Social Network Approach to Analysis of Soccer Game

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Abstract

Video understanding has been an active area of research, where many articles have been published on how to detect and track objects in videos, and how to analyze their trajectories. These methods, however, only provided heuristic low level information without providing a higher level understanding of global relations within the whole context. This paper presents a new way to provide such understanding using social network approach in soccer videos. Our approach considers representing interactions between the objects in the video as a social network. This network is then analyzed by detecting small communities using modularity, which relates social interaction. Additionally, we analyze the centrality of nodes which provides importance of individuals composing the network. In particular, we introduce five centralities exploiting directed and weighted social network. The partitions of the resulting social network are shown to relate to clusters of soccer players with respect to their role in the game.

1. Introduction

During the last several decades, researchers have proposed many object detection and tracking algorithms that have been used to extract low-level information from videos [11], and have been used in domains ranging from wide area surveillance, medical imaging to sport videos [5, 1]. Using this low-level information, many articles have been dedicated to analysis of object trajectories, recognition of actions to deduce higher-level information [2, 5, 12]. These methods, however, commonly focus on information gathered from an individual object instead of providing a global understanding of the roles and activities with respect to relations between the objects.

In contrast to traditional analysis of video, we conjecture that for higher level understanding of the video, relations and interactions between the actors in the social scene need to be analyzed. Hence, we adopt the social network analysis schemes to interpret roles of actors from a global perspective. Social network analysis is a widely researched area in different domains including but not limited to sociology, psychiatry, physics, biology, healthcare and computer networks to understand and explain interactions of actors in their respective system [9]. For example, in healthcare domain, interaction analysis is essential to investigate disease spreading. In biology, protein-protein interactions are used to define a micro level life of a creature. Social networks are also used to understand nonliving entities, such as e-mail databases for defining the social structure in companies.

In this paper, we propose a rather new approach to analysis of video based on interactions between the object in the field of view. Through these interactions, we build a social network and analyze this network using novel social network analysis tools. The resulting information provides a higher level of understanding of the video and the context of happenings. In particular, we selected a soccer game due to the ground truth provided by experts in the field.

The remainder of the paper is organized as follows: Section 2 introduces social network analysis methods and concepts. Also it presents our approach using social network analysis. In section 3, experimental results are shown. Finally, we conclude in Section 4.

2. Social Networks

In this section, we discuss how social networks can be generated as they apply to analyze soccer games. Nonetheless, the proposed approach can be applied to other domains, such as surveillance videos, movies and other sporting events. Given the graph representation of a social network, we then introduce the main analysis tools to extract roles and small communities in the network.
2.1. Construction of a Social Network

Significant events in a soccer game, such as goal, foul and corner kick occur as a result of passing the ball from one player to the next. This suggests the use of players as the actors in the network and passing the ball between the players as the interactions between them. In the sequel of a detection and tracking scheme, these interactions between the actors generate a social network in the form of a graph providing a global view of the game.

Let $A$ be the interaction matrix of social network $G$, which serves as the adjacency matrix of a graph $G$. The $i^{th}$ row and the $j^{th}$ column indicate actors corresponding to the nodes of the graph:

$$A_{i,j} = \begin{cases} w & \text{if } i, j \text{ has interaction, } w \geq 1 \\ 0 & \text{otherwise} \end{cases},$$

where $w$ defines the number of times the ball is passed from one player, $i$, to the other, $j$. In the case when $w = 1$ for all entries, the resulting social network is considered unweighted. In sociology, researchers traditionally assume the interactions are binary, such that the resulting edges are unweighted. In this paper, we extend social network analysis to weighted graphs.

Additionally, due to the fact that the ball is passed from one player to another, the resulting interaction has a direction. This observation results in a directed graph which has been occasionally considered in sociology. As a result, the social network considered in this paper has directed and weighted interactions, which implies that the adjacency matrix $A$ is an asymmetric matrix.

