A novel method for the analysis of sequential actions in team handball

Paul Rudelsdorfer[1], Norbert Schrapf[1], Horst Possegger[2], Thomas Mauthner[2], Horst Bischof[2] & Markus Tilp[1]

[1]Institute of Sport Science, Karl-Franzens-University Graz, Austria
[2]Institute for Computer Graphics and Vision, Graz University of Technology, Austria

Abstract

Performance in team sports crucially depends on the knowledge about the own and the opponents strengths and weaknesses. Since the analysis of single actions only provides restricted information on the game process, the analysis of sequential actions is from great importance to understand team tactics. In this paper, we introduce a novel method to analyze tactical behavior in team sports based on action sequences of positional data which are subsequently analyzed with artificial neural networks.

We present custom-made software which allows annotating single actions with accurate manual position information. The process of building action sequences with the notational information of single actions in team handball is described step by step and the accuracy of the position determination is evaluated. The evaluation revealed a mean error of 0.16m (± 0.17m) for field positions on a handball field. Inter- and intra-rater reliability for identical camera setups are excellent (ICC=0.92 and 0.95 resp.). However, tests revealed that position accuracy is depending on camera setup (ICC=0.36).

The results of the study demonstrate the applicability of the described method to gain action sequence data with accurate position information. The combination with neural networks gives an alternative approach to T-patterns for the analysis of sport games.

KEYWORDS: SPORT GAMES, NOTATIONAL ANALYSIS, ACTION SEQUENCES, GROUND POSITION DATA, NEURAL NETWORK

Introduction

Success in competitive team sports depends on athletes' performance as well as on tactical behavior and strategy. Knowledge of the opponent's strategy can make an important difference in competition. Furthermore, knowledge of strength and weakness of the own team is necessary to improve performance. Therefore, the accurate analysis of game situations is a key factor to success.

To handle the large amount of data necessary in notational analysis the use of computers is well established (Hughes & Franks, 2008). In complex team sports, statistics about the frequency of single events are a common and appropriate tool to get quantitative information about single player and team performance (Meletakos & Bayios, 2010; Meletakos, Vagenas & Bayios, 2011). However, it has some important limitations. Since a single action happens in the context of the game flow, its preceding actions have to be considered to fully understand tactical behavior. Therefore, analyzing action sequences, i.e. chains of single actions, instead of single actions is suggested by Carling et al. (2008). Besides the determination of key actions (e.g. shots in team sports), it is important to understand how they emerge. This can be done by observing their history in the game. In team handball this can be done by observing the passes preceding a shot.

One approach to get deeper insight into the complexity of sport games is the analysis of temporal patterns (T-patterns). Such T-pattern analyses are able to detect events which occur in the same order and with the consecutive time distance, thus typical tactical behavior of a team. The temporal relationship between events is the main idea of the pattern detection (Borrie, Jonsson & Magnusson, 2002; Magnusson, 1996; Magnusson 2000, Magnusson 2005). Summarized in a review by Jonsson et al. (2010), it is shown that a high number of complex temporal patterns are detectable in several different types of sport games like soccer, boxing, basketball, or swimming. One disadvantage in existing analysis by means of T-patterns is the precision of the athlete's position. While some works did not consider the position, others only used a classification according to field zones. Such rough position information might be insufficient in high level sport games where accurate position data is of great importance. Another drawback, which may explain why areas instead of accurate position data are used, is that T-pattern analyses only detect patterns if they coincide exactly. Patterns which differ slightly are not determined although they might be quite important in sports practice.

An alternative approach is to analyze exact position data of action sequences. Lately, Link & Ahmann (2013) used position data to analyze different game situations in beach volleyball. They filter their data with reference to Hansen (2003) who describes that game situations are classified by a trained observer relating to several actions within the whole game situation. After this rough classification they use position data to get deeper insight in the variations of game situations.

A method to automatically identify tactical strategies is to classify action sequences by reference to their position data. Patterns with similar position data can be determined by means of artificial neural networks (Perl et al, 2013). Such approaches have been successfully applied in soccer (Memmert et al., 2011; Memmert & Perl, 2009). In these studies, action sequences described by position data are limited by time windows and patterns are identified by an artificial neural network. Compared to these studies, the presented approach uses action sequences which are limited by the number of actions allowing analyzing the origin of a key action. In this paper, we present a novel method which allows obtaining accurate position data and analyzing sequential data in sport games by means of neural networks. Besides the methodological description we present evaluation data for inter- and intra-rater reliability of the annotation system. Furthermore, we present the analysis of offensive patterns as an example for possible applications. Specifically, we investigate the relationship between the variation of offensive tactics and the overall team success.

Methods

For the generation of sequential position data, a custom built software system, "Movement and Action Sequence Analysis" (MASA) was developed. The process of data acquisition and processing is realized in three general steps: the recording of videos, the annotation of single actions, and the processing and analysis of the retrieved data, as shown in Figure 11.

