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Editorial

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Dear readers:

Welcome to the summer 2009 issue of the **International Journal of Computer Science in Sport (IJCSS)**.

First of all, many apologies for the abstracts notification delay regarding the **7th International Symposium on Computer Science in Sport**. Considering the number of submitted abstracts, though, it is appropriate to look forward to a highly interesting and hopeful event at the Australian Institute of Sport in Canberra in about 3 months.

Two original papers and two reports have been included within this issue.

Michael Beetz, Nicolai von Hoyningen-Huene, Bernhard Kirchlechner, Suat Gedikli, Francisco Siles, Murat Durus and **Martin Lames** propose automated sports games models based on context-senstitive analysing concepts. The authors present also an implementation of their models, illustrating it by the example of the final of the soccer World Cup 2006.

In the paper by **Andreas Grunz, Daniel Memmert** and **Jürgen Perl** a special analysis and simulation method for actions in sport games is presented. The approach applies self-organizing neural networks for the purpose of analysing complex behavioural processes such as those in soccer.

Peter O'Donoghue and **Gemma Robinson** survey the validity of the ProZone3® player tracking system based on a case study where the framework was tested on a single player during a soccer game. The subjects of the investigation include the player's path changes as well as the number of area transitions.

The final report by **Roland Leser**

I hope you enjoy this issue.

If you have any questions, comments, suggestions and points of criticism, please send them to me.

Enjoy the summer!

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ASPOGAMO: Automated Sports Games Analysis Models

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Abstract

We propose *automated sport game models* as a novel technical means for the analysis of team sport games. The basic idea is that automated sport game models are based on a conceptualization of key notions in such games and probabilistically derived from a set of previous games. In contrast to existing approaches, automated sport game models provide an analysis that is sensitive to their context and go beyond simple statistical aggregations allowing objective, transparent and meaningful concept definitions. Based on automatically gathered spatio-temporal data by a computer vision system, a model hierarchy is built bottom up, where context-sensitive concepts are instantiated by the application of machine learning techniques. We describe the current state of implementation of the ASPOGAMO system including its computer vision subsystem that realizes the idea of automated sport game models. Their usage is exemplified with an analysis of the final of the soccer World Cup 2006.

KEYWORDS: GAME ANALYSIS, SPORTS VIDEO PROCESSING, MODEL BUILDING

Introduction

Providing effective support for the interpretation and analysis of sport games requires the systematic and comprehensive observation of games and the abstraction of the observed behavior into informative models. Such models, usually created mentally by coaches and scouts, enable to infer the strengths and weaknesses of individual players and teams as well as of strategic planning and tactical decision making. Due to the human way they are subjective and limited to only small subsets of aspects at one time. In the ASPOGAMO project, we investigate a new generation of sport game models that

- are based on players' positions, motion trajectories, and ball actions as their primitive building blocks;
- represent the interaction between ball actions, game situations, and the effects of ball actions and thereby allow for more comprehensive assessment of the games;
- use concepts such as scoring opportunity, being under pressure, and passing opportunities, classifying situations and interpreting the game events. These concepts are defined transparently and therefore constitute objective criteria for classification and assessment.

- can be acquired automatically by a camera-based observation system.

The benefit of this system is its possibility to model even cognitive abstractions based on an automatically gathered position data pool. The generated concepts are reproducible and revisable and hence objective. If high-level definitions are modified or added, the change is transparently distributed to all other concepts. Although the system will never come close to human cognitive abilities, which are based on a much wider data base, automated models can help and accelerate human analysis of complex activities in sports games. They create new opportunities in sport science to get insights into the process instead of comparing the final results only after the end of the game.

In computer vision, video indexing and the extraction of statistics in major sports games have received a great deal of attention due to their controlled setting, e.g. a soccer field or tennis court with well separable actors and predefined rules for actions. Surveys of computer aided sport analysis are given in (Wang & Parameswaran, 2004b; Yu & Farin, 2005; Setterwall, 2003). The field can roughly be split into indexing and tracking methods. The first divide a predominantly broadcasted video into several labeled parts, while the latter estimate trajectories of moving objects like players or their equipment in recorded images.

In broadcasted material, the shots themselves provide information about the content. Multiple cameras are usually employed to generate different game perspectives and view types such as player close-up, panoramic view or slow-motion replay. Broadcasters adhere to well established video production rules to select video feed for view consistency, making it easy for viewers to follow the game. For example, the sequence of views that tracks a game-service point in tennis usually begins with a close-up of the player preparing to serve, followed by a change to the panoramic court-view after the ball is served, until the break, when view changes to a close-up of the player, who won the point. A close relationship is maintained between the temporal view changes and the semantic game events. Syntactic structures of the game can therefore be reverse-engineered by recognizing these view type changes. Audio cues may also be used; since the crowd is usually quiet during play, the detectable sounds are ball hits, followed by loud eruption of cheers and applause when point is won. Similar structures can be observed in most major sports videos. Much research has been done exploiting these domain constraints by visual information (Ekin et al., 2003), audio clues (Rui et al., 2000; Lao et al., 2006a) and the multimodal integration of video, audio and chroma keying (Babaguchi et al., 2002; Han et al., 2002). Applications have been found almost in all major sports as tennis (Pingali et al., 1998), baseball (Rui et al., 2000; Han et al., 2002), basketball (Zhou et al., 2000), soccer (Ekin et al., 2003; Assfalg et al., 2002) and American football (Babaguchi et al., 2002; Li & Sezan, 2001).

On the other side, tracking methods focus on extracting the positions of the players and the ball or puck in ball games. Different segmentation and motion tracking techniques have been used including color based methods (Xu et al., 2004; Pingali et al., 1998; Duan et al., 2003; Liang et al., 2005), feature extraction (Jin, 1994; D'Orazio et al., 2002) and additional post processing (Yu et al., 2003) for single camera settings as well as some integrating information captured by multiple cameras (Pingali et al., 2000).

While most of them deliver raw trajectory data or simple statistics, Sudhir et al. (Sudhir et al., 1998) not only track tennis players while estimating the camera pose, but also map the spatial data to limited higher level classifications of the scene such as Baseline-Rallies, Passing-Shot, Serve-And-Volley and Net-Game using a lookup table. Similar work was done by Lao et al. (Lao et al., 2006b) integrating also audio cues. Wang and Parameswaran (Wang & Parameswaran, 2004a) classify tennis ball trajectories extracted from videos of calibrated cameras to 58 tactic patterns defined by sport experts using Bayesian inference.

Most of the methods so far reveal semantics in broadcasted material, that have been already encoded by humans, or provide only low-level statistical information based on trajectories as e.g. the covered distance containing far less semantics. Few enrich videos with semantics that are interesting for sport scientists and trainers beside limited classifications. The ASPOGAMO system tries to automatically gather a spatio-temporal information basis and build a rich context-dependent domain knowledge upon it. Transparent definitions can be stated in an objective way allowing the applicability to unseen games, their usage for indexing and may also reveal unknown insights into the structure of team sport games.

We describe the framework instantiated for the soccer domain by giving an overview of the complete system in the first section. It is splitted functionally into two main components: Section 3 details the automated observation system that extracts the position data of all soccer players and ball trajectories from multiple pan-tilt-zoom cameras. The automated models, built on these data, and the generation of high-level analysis are explained and exemplified for the final game of the Football World Cup in 2006 in Section 4. Finally, we draw our conclusions and give future prospects.

System Overview

The ASPOGAMO system extracts meaningful sports game models from video footage presenting an interface for analysis. An overview of the pipeline with the two main components of the ASPOGAMO system, the observation system and the automated hierarchical model is depicted in fig. 1.

Image sequences captured by one or more pan-tilt-zoom cameras - possibly including also broadcasted material - form the input of the system. The observation system bundles state-of-the-art computer vision techniques to estimate camera perspectives as well as to segment and to track all soccer players and the ball in real-time exploiting domain knowledge to make the problem tractable. For example, the segmentation relies heavily on characteristics of the inspected domain as e.g. the appearance of the playing field and is implemented for soccer only, so far. The automatically gathered and possibly revised trajectories are fed by the observation system to the knowledge base. They build the base of all models assuming that this information is sufficient to completely describe a game. The knowledge base is organized as ontology and provides hierarchical models of games. Contextual concept definitions are grounded transparently in the data by data mining techniques supposing valid declarations and adequate data. The model framework is not specific for soccer but can incorporate other sports games as well, given an adjusted conceptualization. Users of the ASPOGAMO system, that are sport scientists, the media and the viewers, can query the knowledge base in terms of the model and receive answers visualized in appropriate ways. Visualizations can be abstract images or videos but also augmented video parts of the original material. All the data needed for augmentation has been already gathered by the observation system. The automated sports game models provide in conjunction with their groundings a rich source of analysis.

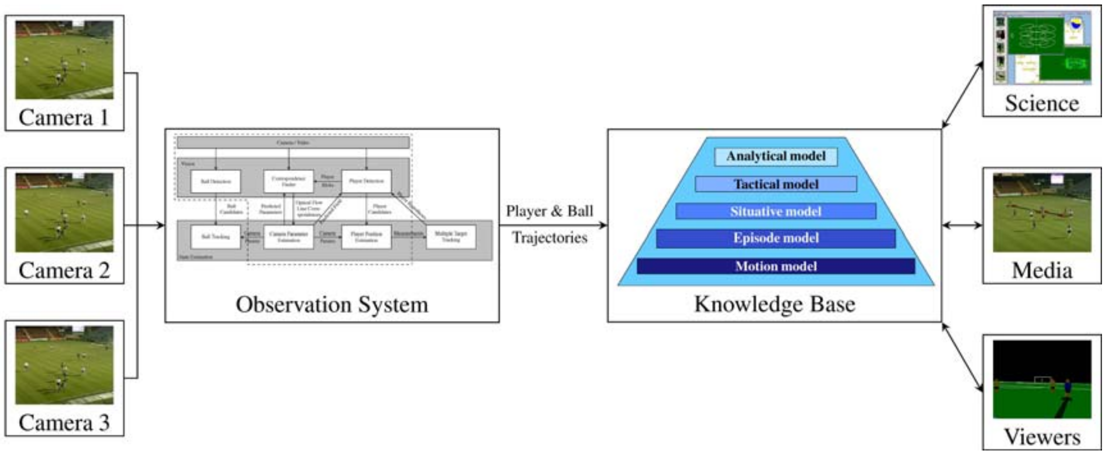

Figure 1. Overview of the ASPOGAMO system.

Observation System

The observation system extracts player and ball motion data from video footage (Beetz et al., 2007; Gedikli et al., 2007; Beetz et al., 2006). For the acquisition of trajectories it is necessary to solve a complex probabilistic estimation problem consisting of subproblems interacting in subtle ways. One of these problems is the estimation of the camera parameters, such as the position of the camera related to the field as well as its pointing direction and zoom factor. Also, the detection of players in the video frames and of team affiliations need to be considered. Finally, the tracking of all players disambiguating them through occlusions needs to be solved by fusing the position estimates from different cameras and integration over time. To deal with all these problems, the observation system consists of two basic components, named the Vision module and the State Estimation module, as shown in Figure 2. The Vision module is in charge of the image processing and computer vision tasks, while the State Estimation module is used to estimate camera parameters and the position of each player.

Based on this functional description, the path followed by the data flow is as follows: The *Vision* module using the *Correspondence Finder* and *Player Detection* submodules, performs the estimation of the camera parameters, and, at the same time, the localization of the players for every image in the video stream. The *Correspondence Finder* uses the predicted camera parameters and player localizations to find line correspondences between the current and previous video frames, avoiding the unwanted effects of possible occlusions. These line correspondences are sent to the *Camera Parameter Estimation*, where a prediction of the camera parameters for the next frame is made. The *Player Detection* combines the predicted camera parameters, the player hypotheses, the results of a local spatial variance filter and a color template matching to deliver the player position measurements to the *Player Position Estimation*. The player positions and their uncertainties are projected to world coordinates. This information is used by the *Multiple Target Tracking* module to combine and associate the individual positions over time to consistent team configurations, and to predict a set of hypotheses required in the next frame.

The dashed box in fig. 2 indicates the parts of the observation system that are cloned for each camera.

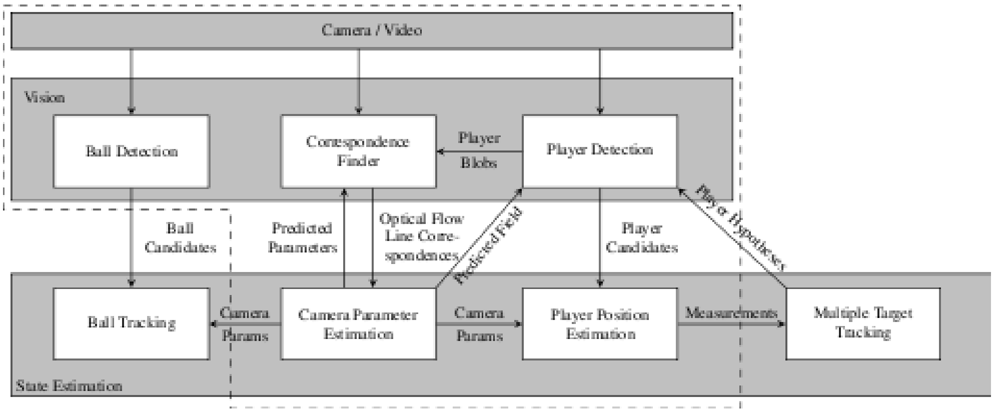

Figure 2. The observation system of MO.

Camera Parameter Estimation

The only sensors used by the ASPOGAMO system are rotating and zooming cameras. Since all measurements are done in the images taken by these cameras, the mapping characteristics of these cameras are required to transform measurements from image coordinates into measurements in real world coordinates. This mapping is mathematically described by the pinhole camera model with one radial distortion coefficient. This model has twelve free parameters, which have to be estimated by the *Camera Parameter Estimation* module.

Estimating all parameters for every frame is unreliable, inefficient and unnecessary, as most of these parameters stay constant during the whole game. Since the cameras are usually mounted on tripods around the field, they are fixed in their position, changing only their orientation and zoom factor to track the game. Considering these kind of camera configurations and making some reasonable assumptions, the camera parameters are split into two sets: the constant parameters, which stay constant during the whole game, e.g. the position of the camera, and the dynamic parameters, which have to be estimated successively for each frame (the tilt and pan angles for orientation and the focal length for zoom). This allows ASPOGAMO to estimate the constant parameters accurately from multiple views beforehand, while increasing the efficiency and robustness of the estimation of the dynamic parameters during the game.

Continious Camera Calibration

ASPOGAMO uses model-based localization for its estimation of the dynamic parameters, where the model describes the appearance and geometry of real world features on the field. The basic idea is to determine the parameters of the camera model that lead to the best fit between the image and the projected field model (see Figure 3). The quality of an estimate is determined from correspondences between model points and image points.

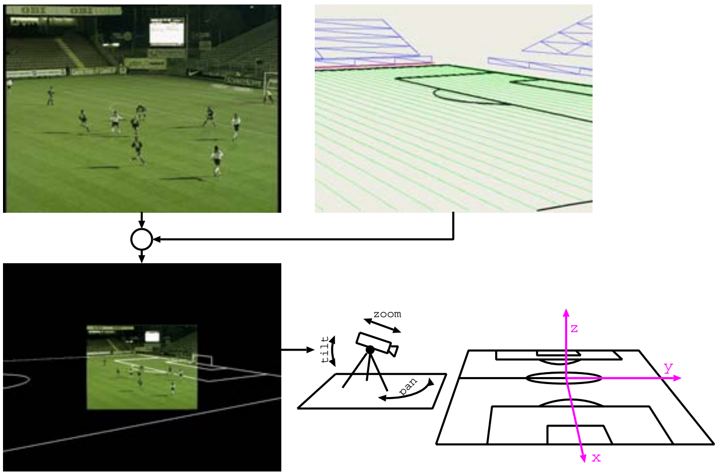

Figure 3. Model based estimation of dynamic camera parameters.

First, predicted camera parameters are used to project the field model onto the image (Figure 4 left). Then, correspondences between image points and model points are searched perpendicular to the corresponding model line (Figure 4 right). Finally, the optimal parameters are determined by minimizing the distances between model points and corresponding image points.

Since the estimation is done successively for each frame, it can be described as a tracking problem and is solved using the *Iterated Extended Kalman Filter* (IEKF) (Bar-Shalom & Fortmann, 1988). IEKF provides also the uncertainty of the estimated parameters as a covariance matrix, which is used to determine the search window for the next time step as well as to determine the uncertainties for the player positions.

Figure 4. Projected fieldmodel using predicted parameters (left), finding correspondences along the search lines (right).

