CameramanVis: where the camera should look?
CPSC 547 Project update

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1. Previous work

CameramanVis relates to both the visualization of sports and the visualization of camera data.

1.1. Visualizing sports data

In sports analysis, player trajectory and occupancy map are widely used for visualizing interesting objects (players and balls). Lines are overlaid on the court to visualize the trajectory of players. For example, Fig. 1 (a) shows the trajectory of team centroid. Also, the derived game phases (e.g. offensive play, defensive play and time out) from the trajectory are visualized by ellipses (Fig. 1 (b)). In Fig. 2, a heat map visualizes the ball occupancy on a soccer court. Goldsberry [6] proposed a more sophisticated heat map to quantify the shooting range of basketball players (see Fig. 3).

Pileggi *et al*. [9] introduced radial heat map (see Fig. 4) to visualize the distance of shots from the net using a series of concentric rings surrounding the attacking goal representing cumulative bins of shots.

Researcher have proposed system level visualization methods on soccer [7], baseball [5] and tennis [10]. However, their work are not directly related this work as this work is to analyze a specific sports broadcasting problem instead of a sports visualization system.

1.2. Visualizing camera data

Cameras have two types of parameters: intrinsic and extrinsic parameters. Camera data visualization usually refers to the visualization of extrinsic parameters which are the 3D position and orientation (Euler angles) of the camera. Fig. 5 shows the classical camera parameter visualization method in which cameras are visualized as pyramids. Because camera parameters are measured relatively to reference coordinates (such as world coordinates), a reference object is necessary except a default coordinate is assumed.

When the number of camera goes up to hundreds, only the dominantly varying parameters are visualized. For example, Fig. 6) shows the trajectory of a camera mounted on a self-driving car. The car traveled about 8 km in a city. The height (z position) of the camera is assumed constant because the variance of the height is much smaller than the x, y positions of the camera. Also, the orientation of the camera is fixed with respect to the car. In this case, the dominating varying parameters are x, y positions of the camera. As a result, a 2D line overlaying on a geography map effectively visualizes the camera data. So, identifying and eliminating invariant camera parameters is very important

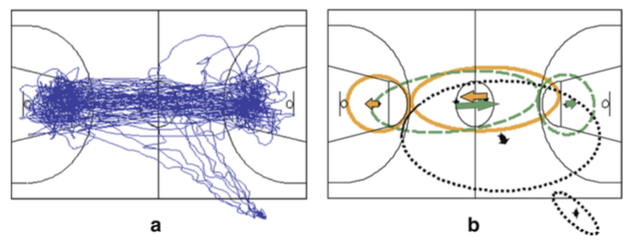

Figure 1. (a) Trajectory of the team centroid; (b) Gaussian mixture models for the three phases of the game. The arrows show the direction and magnitude of the velocity component of the flow vector. Figure from [8].

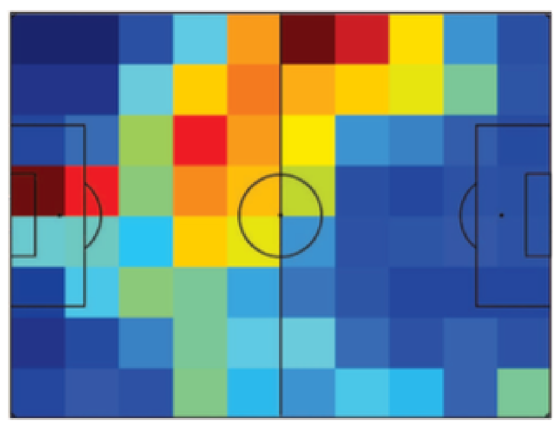

Figure 2. Example ball occupancy map over a match half for a team attacking left to right. Figure from [3].

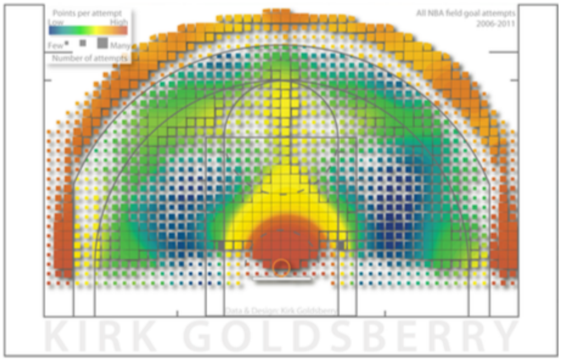

Figure 3. Court vision heat map. The map reveals league-wide tendencies in both shot attempts and points per attempt. Figure from [6].

