Creating a Universal Converter for Soccer Tracking Data

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Abstract

Numerous research works in team behavior analysis rely on human tracking data, often taken from sports games like soccer [1, 2]. In recent years, some kinds of tracking data that provide the coordinates of the players and the ball on the pitch have become available in soccer. However, such data is often stored in different incompatible formats and lacks event markup. Not only positional information but also event information is necessary for many types of research projects. In this study, we provide human tracking data with event markup using an automated recognition procedure. The resulting data will have both tracking and event markup, suitable for further analysis. In addition to player tracking data, AI vs AI matches data also is handled in a similar way. They are not as good as real tracking data, but they can be used to test algorithms and solve the problem that is a lack of data for experiments.

1 Introduction

As the technology of the tracking system has improved, it has become possible to use a large amount of tracking data. It is obtained with several tracking technologies such as TRACAB and Prozone that are video-based real-time tracking technology. They can track the position of the players and the ball on the pitch by using several cameras installed at a stadium and produce positional tracking data on them. It is used for soccer analysts and coaches to analyze team behavior and for engineers to train agents controlled by AI.

Unfortunately, they often face problems using this type of data. First, it does not contain information about events that happened during a match, so they cannot know when and who takes an action such as shot on goal, pass, and movement. The events are detected manually by a human judge, but it takes a lot of time and causes misdetection. Event detection is a major task in soccer analysis, so there are several studies that aim to accomplish this task including T. Imai et al. [3], which used a play recognition method focusing on the spatio-temporal relationship, and K. Richly et al. [4], which used artificial neural network. Next, it is not the same format. There are some kinds of available tracking datasets obtained from real soccer games, but it is inconvenient that very often this data is stored in completely different formats for experiments. It is important to use a lot of data to analyze team behavior or train AI agent, but they cannot be used as they are because of incompatible data formats.

There are two different types of analysis in soccer. The first is tactical and formation analysis. Tracking data is used for this type of analysis because it contains the coordinates of all 22 players and the ball. The second is the performance analysis of individual players. Since event data describes what actions a player takes during a match, it is used to assess the performance of individual players. Tracking data and event data are used for different purposes, so if tracking data with event markup is available, it will be useful for various studies.

The goal of this study is to solve the problems with datasets used in the current experiments as mentioned above. In this study, we developed a data converter that can (1) convert different data formats to one format, (2) recognize events using the positional information of the players and the ball, and (3) construct event information. Our converter extracts important events such as passes, shots on goal, and player movements from tracking data and provides the data that contains both tracking and event data. In this paper, we show how we can recognize events that occurred in real soccer games from several tracking data, as well as solutions to the problems caused by a specific dataset in the recognition procedure. We also developed a visualization tool that allows us to go through game situations and watch events as they occur in order to study the obtained data. This tool has the ability to filter events by team and player, for example, it allows to quickly go through all movements of "Red, 5" player or all passes of one team. It will help to focus on analyzing the behavior of a specific player and team.

2 Method

2.1 Available Datasets

The tracking datasets used in this study are the DataStadium dataset ("DS") provided by Data Stadium Inc [5] and the STATS dataset ("ST") provided by STATS PERFORM [6]. Both datasets contain coordinates of the players and the ball, but there is no information about events in common. The

DS dataset contains additional information about game states such as ball owning team (Home or Away), ball status (Alive or Dead), and the jersey number (-1 or 1 to 99) of each player, and so on. Considering the difference of information the datasets contain, we constructed event channels from these datasets using the developed converter.

In addition to the DS and ST datasets, we employ a Google Research Football dataset ("GRF") [7]. It is obtained in the reinforcement learning environment based on an open-source game that was created by the Google Brain team. The GRF dataset contains not only the positions of the players and the ball but also actions that took place in the game, so we can use them instead of reconstructing events from positions.

2.2 Signality Format

Signality format is data stream format for soccer provided by Signality tracking system [8]. This format can represent both player tracking and event data, so we decided to use this format as the master format. However, this format does not have event information about "shots on goal". Therefore, we extended the existing syntax with an additional shot ball event type. Our converter converts the DS, ST, and GRF datasets into Signality format.