2.2. Modularity Detection

The study of discovering social communities within a network is one of the most important problems in social network analysis. In order to detect such communities, Newman et al. proposed modularity algorithm [6, 7]. The main goal of the modularity algorithm is to find optimum communities that have highest social interaction. Their algorithm finds edge groups by maximizing the number of edges within communities when they are subtracted from expected number of edges. Using an unweighted social network, e.g. $w = 1$, associated cost can be written as[7]:

$$Q = \frac{1}{4m} \sum_{ij} A_{ij} - \frac{k_i k_j}{2m} s_i s_j = \frac{1}{4m} s^T B s,$$  \hspace{1cm} (1)

where, $A_{ij}$ is 0 or 1 denoting connectivity, $k_i = \sum_j A_{ij}$ and $k_j = \sum_i A_{ij}$ are degrees of vertices $i$ and $j$, and $m$ is the total number of edges in the network, such that $2m = \sum_i k_i$. Here $s_i$ and $s_j$ indicate the groups the two nodes $i$ and $j$ belong to, such that $s_i$ is 1 if node $i$ is in group 1, or $s_i$ is -1 when node is in another group.

Maximization of the modularity $Q$ is an NP-hard problem, with several potential methods studied in the literature to provide a solution. In this paper, we used the eigenvectors of the matrix $B$:

$$B_{ij} = A_{ij} - \frac{k_i k_j}{2m},$$  \hspace{1cm} (2)

for maximizing $Q$ [6]. The matrix resembles laplacian commonly used in graph-cut methods and is derived from equation 1. The $B$ matrix studied in social network analysis, however, is a symmetric matrix, such that the modularity maximization requires unweighted and undirected graphs. In contrast, this paper assumes a directed and weighted network structure. In order to maximize $Q$ in a social network with weighted directed edges, we propose a modified $\tilde{B}$ matrix, in the form of:

$$\tilde{B}_{ij} = A^w_{ij} - \frac{k_i^w k_j^w}{2m},$$  \hspace{1cm} (3)

where $A^w_{ij} = A^w_{j,i} = A_{ij} + A_{ji}$ contains the directed edge weights in both directions between the two nodes. Similar to the unweighted case, we keep $k_i^w = \sum_j A^w_{ij}$, and $2m = \sum_i k_i^w$. Detection of communities using $\tilde{B}$ is carried out by maximizing

$$\tilde{Q} = \sum_i a_i u_i^T \tilde{B} \sum_j a_j u_j = \sum_{i=1}^n (u_i^T \cdot s)^2 \beta_i,$$  \hspace{1cm} (4)

In this equation, $s = \sum_{i=1}^n a_i u_i$, and $\beta_i$ is eigenvalue of $\tilde{B}$ corresponding eigenvector $u_i$. In order to mark modularity groups in the network, we assign opposite signed elements of the leading eigenvector in to two groups. For further grouping, we cluster each new cluster recursively.

2.3. Node Centrality

Finding the important actors in a social network plays a significant role in analyzing social structure. Sociology field has studied many different techniques to define importance (ranking) of nodes[3, 8, 9]. Among others, Freeman proposed the most commonly adopted strategies which define three types of centralities: degree, closeness, and betweenness[3]. The definition of these centralities assume that networks are unweighted and undirected. In this paper, we extend these definitions to directed and weighted social networks.
Degree In case of unweighted and undirected social network, an actor’s degree is defined by the number of actors directly connected to it. Extension of this to weighted and directed networks can be intuitively done by introducing in-degree and out-degree computed by summing the weights based on the direction of interaction:

\[
C_{In-Degree}(N_i) = \sum_{j=1}^{g} w_{ji} (i \neq j) \quad (5)
\]

\[
C_{Out-Degree}(N_i) = \sum_{j=1}^{g} w_{ij} (i \neq j). \quad (6)
\]

The resulting degree centralities reflect the local structure of the social network topology.

Closeness indicates how close an actor is to another actor. Closeness directly relates to the geodesic distance (or the cardinality of the shortest path) between two actors. Since closeness consider all pairs of actors, it reflects the global connectivity of the social network structure[4]. Similar to the degree introduced above, due to direction of interaction, closeness centrality is computed in terms of both incoming and outgoing degrees from a node:

\[
C_{In-Closeness}(N_i) = \frac{1}{\sum_{j=1}^{g} d(N_j, N_i)} (i \neq j) \quad (7)
\]

\[
C_{Out-Closeness}(N_i) = \frac{1}{\sum_{j=1}^{g} d(N_i, N_j)} (i \neq j) \quad (8)
\]

where \(d(N_i, N_j)\) defines the geodesic distance between two actors \(i\) and \(j\).