Advanced image processing and probabilistic estimation techniques enable ASPOGAMO to reliably track the camera parameters even when confronted with inhomogeneous lighting conditions, image compression artifacts, fast camera motion, missing line features and noisy and sometimes wrong observations. These techniques are briefly described below.

To deal with blurry lines and edges, ASPOGAMO uses probabilistic color classes and characterizes lines as well as edges by color transitions. Image points corresponding to given model points are found by searching the color distribution along the search line that best fits the expected color transition. Additionally, the variances of the respective correspondences are heuristically estimated from the match.

Most outliers (wrong measurements) are caused by occlusions of field lines by players. Therefore, all correspondences lying within player regions are removed in a first step (See Figure 4 right).

Furthermore, ASPOGAMO uses a robust optimization method to suppress the impact of the remaining outliers to the final estimation. This is done by integrating the robust *M-Estimator* (Huber, 1981) into the MAP estimation of the Kalman Filter.
To obtain reliable estimates for sequences without sufficient field lines, ASPOGAMO uses the optical flow information between subsequent images to predict the camera parameters in the time update stage of the Kalman Filter. In a first step, the relative change in the parameters are obtained in a closed form solution from the homography, which itself is robustly determined by *RANSAC* (Fischler & Bolles, 1981), between both images. Then, this solution is used as an initial point for a non linear least squares estimation, where again the M-Estimators are used to suppress outliers in the measurements.
A monitoring process, using several low level features which complement each other, is used to detect when the estimation fails. In such a case, the estimation process is automatically reinitialized using detected field lines in the image. This however is only possible for images with a sufficient number of visible field lines (e.g. goal area).

Player Detection and Localization

In order to estimate the real player positions, the positions of the players in image coordinates are required along with the camera parameters. Every image in the sequence is processed in three steps: segmentation of regions, that possibly contain players, called blobs, the player localization inside these blobs and the mapping of the player positions in the image to real world coordinates on the field.
The blob segmentation exploits the homogeneity of the green grass field. The spatial variance of the intensity image is thresholded and the regions showing a high variance are assumed to contain the searched players. The threshold to classify the variance image into player blobs and field regions is selected adaptively based on a Maximum Likelihood approach.

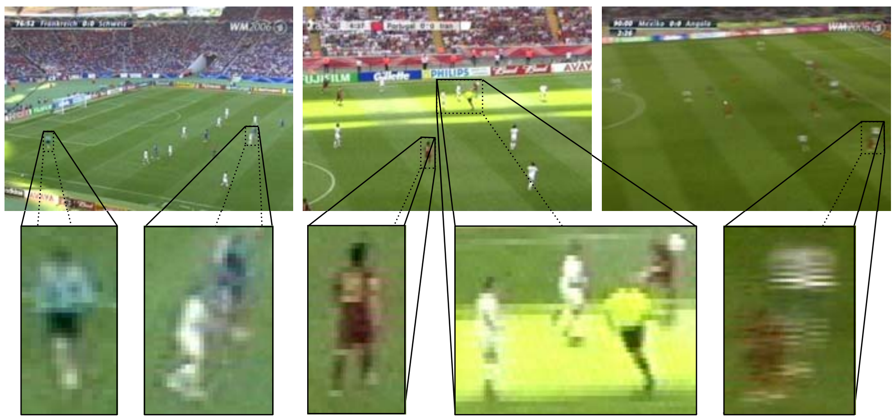

Figure 5. Hard scenes for the player segmentation: bad resolution due to the small player sizes and player occlusions (left), illumination changes due to strong shadows (middle), washed-out of the pixels due to camera motion blur (right).

The next step is to robustly locate the players inside the blobs. A color template matching procedure is applied, where color templates are generated for every different player type. The color template is formed by three sections, where the upper section represents the shirt, the middle the shorts and the bottom the socks of the player. Every section of the template is associated to one or more color classes, which are modeled as Gaussian distributions in the color space. To generate these color classes, some regions containing the most representative colors are selected beforehand from the input video. The system can also handle cases where one team is completely dressed in a uniform color or both teams share some colors between them. If occlusions between players appear, the template matching is supported by the

application of geometrical constraints. These geometrical constraints incorporate the expected player size and their shape.
Finally, the image positions of the players are projected to the field using the already estimated camera parameters. Additionally, the covariance matrix for each player position is propagated from the covariance matrices of the camera parameters and the template matching.
The player recognition is a very challenging task that is effectively tackled by the ASPOGAMO system. Our robust and accurate segmentation of the players accomplishes also small size of the players due to low image resolution, inherent player occlusions, overlapping color classes and blurry images caused by fast camera motion. To get a glimpse of the variety, some of the mentioned challenges are depicted in Figure 5.

Player Tracking

The detection of players is performed locally in every frame for each camera. The task of the *Tracker* module is to form consistent trajectories for all visible players independent from the current view. As there is only one real player configuration at a time, the information gathered in each single camera view has to be fused. In addition, integration over time contributes to consistency and therefore results in a better approximation.
We use a Rao-Blackwellized Resampling particle filter (RBRPF) for multiple target tracking of each single player identity (von Hoyningen-Huene & Beetz, 2009). This particle filter can handle similar appearances of players of the same team, frequent occlusions and false alarms by focusing on the data association problem of multiple target tracking. The RBRPF approximates the posterior over all complete player configurations. Single positions are represented as Gaussians forming a multi-modal posterior to take the uncertainty in the data association of players and detected measurements into account. New states are sampled with an importance density over the possible data associations and an analytical solution to find the optimal Gaussian for the given association and predicted state. Kalman filters deliver theoretically optimal sample distributions and its use refers to the Rao-Blackwellization of the filter. The sampling is based on the approach by (Särkkä et al., 2004; Särkkä et al., 2007), which presupposes either the independence of associations or the knowledge and fast computability of the dependency to make the computation of association probabilities tractable. We relax this assumption by sorting the associations of measurements of a sweep randomly. Only few associations are highly probable for each predicted state and, therefore, the algorithm can make use of memoization to increase performance. A constant velocity model approximates the dynamics of the athletes for prediction; the team affiliation is represented as a simple appearance model, that influences the sampling of associations. We assume clutter or false alarms to be distributed uniformly over the measurement area. Sampled states are weighted according to their fit to the measurements and dynamics and the posterior probability of their state of the former time step. Resampling replicates particles with a high probability by sampling more associations for them. The discreteness of associations allows the subsumption of equal states reduces the computation time for unambiguous player configurations and offers real-time performance in the first place.
The fusion of measurements of different camera perspectives reduces the probability of occlusions and increases the accuracy of the tracking result. It is done by incorporating every measurement sweep sequentially, which is computationally equal to the parallel case. The player detections of each camera produced asynchronously by several independent modules are synchronized to feed the Tracker with the correct sequence of measurement sweeps.

Ball Tracking

In any ball game like soccer, the ball is invariably the focus of attention. Images showing the ball paths have become indispensable for analyzing scenes since they tell about the tactical situation on the field. In ASPOGAMO the tracking of the ball is implemented in every frame for each camera following the particle filter framework (Arulampalam et al., 2002). Particles stand for hypothetical ball states including position, velocity and acceleration in real world coordinates. Every frame, their current state is updated according to the ball dynamics supposing a constant acceleration motion model. New particles are resampled according to their weights of the previous step. Using the known camera parameters, their position can be projected into each monocular camera image. Summation of color template matching in the original image and shape constraints in the variance image determine the new weight of the sampled particle. Since the ball is small in size and always moving, there always exist a motion blur in the color image while detecting the ball. To avoid this problem, the spatial variance of the intensity image is examined. If the ball is occluded by a player, its weight is set to a threshold value that is lower than the usual one exhibited by color and shape template matching. Of course, two cameras are needed at minimum to determine the 3D trajectory of the ball.

Model for Football Games

The outcome of the observation system is a set of ball and player trajectories, that has limited ability for direct inspection because already for a short time period the data set gets too complex to be displayed in a single picture (see Figure 6). Therefore, the raw data have to be reduced or abstracted according to the analysis tasks. A model denotes such a set of abstractions and transformations of data.

The Model Hierarchy

We use a hierarchical structure for our model (Beetz et al., 2004c; Beetz et al., 2004b; Beetz et al., 2004a; Beetz et al., 2005) (see Figure 7) allowing for a bottom up development of model levels. Each level builds concepts upon lower level concepts providing a big range of different model abstraction levels.

The most basic layer of the model, the motion model (Beetz et al., 2004b), represents the positions and motions of the players and the ball. This level can be generated automatically from the position data created by the observation system. The data is stored in a compact and structured way to ease subsequent interpretation and analysis of position information. To achieve this, the continuous motions are segmented into curve segments that can be approximated with a specified accuracy by simple curve functions. The position and motion data do not only build the basis for subsequent building of higher level concepts but already allow for interesting analysis, e.g. static or dynamic heat maps representing the distributions of player positions or velocity profiles of players giving hints on the physical strain of players.

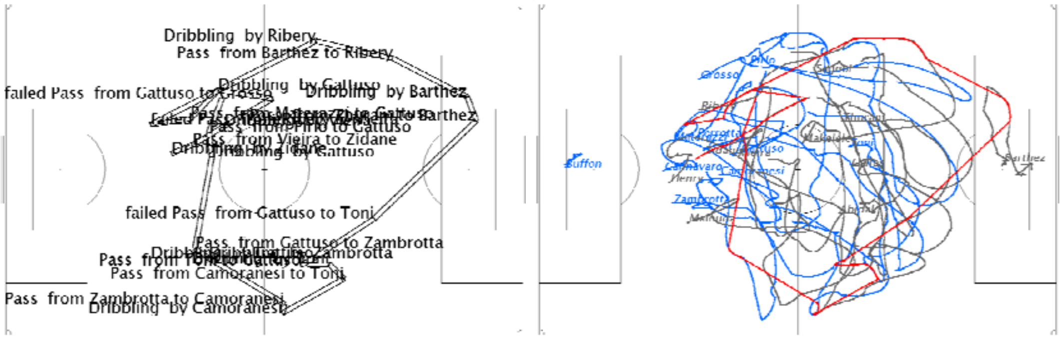

Figure 6. Complexity of trajectories for all players and the ball with corresponding ball actions belonging to only 34 seconds within the World Cup final 2006.

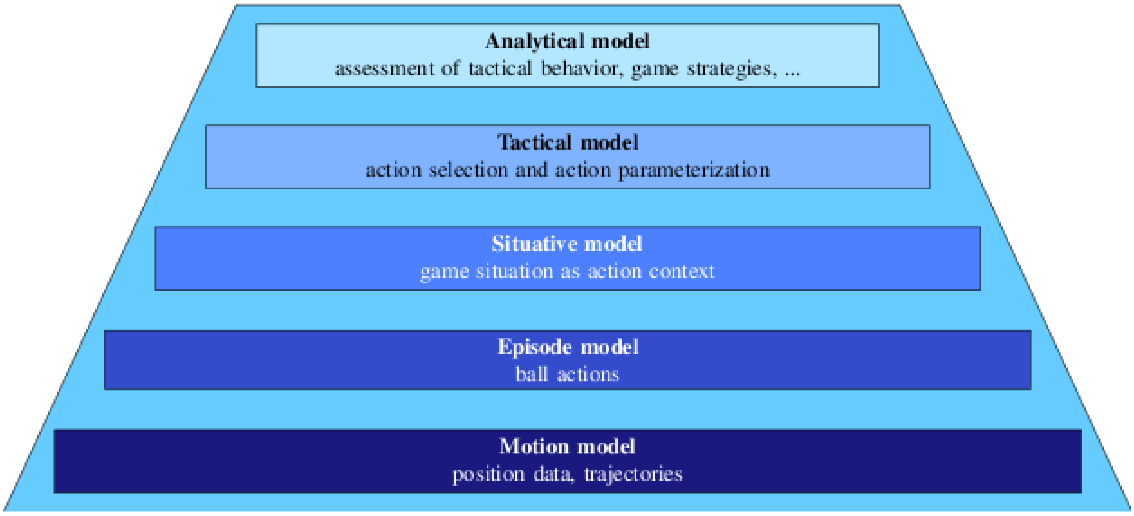

Figure 7. ASPOGAMO model hierarchy.

At the second level of our model hierarchy, ball actions are represented. From the motions of the players and the ball, the system identifies ball contacts as accelerations of the ball caused by a contact with a player. The ball contacts are classified into different categories like pass or shot with sub-categories such as a center or a through ball. This model allows for an analysis of actions, their frequencies and their a priori success rate. Possible analyses include passing dyad or pass success rates of players.

The concept *situation* can be viewed as a snapshot of the game. On the situative level, all features such as player and ball positions as well as their interactions are represented at a specific time stamp. Considering the spatial constellation of passing opportunities, properties such as whether or not a player is being marked or is being attacked are modeled on this layer.

Based on the situation concept, tactical set-ups can be defined on the tactical layer. These include typical action selection criteria of players, action parameterizations or tactical activities.

Finally the analytical level is comprised of assessment models for situations and tactical behaviors as well as the identification of typical attack and defense systems.

The concepts and the relationships between them are stated in form of an ontology allowing an automatic reasoning about them. The ontology has a human readable as well as a parsable interface and constitutes the domain knowledge as well as facts of the seen games.

Visualizations

An abstraction of data can also be done visually, exploiting the advanced visual cognitive abilities of humans. Position information about the players can, for example, be abstracted into heat maps (Figure 8) that represent the probability distribution over player positions on the field. The tactical line-up and positional structure inside a team is made visible by depicting a 11x11 grid which is colored according to the most frequent player label for relative player indices.

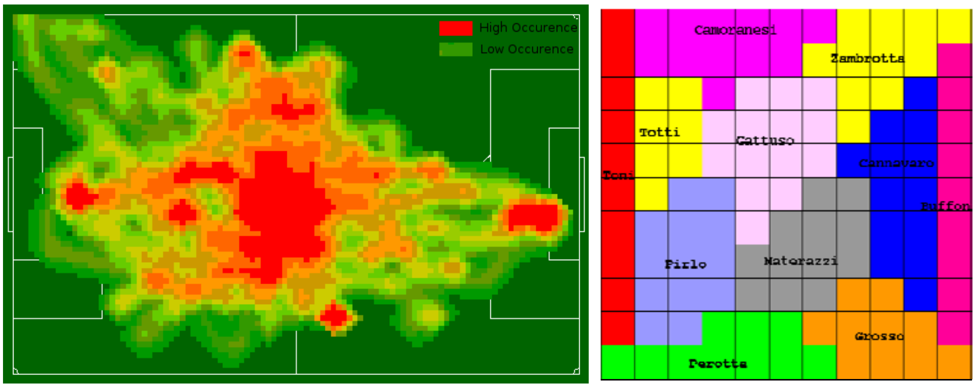

Figure 8. Heat map visualization for Zidane and a grid determining the tactical line-up of the Italian team.

While these visualizations are a big achievement themselves, they are limited to a specific context and new ones are not easily developed without creativity. The visualizations rely on a specific relationship between the data that they depict. The ASPOGAMO system incorporates all data in an ontology providing a convenient way to describe the context needed for a specific visualization. The applicability to specific data subsets or transformations can be deduced automatically by their ontological tags.

Model Acquisition

The central part of our analysis system is the acquisition of an informative model of the observed football game (Beetz et al., 2004a) by applying statistical learning to a number of games resulting in a model of football games in general. This model provides a high abstraction level to view the game as a whole but also allows to perform detailed analysis for special aspects of the game. The system adapts the model automatically, when data for a new game are available.

Our model is divided into two parts: A static part that is not dependent on a specific game or class of games, and a dynamic part that has to be adapted for the context it is used in.

The static part contains concrete definitions of the individual model layers that are independent of a specific game or game class. This part can be specified once for all football games and applied to all games in the same way. It contains general rules and classifications like the offside law, what a successful shot is or the number of allowed substitutions.

The dynamic part consists of concepts that relate to the same definition but different specifications. For example the concept of scoring opportunity has a well defined meaning, but depends on the quality of the involved teams. A given situation would be a scoring opportunity e.g. for a World Cup player, because he would always score, but could not be classified as such for another one (e.g. a junior player). So some (unfortunately most) parts of the model have to be specific to the game, to the teams or to the players and therefore have to be specified relative to their context. We solve this problem by enabling our system to learn the dynamic part from observed games automatically by machine learning techniques given the abstract meaning that is consistent through all contexts (von Hoyningen-Huene et al., 2007).

