teams during a game. Unfortunately, most of the analyses in complex sport games are still based on the counting of single elementary actions, such as passes or shots. A typical shortcoming of this method is the loss of important information regarding the game context and the player interactions, which makes it difficult, if not impossible, to meet the challenges stated. Therefore, a major motivation for the project on team handball reported here is analysis of action sequences, instead of the single actions themselves (see Figure 19.2).

Specifically, our approach goes beyond simply counting single actions and assesses the combination of position and action information in order to understand complex interactions in sport games. To meet the four challenges listed, a significant amount of action sequences and the physical demands in team handball were analysed. Specifically, a unique combination of an easy-to-handle and affordable multiple camera system, a semi-automatic position tracking and event recognition system, and a database for recording single actions and action sequences was developed. In addition, a novel system for analysing action sequences using a two-level neural network was established, going beyond reporting elementary statistics, as described next.

Analysis of action sequences

Similar to previous work (Koch and Tilp, 2009a, 2009b), video analysis enabled the basic structure of sport games to be determined, including information about frequency of observed techniques and their success probability. Using six to eight cameras, information about action position for each video frame can be obtained (Mauthner et al., 2007) and movement paths of athletes recorded with an accuracy of about 1.5 per cent error. In a next step, neural networks were used to evaluate action sequences. This approach has already been used successfully in other similar tasks (Perl, 2002; Jäger et al., 2007).

For network training, each neuron in the network initially contains a vector of position data representing a specific type of playing constellation. For example, \((x_1, y_1, \ldots, x_7, y_7)\) could be such a vector of x-y coordinates of all handball players in a team. Neighbouring neurons can build clusters of similar constellation types, representing specific states or phases of the game.

Figure 19.2  Simplified action sequence of a counter-attacking situation in team handball. Each circle represents an acting player (with number) and simultaneously its single elementary action (including position). The dashed lines represent the path of the ball. The temporal combination of the single actions together constitutes the action sequence.
Neural networks for analysing sports games

process, such as offence or defence formations. Mapping the time series of position data to the corresponding neurons of the net and connecting the neurons by edges results in a two-dimensional trajectory as a simplified representation of the game process (Figure 19.1). In the next step, by connecting the respective meaning to the clusters, like specific defence or offence constellations, the complex game process can be reduced to a one-dimensional phase diagram of the corresponding constellation types. Together with semi-automatic position recording from video, which is used for estimating physical demand, the whole process of data recording, evaluating, and phase analysis can be done semi-automatically.

Furthermore, the phase diagrams themselves build patterns, which, by means of a second-level network, can be analysed for similarity, main types, interaction, success, and even creativity. This two-level approach has been used successfully in a project dealing with basketball free throws, where intra-individual stability as well as inter-individual similarities of throws have been identified (Schmidt et al., 2009; Schmidt, 2012). Using the methods and results from basketball, specific parts of the process trajectories can be identified by neurons in the second-level network as representing types of tactical activities. Following initial training of the first- and second-level networks, and an initial semantic interpretation of the neurons by experts, the automatic recording and analysis of the game is now covered.

The sequence of position data on the first-level net is transformed to a trajectory of constellation types. This master trajectory is subdivided into pieces of equal length, which are tested on the second-level net, resulting in corresponding neurons that classify the respective semantic information. The sequences of resulting time codes, positions, constellation, and semantics can then be transferred to the database. Together with the action classifications, this represents a complete record of the game. Thus, specific action sequences with increased frequencies related to team tactics can be detected and related to game outcome. The recorded action sequences in the database also allow prediction of team/individual behaviour in similar, future game situations.

Statistical methods of cluster and pattern analysis are often preferred over artificial intelligence approaches, like neural networks, because of their simple reproducibility. However, cluster or pattern type detection by means of statistical methods normally needs pre-information, whereas the network approach does not. In the following section, both approaches are compared with each other.

