Sports Training

Development of the "interactivelab" platform for network analysis in soccer

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Abstract - Aims: To introduce a platform called "InteractiveLab" (ILab) for collecting and analyzing ball passing networks during soccer games. **Methods:** The software was organized to collect data through a mobile interface and touch screen and simultaneously access that data from a remote database, allowing the automated acquisition, storage, and processing of data during games through an application from the web. The analysis is based on the concept of social networks, characterized by the interaction of players through passing exchanges. **Results:** This descriptive study presents the construction architecture and functioning of the developed software. It also presents the results of intra- and inter-rater reliability and a comparison with the manual collection method. Data were extracted and viewed according to the attacking unit classifications, with the following four outcomes: (a) interception, (b) lost ball, (c) incompletion, and (d) completion. This classification allows for the configuration of the data for a more precise analysis. Some limitations were highlighted, as well as future projections for the improvement of applications and analysis of the interactions network in the context of soccer. **Conclusion:** It is concluded that the InteractiveLab platform is a viable and beneficial tool that offers new possibilities for analysing performance in soccer. Moreover, given the lack of solutions that work similarly, this product also has market potential.

Keywords: soccer performance, Social network analysis, Game analysis, Software.

Introduction

Social network analysis (SNA) is a methodological tool of multidisciplinary origin (psychology, sociology, anthropology, mathematics, and statistics). The main advantage of SNA is the possibility of graphical and quantitative visualization of abstract concepts from characteristic properties and processes of social reality, as an observable network structure and topology that defines the roles of agents in society. Thus, models and theories formulated based on social concepts can be mathematically tested[1]. One of the peculiarities of SNA is the focus on the relational aspect of the collected data, especially regarding maintenance and/or changes in the interaction patterns that define a network over time[2].

In the realm of sport, the concept of "network" is associated with the way human movement systems establish connections and synergies with each other[3]. This type of network, still scarcely studied in the literature of sports science, is particularly useful not only to analyze the number of interactions that occur in a given sport but also to qualify the pattern of play that is established in the course of individual and collective actions[3].

Analyzing teams' interaction patterns helps to describe and understand the dynamics of the game[4] and allows coaches to optimize team performance. For this reason, game analysis in sports has become increasingly important in the last decade[5]. Match analysis consists of collecting the most important game variables and processing the data to generate a final report that will help identify a team's strengths and weaknesses[6]. The characterization of specific behaviours and collective/individual patterns is also collected and provides important information for decision-making on training planning and the strategy used in each match[7]. Thus, with the match analysis in their possession, coaches acquire a permanent feedback cycle to optimize sports training and decision-making. However, data can be observed, processed, and reported in several ways.

In practical terms, there is currently little suitable software to process data from an integrative standpoint[8]. Most systems depend on a human operator and the analyses are centralized in specific notational variables, such as passes, rebounds, dribbles, or shots. In contrast, other computer software uses automatic tracking systems to analyse player movement variables during games and provide information on the players' activity profile[9]. Despite this current trend in match analysis in practical contexts, the scientific community has been developing different approaches to optimize data collection and use the exact sciences to process data and report key evidence in a quick and easy-to-use manner. Some recent computational and mathematical methods are being proposed and have proved promising in the field of game analysis[10,11].

The literature of sports science has demonstrated the potential and practical applications of network analysis[3],[12-15]. With SNA, it is possible to understand a team's inter-relationship dynamics and identify the players who contribute most to the defensive/offensive process or identify and characterize the formation of subgroups in the team. This information can be particularly useful for coaches during training or even during matches. However, the construction of the cooperation matrix by the user requires a lot of time and work; therefore, the possibilities of online and real-time use are very low, so the potential analysis is mainly after matches[2].

In the case of SNA applied to soccer, semi-computational methods based on human observation are the most appropriate[16]. However, although some general software is available to compute social network metrics, such as SocNetV, AllegroGraph, Automap, EgoNet, Gephi, GraphStream, or NetworkKit[16], such software is not specific to the sport and must be supplied with adjacency matrices from the analysis of sports interactions usually calculated by well-known platforms, such as Excel or engineering software (MATLAB). To our knowledge, so far only one software program, called Performance Analysis Tool (PATO), has been developed specifically to collect sport-specific information for SNA[17]. Even so, although PATO allows the collection of game interaction data in a much more practical and less time-consuming manner, the data must be exported to other software and the results cannot be used in real-time, that is, during the analyzed game.

In an attempt to expand these possibilities, this study aimed to introduce a new platform for interaction analysis (InteractiveLab - ILab) based on social networks in soccer. Specifically, we aim to (1) present the architecture and operation of the platform; (2) describe the possibilities of SNA for the scientific community and practical use; and (3) present the results of reliability based on the analysis of a match of the Copa Libertadores de América, the leading South American soccer competition.