As an example we examine the episode model of our model hierarchy. We can easily specify statically, that a successful pass denotes a ball contact of one player of a team followed by a ball contact of another player of the same team. For unsuccessful passes however, the definition is very hard to specify in a general way. But we can state that the characteristics of unsuccessful passes should be similar to passes regarding the velocity of the ball, the direction, the ball was played in, or the positions of team mates and of opponents. This definition holds for all games even if the attributes are highly correlated with the abilities of the players and, therefore, depends on the league or competition, in which the specific game took place. Transforming this static definition into a data mining task, the system can learn rules for each league that specify which ball actions should be considered as passes and which ones rather as shots. Taking the known set of successful passes, shots and dribblings as training data, a decision tree (Quinlan, 1993) or respectively a regression tree (Witten & Frank, 2005) is learned automatically for each binary classification (pass or no pass, shot or no shot, dribbling or no dribbling). The tree is split into several rules by logical disjunction of the nodes on all possible paths beginning at the root and ending at a leaf. The abstraction comes into play by the pruning of the tree that is a part of the learning algorithm to avoid overfitting. The rules are transformed to descriptions in the ontology and in this way they are integrated into the knowledge base. The description (consisting of the rules) as well as the concept itself (referring to the classification of instances) can be inspected transparently.

There exists also a second class of definitions that contain a dynamic part. Most of the continuous attributes of actions in team sports are discretized into classes like slow, normal and fast or short to far. This is usually done by simple thresholding at predefined ranges. If we look closely to these kinds of concepts, the sensitiveness to their context becomes evident. The velocity of a fast sprint in a international competition obviously differs from values for a burst of speed in the minor league. Still, there is a common definition that partitions the usual velocity range in a predefined number of parts, naming the part with the highest velocities as fast. Partitioning is achieved by data mining techniques called clustering (MacKay, 2003) which iteratively find a locally optimal subdivision. Also a smooth fragmentation can be achieved automatically by using probabilistic assignment to clusters obtained by fuzzy clustering (MacKay, 2003). The partition and the naming of each part is again transformed into descriptions in the ontology to provide a seamless interface.

All these models, the static and dynamic ones, are accessible to the system due to their integration into the ontology. Their definition and semantics can be inspected and analyzed by the user resulting in more alternatives to analyze a football game and attaining more objectivity from the transparency of the models. For example, the user can retrieve the scoring opportunities of the teams and then analyze how they might arise by interpreting the generated rules for the concept. A concept for all situations, in which the ball was lost, could be stated and from the resulting rules, some reasons for the failed ball action may be derived. Clustering the situations, in which the ball was lost, can help in gaining insights, how the opponent team forced the loss of ball possession, etc.

Example of Analysis

In our soccer ontology each pass is assigned to a set of attributes including its length (short, middle, long), speed (fast, middle, slow), direction (forward, cross, back), and risk (risky, safe). Although their definitions contain already dynamic parts, they build the base of further analysis. We present three different kinds of analyses inspecting the passes in the final game (Italy vs. France) of the FIFA soccer world championship 2006.

Defensive pass classes

Instead of examining statistics over all attributes and obtaining a multi-dimensional distribution, the analyzer can ask, "What are the four most typical classes of passes played by defenders?". Therefore, he introduces new concepts to the system that partition all passes of defenders of one team and are named $p_{1,}^{I}\cdots p_{4}^{I}$ for Italy and $p_{1,}^{F}\cdots, p_{4}^{F}$ for France. The subfigures of fig. 9 visualize these new concepts. The four classes for the Italian defenders are the long cross passes, the medium length forward passes, the very long forward passes and the fast forward passes. For the French team, on the other hand, these passes are the long or fast passes not played back, the passes not played long with medium velocity, the slow passes and the fast or medium velocity back passes.
Comparing these two sets of classes, one can see, that, while the Italian team prefers cross passes in the backfield (a) and tries to play long passes to the right wing player, the French team aims at passing to the outside (f) and often plays the ball back to the goalkeeper if there are no suitable pass receivers (h). One can also see that different types of passes are spatially local.

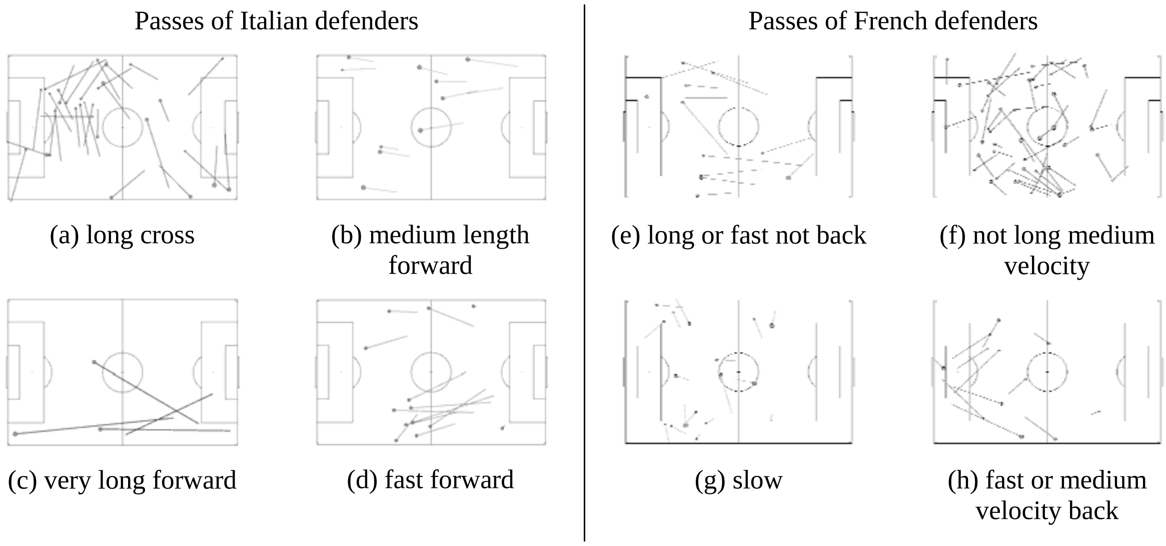

Figure 9. Typical pass types of defensive players of the Italian (a)–(d) and French (e)–(h) team during the World Cup Final 2006. One can see that the passing game of both teams can be characterized using different classes of passes that are typical for the respective teams.

We can also include positional and situational features as well as the roles of the playing and receiving players. With this information, one can analyze the individual classes of the whole Italian team in greater detail, automatically creating descriptions of the classes.

Descriptions of subsets of passes

An example of a more abstract analysis examines the typical passing behavior of a team. We will now describe how this is performed and how it relates the different layers of the model. First, a specific subclass of passes is selected from the episode model by the user, for example, all passes of the Italian team. Next, these passes are partitioned on the situation model layer. This is achieved by an automatic clustering of spatial and situational features, that are computed for the start and end situations of the passes. The automatic clustering delivers regions that need not be specified beforehand but are generated adaptively for existing structure in the data. In our example five clusters were found automatically and can be inspected in Figure 10.

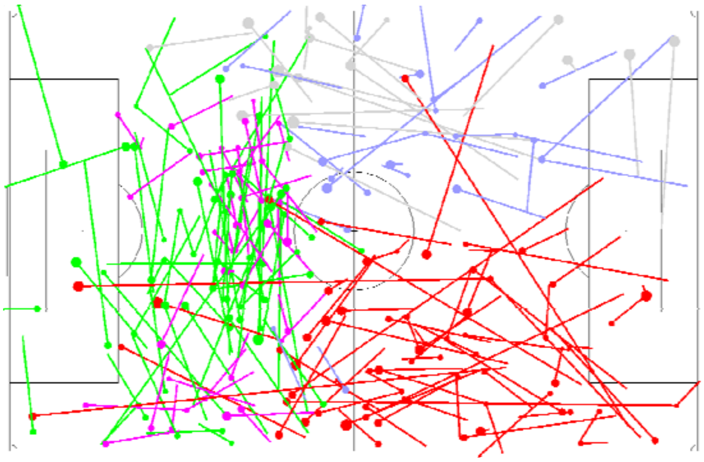

Figure 10. Clusters for the Italian team's passes.

In the next step of the analysis, the system automatically creates several alternative descriptions for the partitions previously found. This is done as follows: first, different non-overlapping feature sets are selected. Decision trees that discriminate between an individual cluster and the rest of the specified passes are learned. All paths to nodes labeled with the same cluster are combined by con- and disjunctions, transforming the decision tree to a rule. This rule constitutes a description of the cluster in terms of the given features. By the use of spatial features only, we get rules that discriminate the clusters spatially and, therefore, form a spatial description of each cluster. In our example, extracted with the x coordinate x_s of the starting and the y coordinate y_e of the final situation of a pass as features, cluster 3 can be described as all passes fulfilling $x_s > -8.52\text{m} \wedge y_e > -0.3\text{m}$, the passes from the French half of the field (reaching 8.5m into the Italian one) to the right side (see Figure 11b) with an accuracy of more than 95%.

These descriptions are sorted by a quality measure derived from the complexity of the rule as well as the accuracy of the description. The accuracy is computed as the ratio of the number of entities that belong to both, the cluster and the describing rule, and the number of entities that belong to at least one of them. Descriptions with high quality measure are presented as alias to the clusters, e.g. the cluster depicted in Figure 11a is described as long cross passes.

Comparing different descriptions

A possible subset of the discarded descriptions still contains interesting information. Short rules that represent sub- or supersets of the cluster are presented as asymmetric descriptions to the user, too. In our running example, the rule $x_e > -3.87\text{m} \wedge y_s > -5.72\text{m}$ (the passes to the front from the right side of the field) defines a subset of the cluster depicted in Figure 11b, again with about 95% accuracy. So, we have the following two simple descriptions that are strongly correlated:

- Firstly the cluster is described as the passes from the right side of the field to the opponent's (front) half (The area is not exactly one half of the field but a partition close to it created by the system from the data) and
- secondly it contains all passes from the front half to the right side of the field.

From these descriptions, the system creates the following rule comparing the different descriptions:

$$x_e > -3.87\text{m} \wedge y_s > -5.72\text{m} \Rightarrow y_e > -0.30m \wedge x_s > -8.52m$$

In other words, the passes from the right side of the field to the front are played from the front to the right.

The consequences of this rule and the propositions following from it are not immediately obvious, because the start and end positions of the passes are intermixed. For an easier interpretation, we group them together to form two rules that state that

- passes from the left front area of the field are not played to the right side of the field and
- passes to the right back area of the field are not played from the front of the field.

Whereas the second rule is a rule that is fairly usual for football games, the first one, the lack of cross passes from the front left side of the field to the right side, is again a specialty of the Italian play.

The two clusters examined in this example make up about one third of all passes played by the Italian team each. So, these two clusters, the extracted rules and their interpretation should give a fairly good insight into the passing behavior and its characterization.

Conclusions

In this article we have presented ASPOGAMO, a new generation of sports game analysis models. Trajectories of the ball and the players extracted from video by our state-of-the-art camera-based observation subsystem build the base of these models. Semantics of higher levels of abstraction are automatically grounded by adapting static concept definitions to the appropriate context of the observed game using statistical learning methods. The automatic and transparent acquisition of high-level facts provides objectiveness and comparability. Games can be analyzed in an explorative and objective way, gathering meaningful sub-categories of concepts and propositions specific for the game that is inspected. ASPOGAMO will provide new opportunities for sport scientists to analyze sports games, support scouts in inferring the strengths and weaknesses of the players and help coaches in the strategical planning and tactical decision making processes. To demonstrate the possibilities of automated sports game models, we provided some exemplar of analysis for the final of the soccer world championship 2006.

For further improvements we will investigate the way of defining new concepts for sport scientists, which can be stated clearly and naturally, but still ensures objectivity and the ability for automated processing. We will examine the scalability of our approach to huge data sets providing a richer source for analysis, but also making high demands on memory and performance requirements of the used algorithms.

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Analysis and Simulation of Actions in Games by Means of Special Self-Organizing Maps

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Abstract

Meanwhile, not a lack of data is the bottle neck of computer based game analysis but – quite the contrary – the huge amount of them: Data can be recorded automatically in high space and time resolution, resulting in a high percentage of irrelevant data hiding the real information. Trainers are experienced in filtering the most meaningful patterns out of those lots of data but then often miss methods or tools for further systematic analyses. The Neural Network-approach follows the trainers' way of pattern recognition, combining it with computer based methods of complex pattern analysis. The contribution demonstrates exemplarily how it works: In a pre-processing the players' positions are grouped to constellations, e.g. representing offence and defence groups. After the net training, the neurons of the net correspond to typical constellation, and trajectories of the neurons represent time-depending processes of the game. The trajectories themselves are then taken as objects of a second level net based analysis, where, by semantic calibration, types of trajectories are mapped to tactical activities – e.g. short or long attacks on the right or the left side. Finally, as an outlook, the second level network not only represents the given tactical dynamics of the game but can be taken for simulating new ones: Instead of just watching, which neuron is activated by a current tactical activity, an alternate neuron can be selected and fed into a game simulator to see what happens if tactics is changed temporarily.

KEYWORDS: GAME, PROCESS, NEURONAL NETWORK, PATTERN ANALYSIS

Introduction

The contribution deals with a project the aims of which are to classify action processes in soccer by means of neural networks and to check the identified process types with regard to their effectiveness in the context of interaction. In particular, those activities shall be recognized, which indicate creativity – i.e. activities, which are original as well as adequate solutions of the regarding situation.
The first part of the contribution presents ideas how to model action processes in games and how to abstract them to characteristic types. By means of an example from basketball – which is easier to present and explain – the major problems and possible solutions are discussed. The second and the third part mainly discuss three questions: How can action processes (e.g., decision-making, creative solutions) be evaluated? What could be a way for

recognizing creative activities? How can simulation be used for prognostic checks of the effectiveness of those processes?

We are aware of the fact, of course, that we can only present first steps and cannot answer all those questions satisfyingly at the moment. However, the first results show that there is a good chance of cracking the bottle-neck problem of game recording and analysis by means of position-based net-analysis.

The data-basis of the investigation is given by the player and ball positions of the Soccer World Championship final from 2006, France vs. Italy. They also build the data scope for the intended creativity analysis. In the following, the methodical approaches of the project and first exemplary results are presented.

Process analysis in games

Positions and tactical constellations in soccer

The main bottleneck in the area of process analysis – in motion analysis as well as in game analysis – is the recording and interpretation of data. Meanwhile, automatic recording of motion data can be said to be standard, while this unfortunately is not the case with game data. However, up to date developments at least enable for automatic recording position data of players and ball, which help a lot for reconstruction of behavioural structures like tactical patterns. Figure 1 presents an interactive program for representing a soccer game. Players of interest can be activated arbitrarily, thereby enabling the visualisation of particular interactive groups like offence and defence.

Figure 1: Interactive program for representing positions in soccer.

The resulting constellations – i.e. collections of the player positions of such groups – form specific data profiles, which can be used for training neural networks, as will be discussed in the second part. The result then is a neural network, the neurons of which represent the

constellations. Finally, those constellations or specific sequences of them can be matched to categories of situations or tactical units from a soccer category system (see Leser, 2006; Grunz, Hillebrand, Memmert, Perl & Schmidt, 2008).
The following section is meant to make plain how those ideas can get to work. By means of the example of free shots in basketball it is demonstrated, how a motion process can be mapped to a neural network and what kinds and levels of net-based analyses are possible.

Net-based process analysis

A main aspect of process analysis in sport is the analysis of time series of positions, constellations, or tactical patterns in games or of positions, angles, or speed of articulations and limbs in motions. Characteristic properties of such analyses are the complexity and the dynamics of the data, which make it at least difficult to use conventional methods like mathematic-statistical approaches for the respective pattern analyses. In turn, experiences with self-organizing maps (SOM, KFM, DyCoN, see Perl, 2001, 2002, 2008) prove that they can reduce complexity without reducing contained information and dynamics as well.
Through the net training, data sets are generated on the (normally about 400) neurons of the net, each representing one type of process step. The attribute values of those data sets represent the components of the corresponding process step. Neighboured neurons can build clusters of similar types.
If the time series of successive data-sets of a process is mapped to the corresponding neurons of the net, and if the neurons are connected by edges in the respective succession then the result is a 2-dimensional simplified mapping of the process. Finally, this 2-dimensional trajectory can be reduced to a 1-dimensional phase diagram. This is done by matching the phase-representing clusters with a semantic scale, which allows for replacing the neurons by the respectively corresponding semantic phase. In Figure 2 colours are used in order to encode the phases and simplify the representation.