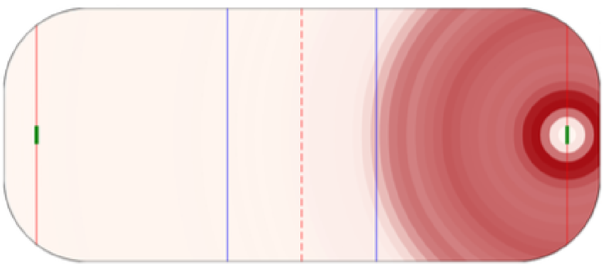

Figure 4. Radial heat map conveys information about shot length. The darkest red ring represents the densest shot. Figure from [9].

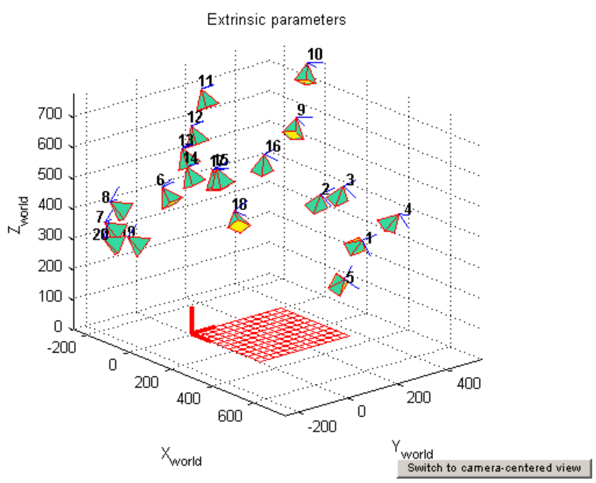

Figure 5. Classical camera parameter visualization. The camera position is located in a 3D space with a reference object (the red mesh). The orientation of the camera is visualized by a rectangular pyramid. Figure from [4].

to effective visualize large number of cameras.

1.3. Visualizing both sports and camera data

Visualizing both sports and camera is used to illustrate data-fusing from multiple camera in sports applications.

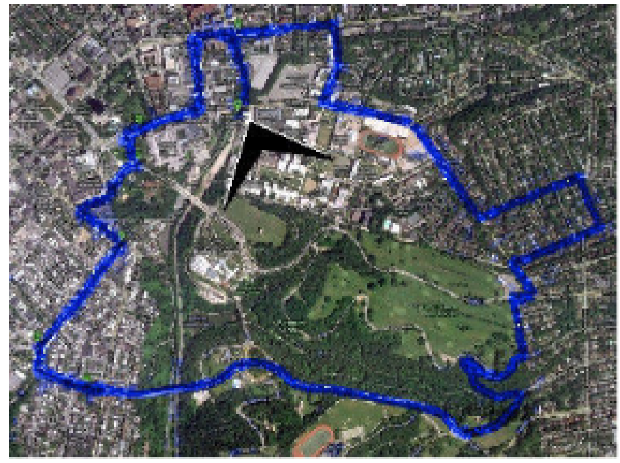

Figure 6. The camera trajectory in an 8 km route. The height of the camera is assumed constant and the orientation of the camera is fixed (looking forward on the road). The reference is from Google map. Figure from [1].

Multiple cameras can cover the whole playing ground with sufficient resolutions. Fig. 7 (left) shows eight cameras looking at a field hockey game. The projected view frustums of cameras are visualized by colored polygons. Meanwhile, Fig. 7 (right) shows the players position in the playing ground using circles with different colors. The overlapping relationship between cameras can be visualized by a graph. For example, Fig. 8 shows three camera positions in a soccer game (left) and corresponding camera graph (right). The corresponding graph represents a set of camera that are used together to localize a player. For example, camera 1, 2 and 3 are used to localize P4.

2. Update according to proposal feedback

Data abstraction The data is time-varying data. The camera angle is diverging data. The feature is multi-dimension sequential data. The player location is spatial data. The dataset is a multiple dimension table. The frame number is the key of an item. Camera angle, feature and player location are attributes of an item.