Architecture and operation of the low-cost InteractiveLab platform

Since 2018, the Group of Studies and Research in Motor Behaviour (GEPECOM), of the State University of Santa Cruz, has been developing a mobile app called "InteractiveLab" (ILab - BR nº 512020002472-6. 06 Jun. 2019), an accessible and low-cost platform that can be used in practical contexts to analyze soccer performance (and can be adapted to other collective sports). ILab essentially collects data on passing exchanges during soccer games by tapping the touchscreen. This allows data to be organized in adjacent matrices for the analysis of social networks and simultaneously produces a visualization of the network in the form of graphs. This innovation, in relation to other devices on the market, enables the real-time collection and viewing of data, which can be used by coaching staff during matches. Furthermore, the application includes a graphic environment of interactions that can be configured and visualized according to the needs of the coaching staff.

The development of ILab was based on the observed functionalities of the PATO software[17], with the added functions or adaptations for use of SNA in real-time. This section initially presents the main features of PATO that were used to develop ILab, which is presented later.

Introducing PATO functionalities

The main feature of PATO is the possibility of creating one (or more) adjacency matrix(ces) that can be used to calculate the SNA metrics, compatible with other related software.

One of the easiest, most reliable, and most widely used connection indicators for the data collector to observe is passing. In a team sport like soccer, passing is the most common individual action performed for the team to direct the ball toward the opponent's goal. Considering passing as a linkage indicator, the criterion of dividing the data is defined by attacking units (sequence of passes without the interception of the ball). An attacking unit can be classified by observing the moment the ball is recovered, followed by a set of passes performed without losing the ball[3,8,12]. When the ball is lost, the attacking unit ends, generating an adjacency matrix that characterizes this attacking unit[8]. To generate an adjacency matrix per attacking unit, a sequence of passes must comprise more than three successful passes[18]. Thus, the division by attacking units helps identify the temporal patterns of the match. To record passes in the adjacency matrix, code one (1) is used to represent a pass from one player to another, and zero (0) is used to represent no pass, as described in the previous works[3,8]. In cases where more than one pass was made in the same direction (e.g. from player 1 to player 2), the code is added to the number of passes in the same attacking unit[8]. In this case, the number of passes per direction represents one weight. As shown in the example in Figure 1, the vertices (nodes) represent the players and the arcs represent the passes and the direction of the connection. In the example of Figure 1, the sequence of passes was as follows: player 1 - player 3 - player 4 - player 1 - player 3 (Figure 1a). This sequence (attacking unit) produces a matrix adjacency with the distribution and weight of the passes, indicating the passers (column) and receivers (row) (Figure 1b). Finally, Figure 1c shows the graphical representation of the attacking unit, with the weight of the passes and intensity of the link through the size of the vertices and arcs. Larger vertices represent a higher number of ball passes. Larger arcs mean that link intensity is greater between the vertices.

Another important feature of PATO software is the possibility of splitting data (attacking units) into different categories that classify each unit into ball flow, attack transition, or counterattack. In addition, each category can be subdivided into a successful or unsuccessful attack. According to the authors[17], this classification of attacking units is important to describe and understand the dynamics of the game.

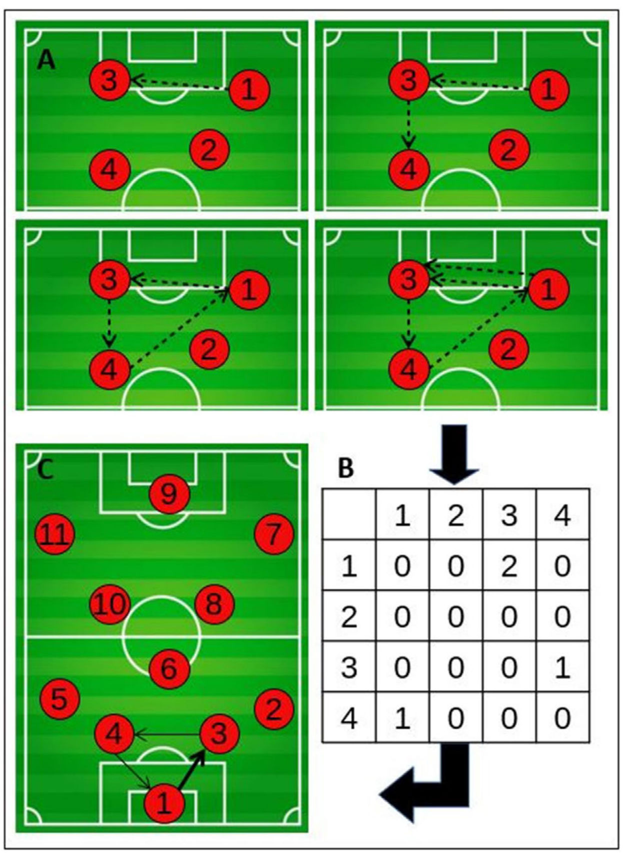

Figure 1 - Process the data collecting: an observation of the real passing sequence; b converting the observation for the corresponding adjacency matrix; c converting for the weighted digraph. Adapted from Clemente et al[17]

In addition to these categories, PATO enables time analysis by periods or time windows. This option can also be interesting to identify patterns of interaction in different contexts. Thus, the software makes it possible to extract the adjacency matrices according to the need and analysis decision of the researcher/analyst. If only an overall analysis is required, it is possible to make a representation for each half or the entire match. In contrast, the matrix can also be extracted when desired, providing the option to continually insert attacking units or restart a new matrix in continued data collection.