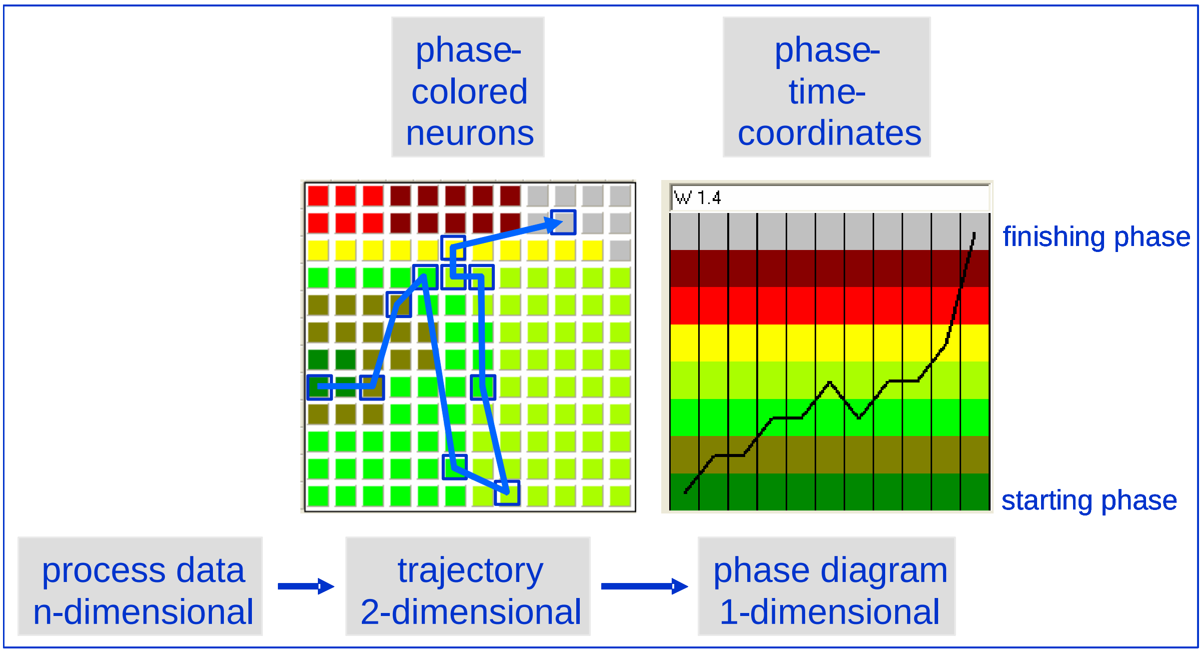

Figure 2: Colour-encoded semantic clusters with process-trajectory (left) and corresponding phase-diagram (right). Both, the trajectory and the phase diagram, represent a basketball free shot.

The following example from basketball free shots (see Figure 2 and 3), which is taken from a PhD-Project of Andrea Schmidt, University of Bremen, demonstrates the advantages of the phase diagram approach with regard to process analysis.

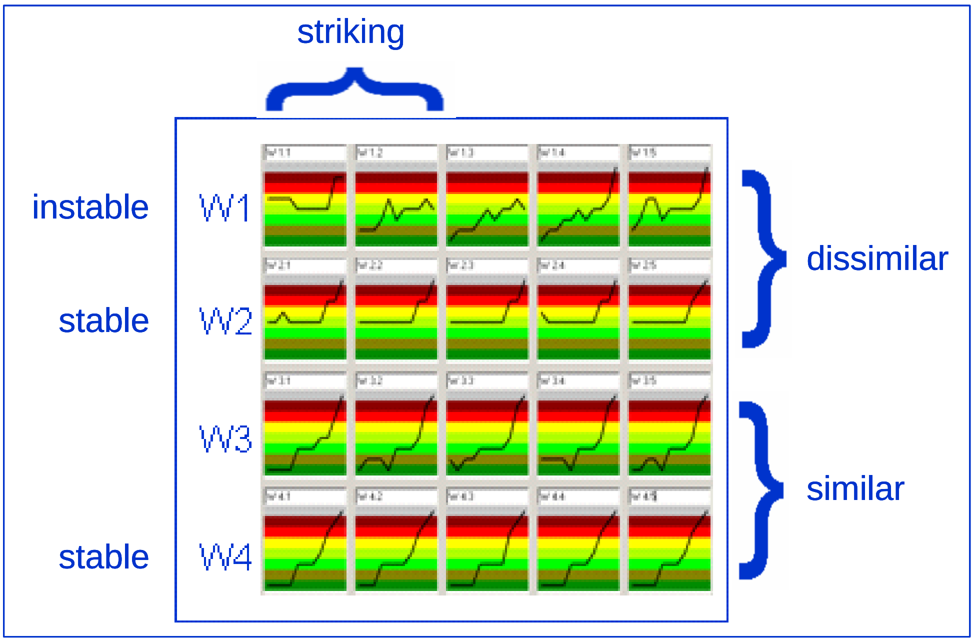

Figure 3: Phase diagrams of 5 free shots of 4 players W1, W2, W3, and W4.

Figure 3 shows the phase diagrams of 5 free shots of 4 selected players. The shots are given as time series with 6 angle data and 6 angle speed data for each of the 11 equidistant points in time. The colour scale represents the standard shot process from the start phase (dark green) to the final phase (brown). Therefore, diagram courses from bottom left to top right are to be expected, as are shown by W3 and W4, while the courses of W2 are unexpected and striking. Moreover, there are differences regarding inter-individual similarity and intra-individual stability: The shot types of W3 and W4 are quite similar to each other but different to those of W1 and W2, which are different from each other, too. Also, the shots of W1 are rather unstable compared to those of the other players (see Memmert & Perl, 2009).

On the basis of phase diagrams, such striking feature analyses also can be done and have been done automatically by means of neural networks on a second level: To this aim, the sequences of phase colours, which encode the shots, are replaced by the sequences of phase numbers, which then can be taken for training a shot net. Each neuron of such a shot net corresponds to a type of shot, and therefore a trajectory on the shot net represent a time series of shots like those from Figure 3.

Again, the neurons can be coloured semantically and so enable for automatically recognizing for example same or similar types, rareness, or quality. Finally, with the assumption of 'creativity = originality + adequateness = rareness + high quality' - which of course is just a way of quantifying the term 'creativity' that has to be discussed very thoroughly (see Memmert & Perl, 2009) - this approach can support automatic detection of those activities, which meet the given definition of 'creativity'.

Project Soccer: Net-based process analysis in games

In the following, the procedure described for basketball free shots is transferred to soccer. Obviously, things in soccer are much more complicated. Therefore it is necessary to explain the approach and the necessary procedures step by step.

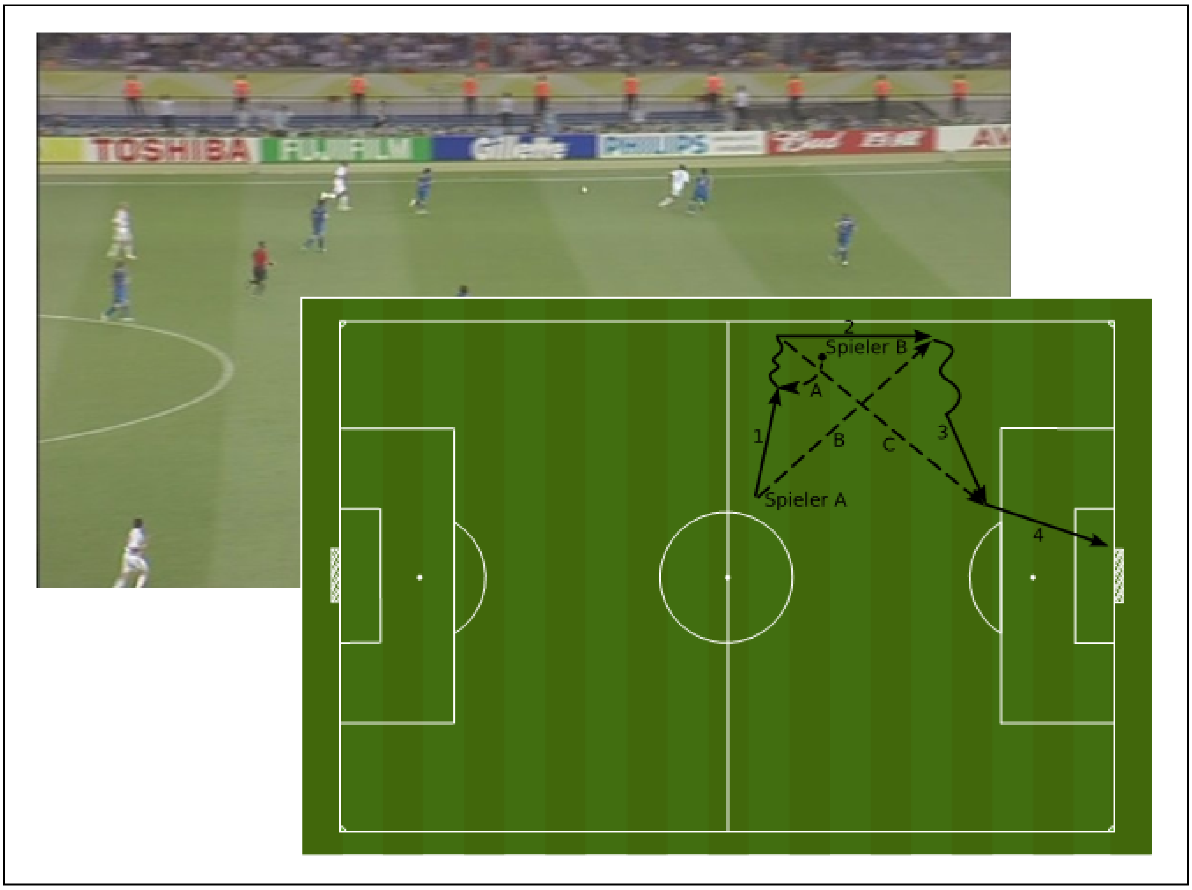

Figure 4: A frame of a video sequence showing a wing play together with a schematic sketch of that type of action, as is used by trainers in order to explain tactical patterns ('Spieler' means 'player').

Assume the following situation: The video sequence of the game shows a wing play (see Figure 4, top left). The positions of the involved players and the type or category of the action can be recorded and stored to a data base by means of an appropriate software tool. A graphical representation of the situation can be given schematically using the recorded player positions (see Figure 4, bottom right).

This example of wing play, of course, is just one way to do it. Figure 5 gives some more examples of wing plays, where not the orientation (left, right, front back) is meaningful but the different constellations and the players' moving. Therefore several patterns of wing play can be distinct, which gives reason for training a neural network with those patterns, using the recorded position data of the corresponding player constellations.

A first problem arises with the number of involved players. The example in the bottom left corner of Figure 5 contains 3 players while the other examples contain only two players. Encoding such constellations by 2 coordinates per player and three coordinates for the ball, the bottom left example needs a data vector of length 9, while the other examples need those of lengths 7. A neural network, however, has a fixed dimension – either 9 or 7 – and therefore cannot be trained with a mix of 9- and 7-dimensional data vectors.

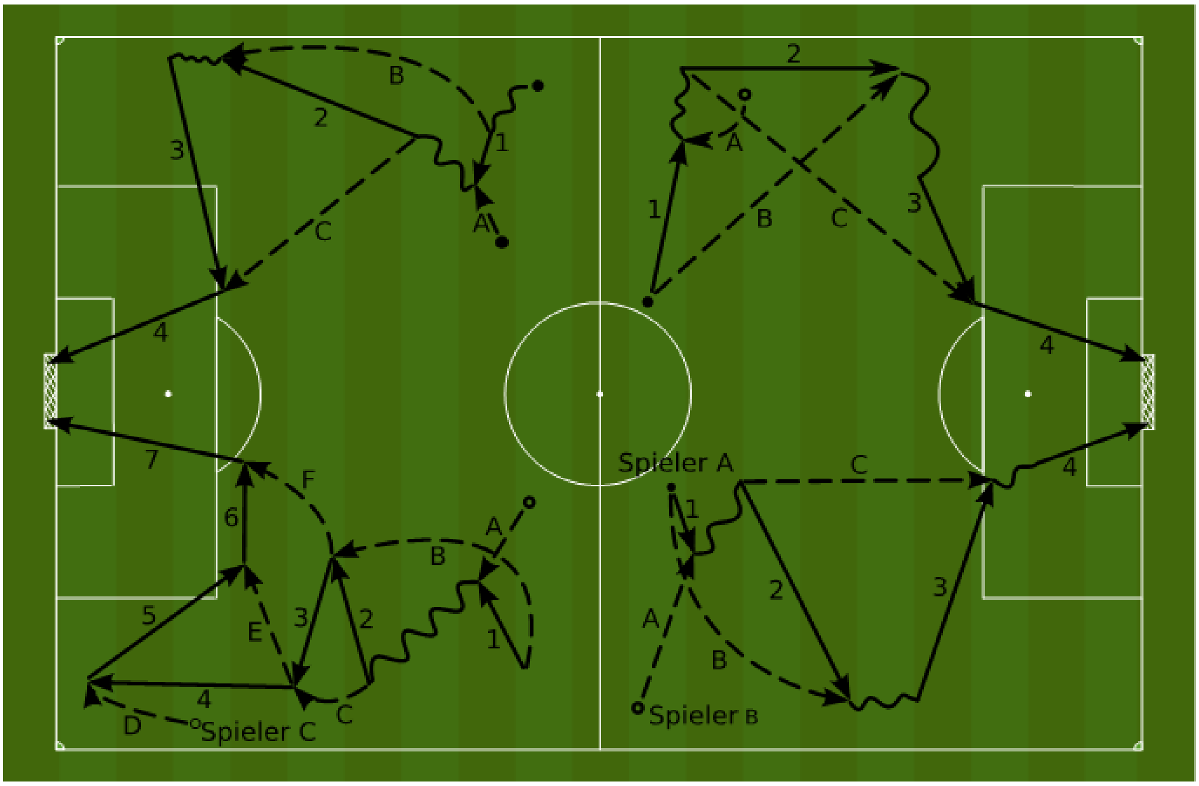

Figure 5: Some variations of the wing play example from Figure 4 (top right), representing different patterns of motion and interaction ('Spieler' means 'player').

One solution could be to train different networks, depending on the respective number of involved players. Another solution that we prefer at the moment is to focus on fixed groups with a constant number of players, representing offence or defence formations, and the members of which are more or less continuously involved in particular constellations or action types.

A second problem is the resolution of the network: In a conventional KFM the topologic distribution of the neurons is constant. This means that, depending on the training strategy, a type with a high number of variations needs much more neurons for being represented adequately than one with a small number. In turn, however, this can result in wrongly dominated areas of action types with high frequencies but only little stochastic variations.

One way to deal with is the approach of GNG (Growing Neural Gas, see Fritzke, 1995), which has a flexible neuron topology and allows for dynamically adjusting the number of neurons to the necessary resolution: A GNG starts with only 2 neurons and generates further neurons on demand – i.e. if, during the training, the deviation between original information and corresponding neuron information becomes relevant with respect to a given threshold. Therefore, different from a KFM, a GNG can dynamically adapt to inhomogeneous resolutions or time-dependent changes of information landscapes.

Figure 6 shows an example of a 2-dimensional projection of GNG with areas of different neuron densities. However, the advantage of the GNG approach, namely its dynamic extensibility, on the other side effects an absence of a fixed topological structure, which is a crucial point in case of presenting clusters or other similarity-connected areas of a GNG. This is the reason why here only 2-dimensional projections can be shown. In the current soccer project it therefore is intended to transfer the idea of dynamical adjustment of neuron numbers to the conventional KFM approach.

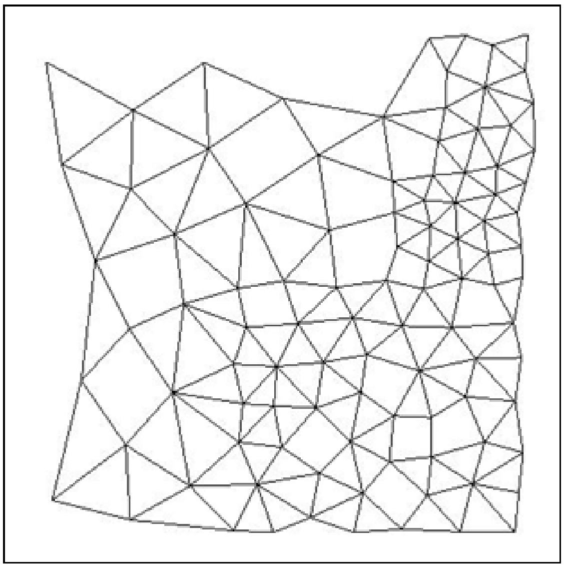

Figure 6: 2-dimensional projection of a Growing Neural Gas with areas of high density (top right), low density (left) and medium density (bottom right).

