Visualizing Temporal Graphs using Visual Rhythms
A Case Study in Soccer Match Analysis

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Abstract: In several applications, a huge amount of graph data have been generated, demanding the creation of appropriate tools for graph visualization. One class of graph data which is attracting a lot of attention recently are the temporal graphs, which encode how objects and their relationships evolve over time. This paper introduces the *Graph Visual Rhythm*, a novel image-based representation to visualize changing patterns typically found in temporal graphs. The use of visual rhythms is motivated by its capacity of providing a lot of contextual information about graph dynamics in a compact way. We validate the use of graph visual rhythms through the creation of a visual analytics tool to support the decision-making process based on complex-network-oriented soccer match analysis.

1 INTRODUCTION

Huge volumes of graph data have been generated in several applications, demanding the development of appropriate tools for storing, processing, and analysis. Examples of applications include social network (Zhao and Tung, 2012; Brandes et al., 2012), sport analysis (Duch et al., 2010; Cotta et al., 2013; Peña and Touchette, 2012; Passos et al., 2011), and urban planing (Nahman and Peri, 2017). One particular class of graphs that is attracting a lot of attention recently are the temporal graphs, which basically represent the insertion and deletion of vertices and edges over time (Leskovec et al., 2005).

In this paper, we are interested in visually representing temporal graphs, with the objective of supporting the identification and analysis of temporal pattern changes. In this context, several approaches have been proposed to the visualization of temporal graphs (Brandes and Corman, 2003; Hurter et al., 2014; Brandes et al., 2012; Beck et al., 2016). Most of the approaches rely on the use of node-link diagrams, where different visual marks (typically circle glyphs) are used for representing vertices and lines to visually represent relations among vertices. Different additional visual properties associated with visual marks (e.g., position, size, length, angle, slope, color, gray scale, texture, shape, animation, blink, motion) are employed to highlight properties associated with both vertices and edges (Beck et al., 2016). A typical challenge faced by those initiatives refers to the visualization of huge volumes of data. In these scenarios, complex interaction controls have been proposed to handle occlusion and to support browsing activities over graph data.

In this paper, we address this problem from a different perspective. We propose a graph-to-image transformation, so that large volumes of sequence graphs can be visually represented in a compact way, enabling fast and easy visual identification of pattern changes. Our solution relies on the use of the *visual rhythm* representation (Ngo et al., 1999). This approach has been typically used for efficient video data processing and analysis (Bezerra and Lima, 2006; da Silva Pinto et al., 2015), as it allows the representation of the whole video content by means of an image, whose columns are defined by the extraction of features from pixels of frames. In this paper, we extend this idea by encoding properties of graph sequences, leading to a representation we name *graph visual rhythm*. For each instant of time, graph properties are represented as a column of an image, allowing the compact representation of important graph features associated with changes of vertices and edges

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over time. Our solution is somehow similar to previous initiatives focusing on encoding graph dynamics using matrix representations (Burch et al., 2011; Vehlow et al., 2013; Bach et al., 2014). Different from those initiatives, however, our approach does not rely on radial layouts, nor on complex representations such as small multiples and stacked matrices. To the best of our knowledge, this is the first attempt to encode complex temporal graph changes in a easy-to-interpret single image representation.

The proposed method is validated in the context of soccer match analysis. Recently, sport science researchers have been dedicated to the representation of soccer match events by means of graphs (Duch et al., 2010; Cotta et al., 2013; Peña and Touchette, 2012; Passos et al., 2011). Usually, players are represented as vertices and their relations (e.g., passes, proximity) are encoded as edges. In some of those applications, graph properties, defined in terms of complex network topological measures are used in the match analysis. In this paper, we describe the use of graph visual rhythms defined in terms of complex network measures for understanding complex temporal patterns associated with the match dynamics.

In summary, the contributions of this paper are twofold: (i) the introduction of a novel compact visual representation for temporal graphs, named graph visual rhythm; and (ii) the presentation of different scenarios of its use in the context of the analysis of real soccer matches using complex network measures.

2 BACKGROUND

2.1 Visual Rhythms

Visual Rhythm is a sampling method widely used to video processing and analysis (Ngo et al., 1999; Guimarães et al., 2003; Chun et al., 2002). Its objective is to transform tridimensional information into bidimensional images by sampling one dimensional information from video frames. Let V be a digital video (in domain $2D+t$) composed of T frames f_t, i.e., $V = (f_t)$, $t \in [1,T]$, where T is the number of frames. Let H and W be, respectively, the height and width from each frame f_t.

The visual rhythm computation consists in using a function to map each f_t into a column of an image in domain $1D+t$. The final image generated is known as visual rhythm image (VR). More formally, the computation of the VR image is defined as follows (Ngo et al., 1999; Guimarães et al., 2003):

$$VR(t,z) = f_t(r_x \times z + a, r_y \times z + b), \qquad (1)$$

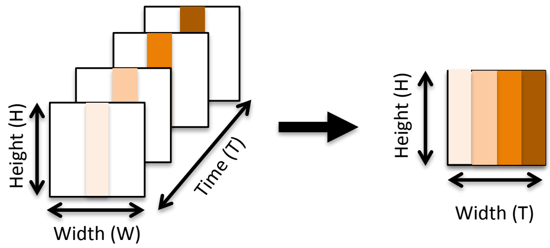


Figure 1: Example of visual rhythm computed by extracting the pixel values defined by the central vertical line. In this example, $r_x = 1$, $r_y = 0$, $a = 0$, and $b = \frac{W}{2}$. This leads to a visual rhythm $VR = f_t(z, \frac{W}{2})$, where $z \in [1, H_{VR}]$ and $t \in [1,T]$, $H_{VR} = H$ is the height of the visual rhythm image, and T is its width.

where $z \in [1, H_{VR}]$ and $t \in [1,T]$, H_{VR} and T are the height (i.e., $H_{VR} = H$) and the width of the visual rhythm image; r_x and r_y are ratios of pixel sampling; a and b are shifts on each frame. Figure 1 illustrates the computation of visual rhythm based on the pixel values defined by the vertical line passing in the center of the frame.

