High-Level Tactical Performance Analysis with SportSense

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ABSTRACT

Team sports like football have become an important economic factor. As a result, the pressure on coaches to succeed is increasing and, as a consequence, so are the expectations of the performance analysts who support the coaches in their work. Until now, performance analysis has been a mostly manual and time-consuming activity, mainly consisting of video analysis. Only since the advent of new analysis tools, these analysts have experienced support for their work. However, most existing tools are mostly limited to simple analyzes and do not support complex tactical patterns. In this paper, we present how the existing SportSense system has been extended by support for dedicated tactical patterns, especially phases, continuous states, and profiles. SportSense has already been a powerful tool to assist performance analysts in running quantitative and qualitative analyzes. The tactical patterns that have been added even better support analysts in their complex tasks, which is shown in the user studies we have conducted.

CCS CONCEPTS

• **Information systems → Information systems applications**; • **Human-centered computing** → *Graphical user interfaces*; • **Applied computing**;

KEYWORDS

Data-Driven Analysis; Video Analysis; Sketch-based Video Retrieval; Quantitative and Qualitative Match Analysis; Performance Analysis; Spatio-Temporal Data; Graphical User Interfaces.

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1 INTRODUCTION

Tactical performance becomes increasingly important in today's football. In contrast to team sports in which players act alone or without significant interaction with their team mates (such as, for instance, in baseball), football tactics are characterized by complex team interactions [15] and are therefore difficult to be represented simply by means of numbers. Performance analysts have to closely interact with the coach on how to prepare the team for an upcoming match. For that, the opponents' tactical patterns, strengths that need to be contained, and weaknesses that need to be exploited, have to be analyzed. In particular, critical moments during the course of a match have to be identified. Without specialized software, performance analysts still rely on the (mostly manual) analysis of video footage [8, 21]. This is a time consuming task and requires many hours of video review [27]. The constant increase in the amount of available data renders the work of performance analysts ever more challenging [5].

SportSense [17, 19, 22, 23] is a system that is designed to support that process by offering performance analysts a way to search for patterns in the data and to quickly find critical moments in the match. Tactical patterns are expressed in terms of sequences of actions in time and space. SportSense provides an interactive timeline as well as a representation of the pitch on which specific patterns can be sketched. Successful and unsuccessful events filtered by time, space, and players involved can be found over multiple matches and the corresponding video scenes can be watched. Other attributes of these events such as frequency and other metrics of intensity can be analyzed interactively.

In order to improve SportSense as an analytical tool, we used the results from [24], where interviews with 6 UEFA Pro Licence coaches were conducted and analyzed, in order to understand the more specific questions a performance analyst has to answer with the existing data and video footage. The basic idea is to create an interface that allows an intuitive translation of the coaches' and analysts' questions into queries. In order to do that, the following new data types have been added to the existing simple "atomic" events in SportSense: (1) phases, (2) continuous states, and (3) profiles.

The contribution of this paper is twofold: First, we show how the new data types (phases, continuous states and profiles) can be integrated in a tactical analysis tool in general and their implementation in SportSense in particular. Second, we show on the basis of a user study the usability and effectiveness of the new functionalities and of the whole SportSense system.

The remainder of this paper is structured as follows: Section 2 surveys related work. Section 3 introduces SportSense, the three new data types, and their application and Section 4 presents details on the implementation of these new features in SportSense. Section 5 reports on the results of the user studies that have been conducted and Section 6 concludes.

2 RELATED WORK

The last years have seen a large evolution in the field of performance analysis in team sports and especially in football. Companies have started to enter this market and have developed commercial software solutions to support football clubs and associations. These can be categorized into three different types. i.) Athlete Management Systems provide a complete suite of modules that are needed to manage athlete performance and development. Some of the providers include analytical tools as additional module. To name an example, SAP Sports One[1] is a software which helps clubs to manage, amongst other things, medical, scouting, and training processes. ii.) Systems that specialize on creating enhanced video content and that are made to generate event data through manual (live-) tagging. Hudl Sportscode[2] or myDartfish ProS[3] are such tools and are widely applied in football clubs. They are also used for the creation of video snippets which can be shared with players or club officials. iii.) Systems following a semi-automatic data generation process. Instat Scout[4], for example, is a service that includes an interface to supply coaches and analysts with statistics on various team and player parameters, e.g., to compare performances. Additionally, video playlists of selected actions can be watched.