2.3 Movements Detection

In soccer, player movement is one of the important events because stats such as distance covered and sprints play an important role in team and player analysis. Therefore, it is a necessary task to detect them.

Many types of movements (sprint, highspeedrun, mediumspeedrun, acceleration, and deceleration) are supported for the Signality format, and they are distinguished by the speed of a player. An approach for movements detection is to apply constant discretization [9], which simply slices the whole game into intervals and calculates the speed of players at the beginning of an interval. In the conversion procedure, the interval is given as a tunable parameter (command-line). In this study, assuming the value for fps is 25, we set a default value for this parameter at 50 because sprints are rarely done for long periods of time during a match and can be completed generally from 2 to 4 seconds. After calculating the speeds of each player at the beginning of each interval, they are compared to some constant speeds to determine the type of player movements. If the speed of a player is faster than the constant speed, a movement event with the jersey number of the involved player, end frame, and the type of the event is added to event channels (see Listing 1).

Listing 1: Python code for movements detection

```python
def add_movements(self):
        movements = {}
        for start_frame in range(1, len(self.episode), self.args.interval):
            end_frame = start_frame + self.args.interval
            if end_frame >= len(self.episode):
                break

            speeds = self.calculate_player_speeds(start_frame, end_frame)
            for idx, speed in enumerate(speeds):
                if speed > MaxSpeed / self.args.fps:
                    continue

                new_event = None
                if speed > SprintSpeed / self.args.fps:
                    new_event = {'end_frame': int(end_frame), 'event': 'sprint', 'player': int(idx)}
                elif speed > HighSpeedRunSpeed / self.args.fps:
                    new_event = {'end_frame': int(end_frame), 'event': 'highspeedrun', 'player': int(idx)}
                elif speed > MediumSpeedRunSpeed / self.args.fps:
                    new_event = {'end_frame': int(end_frame), 'event': 'mediumspeedrun', 'player': int(idx)}

                if new_event is not None:
                    str_fr = str(start_frame)
                    if str_fr in self.events:
                        self.events[str_fr].append(new_event)
                    else:
                        self.events[str_fr] = [new_event]
```

2.4 Passes and Shots Recognition

The action that players take most often during a match is a pass. Also, a shot is the most important event because players need to score a goal to win the match. Therefore, we need to recognize these events.

Pass and shot actions are basically extracted following the recognition procedure [9], which is the rule-based approach. The approach is easy to understand and incorporated into our tool, so we adopted it in order to recognize pass and shot events. A pass event consists of the jersey numbers of the passer and receiver, ball owning team and a pass result. However, we could not construct events with the right information depending on the dataset. Figure 1 shows one example of such situations in the DS dataset, and it can be seen that there are more than 11 players in the red team and the wrong jersey numbers of the passer and receiver are displayed at the top. This is because the DS dataset may contain the coordinates of more than 22 players, not only players who play in a match but also substitute players. This dataset defines the jersey number of substitute players as "-1", so our converter saves a track channel for players with not -1 jersey number so that it can add an event channel with the right jersey number of the involved player.

In the case of the ST dataset, game fragments of the ST dataset typically end before shot-on-goal moments because this dataset consists of very short segments where one of the teams has the ball, and a fragment ends when it loses the ball. Therefore, we have to generate shot events automatically at the timing when a player shoots. To generate artificial shot events where applicable, we added a flag for the command line interface that forcefully adds shot as needed. By using this flag, shot events can be added if a player can shoot at the end of a segment, which is determined by the approach proposed in [10]. This approach decides whether or not a player can shoot to a goal by checking the coordinates of opponents. If any of the opponents is between the goal and the player with the ball, it decides that the player cannot shoot. This approach can recognize possible shot events when a player shoots in the situation where one on one with a goalkeeper, but such a situation is not often seen in real soccer. In most cases such as middle shots from outside the penalty area, there are opponents in front of a player who tries to shoot. Also, a professional soccer player may shoot to a goal even if an opponent is in front of the player to block the shot because the player has the skill that he can shoot even in such a situation. Thus, we improved this approach so that it can add not only shots from near the goal but also shots from outside the penalty area from tracking data by checking the distance between the opponents and the player with the ball.