After having been trained, the net can show the trajectories of action or motion patterns of the respective groups (cf. Figure 7), which can be tactical groups like offence or defence as well as single players or even the whole team. Again, as has been described in the case of basketball free shots, such trajectories can be trained to a second level network, where the neurons correspond to action or tactical patterns like wing play. The result is that a neuron cluster of the second level network represents the different variations of such a pattern.
There are, however, again some problems the most important of which is the number of available data: Supposed, a wing play lasts about only 10 seconds, and also supposed we have only about 6 of such interesting key patterns, each of those key patterns appears at most 90 times a game – which is much too little for a net training. Moreover, in the video material available for analysis some of those key patterns might be missed. The most promising way of handling this problem of available data is to generate them virtually by means of Monte Carlo. Experiences from other projects show that only a rather little number of data sets are necessary for generating training data if they are sufficiently characteristic for the basic pattern structure. This way, even schemes of a pattern like those from Figure 5 would be helpful for data generation.

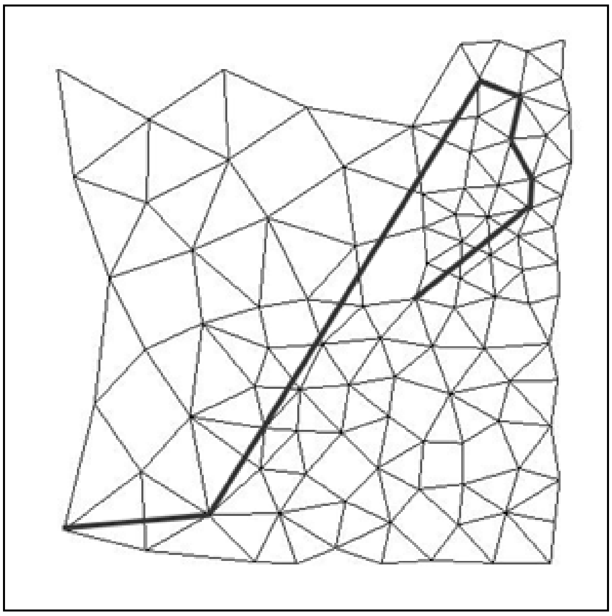

Figure 7: 2-dimensional projection of a Growing Neural Gas with a process trajectory.

A second major problem that can appear has been mentioned above: The sequences or trajectories normally are not of same length. Moreover, some of them might be too long for a reasonable second level net training, where the trajectory lengths define the dimension of the neurons – i.e. the number of attributes or components of the neuron data vectors.
Our experiences from volleyball, squash and table tennis are that the 'sliding window'-technique is the best way of handling this problem: A window of constant length is moved step by step along the trajectory, respectively cutting trajectory pieces of equal lengths, which uniforms the neuron dimension without loosing information.

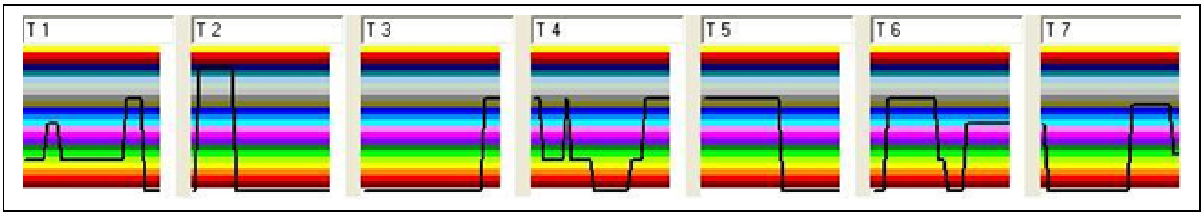

Figure 8: Successive phase diagrams covering 30 seconds each: The colours represent the activities like 'attack left' as phases through which the process – represented by the black line – is moving. In order to recognize the time-dependent process, the diagrams have to be read in their sequential order.

At this point, the situation from basketball free shots from Figure 2 is reached, where only the technical aspects of actions are replaced by tactical ones: Each window-defined trajectory piece corresponds to a neuron as well as to a tactical interpretation as a phase that has to be taken from the category system. Giving the neurons a phase-specific colouring then enables for mapping the action to a phase diagram. Figure 8 gives an example of a continuous sequence of phase diagrams representing tactical patterns of the regarding team.
Of course, this correspondence between neurons and semantics in the same way can be used for automatic generation of a position oriented game protocol as is shown in Figure 9: Following the positions of the selected players the software system from Figure 1 can recognize the player constellations, match them with the once calibrated semantic or tactical

meanings, synchronize it with the time axis and print it out as a time series of actions together with their specific durations.

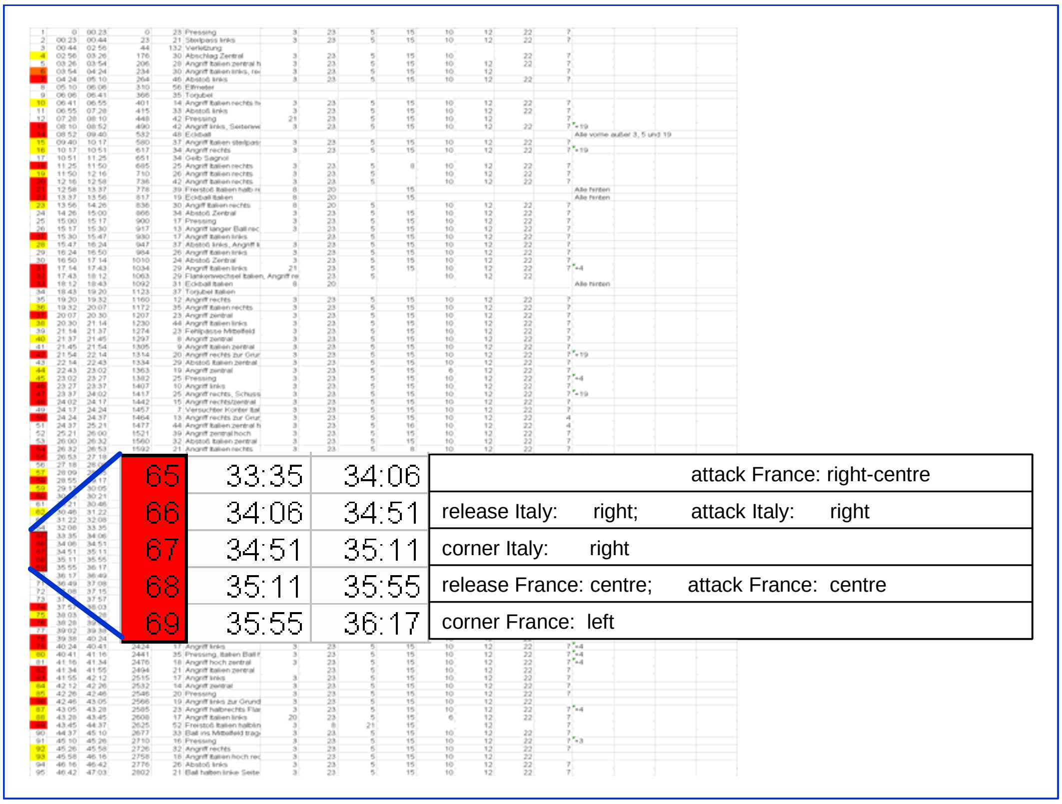

Figure 9: Example of a position-oriented game protocol that can be generated automatically on the basis of a semantically calibrated network.

The most interesting question now is: What can be learned about the interaction of the opponent teams? A first step of those analyses is to compare the tactical patterns of opponent groups like the offence group of team A and the defence group of team B. To this aim, the specific activities of both teams have to be trained to specific nets, respectively. This means: If the team is roughly separated into one offence and one defence groups, 4 nets are needed to describe the actions of each group of each team, which then build the basis for the analysis of interaction patterns.

Figure 10 shows an example for the correspondence of French offence activities and Italian defence activities in the World Cup final in 2006. In order to make the interactive 'rhythms' more obvious, the diagrams are reduced to the parts which the processes run through.

The respective top lines show the time intervals, and the text boxes in the middle show the semantic interpretations that can be taken from the automatically generated protocol.

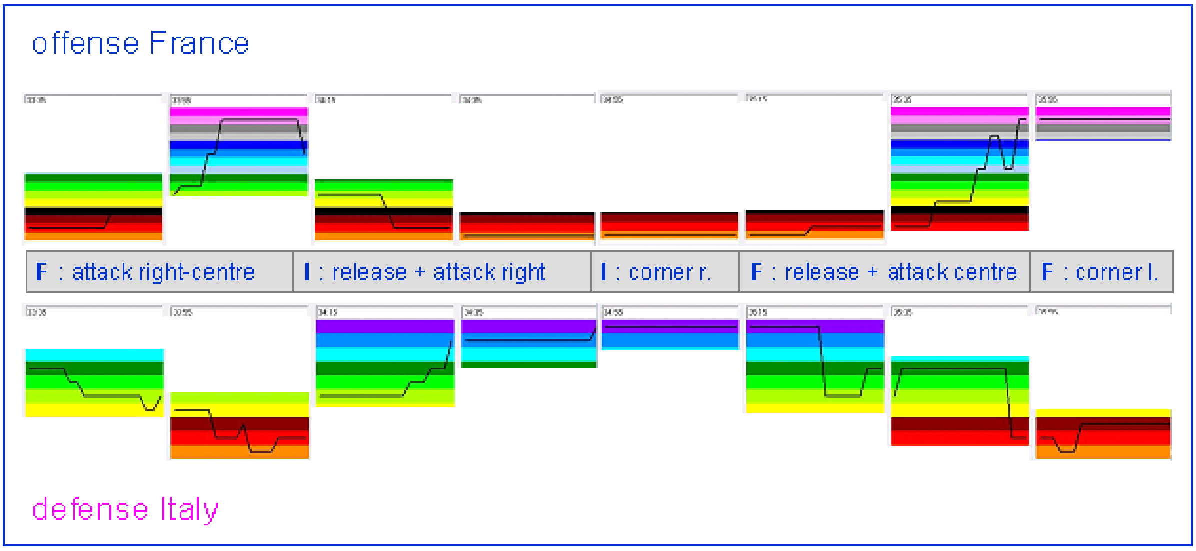

Figure 10: Synchronous phase diagrams of French offence (above) and Italian defence (below): The respective diagrams show offence activities in the upper half and defence activities in the lower half. The black lines represent the processes from France and Italy, respectively, showing the rhythm of offence-defence-interaction which where detected from the underlying networks automatically (also compare Figure 9).

Taking the corresponding phase diagrams from both teams together with the regarding ball positions enables for training a further net with that interaction information, as is shown in Figure 11:

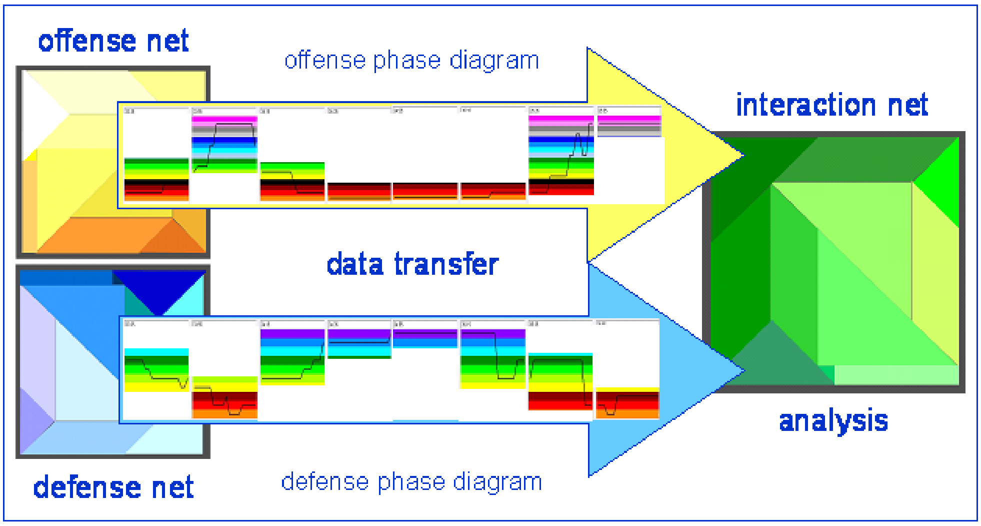

Figure 11: Interaction net, trained with offence and defence information of the opponent teams: In continuation of the approach from Figure 10, the information from the separately trained networks can be combined and fed to an interaction network. Such an interaction network is able to detect and specify types of interaction. With such a net interactions can be classified – i.e. under the aspects of advantage or success of the one or the other team.

This way, it not only seems to be possible to recognize specific tactical behaviour but also to support recognition and evaluation of weak and strong actions, as is discussed in the closing outlook.

Outlook: Measuring, creativity, and simulation

Measuring

One central aspect of game analysis is to quantify the complex qualitative information. Normally, the focus of such quantification is on frequencies and success of actions. If once the position-oriented tactical patterns can be recognized by means of a correspondingly trained network it is no problem to automatically count transitions between such patterns with respect to the corresponding actions. This leads to a matrix of transition probabilities as is shown in Figure 12, matrix top-right.

If, moreover, the corresponding trajectory network is calibrated regarding the success of the represented process, a second matrix can be generated representing the success of those transitions, as is shown in Figure 12, matrix bottom-right. Not least, the probabilities of transitions and their success help for simulating games, as is discussed below.

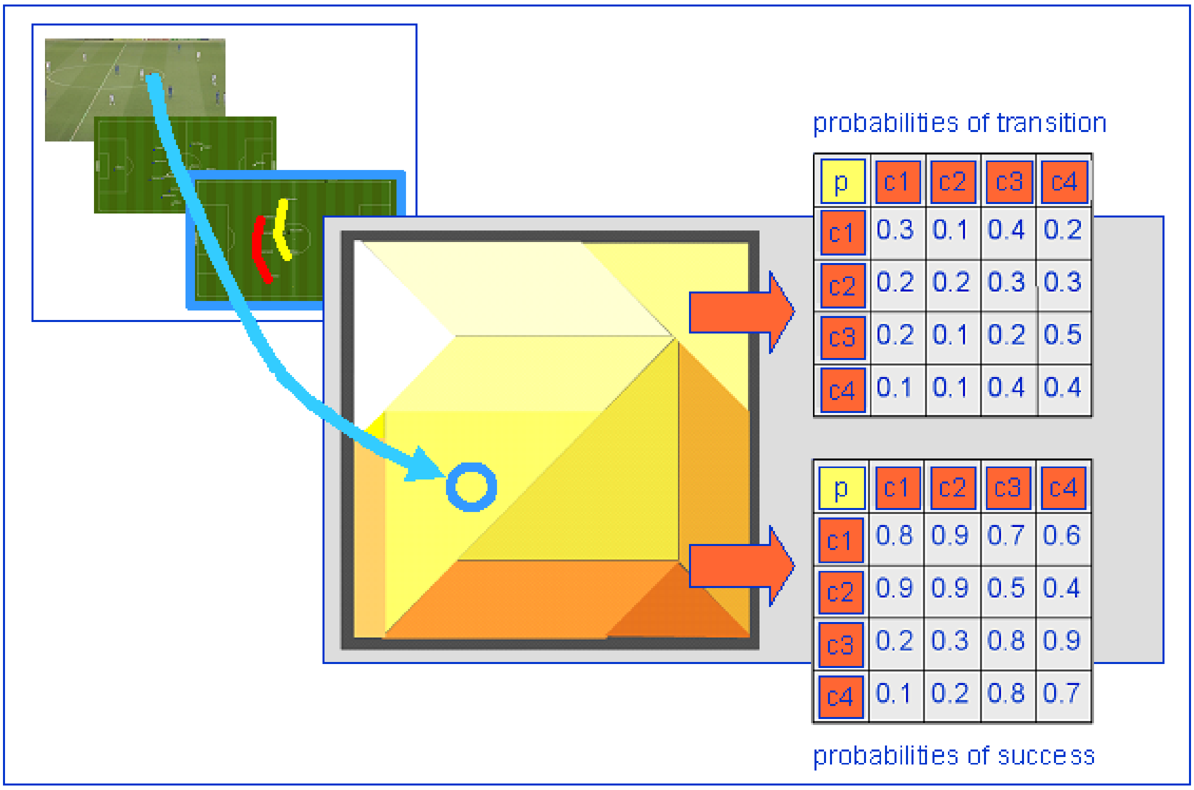

Figure 12: Process analysis resulting in statistic contributions.

Creativity

The information-theoretical relevance of actions can be estimated using their time-dependent frequency profiles. Under the assumption that a creative action is rare as well as adequate (see Sternberg & Lubart, 1999) the information-theoretic relevance together with the semantic evaluation of adequateness enables for measuring and analysing creativity of actions.

Mapped to a network this means that neurons should have the ability of representing not only frequent but also and in particular rare actions. If such a net is calibrated with respect to success or adequateness then the time series of a process is mapped to a trajectory, where the neurons can be recognized to correspond to creative actions. Figure 13 shows an example of a trajectory with a "creative neuron": Compared to the original trajectory (dotted line), the modified one (solid line) contains a highlighted neuron that corresponds to a rare and adequate action (see Memmert & Perl, 2009).

