ForVizor: Visualizing Spatio-Temporal Team Formations in Soccer

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Fig. 1. Analysis of a game between Argentina and Peru. In the upper line, (A) and (B) show the confrontation matrix. Users hover over (A) and the confrontation is shown in (H). (C) shows the statistical indicators in the entire game. (D) shows the statistical indicators before the first goal. (E), (F), and (G) shows the statistical information of the second goal. The bottom line shows the information of five goals in this game.

Abstract—Regarded as a high-level tactic in soccer, a team formation assigns players different tasks and indicates their active regions on the pitch, thereby influencing the team performance significantly. Analysis of formations in soccer has become particularly indispensable for soccer analysts. However, formations of a team are intrinsically time-varying and contain inherent spatial information. The spatio-temporal nature of formations and other characteristics of soccer data, such as multivariate features, make analysis of formations in soccer a challenging problem. In this study, we closely worked with domain experts to characterize domain problems of formation analysis in soccer and formulated several design goals. We design a novel spatio-temporal visual representation of changes in team formation, allowing analysts to visually analyze the evolution of formations and track the spatial flow of players within formations over time. Based on the new design, we further design and develop ForVizor, a visual analytics system, which empowers users to track the spatio-temporal changes in formation and understand how and why such changes occur. With ForVizor, domain experts conduct formation analysis of two games. Analysis results with insights and useful feedback are summarized in two case studies.

Index Terms—Soccer data, formation analysis, spatio-temporal visualization

1 Introduction

Soccer is one of the most popular sports in the world with millions of participants and more than tens of thousands of professionals. The popularity of soccer has promoted the analysis of soccer tactics to improve performance. However, the in-depth analysis of soccer tactics has been hindered due to the lack of fine-grained soccer data. Till the recent advancement of automatic tracking tools provides analysts with the chances to collect sufficient soccer data. Visualization tools are therefore introduced to increase the intuitiveness of data representations and reduce the complexity of pattern recognitions. For instance, SoccerStories [28] can visualize a soccer game in different phases and provide a holistic overview. Facet views are provided to help experts investigate players' actions, such as passes, runs, and shots, identify tactic patterns, and explain outcomes. However, current approaches focus on visualizing low-level information, such as player actions and key events. Team tactics, regarded as high-level tactical strategies throughout a game [35], are neglected in most of existing works.

In soccer, team tactics are mainly determined by team formations (e.g. 4-4-2) on the pitch [35]. Specifically, team formations can be characterized by its inherent spatial information, which indicates the roles and places of players in the game on the pitch. Therefore, team formations affect team performances inevitably in various aspects, such as defining players' roles, increasing coverage, and determining strike strategies. Moreover, during a game, the formation of a team can be changed frequently according to game situations. For instance, changing to a defensive formation after leading the game is common for a team. Considering the significance of team formations, coaches and analysts are strongly motivated to analyze formation changes. However, the spatio-temporal nature of formation changes restricts their capabilities in recognizing and understanding formation-changing patterns. Therefore, the necessity of analyzing team formations and the limitation of existing works have motivated us to develop a visual analytic system for a comprehensive investigation of team formations.

The development of such visual analytic system faces three major challenges. The first challenge is the acquisition of reliable soccer data. Although object-tracking techniques have been extensively investigated, they are not robust enough in real applications. In our practice, the direct application of these techniques to extract players' positions from soccer videos encounters several problems, such as the influence of the

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Manuscript received 31 Mar. 2018; accepted 1 Aug. 2018.
Date of publication 16 Aug. 2018; date of current version 21 Oct. 2018.
For information on obtaining reprints of this article, please send e-mail to: reprints@ieee.org, and reference the Digital Object Identifier below.
Digital Object Identifier no. 10.1109/TVCG.2018.2865041

video resolution on the quality of tracking results, the overlapping of players, and the camera angle. The second challenge is the problem characterization of team formation analysis. Although domain experts, who produce a series of analytic directions and complex concepts, have long experiences in analyzing team formations, most of their work has concentrated on a specific target, thereby lacking a thorough comprehension of the problem domain. The third challenge is the visualization of spatio-temporal team formation changes. According to experts, they need to know the detailed movements of players over time to fully understand formation changes. Multivariate information should be connected with formation changes to determine the relationship between formations and game situations. Moreover, compared with traditional spatial data (e.g. geo-type), team formations have their unique definition of spatial areas (e.g. midfield). Thus, previous visualization methods cannot be applied directly. An intuitive spatio-temporal design for showing the entire continuous spatial evolvement of formation changes in an integrated view is required for formation analyses.

To address the first challenge, we develop a set of interactive labeling tools to complement with automatic object-tracking methods, thereby enabling us to fix tracking errors progressively and efficiently. We establish a semi-automatic framework for fine-grained data collection from sport videos by using these tools. To address the second challenge, we cooperate closely with experts for 10 months. We characterize the problem domain of formation analysis systematically on the basis of summarisations of existing research, as well as expert feedback from weekly meetings and discussions. To address the third challenge, we propose a novel visual design to represent spatio-temporal formation changes. This design allows experts to visually track formation changes and player movements in formations in an entire game and compare the formation-changing patterns of two teams. We introduce ForVizor, a well-coordinated visual analytic system, based on this visual design for the comprehensive analysis of team formations. We create a formation view to visualize formation-changing patterns and relations between formations and game situations. Users can further drill down to a display view to acquire detailed context information of team formations (e.g. players' real positions) and conduct cross-analysis by using useful statistical indicators.

The main contributions of this work are as follows:

- A characterization of domain problems in team formation analysis and a set of design goals.
- A novel tailored spatio-temporal design for team formation data to unfold the formation dynamics and movements of players within formations.
- An interactive visual analytic system that can conduct multivariate analyses of a soccer game based on a higher perspective of team formations.

2 Related Work

This section presents a review of related previous works regarding two problems, namely, soccer analysis and soccer visualization.

2.1 Soccer Analysis

Soccer analysis has been extensively studied in past years. Specifically, many researchers have contributed to the tactical analysis of soccer data. Statistical methods, such as distance-based [3, 8, 15, 27, 39], region-based [10,14,16,21,32,45], and trajectory-based methods were introduced to aid the analysis from various perspectives. For instance, Moura et al. [27] computed the frequencies of team surface area and spread to evaluate the organization of a team. Tovinkere et al. [46] applied a hierarchical entity-relationship-based event model to detect soccer event according to the positions of the ball and the players.

Particularly, team formation analysis has received considerable attention because of its significant impact on team performances. Bialkowski et al. [4–6] used a minimum entropy data partitioning method to detect formations from positions of individual players and identified different patterns of team behaviors in home and away. Wei et al. [47] discovered the top offensive and defensive plays applied in a game based on detected team formations. However, these approaches ignored the spatio-temporal nature of formations and hence cannot be applied directly to the analysis of sequential formation patterns. Perl et al. developed a series of formation analysis tools [18, 30–32] that used a statistical table and a line chart to show the distribution and illustrate the sequential change of formations, respectively. A Voronoi diagram is used to show the covered space of each team to evaluate the quality of formations. These tools partially addressed the issue of analyzing formation changes. Nevertheless, formations were treated as category data in the line chart that discarded the inherent spatial information. Furthermore, these tools failed to support the investigation of relations between formations and multivariate soccer data. In contrast, we propose a novel spatio-temporal design to visualize formation changes and develop ForVizor to support a comprehensive analysis.