Basketball: tactical patterns in basketball – statistical vs. net-based analysis

In a joint research project carried out in 2010 and 2011 between the Departments of Biomechanics/Kinesiology and Applied Computer Science (University of Vienna, Austria), the Institute of Cognitive and Team/Racket Sport Research (German Sport University Cologne), and the National Institute of Physical Education (INEFC; Barcelona, Spain), different approaches were applied in order to identify patterns from position data in basketball. The positions of the players from two semi-professional basketball teams were measured with the Ubisense tracking system (Ubisense Real Time Location System, Ubisense, Cambridge, UK). This system provides positional information based on time difference of arrival and angle of arrival data of radio frequency signals. Six base stations were mounted in the corners and in the middle of the sidewalls of a gymnasium at a height of about 5 m. Small-sized active (signal emitting) tags were attached to the players atop of their heads (see Figure 19.3). Position data of the players were thus obtained with an average frequency of about 5 Hz and an accuracy of about 10–15 cm. In addition, the players and the ball were recorded using standard video cameras placed into the four corners of the gymnasium.
Altogether, a complete basketball match, including 67 attacks of two different types (set plays and fast breaks), was recorded. Based on the video recordings, each attack starting at the instant the ball crossed the midline was described as a sequence of distinguishable events (actions). These events were characterized by the laterality of play determined in three lanes (right, centre, left), as well as an interaction context defined as the dynamic positioning of the ball with regard to the positions of the players of both teams. In particular, ball position was categorized by its location with regard to the forward line, midline, and rear lines of both attacking and defending teams.

T-pattern-analysis (Magnussen, 2000) was performed to detect patterns in action sequences during attacks. Two actions occurring in the same sequence in approximately the same time intervals repeatedly, more often than expected by chance, form a (minimal) T-pattern, with more complex T-patterns formed by sequences of simpler patterns identified using a hierarchical bottom-up procedure. A variety of complex and repeated temporal patterns in the data sets were found using this analysis.

To establish the procedure for identifying different types of offensive and defensive tactics automatically and, moreover, to detect two separate types of attack (i.e. set plays and fast breaks), a hierarchical set-up of special self-organizing maps was developed (Grunz et al., 2012). In a pre-processing step, raw player position data of each basketball team were composed into a sequence of constellations. These constellations were then used to train a DyCoN (Perl, 2004). Following DyCoN learning, typical constellation prototypes became encoded by different neurons, with trajectories of neurons thus representing time-dependent processes of the basketball game. Using the sliding-window technique, these trajectories were taken as input for a second net, with each neuron in the second DyCoN encoding a movement of constellations.

After training, labelled data gained from the set plays and fast breaks were used to attach a soft-labelling to neurons on the second layer. This process enabled classification on the test data, which has shown average results, and more labelled data might be necessary in future to obtain better classification results. However, the neural-network approach was nonetheless

Figure 19.3  Schematic recording of basketball player-position data
Neural networks for analysing sports games

Successful in identifying types of constellations and in discriminating between different offensive and defensive tactics. Preferred tactics of the teams could be detected.

Both T-pattern-analysis and DyCoN analysis, then, were able to identify patterns from position data in basketball. T-patterns represent the tactical context of the events, resulting in high validity of the findings. While T-patterns were able to identify sequences of predefined categories, neural networks can identify constellations not foreseen previously. Applying a neural network approach, however, requires interpretation of the semantic meanings of clusters found in the respective nets by an expert. In the basketball project, a description of event sequences was obtained from video recordings, requiring manual data acquisition. However, in future investigations, this information might be derived directly from position data, given that a feasible solution can be found for assembling a tag into the basketball itself. The neural network approach was able to provide automated analysis of automated position data collected from the radio-wave based system.

Soccer: analysis and assessment of tactical performance

In this section, we present the problem of semantic assessment of game activities, which is particularly difficult in soccer because of the high complexity of game situations. In contrast with review articles about assessment of technical skills (e.g. Ali, 2011), assessment of tactical behaviour in team sports has not been paid much attention until recently (Memmert, 2010; Memmert and Roth, 2007). According to prevalent belief, however, a high level of tactical skills in soccer is important for effective player performances at the highest international levels.

