

Sports Play Visualization System for American Football

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Abstract— In this paper, a sports strategy decision support system, called SportsViz, for ball games is presented. Both the results of statistical analysis and player motions are visualized in an integrated way to facilitate easy decision making by this system. The player motions can be easily aggregated with our newly developed trajectory mining technique for deep consideration on the motions. It is also described here that our system can be effective in football strategy analysis.

Index Terms— Mining, Strategy analysis, Visualization

I. INTRODUCTION

ONE of the most important tasks for the performance improvement of a sports team is to analyze past games from various perspectives. Using past game analysis, the difference between current team performance and ideal performance can be identified and a practice method and tool appropriate for acquiring ideal performance can be determined.

In ball games of two teams composed of multiple players, such as football and soccer, game strategy is important for obtaining better performance results. A good strategy can contribute to game initiative, and consequently, to winning the game. The important work of a strategy planner is to predict the strategy that the opposite team might use. Better prediction can be realized by analyzing opposite team's previous games. For instance, the opposite team's strategy characteristics and use, including play frequencies and situations, are important information for predicting that team's strategy. In particular, in American football games, the strategies used strongly affect the game result. This is because one play is conducted discretely in American football with fixed offence and defense sides, whereas plays in soccer and rugby are conducted continuously by exchanging offence and defense sides.

In general, there are two approaches to planning game strategy: 1) use of a statistical analysis method and 2) use of movement analysis.

Statistical analysis can be applied to calculate the statistical values related to plays and players, such as total scores and losing points, time required for obtaining a score, average play positions, and so on. An effective strategy can be constructed using this statistical analysis [1]. Similar plays that occurred in similar situations can be detected easily with

this method.

Movement analysis is an approach to analyze the game from the perspective of player movements. As each player moves in the game in a way that realizes the current strategy, all player movements, in other words, player trajectories, are important resources for constructing or checking strategies. These trajectories, not only of the players, but also of the ball, can be aggregated to produce more meaningful information, such as player mutual combination and offensive direction. One strategy produces similar player movements even in different game situations.

Although it is natural for these two approaches to be mixed in strategy construction and checking, movement analysis is difficult to use because of small player movements. However, given the rapid progress in sensor technologies, data size is increasing rapidly, unlike a decade ago. In fact, data size is becoming much larger than what a coach can manage directly. Therefore, it is important to support coaches by providing visualized information aggregation calculated from a huge amount of player movement data [2][3].

In this paper, we propose a visualization system of player movements for constructing and checking strategies. The system is developed for American football because all players move in each game based on the strategy decided for this sport. The main concept of the system is that raw data should be aggregated, followed by visualization of the aggregated data.

II. STRATEGY ANALYSIS IN SPORTS

As described in the previous section, the visualization of information aggregated from player movement data is the main concept of our system. The concept is introduced from consideration of the following system requirements.

--Similar play detection and movement analysis using detected similar plays:

As a particular strategy is realized and represented as play classes, an actual play is a class instance. Many similar play instances that occurred in the past are related with an identical strategy. In other words, one strategy can produce many similar plays. Therefore, it is important not to analyze all plays, but to analyze similar plays specified from one strategy. Because this strategy is generally unknown or not recorded, similar plays need to be detected and aggregated as a strategy. Then, movement analysis is applied to the detected similar plays.

--Adding the statistical analysis to movement analysis:
Movement analysis is a key approach for creating a new

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strategy because a set of player movements in one play is one realization of the strategy pre-decided for the play. However, the approach is not omnipotent, and should be combined with the statistical approach in order to reduce false-positives among the plays. That is, all detected similar plays should preferably be related to an identical strategy, and there should be no aggregated plays that are related to another strategy.

--Strategy visualization from various perspectives:

As system users, coaches would prefer to construct and check strategies from analyzed results. Therefore, the system should visualize results according to user preference. Thus, the system provides users with various perspectives, including movement-temporal trajectory, actual play video, and panoramic view of multiple plays.