2.2 Soccer Visualization

Visualization techniques have been extensively integrated into sports analysis, such as table tennis [48], tennis [33], and basketball [11]. In soccer, visualization has been adopted in a wide range of applications, from common infographics for statistical data to comprehensive visual analytic systems. Cava and Freitas [9] and Perin [29] provided tools to visualize game results for easy navigations but neglected the analysis of soccer data. For in-depth analysis, various approaches were introduced to explore soccer data from different perspectives. For example, Soccer Scoop [36, 37] was developed to compare performances of players. Bruno et al. [17] regarded pass networks as directed acyclic graphs and visualize it with network visualization techniques [24]. Furthermore, a feature-driven [19,20,42] method was introduced to show the statistical view of single-player or multi-player and to identify patterns in the different situations of a soccer game. Andrienko et al. [2] proposed a mathematic model that calculates the pressure value imposed on the ball or a player based on players' real positions. This model was further visualized in a heat map to help evaluate the defense and offense phases in a match. Sacha et al. [38] and Shao et al. [40] focused on the trajectories of the players and the ball to abstract movement pattern and identify interesting game situations respectively. An interactive visual analytic system called SoccerStories [28], which visualised a soccer game in different game phases with enormous novel-faceted views, was developed to support the comprehensive analysis of a soccer game. Different with aforementioned methods, Stein et al. [43, 44] integrated abstract visualizations into videos to annotate player movements and tactics on the screen to improve the efficiency of video analysis.

However, throughout these visualization works, few of them focus on team formations, especially the spatio-temporal evolution of team formations. The pressure model [2] introduces a new perspective to examine whether a team formation is keeping well and help analysts identify weakness of teams tactical themes. However, rather than analyzing the spatio-temporal patterns of team formation, this approach focuses more on characterizing part of the positions of the players who are close to the ball. Stein et al. [43, 44] used visualizations to facilitate video analysis and can improve efficiencies on identifying and analyzing team formations in each frame. For formation analysis, however, this work does not provide a holistic view of spatio-temporal evolution of team formations. Machado et al. [26] proposed a system for analyzing a soccer game based on players' spatio-temporal dynamics, which is similar to our work. Specifically, they provided a heatmap-based visualization for visualzing temporal formation changes. Though this visualization has provided a clear summarization, it cannot reveal the spatial changes of formations. Experts also need to know how the current formation change to another formation for formation analysis. Thus, a comprehensive visual analytics system for spatio-temporal formation changes is lacking. To propose such a system, we worked closely with experts to characterize domain problems and formulate several design goals. According to design goals, we created a new layout to illustrate the spatio-temporal formation changes and developed the visual analytics system ForVizor to address the issue of comprehensive analysis.

3 Data Processing

In this section, we start with a brief description of the formation data. Thereafter, we provide a detailed illustration of the data processing pipeline (Fig.2). We first collect raw soccer videos (Fig.2(A)). Later, we use tracking techniques to acquire all players' positions (Fig.2(B)) and map them to a 2D pitch (Fig.2(C)). With players' 2D positions, we utilize a minimum entropy method to detect average team formations and ask experts to label these data to obtain formations (Fig.2(D)).

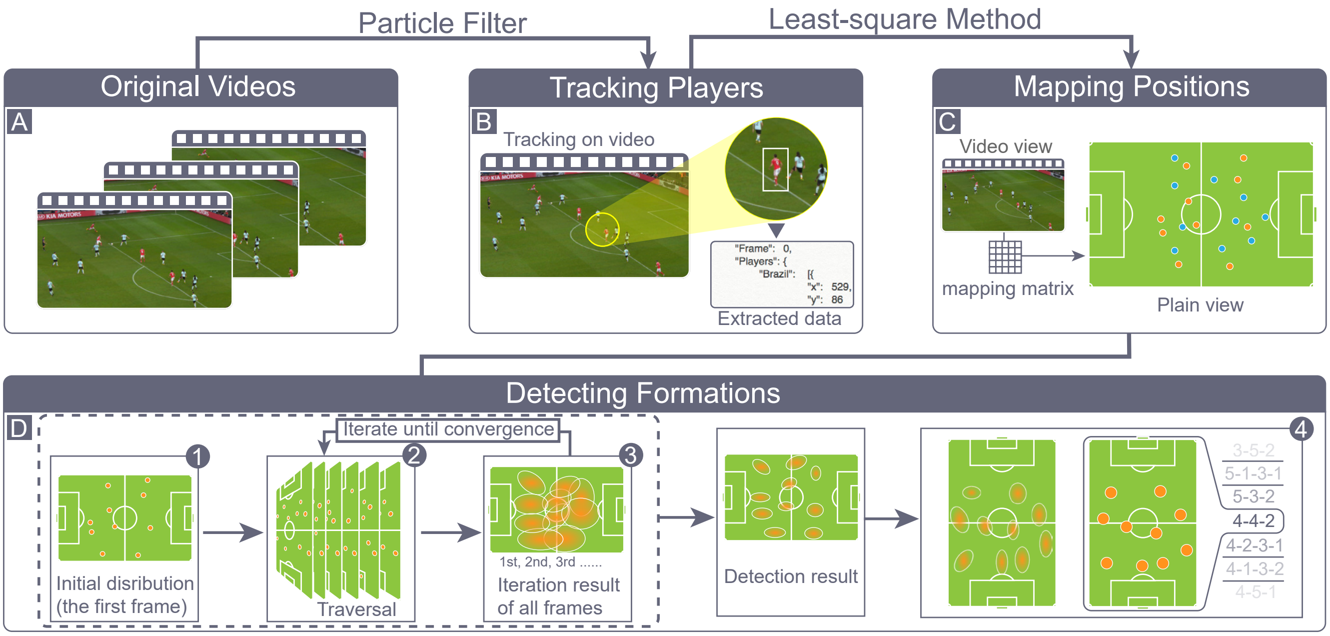

Fig. 2. Pipeline of data processing. (A) Collecting soccer videos. (B) Tracking and collecting the frame-by-frame positions of players. (C) Mapping positions in different frames to a 2D layer. (D) Detecting formation information from the players position data. Formation detection can be divided into 4 steps: (D1) producing initial role distributions for 10 players, (D2) assigning players to different role distributions in each frame, (D3) iterating over D2 until the convergence of the players' assignments, and (D4) labeling the detection result to obtain final formations.

3.1 Data Description

A soccer game involves two teams, 11 players per team, that compete against one another on a grass pitch. The players in a team are likely divided into four roles: goalkeeper, back (or defender), midfielder, and forward (or striker). These roles indicate their relative positions on the pitch. According to the positions, tactical need, or player characteristic, a role would be subdivided into more detailed roles, such as left midfielder, attacking midfielder, and second striker (or shadow striker).

Formation describes the position of players in a team (except for goalkeeper) on the pitch. For example, formation 4-5-1 includes four defenders, five midfielders, and one forward. The five midfielders can be subdivided into three centre midfielders and two offensive midfielders, constituting a formation of 4-3-2-1. Formations are dynamic during a game. To reinforce the attack, more players would be assigned the role of forward, thereby rearranging the formation to 2-3-2-3. When the opponent has strong offensive ability, 5-4-1 may be adopted to strengthen the defence.

3.2 Semi-automatic Tracking

We initially intended to establish an automatic soccer video processing framework that can track objects and map positions for the collection of fine-grained position data. We tested different object-tracking methods, including traditional particle filtering and emerging neural-network-based (YOLO [34] for detection and CREST [41] for tracking) approaches, but none of which can achieve reliable tracking when processing long and fast-dynamic soccer videos. We summarize the major problems in automatic tracking as follows.

Unpredictable behavior. Compared with traditional pedestrian tracking, player tracking must tracks players on the pitch who move rapidly in unpredictable directions when deceptive movements, sudden stops, and heading duels occur, thereby adding difficulty in the tracking task.