It is noteworthy that all these steps are performed without calculating SNA metrics. PATO software is a low-cost data collection tool used to produce adjacent matrices that can be inserted in other SNA-dedicated software.

Introducing ILab architecture and functionalities

ILab (version 3, January 2020) is a platform for collecting, exporting, and viewing SNA data. The platform consists of the following two interaction environments: (1) data collection environment, dedicated specifically for player configuration and for collecting interactions; and (2) visualization environment, dedicated to the graphical presentation based on user preferences. The environments communicate with a middleware server that stores the database for real-time use and to create a database for future use.

The client-server architecture was designed for use in distributed systems. A system is considered distributed when each component of the system is located on different computers but interconnected by a network through the exchange of messages. For the end-user, however, it appears to be a single system[19]. In the case of ILab, there is the collection environment (device A or others) and the viewing environment (device B). In current computing, the client-server model has become the most popular model in system development, and it is used in different types of applications[20].

The most widely used protocols used for client-server communication are FTP (File Transfer Protocol), SMTP, and HTTP. A client-server system can be defined as an application in which a client sends a request to the server and the server provides a response[21]. Due to the client-server architecture, it was possible to develop a platform with several services in the cloud and share data between the different applications, mobile, and web, as shown in Figure 2.

ILab architecture

ILab was developed using the React and React Native libraries for the creation of interfaces with RealmDB as a local database and ExpressJs for the creation of middleware. Both the middleware and InteractiveLab Web were made available for use and testing

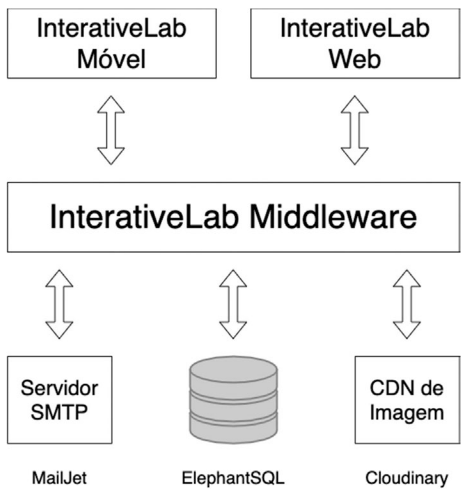

Figure 2 - Client-server architecture applied to the platform.

through the service Heroku. These libraries are described below.

React and React Native: React is a JavaScript library for creating user interfaces and it is currently one of the most widely used development libraries, in comparison with its competitors[22]. React Native, an open-source framework was used to combine the native development of mobile applications with React for creating user interfaces. In addition, the official React Native library was used to create the application for iOS and Android (tablets and smartphones).

Realm DB: RealmDB is a non-relational database that has integration with several programming languages and devices. RealmDB was selected because it has recently become popular and includes more readily available updated study material. In addition, it allows for easy integration with the React Native library[22,23].

ExpressJS: ExpressJS is a library that allows the creation of web applications and APIs for Node.js. This library was chosen because it is flexible and provides a robust set of resources for creating HTTP services and middleware, thus allowing the creation of applications of all sizes[24].

Socket.IO: Socket.IO is a JavaScript library that abstracts the use of WebSockets and allows real-time communication by transferring information as soon as it is published without the need to request information[25].

ElephantSQL: ElephantSQL is a DBaaS (Database as a Service), remote database service, which makes use of the PostgreSQL database. With this service, it is possible to create and configure a PostgreSQL instance automatically. Each user has the option to create up to one free instance for use and automatic backup without the need for additional configuration.

Mailjet: Mailjet is an email solution that does not require specific settings. It is used to send marketing emails and includes an API for sending and receiving emails via SMTP (Simple Mail Transfer Protocol).

Cloudinary: Cloudinary is a storage and management service for various types of media, such as image, video, and audio. With this service, it is possible to automate image-processing pipelines, from uploading to downloading images through the CDN. The CDN stores content on servers near the client by caching and then sends the content based on the geographic location of the person who made the request. This process saves internet bandwidth and reduces file download time[26].

Heroku: Heroku is a PaaS (Platform as a Service) based on a container system used for implementing and running modern applications[27]. Heroku provides a type of VPS (Virtual Private Server), called Dyno. Dynos are web servers that are configured automatically, using the project settings to identify the needs of each language, and can receive all types of web applications.

Platform building methodology

Defining and organizing interaction data

To enable the collection of interaction between players, it was necessary to define how this data would be treated on the platform so it could be understood by all applications. Following the proposal of Clemente et al.[28], and the characteristics of PATO, the methodology for collecting passing exchanges between players was defined as follows:

- Interactions: passes exchanged between players in each attacking unit;
- Attacking Unit (AU): a sequence of interactions until interception, shot, or loss of ball possession, resulting in an adjacency matrix;
- Adjacency matrix: represents the direction and weight of AU interactions. At the end of the match, all matrices (AUs) are added up, resulting in a final matrix of the match.