The present standard is to assess tactical performance in soccer by means of game observation (Franks, 1985). Qualitative game observations are less objective and less systematic (less structured and less comprehensive), use subjective impressions of the observers, and take advantage of the experiences and know-how of experts (Leser, 2006). In contrast, quantitative game observations proceed in an objective fashion, using predefined observation schedules (e.g. category systems) to collect data. Subsequently, these data are evaluated and indices calculated to value the whole-player performances or individual performance components (Baca et al., 2004; Leser and Baca, 2008; Memmert and Harvey, 2008). Both qualitative and quantitative observation methods imply a high expenditure of time for data evaluation (often several days) and objectivity between two observers is often lower than desired.

In recent years, progress in computer science has made it possible to provide position data and thus track player movements (Baca, 2008). In turn, a concept for automatic analyses and assessments of tactical behaviour based on position data using a net-based approach is now becoming possible for the first time. With this in mind, the first part of the soccer project was focussed on the recognition of tactical behaviour in games. An expert categorized the 2006 FIFA World Championship final based on video and position data. The categories were short and long game initiations, counter-attacks, and standard situations (e.g. throw-in, free kick, and corner kick). The identified tactical sequences were used for training and validation of the developed architecture of dynamical controlled neural networks (Grunz et al., 2012). The method is analogue to that described previously for identifying fast breaks and set plays in basketball. Comparison of results gained from expert categorization to those from the architecture showed good average recognition rate for each category (see Table 19.1). Game opening and standard situations were identified with high probability by the neural network, although counter-attacks showed poor recognition rate due to high variability in the pattern.

The second part of the soccer project focussed on assessment of tactical performance using a software compound Neural Network Assessment System (NNAS). The NNAS uses a hierarchy
J. Perl et al.

Table 19.1 Comparison of results based on a hierarchy of neural networks and an expert categorizing the 2006 FIFA World Championship data. High recognition rate is achieved in standard situations but the architecture was unable to detect all game initiations. Attacks and counter-attacks show high variability and poor recognition rate.

<table>
<thead>
<tr>
<th>Category</th>
<th>Experts</th>
<th>Net-based analysis</th>
<th>Recognition rate</th>
</tr>
</thead>
<tbody>
<tr>
<td>Game initiation</td>
<td>131</td>
<td>110</td>
<td>84%</td>
</tr>
<tr>
<td>Throw-in</td>
<td>27</td>
<td>27</td>
<td>100%</td>
</tr>
<tr>
<td>Free kick</td>
<td>16</td>
<td>14</td>
<td>88%</td>
</tr>
<tr>
<td>Corner kick</td>
<td>12</td>
<td>12</td>
<td>100%</td>
</tr>
<tr>
<td>(Counter-)attacks</td>
<td>49</td>
<td>29</td>
<td>59%</td>
</tr>
<tr>
<td>Sum</td>
<td>235</td>
<td>192</td>
<td>86%</td>
</tr>
</tbody>
</table>

of DyCoNs as a basis and was developed in previous work by Grunz (VisuCat, pre-processing) and Perl (SOCCER, assessment/post-processing) (for details, see Perl and Memmert, 2011). The aim of NNAS is to develop and verify concepts and methods for assessing observable behaviour of soccer players and, especially, to automatically judge tactical performance. This is done by means of automated position tracking (players and ball) and artificial intelligence. Application of methods of artificial intelligence, in particular neural networks, can be helpful in describing, analysing, and evaluating game situations for objectively identifying tactical performance components in soccer. In addition, such computational analysis offers a dramatic time advantage concerning evaluation of position data (e.g. from 6–8 hours to 2 minutes, say). Small efforts in data acquisition enable accumulation of huge amounts of data, bringing new opportunities for theory construction and practical applications. For example, automatic assessment of tactical behaviour in time-limited soccer situations, such as during half-time, will be possible in future.