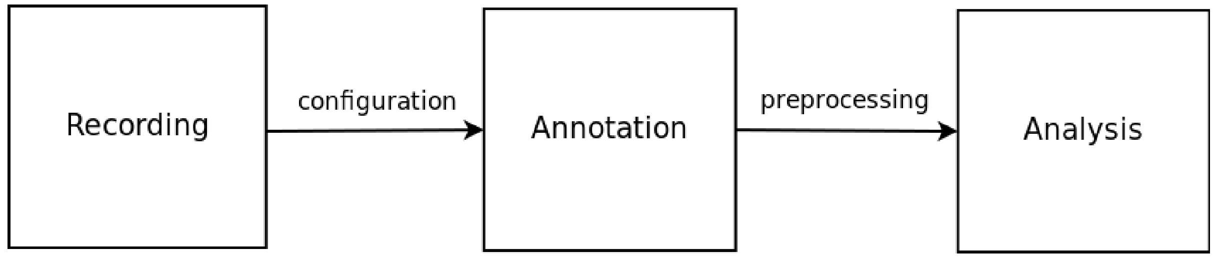

Figure 11: General process of data acquisition and processing

Recording

In order to cover the entire area of a team handball field of size 40x20 m with sufficient resolution, we deploy a multiple camera system as shown in Figure 12. We choose network cameras (Axis P1346 and P1347) which provide live-streams with a resolution of 1024x768 pixels at 20 frames per second. The streams of up to 8 cameras are sent to a central processing server which synchronizes the incoming video data based on the time stamp information provided by each camera sensor. Depending on the recording environment, the camera sensors are either directly connected to the recording server over a wired local area network (LAN) or using high performance wireless access points, e.g. if Ethernet cables may not be placed due to location-specific restrictions. The synchronization via the sensor time stamps allows to detect network communication errors, e.g. if data packets are lost during transport. In such cases, the corresponding camera image is marked as unreliable and replaced by the preceding frame to ensure synchronized processing of all video streams.

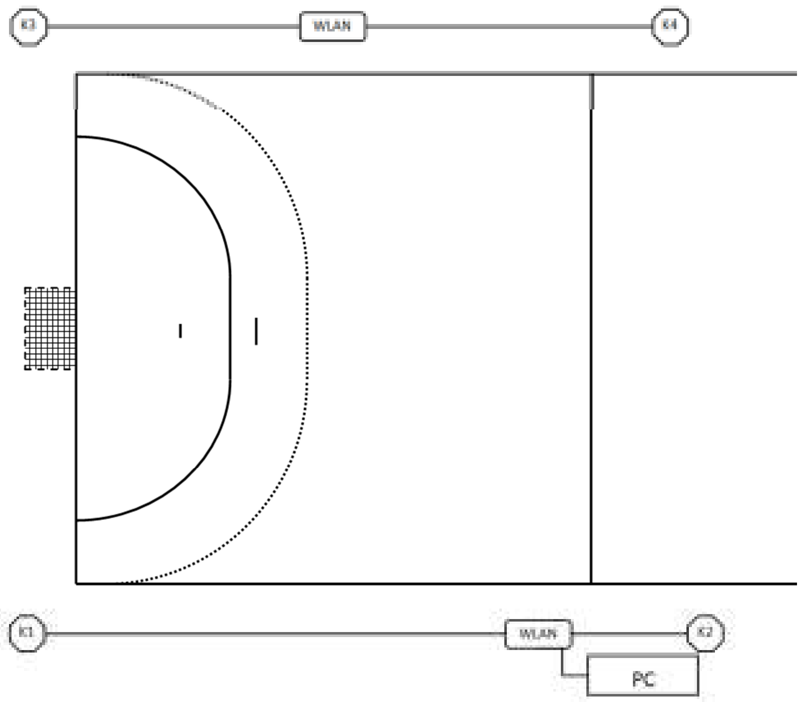

Figure 12: General setup of the test environment for the system evaluation (K... camera, PC...personal computer, WLAN...wireless network router)

Furthermore, the incoming video data must be pre-processed in order to obtain correct measurements for the analysis. In particular, this is done using a two-step procedure consisting of rectification - to account for lens distortion effects - and registration - to obtain metric coordinates from pixel measurements, - as follows.

Camera Calibration

Since the projection of 3D real world points onto a 2D image plane discards information, the camera network must be calibrated prior to obtaining meaningful measurements. This calibration allows for computing metric measurements from the recorded image data using the widespread *central perspective projection* model, also known as *standard pinhole camera*, which assumes that no lenses are used, i.e. the camera aperture is a single point, the pinhole (Hartley & Zisserman, 2004). This model follows the principle of col-linearity, i.e. each real-world point is projected by a straight line through the projection center (optical center) onto the image plane, as illustrated in Figure 13.This means that all three points, i.e. the real-world point P, the center of projection C, and the imaged point $(x, y)^T$, are located on the same line. Projecting a real-world point onto the image plane can now be done as follows.