--Visualization of analyzed information in ease-of understanding:

From a user perspective, analysis results should be visualized such that the user can easily understand the results in a short time. Moreover, because the amount of raw data is enormous, the amount of data displayed on the screen should be reduced while maintaining the points from the analysis results. Not much data should be on the screen.

In this paper, we describe a visualization system of sports play for strategy construction and checking that meets these requirements.

III. A VISUALIZATION SYSTEM, SPORTSVIZ

A. Basic concepts

We develop a visualization system of sport plays for constructing and checking sport strategies. Currently, the system is only applicable to American football, although the type the target sport is not limited to American football, and the system can be applied to other ball sports with minor modifications. The basic concepts of our visualization system, called SportsViz, are described below, and these are introduced to meet previously described requirements.

--The definition of sport play similarity is proposed and employed to extract a group of similar plays among many previous plays. With this similarity, a set of similar plays can be clustered in one group, which is effective for a user to check actual plays in the group in order to construct a new strategy and find problems with the current strategy. The details are described in the next section.

--Interaction between system and user is supported with a limited flexible process. Completely flexible interaction causes users to not use the system easily. It is important for the limited flexible interaction process to make the system friendlier and easier to use. The fixed usage process is described later in this section.

--Multiple plays are displayed on the same screen simultaneously. Because the main user of our system is a strategy planner or strategy instructor such as a coach, he/she would likely prefer to view many valuable past

plays comparatively. Therefore, the system can display multiple plays simultaneously and on the same screen.

--Video output is supported because video of past plays is important in order to understand such plays readily, which cannot be done as easily with player movement drawings. Users can view a video of a particular play any time by selecting the play on the screen.

Our proposed system, which meets the previous requirements with these concepts, is described next.

B. System functions

The system consists of the following three functions.

--Search function:

The system extracts all of the play data that fulfills the input value from the game record database.

--Play classification function:

System classifies plays using the trajectory that corresponded to extracted play data.

--Visualization function:

The system creates cluster tabs at the top of analysis result display screen. In addition, the system displays the player position and trajectories above the court image.

C. System flow

The procedure showed at Fig 1.

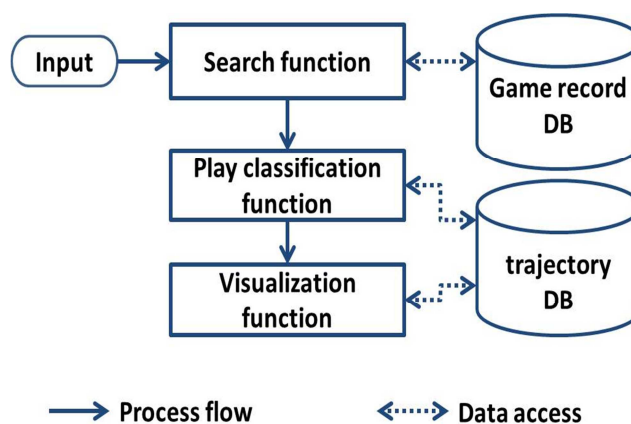


Fig. 1. System process flow.

D. System structure

System consists of two interface parts (Fig 2 and Fig 3). Execution environment is shown in Table1.

TABLE I
EXECUTION ENVIRONMENT

OS	Windows7
CPU	CORE i7
Programing language	Java, R 3.0.2
Database	MySQL

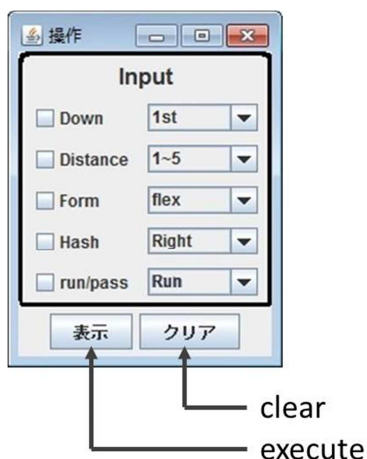


Fig. 2. Input interface that user select input items and input value.

