Using A Bayes Classifier to Draw the First Down Line on a Football Field

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Abstract— **The goal of this project was to draw a line on an image of a football field without marking on the players. This project was motivated by Sport Vision, developers of the first down indicator used for television broadcasts of football games. The scope of this project is limited to distinguishing between the field and other objects in an image. The images used to test my program were either recorded from television broadcasts and captured with a frame grabber, or taken with a digital camera. All software and calculations were done using Mathematica. Each image was segmented using XV. A Bayes classifier was utilized to determine if a pixel should be colored. The next step for this program is to determine where to draw the yellow line in real time while panning and tilting the camera.The goal of this project is to cost effectively draw a line on an image of a football field without marking on the players. This project was motivated by Sport Vision, developers of the first down indicator used for television broadcasts of football games. The scope of this project includes distinguishing between the field and other objects in the image while the camera is panned and tilted. This project will be carried out in three phases. The first phase involves scanning images and correctly drawing the first down indicator. The next phase requires building detectors to determine the orientation of the camera with respect to the field. The final phase will be completed by integrating the pattern recognition software with the camera tracking hardware.**

The images used to test the recognition algorithm were either recorded from television broadcasts and captured with a frame grabber, or taken with a consumer grade digital camera. All software and calculations were done using Mathematica. Each image was segmented using XV on a Linux PC.

Several steps must be taken before the classifier can correctly draw a line on the image. Since the captured digital video is a sequence of images, stills were used to develop and test the classification algorithm. Once a test image was selecte, its camera view had to be calibrated to the field. This process involved segmenting out images with pixel values corresponding to each class as shown in figure 1.

Fig. 1. **Segmented images**

The different pixel clusters were assembled and RGB plots were generated. To represent the distribution of the pixels for each class, the mean and covariance for each class was calculated. Upon looking at the distributions of the test image, it was decided to use the video-imposed scoreboard pixel distribution as the not-grass class. As shown in the image below, the video imposed scoreboard contained a lot of white, black, yellow, and red pixels. Based on the limited range of pixel values for each team uniform, the scoreboard distribution proved to be a sufficient choice for the non-grass class.

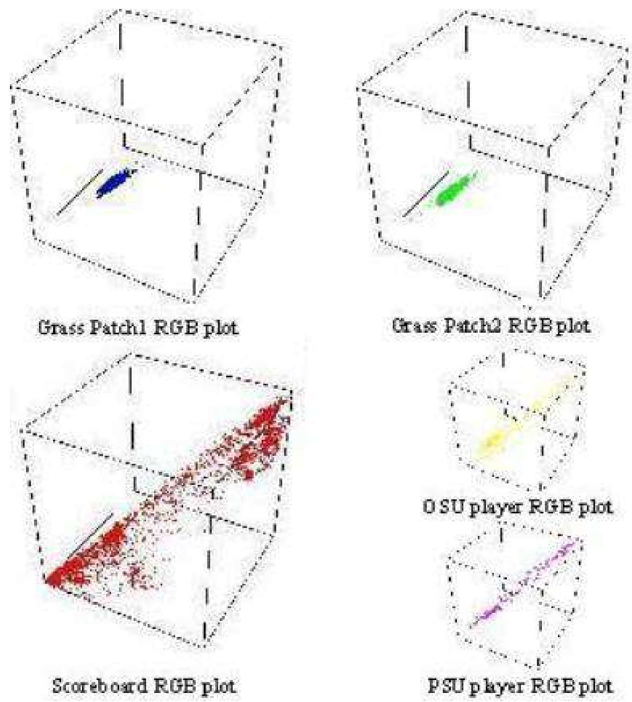

Fig. 2. **Segmented pixel distributions**

After plotting the two different grass patch distributions, the initial plan was to use only one of them to classify a pixel as grass. Due to variations in shading, this method proved too selective to correctly classify a known test pixel. Therefore, both of the grass-patch samples were used to represent the grass class.

XV was used to find the coordinates of two different

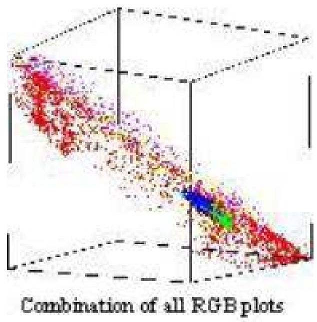

Fig. 3. **Combination of segmented pixel distributions**

points along one of the lines running across the field. After calculating the slope, Mathematica's ceiling function was used to determine the integer location of the pixel to be tested. With the slope and (x,y) coordinates of the reference line, it was time to test each of the pixels along the intended line.