Once classified, each AU is recorded by an adjacency matrix and stored in the form of a JSON (JavaScript Object Notation) object list, which is a notation that allows information to be organized in key/value format[29], thus enabling the transport of this information to any programming language. The case of the adjacency matrix is different since the conversion from attacking units to the matrix is required only when the user wants to analyze specialized software (similar to PATO). Therefore, it is generated at the end of a match and converted to CSV (Comma Separated Value) format, in which the values are separated by commas. With CSV, a matrix can be easily viewed and read by any network analysis program.

Categorizing the AUs (Attacking Units)

As previously defined, an attacking unit is the sequence of passing exchanges between members of a team (interactions between players) until the loss of ball possession. ILab stores all pass sequences to ensure all available data of the match is collected. The AUs are categorized according to their outcomes according to the following criteria:

- Intercepted: When the AU ends with a pass interception, disarming of a defender, or a pass/ball control error. There is no kick on goal;
- Shot error: When the AU ends with an unsuccessful shot. There is the intention to kick on goal;
- Scoring: When the AU ends with goal scoring.

This categorization allows the personalized analysis of each type of AU, as well as temporal analysis since each AU is time-stamped when it ends.

ILab layout and functionalities

Data collection

To create a specific software for SNA of the interactions in soccer matches, it was necessary to generate a user-friendly application for coaches and sports researchers in any situation. The first criterion was to allow the information of interest to be registered and remotely stored in middleware, so it would be available to any external application with access permissions. This information is protected by a login system (Figure 3a/b) that stores user data on a remote server and restricts access to the data it collects. Thus, users can log into various devices and gain access to all the information they created.

For the collector, the ILab app can be divided into the following screens (Figure 3).

- Registration screens: (1) option to register teams (Figure 3c); (2) option to register prior game confrontations and statistics and confrontations to make the application more intuitive (Figure 3d); and (3) option to register and view players (Figure 3e).
- Data collection screen: (1) layout of the players distributed in the game space, configurable as desired for data collection (Figure 3f); (2) classification option of each attacking unit (Figure 3g); and (3) option of pauses and completion of data collection (Figure 3h).
- Extraction screen: match completion screen, with the option to export the start code for viewing on ILab Web (Figure 3i e 3j).

Viewing

The ILAB web application was developed together with the third version and comprises a data viewer that can be accessed through any browser with internet access. It provides access to match data by uploading a completed match extracted from the mobile application or by using a match identifier key that can be shared from within the application (Figure 3k). With the match key, during collection, it is possible to track data on the screen and simultaneously collect and apply the same configurations available in the mobile application (Figure 3l). Thus, ILab Web allows simple and intuitive viewing in a tactical layout defined within the application. Moreover, collection can be viewed in real-time and can be used by coaches and technical committees on tablets, mobile phones, or computers during the match. The middleware was developed using Typescript and Express.js, hosted on Heroku, as it allows the use of HTTPS for free without the need for configuration. The ElephantSQL service was used as a remote database and Mailjet was used as a remote SMTP server. Both services have a free-use version that met the needs of the platform. It was organized according to the MVC standard and available routes are created automatically following a resource tree, defined by the folder hierarchy. The middleware has two layers of authentication for making a call. One authentication occurs through the "API Key", which is linked to an email address and allows viewing of middleware users. This layer shows the application that is making the calls and the developer/company responsible for those calls. The second authentication, which is done on some routes, is that of "User". It involves the standard login pattern, linked to an email address and a password. When an account is created, a password hash is stored using a random key generated when the middleware is created. Whenever a login attempt occurs, it is possible to check if these credentials are correct. A session token was also developed for users to authenticate again without needing to log in.

How to use ILab

When opening the application, the first step is to register the team(s) for analysis. ILab allows registration of the team name and crest. Subsequently, players must be registered. Players can be registered using a name, number, and photo. These possibilities extend the options for identifying players during data collection. After team registration, the confrontations that will be analyzed are identified. Finally, before starting data collection, the user can either apply the available layout, which is configured based on the tactical positions of the players or distribute players in a different arrangement. Thus, after arranging the players, the user can save the layout to initiate data collection.

Unlike PATO, ILab allows analysis of only one team on the device. However, the other team can be analyzed on another device connected to the same server (ILab Web) so the results of both teams can be viewed by the coach/researcher.