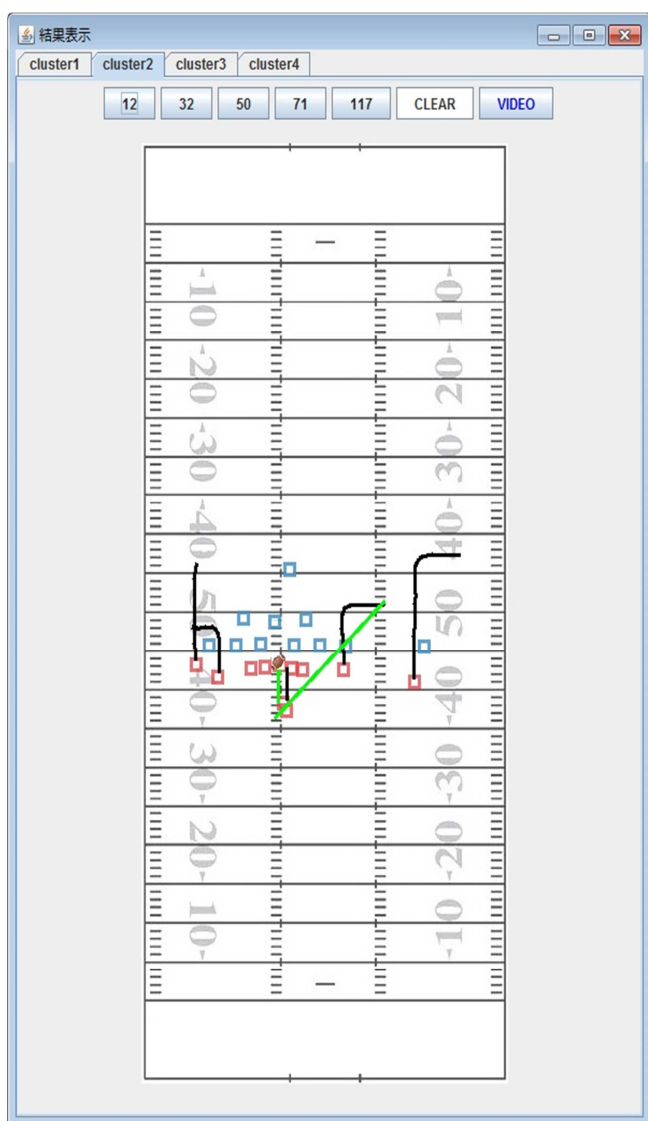


Fig. 3. Output interface that the system display analysis result.

1) Input

There are five input items in panel.

--Down

In American football, there are four attack plays in one attack series. Each attack play is called first down, second down, third down and fourth down.

--Distance

This is the distance for the end line from the ball position when the play starts. The user selects an input value from seven types of distance range.

--Form

This means the offence formation.

--Hash

This is the ball position when the game started. The user selects the side (Right, Middle, and Left) of the court based on the direction of the attack movement.

--Run/Pass

There are two types of attack. The user selects run play or pass play.

2) Output

There are three parts in output panel.

--Cluster tab

These tabs indicate the play classification results. Each cluster is assigned to a tab. Multiple plays that are classified to a similar play are gathered in one cluster tab.

--Play number button

The number on the button is the play number, and it is used as the name of the play. When the user clicks the button, the play data are displayed below the play number button. If the user clicks the VIDEO button, a video of the play starts.

--Display area

The system displays play data in this area. Player position and trajectory and ball position and trajectory are displayed above the court image. These data are expressed with lines and marks.

E. System usage

1) Preparation of analysis

First, the user selects more than one input item. This system can analyze a local scene by selecting many input items. When the user clicks the execute button after selecting input items and a value, the system starts the analysis.

2) Analysis result

The user selects one cluster from the cluster tab at the top of the output panel. After selecting the cluster, the user clicks the play number button in which he/she is interested. Then, play data are visualized on the display area. If the user clicks the CLEAR button, the information on the court image is cleared. The system plays a video of the selected play when the user clicks the VIDEO button.

IV. SIMILAR PLAY DETECTION METHOD

The number of instances of a characteristic play and the varieties of similar play patterns in a game can be determined by play classification. In this paper, a trajectory method is used in play classification.