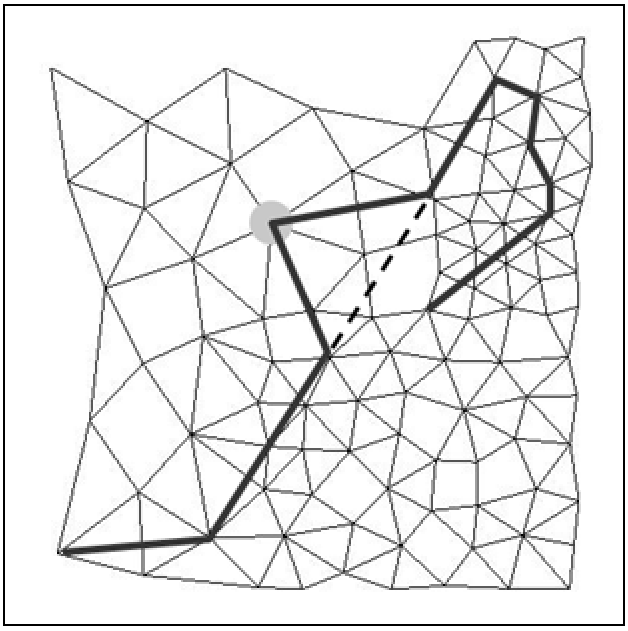

Figure 13: Example of a trajectory containing a creative neuron (grey circle), representing a rare and adequate action.

The net-based handling of rare information needs two additional features that exceed the abilities of conventional KFMs: A first point is the dynamic organisation of neurons, which is mentioned above in the context of neuron resolution and GNG-approach. Such dynamic neurons are necessary in order to register new information with high information-theoretical relevance during the training process (Memmert & Perl, 2009; Perl, Memmert, Bischof & Gerharz, 2006). A second point is the dynamic change of that relevance: If during the training the respective information becomes more frequent its relevance can decrease – or increase again, if the same information becomes rare again.
Currently, our working group in Mainz is developing the network "DyCoNA", which completes the dynamic properties of DyCoN (see Perl, 2001, 2002) by those dynamic creativity neurons. A first prototype is working successfully. Figure 14 demonstrates, in the simpler case of motion process analysis (also see Figure 2 and 3), how it works: The left graphic shows a phase-coloured network, where the colours correspond to the quality of a motion process from bad (magenta) to excellent (dark green). The right graphic shows the same network under the aspect of rareness where the yellow neurons represent rare processes, while the grey neurons correspond to frequent standard ones.

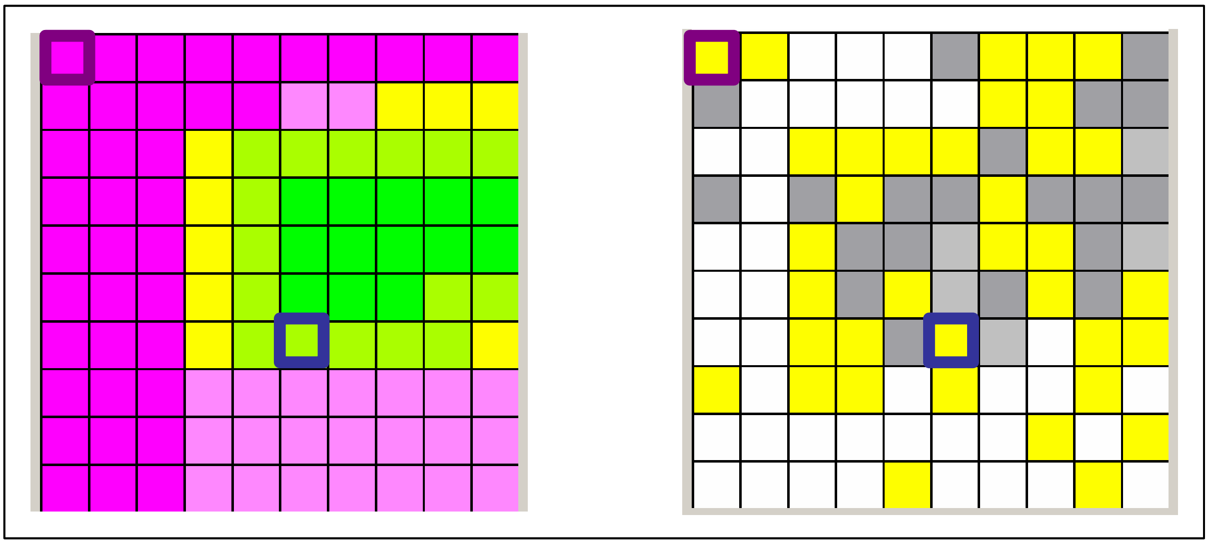

Figure 14: Network with quality-coloured neurons (left: magenta = bad, … , green = excellent) and frequency-coloured neurons (right: yellow = low frequency, grey = high frequency). The highlighted neurons are explained in the text below.

Combining the information from both types of semantics leads to specific evaluations of tested activities: An activity that corresponds to the blue highlighted neuron in Figure 14 is of good quality (left network, light green neuron) and of low frequency (right network, yellow neuron). This activity therefore is indicated to be creative. In the magenta case the corresponding activity is indicated to just rare but bad.

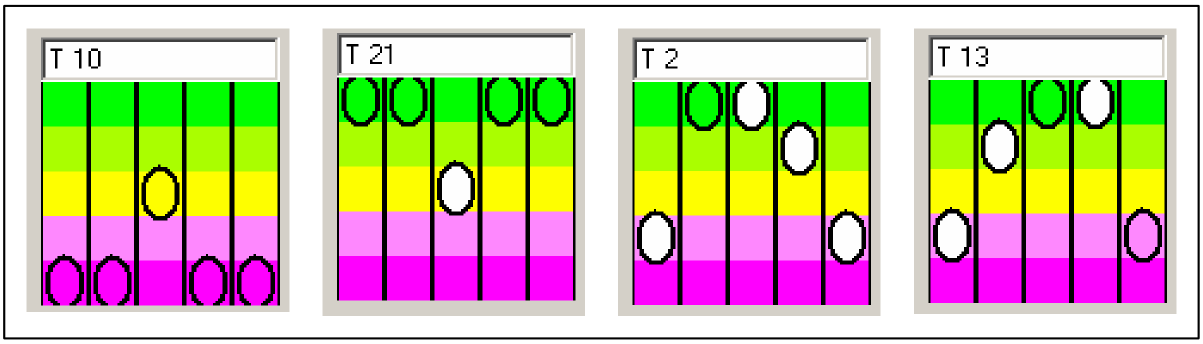

Figure 15: 4 series of activities on coloured quality scales (magenta = bad, … ,green = excellent) and with white highlights indicating rareness.

Figure 15 gives an example of 4 series of 5 activities each, showing quite different behaviours (also compare Figure 3): The first series contains only more or less bad activities without any creativity. In contrast, the activities of the second series are excellent except the third one, which is rare (white highlight) but not creative because its quality is just fair (yellow range). The third and the forth series show creative activities (white highlights in the green ranges) as well as rare but not adequate and therefore not creative activities (white highlights in the light magenta ranges).

Simulation

An advanced application of this approach, which currently is dealt with in a project supported by the German Research Association (DFG), is to analyse as well as simulate tactical behaviour, creative actions, and dynamic learning in games. To this aim, the analysis process starts as is described above: The current step of the game process is tested on the network, activating the corresponding (blue) neuron, which then returns information in different semantic categories like type of activity, degree of creativity, probability of success, or probability of transition to other activities (also see Figure 12).

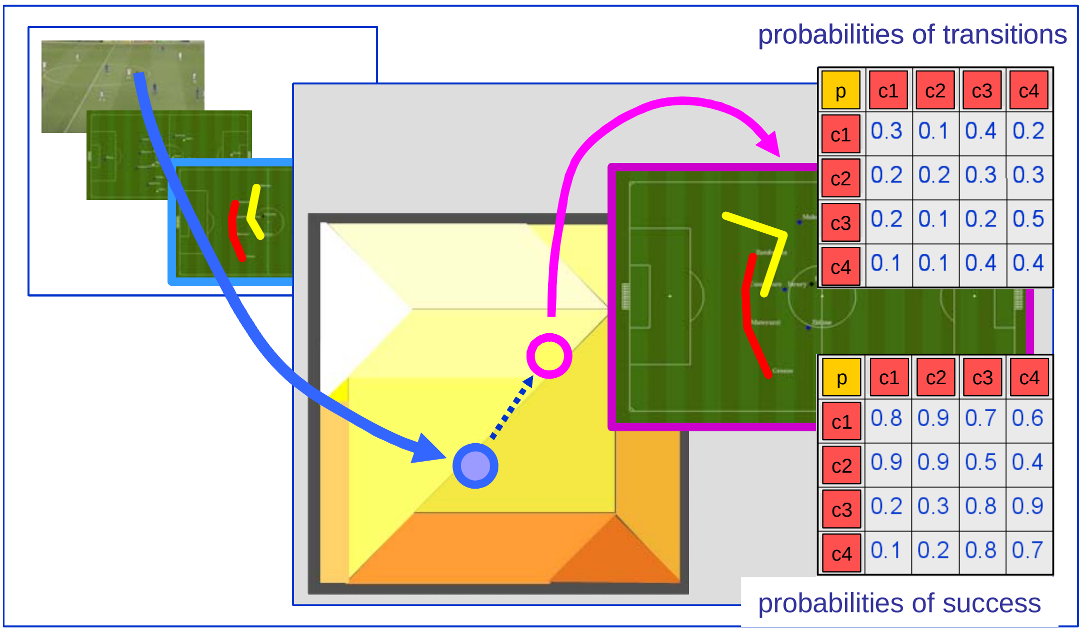

Figure 16: Simulative replacement of activities and simulation of the resulting process by means of transition and success matrices.

As is shown in Figure 16, the idea is to replace the current activity by a simulative one (violet neuron), which could be more creative or more successful, to simulate the resulting process by means of transition and success matrices and then analyse the resulting simulated process under the aspect of improving the team's tactical behaviour.

Conclusion

Successful experiences from a number of projects, dealing with motion processes as well as with game processes, encourage applying self-organizing neural networks to analyze even complex behavioural processes like those of soccer. A number of special concepts and features like dynamic adaptation by means of PerPot, dynamic learning approaches like DyCoN, or the approach of dynamic neuron generation like GNG as well as phase diagram analysis and hierarchical net architectures are helping a lot to solve the difficult and sometimes subtle problems we have been faced with during the soccer project.

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Validity of The ProZone3® Player Tracking System: A Preliminary Report

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Abstract

The purpose of the current investigation was to validate an automatic path change feature developed for the ProZone3® system using a case study where a single player was filmed during 97 minutes actual match play. The player's path changes were analysed in detail by a human observation process and compared to the path changes determined by ProZone3®. A secondary aim was to validate the times when the player entered different areas of the pitch that were recorded by ProZone3®. There was a good strength of inter-observer agreement for the human observation process for identifying path changes (κ = 0.71) and for the pitch areas entered by the player (97.0% of areas entered were agreed within 1s). There was a moderate strength of agreement between the human observers and ProZone3® for path changes (κ = 0.41) with many of the disagreements being expected given the limitations of human observation of movement. There was a good strength of agreement between the human observers and ProZone3® for the pitch areas entered (between 95.7% and 96.7% of areas entered being agreed) with almost all of the disagreements being where a player was within 1m of the boarder between 2 pitch areas.

KEYWORDS: TIME-MOTION ANALYSIS, AUTOMATIC PLAYER TRACKING, TURNING, VALIDITY, SOCCER

Introduction

The movement patterns of soccer players can be used in the investigation of work rate (Reilly and Thomas, 1976; Withers *et al*., 1982; Bangsbo *et al*., 1991; O'Donoghue, 2008) and in the evaluation of tactics (Erdnann, 1992). Methods used to analyse movement in sport have progressed from manual notation systems (Reilly and Thomas, 1976; Liddle *et al*., 1996) to computerised systems with intensive human operator activity (Steele and Chad, 1991; O'Donoghue *et al*., 2001) to automatic player tracking with minimal requirement for human operators (Gamble *et al*., 2007; Di Salvo *et al*., 2006; Di Salvo *et al*., 2009). It is necessary to establish the validity of any measurement technique used in the recording of movement in sport. Even highly calibrated fully automated biomechanical analysis systems are prone to measurement error with data smoothing processes being applied to the raw recorded data (Bartlett, 1997).

The automatic player tracking systems apply computer science technology developed over the last 30 years. Carling *et al*. (2008) surveyed the automatic player tracking systems that are commercially available, including GPS-based systems, image processing-based systems and electronic signal transmitting systems. The ProZone3® player tracking system

(ProZone®, Leeds, UK) uses image processing algorithms to track players with periodic input from human operators to distinguish different players who may have moved within close proximity of each other (Di Salvo *et al*., 2009). Di Salvo *et al*. (2006) described the equipment and software used in a typical ProZone3® installation. The ProZone3® player tracking system operates using 8 to 10 fixed cameras that are installed at a stadium of a client club. The cameras are positioned so as every part of the pitch is covered by at least 2 cameras. The video recordings made by the cameras are sent to a video distribution box which concurrently sends copies of the video signal to the primary capture equipment (a data server running ProZone's data capture software) and backup capture equipment. Video files captured at the stadium are transferred onto the main server at a ProZone processing centre where the automatic tracking software is applied to the synchronised video recordings. The videos are initially tracked in isolation before the tracking data are combined to produce a single timed sequence of pitch co-ordinates for each player. A quality control process involving trained human operators then verifies the tracking of each player where the automatic tracking process may not be able to distinguish between players who move within close proximity of each other. Di Salvo *et al*. (2009) reported that this verification process is typically applied to the player movement recorded during 42% of match time. This can be a lengthy process, but it can be completed in time to allow client clubs to interactively analyse the within match 24 hours of the match completing.

Di Salvo *et al*. (2006) undertook a study to validate the system against data recorded by speed gates during a stadium test where a set of 6 participants performed a series of planned runs. The 6 players performed 15 m flat out sprints, 20 m runs with a 90^o turn in the middle, a 50 m run with the first 30 m being in a straight line and the last 20 m being curved, and a 60m straight line run with audio pace control. This study found that there was a good strength of absolute and relative agreement between the speeds determined from the speed gate data and those determined from the sequences of participant location co-ordinates recorded by ProZone3®. Di Salvo *et al*. (2009) reanalysed the data from Di Salvo *et al*.'s (2006) stadium study using mixed model repeated measures ANOVA tests and percentage coefficient of variation. The coefficient of variation for the pooled data was 0.4% which is further evidence that the velocities derived from the timed player locations recorded by ProZone3® are highly accurate.

Carling *et al*. (2008) criticised the reliability techniques used in the evaluation of automatic player tracking systems for the following reasons :

(a) Players performed the tests in isolation which did not reflect the game of soccer where multiple players will be playing during a match.
(b) The systems need to be validated using movements that are representative of movement in soccer performance, especially turning, backwards movement, sideways movement and shuffling movements.
(c) Systems need to be tested in different lighting conditions.
(d) Movement that required human operator intervention should be included and inter-operator agreement determined.

Di Salvo *et al*. (2009) also recognised the need to establish the reliability and objectivity of systems requiring human verification or correction activity. They did an inter-operator and intra-operator agreement study using ProZone3® data of 2 different players. The data were grouped into 5 minute samples allowing reliability coefficients of variability to be determined within operators and objectivity coefficients of variability to be determined between the 2 operators. This was done for the percentage of time and the percentage of distance covered in different speed sub-ranges. The overall objectivity coefficients for time based data were less than 5% and objectivity coefficients were less than 10% for sprinting. This is evidence that the automated and human verification elements of ProZone3® together produce values for the percentage of time spent in different speed sub-ranges that are accurate enough for coaching and scientific applications.

Other general issues in the validation of time-motion systems were identified by Carling *et al*. (2008). There is neither a gold standard test for time-motion analysis systems for soccer nor is there agreement about the speed ranges to be used to represent different classes of locomotive movements such as walking, jogging, running and sprinting. One contentious statement by Carling *et al*. (2008) was that it is necessary to evaluate within player "error" between games. In sport, many aspects of sports performance vary between matches (O'Donoghue, 2004). There are many sources of variability in sports performance including the importance of the match, venue and the quality of the opposition (Taylor *et al*., 2008). McGarry and Franks (1994) stated that opposition effects are the largest source of variability in sports performance. Work-rate indicators (and technical effectiveness and tactical indicators) can be measured reliably and reliable data can be used in the investigation of match to match variability in player performance. Essentially, reliability of measurement and stability (or consistency) of player performance are two separate issues.

