INTRODUCTION TO COMPUTER VISION

ICE HOCKEY PARAMETERIZATION

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INTRODUCTION

The National Hockey League(NHL) has yet to implement player/object tracking data like other major sports organization (National Basketball League, National Football League, World Cup Soccer), this paper we start the ground work for player/object tracking from broadcast video for the NHL. Player/object tracking was established in those leagues using radio frequency identification(RFID) tags and since a plethora of data has assisted in player/coaches/analyst understand of their respective sports. We suggest using computer vision techniques on video broadcast data for player/object. To determine the (x, y) coordinates of players/objects on the ice you will need to parameterize the ice, thus having a pixel to world ice location. The difficulty of using broadcast video is that the zoom, angle, and direction of the camera will move throughout the broadcast. There are four camera angles, behind the net, between the players benches, corner cameras, and a elevated side ice camera angle. We will only focus on the main camera angle from the side of the ice looking towards the players benches because this angle is used the majority of the time and has the most information about the game. The video we will test are highlights from a game between the Washington Capitals at the Edmonton Oilers and only certain clips will be analysed to test the proof of concept. Every NHL ice area has a standardized playing surface (figure 2), but all arenas have different advertisements along the boards, plus each team has multiple home and away jerseys that could affect the strategies used in this paper.

RELATED WORK

Player/object detection and tracking are continuous areas of research and applying those techniques could provide possible answers for the hockey tracking. The core of moving object detection can be broken down into detection of objects, segmentation of objects and tracking of objects. Our goal is to begin the process of player tracking and many of those papers take a

sophisticated approach where we are using a rudimentary approach to quantify the playing surface.

Detection of Objects

From [10] we see a technique for spatiotemporal visual saliency using phase spectrum which is easy to implement and is computationally efficient. Shows great improvement in interest point detection and deviation detection on two real image datasets, CRCNS-ORIG and DIEM. Khan[8] uses spatiotemporal Gaussian mixture model (STGMM) is used for object detection by implementing Kalman filter with past information for partially occluded objects. Lu [15] creates a system that detect and track multiple players by estimates the homography between video frames and the field to then identify the players. Those detection techniques could be possible approaches toward detection but would then need a translation to pixel to real world.

Segmentation of objects

Team sports create difficulties determining individual players which is what [1] attempts to solve using least entropy data partitioning technique. This "role-based" approach gives each player a segment that allows separation from other players. Li [12] takes a novel look at segmentation by learning and extracting attributes on segments of an object. From those attributes they then create a ranking system to classify those segments. Jain [13] proposes a end-to-end learning framework to segment objects in videos using convolutional neural network which fuses motion and appearance in a unified framework. Segmentation would be an important approach for future work to eliminate irreverent areas, such as the crowd.

Tracking of objects

Liu[6] takes a new approach using optical flow with support vector machines(SVM) on broadcast sports video for action recognition. They study tennis and badminton and display excellent results tracking players. Using advance particle filter tracking [3] from moving edge information and color for tracking, Chen uses a bounding box to insure the object is contained in each frame of the video. Gaussian mixture model (GMM) and optical flow analysis method are compatible with each other and [4] developed a new tracking from the three different Gaussian distributions, the average, standard deviation and weight respectively. Liu [] extracts noisy detentions from basketball and field hockey to describe the current state of the game then creating a affinity model for each player and time instant random decision forest based on current tracking. The resluts were successful in tracking 10 and 20 players for several minutes. Comaniciu [5] proposes kernels for nonrigid object tracking using an isotropic kernel for spatial masking, success show for exploitation of background information, Kalman tracking, and face tracking.

Object Tracking with Moving Camera

In our problem our camera is location but the direction it faces changes to follow the play of the game, we focus on related papers in object tracking with moving cameras. Burt [9] look at foveation, two-stage motion computation, tracking, and one-component-at-a-time segmentation. They use helicopter footage and obtain real-time precise results. Sharma [11] has a similar problem statement with the observer collecting images and from optical flow pattern due to egomotion which is designed for navigational systems. Markandey [14] proposes a technique for autonomous detection of moving targets from infrared imagery with from success with satellite data. In general, there has not been much research specifically focused on hockey surface parameterization or player/object tracking.

METHODS

The general approach in this paper is to use the unique advertisements along the boards of the ice arena as templates and then use those templates to identify where the camera is looking on the ice. This general approach would be effective because each arena has unique advertisements that can be used. Figure 2 shows dimensions of the playing surface, the lines on the ice surface are the same for every NHL arena. Figure 1 shows two blue-lines, each line can be constantly found while the line is in view of the broadcast footage, but there are time when the camera frame does not show the blue line at all which is why we must capture the templates between the blue lines and goal line on each side of the ice to then be able to determine where the camera is facing. Below we discuss the methods used in the is paper but because each method is occurring at the same time we will start with the general ideas and move towards the specific techniques. For this paper we will determine the center ice dot as the origin of the ice with the x axis being right to left with the y axis being up and down, positive directions will be right and up. We will only address the x direction in this paper, the center ice red line will be the $x = 0$ line across the ice.