Loss of player characteristics. To grab the position of every player, we use match videos captured by Pixellot, a low-cost system that can generate the panoramic view of the football field automatically to ensure that all players are included in the picture. In long-shot pictures, the characteristics of players are lost and insufficient in distinguishing among different players, particularly when two players from the same team cover one another and their instant moving directions are similar. If the players get together to build up a wall, the situation goes worse.

Our approaches. For two reasons, we employed an interactive tracking method based on the color histogram and particle filter, commonly used methods for tracking in computer vision. For one thing, the automatic tracking accuracy is guaranteed when the tracking target is far away from other players, and when errors occur, we can easily fix them by pausing and re-marking. For another, the amount of calculation is small and the tracking can be accelarated to improve the efficiency.

At first, a user is required to select a specific player in the first frame as a target for tracking. The 2D position of the tracking player is shown in the pitch for confirmation. The tracking will stop in three cases. The first one is the shifting of the tracking target. When the user notices that the tracking box shifts from the original player to another player, he/she can stop the tracking, click the revise button, and re-click the original player for correction. The second one is the occlusion of the tracking target. For some special soccer events, such as building up a wall, players can be totally occluded, which poses a challenge for automatic tracking. It would be unnecessary to do tracking in those events and the user can manually set players positions in those events. The last one is the low confidence probability of a tracking result. For every frame of tracking, the particle filter method produces a confidence probability of the tracking result. If the confidence probability is lower than a predefined threshold, the system will stop tracking and request a manual correction. With this method, the position information of a game could be obtained within six hours by two users.

3.3 Position Mapping and Smoothing

We need to further map the tracking result to a 2D pitch to acquire real positions. The players could be viewed as standing on the same plane in the video, which is a projective transformation of the positions in the real world. In a similar way, we can estimate the perspective transformation between the video plane and the 2D plane, represented by homography, a 3×3 matrix, in computer vision. In our case, we chose six key points on the touchlines and used the common least-squares method to compute the homography.

The positions of players are affected by random noise and user behaviours which result in shakiness and abrupt shifts of predicted positions. We adopted mean filtering to smoothen the results.

3.4 Formation Detection

Traditional soccer analysis focuses on the readily quantifiable characteristics of soccer games, such as possession percentage and distance coverage. Automatic formation detection remains unresolved. Therefore, soccer coaches and analysts need to manually recognize different

Fig. 3. Main stages of our work. (A) Prototype system. (B) Problem characterization. (C) Visual design. (D) Data processing. (E) System implementation.

formations from videos, but this approach is time-consuming and poses challenges for visualizing formation changes.

To resolve the problem of formation detection, Bialkowski et al. [6] developed a formation generation algorithm that is equivalent to a constrained K-Means. The algorithm assumes that the dominant formation of a team in a game is stable in each half of the game. Assigning roles to every player on the field can be viewed as an assignment problem, where the numbers of agents and tasks are the same given the positions of players on every frame. The cost matrix (or entropy matrix) is defined as follows,

$$E = \begin{pmatrix} e_{11} & e_{12} & \cdots & e_{1n} \\ e_{21} & e_{22} & \cdots & e_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ e_{n1} & e_{n2} & \cdots & e_{nn} \end{pmatrix} \tag{1}$$

where e_{ij} denotes the entropy created by assigning the agent i (or player i) to the task j (or role j). The entropy is formulated as

$$e_{ij} = -\log P_j(x_i) \tag{2}$$

The algorithm begins from the first frame and initializes the distribution of roles with the actual positions of the players. Furthermore, the algorithm iterates through every frame and assigns roles to the players to minimize total entropy. The solution of the assignment is computed with the Hungarian algorithm [22].

Experts state that the assumption of the aforementioned algorithm contradicts real scenarios, where the formation of a team would actively change during the game. A team usually chooses between a dominant offensive formation and a dominant defensive formation. For example, the transition from defensive 4-2-3-1 to offensive 2-3-2-3 is popular in recent years. In practices, the experts would segment the game into periods by identifying events of team A attack and team B attack. Thereafter, they analyze formations of both teams in every period. We followed their segmentation method and detected formations for each period. Frames with dead balls were eliminated to refine the result. We then invited domain experts to label the average formation and obtained the final result. The evaluation of the model can be seen in Sec. 6.1.

4 Background and System Overview

This section presents the background of this work which includes several important milestones. We introduce the requirements summarized from domain problems and expert feedback and derive design goals that can fulfil the requirements. Lastly, we provide a brief demonstration of the system components.

4.1 Requirement Analysis

We have collaborated with a group of soccer analysis experts for 10 months to develop a visual analytic method of team formations. The group of experts is composed of a top soccer coach (SC) in Asia, a senior sport analyst (SA), several professional soccer players (SP) and PhD students (PhD) in sports science. The SC and SA have worked together on soccer analysis for decades and published a green book about the national soccer team. The SPs and the PhDs have played soccer for years, and some PhDs have several research materials on soccer analysis. They investigate a game by repeatedly watching videos and reading the statistical tables that record several KPIs (e.g. goals, passes and fouls). The videos help them focus on the movement of players to analyze teamwork strategies during a particular phase, such as before a goal. They can assess the performance of a player or a team using the KPI tables. However, the experts claim that these ways are time- and labour-consuming and are possibly generating results that are not insightful and comprehensive enough. Thus, they believe a proper visualisation system for soccer game analysis with friendly interaction is necessary. Existing visualisation systems, such as SoccerStories [28], lack the well-focused tactical analysis of team formations. Thus, we cooperated closely with the domain experts over the past year to develop a comprehensive visualisation system for team formation analysis. We held weekly meetings with them to characterize the problem domains, iterate the system design and refine the final system. The main stages of the development process are as follows.

Applying prototype system (two months): Experts were not familiar with visualizations in the beginning. Therefore, we developed a prototype system based on SoccerStories and added useful functions to enhance the system (Fig. 3(A)). We asked experts to apply the prototype system for tactical analysis. The experts were satisfied with the efficiency of visualization but found that the team formation analysis was largely neglected. This gap has motivated the study of incorporating visualization techniques in team formation analyses.

Characterization of domain problems (one months): We obtained professional knowledge of team formation analysis through weekly communications with the experts (Fig. 3(B)). We then characterized the problem domain and summarized the initial requirements.

Iteration of system design (three months): We made rounds of surveys about team formation analysis to concrete the requirements and refine the system design (Fig. 3(C)). We revised the requirements and applied them to improving the design draft whenever new insights were gained. These changes would be discussed during weekly meetings with the domain experts and the proper ones would remain.

Processing of soccer data (three months): This stage was synchronous with the iteration of system design. We developed several interactive tools for the semi-automatic data collection (Fig. 3(D)) of data through trial and error. We obtained enough data with the help of the SPs and the PhDs.

Development of system (three months): After the preparation of the design and data, we worked on the development of the alpha-version system (Fig. 3(E)). We revised the system based on expert feedback on user experience and produced the beta-version system. The revision and enhancement of the beta-version system were continued throughout the development process.

The requirements for formation analysis are concluded as follows:

R1 ***How do game situations evolve over time?*** Experts need to obtain an overview of the evolution of game situations over time, such as key events and statistical indicators (e.g. centroid distance and ball possessions). This overview can help the experts understand the characteristic of the game and quickly locate to interesting points.

