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Detecting tactical patterns in basketball: Comparison of merge self-organising maps and dynamic controlled neural networks

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ORIGINAL ARTICLE

Detecting tactical patterns in basketball: Comparison of merge self-organising maps and dynamic controlled neural networks

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Abstract
The soaring amount of data, especially spatial-temporal data, recorded in recent years demands for advanced analysis methods. Neural networks derived from self-organizing maps established themselves as a useful tool to analyse static and temporal data. In this study, we applied the merge self-organising map (MSOM) to spatio-temporal data. To do so, we investigated the ability of MSOM's to analyse spatio-temporal data and compared its performance to the common dynamical controlled network (DyCoN) approach to analyse team sport position data. The position data of 10 players were recorded via the Ubisense tracking system during a basketball game. Furthermore, three different pre-selected plays were recorded for classification. Following data preparation, the different nets were trained with the data of the first half. The training success of both networks was evaluated by achieved entropy. The second half of the basketball game was presented to both nets for automatic classification. Both approaches were able to present the trained data extremely well and to detect the pre-selected plays correctly. In conclusion, MSOMs are a useful tool to analyse spatial-temporal data, especially in team sports. By their direct inclusion of different time length of tactical patterns, they open up new opportunities within team sports.

Keywords: *Neuronal networks, basketball, pattern recognition, performance analysis*

In any kind of team sport, the main goal as an athlete or coach is to win. Therefore, you want to be ahead of your opponent. To always be ahead, you need to know your opponent as well as yourself and how both counterparts interact within the game. Measuring match performance has seen a lot of development in recent years (Lago, 2009; Perl & Memmert, 2012). A critical review by Mackenzie and Cushion (2013) on performance analysis in football focused on the influence of the recent research on applied practice. As the main issue, they discussed that research and analysis are retrospective with a major time gap and that the interaction processes within a team game is rarely investigated. The lack of actuality of scientific findings is seen as the most limiting factor to translate them into the day-to-day work in team sports. The best example for this is the outstanding work of Cervone, D'Amour, Alexander, Bornn, and Goldsberry (2014). By using tracking data of actual basketball games, they are able to simulate and forecast an offensive play and the probability to score a basket. In a recent Internet article, one of the main authors (Goldsberry, 2014) described that all their predictions are based on data of the last season and are therefore not up to date. He further explains how challenging it was to prepare the group and pre-process of the giant amount of tracking data they had. It took them months to prepare the data for the actual analysis. Hence the question is whether it is possible to pre-group such data and get such findings within a day or week instead of months.

In this recent study, we used neural networks to try to solve this problem. Therefore, we used two different types of artificial neuronal networks (self-organizing maps, SOM) to identify plays and offensive actions of a team automatically and to display the interaction process of two teams within a game in basketball. The learning approach of the machine showed satisfying results in recent pattern recognition tasks for movement patterns (Perl, 2004; Schmidt, 2012), as well as for creativity (Memmert & Perl, 2009a, 2009b) and tactical patterns in football (Grunz, Memmert, & Perl, 2012). In the following,

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we will first give a short introduction of the method of SOM, completed by some extensions of the standard SOM approach we used in this study. Further, we will discuss the pros and cons of the different approaches and if they are able to find specific tactical behaviour.

Self-organizing maps

The SOM developed by Kohonen (2001) is an artificial neural network and is categorised as an unsupervised method. A SOM consists of a set of artificial neurons that are connected to each other through edges like nodes in a common net. Associated with each neuron (node) is a weight vector of the same dimension as the input data vector and a position in the map space. Usually, they are arranged in a rectangular grid. During the training phase, the network adapts itself to the distribution of the data used for training. After training, each neuron encodes a different pattern. In an additional step, the neurons encoding similar patterns are grouped together leading to only a few groups of neurons. These groups are also often referred to as clusters. For each cluster, a representing prototype can be constructed. The type of pattern found by the network is determined by the data type that is used for training. If the network is trained with movements of one group of players, the resulting patterns will encode typical movements of that group. However, when analysing team games, data are not given in a strict vector form. Indeed, a play in team games can vary from two seconds up to several minutes. If SOMs shall be used as a data mining tool in these domains, appropriate data pre-processing is usually necessary. In general, appropriate pre-processing is task-dependent, time-consuming and often accompanied by a loss of information (Hammer, Micheli, Sperduti, & Strickert, 2004). Thus, SOM might fail unless the training is extended or SOM extensions are used. Two fundamentally different ways to extend SOMs can be found in literature (Hammer & Jain, 2004): The first option is to decompose complex structures into basic constituents and to process them separately, mostly by using a hierarchical structure of several networks. Second, the operations of single neurons can be extended to directly allow complex data structures as input.