Also academia has recently shown increased interest in the field of performance analysis in football. The goals of these approaches are to develop relevant indicators or metrics to quantify and/or to visualize performance on the pitch. While some authors are focusing on specific and complex concepts like, for instance, the calculation and visualization of dominant regions [28], open spaces [11], or pressure [4], others are focusing on the development of new key performance indicators (KPIs) to measure the performance of players and teams more reliably. Examples therefore include dangerousity indices [14], off-ball scoring opportunities [27], or off-ball advantage [15]. Yet other approaches try to automatically detect events or patterns of events directly from spatio-temporal tracking data [8, 18, 19]. In the last years, also machine learning approaches were increasingly applied to find solutions for football-specific problems like the identification of tactical team formations [26], the analysis and comparison of defensive behaviour [13], or the development of so-called movement models [6].

As a result, some interesting innovative software tools for sports analysis have been developed in academia over the last years. Pileggi et al. [16] present a system for ice hockey which strongly focuses on visualizations to enhance the workflow of an hockey analyst. A tool for football analysis is presented by Benito Santos et al. [5]. It allows a user to interactively search for and visualize physical and inter-player metrics. Another system from Stein et al. [28] supports an integrated visualization of football data in the video to enhance the video analysis process. Other interactive approaches where the user can formulate queries by drawing sketches in the UI are shown, for instance, in the work of Richly [21] and Sha et al. [25]. Al Kabary et al. [3] have shown how a team sports analysis system can be deployed in Cloud in a way that scales to large data collections of an entire season.

3 THE SPORTSENSE SYSTEM

SportSense is a tool for performance analysis in team sports. It was mainly developed for football in close collaboration with experts from sports practice, i.e., coaches and analysts, and from research, i.e., computer scientists and sport scientists. The system combines tracking data, event data, and video footage for the analysis. One of the main functionalities is the querying for events and patterns of events by means of drawing sketches. The resulting list of events is visualized on the timeline and on the drawing area of the SportSense UI. The selection of particular events prompts the video to play a few seconds before the event happened. Furthermore, the calculation of statistics is supported.

SportSense as presented in [23] enables coaches and performance analysts already to answer simple questions like, for instance, what happened when, where, and how many times during a match or over several matches. This allows a first and very lightweight tactical analysis of the opponent or the own team. SportSense also allows the user a deeper analysis by directly searching for patterns of events applying event cascades [1, 2, 23]. Movement analysis of players and the ball is supported as well, so that one can search for and visualize motion paths in certain regions of the pitch [1] or even during specific situations [22].

However, there was still a semantic gap between the concepts which one can search for with SportSense and concepts used by coaches and analysts in their tactical reasoning which we close by integrating data types presented in [24]. In [24], concepts used by coaches are identified from interviews by defining and analyzing the terminology of a coach when preparing for the next match. The concepts are then classified in four data types: (1) atomic events, (2) phases, (3) continuous states, and (4) profiles. Until now, SportSense could only be used to search and analyze lists of events. We extended the system by considering phases, continuous states, and profiles.

In the following subsections the integration of the three data types phases, continuous states, and profiles into SportSense is presented and the usability is shown with at least one example per data type.

3.1 Phases

Phases serve to segment a match. This facilitates the analysis task because one can precisely state in which phase certain events or scenarios happened. In [24] phases are defined as intervals having a beginning and a dedicated end. Specific metrics can be aggregated over the duration of a phase. Tactical periodization offers a good example of describing the tactical context and thus segments the game into the four phases: (i.) *offensive organization*, (ii.) *transition*

[1]https://www.sap.com/products/sports-one.html
[2]https://www.hudl.com/products/sportscode
[3]https://www.dartfish.com/pro_s
[4]https://instatsport.com/football/instat_scout

from attack to defense, (iii.) *defensive organization*, and (iv.) *transition from defense to attack* [9]. These four phases form the basic segmentation of a football match and during each phase, a plethora of information can be aggregated, e.g., the total number of forward passes during offensive organization. But there are much more phases in the course of a football match coaches are interested in. Other phases can be defined using a continuously measured metric. Being able to quantify the pressure on the ball carrying player lets you define high pressure phases using some sensible threshold. In this paper we focus on two phases in detail: *pressing phases* and *transition phases*.