R2 ***What is the frequency of formation pairs? What is the statistical difference between two teams' formations?*** Experts need to know how many formations have been used, every formations usage time, differences between two teams frequently used formations and the frequency of formation pairs (e.g. 4-4-2 versus 4-3-3). Uncovering such information can provide experts with a summary of utilized team tactics and different characteristics of two teams in a game.

R3 ***How do formations of a team change over time? How do formations of the two teams co-evolve over time?*** Experts state that formations can be changed in reaction to game situations based on team tactics. Thus, experts are interested in analyzing formation and changing patterns to identify specific team tactics. Moreover, the formation change of two teams can be related, as one team may decide to change the formation according to the opponents formation. Experts look forward to detecting the co-evolutionary relationship of the two teams formations.

R4 ***What is the effect of a formation change?*** A formation change can bring significant effects on a teams performance. For instance, a successful formation change can effectively alter the game situation which causes a conversion from falling behind to leading

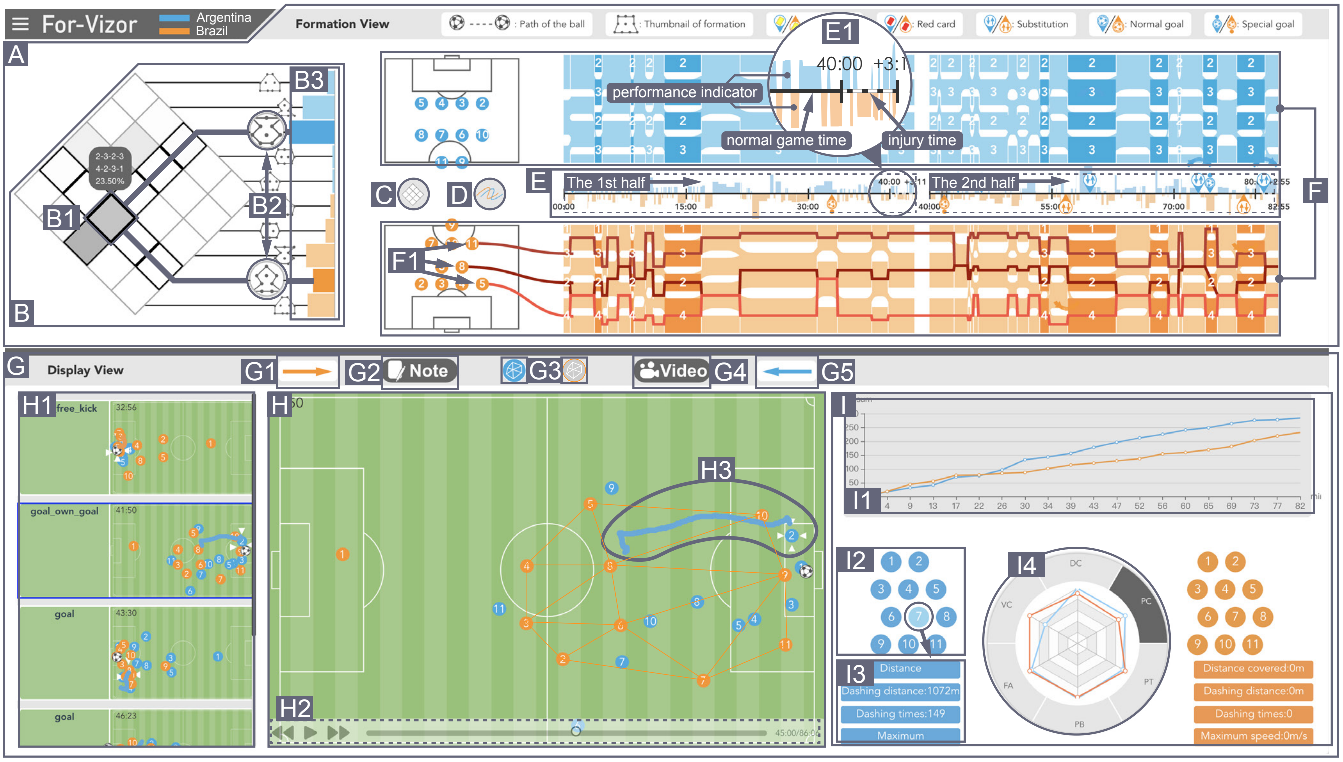

Fig. 4. System interface. The system comprises two views, namely, a formation view (A) and a display view (G). Formation view contains a confrontation matrix (B), a narrative timeline (E), and two formation flows (F). Display view contains a pitch (H) and a statistical dashborad (I).

the game. Therefore, experts want to know whether a formation change can bring positive or negative effects on a team to obtain guidance for formation selections.

R5 ***What is the reason for a formation change?*** The reason for a formation change is complicated. It is related to player skills, current scores and opponent situations. Thus, experts need to uncover the implicit reason to make sense of formation changes and to facilitate the understanding of the decision-making process of formation selections.

R6 ***How does a player perform in particular formations?*** Different teams can have different performances with the same formation because of the variety of players. Therefore, experts need to evaluate the performance of a player in particular formations to determine the deep reason why a formation performs well or bad.

4.2 Design Goals

Based on requirements, we derive several design goals as follows:

G1 ***Narrative timeline visualization of game situations.*** Experts are familiar with timeline visualisation because it has been adopted in numerous soccer applications as a report of a soccer game. Furthermore, this method aims to provide a narrative visual summary of key events. Thus, experts suggest that we encode more information in a timeline to represent the evolution of game situations (R1).

G2 ***Spatio-temporal representation of formation changes.*** A formation change implies that several players in an area flow to another area. Traditional designs use a sequence of formation names to represent formation changes, which hides variation details and breaks the continuity. For an in-depth investigation (R3-6), experts look forward to an effective visual design to disclose the spatio-temporal variation and thus enable the visual tracking of temporal changes of different areas and movements of individual players.

G3 ***Visual connection of formation changes and multivariate information.*** Experts need to tightly integrate formation changes and multivariate information to evaluate the effect and discover the reason of formation changes (R4 and R5). For instance, they would attempt to determine whether goal events happen after a formation change and what the game situation is before the formation change. Therefore, experts require a visual connection (e.g. juxtapose and coordination) to help link the data for the analysis.

G4 ***Comparative analysis of two teams' formations.*** Experts require a comparative analysis to compare the frequency of formation pairs (R2) and the formation changes of two teams (R4). This can help experts identify different characteristics and formation changing relationships between two teams. The statistical indicators of two teams should also be compared (R5) to assess the performance.

G5 ***Context-preserving view of game statistics.*** Experts refer that the analysis of game statistics is essential for assessing the performances of teams and players (R1, R4 and R6). However, the drawback of missing context information limits the understanding of game statistics. Therefore, experts need a coordination between game statistics and context information on the pitch to facilitate the comprehension of game statistics.

G6 ***Intuitive glyphs of soccer data.*** Experts mention that they are accustomed to the illustration of soccer data in traditional soccer analysis. For instance, they demonstrate a formation by illustrating players realistic positions on the pitch. However, most of the illustrations cannot be directly applied in a visual analytic system given the limited space. Therefore, experts expect us to design a group of intuitive glyphs based on traditional illustrations to visualize different events, formations and statistical indicators (R1R6).

4.3 System Overview

We design ForVizor for the visual explorations of team formation data. ForVizor can assist experts identify evolutionary formation patterns, interpret implicit reasons of formation changes and evaluate performances of certain formations. The system includes two views, namely, the formation view and the display view. The formation view aims to provide a holistic view of team formation changes and game situations. Users can drill down to the display view and further investigate formation variations. The display view shows the detailed position information of each player accompanied with multiple statistical indicators.