To start data collection, the collector presses the "play" button (Figure 3f), which triggers a timer indicating the collection is active. Once the timer is active, the collector should only touch the icons of the players who receive the ball to record the sequence of passes. Each time a player icon is touched, it is highlighted in a different color (as shown for player No. 6 in Figure 3f and,

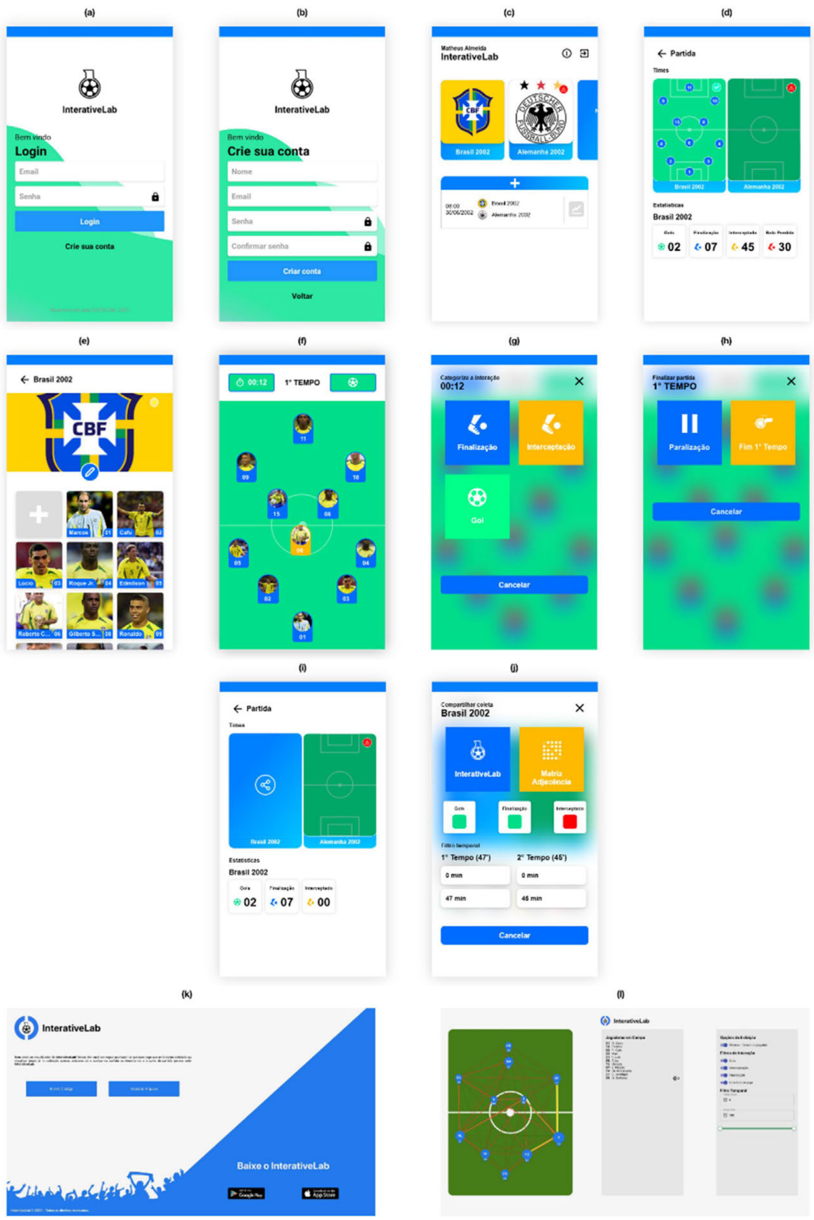

Figure 3 - Screens for ILab: (a) login, (b) account registration, (c) team registration, (d) matches registration, (e) players registration, (f) distribution of players in the collection environment, (g) the ratings of the Attack Units, (h) the screen for stopping or closing data collection, (i) sharing screen and presentation of general game statistics, (j) screen to define parameters for viewing in Ilab or exporting data, (k) screen for entering the data identification code and starting the upload, and (l) real-time display screen with configuration options for viewing data.

optionally, triggers a brief vibration on the device (vibration mode enabled). These indicators show collectors that the markings were selected effectively without having to check visually. Thus, in the system, the designated receiver player automatically changes to the passer player when the next receiver player is selected, and so on until the AU is completed.

After the AU is completed, it must be classified according to the available options, namely “intercepted”, “shot error”, and “scoring” (Figure 3g). After classification, the software encodes the attacking unit and converts the information into an adjacency matrix. As in the case of PATO, ILab allows for exporting of the adjacency matrix at any time during data collection, both for analysis in external software (with .CVS extension) and for viewing on ILab Web (Figure 3j).

It is important to highlight that the registration of interactions by ILab continues even after export. When exported, the file is automatically named according to the selected configuration (Figure 3j) for export or Figure 3l for viewing within ILab). The configuration options are:

1) Time configuration: users can select the match time they want to analyze by entering the start and end time, referring to the data collection time;
2) Configuration by attacking unit characteristics: users can select only the matrices that were "intercepted", ended in a "shot error", and ended with a "scoring", or a combination of configuration, such as "intercepted" and "shot error" together, or "shot error", and "scoring", among others.

Viewing the data in the ILab viewer

To view the interactions in the ILab environment, users must only choose the preferred configuration. Once selected, the graph shown in Figure 3l will appear for analysis. In this graph, nodes (or vertices) represent players, and interactions (links) represent passes. The magnitude of the nodes expresses the player's participation indicates the number of passes made. The magnitude and colors of the lines, however, represent the number of passes made between players. Thus, considering the illustration of Figure 3l, the wingbacks and defenders performed well, as did the attacker "BH" (indicated by the magnitude of the node). Regarding the interactions, the right wingback "R" interacted strongly with the players "ER" (greatest number of passes performed), "RC", and "A". In general, the ball circulated more among the players positioned on the right of the field.