A more general definition of visual rhythms assumes that it is possible to use a function $\mathbb{F}$ to represent each frame of a video as point in an n-dimensional space. Let f_t be a frame defined in terms of $\mathbb{D}$, a set of pixels. Function $\mathbb{F}$ is defined as $\mathbb{F} : \mathbb{D} \rightarrow \mathbb{R}^n$. For example, a widely used implementation of function $\mathbb{F}$ relies on the computation of the histogram associated with each frame f_t (Guimarães et al., 2003). In this case, the visual rhythm image is a 2D representation encoding all frame histograms as vertical lines, i.e.,

$$VR(t,z) = \mathcal{H}(f_t), \qquad (2)$$

where $\mathcal{H}(f_t)$ is a function that computes the histogram of frame f_t, $t \in [1,T]$ and $z \in [1,L]$, T is the number of frames and L the number of histogram bins.

2.2 Complex Network Measurements

Soccer is one of the most difficult sports to analyze quantitatively due to the complexity of the play and to the nearly uninterrupted flow of the ball during the match. Indeed, unlike other sports, in which individual game-related statistics may properly represent player performance, in soccer it is not trivial to define quantitative measures of an individual contribution (Duch et al., 2010). Moreover, simple statistics such as number of assists or number of shots may not provide a reliable measure of a player's true impact on team performance and, consequently, the outcomes of a match (Duch et al., 2010; Moura et al., 2014). Instead, the real contribution of a given player sometimes is hidden in the plays of the team, such as participating from a passing sequence to a shot on goal (Duch et al., 2010). This type of information is important to detail the role of a team member on team performance. Thus, this study uses complex network measurements for extracting features from graphs to represent individual behavior and thus to represent team performance using a visual analytical tool. Two measurements were considered in this work: Diversity Entropy and Betweenness Centrality.

2.2.1 Diversity Entropy

The dynamic aspects associated with passes among players in a match (such as the 'ball flow' among the players of a team) are important cues for game tactical analysis (Duch et al., 2010). In this paper, we use the diversity entropy (Travençolo and Costa, 2008; Travençolo et al., 2009) as a variable to characterize the dynamic nature of the match, characterizing the possibility of passes among players.

Diversity Entropy considers the transition probability ($P_h(j,i)$) that a node i reaches a node j after h steps in a self avoiding random walk. Let Ω be the set of all nodes but i. The normalized diversity entropy of a node i is defined as (Travençolo et al., 2009):

$$E_h(\Omega,i) = -\frac{1}{log(N-1)}\sum_{j=1}^{N}\begin{cases} P_h(j,i)log(P_h(j,i)), & \text{if } P_h(j,i) \neq 0,\\ 0, & \text{if } P_h(j,i) = 0.\end{cases} \quad (3)$$

2.2.2 Betweenness Centrality

In this paper, the centrality of players in a match is related to his role in the passing flow along the time. We used betweenness centrality to characterize the role of players in terms of the graph shortest paths with which the players are involved.

Betweenness centrality (Costa et al., 2007) of a node u is quantified as the sum over all distinct pairs of vertex i,j of the number of shortest paths from i to j that pass through u ($\theta(i,u,j)$) divided by the total number of shortest paths between i and j ($\theta(i,j)$):

$$B_u = \sum_{ij}\frac{\theta(i,u,j)}{\theta(i,j)} \quad (4)$$

3 GRAPH VISUAL RHYTHMS

We define a temporal graph $\mathcal{G}$ as a sequence $\mathcal{G} = \langle G_1, G_2, \ldots, G_T\rangle$, where $G_t = (V_t, E_t)$ is a weighted graph at timestamp $t \in [1,T]$ composed of a set of vertices, V_t, and a set of edges, E_t. We refer to the graph defined at a particular timestamp t (say G_t) as an *instant graph*. By building one graph for each instant of time considering the vertices' interaction, it is possible to capture the temporal nature of the graph dynamics. Our goal is to represent the interaction among vertices at each instant using a visual rhythm representation GVR. We follow a similar formulation employed in Eq. 2 to define GVR:

$$GVR(t,z) = \mathcal{F}(G_t), \quad (5)$$

where $\mathcal{F}_{G_t} : \mathcal{G} \rightarrow \mathbb{R}^n$ is a function that represents a graph $G_t \in \mathcal{G}$ as a point in an n-dimensional space, $t \in [1,T]$ and $z \in [1,n]$.