ForVizor is a Web-based system with two components: a back-end for collecting and processing fine-grained soccer data and a front-end for visualizing soccer data. We use OpenCV to implement the back-end

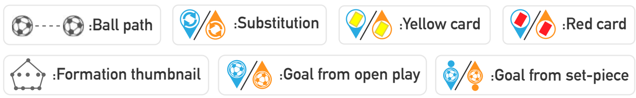

Fig. 5. Glyph illustration of events and formations

and the Vue.js 2.0 framework to implement the front-end.

5 Visual Design

Following the design goals, we design the formation view (G1, G2 and G4) for revealing formation changes, the display view (G4 and G5) for providing more context information of formations, multiple intuitive glyphs for representing soccer data (G6) and a series of interactions to coordinate all components (G3).

In the formation view (Fig. 4(A)), we use a *narrative timeline* (Fig. 4(E)) to present the evolvement of game situations (G1). A *confrontation matrix* (Fig. 4(B)) is provided to show the frequencies of formations utilized by two teams and the distribution of formation pairs, which assists users in summarizing the difference between the formations of two teams (G4). We propose a novel design called *formation flow* (Fig. 4(F)) to intuitively exhibit the dynamic changing process of a team's formations (G2). The two teams' formation flows are juxtaposed to investigate co-evolving patterns and conduct comparative analyses (G4). For detailed investigation, users can select a specific timespan on the timeline to drill down to the display view. The display view (Fig. 4(G)) contains two parts: a *display pitch* and a *statistical dashboard*. The display pitch (Fig. 4(H)) supports the dynamic exhibition of the positions of players (G4). The statistical dashboard (Fig. 4(I)) provides statistical analysis based on several key performance indicators and is coordinated with the display pitch (G4 and G5).

We use blue and orange to encode the two teams respectively. The color encoding is unified in the entire system. We refer the blue team as *teamA* and the orange team as *teamB*. We explain our visual designs in detail as follows.

5.1 Formation view

Narrative timeline: We follow the design of various media reports of soccer games and use a timeline to illustrate the evolvement of game situations in a narrative manner. The timeline (Fig. 4(E)) progresses from left to right. We divide the timeline into two pieces to represent the first half and the second half of a game. The solid line represents normal game time and the dashed line represents injury time (Fig. 4(E1)). We sequentially place the glyphs of key events on the timeline according to their time of occurrence. The demonstration of key event glyphs is shown in Fig. 5. Users can hover on each glyph to see the detailed information of corresponding events. The two bar charts on the timeline (Fig. 4(E1)) show the evolvement of two teams' defense indicators respectively. Specifically, the bar height at a timepoint encodes the defensive performance of a team at that time (the higher the worse). For the defense indicator, experts suggest using the average value of the distance between the ball and the closest player per minute.

Confrontation matrix: We employ a matrix Fig. 4(B) to show the frequency of formation pairs. Each column of the matrix corresponds to the formation of *teamA* and each row corresponds to the formation of *teamB*. Each cell (Fig. 4(B1)) in the matrix represents a specific formation pair. The frequency of formation pairs is encoded by the luminance of cells. A deep color means a high frequency. We use a bar chart (Fig. 4(B3)) to show the frequency of formations for each team. To well coordinate the matrix and the bar chart, we transpose the matrix and connect each bar to corresponding rows and columns in the matrix. Glyphs of each formation (Fig. 5) are added (Fig.4(B2)) for labeling. Users can hover on each cell, and the corresponding matrix row, matrix column, connected bars, and formation glyphs are highlighted.

Formation flow: We propose a novel design formation flow to visualize spatio-temporal formation changes (G2). Experts state that each formation with 10 players can be divided into three or four spatial areas: forward, midfield (sometimes can be subdivided into offensive and defensive midfield) and back. The change of formations can be seen as the fluxion of players from one area to another. This process is similar to Sankey diagrams [7, 12, 13, 25], which has inspired the design of the formation flow. The formation flow could reveal the overall changing patterns of formations over time while preserving the continuous flowing processes between spatial areas in formations.

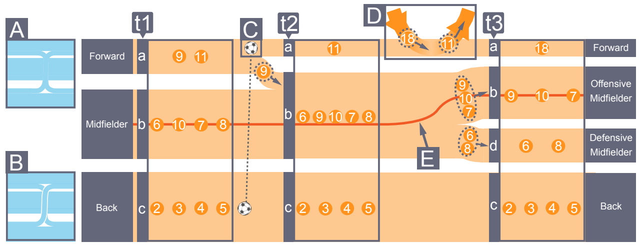

Fig. 6. Illustration of a formation flow of *teamB*. At t1, *teamB* uses 4-4-2, while at t2, *teamB* changes from 4-4-2 to 4-5-1. At t3, *teamB* changes from 4-5-1 to 4-2-3-1. (A) Overlapping subflows. (B) Adding white borders to a subflow. (C) Glyph of ball possession. (D) Glyph of substitution.

In Fig. 6, we use a formation flow to illustrate the formation changes of *teamB* between $t1$ and $t3$. At $t1$, three subflows, which are encoded by y-coordinates, represent three spatial areas of the formation (4-4-2). Specifically, subflow (a), (b), and (c) represent forward, midfield, and back of the formation, respectively. The thickness of each subflow is proportional to the number of players that fall in the corresponding spatial area. Formation changes are represented by the split and merge of subflows. For instance, subflow (a) splits into two subflows at $t2$, and one of the subflow merges with subflow (b). This scheme means that a player in the midfield moves to the back at $t2$, which causes a formation change from 4-4-2 to 4-5-1. A thread (Fig.6(E)) laid in subflows is used to show a player's movements within formations over time. For the formation flow of *teamA*, the encoding of y-coordinates is reversed to emphasize the opposing relation of two teams. Additionally, there may be overlaps between subflows (Fig. 6(A)). To resolve this issue, we add white borders for subflows (Fig. 6(B)) to help users distinguish between subflows.

We place the glyph of substitution on formation flows to closely connect formation changes with game situations (G3). According to experts, the substitution is highly related to the spatial information of formations. Thus, we further place them on the formation flow. As shown in Fig.6(D), we place two arrows to encode the behavior of substitution. The arrow pointing out from subflow (a) means that a player in this subflow is replaced with a new player, whose position is encoded by the other arrow that points into subflow (a). Thus, this glyph demonstrates the replacement of a striker.

Design alternatives: As shown in Fig. 7, in addition to formation flow, we have created two design alternatives based on previous spatio-temporal visualizations. To our knowledge, spatio-temporal methods [1, 23] can be roughly divided into two categories, namely, separated views and integrated views. Therefore, we created three design alternatives based on this taxonomy and discussed with our collaborators to choose an appropriate design for visualizing formation changes. Specifically, in Fig. 7(A), we employ separate views for the visualization. A line chart (Fig. 7(A1)) is used to visualize the temporal change of formations and a pitch chart (Fig. 7(A2)) is used to show the spatial information of one selected formation. However, according to experts, this design discards the geometric features of formations and encodes formation changes in an abstract manner, and thus is unsuitable for their analyses. In Fig. 7(B), we use intuitive glyphs to represent formations and a small-multiple design to represent the temporal change of formations. This design can preserve the spatial and temporal information of formations in an integrated view. Nevertheless, the information of how previous formation change to the current formation is ignored in this view, and thus hinders the analysis. Based on these considerations, we adopt formation flow as the final design.

Interaction: The formation view includes interactions as follows.

◇ **Hide confrontation matrix.** When focusing on investigating the pattern of spatio-temporal formation changes, users can click on the button (Fig. 4(C)) to hide the confrontation matrix and obtain more visual space for formation flows.