Fig. 4. **Image of line formed by stretched pixels**

To test if a pixel belonged to the grass or not grass class, a Bayes classifier was constructed using the mean and covariance of each class. Since the majority of the football field contains green grass, the following prior probabilities were used:

GrassPatch1 = 99.99GrassPatch2 = 99.99Digit = .01

If a tested pixel was found to have a greater probability under GrassPatch1 than Digit, the pixel was colored. If the pixel had a greater probability under Digit, the probabilities between GrassPatch2 and Digit were compared. If Digit's probability tested greater, the pixel remained uncolored and the algorithm moved on to the next pixel to test. After all testing and coloring was finished, the modified image was redrawn. To adequately test the algorithm, two sets of line lines were drawn – one through the red players and another through the white players as shown in figure 4.

The results of the line drawing were good but some pixels were incorrectly classified. To calculate the error, the new image was inspected and the incorrectly colored pixels were identified. For the blue line the typical error was about 12 percent. However the orange line shows a larger number of missed pixels especially near the white line. By inspection, the classifier had a difficult time with pixels next to white lines and light colored portions of the field. This is a result of the wide range of pixel values represented by the scoreboard and the concentrated distribution of the grass patches.

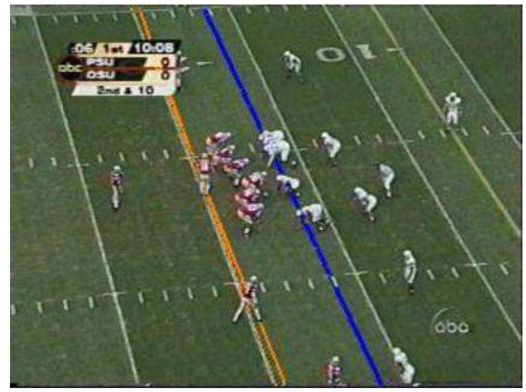

Fig. 5. **Captured image of a football field**

To improve the models, a mixture of Gaussians should be used for the grass and non-grass classes. The grass regions can be better represented by using multiple samples. Care also needs to be taken when segmenting out the non-grass images because allowing grass into the segmented images distorts the distributions. To make the non-grass class more robust the distributions of players, numbers, and images on the field need to be added. After trying the first image, the algorithm was tested against a field that had patches of snow on it. As with the image above the orange and blue lines were used to demonstrate how well the classifier recognized players. The purple line was drawn over the 40-yard line and the green line was drawn over a snow covered patch of grass.

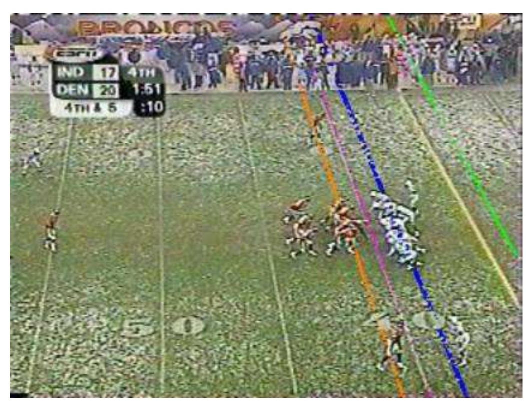

Fig. 6. **Captured image of a snow covered football field**

Since the snow is similar in color to the digits on the field the classifier performed poorly. Patches of grass covered with snow were added to the grass class to improve the classifier's results. This helped, however pixels were still colored incorrectly. In fact, the white jerseys were mistaken

for grass and colored blue as seen in figure 5. As stated earlier, the improvements for classifying the test image would also benefit this image. However, the algorithm's effectiveness will continue to deteriorate as the amount of snow on the field increases.

Hardware

The next step is to use sensors to keep track of the camera's orientation as it changes. Optical encoders will be used as a low cost alternative to pan and tilt sensors. The movement of the encoders will be determined using an LS-7166 quadrature encoder counting chip. A microcontroller with a UART will be used to relay the position of the optical encoders to the host computer. The software used to integrate the line drawing and the camera tracking will be written in C. The software will interpret the movement of the camera and adjust the slope of the drawn line in response to changes in the camera's position.

Conclusions

This system will prove that the first down indicator on a football field can be drawn inexpensively with standard equipment. Applications are limited, since Sport Vision already covers both Pro and College football games. The hardware for tracking the camera's movement is currently under construction. Once the integration between the sensors and the software is complete, a method will have to be developed for reacting to the zooming of the camera.