Hierarchical approach

Perl and colleagues used a dynamical controlled network (DyCoN; Perl, 2004) derived from SOM to detect tactical patterns for each team (Grunz et al., 2012; Memmert & Perl, 2009a, 2009b). DyCoN overcomes several technical limitations in a SOM: most important, the inability to learn continuously. This extension of a normal SOM results in better adaption to input data with less training data. This enhancement of a “normal” SOM is crucial for the hierarchical approach because the net can be trained continuously. Therefore, specific tactical patterns (plays) can be inserted into the net in a second and third training step. Otherwise, this data might be under-represented in the net. To analyse team games, a first net will be required with the positions or the actions of each player as an input vector. The resulting network groups similar actions or constellations of positions; those areas of high similarity are referred as clusters. Subsequently, the net is fed with similar data in chronology of the game. This results in a second input vector, containing a time series of chronological taken positions or conducted actions and therefore a time-related behaviour of the players (play). With the second input vector, a second net can be trained that represents tactical behaviour. The resulting net could be labelled with specific tactical pattern of interest for further analysis.

The feasibility of this approach was shown by Grunz et al. (2012) by analysing specific tactical patterns in soccer (game initiations). However, one major problem that has not been mentioned above is the transfer of information from the first network layer to neuron information of the second layer: As stated before, information sequences for training and testing neurons have to have a fixed length because the weight vectors of network neurons are defined that way. But trajectories as mappings of movement patterns normally do not have such fixed lengths. There are two ways to handle this problem.

On the one hand, different copies of networks can be used for movement patterns of different length, e.g., one network for patterns of length 3, one for length 4, one for length 5, and so on. This approach needs a huge amount of training data for the different networks, which moreover makes it difficult to compare sequences of the same type but of different length, which means the same behaviour only differing in several seconds would not be classified as the same.

On the other hand, the architecture can be restricted to a fixed sequence length – e.g., corresponding to the smallest detectible pattern length. In this case, a pre-processing and a post-processing step are necessary. The pre-processing uses the sliding window technique for stepwise departing trajectories in pieces of equal length, which are classified by the neurons of the second level networks. After that classification, the post-processing can compose larger patterns from the fixed length entries of the classified neurons. However, this procedure is not easy because it has to be decided automatically which partial patterns can be or have to be combined to complete ones, preserving the original semantic meaning. This could cause the problem that the most important information could be cut or underrepresented in the input vector.

Recursive approach

A possibility to include a larger amount of time-dependent information with an unset vector dimension is SOM using recursive data models. Applications of this approach can be found, for example, in bioinformatics (Baldi, Brunak, Frasconi, Soda, & Pollastri, 1999), chemistry (Bianucci, Micheli, Sperduti, & Starita, 2000) or image recognition (Diligenti, Frasconi, & Gori, 2003). In comparison to standard SOM, their neurons include a weight and a context vector. Therefore, the input of previous data is presented in the context vector and the actual input in the weight vector. During training, the net adapts to the presented data by using a linear combination of both vectors. Therefore, temporal information is maintained during training. To further analyses, receptive fields need to be used to classify and visualise data. They give back the most activated clusters for data mining and can be easily set to a specific time length.

This approach allows training with data of different time length and their clustering by similarity. The classification of new data uses a set time length but can be easily manipulated. This is especially important for analysing team games. With this approach, we are able to train a net with a small amount of data. Further, different tactical behaviours are represented within this net and can be analysed by adopting the receptive fields.

