Action sequence analysis in team handball

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ABSTRACT

Schrapf N, Tilp M. Action sequence analysis in team handball. *J. Hum. Sport Exerc.* Vol. 8, No. Proc3, pp. S615-S621, 2013. The analysis of game situations in sports games is essential for development of successful game tactics and planning of training. Carling (2008) suggested analyzing action sequences because the study of single actions only gives restricted insight into team's behavior. The aim of the present study is to analyze action sequences in team handball to identify offensive behaviors. For the study 6 games from the EURO-Men-18 in Austria were recorded. Special categories for annotation were defined to assess single actions which then have been merged into action sequences. Shots and up to 5 passes prior the shot were annotated with custom-made software. Out of 3212 actions, each containing information about video time stamp and ground position, the software generated 612 action sequences. To identify different behaviours, similar action sequences were determined using artificial neuronal network software (Perl, 2002). To optimize network performance the dataset was enlarged with noise of 15% to a quantity of 3060 action sequences. Subsequently, the network with a dimension of 400 neurons was trained. Each neuron represents an action sequence pattern. Similar neurons are grouped to clusters representing similar behaviour. The artificial network recognized 32 clusters. Additional, 10 single neurons could not be classified to a cluster. Therefore, 42 different offensive team behaviours were identified whereby 8 clusters represented 49% of the actions sequences. The study revealed the potential to identify playing patterns by analyzing action sequences with artificial neuronal networks. Expert review of the recognized patterns showed a promising accordance with actual playing patterns. Future steps will be the detection of preferred tactics in single teams, the integration of goal success and the identification of successful offensive tactics.
Key words: TEAM HANDBALL, ARTIFICIAL NEURONAL NETWORK, OFFENSIVE PATTERNS, TEAM SPORTS.

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INTRODUCTION

Where and when opposing players initiate an offensive action, which strategy must be chosen to gain a promising shot position, or which type of shot is preferred by the opponent? These are essential questions for the development of successful game tactics and subsequently for planning and controlling of the training of different tactical, technical and physical skills in team handball. Therefore, analysis of game situations is a key factor to success. The application of computers for notational analysis allows the evaluation of a large number of game elements (Hughes & Franks, 2008). Performance indicator analysis of actions can give a general view about trends and differences and can reveal valuable information about the strength and weak points of teams (Meletakos & Bayios, 2010; Meletakos et al., 2011). However, since focus on single action analysis only gives restricted insight into tactical behavior, Carling et al. (2008) suggested analyzing action sequences, i.e. chains of sequential single actions. Nevertheless, up to date research in the field of actions sequences is rare. Attempts analyzing dependencies between single actions in terms of actions sequences in beach-volleyball (Koch & Tilp, 2009) have shown the additional value of connecting actions to sequences. Lately, Link & Ahmann (2013) used position data to analyze action sequences also in beach-volleyball. Interesting approaches to analyze action sequences as temporal patterns (T-patterns) in sports like soccer, boxing, basketball, and swimming are summarized in a review by Jonson et al. (2010). Regarding team handball, Lopes et al. (2010) used sequential analysis and the detected temporal patterns to determine structures in defense systems. However, to our knowledge so far no study was done to identify offensive behaviors on team handball by analyzing action sequences. Therefore, the aim of the present study was to classify sequences of position data of game actions in team handball to identify offensive behaviors.

METHODS

For the present study 6 games from the EHF EURO-Men-18 Championship in Hard (Austria) were analyzed. Analyses of the 6 games included data of 8 teams (Croatia, Denmark, Finland, Romania, Serbia, Slovenia, Spain and Switzerland). Each game was captured by 8 cameras to cover the whole playing area and to be able to calculate ground position of players. Subsequently, all shots and up to 5 passes prior the shot where annotated with custom-made software. Figure 1 shows the user interface of the software's annotation dialog.