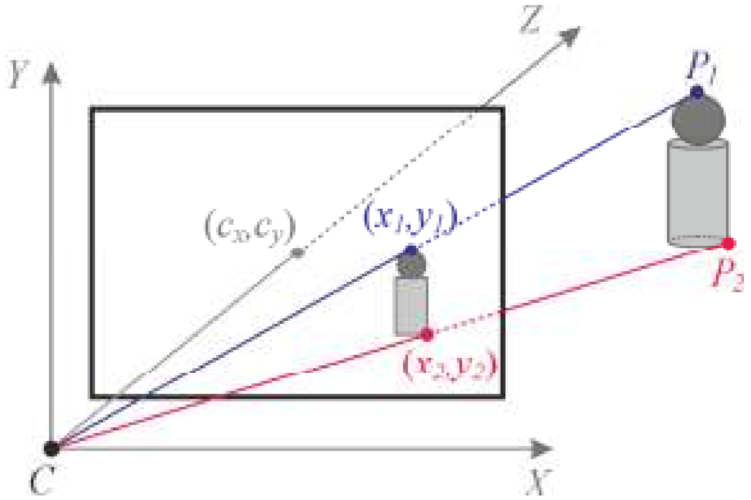

Figure 13: Image formation using the pinhole camera model, assuming that the camera coordinate axes are aligned with the world coordinate system. Following the col-linearity principle, 3D real-world points Pi=(Xi,Yi,Zi)T are projected by a straight line through the optical center C onto the image plane coordinates (xi,yi)T

First, the point's coordinates $P = (X, Y, Z)^T$ are transformed from the world coordinate system to the camera coordinate system, i.e. $\tilde{P} = (\tilde{X}, \tilde{Y}, \tilde{Z})^T$. Therefore, the point needs to be translated and rotated with respect to the camera pose. This transformation is defined as $\tilde{P} = \mathbf{R}P - \mathbf{R}C$, where **R** denotes the rotation matrix of the camera. In a subsequent step, the point is projected onto the image plane of the camera. The corresponding transformation is defined by the camera's intrinsic parameters, namely:

- the focal lengths for the x and y dimensions, i.e. f_x and f_y, which define the magnification in the corresponding direction,
- the factor γ to account for a possible skew between the sensor axes - in case the sensor is not mounted perpendicular to the optical axis,
- the location of the optical center, also called principal point, i.e. the pixel coordinates $(c_x, c_y)^T$ where the optical axis intersects the image plane - this position is used as a translation vector, since in general, the origin of coordinates in the image plane (mostly top-left) is not at the principal point.

Using the intrinsic camera parameters, $\tilde{P}$ can now be projected onto the image plane to obtain the pixel coordinates $(x, y)^T$ as:

$$x = \frac{f_x \tilde{X} + \gamma \tilde{Y}}{\tilde{Z}} + c_x, \quad y = \frac{f_y \tilde{Y}}{\tilde{Z}} + c_y.$$

The pinhole model assumes a linear projection, i.e. straight lines in the world project to straight lines in the image. Therefore, it is only an approximation of the real camera projection, since in general, standard lenses usually suffer from distortion and thus, image coordinates are displaced. Most frequently, camera lenses suffer from radial distortion, which manifests itself as a visible curvature in the projection of straight lines, specifically near the image borders. Hence, in order to apply the pinhole model, the distortion needs to be corrected in a pre-processing step, i.e. the images need to be rectified.

According to Szeliski (2010), lens distortion occurs during the initial projection of $\tilde{P}$ onto the image plane. Hence, image correction needs to be applied at this place. Therefore, let $(\hat{x}, \hat{y})^T = (\tilde{X}/\tilde{Z}, \tilde{Y}/\tilde{Z})^T$ denote the normalized image coordinates, obtained after the perspective division, and before scaling by the focal length and shifting by the optical center. Following Hartley and Zisserman (2004), the correction can now be applied by using a Taylor expansion to approximate the true radial distortion. Thus, we obtain the normalized image coordinates $(\hat{x}_d, \hat{y}_d)^T$ after accounting for the distortion as

$$\hat{x}_d = \hat{x}\left(1 + \kappa_1 r + \kappa_2 r^2 + \kappa_3 r^3 + \ldots\right), \quad \hat{y}_d = \hat{y}\left(1 + \kappa_1 r + \kappa_2 r^2 + \kappa_3 r^3 + \ldots\right),$$

where $r = \sqrt{\hat{x}^2 + \hat{y}^2}$ is the radial distance from the image center and κ_i are the radial distortion coefficients. After this correction, the rectified pixel coordinates can be computed as:

$$x = f_x \hat{x}_d + \gamma \hat{y}_d + c_x, \quad y = f_y \hat{y}_d + c_y.$$

Note that the choice of the order of the polynomial actually depends on the camera optics, i.e. distortion models for wide-angle lenses as used in our experiments require higher-order polynomials to provide an accurate correction, in contrast to distortion models for standard consumer camera lenses. Specifically, we assume a third order radial distortion model and use a publicly available MATLAB toolbox (Bouquet, 2013) to estimate both, the intrinsic camera parameters, as well as the distortion coefficients by recording a known checkerboard pattern. This so-called intrinsic calibration allows for pre-computing a mapping from recorded image pixels to pixels of a rectified image and thus, the computational effort to correct for lens distortion required at runtime decreases to a simple lookup of corresponding image coordinates.

Annotation of actions

The MASA application is a prototype tool where the gathered video data is annotated. It connects video data with user input and stores it in a database. The user input consists of the type of action and its field position.