◇ **Show formation pairs.** When hovering on a matrix cell, the corresponding formation pair is highlighted in the two formation flows (Fig. 4(F)), showing when two teams use this formation pair. Users can further combine with game situations and identify which team

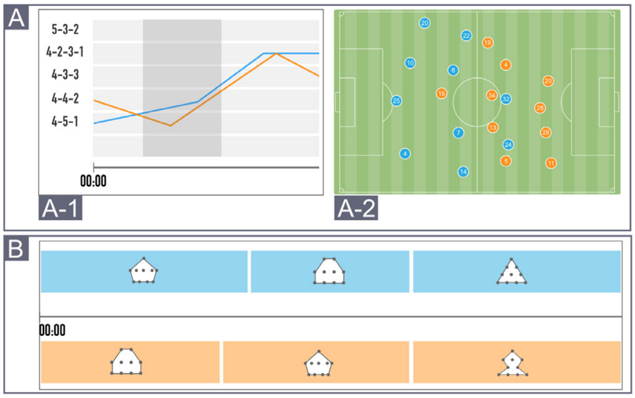

Fig. 7. Design alternatives of showing spatio-temporal formation changes. (A) Separated views. (B) Small multiples.

gains a better performance.

◇ **Show ball possessions.** Users can click on the button (Fig. 4(D)) to see ball possessions. Each ball glyph (Fig. 6(C)) represents a transition of the ball, and the glyph's position encodes the spatial area in which players are holding the ball. Dashed links are used to connect successive ball transitions of the same team to show the conversion of ball possession between *teamA* and *teamB*. Therefore, users can quickly know how long a team has controlled the ball.

◇ **Display players' movements.** To see a player's movements within formations, users can click on the corresponding player on half pitches (Fig. 4(F1)). As shown in Fig. 4(F1), a deep orange thread presents the position of Player 11 by time. Users can click on multiple players on half pitches to compare the movements of players. These players' threads will be displayed in different styles (Fig. 4(F1)) for distinguishing.

◇ **Panning and zooming.** Due to the limited visual space, short-term formation changes (e.g. less than 15 seconds) could not be clearly seen in formation flows. Therefore, we offer panning and zooming interactions for users to explore the formation flow. Users can scroll on formation flows to amplify the visualization on x-coordinates and drag formation flows for panning.

5.2 Display view

Display pitch: A plain view of the pitch (Fig. 4(H)) can offer an intuitive view for investigating the movement of the players and the ball. Users can use the control bar (Fig. 4(H2)) to manipulate the display of dynamic position data. The two arrows (Fig. 4(G1) and (G5)) indicate the two teams attacking directions. At the left side (Fig. 4(H1)), a list of interesting timeframes (e.g. soccer events) involved in the selected duration is abstracted for direct inspections. For the timeframe of goal events, we highlight the player who scores the goal and show his trajectory in past 10 seconds (Fig. 4(H3)). If users find an interesting timeframe while watching the animation on the pitch, they can click the note button (Fig. 4(G2)) and save it in the left list. For confirmation and further analysis, users can click on the video button (Fig. 4(G4)) to display the game video. The video play is coordinated with the control bar. Moreover, users can click the two circular buttons (Fig. 4(G3)) to display the triangular formation of the corresponding team.

Statistical dashboard: The dashboard consists of several key statistical indicators for measuring team performances. Experts are familiar with the usage of radar charts for statistical analysis. Thus, we employ a radar chart (Fig. 4(I4)) to visualize the average value of these statistical indicators of two teams for comparative analysis. Users can click on each segment of the radar chart and the time-variation of the corresponding statistical indicator would be shown in the above line chart (Fig. 4(I1)). The Explanations of statistical indicators are as follows.

◇ Distance covered: The total moving distance for each team.

◇ Line variance: The variance of distance between positional lines (forward, midfield, and back) in formations to help experts understand whether a team is keeping the formation well.

◇ Area covered: The area covered on the pitch for each team to evaluate offense and defense.

Table 1. Accuracy evaluation of the formation detection model.

Game	ARG Vs BRA		ARG Vs PE	
Team	Argentina	Brazil	Argentina	Peru
Accuracy	89.2%	95.3%	96.8%	95.7%

◇ Pressure on ball: For defense, a formation should impose pressure on the ball to prevent attacks. We use the method proposed by Andrienko et al [2] to compute the pressure value to disclose the performance of formations in defense.

◇ Possession time: The possession time for each team.

◇ Pass completed: The count of passes for each team.

Moreover, this view provides the details about the personal performance of each player (Fig. 4(I3)), such as dashing times and dashing distances. Users can click on a player number (Fig. 4(I2)) to see these values.

6 Evaluation

This section demonstrates the evaluation of our work. For evaluations, we use two games of the Under-15 Football Championship organized by CONMEBOL. One is finals between Argentina and Brazil and the other is semi-finals between Argentina and Peru. We first present an evaluation of the formation detection. Thereafter, two case studies are presented to evaluate the effectiveness of ForVizor. We deployed ForVizor on the Web and invited four domain experts to conduct the case studies. Expert A is a senior coach (SC) with an Asian Football Confederation coaching certificate. Expert B is a senior data analyst (SA) in sports science. Expert C and D are former professional players of the China Football Association Super League and have a PhD in sport science. Before the case studies, we held a meeting with experts to show how to use the system. After the case studies, we interviewed with experts to collect their feedback and suggestions.

6.1 Model Evaluation

For evaluations, we first asked experts to manually label team formations from inspecting videos to acquire ground truth data. We then obtained the automatically detected formations using the model in Sec. 3.4. We compared the detection result with the ground truth data frame by frame. The result (Table. 1) showed that the model achieved high accuracy for all teams in the two games. Therefore, we used the automatically detected formations for our case studies.

6.2 Case 1: Turn the tide

This case is about the game between Argentina and Brazil. We invited expert A to analyze this game. At first, expert A looked at the timeline to obtain an outline of the game. He found that Brazil scored two goals first, but Argentina hit three goals in the second half, which turned the tide. He then looked at the confrontation matrix to obtain an overview of two teams' formations. He immediately found three dark cells that represent three formation pairs, namely, Argentina 4-2-3-1 versus Brazil 2-3-2-3 (Fig. 8(A)), Argentina 2-3-2-3 versus Brazil 4-4-2 (Fig. 8(B)), and Argentina 2-3-2-3 versus Brazil 4-2-3-1 (Fig. 8(C)). He explained that 2-3-2-3 is an attacking formation that features pass and control. In contrast, 4-2-3-1 is employed to augment defense while 4-4-2 is employed for a counter-attack. The bar chart showed that Argentina applied 2-3-2-3 more than Brazil in the game (Fig. 8(D)). Thus, he deduced that Argentina established dominance over the game. For confirmation, he looked at the team performance indicators provided by the statistical dashboard. In the radar chart, he found that two teams were similar on possession time (Fig. 8(G)), but Argentina had far more passes than Brazil (Fig. 8(F)) (i.e. passing and control playing style). Argentina's line variance was smaller than Brazil (Fig. 8(E)), which meant that Argentina maintained better formations than Brazil did. This phenomenon explains why Argentina can turn the tide to some extent.

For further investigation, the expert hovered over the matrix cells to see when these formation pairs appeared. Fig. 8(B1) shows that Brazil mostly employed 4-4-2 for defense and counter-attack in the first half, while they turned to 4-2-3-1 more in the second half (Fig. 8(C1)) for defense, especially that of midfield to hinder attacks from Argentina. The expert combined the narrative timeline and explained that Argentina equalized the score (Fig. 8(C2)) at the beginning of the second half, and this setup caused Brazil to change formations. However, this formation change did not prevent Argentina from turning the tide.