A. Play distance definition

The distance between plays is defined as “play distance” for play classification. Plays are connected to form similar patterns based on play distance and this can be used to judge whether plays are alike or not alike. With a ball game, the position of both balls and players are represented by coordinates and their motion can be represented by trajectories. The system that has been developed in this paper uses the trajectories to calculate play distances and play distance to determine play classification.

There are many trajectories in the play data of a game and thus the same position players between the plays must be determined. Same position players are determined by their start position based on the ball position when the play started.

B. Play distance calculation

Before calculating the distance between each play, the system carries out parallel translation on all trajectory data in a play until the ball’s start position is the point (0, 0). The process shown below is performed when calculating the distance between two plays.

1. The nearest players in the start position are set as the same position players.
2. The distance between the trajectories of the same position players is calculated.
3. The sum total of all distance between trajectories of the same position pair in plays is set as distance between the plays.
4. The analysis system calculates the distance between all plays in the game.
5. The trajectory distance is calculated from play distance.

C. Trajectory distance for play distance calculation

When the trajectory distance between two trajectories is close, these trajectories are deemed to be similar. Dynamic time warping (DTW) is an algorithm used to calculate similarity between time series data. Since DTW can respond flexibly to a change in time-axis in each time series data, it is also applicable to the trajectory data in which length differs [4].

For example, there are two trajectories, each length are n and, $T_a = [(x_{a1}, y_{a1}), \dots, (x_{an}, y_{an})]$ and $T_b = [(x_{b1}, y_{b1}), \dots, (x_{bm}, y_{bm})]$. DTW distance of T_a and T_b , is $D_{dtw}(T_a, T_b) = f(n, m)$.

$$f(i, j) = f_0(i, j) + \min \begin{cases} f(i-1, j-1) \\ f(i-1, j) \\ f(i, j-1) \end{cases} \quad (1)$$

$(i = 1, \dots, n; j = 1, \dots, m)$
However, $f(0, 0) = 0, f(i, 0) = f(0, j) = \infty$

And, $f_0(i, j)$ is defined as distance between two points.

$$f_0(i, j) = \sqrt{(x_{ai} - x_{bj})^2 + (y_{aj} - y_{bj})^2}$$

V. EXAMPLES OF STRATEGY CONSTRUCTION AND CHECKING

1) Case1

When the user selects “run” from the “run/pass” item and “twin” as the “form” item, plays are classified mainly into four clusters (two types of attacks and two types of attack sides).

--Inside attack

The ball carrier attempts to obtain a gain through defense line.

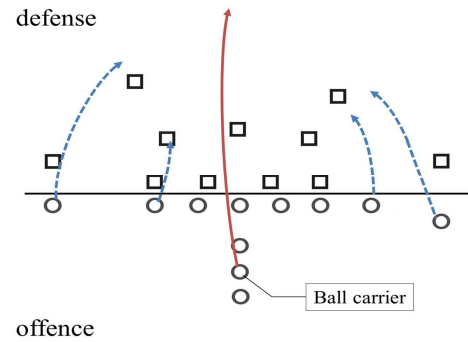


Fig. 4. The attack image of inside attack

There are two types of side: right side and left side as shown in Fig 5.