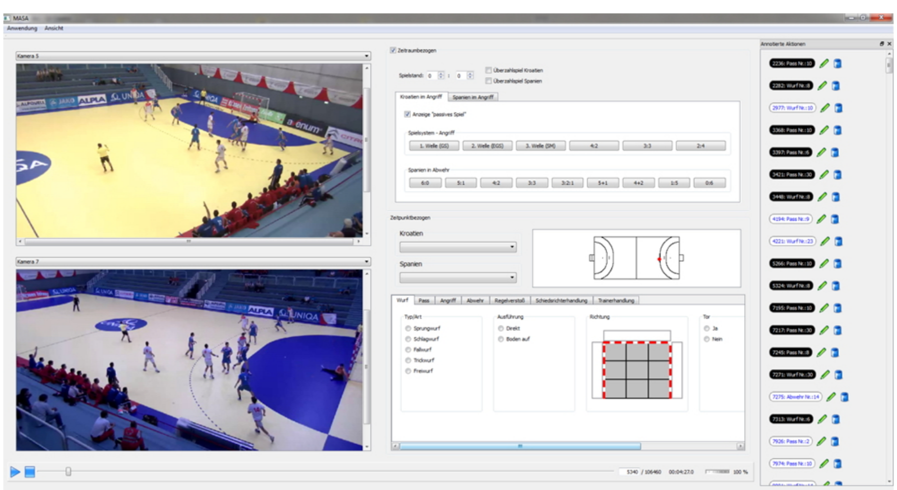

Figure 1. *User interface of the software's annotation dialog*

Each annotation includes the video time stamp of the action and the ground position of the ball carrier on the field. The annotation of each passing action also included the ground position of the receiving player. Furthermore, shot actions were annotated including shot position. In total 3212 single actions were recorded.

Subsequently, each shot action and the related passing actions were combined to an action sequence. The result of this procedure has lead to 612 action sequences. Thus, each of these action sequences represents the path of the ball from the last 5 passes to the shot-position as shown in Figure 2.

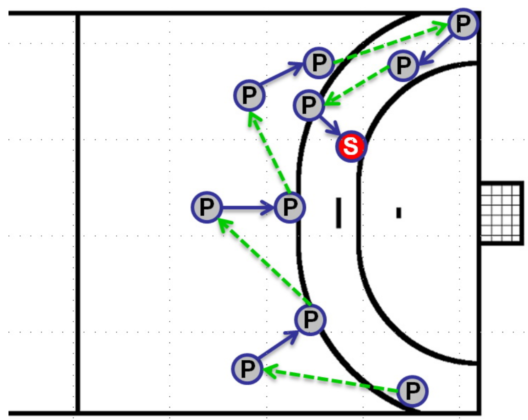

Figure 2. *Schematic display of the ball path during the last 5 passes prior to the shot (P…Pass, S…Shot, solid line…running path, dashed line…passing path)*

In order to analyze the action sequences, artificial neuronal network software (Perl, 2002) was used. In order to obtain suitable entropy for the training-process of the net, original data had to be enlarged to an amount of 3060 datasets by quintupling it with a noise of 15%. To minimize unwanted learning effects during the net training, datasets were also permutated.

Subsequently, the artificial neuronal network with a dimension of 400 neurons was trained to classify these action sequences. As a result, each neuron of the network represents an action sequence pattern. Furthermore, the artificial network pools similar neurons to clusters. These clusters represent similar offensive playing behavior. Similarity resolution, a parameter which defines the selectivity between similar and dissimilar neurons, was set to 70%.

For the analysis of action sequences, the artificial neuronal network was tested with the original dataset. Subsequently, patterns of action sequences were plotted to review the affiliation of the single action sequences to the corresponding cluster and the most often played patterns where outlined.

RESULTS

The results of the training process of the artificial neuronal network lead to an amount of 32 clusters. 10 network neurons could not be assigned to a cluster. Thus, these single neurons represent different playing patterns. Summarizing, the net identified 42 different offensive strategies (32 clusters and 10 single neurons) of the different teams. Figure 3 show the result of the net-training whereas Figure 4 shows the frequency distribution of played action sequences related to the identified clusters.

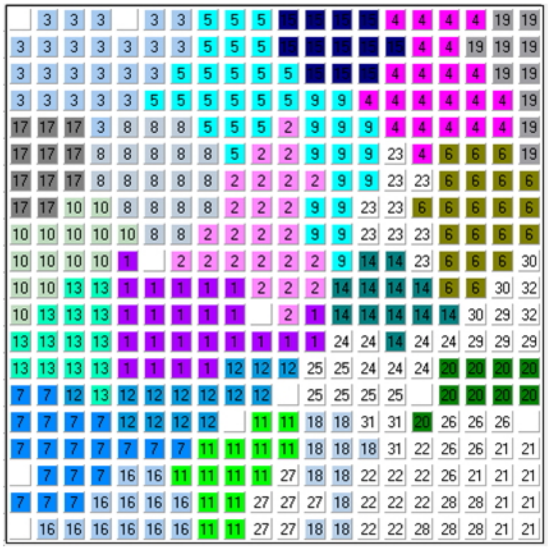

Figure 3. *Result of the artificial neuronal network after the training process (square…neuron, squares with same number/color…cluster)*

When testing the net with the original action sequence data, all of the original action sequences could be assigned to a neuron. A benchmark for the similarity of actual played action sequences and the patterns they were assigned is the average deviation. In this study the average deviation was 2.9%. This means that the average distance between the position of a single action and the corresponding position at the representing neuron lies within 1.2 meters.

