# Getting Positional Play Data - It's, likely, in the crowd

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## 1 Introduction

Sports analysis is used to find deeper insights into understanding athlete performance and team strategy. One limitation to continuing progress in this area is acquiring data that represents player and puck (or ball) movement. In some sports, such as baseball and cricket, there are significant statistical events that are reasonably easy to record. Other sports, such as hockey and soccer, have few statistical events and might be better described as flowing sports. It is much more difficult to acquire data in these flowing sports. One solution is to use tracking devices, in the form of micro-chips embedded on players; however, there remain a number of challenges to using this embedded technology. For example, if a league does not impose the technology on all teams, why would an opposing team wear tracking devices that could potentially expose their team's behavior? Similarly, to develop systems for automated scouting at the farm, high-school, and youth level, the technology cost for mass adoption is prohibitive. Existing commercial systems, such as SportsVU [2], can do this visual tracking, but again, this system with it's hundred thousand dollar system cost is too great to be deployed on a massive scale. In this work, we investigate two possible approaches to acquire hockey data independent of using tracking devices at a low cost.

*Existing Video Tracking Solutions*
To our knowledge there are three key systems in industry used for tracking/analyzing sporting events that work via the processing of video (non-embedded devices). As these are all industry based solutions, we only know about these systems based on what can be found on the internet. In this section, we will briefly describe each section and describe why the system is not suitable for large scale tracking and scouting which requires low cost, portability, no need for major site installation, and tracks players and implements.

The first video based system to be adopted into sports is Hawk-Eye [1], which has been used in cricket, tennis, snooker, and other sports to track the balls in the respective sport. This system uses a series of cameras and triangulation techniques to determine the location of the ball(s). For example, in tennis there are 10 high-speed cameras in fixed locations around the court. This type of system is insufficient for our application since it does not satisfy any of the above requirements.

As mentioned earlier, SportVU [2] is a system similar to Hawk-Eye except this system can track players and the implement(s). This system has been installed for professional teams in European football and basketball. SportVU is reported to be installed in half of the NBA teams arenas as of 2013, and the installation price is around 100,000 USD. There is little information on how the system works, but we suspect that it uses image processing techniques on fixed cameras in birds-eye views since this allows for easy tracking of players $x$ and $y$ locations. We also suspect that there is some human intervention to keep track of player identification, but there is no evidence one way or another, and there is no way of guessing how much human interaction is required.

The Opta system performs tracking of players and implements by using an internal crowd sourcing method with their employees, and has been most notably used to provide data acquisition for European football. Though we have no direct information on how their system works, their videos describing their products shows applications that suggest they use employees along with their software system to translate game footage into tracking data (`http://www.youtube.com/watch?v=Z52mmpF2wLg`, Dec. 2013). Opta's system has many of the same ideas as our crowd source approach with the exception that we attempt to use a public crowd, and therefore, should have significantly lower costs. From a time perspective, a game of football lasts 90 minutes and their are 20 active players to track location. Therefore, without any additional techniques it takes approximately 32 man hours to track a game (including the ball).

## 2 Data Acquisition Systems

The focus of this work is on acquiring positional player data and implement movement via video footage. Given a collection of records ordered by t (time) we can calculate a number of things such as player speed, rate of player fatigue, and team movement. Our first approach to acquiring this data is to use image processing techniques. We will describe the challenges with this approach and then will describe our second approach, crowd sourcing.

*Image Analysis Approach*
Image tracking capabilities continue to improve using advances in artificial intelligence and increased computing power. Our initial attempts to create this system were inspired by the OpenTLD vision tracking system [4]. OpenTLD is a real-time tracking system that learns about the object it is tracking as the video proceeds. Our first attempts tried a number of techniques, but determined

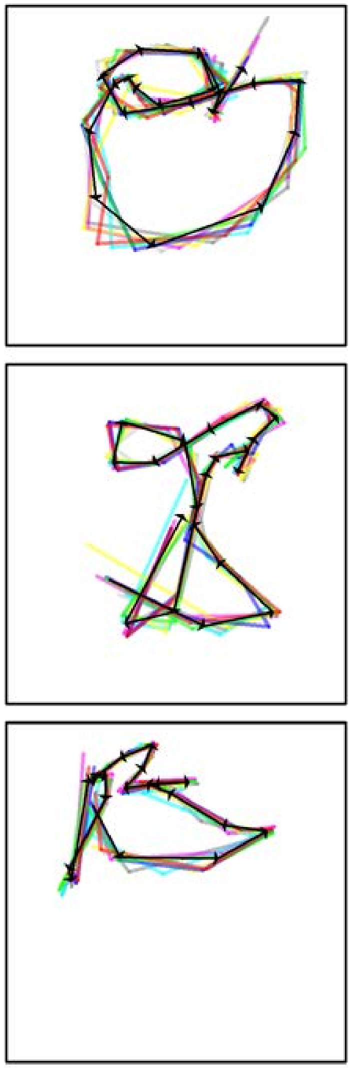

**Figure 1** : Tracking results for three players

that the technical requirements and costs are too great.