Camera angle The range of camera angle is in $[-56^o, 55^o]$ with 0 in the middle. Negative angle means the camera looks at the left side soccer court.

Feature Fig. 9 shows how player positions are mapped to 14 dimension feature. The feature is multi-scale. In each scale, the player positions are radially mapped to cells. Multiple players will locate within a single cell. At the moment, Euclidean distance is used to measure feature distance. Other optional distance is Manhattan distance as it is robust in high-dimension. As I have no clear idea which

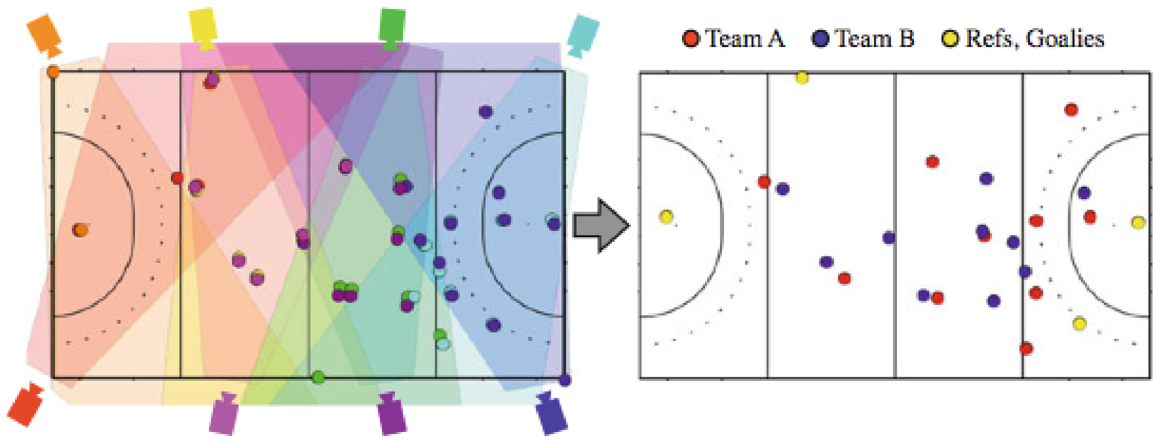

Figure 7. Multiple camera views of field hockey game. Left: the view frustums are visualized by different colors. Right: different teams (or others) are represented by color circles. Figure from [2].

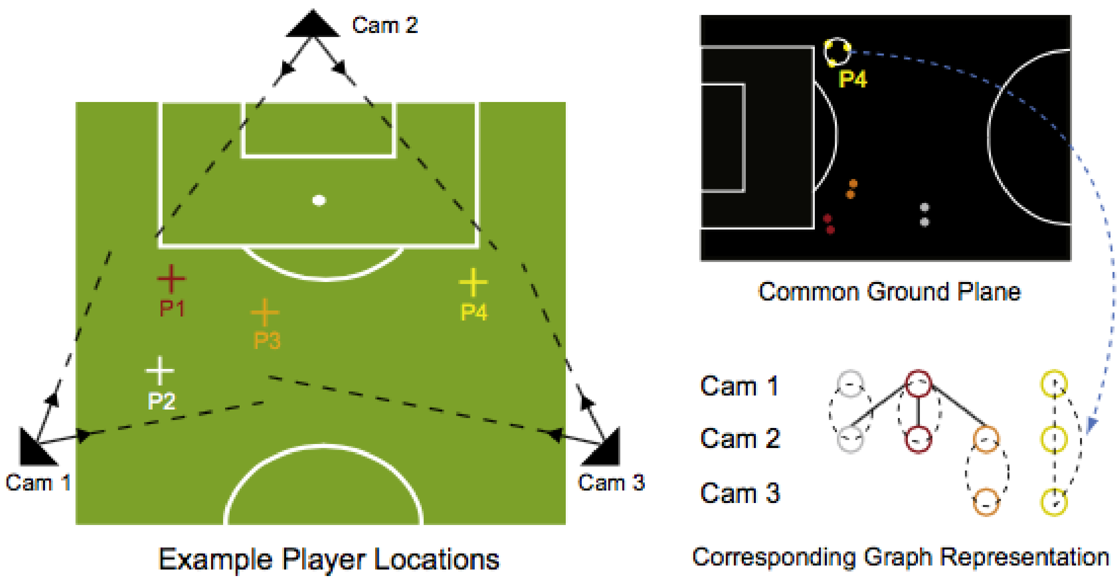

Figure 8. Player captured by multiple cameras. Left: camera location and the field of view. Right: camera graph.

metric works best for multi-scale feature data. I plan to provide multiple options and let users decide which one they want to use.