3.1.1 Pressing Phases. Pressing is an important concept in modern football. Depending on a teams' playing philosophy, it is applied in a certain zone of the pitch to set the opponent player under pressure with the intention to regain possession of the ball. Coaches want to know where, how intense, and for how long a team exerts pressure above a certain intensity. Furthermore, effective pressing phases often lead to critical shifts in game states. The rapid segmentation into pressing phases therefore accelerates the time-intensive task of the opponent analysis.

SportSense supports the detection as well as the visualization of pressing phases. The only requirement is to have a definition that allows to quantify the pressure exerted on the ball carrying player. For the calculation of our so-called *pressing index*, which has been designed in collaboration with a practitioner (coach with an UEFA Pro Licence), we use Equations 1 and 2. The variables are explained in Figure 1.

$$PI_i = \begin{cases} \frac{v_p + v_b}{D}, & \text{if } \frac{v_p + v_b}{D} \geq 0 \\ 0, & \text{otherwise} \end{cases} \tag{1}$$

$$PI = \sum_i PI_i \tag{2}$$

Equation 1 shows the calculation of the contribution of the i-th defending player (PI_i) to the overall pressure exerted on the ball carrying player (PI). The variable v_p is the norm of the speed vector of the defending player projected on the direct line between defending player and ball. The variable v_b is the norm of the speed vector of the ball projected on the direct line between defending player and ball. Negative pressure is excluded, because a defending player running away from the ball will exert no pressure. The overall pressure (PI) is the sum of the individual contributions of the defending team (see Equation 2). Usually, only the players in close proximity to the ball have an essential contribution to the pressing index, while the effect or more distant players is negligible.

With the definition of two thresholds, one for the minimum intensity of pressing, and a second one for the minimum duration of a phase, it is possible to calculate the pressing phases for both teams in a match. A pressing phase terminates if the value of the pressing falls under the defined threshold.

To get the results visualized in the UI, the user simply has to click the Team Tactics dropdown menu and select the option "Pressing Phases" (see Table 1 for a list of all options). The results are then visualized as small bars in the timeline of the SportSense UI (see Figure 2). The color of each bar indicates the corresponding team.

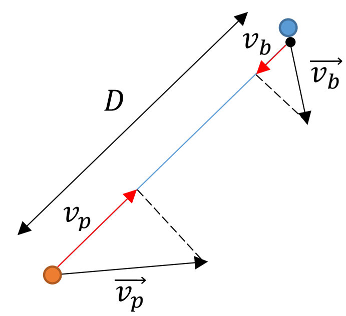

Figure 1: Pressing Index Model representing the individual contribution PI_i of the i-th defending player (orange dot) on the ball carrying player (blue dot). The defending player's speed towards the ball (v_p) is the norm of the player's speed vector ($\vec{v_p}$) projected onto the line that connects the defending player with the ball. The ball's speed towards the defending player (v_b) is the norm of the ball's speed vector ($\vec{v_b}$) projected onto the line that connects the defending player with the ball. D represents the distance between defending player and ball.

By clicking on one of the bars, the video player directly jumps to the corresponding scene and the analyst can search for details in this specific situation, e.g., certain team behaviours. Additional information on each phase is given by hovering over the bars. The user will see the minimum, maximum, and average pressing values as well as the duration of the hovered phase.

3.1.2 Transition Phases. Transitions can be critical because it is easier to gain territory as long as the defense is still unorganized after loosing possession of the ball [12]. In these phases, it is important for the defending team to get organized as quickly as possible and for the offensive team to exploit the situation to quickly gain territory.

SportSense detects transition phases by checking for all ball possession changes in the data. The start of the phase is the moment of the possession change. In SportSense, the duration of transition phases is fixed at 5 seconds.

To find and visualize these phases, the user has to specify the match and the team of interest for the analysis. After that, a click on the Team Tactics dropdown and the selection of either "Transition Offensive" or "Transition Defensive" (see Table 1) leads to the results. In analogy to the pressing phases, these are visualized as small bars in the timeline of the SportSense UI (see Figure 2). Additionally, the starting point of each transition phase is depicted in the drawing area of the UI. With the latter, potential patterns could already be detected at first glance if, for instance, clusters are visible on the pitch. This would indicate that there is one or several regions on the pitch where a team wins/looses possession of the ball very often and could either imply a team's strength or weakness.