It should be noted that the ILab viewer does not calculate SNA metrics; it only produces a graphical visualization of interactions. To calculate these metrics, data should be extracted to other SNA-specific software, such as SocNetV mentioned above. The possibility of calculating the key metrics used in soccer is being evaluated for future versions. However, since the main purpose of ILab is real-time use during matches, qualitative assessment seems more appropriate for technicians to make tactical and strategic decisions during matches. Future research should address the efficiency of this type of visualization in the actions of coaches during matches.

Reliability of the ILab platform: a pilot study

To measure the reliability of the data collected by ILab, a pilot study was conducted using an intra-rater test-retest evaluation protocol with a 10-day interval, and an evaluation protocol that compared the data obtained by ILab with the data obtained from manual, pencil, and paper collection. The analyses were performed in an experiment comparing the results in the SNA of professional soccer games of the Copa Libertadores de América. The match was Club de Regatas Flamengo vs. Club Atlético San Lorenzo de Almagro, at Maracanã stadium on March 08, 2017, for the Copa Libertadores de América in the 1st round of the group stage (Available from: https://www.youtube.com/watch?v=uC6b77E6BEI). The game was analyzed using VT provided by YouTube. The analyses were performed in the Laboratory of Studies and Research in Motor Behaviour - GEPECOM/UESC.

Intra-rater and inter-rater assessment

According to Clemente, Martins, and Mendes[16], low-cost game analytics solutions using social network analysis (SNA) should comply with some requirements to ensure data reliability. In the specific case of collective sports, the variability of actions and variations of contexts can lead to subjectivity[30]. Any subjectivity compromises data collection and the interpretation of results. For this reason, a test and retest for intra- and inter-observers should be performed to prevent errors and differences between observers. Generally, a test-retest with 20% of the sample will ensure the reliability of the data. In some cases, a minimum of 10% of the complete data is sufficient to test the reliability of procedures[31]. Another alternative is to follow a 15- to 13-hour teaching/training protocol, to consolidate the analysis criteria. After this procedure, the same test sample should be analyzed on two occasions with a 25-day interval[32]. The two- or three-week interval will minimize the effects of the observer's familiarity with the task[33].

After data collection, the reliability test can be tested using Cohen's kappa coefficient[32]. In the case of more than one observer, the test-retest should be analyzed for intra-observer (reliability for the same observer on two occasions) and inter-observers (reliability between different observers on two occasions). Values greater than 0.61 in Cohen's kappa coefficient are sufficient to consider data reliable, thus indicating a conventional level of acceptance[34]. In contrast, if a lower value is reached during the test, another round of observer training should be performed[16]. Considering these guidelines, in our pilot study, Cohen's kappa coefficient was used for intra-rater and inter-rater assessment. The raters were coaches of amateur teams who had received specialized training for a week (20 hours) to familiarize themselves with the ILab software and the established criteria for record standardization. This process aimed to reduce the effects of the observer's subjectivity in match analysis. For the intra-rater assessment, the same rater measured the same match on two occasions with a 28-day interval, resulting in a kappa value of 0.76. For the inter-rater assessment, two raters measured the same match at the same time and place. The result revealed a kappa value of 0.71. Both results suggested the reliability of the data collected with ILab.

ILab vs. manual assessment

To verify the reliability of the collection methods, the data of the passing exchange between the players (adjacency matrix) were analyzed at different times, by the same collector, in two ways:

1) Manual record: manual recording is commonly used for social network analysis. This form consists of manually recording, on a spreadsheet (paper or electronic), the ratio of passing and receiving players in each attacking unit. That is, it registers the player who passed the ball and the player who received it, consecutively, until the attacking team loses possession of the ball (i.e., attacking unit). In this way, by the end of the game, all attacking units (of both teams) are documented in an adjacency matrix (11 × 11), where the sum of each possible interaction (player-player) is shown. This recording was performed with a recorded game using pause, rewind, and fast forward of the video, when necessary. The manual recording was considered here as the "gold standard", as it is the most consistent way to log the interactions of a game.
2) Recording with ILab: The app was used for recording in real-time, without the pause or rewind features of the video. In this case, the collector recorded the interactions using the touchscreen, by tapping the circles corresponding to the players according to the sequence of passes in each attacking unit. The virtual data collection environment is shown in Figure 3f.

After data collection, the adjacency matrix was stored for SNA. In the present collection, the data were sent by e-mail for analysis of network metrics. Both manual recording and recording using ILab allowed the creation of adjacency matrices that could be sent for analysis in Social Networks Visualizer software, version 2.5[35]. This software is a graphical application used to analyze and view social networks. It allows users to load data into sociomatrices and subsequently analyze the mathematical properties of the corresponding social network and compute basic graphical properties, such as density, diameter, and clustering coefficient, as well as more advanced structural measurements, such as centrality and prestige indices, among others. For this purpose, the software must be loaded with an adjacent matrix created using other software.