Figure 2 illustrates the computation of a graph visual rhythm for a temporal graph. Changes in the graph sequence are highlighted in red. For example, at timestamp t_2, an edge linking vertices v_2 and v_4 is created. At timestamp t_n, vertex v_5 is created along with an edge from v_5 to v_3. In this example, function $\mathcal{F}_{G_t}$ computes the degree of vertices for each instant of time (arrows labeled with A). The degree information is later used to create the graph visual rhythm

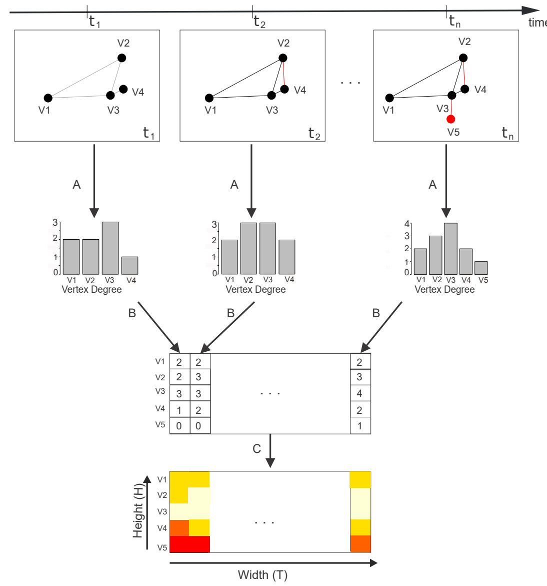


Figure 2: Flowchart illustrating how a graph visual rhythm is extracted.

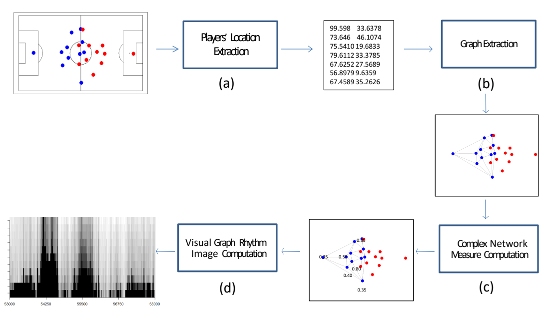


Figure 3: Analysis framework.

image (arrows B). Again different visual properties (e.g., color, opacity) may be used to highlight graph changes. In the case of the example, a heatmap-based color layout is employed (arrow C).

4 CASE STUDY: SOCCER MATCH ANALYSIS

This study is based on the use of graph visual rhythms for identifying events on temporal graphs associated with soccer matches.

4.1 Soccer Match Analysis Framework

The graph-based soccer match analysis framework employed in this study comprises four steps, as illustrated in Figure 3:

(a) Extraction of players' location in field over time: This step is accomplished using the DVideo software (Figueroa et al., 2006a; Figueroa et al., 2006b) applied to official soccer matches. This process starts with soccer match videos and results in files containing players *xy* location on the pitch and annotation related to match events, such as passes accomplished, fouls, shots on goal, among others. The extraction frame rate is 30 frames per second, so for a typical 45-minute half time of a match, we have 81,000 frames. We used a dataset related to two official soccer matches (referred to as Match 1 and Match 2 along the paper) of the Brazilian Professional First League Championship.

(b) Graph Extraction: This step builds graphs from soccer match frames. In our experiments, two different kinds of graphs were built: Delaunay Triangulation Instant Graphs and Flow Networks, which are detailed in Section 4.2.

(c) Complex Network Measure Computation: This step comprises the approach described in Section 2.2. Basically, complex network measures are computed from graphs obtained in Step b. In this experiment, two measures were considered: Diversity Entropy and Betweeness Centrality. In this context, these measures are extracted by $\mathcal{F}_{G_t}$, the function that encodes one graph into a column of a graph visual rhythm.

(d) Visual Graph Rhythm Image Computation: This step is concerned with the creation of graph visual rhythm images. From those images, it is possible to analyze patterns that represent match events such as attacking and defensive strategies from each team.

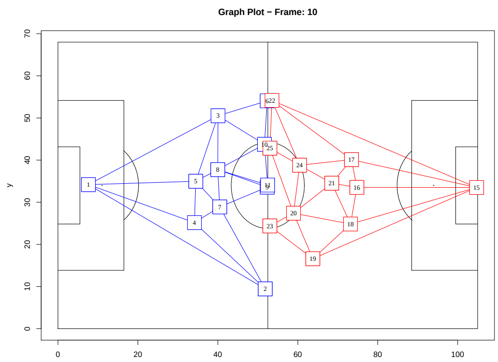


Figure 4: Examples of Delaunay Triangulation instant graphs of two teams (represented in blue and red).

4.2 Soccer Temporal Graphs

Our analyses are based on the characterization of interaction among players along the match. Let $\mathcal{G}'$ be a sequence $\mathcal{G}' = \langle G_1, G_2, \ldots, G_T \rangle$. A vertex $v \in V_t$ is associated with a player, whereas an edge $e_{jk} \in E_t$ connecting two vertices $v_j \in E_t$ and $v_k \in E_t$ is defined based on the location (or any other relation) of players (v_j and v_k) of the same team at timestamp t. The weight $w(e_{jk})$ may encode different properties of the interaction of players, such as their distance – possibly measured by the Euclidean distance of players j and k in the field – or the number of passes between them.

Considering the importance of interaction between players on soccer matches, we consider two different approaches for constructing temporal graphs: Instant Graphs based on Delaunay Triangulation and Flow Networks. Both of them take into consideration passes between players from the same team. Instant graphs represent possibilities of passes according to the players' position on the pitch at each timestamp, while Flow Networks represent all accomplished passes between players in a time interval.