3.2 Continuous States

Continuous states are dynamic metrics which are evolving over time [24]. Typically, they are of special interest during phases, but

Figure 2: SportSense UI with video, drawing area, filter area, timeline, buttons for the statistical analysis, and dropdown menus for the tactical analysis. The visualized results show the Pressing Phases and offensive Transition Phases (of one team) of the first 45 minutes of the match.

Table 1: The two dropdown menus Teams and Players and the corresponding options for Tactical Analysis with SportSense.

Teams	Players
Pressing Index	Pass Network
Pressing Phases	Speed Analysis
Transition Offensive	
Transition Defensive	

they can also exist independently. When applied to football, many examples for continuous states can be identified. In the context of physical performance data, the easiest example is the heart rate of a player. Another example is the player's speed in a certain event, phase, or even over the whole match. From a tactical perspective, one can take the number of players behind the ball during defensive play phases ("Fall Back" [24]), or the evolution of the pressing in certain situations as examples. In the following, we present the two continuous states *pressing index* and *player speed* in more detail.

3.2.1 Pressing Index. As already explained in Section 3.1.1, pressing is a very important concept in football. But not only pressing phases are interesting for coaches, also the intensity of the pressure in certain situations can be valuable for the analysis. If a player, for instance, has the tactical requirement to set the center backs of the opponents team under pressure and to disturb their build-up play, it would be interesting if and to what extent the player succeeds in this task.

To visualize the pressing index, a user first needs to select a match of interest in the filter area of SportSense and then to click on the Team Tactics dropdown. Afterwards, Pressing Index has to be selected (see Table 1). The results are then shown on the lower part of the timeline as a line graph with two lines, each representing a team (see Figure 3). Because the upper part of the timeline is still visible, a coach can search for specific events and is able to take a look how intense the pressing was during that specific events and even watch the corresponding video scenes.

3.2.2 Player Speed. When analyzing matches or training sessions, the physical load is always a very important element. Especially strength and conditioning coaches are interested in the amount and intensity of accelerations, decelerations, as well as the time and distances a player spent in different speed zones. Speed is a very important tactical element as well, because it can indicate the transition from build-up play to attacking play which possibly leads to chance creation.

To initiate this type of analysis, a user has to first select a match and at least one player of interest in the filter area of the SportSense UI. After that, the user hast to click on the Player Tactics dropdown and to select the Speed Analysis option (see Table 1). After processing, the results are shown on the lower part of the

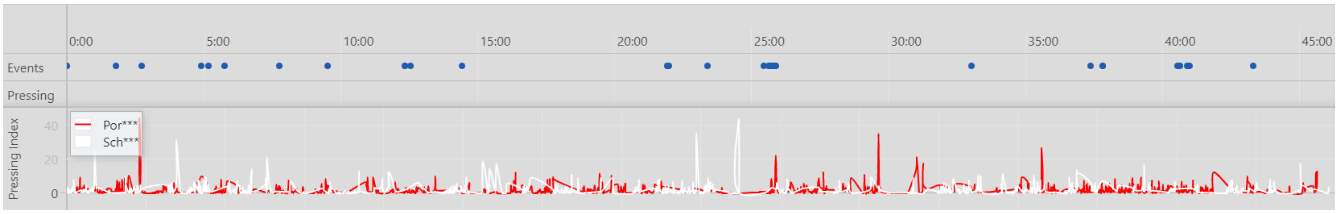

Figure 3: Pressing Index visualization together with events (blue dots) in the SportSense UI.