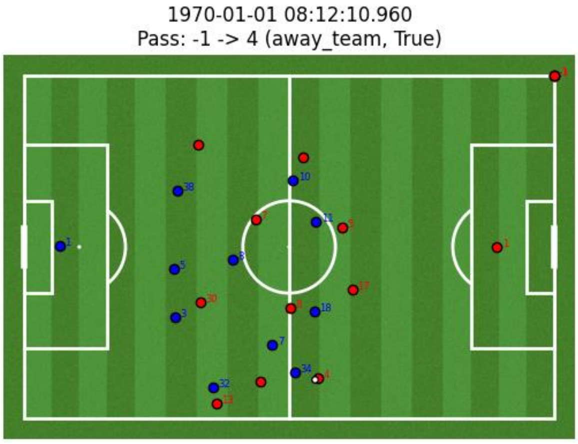

Figure 1: More than 11 players tracking data and event data with wrong jersey numbers in the red team.

3 Results

We evaluated the results of event recognition by comparing the number of recognized events in five DS datasets, which are full matches of the Japanese professional league (J1 league), and the stats of the league. We used the DS datasets captured in 2011, but the stats of the league in 2011 is not available now. Instead, we used the stats from 2015 to 2021.

3.1 Result of Movements Detection

As a result of movements detection, three types of movements (sprint, highspeedrun, and mediumspeedrun) were detected. Figure 2 shows one of the detected movement events that we can see using the visualization tool. This situation is a counter-attack by the blue team, and it can be seen that

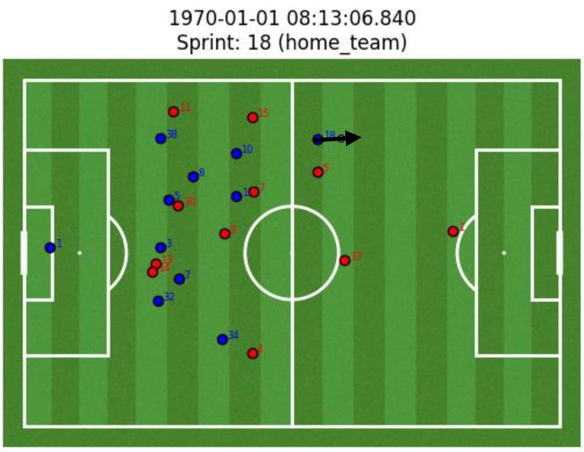

Figure 2: A detected sprint in the DS dataset

player 18 of the blue team who is the closest to the ball takes a sprint action. It is natural for the player to sprint in this situation, and we confirmed that our converter could detect such player movements in situations where players may sprint. Table 1 shows the number of detected sprints in the DS datasets and sprints that players made during a real match according to J1 league stats [11]. It can be seen that the number of detected sprints is close to the number of sprints made in real soccer games.

Table 1: The number of sprints

	Sprint stats	Detected sprints
Max	186	177
Min	137	129
Average	160	153

3.2 Result of Passes and Shots Recognition

After using the improved pass and shot recognition procedure, these events were extracted more accurately. As for the ST dataset, we generated an artificial shot where applicable, and figure 3 shows an added shot event by player 9 of the blue team from middle-range. Even when an opponent is in front of the player who tries to shoot, if the distance between the opponent and the player with the ball is farther than a certain distance, our converter became able to add shot events automatically by judging the player can shoot to the goal.

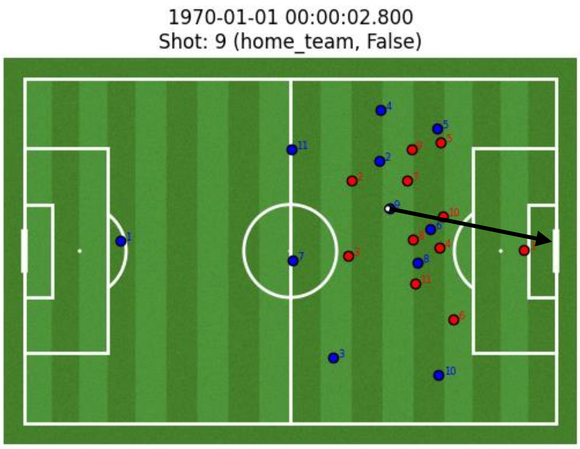

Figure 3: An added shot in the ST dataset

Regarding the DS dataset, we can see the right jersey numbers that are related to the players who take an action. Figure 4 shows a pass event recognized after improving. As can be seen at the top of this figure the accurate jersey numbers of the passer and the receiver are displayed.