Metrics analysed in SNA

All matrices were imported to Social Networks Visualizer software, version 2.2 (SocNetV). Four metrics were used for the analysis:

I)Density (DE): measures the overall relationship between players;

(II)Centralization (CE): measures the level of homogeneity of the interactions network;

(III)Clustering coefficient (GC): measures the degree of connectivity with surrounding (immediate) players; and

IV)Centroid player (CP): measures the most sought-after and connected player(s) in the interaction network.

Data analysis

After calculating the variables, the results of each method (manual vs. application) were compared. Since the comparison was only carried out with one game, the calculation of statistical differences was unfeasible. Thus, data were interpreted in each method, seeking to highlight differences in the interpretation of the analyzed phenomenon.

Results

The comparison of ILab x manual recording was performed to determine the reliability of the software for the analysis of soccer performance in real-time. As a methodological option, quantitative and qualitative results from the manual recording were compared, acquired after the match with the use of pause and image recovery.

In this session, quantitative data related to the global parameters (density and centralization) and local parameters (centroid player and clustering coefficient) of the network are initially presented. Then, qualitative data based on the graphs are presented. Finally, the technical and operational difficulties are systematized in a table, highlighting possible improvements to the platform.

Quantitative parameters

The global parameters (density and centralization) of the network are presented graphically for each data collection mode (manual vs. InteractiveLab).

Figure 4a shows that the density variation was 1%. The density value was 0.745 for the manual format and 0.754 for ILab. The centralization of the group also varied 1%, with a value of 0.28 for the manual format and 0.27 for ILab.

Of the studies reviewed to date, none reported significant differences in-game behaviour with a variation rate below 5%[36-38]. This suggests that at least in relation to the global network parameters, the differences found do not affect the interpretation of game dynamics. Figure 4b shows the local parameters (centroid player and clustering coefficient) of the network for each data collection mode (manual vs. InteractiveLab).

In general, all players showed a good level of participation in the game, both in the manual collection and in ILab. The least active players in ball exchanges were players 1, 10, and 11, corresponding to the goalkeeper and the two attackers. Some difference was observed in players 3, 4, 8, 9, and 11. For the clustering coefficient, greater differences were observed, indicating similar values only for players 1, 4, 6, 10, and 11. Players 2, 3, 5, 7, 8, and 9 showed some difference but did not change the interpretation of the clustering locations in the network.

In the literature consulted, local network parameters have been less explored, as they are more sensitive to the game dynamics[36]. This sensitivity comes mainly from

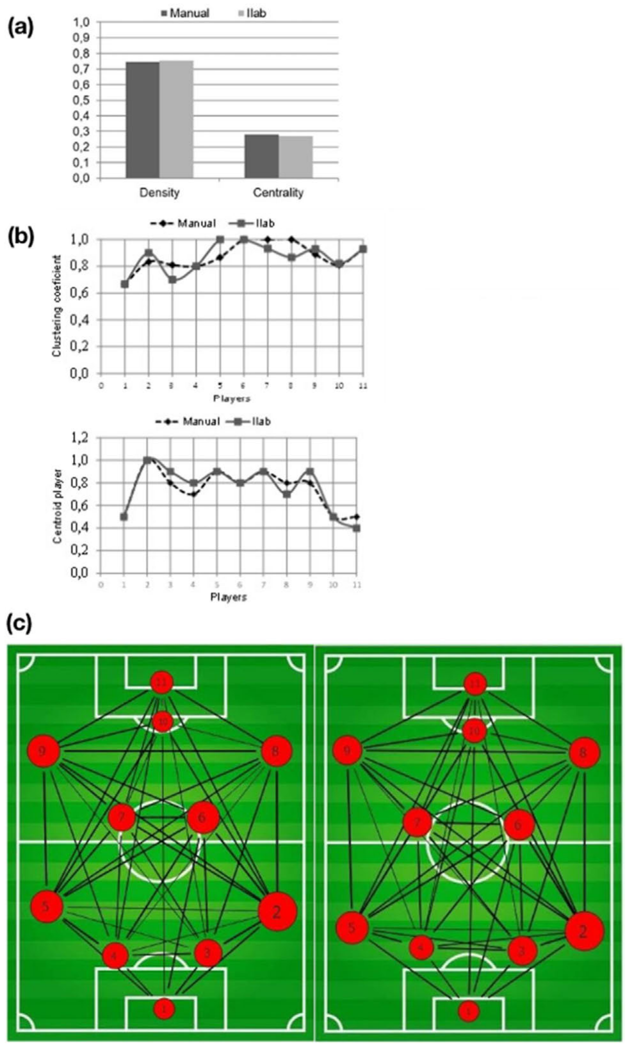

Figure 4 - Description of the analyzed parameters obtained in manual x ILab collection: (a) density and centrality values, (b) centroid player and clustering coefficient values, and (c) description of the network formed by the players. The lines indicate the interactions (passes) performed. The circle indicates each player and its magnitude indicates the participation rate. The figure on the left represents the manual collection and the figure on the right represents ILab collection. Source: Research data.

methodological differences in studies and plays judgments when collecting interactions (effect of subjectivity). Regarding the methodology, it is still necessary to standardize the sequence of players, especially in relation to the clustering coefficient. Depending on the numbering of the players, differences in the subgroups are highlighted. In the present study, we used the ordering proposed by positional functions, according to Clemente et al[17].