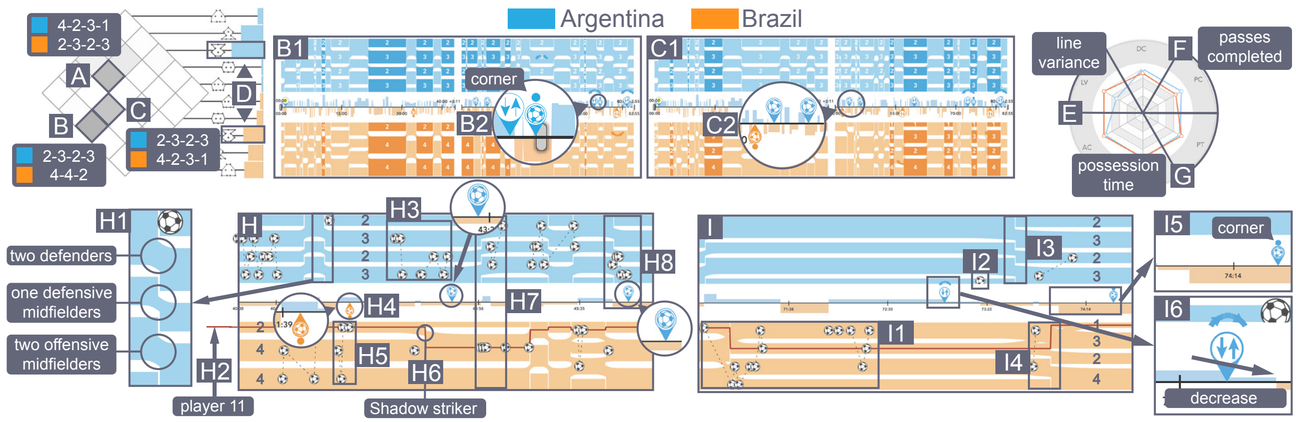

Fig. 8. Pipeline of the first case. (A), (B), (C), and (D) show the confrontation matrix. Users hover over (B) and (C) and the corresponding confrontations are shown in (B1) and (C1), respectively. (E), (F), and (G) show the statistical indicators of Argentina and Brazil. (H) shows the detail formation changes and game situations at the beginning of the second half. (I) shows the detail information of the last goal of Argentina.

From these observations, the expert suspected that the beginning of the second half was the turning point of this game. Thus, he focused on this period and zoomed in to see the details. As shown in Fig. 8(H), Argentina alternated their formations between 2-3-2-3 and 4-2-3-1. To change from 4-2-3-1 to 2-3-2-3, two defenders, one defensive midfielder, and two offensive midfielders moved forward (Fig. 8(H1)). The expert explained that this was a smooth formation change that allowed for a flexible switch between attack and defense. By contrast, Brazil mainly maintained 4-4-2 for counter-attack, in addition to moving a striker backward (Fig, 8(H6)), to change from 4-4-2 to 4-5-1 for increasing the defense. By inspecting player flows, the expert realized that the dropping striker was Player 11 (Fig, 8(H2)), a shadow striker in 4-4-2. Noticing the different formation-changing patterns, the expert commented that Argentina was proactive toward attacking while Brazil preferred to seek chances for quick attacks.

The expert then combined game situations with aforementioned formation changes for further analysis and found that Brazil regained the ball and passed the ball to a striker (Fig. 8(H5)) for a quick attack after continuous attacks from Argentina. At that moment, Argentina was still holding 2-3-2-3 and failed to change to a defensive formation in time. As shown in Fig. 8(H4), the average distance value of Argentina was high. This finding represented poor defense, which led to an own goal. By that time, Argentina had lost two goals. Nevertheless, they did not allow for any spare time for Brazil. The expert noticed that Argentina continuously attacked with 2-3-2-3 and obtained much ball possessions (Fig. 8(H3)). Meanwhile, Argentina imposed considerable pressure on Brazil, forcing the latter to change from 4-4-2 to 4-5-1 for a deep defense (Fig. 8(H6)). Argentina then successfully seized a chance and scored a goal. To verify this goal, the expert turned to the display view for additional details. Through replaying plays' movements, he noticed that Argentina continuously passed and controlled the ball around the box. Player 10 finally made a shot and scored a goal. Back to the formation view, the expert found that Brazil quickly lost the ball (Fig. 8(H7)) after kick-off. Argentina then used 2-3-2-3 and scored an additional goal to even the score (Fig. 8(H8)). The expert explained that Brazil was underprepared for the continuous attacks from Argentina in the beginning of the second half, thus losing predominance.

Then the expert inspected the third goal of Argentina to see how they reversed the game. As shown in Fig. 8(B2), this crucial goal came from a corner nearly at the end of the game. According to ball possession (Fig. 8(I1)), Brazil had been in control of the ball for a long time before Argentina regained it. Afterward, Argentina substituted a new player, and the expert found that the average distance value of Argentina was decreased (Fig. 8(I6)). This reduction represented an improvement of defense effects, which helped Argentina rapidly regain the ball. Brazil performed a closing down and repossessed the ball at once, but Argentina successfully controlled the ball again (Fig. 8(I2)). With the ball, Argentina quickly changed to 2-3-2-3 to attack (Fig. 8(I3)). Correspondingly, Brazil changed to 4-2-3-1 to defend (Fig. 8(I4)). However, according to the higher average distance bar (Fig. 8(I5)), Brazil could not defend in time. This lapse allowed Argentina to win a corner, which was a chance for the crucial goal.

6.3 Case 2: Overwhelming victory

We invited expert B to analyze this case, which was a game between Argentina and Peru. At first, the expert desired to obtain a summary of the game from different perspectives, thus inspecting different components one by one. From the timeline, he realized that the game result was 4-1 for Argentina vs. Peru. Particularly, the expert found that three of Argentinas goals were place kicks, including one penalty kick and two corner kicks. Therefore, he suspected that Argentina had dominated the game. Thereafter, the expert turned to the confrontation matrix and noticed two deep dark cells. The upper cell (Fig. 1(A)) represented 2-3-2-3 of Argentina against 4-2-3-1 of Peru. The lower one (Fig. 1(B)) represented 4-2-3-1 of Argentina against 2-3-2-3 of Peru. The upper cell was darker than the lower one, which meant that Argentina used more attacking formation (2-3-2-3) than Peru did. The expert further hovered on the upper cell to explore this confrontation. Fig. 1(H) shows that Argentina attacked most of the time, thereby dominating the game. The dominance of Argentina was confirmed through statistical indicators, namely, passes completed and possession time (Fig. 1(C)). On the basis of these results, the expert concluded that this game was an overwhelming victory for Argentina.

He then decided to investigate each goal in detail. According to the statistical view (Fig. 1(D)), Argentina controlled the ball for an extended period before the first goal and did not score as soon as expected. After 23 minutes, despite the strict defense of Peru, Argentina still managed a breakthrough in 2-3-2-3 with intense pass and control (Fig. 1(I)).

Before Argentina began to dominate the game, Peru showed suspense. Soon after the first goal of Argentina, Peru launched a fast counter-attack in 2-3-2-3 (Fig. 1(J)). Correspondingly, Argentina changed from 2-3-2-3 to 4-2-3-1 in defense. However, Peru still scored a goal. The expert selected this duration for further study in display view. In this view, the expert first observed the movement of the players on the pitch. Peru Player 11 regained the ball and passed it to Player 6 (Fig. 1(J1)). Player 6 controlled the ball and swiftly cut in the box. Argentina Player 3 attempted to tackle Peru Player 6 but failed to do so in time, thereby allowing the latter to score. Moreover, according to the triangular lines on the formation of Peru (Fig. 1(J1)), they formed a well-organized 2-3-2-3 for attack.