To summarise, SOM can be a useful tool to analyse team games. Grunz et al. (2012) were able to receive some first promising results while using the hierarchical approach. As we are aware of the shortcomings of this approach, we like to use the recursive approach as a new way to analyse team games. To introduce this approach, we analysed a regular 5 vs. 5 basketball game. Basketball is especially suitable to prove the feasibility and pros and cons of both approaches because the interaction processes are time-limited (maximum time for one attack is 24 seconds). In addition, the tactical behaviour in basketball is mostly designed by running specific plays. Therefore, it is less chaotic and gives us the possibility to evaluate both approaches.

Methods

Data collection

Position data of 10 players of one basketball game and of three different pre-selected plays (fastbreak, horns and high pick) were recorded via Ubisense tracking system (see Baca, Dabnichki, Heller, & Kornfeind, 2009). Ubisense is a position tracking system recording the movement of the players with a frequency of 4.7 Hz. The positions of all 10 players were recorded during the basketball game. The pre-selected plays were each performed 15 times without an opponent and the movement of the five players of one team was recorded as well. We used three plays that differ in their time of execution. Fastbreak lasted between 5 and 10 seconds, whereas horns and high pick lasted between 15 and 20 seconds. Horns and high pick were selected because both plays start with similar positioning of the players (2-1-2 offensive scheme). Therefore, it should be easy for both approaches to distinguish between fastbreak and the other plays, but hard to classify horns and high pick correctly. Players were students of the University of Vienna and played basketball on a semi-professional level (third league in Austria). The study was approved by the local Ethics Committee, and all participants signed an informed consent statement before testing began.

Pre-processing

To synchronise the position data and remove artefacts, several positions of one player were averaged to one position every second. In addition, the movements of the opposing team were mirrored to be able to compare the movements of both teams. Therefore, all attacking movements were congruently from left to right. The resulting input vector contained the x- and y-coordinates of all five players of one team. The data of the first half of the basketball game and the data of 45 plays were merged together and randomised for training in both approaches.

Training "hierarchical approach"

After training the input vector, the resulting net, consisting of 400 neurons, represents a set of x-and y-coordinates of five players (further described as a constellation) in each neuron. Similar constellations are grouped within the net into clusters (see Figure 1). Sequences with a length of 20 seconds were generated from the continuous player positions of the first half. A sliding window of five seconds was used to automatically include the start and end of play. Those sequences were given to the net for classification resulting in a sequence of cluster alignments. Examples for the alignments for each of the three pre-selected plays can be seen on the right side of Figure 1. In each example, the different colours of the phase diagrams (right side of Figure 1) represent the equivalent cluster (constellation) of the net on the left side. Every dot in the phase diagrams means that the five players are currently moving in one specific constellation. Overall, the