The number of passes and shots made during a real match according to a summary of the season in J league [12] and the number of passes and shots recognized in the DS datasets are shown in Table 2 and Table 3. Our converter can recognize them that are actually made in the real game with high precision, but it recognized them not intended by a player as well.

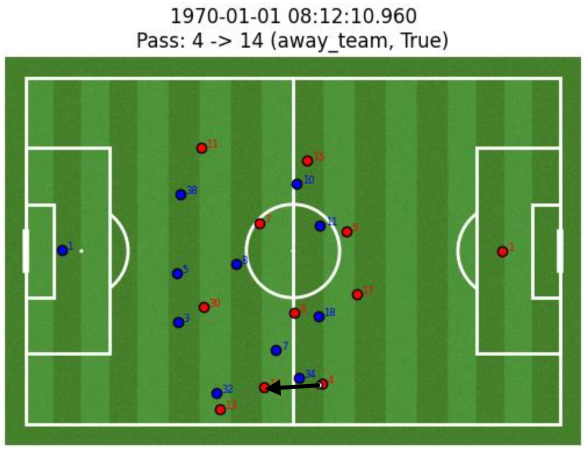

Figure 4: A recognized pass with the accurate jersey numbers of the passer and the receiver in the DS dataset

Table 2: The number of shots

	Shooting stats	Recognized shots
Max	17	24
Min	10	6
Average	13	12

Table 3: The number of passes

	Passing stats	Recognized successful passes	Recognized unsuccessful passes
Max	663	672	252
Min	342	286	133
Average	480	430	178

4 Discussion

Player movements were detected using a constant discretization approach from tracking data. While the approach is so simple and easy to implement, there are many bad things. For example, the number of player movements varies greatly depending on the value of the interval parameter. The higher the interval is, the smaller the numbers are. Also, there is a lot of jitter and other erratic movements in tracking data because cameras and tracking software are unable to determine coordinates with enough precision. However, this approach does not take into consideration them. We think that another approach should be used to improve the accuracy of detecting player movements. One of the possible approaches is to smoothen the trajectories before analyzing them [13]. It is more complex than the one used in this study, but we believe that it will detect player movements more accurately.

As for the passes and shots recognition, they sometimes were incorrectly recognized. The misrecognition of these events occurs because of ball jitter. It is an artifact of data processing and it is difficult for our converter to ignore that. Also, there are other obvious causes in pass events recognition. For example, a situation where an opponent clears or blocks the ball may be recognized as a pass. In addition, when there are multiple players near the ball during a set piece, some passes are recognized among those players until the set piece ends. Such misrecognition occurs because the recognition method used in this study recognizes pass events when a player possessing the ball changes. In the future, we will need to solve this problem by using a more advanced event recognition procedure such as proposed in [3, 4] or improving the rule-based approach used in this study.

5 Conclusion

In this study, we developed the converter that has the ability to integrate incompatible data producers under the Signality format and reconstruct important events such as player movements, passes, and shots on goal. Our converter could be used in many research works related to soccer because it can provide tracking data with event markup. However, other events should be analyzed in soccer, for example, free kicks, corner kicks, tackles, and so on. If it becomes able to recognize these events, it can be used for further analysis. A lot of data is required for training agents and analyzing team behavior. Our tool will solve the problem that is a lack of data by using various datasets in the same format. In soccer, there are some available datasets provided by several providers such as SPORTLOGIQ, DataFactory, and Sport radar other than the datasets used in this study, so we will be able to get more data if we can convert these data in a similar way as well.

References

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