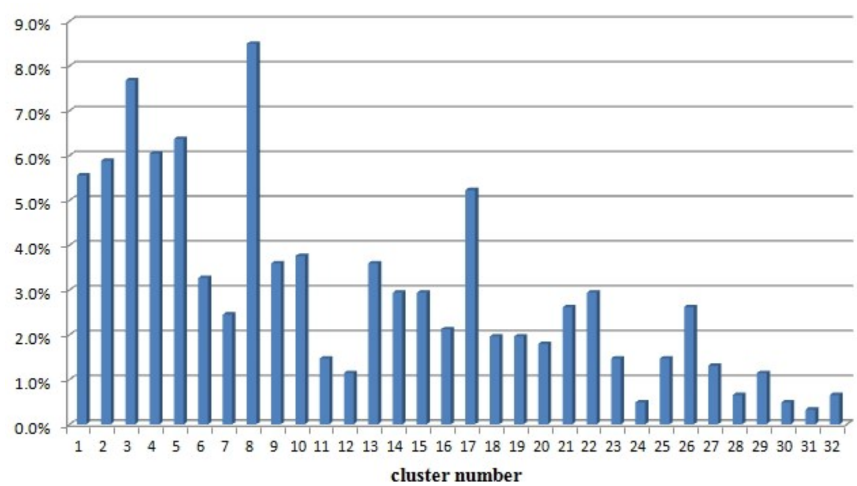

Figure 4. *Frequency distribution of played action sequences related to the identified clusters*

DISCUSSION AND CONCLUSIONS

Results show, that artificial neuronal networks are able to classify action sequences played in team handball and therefore identify offensive patterns. First expert reviews indicate that the classification and assignment of the original action sequences have a promising accordance with the detected patterns of the neuronal network. The amount of detected patterns appear to be manageable and accurate so that advises of practical relevance to coaches and athletes can be given.

A closer inspection of the most often played patterns revealed that 49% of all played action sequences are represented by only 8 clusters as shown in Figure 5.

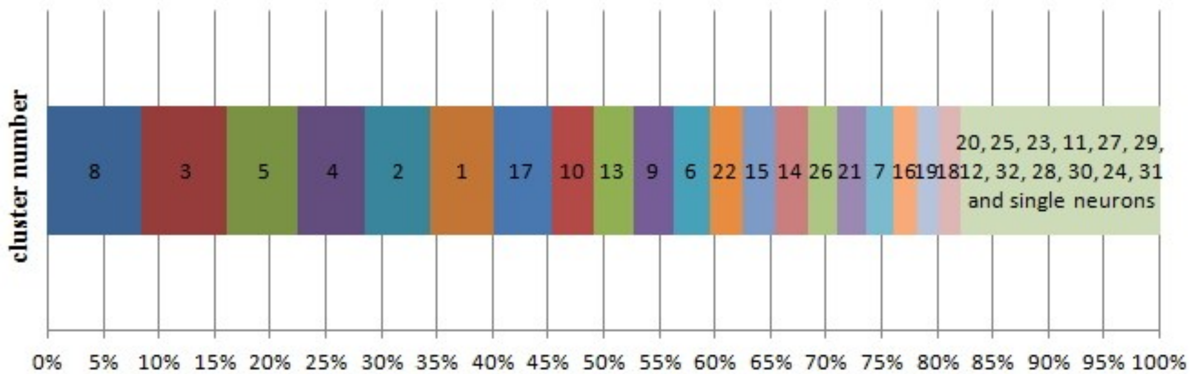

Figure 5. *Cumulative frequencies of played patterns*

As shown in Figure 6, shot position of playing patterns is in some cases very similar. Classical approaches to analyze shot attempts would not be able to differentiate between these actions because important context information, i.e. how the team got to the shot position, is missing. Adding information about shot success and the involved players, one can assess the different offensive tactics which lead to a promising shot position. Therefore, an important advantage of action sequence analysis against classical analysis of single actions is the potential to get information how teams behave to obtain success.