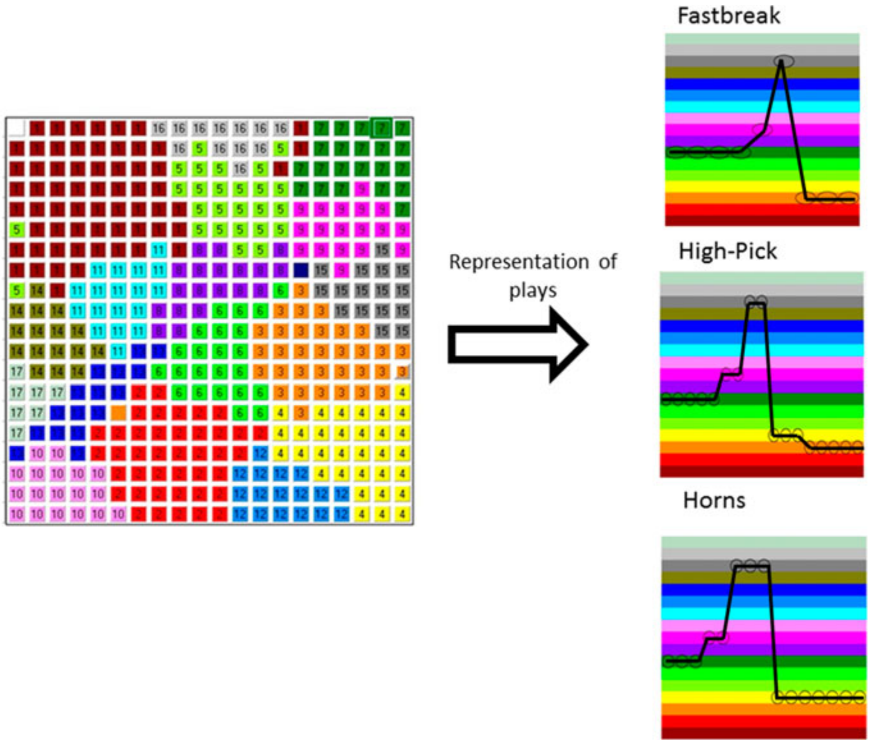

Figure 1. The first net of the hierarchical approach represents a constellation of five players in each neuron. Similar constellations are grouped into clusters, illustrated by different colours. On the right side, the pre-selected plays are presented as time series of the clusters. [To view this figure in colour, please see the online version of this journal].

phase diagram visualises the movement from one constellation to another over the curse of one play. By design, all plays started with a rebound in one half, this is represented in each of the three examples as each play starts with the same cluster (constellation). Furthermore, high pick and horns are both starting with the offensive team moving into a 3–2 arrangement of the players in the opposite half. This movement is apparent as well in the phase diagrams of plays as they go through the same clusters (cluster 9 and cluster 15) within in the first five seconds after the rebound and distinguish afterwards. By using this phase diagrams, the input data could be transformed into sequences of constellations. Each of these sequences represents a complete play of 20 seconds, instead of a constellation of one second. They were used to train a second net (100 neurons), representing a play of 20 seconds in every neuron (Figure 3).

Training "recursive approach"

We reprogrammed a merging self-organizing map (MSOM), using the earlier introduced recursive approach by Strickert and Hammer (2005). To evaluate programming, we used a Mackey-Glass series and were able to reproduce the results of Strickert and Hammer (2005). To train the MSOM, consisting of 100 neurons, the same input vector was used as for the hierarchical approach. To classify the three pre-selected plays, they were calibrated on the net. By doing so, each neuron representing one of those plays was marked (see Figure 2). For visualisation and classification, we used receptive fields with a time length of 20 seconds.

Evaluation

The entropy was calculated for both approaches as a measure of how the SOMs adapted to the training data (Schraudolph, 1995). A high entropy (near 1.0) would indicate a good representation of the input data on the net, what is the basis for a further analysis. To evaluate the classification of both approaches, the second half of the basketball game was tested. Both nets automatically classified the movements of a team and looked for the occurrence of the pre-selected plays. Two basketball experts watched the second half of the game and found 19 fastbreak, 4 high pick and 3 horn plays run by both teams. The findings of the SOMs and the experts were compared to calculate the precision of both approaches. As this measure would just account for the accuracy of finding the pre-selected plays, it was inaccurate to evaluate the SOMs. To evaluate the accuracy of the classification correctly, not classified plays have to be considered as well. Therefore, we used the term accuracy as described by Powers (2011, see Equation 1), taking the correctly classified