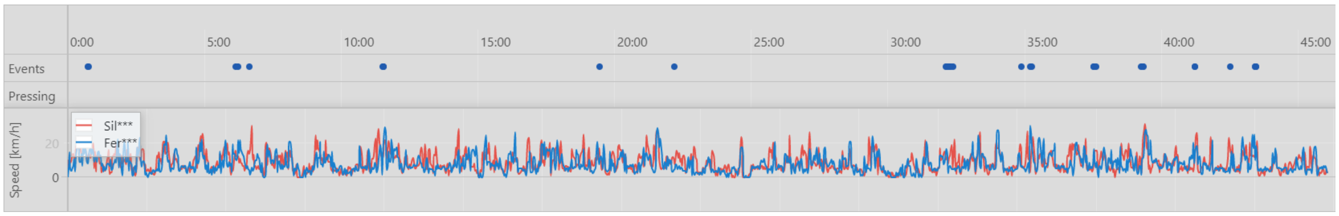

Figure 4: Player Speed Analysis visualization together with events (blue dots) in the SportSense UI.

timeline as a line graph with as many lines as players are selected (see Figure 4). Analogous to the Pressing Index, events are still visible on the upper part of the timeline. This shows the speed values of the selected players in all the situations the coach is about to analyze.

3.3 Profiles

Profiles express general statements about players or teams. In contrast to phases and continuous states which both are time dependent, profiles represent aggregated information for participating entities. They are used to characterize players and teams by aggregating information over several matches [24]. Typical profiles in the context of football are, for instance, preferred line-ups of a team, the physical fitness of a player, or characterization of interactions between players, e.g., how each player is involved in the passing of the team. The latter will be presented in more detail in the following section.

3.3.1 Pass Network. Detecting key players is one additional aspect coaches would like to know when preparing for the next opponent. If there is one key point in the opponent's play like, for instance, the player who successfully competes the most passes with his teammates, this will likely play an important role in the coach's tactics. If there is, for instance, the left center back being the player who mainly starts the build-up play of the opponent, it is clear for the coach to try with his team to disturb that specific player. To quickly detect such key players, so-called *pass networks* can be calculated and visualized. The network approach to measure different kinds of interactions is not new and was already introduced in the context of football by other researchers [7, 10, 20]. In combination with further interactive visualizations, it is a quite powerful concept and increases the efficiency of the performance analysis.

SportSense is able to visualize pass networks. The calculation is done by iterating through all successful passes and by summing up the passes for each player and the corresponding receivers and the links between all players. To see the results in the UI, a user has to click on the Player Tactics dropdown and to select the Pass Network option (see Table 1). After processing, the results are shown on the drawing area of the SportSense UI (see Figure 5). Each node represents a player and the size of the node represents the total number of played successful passes. The bigger the node, the more passes are played. Edges between two nodes represent passes between two players. The thickness of the edge represents the number of passes. Thicker edges are equivalent to more passes between the corresponding players. When hovering either over the nodes or the edges, more details are displayed to the user like, for instance, the exact number of passes of a player (node) or between two players (edges). With this kind of visualization it is very quickly possible to detect the key players or even key connections as this will be the biggest nodes or the thickest edges, respectively.

4 IMPLEMENTATION

The architecture of SportSense consists of three parts: (1) a Web Client where the user can define queries, for instance by drawing sketches or fulfilling other interactions with the UI, (2) a MongoDB REST Proxy which translates the queries into database queries and communicates them to the database, and (3) a MongoDB database instance, where the spatio-temporal tracking data, the event data, and the pressing information are stored (see Figure 6). While the Web Client is written in Typescript, Java is the programming language used for the implementation of the MongoDB REST Proxy [23]. The code for both parts of the system, the Web Client and the REST Proxy, is available under an open source license[5]. In the following, we show how the new extensions presented in Section 3 are implemented in SportSense.

For all three data types phases, continuous states, and profiles we made use of different components of the vis.js[6] library. The first component is the Timeline which supports, amongst other functionalities, to zoom in and out with the mouse wheel. We

[5]https://github.com/sportsense
[6]https://visjs.org/

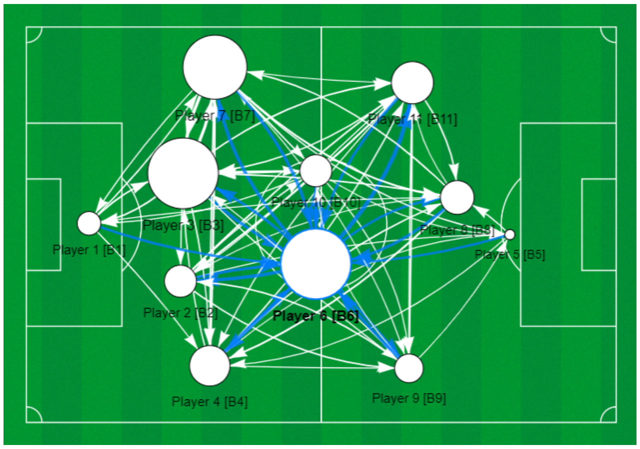

Figure 5: Pass Network visualization in the SportSense UI. Each node represents a player, while edges represent the passes between them. Player 6 is selected and the corresponding edges are highlighted in blue to allow a better overview.