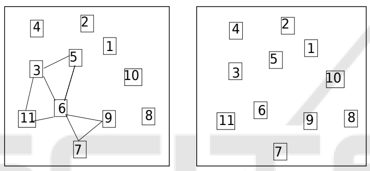
4.2.1 Instant Graphs based on Delaunay Triangulation

In this representation, for each time stamp, it is computed the Delaunay Triangulation (Preparata and Shamos, 2012) considering as input the players' position in the pitch. Two triangulations are computed, one for each team. Figure 4 shows examples of instant graphs. Blue vertices (players labeled from 1 to 11) and edges represent Team A, while red ones (players labeled from 15 to 25) represent Team B.

4.2.2 Flow Networks

One important research venue refers to the identification of interaction patterns among players for a given time interval. One common approach relies on the use of Flow Network (Duch et al., 2010). Flow network graphs can be defined as $G_{t_i,t_j}(V,E)$, in which vertices are players from a team, and weighted edges represent passes accomplished between them during a time interval $[t_i,t_j]$.

We extend this approach by proposing ball possession flow networks. Those networks show paths that only happen in time (Santoro et al., 2011; Casteigts et al., 2011), which means that no instant graph has all the edges shown in a flow network. Basically, we extract different flow networks, which represent ball passing among teammate players within the time interval in which they have ball possession. Figure 5 shows two possession flow networks. In Graph (a), the team has the ball, and accomplishes eight passes among teammates. Graph (b) illustrates the match situation in which a team has the ball possession, but no passes are accomplished until losing the ball possession again.



(a) (b)

Figure 5: Examples of Ball Possession Flow Networks. (a) Graph from a team that performed eight passes among teammates during a ball possession interval. (b)In another ball possession interval, no passes were performed.

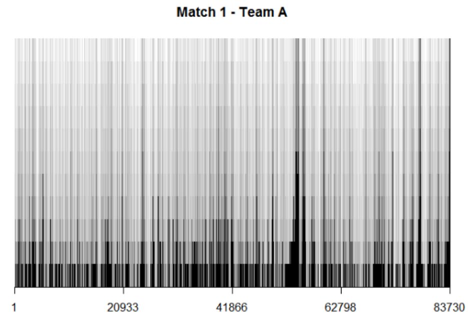
5 ANALYSIS AND DISCUSSION

This section discusses several usage scenarios in which graph visual rhythms are used to identify visual temporal patterns related to teams' strategies when defending or attacking.

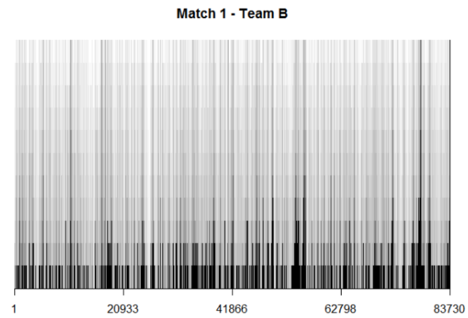
5.1 Defensive Patterns

The first usage scenario considers the use of graph visual rhythms in the identification of defensive patterns.

Considering the first half time of a match, we generated the Delaunay Triangulation Instant Graphs and computed the Diversity Entropy from each node in the instant graph ($\mathcal{F}_{G_t}$). For each instant graph, diversity entropy values were ordered and linked together vertically resulting in an image GVR_{xy}, where x is equal to the amount of frames from the match and y is amount of players from graph (11 players in



(a) Match 1 – Team A



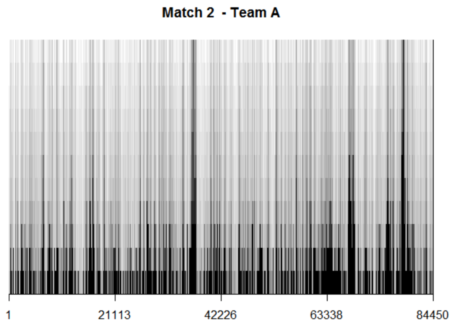
(b) Match 1 – Team B

Figure 6: Graph visual rhythm images for teams of **Match 1**.

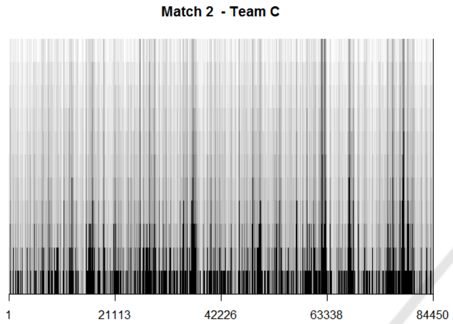
each team). Diversity Entropy values between 0 and 1 in GVR_{xy} were normalized to 0 to 255, generating a grey-scale image. In this case, lower entropy values are darker, and higher values are lighter. For the player who has ball possession, entropy values may be associated with the 'complexity' of the decision-making scenario. If entropy is high, it means that the player has many options (i.e., teammates) to interact with and this is a less complex situation in case that the player has to perform a pass as fast as possible. On the other hand, lower entropy values may represent few teammates to interact with. This complex situation requires the player to evaluate this scenario more carefully, identify who are these few options of interaction, and thus make the decision to perform a pass.

Figures 6 and 7 present the resulting graph visual rhythms images obtained for teams of two matches (Match 1 and Match 2). In both matches, Team A is the same. It is possible to notice a clear pattern, defined in terms of vertical darker blocks, that distinguishes all images. Considering the performance of Team A in both matches, we can observe that there are darker regions for Match 2, which means that players of Team A in this match were usually not free, i.e., there were opponents close to them more frequently.