Data and procedure: Recent technical improvements allow complete capture of x-y position data of all 22 players and ball for the entire game duration (e.g. 90 minutes). With a sampling rate of 25 frames per second, 270,000 x-y-data per player and ball are produced in 90 minutes. Thus, when looking at all data, one gets 6,210,000 x-y-data (i.e. 23 x 270,000) for a game, give, or take. Transformation of position data into team formation data has been mastered so that transformation of respective semantic assessments works properly. Also, an automatic match protocol can be created and action type analyses conducted with the hierarchical structure of the analysis sequence being automated in usable software (see Figure 19.4). Otherwise a lot of work would be necessary when undertaking team formation analyses.

Categorization: To examine prototypical geometric patterns with NNAS and to recognize and typify team formations, a software tool was developed in the frame of a feasibility study for stochastic generation of geometric patterns. Thus, prototypical position data for specified player combinations and team formations were generated which function as a basis for pattern recognition tests. Tests with soccer data confirm this initial approach.

Validation: Results from net analysis can be compared with video-based expert analyses with the help of a software tool for automatic match evaluations. This automatic validation analysis can be conducted using different tolerance thresholds (e.g. recognition of the same action with time difference of 5 per cent). For validation of the trained nets, the results of the traditional game analysis (‘gold standard’) and the NNAS results were compared. The results showed high accordance with traditionally identified group tactics, with playmaking, set pieces (further differentiated into throw-ins, free kicks, and corner kicks), and shots on goal also identified in the hierarchical net-based approach.
Neural networks for analysing sports games

If validity of the NNAS tool can be ensured, it will be an important step towards identifying tactical performance components in team sports objectively. This would be of great benefit for sports practice, not only for talent selection in different youth sports (e.g. basketball, team handball, soccer, field hockey, tennis) but also in analysis of professional team sports. Apart from being aware of the components of sports performance and their interactions, the diagnostic possibilities of neural net analysis should also be considered. Diagnostics can be helpful in both sports practice (e.g. for sophisticated assessments of player performances) and science (e.g. for evaluation of sports teaching approaches). Information technology advances now provide a lot of data for many facets of sports, and fast automated systems for assessing tactical behaviour in game sports are desirable too. These demands have been met only to a limited extent in the past and high synergetic potential exists between the sports and computer sciences for tackling these issues in future (Balagué and Torrents, 2005; Memmert and Perl, 2009a, 2009b).

Figure 19.4 Screenshot from the team formation recognition software SOCCER. Top left: Selection screen for the data of both teams, including a scrollbar for revision of the entire game, the team formation overview screen, and the synoptic table, which lists the number of formations as well as the coincidence frequencies for the entire playing time. Bottom left: Frequently occurring team formations are framed by rectangles; infrequently occurring team formations are framed by ellipses. Clicking one of those entries shows the static distribution of those formation coincidences (right). It also activates a list of corresponding time sequences, which can be clicked (e.g. 1,855 to 1,866) to show the dynamical development (top right) and the current position of the formation on the playground (left). Top right: Simplified view of a team formation, the group’s key aspects and the key aspects of the combination of the offensive and defensive groups.
Concluding remarks

The net-based game analysis approach is a promising way of combining automatic position tracking with computer-based tactics assessment, oriented not just in statistical numbers but in the dynamical process patterns themselves. In turn, data reducing and condensing techniques enable handling of tactical patterns without losing key information for statistical analysis. Cooperation of artificial neural networks, T-pattern-analysis, and tools like the Neural Network Assessment System allows a fruitful combination of qualitative pattern recognition and quantitative statistical analysis.

Some open problems, however, have to be dealt with in future. One major technical problem is recording ball position, which up to now has had to be tracked manually. Also, qualitative judgements of situations like ‘ball possession’ or ‘opening an attack’ are difficult to detect by automatic programs and currently, therefore, have to be added manually too. It might be that more detailed analyses of the movements of players and ball in future work can find patterns indicating such qualitative situations. In this case, a combination of automatic video data tracking with automatic position data recording and pattern analysis offers a promising and attractive way of solving these problems.

References

Neural networks for analysing sports games