implemented extended functionalities of the Timeline component by using additional rows within the timeline for the visualization of Pressing Phases and Transition Phases, respectively. With defined ranges (start and endpoints), which is the central characteristics of phases, one is able to display items (phases) as colored bars in the timeline. We decided to use the team colors for an easy detection of the corresponding phases at first glance. By assigning each item to a group, one can influence the row in which it will be visualized. In our case, we have implemented three groups: (1) Events, (2) Pressing Phases, and (3) Transition Phases (see Figure 2). Additionally, information can be shown either in text form in the item itself or by hovering over it.

For the visualization of continuous states, we decided to use the Graph2d component of the vis.js library. This allows the display of bar charts and line graphs on an interactive timeline. Unfortunately, it is not possible to combine the timeline and the Graph2d components in one single instance. We solved the problem by adding event listeners, which allow a synchronous behaviour of the timeline and the Graph2d instances during dragging and zooming activities of the user. The continuous states Speed Analysis and Pressing Index are visualized as line graphs. Each line can be assigned to a group which also defines the line color. For the Pressing Index, each line is displayed in the team color. For the visualization of the players' speeds, we decided not to take the same color for all players of one team, because this would lead to very cluttered visualizations when analyzing more than one player of a team. Therefore, each line of the analyzed players is drawn in a different color.

For the implementation of the Pass Network, which is one concrete example of a profile, we made use of the network component of the vis.js library. As the name indicates, this component allows to display dynamic and customizable network views. The size of the nodes can either be fixed or dynamically adapted using a specified value, in our case the number of successful passes. The position of the nodes can also be defined using x/y-values. For our visualization, we positioned the nodes according to the tactical line-up

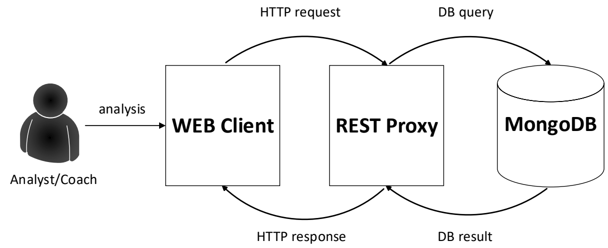

Figure 6: Overview of the SportSense architecture.

of each team. Edges can also be implemented either with a fixed thickness or a dynamically adapted thickness by adding a value, in our case the number of successful passes between the involved players. Of course, the color for each node and edge can be set differently. For our visualization, we applied the team colors for nodes and edges. Finally, information can be shown in text form inside or below each node and edge, respectively, and also by hovering over one of it.

5 EVALUATION

A user study with 15 participants was conducted to evaluate the usability of the new functionalities and to rate the overall usability of the SportSense system. Each participant had a sport background and worked at the time of the evaluation either as a sport scientist or as a football coach. After the introduction to the system by the developer, the participants had to solve nine different tasks and to rate the difficulty of each task on a Likert scale from 1 ("very easy") to 5 ("very hard"). Therefore, we used two screens, one with the SportSense software and another one with the form for the rating process. For the latter, we used Microsoft Forms[7], which allows an easy export of the results and facilitates the evaluation process. For each task, additional textual feedback was possible via a textbox inside the form.

The nine different tasks cover many of the functionalities of SportSense with a strong focus on the new ones and are listed in the following:

Task 1: Select a team and search for all successful passes in the right half of the pitch.

Task 2: Search for all goals and shots in the first 30 minutes of a match.

Task 3: Select "Freehand Motionpath" and draw a small path of the ball on the left half of the pitch. Search for the longest ball trajectory in your path.

Task 4: Open the Statistics "Teams". Select a team. How often has the team exerted Pressing Phases?

Task 5: Select a match and click on the Tactics "Teams" dropdown menu. Select Pressing Phases. How many Pressing Phases were exerted by both teams?