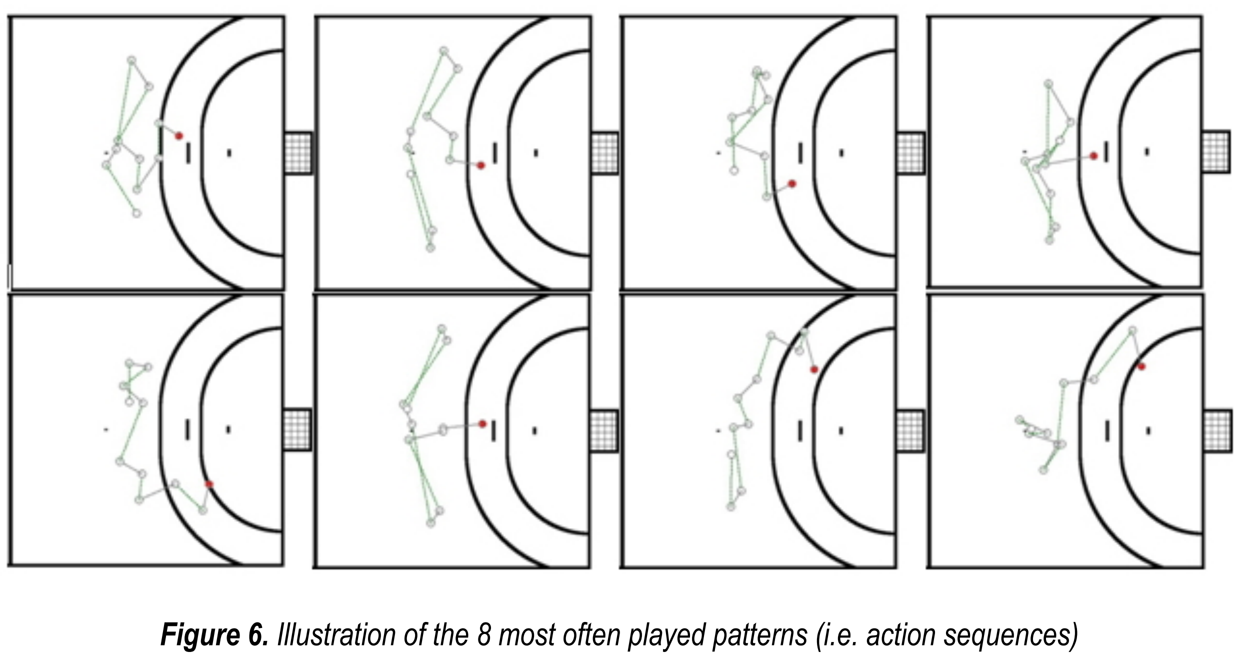

Figure 6. *Illustration of the 8 most often played patterns (i.e. action sequences)*

However, results have to be taken with care due to possible shortcomings of the used dataset and the preprocessing for the training of the artificial neuronal network. The used dataset contains action sequences with a length from 1 to 5 passes prior the shot. Further attempts with a fixed quantity of passes prior the shot have shown that action sequences with a small number of passes may distort action sequences with a larger number of passes. Thus, further studies are needed which use separate neuronal networks for each quantity of passes prior the shot. A second shortcoming may appear with extremely rarely occurring action sequences. These action sequences possibly affect the assigned neurons insufficiently during the training process and may result in incorrect patterns. To bypass this shortcoming, extremely rare action sequences could be identified and duplicated within the preprocessing of data for the network training. Furthermore, noise ratio for the duplication of the dataset for the net-training affects training-results. E.g. lower noise ratio may lead to better selectivity between the neurons and therefore a smaller deviation for the most often played patterns will be gained.

Summarizing, the study revealed the applicability of artificial neuronal networks to identify offensive patterns in team handball. Methods used in this research are able to detect playing patterns in appropriate amount and with promising accordance to actually played actions sequences. In addition, it could be found out, that dominating patterns exist in team handball.

An important future application will be the analysis of preferred offensive tactics of individual teams and possible temporal assignments of different playing-patterns, e.g. in the game end phase or during time-penalties. Moreover, the integration of goal success data will enable to classify action sequences into successful and non-successful patterns. With this information successful offensive tactics can be identified. Another future goal is to integrate defensive behavior of the opponent team to analyze interaction between the opposing teams.

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