The graphical user interface consists of three major parts as shown in Figure 14. (1) The video area where by default two videos are displayed. (2) An action area where, depending on the predefined category system, available actions are visible, including a top view of the playing field and a game overview including the present score. (3) A list containing all annotated actions.

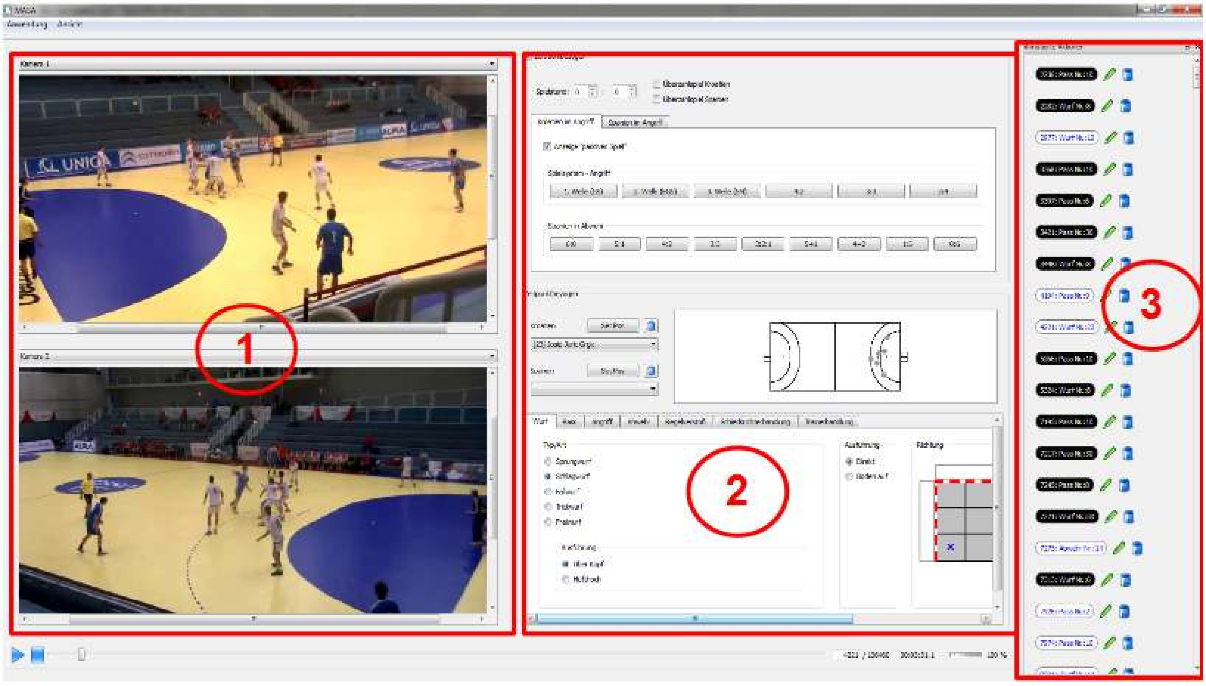

Figure 14: Overview of the MASA-GUI, parts (1)-(3) described in text

The video area in MASA is designed for a multi-camera setup. While it is possible to have only one video source, most situations require multiple views from different angles and positions to cover the area of interest. It is also possible to annotate ongoing games live in real time and link the video footage later.

A complete notation includes information about the time, the position, the type, and the protagonist of the action. The instant of time is determined by the video frame. All other information is added in the action area of the GUI with the following steps.

To specify the type of action, actions must be classified first. The action area is a graphical representation of a category system that is used to identify different types of actions. For example shots, passes, referee or coach interferences. These general categories are called root categories and are represented as tabs in the action area (see Figure 15).

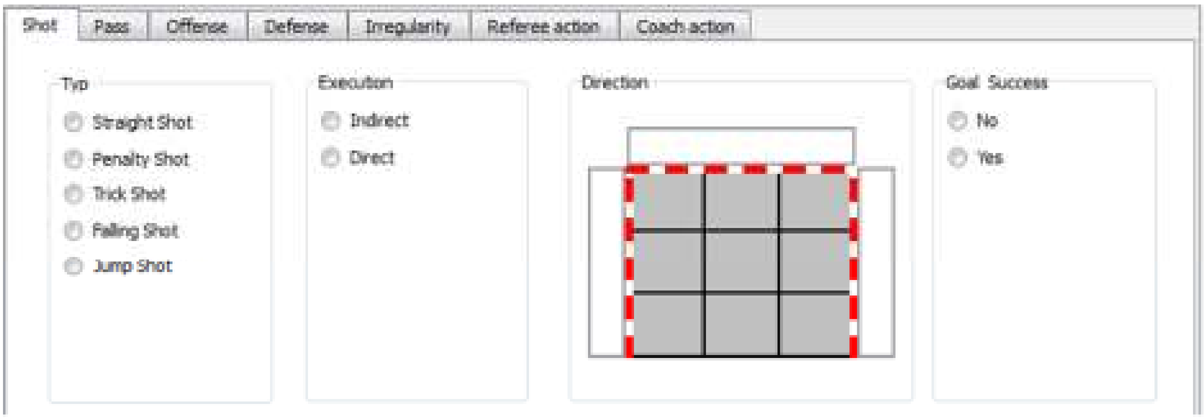

Figure 15: Action area of the MASA application

Each root category is then specialized in subcategories which can as well be specified recursively. A shot e.g. has different properties such as shot technique, quality, and shot direction. If necessary, special widgets can be assigned to the properties e.g. a frontal representation of the goal facilitates the input of the shot direction (see Figure 15).