Templates for Location

The entire ice surface is standardized as figure 1 shows, thus if you can detect an object on the ice you can then parameterize the ice show in the camera frame. Locating templates on the ice can be done many ways, using object detection techniques such as Scale-Invariant Feature Transform(SIFT)[7] or the faster feature extractor Speeded-Up Robust Features(SURF)[2], but

Figure 1: Edmonton Oilers Ice Arena with 11 Templates

for computational efficiency we simply use template matching which worked well for our problem.

Table 1 represents what template translates to on-ice x coordinates depending on where in the frame the template is located. For example, if we detect template 3 in pixel 500 in the camera frame, then a perpendicular from that template is on the $x - axis = -58$ feet from the $x = 0$ line (center red line).

Template Ice x Coordinates		
Template	x on Ice Location	Pixel x Frame location
1	-100:-75	200-1280
2	-75:-62	400-800
3	-62:-49	400-800
4	-49:-36	400-800
Left Blue-line	-36:-13	200-1000
Center Red Line	-13:13	200-1000
Right Blue-line	13:36	200-1000
8	36:49	400-800
9	49:62	400-800
10	62:75	400-800
11	75:100	400-800

Table 1: Shows the x coordinate depending on what template found and where it is located in the camera frame.

Searching for Templates

With eleven templates, if you search for all of the templates you will find something in the frame that will match the template. We attempted using thresholding to determine what templates were in the frame but due to the similarity of each template and occlusion we could not use this. We determined that only searching for one template was sufficient then as the camera angle shifted and the template shifted to one side or the

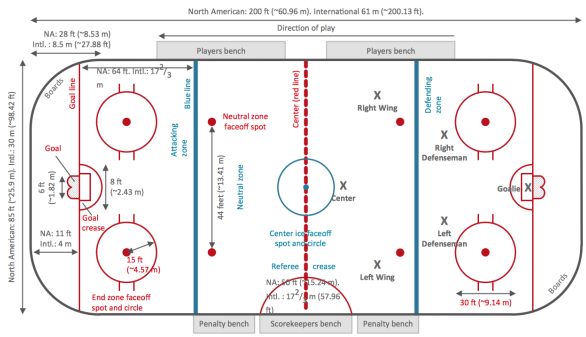


Figure 2: Dimensions of NHL Ice Rink

other of the frame we would then search for the next template depending on which direction the camera is moving. For example, if we detected template five and over time the template location moves to the right of the frame then the camera is moving to the left and we need to search for template four.

```
Result: How to capture templates
while Frames open do
    space available for template capture;
    if Space>220*index number then
        Save Capture Template;
        Set index for next template;
    else
        continue ;
    end
end
```

Algorithm 1: Searching for Templates

Template Capture

To use templates to determine the direction of the camera you must capture those templates. We wanted to build a generalized algorithm that could work for multiple arenas so we start the game with a blank template set then as the camera reveals more of the ice we save those templates. Every NHL game starts the same way in the center ice dot or our origin. You then can locate the blue-line depending on which way the camera goes. There is a yellow board that surrounds the ice surface that can also be found constantly. Once an advertisement is available to capture then we create a mask using the blue-line and the yel-

Figure 3: Top, Middle, and Bottom: Show template eight, nine, and ten to the right of the positive blue-line

low boards. Each advertisement is the same length and height because the advertisements are similar size and spacing. We found 220 pixels for our template length and 65 pixels high from the yellow boards, which corresponds to 13ft by 3.5ft real world dimensions.

Blue-line & Yellow Board Detector

We use same techniques for the blue-line and the yellow board, so we will discuss both here. We start by changing our image into an Hue, Saturation, Value (HSV) then set range of values for the hue to between, for blue 110-130 and yellow 10-35. Then change the image into a binary image using the threshold of 130-255. We then using opening and closing to focus our search, for the yellow board detector we use a unique kernel of size (15,25) to increase the connectivity of the right to left part of the board and overcome occlusion. The slope of the line across the blue-line will be how we determine which blue-line we are detecting. A positive slope will be on the positive side of the ice and negative will be on the negative side of the ice.

Blue-line Location

To locate the blue-line we use the blue-line and yellow board detectors together to determine where the blue-line meets the boards. Lets look at the blue-line first, we loop through each contour captured and then save the index from the largest and the smallest y value. From those two points we draw a line. We do a similar think for the yellow boards except the smallest and largest x value then drawing a line between each. Figure 5 shows those lines and then the location of the blue-line and yellow board.