Another important point is in relation to the judgment of the collector when considering an attacking unit. Defining criteria for the start and end of each attacking unit and for when there are possible partial interceptions is important and affects the final result. This may have occurred in the present study. It was not possible to identify an error pattern (i.e. overestimation or underestimation). This means that in some moments, the interpretation of the play may have been decisive for the few differences observed. Importantly, there were two substitutions in the game, which may have affected player identification when collected in real-time. Clavijo, Corrêa, and Menuchi[38] demonstrated that substitution in another position has an effect on network interaction and, consequently, on the interpretation of local parameters.

Qualitative visualization

Figure 4c illustrates the network presentation and shows the interactions and the most requested players in the match. In general, similar behaviours are observed between the two methods of data collection. Both networks demonstrated the same most in-demand players and those who attracted the values of centralization. In terms of interpretation, the graph indicates the strong performance of the wingbacks (players 2 and 5) and midfielders (players 6, 8, and 9). In relation to interactions, stronger interactions can be observed from the midfielders to attack than interactions in the defensive sector. It is important to highlight that the main function of ILab is to provide a graphical visualization of the overall behaviour of the interactions network in the game, as shown in Figure 4c. Although the quantitative values were compared here, coaches do not use them in the field during games. Usually, quantitative data is used after games to try to identify patterns of team and opponent interaction. In contrast, the use of social network analysis throughout games has not yet been identified in the scientific literature. For the authors of this study, graphical visualization seems to provide potential information to coaches during games. In this sense, a real-time collection using ILab proved efficient. In real-time, each doubt can become an error that, when accumulated over time, can provide results that do not represent the behaviour of interactions during the game. Thus, it is worth noting that the quality and reliability of the measurements depend on a trained collector who is familiar with each player on the analyzed team(s).

Practical application and future development

In addition to applications for sports science, ILab software was designed to provide a visualization of the network based on the level of interaction and interdependence between players. Using the ILab viewer, the nodes (representing the players) and the connections (representing the interactions, e.g. the passes) will have different sizes to represent the strength of the player's performances and interactions, respectively (Figure 3l). With this, the coach will be able to identify which players interact with which players and the strength of this interaction. He or She will also be able to identify the individual performances, as well as the changes that occur throughout the match, the players that assume a more connective role, and also the formation of subgroups capable of predicting the most common ball circulation in certain contexts. Using the AU classification settings and playing time, the coach can also check specific moments and the topology of passes in certain attack contexts, compare events (eg, changes in substitutions or strategic changes), and assess the progress of the exchange of passes. In addition to the "real-time" use, the possibility of storing data collections will enable the creation of an information database to be used in the analysis of the teams' style of play in order to implement more accurate strategies behaviour.

Some limitations can be highlighted for future software development. The first is related to the type of interaction analyzed. Although ILab was designed for the analysis of the "player passing networks", new features are being thought, such as the "pitch passing networks" (where nodes are specific regions of the field connected through passes made by players occupying them), and "pitch-player passing networks" (where nodes are a combination of a player and its position at the moment of the pass). The second limitation relates to the emphasis given to the attack, disregarding the defensive organization. For this, the network analysis must be associated with other analysis techniques that allow the observation of the defense. Finally, most of the metrics used in the social interactions model are based on the ball's circulation paths (connections), which may be inappropriate for some sporting contexts. In this sense, as ILab is used, the demands and needs will arise so that new solutions can be implemented.

Conclusions

This study introduced ILab and described its architecture, functionality, and compatibility with other software. The reliability of data was evaluated and the results were positive and satisfactory. As an innovation to other methods of data collection, ILab showed that real-time graphic analysis and visualization are possible. Although there is still no record of this visualization in real-time, the graphical properties provide a view of density, centrality, and specific participation, as well as the formation of subgroups during games. With this information and the possibility to configure the attacking units of interest, coaches can evaluate the strategic organization or the effects of substitutions or tactical changes during games. Thus, we conclude that the ILab platform is a promising tool to collect data for SNA and obtain a graphical visualization, using free, user-friendly software in real-time. Moreover, data can be easily exported to multiple SNA-dedicated software. Although ILab was developed specifically for the analysis of soccer, it can be easily adapted to other collective sports modalities. New layouts will be available soon. In general, the computational application developed on this platform can provide valuable insight into the complex mechanism underlying success in soccer. ILab can be used both for scientific research in the field of sports science and in the practical context by coaches and technical teams when evaluating and developing teams. ILab can help the technical team by storing several games and creating a database that can be accessed and used, as needed and at any time, to evaluate their teams and guide their training, as well as to evaluate opponent teams.

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