The protagonist and timing are annotated in a widget combined with the video area. A click on the playing field in the video area calculates the actual position on the field in Cartesian coordinates. The player can then be selected from a combo box (see Figure 16). Additional position information, for example the formation of the defense team, can be set as well.

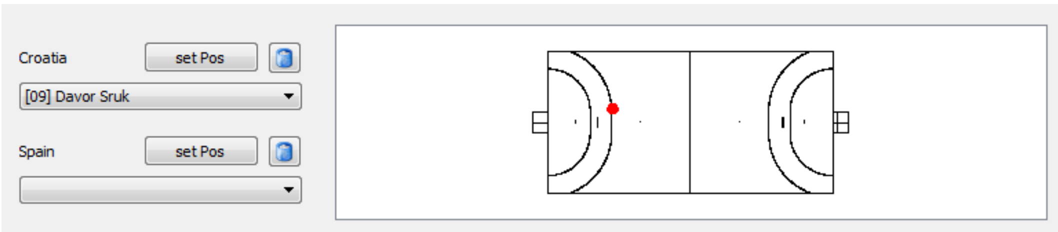

Figure 16: Position and player part of action area of the MASA application

The list area (see (3) in Figure 14) offers the opportunity to navigate through a game and alter previous inputs. A list item shows the player number in team color and the annotated action. List items are linked to the video with time stamps which allows the user to review, edit, or delete the related action.

MASA is open source software based on the Qt framework. Additional libraries are OpenCV and qwt. While qwt contains GUI components for the graphical display of data, OpenCV is a video processing library. Furthermore, MySQL is used as a database engine. All of these libraries are available on Microsoft and Linux-based operating systems. Working builds of MASA exist on both of these systems. MASA was not only created for the purpose of analyzing team handball games with neuronal networks but for a broad spectrum of tasks. The primary application area of the software is scientific. This is due to the fact that the manual position determination is a time-consuming task and the analysis with neural networks is not trivial. However, the annotation tool MASA itself is suitable for sport practice and valuable for coaching staff. The classification system is not static and can be customized to a wide area of needs with a built-in creation tool explained in the next section. The flexibility of the annotation process and the opportunity of exact position determination in addition with the mutli camera option are the main features that distinguish MASA from other software tools used in Team Handball.

Database model

The base for the flexible structure of MASA is the database model used and the dynamic GUI creation.

The data structure of a category system can be represented as a multi branch tree, with first level categories called root categories. Branches and nodes are stored in a table and have id numbers of their parents and certain properties. One of the properties determines how a branch is represented in the GUI, for example as multiple choice selection, text entry, or checkbox widget. Since the demands in different sports are varying, the structure of the category system is created by the user for his/her individual needs within the application. The user-built category system is used as an associative entity for the data in the annotation process. The advantage of a system that allows users to define their own categories is that such a tool can be used for a wide variety of tasks without overloading the GUI and making the annotation process as easy as possible.

Position determination

To accurately obtain metric positions of the team handball players, the transformation from image points to real world locations on the ground plane must be known. Therefore, we register each camera image with a known ground plane model by estimating a plane-to-plane projective coordinate transformation (*homography*). Since a homography is defined by a 3x3 projective transformation matrix, it provides 8 degrees of freedom and thus, at least 4 non-collinear corresponding point matches between image coordinates and ground plane coordinates must be available to estimate the transformation (Hartley & Zisserman, 2004). In particular, the user provides a set of corresponding points from a camera image and the ground plane model by selecting salient points such as corners of the handball field, markers on the goal, or previously placed markers within the field. If the user provides more than the minimum number of corresponding image points, we apply RANSAC (Fischler & Bolles, 1981) to robustly estimate the projective transformation matrix **H**. Given the estimated homography **H**, metric locations can be obtained from image locations using homogeneous coordinates (Bloomenthal & Rokne, 1994) as follows. First, the image pixel at location (x, y) is represented as a homogeneous coordinate by padding its coordinate vector with 1. This allows to formulate the projective transformation as the matrix multiplication $(\tilde{X}, \tilde{Y}, \tilde{W})^T = H(x, y, 1)^T$. To obtain the corresponding metric coordinates $(X, Y)^T$ on the real-world ground plane, the projective coordinates must be divided by the scaling factor $\tilde{W}$, i.e. $(X, Y) = \left(\frac{\tilde{X}}{\tilde{W}}, \frac{\tilde{Y}}{\tilde{W}}\right)$.

Within the presented process of analyzing action sequences in team handball, several working steps have to be performed. Most of these steps are standard procedures in notational analysis and have been evaluated extensively in the literature (Carling, Williams & Reilly, 2005; Hughes & Franks, 2004; Tilp et al., 2006). However, the determination of position is novel and therefore will be evaluated in this paper.