Reliability studies in performance analysis have typically been undertaken applying the system being tested to the same performance data and reporting the level of agreement or error between observations (Hughes *et al*., 2004). Intra-operator agreement studies and inter-operator agreement studies have been recommended for any system involving human input as part of the data gathering process (Carling *et al*., 2008). O'Donoghue (2007) questioned the value of intra-operator agreement studies on the grounds that they might be testing operator ability to recall events that occurred during the given performance and that a good level of intra-operator agreement merely shows that an individual operator can consistently classify events. To demonstrate that the system is independent of an individual operator's perception of events, inter-operator reliability tests are essential. O'Donoghue (2007) stated that if a system has been evaluated using an inter-operator reliability test, there is little benefit to applying an intra-operator agreement test.

There are recognised problems in undertaking a reliability study of a system like ProZone3® in the manner traditionally done in performance analysis research. This would require two independent copies of the system (software, hardware and human operators) to cover the same match. It would not be acceptable form a quality assurance point of view to use the same cameras, as the automated parts of the 2 copies of the system would produce identical results meaning that the reliability test would only establish the reliability of the human elements of the system. With 2 sets of 8 to 10 cameras looking at the same match, the reliability test would be able to assess if the two different views of play lead to similar results for player locations and velocity profiles. The cost and practical problems of doing this at a soccer stadium are prohibitive. Another issue that needs to be considered is that there may be an algorithmic error in the image processing software that leads to the two copies of the system producing an identical incorrect result. This would lead to the system being deemed to be reliable simply because 2 independent observations of the same match by the system produced consistent results and actual error with respect to actual player movement would be unknown.

Given the logistic problems of undertaking a reliability study using 2 copies of the system and the inability of such an approach to identify algorithmic error, a novel approach is needed to assess the quality of data gathered by the ProZone3® system addressing the points made by Carling *et al*. (2008). There is no gold standard technique that ProZone3® data can be

compared with and most systems used in time-motion research have limited reliability (McLaughlin and O'Donoghue, 2001; O'Donoghue *et al.*, 2005).
The criteria established by Carling *et al.* (2008) that representative movements are included in any test and that multiple players are involved concurrently can be addressed by using an actual match. Using actual match data recorded by ProZone3® will cover the whole process of data gathering by the ProZone3® system including automated and human operator tasks. The approach to be used in the current investigation involves comparing the results for a single player recorded by the ProZone3® player tracking system and those obtained using a human operator intensive system applied to a video recording of the on-field activity of the same player for the entire duration of the match used. This is therefore a validation study rather than a reliability study. Given that it is difficult to assess velocity of movement from video recorded data and that Di Salvo *et al.*'s (2006 and 2009) studies specifically investigated this aspect of movement, the current investigation specifically validated the following alternative aspects of movement:

(a) Path changes during movement
(b) Transitions between areas of the pitch by the player during the match.

The analysis of path changes in team games is important as many path changes include turns that are associated with agility requirements of games (Bloomfield *et al.*, 2009; Robinson and O'Donoghue, 2008; Young *et al.*, 2002) as well as injury risk (Williams and O'Donoghue, 2005). Cutting movements are examples of path changes that involve lateral movement that is associated with ankle injury risk (Simpson *et al.*, 1992).
An inter-operator agreement study is essential to establish the reliability of the human operator intensive system that the ProZone3® player tracking system is being validated against. Figure 1 shows that this necessitates 3 separate comparisons for each of the two aspects of movement of interest.

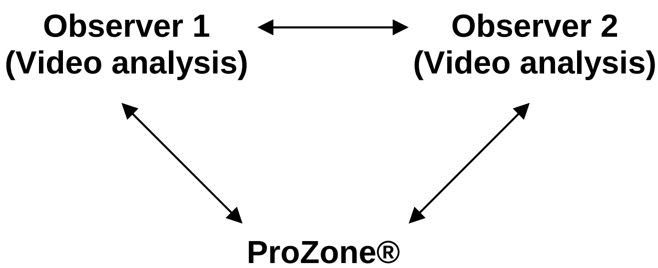

Figure 1. Comparisons made between observations.

Methods

Path changes

Path changes, direction of travel and turning are separate aspects of movement that it is necessary to distinguish when analysing any of them (Robinson and O'Donoghue, 2008). Robinson and O'Donoghue (2008) distinguished these as follows:

- ***Direction***: direction refers to whether the player is moving backwards, forwards or sideways with respect to the aspect they are facing or if the player is stationary.
- ***Path Change***: path refers to the path being travelled by the player, irrespective of whether the player is moving backwards, forwards or sideways within that path of movement. Therefore, a path change is relative to the path previously travelled before

the turn or direction change event rather than being related to the aspect faced by the player.

- ***Turning***: turning is where the player changes the aspect faced during movement irrespective of whether a path change in their movement occurs or not. Indeed, the player may turn when moving or when remaining in the same location.

Neither ProZone3® nor any other image-processing tracking systems currently identify whether a player is moving forward, backwards or sideways (‘body plane movement’) and, therefore, neither direction of movement nor turning during movement can be detected by the system. However, path changes can be detected and many path changes involve turning (Robinson and O’Donoghue, 2008). The current investigation uses the three path change types identified by Robinson and O’Donoghue (2008) which are identified by a path change feature developed for the ProZone3® system:

- Sharp path change to the left
- Sharp path change to the right
- Disjointed path change

Figure 2 shows that these are defined with respect to the path travelled before the path change occurred. The path changes are defined objectively in terms of angle of turn. However, actual path changes made by players rarely involve completely straight line movement before and after the path change. Figure 3 shows the difference between a path change in theory and one recognized within ProZone3® data for a player. Therefore, some further definitions are required to operationalise the path changes recognized within the ProZone3® data and by human observers during video observation of the player’s performance. The movement about the “point” of the path change is considered in 3 sections:

(a) From -1.0s to -0.3s before the path change is made
(b) From -0.3s before the path change to +0.3s after the path change
(c) From +0.3s to +1.0s after the path change is made

Turns are different to arced runs (Bloomfield *et al*., 2004) as the player does not turn within the arced path of movement during an arced run. Similarly, path changes are different to arced movements as path changes involve a small period of time where the direction of movement changes while during arced movements, the player’s direction gradually changes while the player moves in an arced path. During the development of the path change identification algorithm, the authors had to consider how much a path before or after the point of path change could deviate from being a straight line and still be considered straight enough to be part of a path change rather than an arced movement. Various curves were drawn and visually inspected by the authors, in an attempt to identify a maximum deviation from the mean direction of a curve would be a suitable limit for the algorithm being developed. If the maximum deviation angle was too large, arced movements could be mistakenly identified as path changes. If the maximum deviation was too small, path changes would be mistakenly identified as arced movements. The visual inspection process eventually lead to an agreed maximum deviation from the mean direction of a movement path being 15^o for that movement path to be considered straight enough to be included in a path change. Therefore, sections (a) and (c) are defined as straight enough if all of the movement made (each 0.1s of the movement) is in a direction that is within 15^o of the mean direction. It was recognized that the process of making the path change would results in angles of movement that would exceed the 15^o difference allowable before and after the point of the path change. Therefore, section (b) of the movement was allowed to represent the process of making the path change in between travelling in the initial direction before the path change (section (a)) and travelling in the new direction after the path change (section (c)). During a pilot study of the player's movement, the number of path changes performed was found to decrease as different speeds were required. For example 341 path changes including movement at 2m.s^{-1} or faster were found in the ProZone data but only 49 path changes including movement at 4m.s^{-1} or faster were found. The purpose of the current investigation was not to determine the reliability of turns performed at a high intensity, but to use detection of path changes as part of a process validating the location of movement. The total of 341 path changes performed at 2m.s^{-1} or faster was deemed large enough but manageable enough for the current investigation. Therefore, the criteria for inclusion of path changes in the current investigation required the player to be moving at 2m.s^{-1} or faster at some point between -1.0s before the point of path change and +1.0s after the point of path change. This speed (7.2 km.hour^{-1}) was deemed sufficiently above the 6 km.hour^{-1} typical of brisk walking to require the player to be at least jogging. A further constraint on the recognition of path changes was that no more than 1 path change could be counted during any 1s of the player performance.

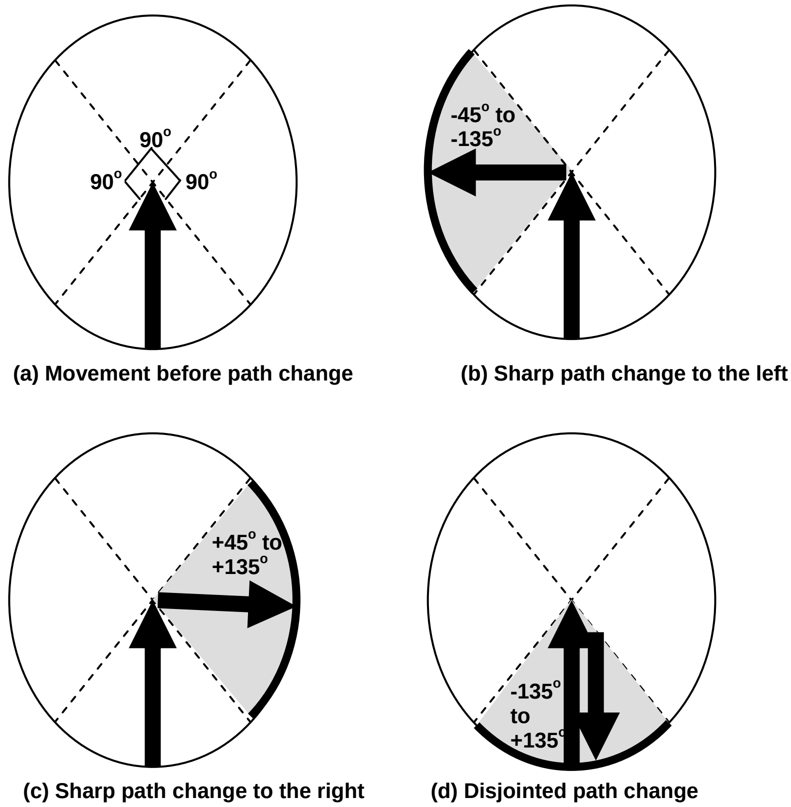

Figure 2. The three types of path change.

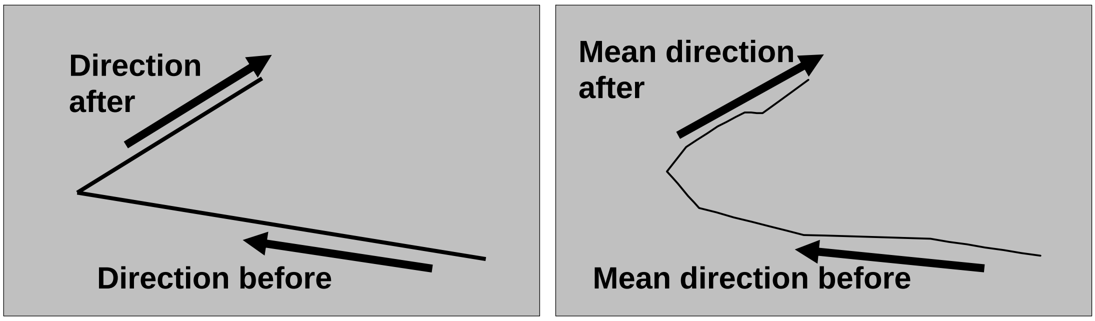

Figure 3. A sharp path change to the right (a) in theory and (b) in practice.

Areas of the pitch

The ProZone3® player tracking system was used at the stadium of an FA Premier League football club where it is installed to record movement on a pitch of length 105m and width 66m. Figure 4 shows the 17 areas of the pitch used within the current investigation. These areas were chosen so as the pitch markings could be used to assist the human observers in determining the area. The grass had also been cut in a manner that assisted the identification of pitch area.

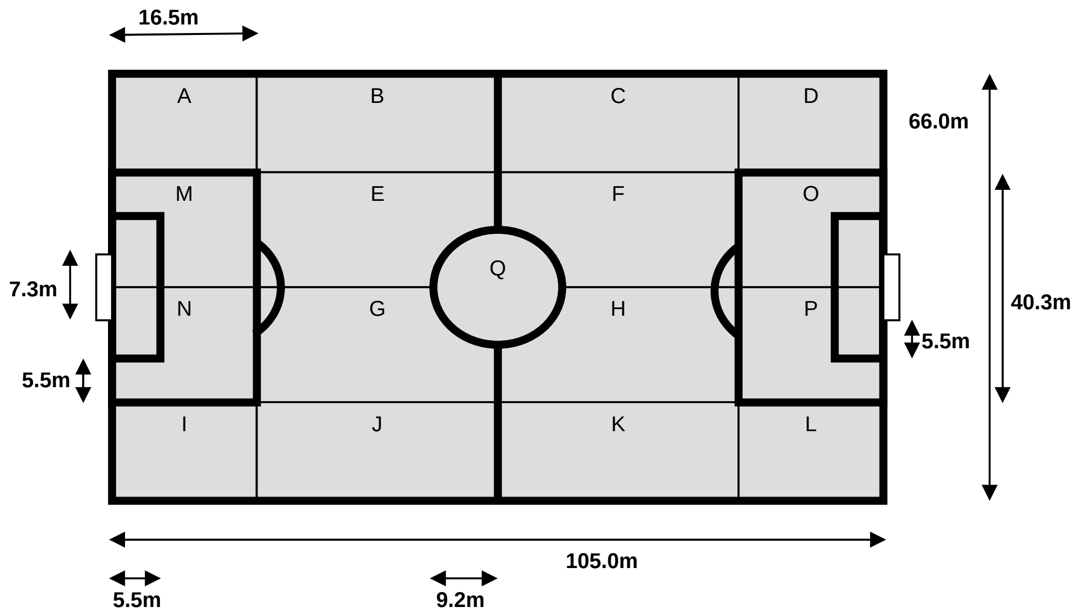

Figure 4. Areas of the Pitch.

Processing of ProZone3® player tracking data

A spreadsheet containing the pitch co-ordinates for the player's location ever 0.1s during the match was provided by ProZone Ltd with the permission of the player's club. The ProZone3® path change identification feature was developed and tested by the authors to identify the times at which any sharp path changes to the left or right or any disjointed path changes were performed. No more than one path change could be determined per second and the 2s period around which the path change was recognized had to contain some movement performed at $2m.s^{-1}$ or faster. A list of times of path changes and type of path change was produced. Secondly, the spreadsheet was programmed to identify the times at which the player entered a new area of the pitch. A chronological list of areas entered was produced that also contained the time at which each area was entered.

Human Observation

The authors were permitted to film the player's performance during the match from the gantry used by the press. The authors' recorded a half of the match each to help reduce the risk of filming errors when following the player. A Panasonic NV-GS75 camcorder was used to record the player's on-field activity onto DV tape and a Kodak Gear 66 inch tripod was used. The video recording of the player's on-field activity during the two match halves was transferred via firewire cable into a Qosmio, Toshiba NV100 12A netbook computer and stored as a pair of media files. The authors independently watched the video twice each; once to record the sequence of path changes made by the player and once to record the sequence of areas entered.

Data Analysis

Given that there were 2 human observations as well as the sequence of path changes produced by ProZone3®, there were 3 pairs of path change lists to be compared. Each pair of path change sequences was processed by matching any corresponding path changes recorded within 1s of each other. There were occasions when one list included a path change and the other did not, requiring a fourth data value ("none") to be used. The time-matched sequences of path changes were then formed into a pivot table allowing the kappa statistic to be computed. The weighted version of the kappa statistic (Cohen, 1968) was used in the study, weighting any disagreement between neighboring 90^o sectors as 0.25 of an agreement. The guidelines of Altman (1991) for interpreting kappa were used with values of over 0.8 being deemed a very good strength of agreement, values of over 0.6 being deemed a good strength of agreement, values of over 0.4 being deemed a moderate strength of agreement, values of over 0.2 being deemed a fair strength of agreement, and values of over 0.2 or lower being deemed a poor strength of agreement. Where any disagreements occurred, the video was inspected to determine the nature of the disagreement.

Similarly, each pair of timed sequences of areas entered was processed by matching any corresponding area entries recorded within 1s of each other. There were occasions when one list included an area entry and the other did not. The time-matched sequences of path changes were then inspected to identify any disagreements in areas entered and occasions where the lists agreed on an area being entered but disagreed on the time at which this occurred. The percentage of areas entered agreed within 1s as well agreed outside 1s were determined as measures of reliability. Where any disagreements occurred, the video was observed to learn about the nature of the disagreements.