By zooming in the graph visual rhythms of Figure 6 for the frames in the range defined between



(a) Match 2 – Team A

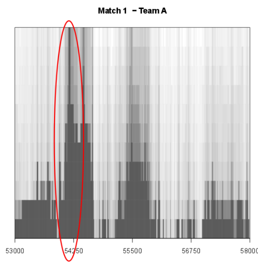


(b) Match 2 – Team C

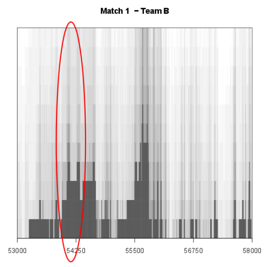
Figure 7: Graph visual rhythm images for teams of **Match 2**.

55000 and 58000, we obtain the images shown in Figure 8. We plotted the corresponding graph from the instant highlighted in red, to analyze the game strategy employed in the time period related to a darker block. It is possible to observe that for a darker block, Team A (in blue) is compressed in a defensive strategy while Team B (in red) is attacking. Team B is well positioned in the field with many possibilities of passes among players, which is represented in its own graph visual rhythm image. Thus, entropy values may represent team strategy both in attacking and defending perspectives. The distances among teammates define the team compactness on the pitch during attacking and defending actions (Moura et al., 2012; Moura et al., 2013). In this case, Team-A players occupy the field in a very compact way, with a no clear purpose of performing a man-to-man marking. This strategy may favor the attacking team in order to allow a greater number of options for passes between players. If this condition is maintained over time (which is easily detected in the graph visual rhythm image), it may indicate a technical and tactical superiority for the team with lower entropy values.

One goal was scored by Team A of Match 1 at frame 24825. Figure 9 shows the graph visual rhythm images associated with this moment. It is interesting to notice that Team A was attacking, but, differently from the situation depicted in Figure 8, both teams have higher diversity entropy scores. In this case, this phenomenon is observed due to the fact that the goal was originated from a corner kick.



(a)



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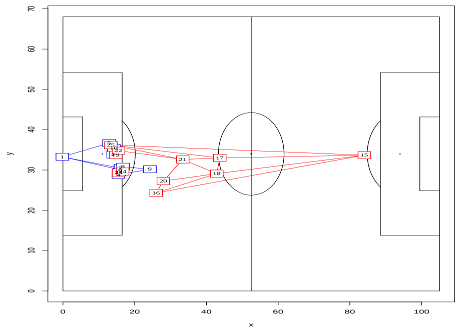
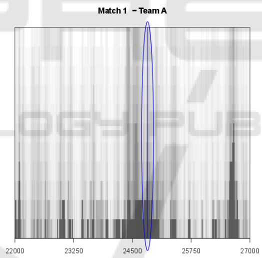
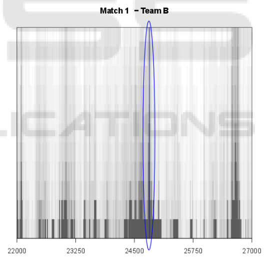


(c)

Figure 8: Graph Visual Rhythm in details: Highlighted dark block and the corresponding match situation. Team A (in blue) is compressed in a defensive strategy while Team B (in red) is attacking.



(a)



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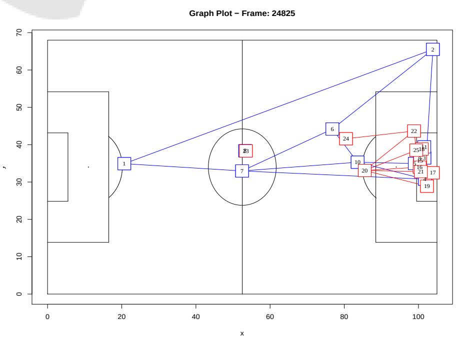


(c)

Figure 9: Graph visual rhythms of teams at a goal event timestamp.

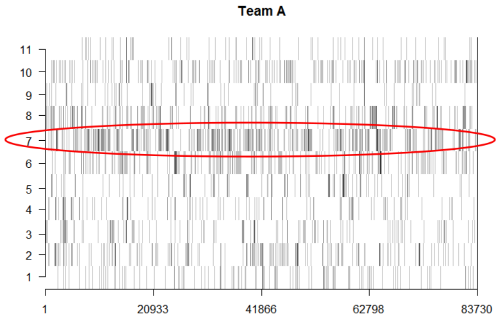
5.2 Most Valued Player: A Centrality-oriented Perspective

We conducted a preliminary study considering the computation of the betweeness centrality applied to instant graphs. The intention here is to support the identification of players whose centrality scores are higher during the match, and so they could be considered more valued than others in the game strategy. Figure 10 shows the centrality-based graph visual rhythm image for Match 2, using darker colors to highlight players with higher centrality scores. It can be noticed that during almost all the match, centrality scores are low for most of the players. The low and homogeneous centrality scores show that there was no ‘star topology.’ Each had nearly the same connectivity, indicating that the teams did not depend on one single player (Clemente et al., 2015).

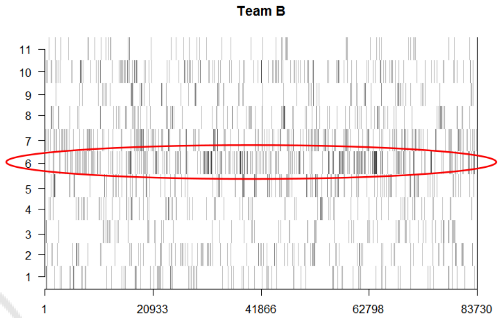
We can also notice that for Player 7 of Team A, there were darker pixels along the match. By analyzing his performance during the game, we could realize that this player was involved in more passes than all the others (47 passes in the first half time, while the team’s passes average was 33.1), which could mean that he was well positioned in the pitch during ball possession.