Evaluation of the position determination

To evaluate the accuracy of the position determination, real world coordinates were compared with coordinates determined with the help of the MASA-software. Since camera positions are symmetrical for the handball field, only one half of the field with marked and measured lines was recorded with four cameras from typical views during game situation. Following the configuration of the camera setup, a set of predefined points were tagged by the assistance of the software system Figure **17** shows the schematic layout of the evaluated points.

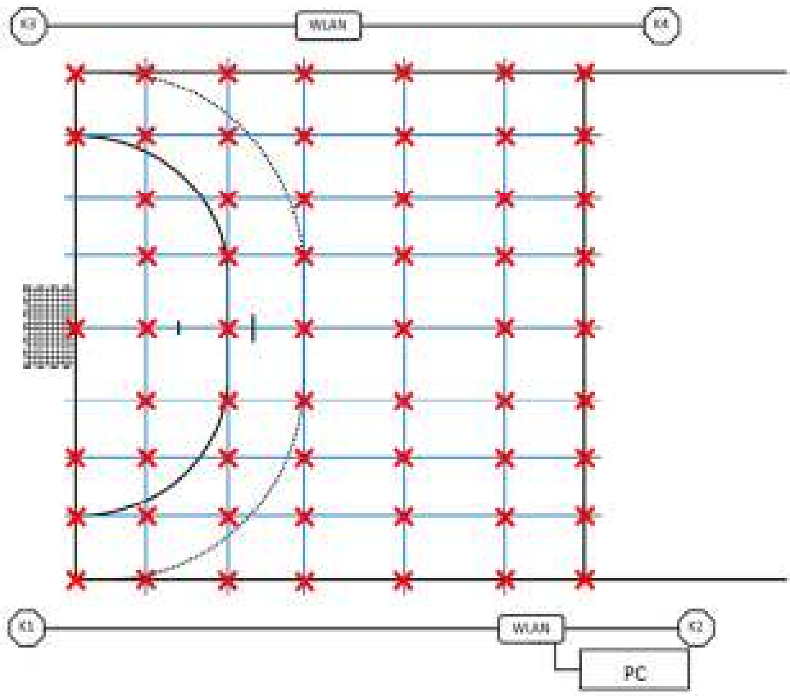

Figure 17: Schematic layout of the tagged points considered in the evaluation. In the presented camera set-up the non-marked points of the line grid close to the goal lay in the blind spot of the cameras K3 and K1 and are far away from the cameras K4 and K2. Since these areas are not relevant during a handball game, we did not evaluate accuracy.

The annotation was done separately for every camera. In total 125 points were annotated within one single test-session from the different camera views. Differences between the real world coordinates and the computed coordinates were calculated to estimate errors. Means and standard deviations of these differences were calculated per camera and for the entire test recordings.

To validate inter-rater reliability of the position determination, two different raters annotated the set of points with two different camera setups, i.e. with different homographies. To test intra-rater reliability, one tester performed a retest after one week. The statistical analysis of the measurement was performed with MS Excel 2010 and SPSS 20. Test results were assessed by the intraclass correlation coefficient (ICC) between the different raters, between the different camera configurations, and between the test and the retest, respectively.

Data processing and analysis

Generating input vectors

The database does not contain action sequences but the annotated single actions. Therefore the data of interest needs to be extracted and formatted into an input vector that can be handled by the neural network software DYCON® (Perl, 2002).

In the preparation process coordinates have to be scaled for the neural network software and transformed to account for the changeover of teams following half time.

The amount of data put into the neural network for one game situation is limited due to technical properties and game play relevance, i.e. passes before penalty shots are not relevant for the shot action. In this study the number of actions before a shot was chosen in contrast to the “sliding-window method” mentioned by Memmert et al. (2011). Consultation with experts and literature study resulted in the conclusion that five passes prior to a shot is an adequate number to properly cover important tactical information.

To study action sequences in team handball the input vector for the neural network consists of coordinates which represent the path of the ball from five passes before the shot and the shot itself. Therefore the input vector has the following format:

P R P R P R P R P R S (S= shot, R =receiver, P = passer).

Each of these points consists of an x- and a y-coordinate. The coordinates are harvested automatically from the database with an appropriate algorithm. Thus, a discrete action sequence covering the way of the ball is created. Shots with less than five actions, for example a penalty shot or a fast break play, are excluded from the input data.

Analysis of action sequences

In order to analyze playing behavior and team tactics, the action sequence data of players’ positions is analyzed by means of artificial neural network using the DYCON® software (Perl, 2002). The software is able to classify the action sequences and as a result, each neuron of the network represents a playing pattern. Furthermore, similar patterns are summarized to clusters, which then represent similar playing behavior. An example of a neuronal net and some of the found patterns are shown in Figure 18.