Figure 4: Top: Shows Yellow board being detected; Middle: Shows the blue-line being detected; Bottom: Original Image

Figure 5: Lines Draw through contours of blue-line and yellow board to locate where the blue-line and boards meet

EXPERIMENTS AND RESULTS

Implementing the algorithm on two section of play as a proof of concept. The first video is the start of the game and we have no templates of the arena. Figure 6 show clips from a video recorded of the algorithm capturing templates. You can see that each template is captured but I am missing the full template 4 by 13 pixels. In 80 frames, 4 templates are captured which can then be used later in the game.

The second example is now using those templates to to then determine the direction of the camera and next steps, the location of the template on the ice.

Over the 183 frame clip there are 20 frames that either misidentify a template incorrectly finds no template at all. On a very small sample this has an accuracy of 89%.

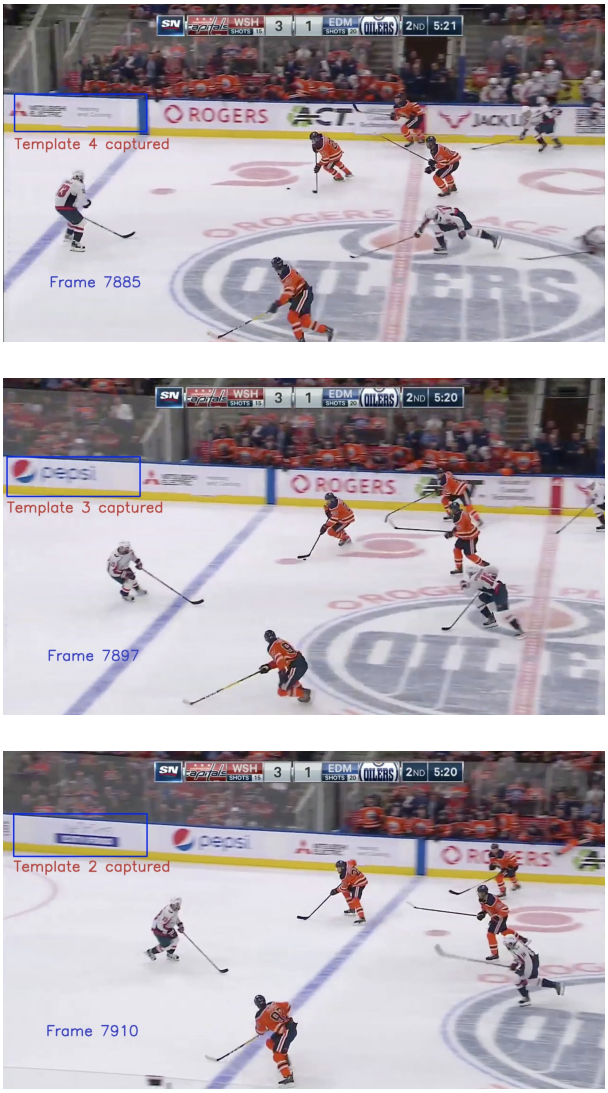


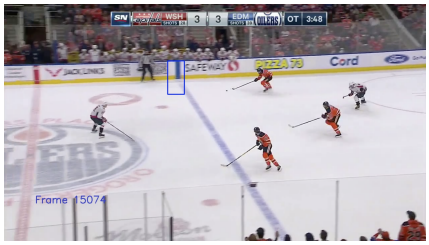
Figure 6: shows clips from the video from it capturing templates as they are reveled

DISCUSSION

Quantifying the ice surface was a challenge due to occlusion, changing video zoom and quality, various colours changes, and fast movement but beside those challenges I believe that the proof of concept has been shown that with fine tuning you would be able to capture templates and then use those to then determine the direction of the camera and a single axis on the ice. Limitations are when the camera angle zooms in directly or when you a far corner of the ice and there is not template in view. There are times when the blue-line finder would think a player was part of the blue-line thus causing issues with the line being drawn across. Future work would be to capture more templates across the arena and then possible use multiple templates for basing the direction from and creating more robust techniques to handle various situations. Also, attempting to use this algorithm at another ice arena with different teams would also test the methods used in this paper. Different faceoffs locations and have a strategy for capturing those places on the ice. Overall, this paper can be the framework for player/object tracking to then use for a coordinate system on the ice.

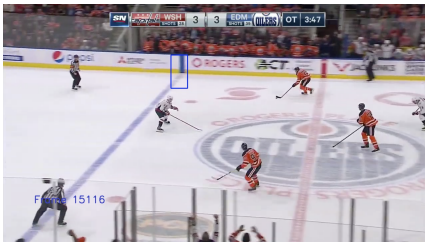
(a) Template 11 location

(b) Template 10 location



(c) Right Blue-line template location

(d) Center Red-line Template location



(e) Left Blue-line template location

(f) Template 3 location

Figure 7: Shows a camera shifting from right(a) to left (f) and what template (blue square around the template) is being used to determine the direction.

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