This same pattern is observed for Team B. It is possible to observe a darker pixel line for Player 6, who was also the one involved in more passes (42 passes in the first half time against the team’s passes average of 26.4). We observed similar patterns for other matches: players with higher centrality scores, when compared to teammates, are involved more frequently with successful passes. Thus, graph visual rhythm images allow to identify players who had influential contributions in a specific match, and, applied during the entire tournament, they may help coaches to identify the most important players. In other words, it helps to answer in an objective manner whether, for example, the most famous players fulfilled the expectations placed on them (Duch et al., 2010). However, in a collective evaluation, both entropy and centrality may be interpreted with caution. The work of (Grund, 2012) shown in 760 matches in the English Premier League that high levels of interaction (i.e., passing rate) lead to increased team performance. However, centralized interaction patterns lead to decreased team performance. In fact, even in a social context, teams with denser networks had a tendency to perform better and remain more viable.

Furthermore, these variables, analyzed over the match, may help also to identify who are the players more affected by fatigue. By decreasing the number of players involved, it is possible to allow some



(a) Match 2 – Team A



(b) Match 2 – Team C

Figure 10: Graph visual rhythm images based on the players’ centrality for **Match 2**. We highlighted in red the players with higher centrality scores.

players to rest actively. Moreover, it can characterise teams’ attacking strategies. The direct play may increase centrality among some players and involves a lot of participation from forwards and strikers, for example (Clemente et al., 2015).

5.3 Patterns of Passes

We also investigated the possibility of using graph visual rhythms for analyzing patterns of passes. In this case, we have employed graphs defined by Flow Networks. From soccer matches, we computed the Ball Possession Flow Networks, in which vertices are players and edges are passes accomplished among teammates while the team has the ball possession. Considering the first half time from each analyzed match, it is possible to construct N different flow network graphs, considering all N time intervals in which each team has the ball possession. We computed the graph visual rhythm image for each team in a match. This image contains all passes accomplished among teammates in each ball possession flow network, i.e., in this case, $\mathcal{F}_{G_t}$ computes the occurrences of passes among players. Pixels representing an specific pass performed in a network were colored according to the location in the pitch where the ball passing occurred.

Figure 11 shows color patterns used. We divided

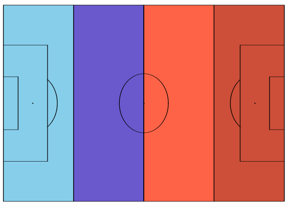
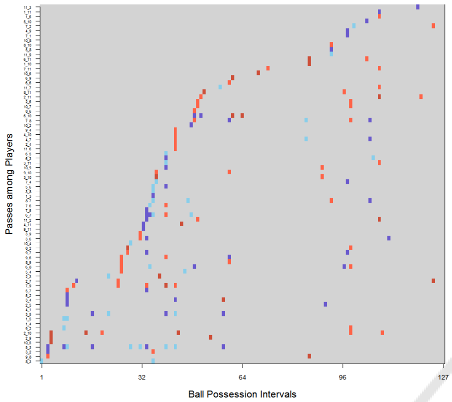
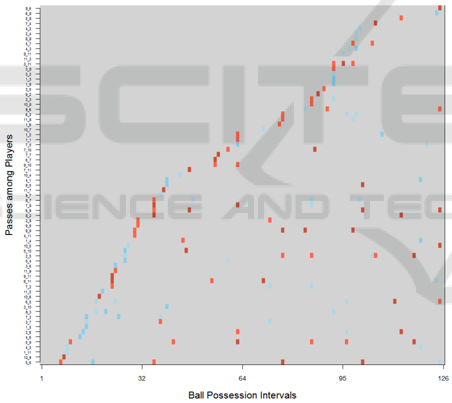


Figure 11: Pitch color patterns: defensive area in cold colors, while attacking area in hot colors.



(a) Match 1 – Team A

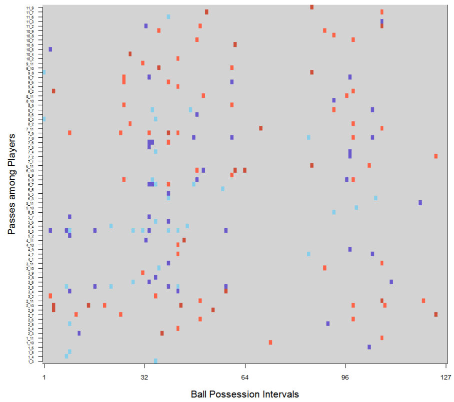


(b) Match1 – Team B

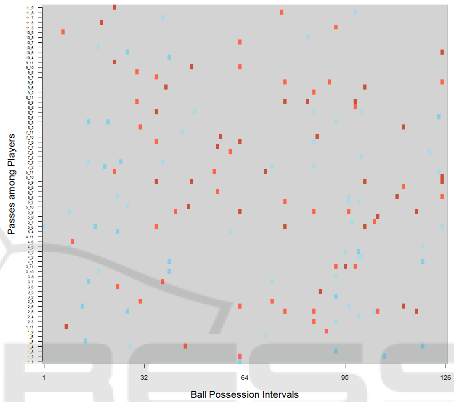
Figure 12: Graph visual rhythms encoding the patterns of passes of teams in **Match 1**.

the pitch in 4 sections, where defensive area of a team was colored in cold colors (light blue and dark blue), while attacking area of a team (the opponent's pitch) was colored in hot colors (light red and dark red). Also, when a network does not have any edges (no passes performed), all its pixels are grey. Using this color pattern, it is possible to visually understand patterns of passes for a team.