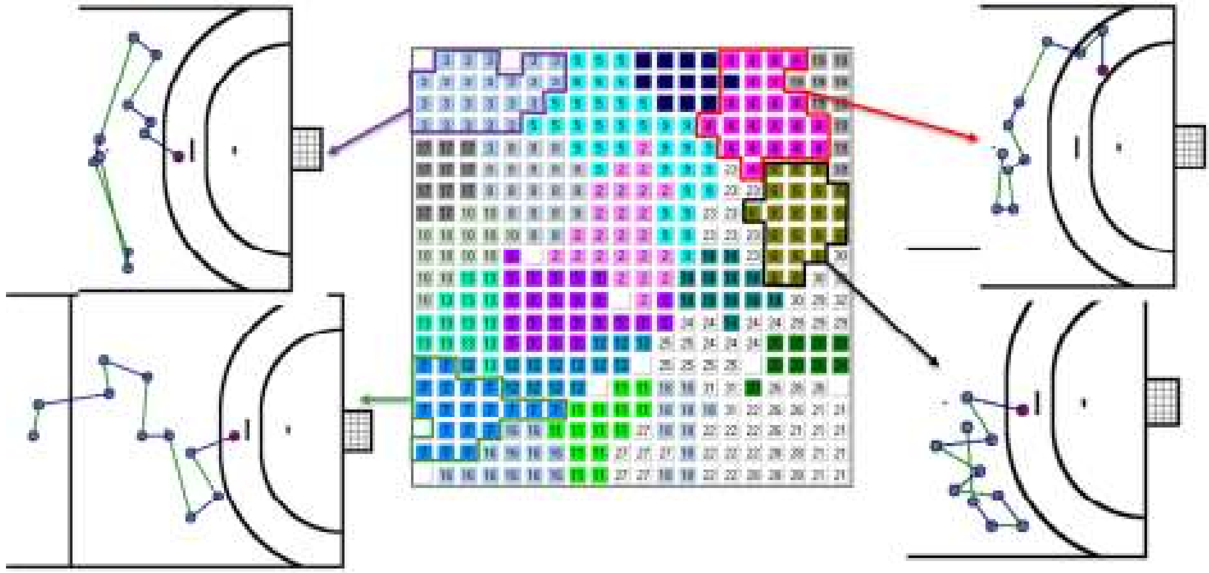

Figure **18**: Centre: Exemplary result of a neural network analysis showing different patterns. Boxes represent single neurons. Neurons in same colors represent clusters, i.e. representation of similar offensive patterns. Left and right: Exemplary offensive patterns determined by the network which show the ball path consisting of five pass positions (blue dots) and the shot position (red dot). Green lines represent ball paths and blue line represent running paths.

Schrapf & Tilp (2013) have already shown that offensive patterns can be determined with the presented method. They also have shown that some patterns are more successful than others. One could assume that the variation of offensive team tactics might be a success factor. Therefore, we analyze the relation between the variation of offensive patterns and overall team success from six games (eight teams) during the European U18 Team Handball Championship 2012 in Austria. There are several possibilities to operationalize variation in playing patterns. For this study we operationalize variation by determining the number of different patterns used by each team. The amount of different offensive patterns is determined by neural network analysis as described above and the overall team success is assessed by the final tournament ranking position. The relation is determined with Spearman's correlation coefficient.

Results

Evaluation of position estimation

The average error of the position estimation is 0.16 m (± 0.17 m). A detailed overview about the error rates per camera is shown in Table 6.

Table 6: Error rates of position estimation (values in meter)

	Minimum error	**Maximum error**	**Average error**	**Standard deviation**
Camera 1	0.03	0.53	0.14	0.10
Camera 2	0.01	0.70	0.13	0.12
Camera 3	0.01	0.98	0.22	0.22
Camera 4	0.01	1.15	0.15	0.17
Overall	0.01	1.15	0.16	0.17

An overview about the smallest and largest error rates is shown in Table 7. Error rates of test runs with best and worst average error rates are indicated for each camera view from all test runs with different camera settings and different testers.

Table 7: Error rates of single cameras from best and worst experiment based on average error (values in meter)

	Best case				**Worst case**			
	C1	**C2**	**C3**	**C4**	**C1**	**C2**	**C3**	**C4**
average error	0.13	0.09	0.16	0.11	0.16	0.17	0.27	0.21
standard deviation	0.07	0.04	0.13	0.05	0.10	0.16	0.26	0.25
minimum error	0.03	0.03	0.03	0.03	0.03	0.01	0.03	0.01
maximum error	0.28	0.24	0.61	0.22	0.44	0.62	0.98	1.15

Table 8 shows the quartiles of the single error rates. It indicates that 75 % of all errors are below 0.20 m. The 90% quantile error rate is at 0.33 m.

Table 8: Quartiles of the error rates (values in meter)

	From	**To**
1st quartile	0.01	0.06
2nd quartile	0.06	0.11
3rd quartile	0.11	0.20
4th quartile	0.21	1.15

The intraclass correlation coefficient (ICC) for verification of the software systems inter-rater reliability is 0.92 (significance level 0.000) regarding different test person and same camera setup. The intra-rater reliability test lead to an ICC of 0.95 (significance level 0.000). A retest with different camera setups and the same test person lead to an ICC of 0.36 (significance level 0.000).

Relationship between offensive pattern variation and overall-success

The analysis of offensive action sequence by neural networks revealed that the different teams played between 18 and 27 different offensive patterns (examples in Figure 18) per game A correlation coefficient of r_s=0.6 (Spearman) however, indicates a rather low relationship between offensive variation and success (Figure 19).