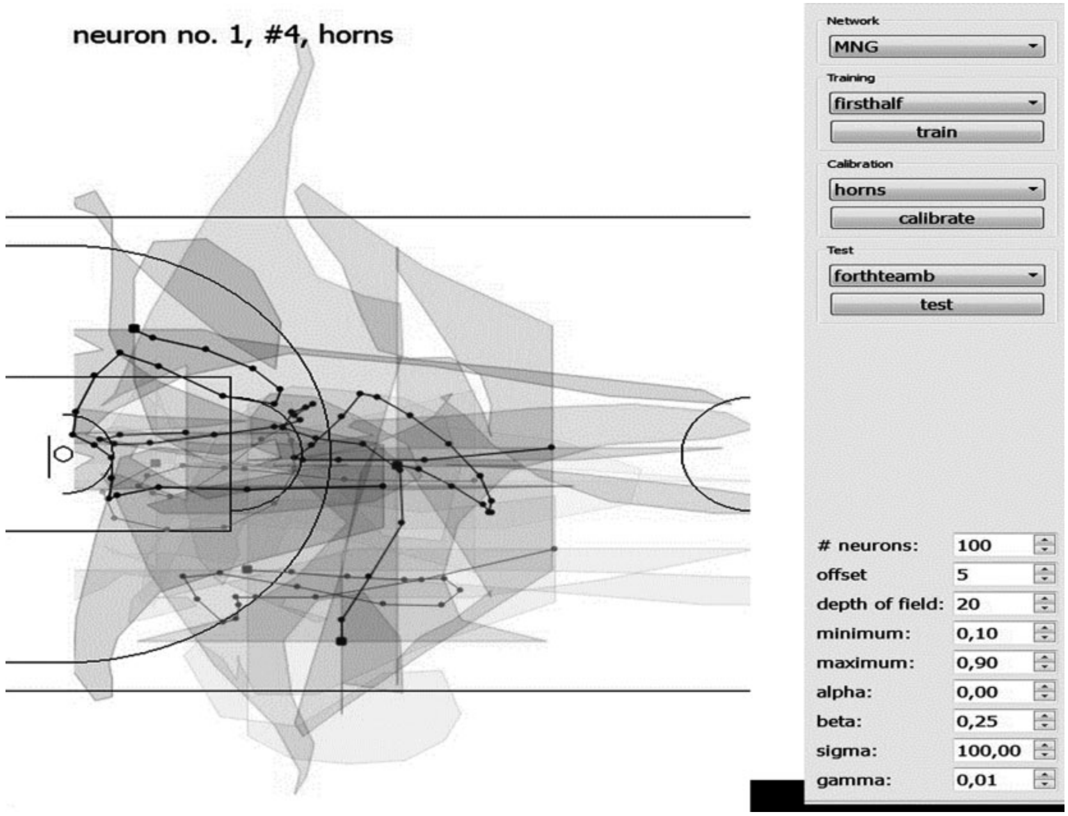

Figure 2. Visualisation of the horns play within the software tool of the recursive approach with each coloured line representing the movement of one player and the shadow in the same colour representing the double standard deviation of the movement in both coordinates.

and not classified plays in relation to the overall number of plays (60 per team per quarter).

$$\text{Accuracy} = \frac{\text{number of true positives} + \text{number of true negatives} \quad 12}{\text{number of true positives} + \text{false positives} + \text{false negatives} + \text{true negatives } 13} \quad (1)$$

Results

Both approaches resulted in one SOM that was able to classify new position data. They showed a good fit to the training data, with a calculated entropy of .82 (hierarchical approach – DyCoN) and .78 (recursive approach – MSOM), respectively.

The hierarchical approach was able to automatically distinguish between 13 different tactical behaviours (see Figure 3). Those can be divided into three defensive plays (man-to-man defence and two zone defences), six offensive plays, one cluster-marking transition from offense to defence and two set-plays (throw-in and free throw). The pre-selected plays were represented in different clusters. Fastbreak was represented in cluster five, whereas high pick and horns were represented in clusters one and eight (Figure 3). As intended, the SOM was able to clearly distinguish between high pick and horns, although they were almost identical in first seconds. The recursive was able to distinguish these plays as well as in differing sets of neurons.

The evaluation of the precision of the second half's automated classification showed mixed results. The hierarchical approach classified 24 of 25 pre-selected plays correctly and two plays incorrectly as one of the plays of interest (see Table I). Furthermore, it classified 93 plays that did not belong to one of the three trained categories as correctly as plays of no interest which results in overall correct classified plays of 117 out of 120. The MSOM using the recurrent approach classified just 13 of 25 pre-