Besides the heat map, the feature will also be visualized on a soccer court 13. Cells have different colors which represent the value of each dimension in the feature.

Details about sampling It will be deleted.

Player location view It will be promoted to rank 1 (complete). In contrast, the query two and three in Query view will be moved to rank 2 (optional).

Outlier detector I assume the relationship between the feature and camera angle is "positive": if the distance of two frame is small in feature space, their camera angle difference should be small. So the outlier frames are a pair of frames that have small distance in feature space but have large distance in camera angles. The purpose of outlier detector is to find these frame pairs. Different distance metrics will be explored.

Output of outlier detector Besides frame numbers, the output will be visualized by the feature on the soccer court. It also will be visualized by player position (original data) on the soccer court.

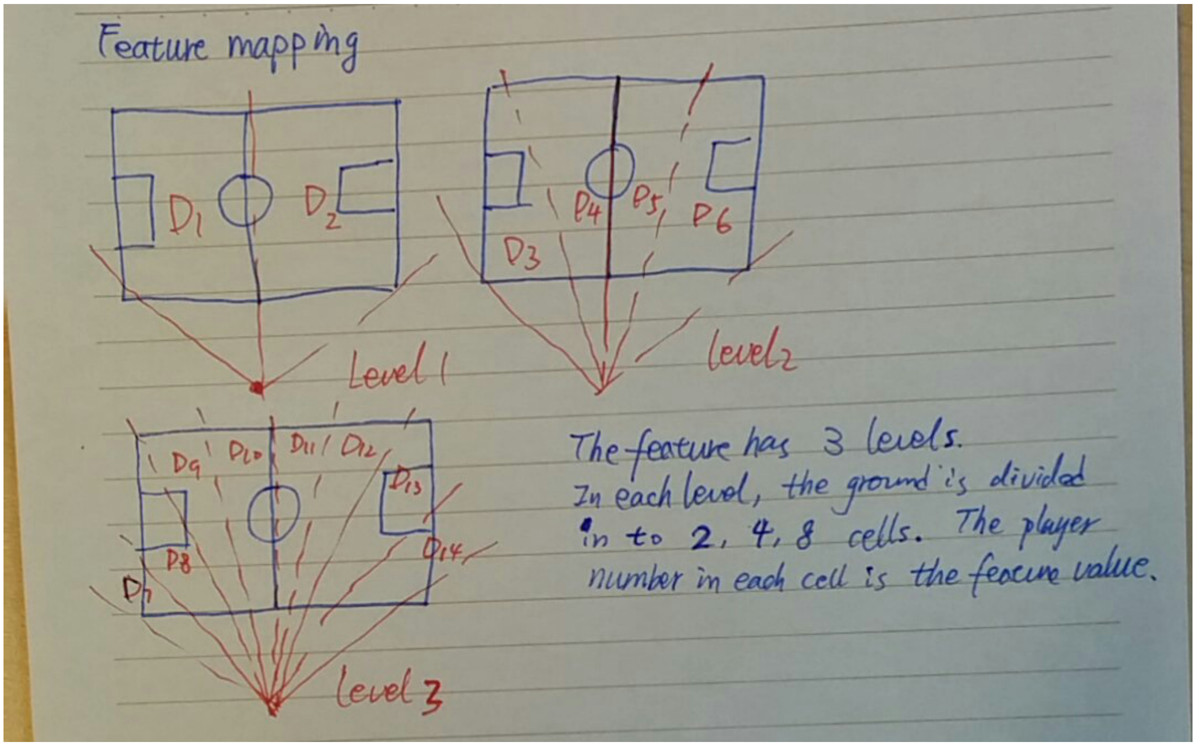

Figure 9. How player positions map to the feature. The feature has three scales. In each each scale, the soccer court is radially divided into 2, 4 and 8 cells. The number in each cell is the feature number.