*Crowd Source Approach*
Our second approach to sports data acquisition is based on crowd sourcing. Crowd sourcing has a group of diverse and loosely connected people that are used to do work. This approach to getting work done differs from a traditional organized group by its loosely defined participant roles, scale, and goal orientation. More traditional approaches use employees or outsourcing, but crowd sourcing typically has repeatable task orientation and very larges scale [3]. Examples of these systems include Amazon's Mechanical Turk (MTurk), the Linux operating system, and Wikipedia. For a better understanding of crowd sourcing and how problems are solved by the crowd we suggest *Infotopia - How Many Minds Produce Knowledge [6]* and *The Wisdom of Crowds [7]*. Crowd sourcing has been, previously, applied to data acquisition in sports by Spiro *et. al.* [5].

Our approach is to build a web based system that allows fans to help out their teams by doing the player and implement tracking for games. We have developed an HTML5 based front-end that allows a user to load a film clip and use their mouse/finger to track a player, and the mouse/finger provides $x$ and $y$ values. Once the user tracks a player or implement, they can add additional information such as the players number they tracked, and then they submit the data to the back-end server.

*Processing Footage from Angles*
One of the key human computational aspects that is key in a system, such as ours, that is required to be low cost, portable, and easily installed is dealing with the camera and the video it generates. As described earlier, the key advantage of a crowd sourced solution to sports analysis is that even from one video feed at an angle and with a moving camera a human can reasonably estimate where a player is on the field of play.

In our system, we allow for this by playing the video and having the user track player movement on an adjacent field of play with their mouse. For example, the user might see footage from a hockey game that is at one end of the ice. As they follow a player, they move their mouse or finger on the adjacent field of play where they think the player currently is. A human can quickly assess which end the player is based on the presence of the net, boards, goalie, and other simple visual cues that a vision algorithm can not easily deal with or use. Similarly, if the camera view moves with the play, humans can make similar estimates of player location. We have not yet tested the accuracy of such estimates, which we believe needs a large scale deployment and crowd to test, and we leave this as future work.

## 3 Tracking with FanTrack

The difference between commercial systems such as the one, speculatively, used by Opta and our crowd source approach is that the crowd is not trusted, in our case, compared to a single expert employee. To provide some insight on how the crowd can be used to collect this data, we show results from a small experiment for a hockey clip that lasts 20 seconds given to 8 different users.

Figure 1 shows three separate instances of the eight users tracking a unique player from the hockey scene. Each users tracking is shown by a transparent color, and the arithmetically averaged points are illustrated in black. The average of the crowd sourced tracking also has an arrow to indicate the flow of the tracked player.

## 4 Challenges with our Approach

*Motivation*

For FanTrack, we believe motivation for people to crowd source the tracking can be dealt with in a number of ways. First, fans tend to want to feel like they are part of the team, and helping the team by providing tracked data is a simple way for fans to get involved. Second, simple rewards such as access to game telecasts could be used to get users involved.

*Quality Control*

There are two major concerns with a system such as FanTrack in terms of quality control. The first concern is bad user tracking, but as we showed in the previous section that averaging user tracking data results in a reasonable result, and as the number of users increases the quality improves. To improve the results further, it is conceivable that a hybrid system could be created where crowd sourced data is used to help a post image processor that refines the final results after averaging.

The second concern is malicious users who provide bad tracking data. In this case, it is possible to imagine a system where this data could be filtered out if there are sufficient number of users who have already provided tracking data. The filtering algorithm would basically remove outliers from the data set. If, however, there are not sufficient number of previous tracking data then this problem might be difficult to deal with. Some of the gamification ideas for dealing with motivation might help improve the filtering of bad data.

*Bookkeeping*

An additional factor related to quality control that we have not yet described is how to identify and record the players being tracked. In our experiment, the users were given specific players to track. In a full scale system of FanTrack, one of the significant challenges is how to track players and even identify players from a video clip.

*Aggregation*

Aggregation is closely related to quality control for FanTrack. The previously described ideas on how to filter out bad tracking data may also be useful for improving aggregation. Our arithmetic average approach for combining user data is a simple approach that can be improved on significantly. In addition to using a post image processing algorithm and improved filtering techniques, a number of system parameters may improve the quality of the tracked data. For example, we can improve the tracking data by both increasing the size of the video frame and increasing the sampling rate from one sample per second to a greater value. Both will improve the resolution of the tracked data.

## References


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