According to the statistical view (Fig. 1(E)), the variance of the distance between adjacent position lines of Argentina was larger than that of Peru. This discrepancy indicated that Argentina maintained their formation poorly. Additionally, the areas of the two teams were nearly identical (Fig. 1(F)). As we know, the area of formation of Argentina should have been as small as possible becasue they were defending. The expert clicked this indicator. As the line chart above shows (Fig. 1(G)), the area of the formation of Argentina was shrinking but not rapidly enough. Therefore, the counter-attack of Peru was excessively swift that Argentina failed to shrink the area and reorganize their formation to defend in time. These developments led to the team's outstanding goal. Finally, the expert confirmed the analysis with raw videos.

Afterward, Argentina consecutively scored three goals and won the game indubitably. The second goal of Argentina came from a penalty kick at the end of first half; it was also a counter-attack (Fig. 1(L)). After Argentina regained the ball, they quickly changed from 4-2-3-1 to 2-3-2-3 (Fig. 1(K)), and the ball was passed to the strikers. Peru reorganized their 4-2-3-1 to defend but the effect was poor (the orange bar was high in Fig. 1(L)). Possibly, Peru made a defensive foul and conceded a penalty kick to prevent the strikers of Argentina from cutting deep into the box. The two other goals were both set-piece ones in the second half (Fig. 1(M) and (N)). Pressed by the frequent attacks from Argentina, Peru failed to invariably focus and conduct high-intensity defense. Argentina took advantage of the defensive slack of Peru and scored two set-piece goals.

6.4 Expert Feedback

We invited the experts that collaborated with us to analyze two games through our visualization system. After their trial on our system, we conducted an in-depth interview with them one by one. They thought highly of our system and were satisfied with its intuitiveness and professionalism. We summarize their useful feedback from three aspects and furher extract several insights for soccer formation analysis.

Visual Design: Experts were particularly impressed by the design of formation flow due to its innovation and intuitiveness. Compared with traditional video analysis, the formation flow can significantly improve their analysis efficiency for recognizing and understanding formation changes and evolutionary patterns. Moreover, the experts approved the personal flow of each player because it can help them analyze the formation change at the macro level and evaluate the performance of the players in the context of formations at the micro level. However, the experts also commented that the information presented by the formation flow might be a bit dense, as all formation changes were visualized. The experts would like to identify frequent and typical formation changing patterns at the beginning of the analysis and drill down to details according to their interests. In addition to the formation flow, the pitch and the statistical dashboard were also well received by the experts. The SA stated that the key performance indicators made it easier for him to assess not only the performance of a whole team but also that of a single player.

System Interaction: Experts felt that the interactions of the display view were useful. They were able to easily adapt their experience of traditional soccer analysis with the aid of useful interactions provided in the display view. For example, the SC stated that the interaction of showing the triangular partition of a team formation on the pitch could help him effectively understand the distance between lines of formations and estimate whether a team is well keeping their team formation. The experts also suggested that the statistical radar chart should be strengthened by allowing users to configure which indicators to show. Furthermore, the experts appreciated the coordination between the 2D pitch and the raw soccer video, which enabled a quick confirmation of the analysis result. However, the experts suggested that more interactions could be added for video analysis, such as connecting players that stay in same lines of formations (e.g. forward) to explicitly show team formations on the video.

System Usability: According to experts feedback, the experts were satisfied with ForVizor and considered it as a comprehensive visual analytic system that could fulfill their requirements of formation analysis. At the end of the interview, the SC commented, *"The system does provide a novel way for formation analysis, stunning and practical. If possible, I hope it can be employed by the national team"*. However, the experts also raised concerns for analyzing multiple soccer games. They explained that soccer analysts tended to analyze a series of games for a specific team and find out the teams major tactics. Thus, they suggested integrating the functionality of comparing multiple games formation changes in the future.

7 Discussion

Significance. Soccer data contains much valuable information, and this condition attracts researchers to propose various work to analyze different attributes (e.g. shooting, passing and ball possessions) to improve team performances. Among various attributes, team formation is a special attribute because it assigns players to different tasks which regulates player actions to some extent. Considered as a high-level tactic, team formation acts as an important context that can influence the group tactics of several players and individual tactics. Thus, we believe that revealing the information of formation changes could benefit not only formation analysis but also a variety of soccer analysis works. Therefore, we create a novel visual design to characterize the spatio-temporal formation changes in an integrated view. We further develop ForVizor based the spatio-temproal design to strengthen formation analysis. With ForVizor, users can quickly identify spatio-temporal formation-changing patterns, understand reasons behind formation changes, and learn related effects on game situations. The case studies and expert feedback evaluate the usefullness of our system.

Limations. The first limitation is the lack of video data. Currently, we use two soccer games to illustrate the usefullness of our system. It would be more convincing to evaluate more soccer games with the system. However, the acquisition of high resolution panoramic raw soccer videos is difficult, which limits the scalability of our analysis. The issue of acquiring high-quality panoramic soccer videos can be addressed by setting tailored cameras. In the future, we plan to evaluate more games in particular of the same team to understand how tactical schemes evolve in different games. The second limitation is the visual design of team formations. More spatial information remains to be visualized for understanding formation changes. According to experts, except for the formation, the real position of players on the pitch is also important. For example, a team with formation 2-3-2-3 that stays in the front of the pitch can represent a predominant attack, because the ball is close to opposing teams' box. Staying in the midfield means that the team controls the ball and seeks for a chance to push forward. Therefore, visualzing all these spatial information is non-trivial and worth for further investigation. The third limitation is the performance of the data processing procedure. Applying state-of-the-art tracking methods could significantly improve the performance. However, the data processing procedure is not the focus of this work. Nonetheless, we plan to accelerate the speed of data processing in our future work.

8 Conclusion

This study proposes an interactive visual analytic system called ForVizor to help analysts comprehensively investigate formation changes over time. This study is the first attempt at analyzing formations with visualizations. We closely collaborate with experts and characterize a set of domain problems and design goals. We create a novel design called formation flow based on the design goals to visualize formation-changing patterns and disclose the continuous spatial flows of formations in one view to enable the visual tracking of the variation of specific spatial areas and players for in-depth analysis. Multiple coordinated components are designed to combine with formation flows to understand the effect and explain the reason for formation changes.

In the future, we plan to extend the formation flow to encode not only spatial flows between spatial areas but also variations within spatial areas. Visualizing this kind of player movements can help experts more comprehensively evaluate a player's performance and a team's tactics. We also plan to extend ForVizor for increasing the generalizability. For example, for analyzing multiple games, we can convert each formation flow of a game into an abstract glyph so that users can explore through different games' formation glyphs and navigate into the detail of a specific game. Moreover, the concept of formation is not limited in soccer. In many team sports, such as American football, volleyball, and hockey, team formations are also an important part of tactics. Thus, the spatio-temporal design of formations could also be applied in these sports to facilitate tactical analysis.

Acknowledgement

The work was supported by National Key R&D Program of China (2018YFB1004300), NSFC (61761136020, 61502416, 61772456), NSFC-Zhejiang Joint Fund for the Integration of Industrialization and Informatization (U1609217), Zhejiang Provincial Natural Science Foundation (LR18F020001), the Fundamental Research Funds for the Central Universities (2017XZA217), and the 100 Talents Program of Zhejiang University. This project was also partially funded by Microsoft Research Asia.

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