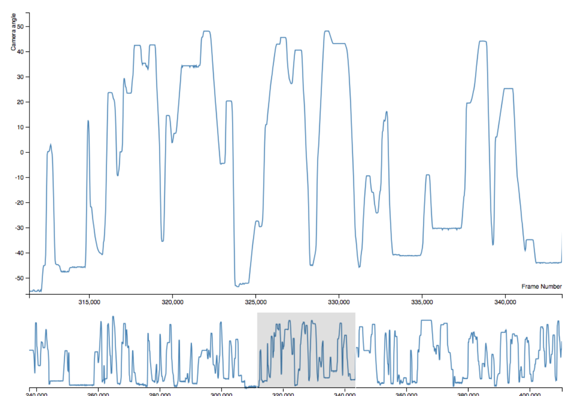

Figure 10. Camera angle view. It shows the camera angles in multiple scales. The top sub-view is the detailed view. The bottom sub-view is the global view. Users can select data using a brush in the global view.

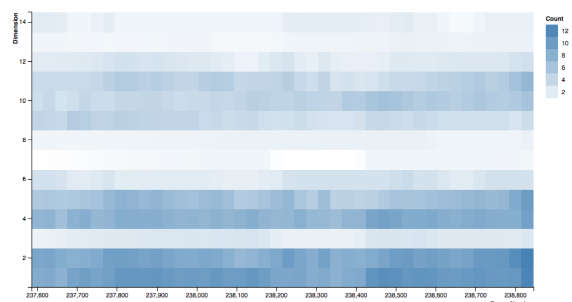

Figure 11. Feature view. Now it only has global view. A brush will be added in the bottom so that users can select data for detailed view.

3. Milestones update

Obstacles The project supports different tasks and I implement tasks in separate web pages now. Eventually, I have to put them together and add linked highlighting between different views. Making multiple views working together will be one of most time consuming work.

Changed plan It is in Section 2.

Updated milestones

- **Nov 10** Start camera angle (line chart) and feature (heat map)views. **Finished** in Fig. 10 and Fig. 11.
- **Nov 17** Finish linked highlighting between line chart and heat map. **Delayed**
- **Nov 23** *Status updates due*. Finish query one and query two. **Finished query one** in Fig. 12. **Query two is moved to be optional.**
- **Nov 30** Finish query three. **Output method is modified.** A soccer court feature is in Fig. 13.
- **Dev 7** Complete the over view and query view. Start prepare presentation.

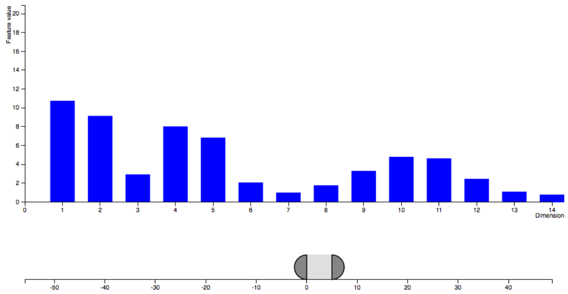

Figure 12. Query view task one. The top sub-view shows the query output which is the mean and standard deviation (to be added) of each dimension of features. The bottom sub-view is the sliding bar that is used to set a camera angle range.

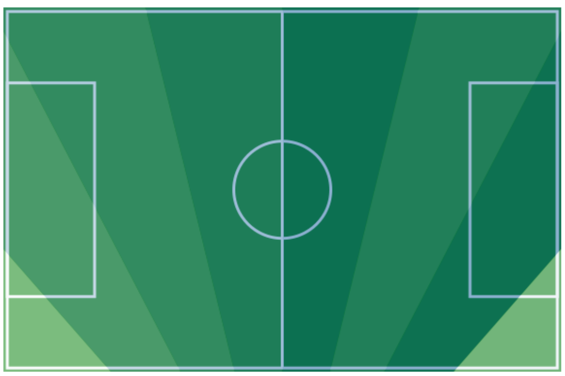

Figure 13. Feature composed on a soccer court. Colors are used to visualize the feature value.

- **Dev 15** *Presentation deadline*. Start player location view. Draft the final paper.
- **Dev 18** *Paper due*. Finish the paper and record the demo video.

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