Task 6: Select a match, a team, and click on the Tactics "Teams" dropdown menu. Select Transition Offensive. How many Offensive Transitions had the team during the match?

[7] https://forms.office.com

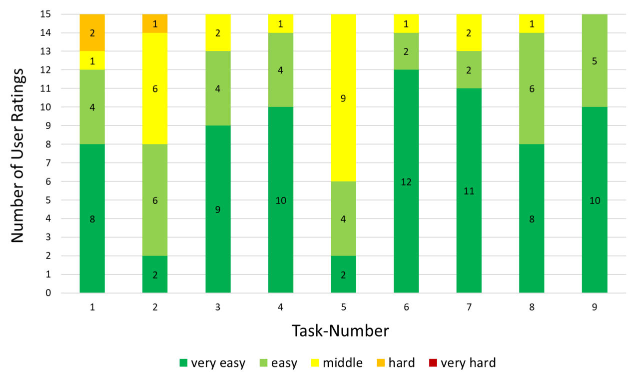

Figure 7: Results of the evaluation with 15 participants showing the difficulty rating for the nine different tasks.

Task 7: Select a match and click on the Tactics "Teams" dropdown menu. Select Pressing Index. Wait for the result and search for the peak value of the Pressing Index.
Task 8: Select a match and one player. Click on the Tactics "Players" dropdown menu. Select Speed Analysis. Wait for the result and search for the peak value of the Player Speed.
Task 9: Select a match and a team. Click on the Tactics "Players" dropdown menu and select Pass Network. Who is the player with the most successful passes of the team?

Finally, after finishing the nine tasks, participants had to rate the overall usability of SportSense via a star rating from 0 stars ("very bad") to 5 stars ("very good"). Again, participants could give feedback via textual comments, for instance if they have suggestions for further improvements of the software. The average time for solving the user study was 20:07 minutes.

The difficulty ratings of the nine tasks show quite good results (see Figure 7). As can be seen in the graph, the participants rated the difficulty of most tasks either as "easy" or even "very easy", which results in large light green and dark green bars. The only task that stands out with a large yellow bar is Task 5, where more than half of the participants rated it with a difficulty of "middle". Inspecting the textual feedback for Task 5 shows, that for many participants it was not very intuitive how to search for the total number of Pressing Phases. We will address that point in our future work, for instance by adding a small text box where the most important information is summarized explicitly in the timeline and not only by hovering over specific items. The difficulty rating "hard" could only be observed for Task 1 and Task 2. When taking a closer look on the textual feedback of those participants, it becomes clear that this were just start-up difficulties. After the first two tasks it was clear for them how to interact with the software. Furthermore, none of the tasks was rated with a difficulty of "very hard". The average value of all difficulty ratings is 1.68 (standard deviation: 0.83) and therefore the overall task difficulty can be declared as "easy".

When generally looking on the textual feedback of the participants, one idea for improvements is mentioned more often and concerns the Speed Analysis as well as the Pressing Index. In both cases, the results are visualized as line graphs in the SportSense UI. The recommendations of the participants were that first the exact value should be visualized when hovering over one specific point of the line and second, that it would be interesting to see the corresponding scene in the video when clicking on one point of the line graph. This functionality is already supported for events and also for phases, but not yet for continuous states. We will address this as well in our future work.

The average value for the overall usability rating of SportSense is 4.53. Therefore, the usability of SportSense can be declared as "very good".

6 CONCLUSIONS

In this paper, we have presented the extension of the existing SportSense system towards support for the analysis of dedicated tactical patterns, in particular phases, continuous states, and profiles. This addresses an urgent demand of performance analysts in team sports and closes or at least narrows the semantic gap in performance analysis. The evaluation of SportSense has shown the effectiveness and user-friendliness of the system.

In our future work, we plan to refine existing high-level tactical concepts, for instance by fine-tuning pass networks to consider only certain types of passes (e.g., vertical passes) or to limit the analysis to passes in certain situations and/or areas. Moreover, we plan to add more high-level individual and team-tactical concepts to SportSense such as, for instance, build-up play, attacking/defensive play, dominance, space creation, room control, etc. These concepts will be parameterizable and thus customizable. Moreover, we will also add corresponding visualizations.

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