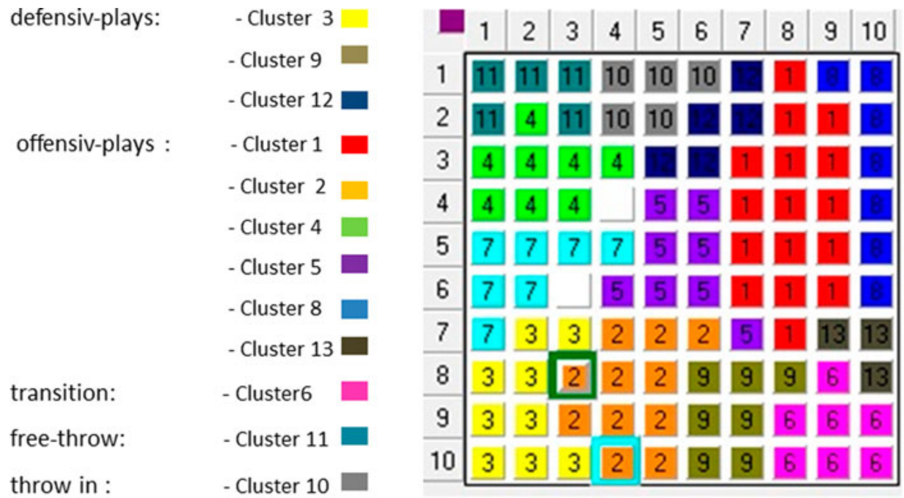

Figure 3. Second net of the hierarchical approach. Representing a play of one team in every neuron. Similar plays are grouped in cluster, illustrated by the same colour. [To view this figure in colour, please see the online version of this journal].

selected plays correctly, 12 plays of interest that were not, 12 incorrectly not of interest, but did classify 83 plays correctly as not of interest. By taking the total amount of plays into account (120), the hierarchical approach achieved an accuracy of .975 and the recurrent approach of .8 (see equation 1). That means the classification by the SOMs was correct in 97.5% and 80% of all cases, respectively.

Discussion

As demonstrated by the results, we were able to automatically find and classify tactical behaviour based on tracking data. Both the used approaches showed promising results to use them in practical application. Regarding to the entropy values, both net approaches adapted adequate to the presented data. The hierarchical approach showed a slightly better adaption as reformulated pointed out by the entropy (Schraudolph, 1995). This could be explained by the different SOMs of both approaches. In the hierarchical approach, DyCoNs were constructed to adapt to a given data structure even with a small amount of data (Perl, 2004). An MSOM, which was used in the recursive approach, needs a lot more data points to concede the same entropy by construction (Hammer et al., 2004).

The differences in the adaptation to the data can partly explain the differences in classification accuracy. The hierarchical approach was able to classify the whole second half of the basketball game almost correctly. In contrast, the recursive approach only classified 80% of the data correctly. We think that this is due to the differences in the training of both approaches. As stated before, the MSOMs need far more data to adapt to the input data. The main reason for the lower accuracy of the MSOM was the misjudging of the horns play. Because this play was least performed in the input data (first half of the game), the MSOM was not able to properly represent it. Nevertheless, those results were on a satisfactorily level, as a similar study by Grunz et al. (2012) could classify 84% correctly with the hierarchical approach in soccer. However, they did just distinguish between two patterns.

Despite the differences in the accuracy, we were able to demonstrate that both architectures of neural networks are basically capable of detecting categories of tactical patterns. Further, they have the advantage, in relation to other pattern recognition approaches like Markov models (Diligenti et al., 2003) or a boosting algorithm (Barros et al., 2011), that each neuron has a clear meaning which is comprehensible at all times.

Table I. Results of the classification of the pre-selected plays of both approaches in relation to their actual appearances

	Fastbreak		High pick		Horns	
	3. quarter	4. quarter	3. quarter	4. quarter	3. quarter	4. quarter
Hierarchical approach	10	10	3	1	0	2
Recursive approach	3	3	3	2	7	7
Observed plays by experts	9	9	3	1	1	2

For the first time, we were able to utilise the recursive approach to detect tactical patterns in team games. By this, we could overcome the drawbacks of the sliding window technique within the hierarchical approach. However, much more data is needed to train this Neuronal Networks appropriately. As there are cameras in every basketball arena in the National Basketball Association for optical player tracking since this season, the amount of available data should increase during the next years.

To sum up, we transferred the established recursive approach to analyse time series on tracking data of a team game. The implemented net showed promising results that should be even better with a greater amount of available data. Moreover, it overcomes some major shortcomings of the hierarchical approach used in previous studies (Grunz et al., 2012; Memmert & Perl, 2009a, 2009b). In addition to those previous studies, we used not trained data to evaluate the accuracy of the networks and consulted basketball experts to verify our findings.

Our findings extend the concept of neuronal networks and offer import impact for performance analysis in team sports. The introduced SOMs can be easily trained with tracking data of one or more teams and automatically classify the conducted actions in real time. This could be a big step for the scientific community to be up to date with their analysis as demanded by Mackenzie and Cushion (2013).

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