We analyzed the first half time of the same two matches. The resulting graph visual rhythm images are shown in Figures 12 and 14. The Y axis has labels of players involved in successful passes (e.g., passes from player 3 to player 10), and the X axis refers to the flow networks considering ball possession. It is



(a) Match 1 – Team A

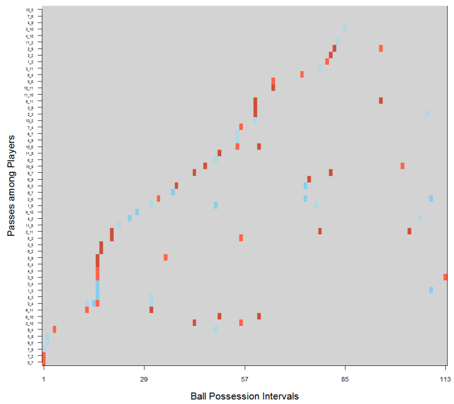


(b) Match1 – Team B

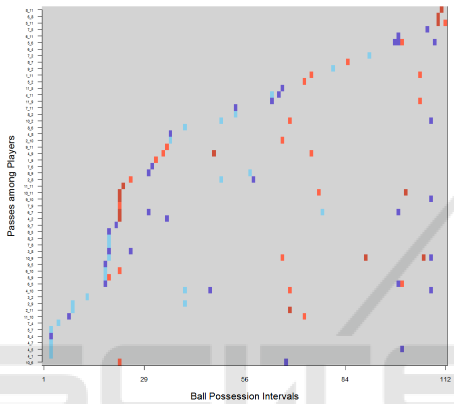
Figure 13: Graph visual rhythms (ordered by players) encoding the patterns of passes of teams in **Match 1**.

possible to notice some patterns in each match. During Match 1 (Figure 12), Team A performed more passes among teammates than Team B (more colored pixels in image of Team A). Also, Team A has longer vertical lines of pixels colored, which means that for each ball possession, many passes were activated involving many players. Figure 13 presents a graph visual rhythm for this same match, but now with y-axis representing passes ordered by players (from player 1 to 11). It is also possible to notice that many passes (vertical pixel lines) involve both defensive, middle, and forward players, in different field regions. Furthermore, some passes occurred many times along networks, and some of them only in its defensive area (cold-colored pixels). Team B has performed less ball passes, and passes in a single ball possession period involve only two players. Most of those passes occur in the attacking area (predominance of hot-colored pixels).

During Match 2 (Figure 14), Team B has performed more passes than Team A. It is interesting to notice that many of them occurred in its defensive area (predominance of cold-colored pixels), while

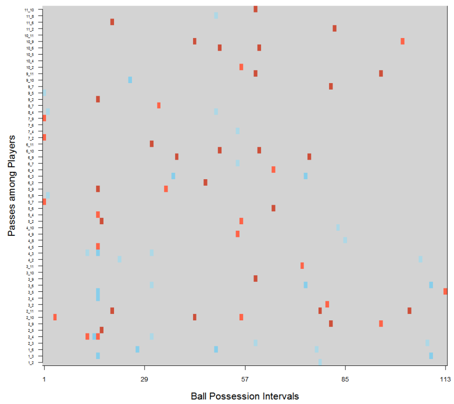


(a) Match 2 – Team A

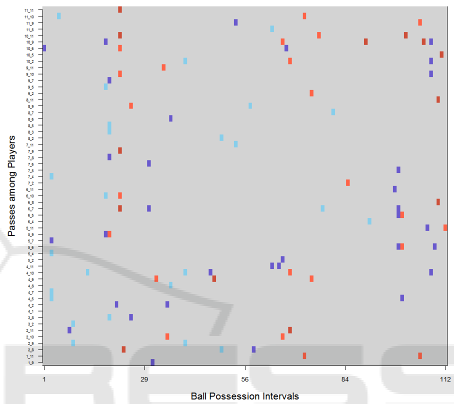


(b) Match 2 – Team C

Figure 14: Graph visual rhythms encoding the patterns of passes of teams in **Match 2**.



(a) Match 2 – Team A



(b) Match 2 – Team C

Figure 15: Graph visual rhythms (ordered by players) encoding the patterns of passes of teams in **Match 2**.

team A performs more passes in the attacking area. Figure 15 presents a graph visual rhythm for this same match, but now with y-axis representing passes ordered by players (from player 1 to 11). It can be noticed that ball possession involves few players. In this match, Team C performed passes involving more players, from defensive to forward players. Note also that for two different matches, Team A has very different performance in terms of patterns of passes (see Figures 12(a) and 14(a)).