Results

Tables 1 to 3 summarise the comparison of the three different timed sequences of path changes. Table 1 shows that there was a good strength of inter-observer agreement between the two authors for path changes ($\kappa = 0.71$). There were 36 occasions where a path change was recognised by one observer and not the other. Inspection of the video recorded player movement revealed 3 main sources of disagreement between the human observers. Firstly, there were situations where the path changed by an angle close to 45^o to the left or close to 45^o to the right. One observer would have recorded this as a path change to the left or right while the other observer would have considered the player to have continued moving without a path change. Secondly, there were occasions where the movement before (or after) the point of path change was not considered to be straight enough by one of the observers. The third main area of disagreement was where a path change of about 135^o to the left or right was performed. One observer recorded this as disjointed while the other observer recorded this as a sharp turn to the left or right. There were only 5 occasions where one observer recorded a sharp path change to the left while the other recorded a sharp path change to the right.

Table 1. Inter-observer agreement on path changes during human video analysis.

Observer 1	Observer 2				
	Disjointed	Sharp Left	Sharp Right	None	Total
Disjointed	84	5	3	3	95
Sharp Left	7	92	3	2	104
Sharp Right	7	2	92	10	111
None	2	9	10		21
Total	100	108	108	15	331

Tables 2 and 3 show that there were more occasions where path changes were recognised by the human observers but not by ProZone3® than occasions where path changes were recognised by ProZone3® but not by the human observers. The kappa values of 0.41 and 0.41 represent a moderate strength of agreement between ProZone3® and the human observers. The path changes that were identified by human observers and not by ProZone3® were occasions where several path changes occurred in a short period of time such that there was not a full second between the path changes. This occasionally involved none of the path changes identified by humans being identified by ProZone3® as neither section (a) nor section (c) of each path change were straight enough for the required 0.7s of the section.

Table 2. Agreement between first human observer and ProZone3® for path changes.

Observer 1	ProZone3®				
	Disjointed	Sharp Left	Sharp Right	None	Total
Disjointed	73	7	8	7	95
Sharp Left	9	73	2	20	104
Sharp Right	8	3	83	17	111
None	1	37	37		75
Total	91	120	130	44	385

Table 3. Agreement between second human observer and ProZone3® for path changes.

Observer 2	ProZone3®				
	Disjointed	Sharp Left	Sharp Right	None	Total
Disjointed	76	13	3	8	100
Sharp Left	10	73	2	23	108
Sharp Right	4	2	84	18	108
None	1	32	41		74
Total	91	120	130	49	390

There were 5 main causes of path changes being recognised by ProZone3® but not by the human observers. Firstly, the activity before or after the point of turn may have been judged by the human observer based on distance travelled rather than on the 0.7s time. Where a player decelerates rapidly after a path change, he may travel a very short distance at a slow speed but still take 0.7s or more to do so. Secondly, there were occasions where the player moved in an initial direction and then was stationary for an observable period of time less than 0.6s in duration before starting to move again in a different direction. The human observers classified this as two separate movements and not a path change during a movement. However, the ProZone3® path change feature did not place any restriction on the movement or lack of movement performed in section (b) during the 0.6s around the point of path change. The third area of disagreement between the human observers and ProZone3® was where path changes appeared to be gradual and not straight enough to the human observers but in fact did satisfy the criteria for being classified as one of the three path changes of interest. The fourth area of disagreement was where path changes on the boarder of two 90^o sectors were confused between disjointed and sharp path changes on some occasions and between sharp path changes and no path change on others. The fifth source of disagreement between the human observers and ProZone3® were occasions where the player was walking but did achieve a speed of $2 m.s^{-1}$ at some point within 1s before or after the point of path change. On such occasions, the human observers did not record a path change taking place.

Table 4 summarises the timed sequences of area entries recorded by the two human observers. The two observers agreed on the sequence of areas entered to the nearest second for 97.0% of area entries recorded. This increased to 99.0% when the time of area entry was allowed to differ by more than 1s. Where the observers agreed on an area entered but the time of area entry was outside 1s, the maximum difference between the times recorded for area entry was 2s. Observer 1 recorded all of the area entries recorded by Observer 2 while Observer 2 recorded 99.0% of the area entries recorded by Observer 1. The 5 occasions where observer 1 recorded an area but observer 2 did not involved the player being on the line between 2 areas.

Table 4. Frequency of areas entered according to the 2 human observers.

Area	Agreed within 1s	Agreed outside 1s	Observer 1 only	Observer 2 only	Total
A	3				3
B	13				13
C	17				17
D	6				6
E	60	2			62
F	58		1		59
G	72		2		74
H	77	1	2		80
I	2				2
J	26				26
K	29	1			30
L	4				4
M	21	1			22
N	18				18
O	12	1			13
P	21				21
Q	42	4			46
Total	481	10	5	0	496

Tables 5 and 6 compare the timed sequence of area entries recorded by observer 1 and ProZone3® and by observer 2 and ProZone3® respectively. ProZone3® recorded areas entered that the human observers did not on more occasions than the human observers recorded area entries that ProZone3® did not. The timed area sequence recorded by ProZone3® agreed with 90.9% of area entries for Observer 1 and 93.9% of the area entries for Observer 2 to the nearest second. This increased to 95.7% (ProZone3® v Observer 1) and 96.7% (ProZone3® v Observer 2) when entry times were allowed to vary by more than 1s. The maximum difference between the time of an area entry recorded by ProZone3® and a corresponding area entry recorded by a human observer was 5s. These percentage agreement figures are based on an artificially high total number of occasions due to some area entries being recorded by human observers and not by ProZone3® and vice versa. Observer 1 and observer 2 recorded 96.6% and 97.6% of the area entries recorded by ProZone3® respectively. ProZone3® recorded 99.0% of the area entries recorded by Observer 1 and 99.0% of the area entries recorded by Observer 2.

Table 5. Frequency of areas entered according to Observer 1 and ProZone3®.

Area	Agreed within 1s	Agreed outside 1s	Observer 1 only	ProZone3® only	Total
A	2	1			3
B	13				13
C	17				17
D	6				6
E	57	4	1		62
F	57	1		1	59
G	68	3	1	9	81
H	75	3		6	84
I	1		1		2
J	24	2			26
K	29	1			30
L	3	1			4
M	19	2	1		22
N	16	1	1		18
O	12	1			13
P	21				21
Q	42	4		1	47
Total	462	24	5	17	508

Table 6. Frequency of areas entered according to Observer 1 and ProZone3®.

Area	Agreed within 1s	Agreed outside 1s	Observer 2 only	ProZone3® only	Total
A	2	1			3
B	13				13
C	17				17
D	6				6
E	59	2	1		62
F	58	1			59
G	70	3	1	7	81
H	78	2		4	84
I	1		1		2
J	24	2			26
K	30				30
L	3	1			4
M	20	1	1		22
N	16	1	1		18
O	13				13
P	21				21
Q	46			1	47
Total	477	14	5	12	508

There were three sources of error where ProZone3® failed to record an area entry viewed by the human observers. Firstly, was where the player briefly moved through the corner of an area. Secondly, were occasions when the player only moved into the area momentarily. Thirdly, were occasions where the player moved less than 1m into the area. Where ProZone3® recorded an area entry that was not viewed by the human observers, video inspection revealed that the player moved within 1m of the corner of the area, often touching the boundary of the area. Where the time of entry differed by more than 1s, the player was obscured by other players during a goal celebration.

Discussion

Image processing is an area of computer science that has developed to the extent that it is now being applied in many fields including the analysis of movement in sport. This technology has both advantages and disadvantages for the analysis of movement in sport. The advantages are the accurate recording of movement and the provision of an integrated feedback interface comprising general statistics, movement displayed on a pitch image and video sequences from the match. This data can be used to evaluate both tactical and physical aspects of performance. Isochrones link players within positional units (Erdnann, 1992), such as the defence, and can be animated using systems like ProZone3® for critical times of the match. Speed ranges used to represent different locomotive movements such as jogging, running, high speed running and sprinting can be tailored to individual players. Sprints, accelerations, decelerations and other movement events can be displayed on a pitch image and manipulated directly on pitch image allowing detailed information and video sequences to be displayed in a flexible and efficient manner. The ability to automatically identify path changes performed allows relevant video sequences of players performing turns and cutting movements to be displayed. These video sequences allow conditioning and medical personnel to make detailed analyses of player movement technique in order to evaluate agility and injury risk respectively (Robinson and O'Donoghue, 2009). This can help effective interventions to be made to improve agility and reduce injury risk.

The main disadvantages of the use of image processing technology in movement analysis are cost and the fixed installation. Elite professional sports such as soccer can justify the cost of this technology on coaching and economic grounds. If an intervention results in a highly paid elite player avoiding a single injury that would have prevented him from playing for a month, a large part of the cost of the technology will be justified. The system requires a fixed stadium installation and does not have the portability to be used in away matches. This is a disadvantage, but ProZone3® data is part-owned by the clubs and data from away matches against opponents who also use ProZone3® is provided to the travelling club as well.

When the results of this investigation are considered together with those of tests performed by the subjects in Di Salvo *et al*.'s (2006) stadium study and the inter-operator objectivity tests conducted by Di Salvo *et al*. (2009), the ProZone3® automatic player tracking system can be accepted as sufficiently accurate for use in scientific research as well as to support decision making within elite soccer coaching. O'Donoghue and Longville (2004) argued that reliability of performance analysis data was even more important in coaching contexts than in academic research because important decisions relating to preparation and tactics to be used are informed by such information.

The use of the 17 areas defined in the current investigation was the best way to ensure reasonable accuracy of location data entered by human observers. The agreement between the pitch area transitions observed by the human observers of the video recording of the player's match activity and the area transitions derived from the ProZone3® player tracking data indicate that the system accurately records the location of movement. The ProZone3® data was captured before the authors made the decision to use 17 pitch areas and, therefore, the ProZone3® player tracking system has not been specifically tuned just to identify area transitions accurately according to a 17 area benchmark but has been developed to record movement in all pitch locations accurately. While the movements within each of the 17 areas have not been tested due to the limited ability of human observers to judge location (Martin *et al*., 1996), the fact that the locations (area boundaries) that were chosen for testing have been recognised accurately indicates that location of movement in general can be accurately recorded by ProZone3®.

Further evidence to support the accuracy of ProZone3® for determining the location of movement comes from the analysis of path changes. Those path changes that were not agreed by ProZone3® and the human observers were exclusively due to the human observers not correctly applying the definition of path changes used in the current investigation. For example, more than one path change per second was recorded on occasions, path changes where the player was incorrectly judged to be moving at less than $2m.s^{-1}$ were not counted by the human observers and there were occasions where path changes involved changes of around 45^o or 135^o leading to a strong possibility of misjudging the type of path change. Inspection of the player video at the times where ProZone3® indicated path changes to have occurred revealed a similar movement path by the player to the path plotted graphically using the ProZone3® recorded co-ordinate data for the 1s before to the 1s after the point at which the path change had been identified. There were over 257 occasions where the type of path change was agreed by ProZone3® and both of the human observers. The authors inspected the match video for a systematic sample of 52 path changes (looking at each 5th path change from the first to the 256th) and the general pitch location recorded for the player's movement as well as the direction of movement before and after the point of path change agreed with the path plotted from the ProZone3® data from 1s before to 1s after the path change was made. Given that the ProZone3® data was recorded before the path changes used in the current investigation were defined, there is very strong evidence that ProZone3® accurately records the location of movement. The system could not have been tuned to accurately record path changes in particular and, therefore, the inspection of the video at the times of the 52 path changes sampled from those identified by ProZone3® can be viewed as looking at movement location in general rather than merely path changes.

The times of path changes and area changes recorded by the human observers were to the nearest second according to the video time displayed by the Microsoft Media Player interface used to view the video. This is a limitation that means that while the current investigation assures the reliability of the location of movement to the nearest second, it cannot be claimed that the current investigation demonstrates the reliability of instantaneous speed of movement. Speed is computed by dividing distance covered by time taken and, therefore, any underestimate of time could lead to an overestimate of speed even when the distance covered is measured accurately. However, the accuracy of location recorded by ProZone3® means that overall distance covered by the player can be deemed to be accurate. The stadium test performed by Di Salvo *et al*. (2006) has demonstrated that ProZone3® can accurately record speed of movement. This was done using speed gates which have a greater precision of time measurement than the video recording and playback used in the current investigation. The further analysis of Di Salvo *et al*.'s (2006) data and the inter-operator agreement study done with real match performance data by Di Salvo *et al*. (2009) also provide evidence that speed data derived from ProZone3® is highly accurate. Therefore, readers are encouraged to use Di Salvo *et al*.'s (2006 and 2009) studies as evidence of the ProZone3® player tracking system's ability for determining speed of movement and the current investigation as evidence of the reliability of the system's ability to record the location of the player. While the limited accuracy of 1s used in the video observation is not sufficient for estimating speed of movement, it has been found to be sufficient for identifying the time of movement events. O'Donoghue and Longville (2004) stated that a system only needed to be sufficiently reliable for the purpose of its use. The specific use of the netball analysis system used by

O'Donoghue and Longville (2004) was to identify and play back video sequences using a sufficiently long pre-roll time that a mean absolute error of 0.21s did not hinder the use of the system. Similarly, in the current investigation, a limited agreement of time of an event of 1s does not prevent ProZone3® from being used to identify path change events and entry into different areas of the pitch. Further investigations of the reliability of ProZone3® using other movements such as decelerations (Bloomfield *et al*., 2009) and on-the-ball activity would provide further evidence of the accuracy of the system. Another area for providing further evidence is repeating the current investigation but under different lighting conditions (Carling *et al*., 2008). Stadium tests, such as the one done by Di Salvo *et al*. (2006), are very useful for comparing speed of movement derived from ProZone3® data with speeds measured using timing gates. Soccer involves intermittent high intensity activity (Bangsbo, *et al*., 1991; O'Donoghue *et al*., 2005) and, therefore, future stadium tests are encouraged to use intermittent high intensity protocols that are representative of the work rate in soccer.

The current investigation has wider implications for reliability testing of systems used in performance analysis of sport. Many reliability studies in performance analysis of sport have focussed purely on reliability statistics. The current investigation has shown the value of inspecting disagreements in a qualitative way and providing readers and system users with richer information about the nature of such disagreements. This avoids misinterpreting reliability levels as low through naïve misuse of statistics. The interpretation of kappa in the current investigation was based on Altman's (1991) guidelines. It should be noted that in the current investigation, there were occasions where ProZone3® recorded a path change (or area entry) and the human observers did not and vice versa. However, all of the occasions where both ProZone3® and the human observers agreed that no path change was being performed or that the player was not moving into a new pitch area were not included in the calculation of kappa. Therefore, the moderate level of agreement found for path changes was achieved despite using a very stringent application of the kappa statistic. Furthermore, any disagreements in path change were treated equally no matter if they were disagreements between bordering 90^o sectors or total disagreements between sharp path changes to the left and right. The weighted kappa statistic that was used to evaluate the areas of the shooting circle where a netball player shoots from (Robinson and O'Donoghue, 2007) would have been beneficial in the current investigation. Other implications for reliability investigation in performance analysis are relevant in situations where automated techniques are used to record events. There is always the possibility of an algorithmic error in the system which might not be detected in the type of reliability test traditionally done in performance analysis. Two independent copies of such a system, even if viewing the events of interest from different angles, might make the same data recording error leading to an agreement that would be misinterpreted as accurate measurement. The novel approach applied in the current investigation helps avoid such situations.

The main advantage of the approach used in the current investigation is that data were used from a real match played at a very high level of soccer. This ensures a high level of ecological validity with match specific movements being performed by the player. The way in which the grass on the pitch had been cut was also advantageous to the current investigation, but this cannot always be guaranteed if using this approach. There are also some disadvantages of the approach used that must be recognised. The data used came from a single performance by a single player and may not be representative of typical frequencies of path changes performed in elite soccer. The human observation process that the ProZone3® system was validated against had limited reliability and understanding of the movements performed would not be as good as in a controlled experiment such as Di Salvo *et al*.'s (2006) stadium study. The weather and light conditions were very favourable to filming both for the human observation process and the ProZone3® analysis in the current case. An extension of the current approach to use performances under different weather and lighting conditions would be beneficial (Carling *et al.*, 2008). The approach used is useful for validating the location of movement, but requires inferential reasoning to validate measures of distance covered by players. The point of a path change is considered as a period of 0.6s irrespective of the speed of movement. This is a disadvantage because players can turn more sharply at lower speeds than at higher speeds (Grehaigne *et al*., 1996).

Conclusion

In conclusion, the current investigation has found that the location of player movement recorded by the ProZone3® player tracking system and hence the total distance covered is sufficiently accurate for scientific research and coaching applications. When these results are considered together with those of Di Salvo *et al.*'s (2006) stadium test of the validity of the speed of movement recorded by the system, there is very strong evidence that the ProZone3® player tracking system is accurate for determining distance from the timed sequence of player locations recorded during a match. Future research should apply similar approaches to validating other player tracking systems that are commercially available.

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