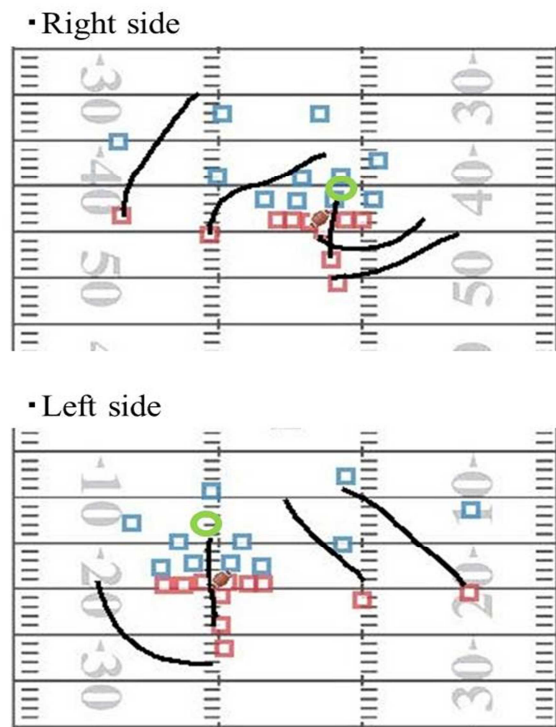


Fig. 5. The display examples in inside attack pattern

--Outside attack

The ball carrier attempts to obtain a gain in the area with no defense line. Other attacking players create a space for the ball carrier.

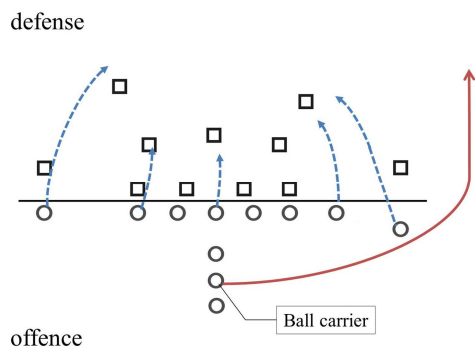


Fig. 6. The attack image of outside attack

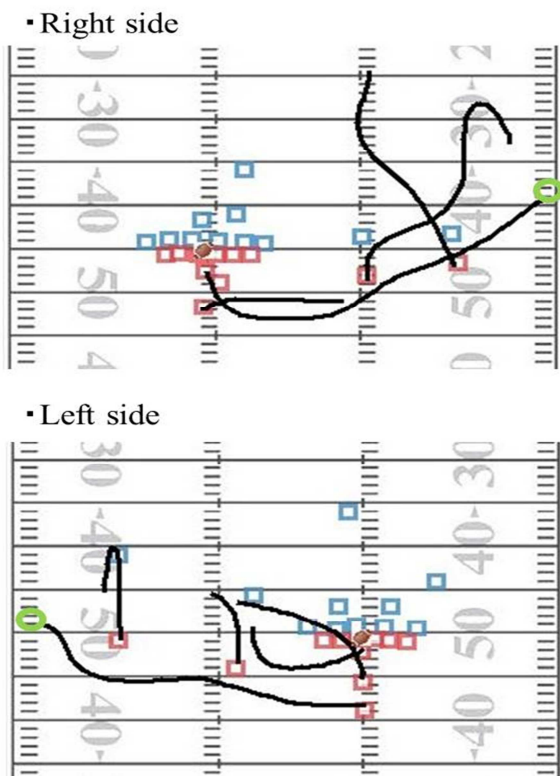


Fig. 7. The display examples in outside attack pattern

In a similar play situation, the user can find the attacking pattern based on the direction of attack. Moreover, the user can considerate the features where the side attacking player in the inside attack moves to the center front position, and the attacking player in the outside attack moves to the front. As illustrated by this case, the user can find the differences in play strategy using the proposed system.

2) Case2

When the user selects “twin” as the “form” input item, the user can find the plays that are not in the same situation in the same cluster.

In statistical analysis, the plays as shown in Fig. 8 are divided into different play categories because the play type is run or pass. However, these plays have the same strategy. The user can consider the strategy using movement data in this system.