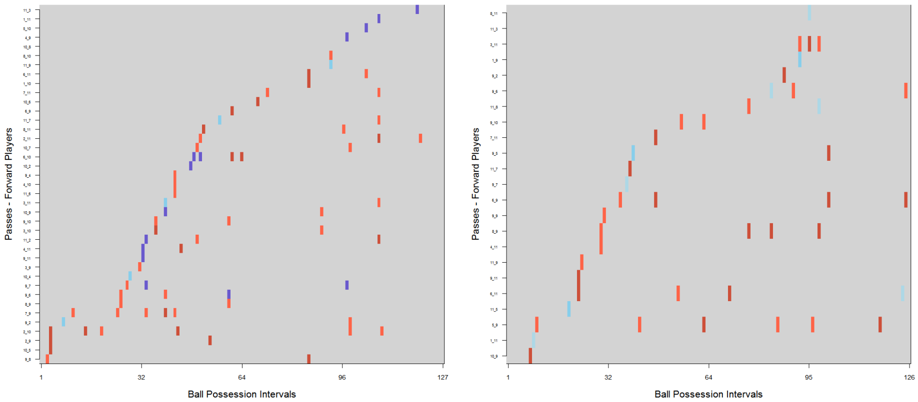
5.4 Pass Patterns in Attack Actions

It is also possible to create graph visual rhythm images considering a subset of players. For example, it might be interesting to show pass patterns involving only forward players. With this purpose, we created graph visual rhythms from passes involving only players with role, which is depicted in Figure 16. In this case, we refer to Match 1. We can observe that not only did forward players of Team A accomplish more passes than players of Team B, but also they accomplished those passes in the opponent area (predominance of hot-colored pixels). We can conclude that Team A exploited more frequently the strategy of using multiple passes in attacking actions.

5.5 Soccer Visual Analytics Tool

We have created a soccer visual analytics tool that integrates the different graph extraction approaches, and visual rhythm image computation algorithms described in this paper. This tool allows loading data about soccer matches (usually, information about players' location over time), and encode them into graphs, depending on the type of analysis defined by the user. All complex network measures described in this paper were implemented, so it is possible to visually analyze them by means of graph visual rhythms.

Figure 17 presents a typical usage example. In this case, we have graph visual rhythm images of two teams computed from instant graphs represented by the diversity entropy of their vertices. By clicking on the side-bar check boxes (area labeled with A), a user can highlight match events, as goals and attacking moments, and also, can define a specific period of



(a) (b)

Figure 16: Graph visual rhythms encoding the patterns of passes of **forward players in Match 1**.

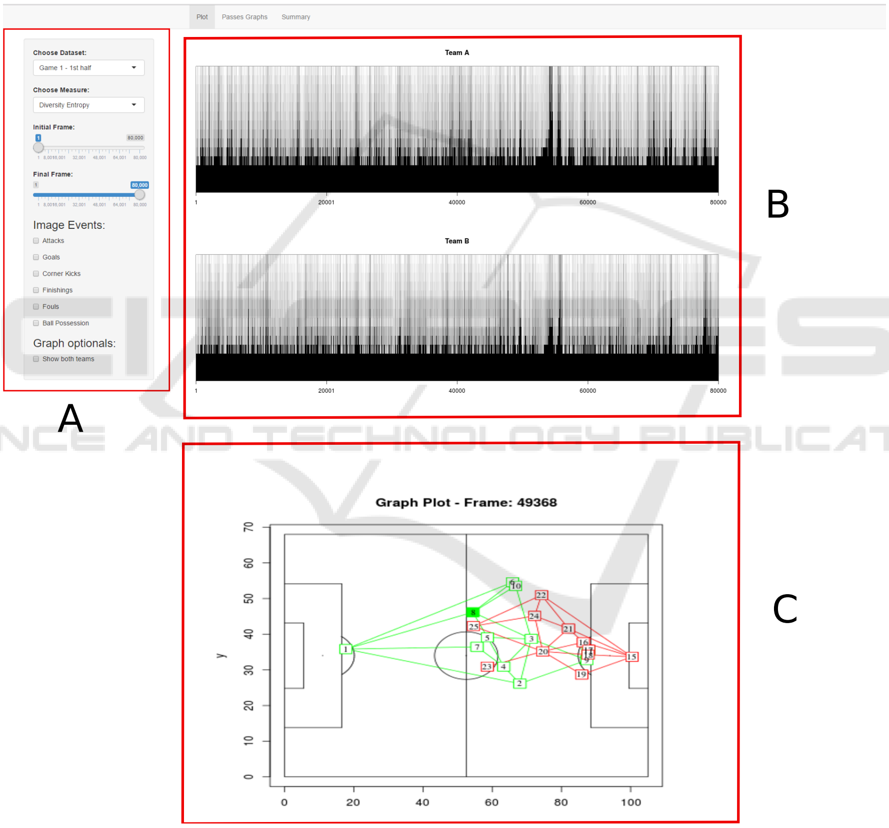


Figure 17: Screen shot of the soccer visual analytics tool developed.

time for zooming in targeting specific regions of the images (shown in region B). User can also view corresponding graphs or temporal graphs videos, by clicking anywhere on the graph visual rhythm image, or selecting an area of interest in the image (field graph view in region C).

6 CONCLUSIONS

This paper has introduced the graph visual rhythm representation, a compact visual structure to encode changes in temporal graphs, making it a suitable solution to handle large volumes of data. We demonstrate its applicability in several usage scenarios concerning the analysis of soccer matches, whose several dynamic aspects are encoded into temporal graphs.

This research opens novel opportunities for investigation related to the use of several image processing algorithms to highlight important patterns in temporal graphs. We plan to follow this research venue in our future work. We also plan to incorporate matrix reordering methods (Behrisch et al., 2016) aiming to improve the identification of changing patterns in graph visual rhythm representations. Another issue refers to the implementation of suitable visualization approaches to handle players' substitutions in a match.

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