**Abstract**

The aim of this project is to make a machine learning system which will detect the direction in which the offensive team is playing in football videos. This information is necessary when we have to make automated computer vision systems which will provide us with analysis of the footabll games for coaching purposes. To develop such a system, we have used KLT Tracking system to track seemingly interesting points in the videos and then, use Machine Learning algorithms of Decision Tree and Decision Stump with Boosting to identify which player tracks are important in making the decision for the direction of the offensive play.

**Introduction**

To come up with good and effective solutions for football coaching softwares, we require to track players, look for prominently used strategies by different teams, etc. In general we need to find all those properties of a football video that the coach can use to better train his own team, given a set of videos of the opposition team. To do so, in the absence of such a coaching software, the coach or his team of assistants have to look at numerous plays of the team and decipher the playing strategy of the teams. Even after the coach is done doing this, he now has to send out a great deal of documentation to the players so that they know their roles in the game. This leads to a lot of time spent in auxiliary work which can be automated.

The aim of this project is to help develop a part of such a coaching software. This project will aim at recognizing the direction of the offensive play given a video. This analysis can then be used to make comments about the team that is on offense, the orientation of the players on the offensive team and the player movements in both the teams. It will serve as a major step in developing the coaching software as many other elements of the coaching software are dependent on it.

**Methodology**

In order to recognize the direction of offense we need to know some domain knowledge about football. We will provide with a brief overview of the domain knowledge that we require for this project. Usually when the two teams line up for a play in the game of football, we have two players known as “Wide Receivers” standing at the ends of the filed along the line of scrimmage. The line of scrimmage is the line that separates the two teams at the moment of snap. The moment of snap is the time at which the players start to play the game for each play.

These two wide receivers are instrumental in the detection of the direction of the play as they run fast down the field in the direction of offense from the moment of snap and can be used to determine the direction of the play. If we are able to get good and long tracks on these players and if we are able to tell that these tracks belong to the wide receivers, we can find the direction of those tracks and ultimately determine the offensive direction of play.

We decided to use KLT tracks to do the video tracking on different points in the video. We have seen that the KLT tracking method, select points that have a high gradient with respect to its neighbors. This makes it select “interesting” points such as corners in the image. We want to use these interesting points and specify which of these points correspond to the wide player on the pitch. Using KLT tracks, we can get the length of the track easily by simple geometric computation on the track features. Also, we can get the distance of the track from the bottom edge of the frame.

We use KLT tracks to generate a dataset for the videos with the following features.

a. Track Number

b. Starting Point Co-ordinates of the track

c. Ending Point Co-ordinates of the track

d. Normalized length of the track.

e. Normalized distance of the track from the bottom edge of the figure.

f. Direction of the track.

After getting such a dataset from the KLT tracks, we have to find out a way to determine which of these tracks belong to the wide receiver. We can now use the domain knowledge to determine where to look for the receivers. They will be at the near end and the far end of the field. Also, since they run fast, they will have longer tracks as compared to anyone else on the field. Hence, we have to look for long tracks on both the ends of the field.

We can plot a sample dataset as shown in the following image.

{Put image here}

Here the Y-direction represents the length of the track while the x direction represents the closeness to the bottom edge of the field. If x = 1, then the track is nearest to the bottom. If x = 0 the it is farthest from the bottom.

Now, we have to find a region in this plot where the receiver tracks will be. Using the domain knowledge and the inspection of various videos, we come to know that the receiver tracks will more often that not be in the highlighted part in the figure. But, this region will change from video to video as the orientation of the videos, the resolution quality and even plays will be different in different situations. Here is where we use the machine learning algorithms to determine the rectangle to be considered for determining the direction of play.

We have used the machine learning algorithm to identify the best rectangle which will denote the direction of play. We predict the direction of play by considering a majority vote of all the tracks that fall within the rectangle. If the majority are moving in left direction we say that the direction of the play is left.

**Features**

The features that we have considered here are as follows :

a. Length of the track.

We know from the domain knowledge that the wide player will be the one who will make a big rush down field so that we will get good, continuous and long tracks on him. Also, the other players, like free safety, quarter back or the guard players will not move much in the first one and a half second and will have relatively smaller tracks. So, we wish to select those tracks that have a high length as feature.

b. Distance from the edge of the field.

As mentioned before we know that the wide players will be on the near side of the field. The orientation of the play recording is always such that the wide player that we want to track will always be on the bottom most part of the frame. So, we have selected the distance from the edge of the field as our next feature.

c. Track direction with respect to the field.

This information is vital, since one player will have multiple tracks in one and a half second which will all be close by and going along the same direction. So, if we include the information of the direction of the track (left or right) we will be able to make the differentiation between the noisy tracks and actual wide player tracks better. Thus, the reason for selecting this as a feature.

In short, we want to track those points that have a high length and are closer to the edge of the field, moving in one direction so that we can say that the tracked point is a wide receiver.

*{– Michael, I have no idea where to put this. Maybe in the features or maybe in the methodology. We may be able to put in the results section too. –}*

Decision tree/stump features:

For Decision tree and Decision Stump, we have used 60 different features. These 60 features are the predictions of 60 different rectangles. For the decision tree we expect that the classifier will not work as correctly since it will learn a decision boundary based on very weak features. Instead if we use the AdaBoost method we find that we get better results. So, we populate the dataset as a combination of 60 features and learn by using a weak classifier, i.e. Decision Stump. After giving enough training data by actually calculating the ground truths for the videos, we use boosting to learn a good hypothesis space. This hypothesis helps us to correctly identify the rectangle that we should be using given a KLT video dataset and helps us to achieve more accuracy.