Betweenness explains how an actor can control other two actors, which do not have direct connectivity between them. It is an important global centrality measure, which investigates the strength of connectivity between the actors in the network[4]:

\[
C_B(N_i) = \sum_{j<k} \frac{g_{jk}(N_i)}{g_{jk}}, \quad (9)
\]

where, \(g_{jk}\) is the number of geodesic paths between two actors \(N_j\) and \(N_k\), and \(g_{jk}(N_i)\) is the number of geodesic paths between the \(N_j\) and \(N_k\) that contains actor \(N_i\).

3. Experiment and Result

Without the loss of generality, we have selected a soccer video to analyze the effectiveness of the social networking paradigm to video analysis. An important motivation to this selection is the availability of the ground truth and statistics of the game provided by field experts. Particularly, we have chosen a game between Korea and the United Arab Emirates (UAE) for the 2010 World Cup Qualifiers. Based on the interactions between the players, we constructed two social networks for both teams as shown in Figure 1. In the following, we used the weighted and directed social network to extract communities (modularity cut) and importance groups (centrality cut).

Figure 1. Social network for Korean(left) and UAE(right) teams. The width of the lines indicate the weight of the edges.

In our experiments, each team consists of 11 players with known initial positions defined by their role of play, such as the goal keeper, defender, mid-fielder, and forward. We tabulate the ground truth position of the players in Table 1. We should note that these ground truth associations do not define the structure of the current game as the coach can change the positions of the players during the game.

<table>
<thead>
<tr>
<th>Team</th>
<th>Goalkeeper</th>
<th>Defender</th>
<th>Midfielder</th>
<th>Forward</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>1</td>
<td>2,3,8,9</td>
<td>4,5,10,11</td>
<td>6,7</td>
</tr>
<tr>
<td>B</td>
<td>1</td>
<td>2,3,5,9</td>
<td>4,7,10,11</td>
<td>6,8</td>
</tr>
</tbody>
</table>

In Figure 2, we illustrate the modularity clustering using the proposed weighted approach. This clustering results (communities) indicate the quality of the game in terms of how the players followed the coaches directions. Particularly, we can note that the Korean team players have long passes on both the left and right sides. The strong connections between the players of different positions suggest a more connected Korean team, which has resulted in a win over UAE. In contrast, the communities detected for the UAE team are more homogenous.
with respect to the ground truth player positions. This observation is correlated with UAE’s defensive game plan. In addition, we can see that the communities for both teams are strongly correlated with the ground truth given in Table 1 and the game plan discussed by the narrator of the game.

Figure 2. Communities formed using modularity detection for Korean(left) and UAE(right) teams.

In contrast to modularity clustering, centrality clustering groups actors based on their importance and activities during the course of the game. Considering that the there are five types of centralities, we chose to represent each actor using a centrality feature vector in five-dimensions. The similarities between the nodes can then be defined based on the distance between the features. For experimental purposes, we have used the Euclidean distance and generated a complete graph with node weights representing the distance between the nodes. Application of normalized graph-cut [10] on this graph results in clustering results tabulated in Table 2. A closer look at the clustering suggests that players 8 and 10 in the Korean team have similar significance during the play. This is manifest during the game, where player both players play closely with the forward players despite being midfielders. The midfield players, except for player 5, in the Korean team change their positions dynamically. The stability of player 5 results in him having a more central role in the game, which resulted in an independent cluster. The UAE team, which lost the game, has a more uniform distribution of cluster members which also confirm the ground truth provided in Table 1. This observation is due to the fact that the ball passing is commonly observed between the players with the same role. For instance, forward players played together rather than passing the ball to and from midfielders. This organization resulted in isolated gameplay between players of certain characteristics.

4. Conclusions

In this paper, we propose social network approach to analyze videos. We leverage the state of the art from analysis of individual’s trajectories to global understanding of the scene in terms of the roles of the actors in the scene. In order to realize this, we have extensively used social networking concepts by extending them to social networks with weighed and directed graphs. Our experimental results on soccer video have shown that the proposed concept is correlated with the expert analysis of the game.

References