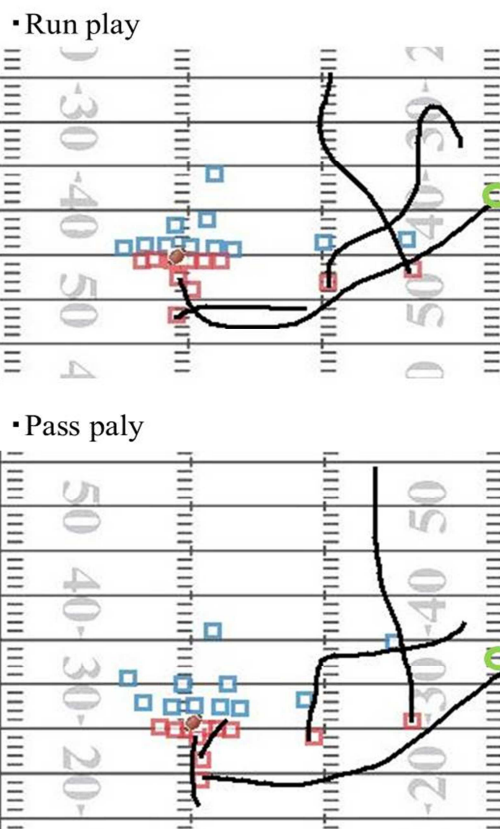


Fig. 8. Same strategy attacks

Statistical data were not associated with movement data or information. Analyzing sports game data requires considerable time. However, this visualization system considers both types of data using trajectory data. Therefore, the time required for analysis is reduced. Moreover, as player trajectories are displayed on the court figure, the user can visualize the entire movement in a play more easily.

VI. RELATED WORK

--Types and evaluation of visualization application

Visualization and these methods are used in various fields. In sports, we can obtain visual information from television, newspapers, and websites. Team sports can be considered as complex activities that contain a considerable number of abstract datasets and participant categories, such as athletes, coaches, referees, and spectators. It is necessary to decide how to display the data. Therefore, in this work, the field of visualization has been applied within team sports in various ways to provide these participants with representations of such datasets [5]. A model is proposed to classify sports visualizations along conceptual axes. This model will allow future or potentially untapped applications of team sports visualization to be identified and classified.

--Visualization of statistical data

Data analysis is necessary to improve team performance in sports. Most analysts use statistical software packages to obtain game results from data. However, data visualization is important to understand the game. Visualization analysis uses not only graphs and figures from statistical data, but also court figures. For example, in ball games such as basketball and football, shooting frequency is displayed on a court

figure as a heat map [6][7][8]. By using a visualization method with a court figure, attack tendency can be understood more easily than with statistical analysis only.

VII. CONCLUSION

In this paper, we proposed a visualization system that uses both statistical analysis and motion analysis where play classification was realized using trajectory mining. In this system, the type of attack pattern and the play of each pattern can be understood dynamically and visually. In the future, we plan to improve the play classification method by making play tendency determination easier.

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REFERENCES

- [1] Cathal M. Brugha, Alan Freeman, Declan Treanor. Analytics for Enabling Strategy in Sport. OR55 Annual Conference, pp.138-150. 3-5 September 2013.
- [2] Hiroshi Inaba, Tsuyoshi Taki, Shin-ya Miyazaki, Jun-ichi Hasegawa, Mitsuhiro Koeda, Hidehiro Yamamoto, Kaoru Kitagawa. Visualization of Human Body Sensing for Supporting Sports Motion Analysis. the Society for Art and Science Vol. 2 (2003) No. 3 P 94-100. 2003.
- [3] Toshihiro Tani, HungHsuan Huang, Kyoji Kawagoe. Sports Play Visualization System Using Trajectory Mining Method, Fourth Postgraduate Consortium International Workshop on Innovations in Information and Communication Science and Technology (IICST 2014), 5 pages, Warsaw, Poland, September 3-5, 2014.
- [4] Yasushi Sakurai, Christos Faloutsos, Masashi Yamamuro. Stream Processing under the Dynamic Time Warping Distance, DEWS2007.
- [5] Mitchell Page and Andrew Vande Moere. Towards Classifying Visualization in Team Sports. IEEE CGIV06, pp.24-29,2006.
- [6] Gopal Pingali, Agata Opalach, Yves Jean, and Ingrid Carlbom. Visualization of Sports using Motion Trajectories. 12th Annual IEEE Visualization Conference, October 21-26, 2001
- [7] Hannah Pileggi, Charles D.Stolper, J.Michael Boyle, and John T.Stasko. SnapShot:Visualization to Propel Ice Hockey Analytics. IEEE, VOL 18, NO 12, December 2012.
- [8] Charles Perin, Romain Vuillemot, and Jean-Daniel Fekete. SoccerStories:A Kick-off for Visual Soccer Analysis. IEEE VIS 2013.