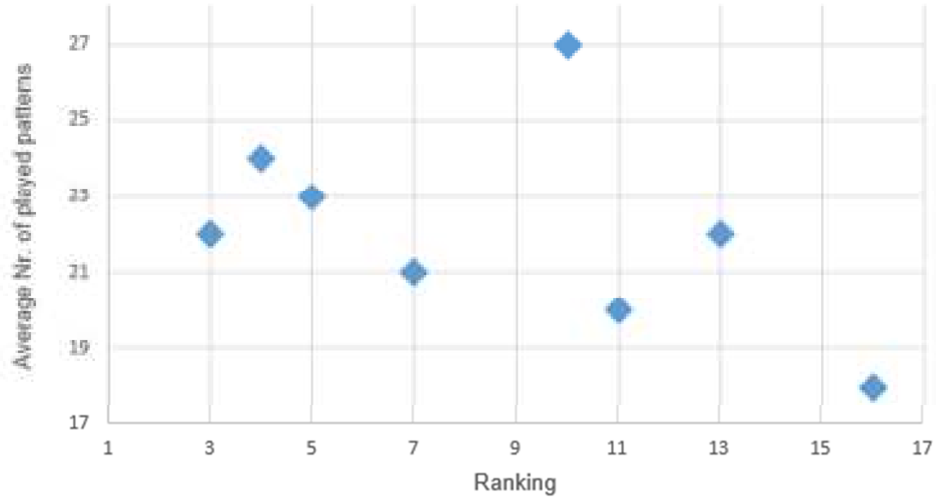

Figure 19: Number of offensive patterns played by teams and the final tournament ranking of the analyzed teams

Discussion

Evaluation results show that the presented system is able to produce action data including accurate position data to create action sequences in team handball. Due to the flexible annotation process almost any type of action with user-defined details can be captured. The independent procedure for extracting annotated data allows obtaining arbitrary data sets by combining single action data stored in the database.

Due to the open nature of the system components, it is possible to adjust the working effort to specific problems. While researchers might use the system to perform detailed but also time-consuming analyses, sport practitioners might create simple but effective category systems for their requirements. The notation process for example is not bound to a specific camera system, but can handle any form of video data. Input vectors for the neural network can also be generated from data sets of other annotation systems. Furthermore, data gathered from the notation process can be used for classical analyses like shot statistics etc.

An important aim of the study was to evaluate if the accuracy of position determination is sufficient to analyze sequential actions in team sports. An average error of 16 cm indicates that the system provides appropriate position data for this task. Considering the area taken by an athlete standing or the deviations during running movements, the error appears negligible. Statistical analyses of the error occurring the evaluation show a very well inter-rater reliability (ICC of 0.92) and also an excellent intra-rater reliability (ICC of 0.95). However, evaluation of the system's objectivity regarding different camera setups has led to a rather low ICC of 0.35. From this can be concluded that the preparation of the system's camera setup has a significant effect on the results of the position estimation. Moreover, best and worst case values of the evaluation show that the maximum error due to an improper camera setup can be above 1 m. Such an inaccuracy would definitely lead to non-satisfying analysis results. However, a closer examination of the average results of the different camera setups reveals that worst results for each single camera only leads to an average error of 27 cm. A detailed analysis of the field areas with greater error rates show that error rates increase at the bottom end of the single views, i.e. when the point of interest is in great distance from the camera (e.g. the left corner seen from camera 2 in Figure **17**). Considering the software's ability to select positions from different camera views, the user is able to minimize errors by selecting positions onto a view, where the player is in the front of the video. Moreover, the 90% quantile of all test data is at 33 cm, which shows that there are only a few positions on the field which are determined with mediocre accuracy. Overall, error rates determined in the present study are similar to other positional determination system, i.e. visual position estimation in beach volleyball with average error rates from 0.25 to 0.35 m (see Figure 12 in Mauthner et al., 2007), large scale motion acquisition in team handball with a root mean square (RMS) error of 0.18 to 0.64 m (Perš et al., 2002) or photogrammetric technique in order to determine referee position during a football match with a RMS error of 0.23 and 0.17 m for x- and y-axis, respectively (Mallo et al., 2007).

The process of classifying action sequences from position data by means of artificial neural networks was already described by Schrapf & Tilp (2013). They reported that the system is able to successfully identify offensive playing patterns by classifying action sequences in junior team handball. The obtained amount of detected patterns appears suitable for the use in sports practice. Their study revealed dominating offensive patterns as well as varying success rates of used offensive strategies in team handball.

Conclusion

Summarizing, the study revealed the applicability of the used method to gain action sequence data with accurate position information which can be used to analyze tactical behavior in complex sport games like team handball. The presented system enables annotating single actions live during matches or off-line from recorded videos. Exact position information can be added in an off-line process. Subsequently, appropriate data export algorithms are able to merge single actions into sequences of actions which are then analyzed by artificial neural networks. First analyses with position data of action sequences from team handball (Schrapf & Tilp, 2013) already indicate the applicability of the proposed method.

Future challenges will be the inclusion of defensive team behavior in the analyses and the application of the system in sports practice. Especially the interaction between the opposing teams may lead to valuable information for coaches to improve the tactical training and the tactical behavior during competitions.

Acknowledgement

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