LegoTracker: An Intelligent Modular System for Large-Scale Sports Tracking

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Abstract

Sports tracking systems such as MLB Advanced Media's Statcast[1] revolutionized sports analytics and the way coaches manage players and approach the game. However, for past decades sports tracking was limited to a rough representation of each player by a single point and often relies on special markers integrated into sports apparel. Recent advances in deep learning and computer vision algorithms enabled markerless detection of human pose. We propose a novel modular sports tracking system providing significantly higher level of detail in game tracking. Comprising of independent units, each running state-of-the-art algorithms for player detection and tracking, it provides a full skeleton representation for each player over a large game field as well as high level game events with precise timing.

Introduction

A typical sports game like soccer or baseball takes place on a field of ≈100 meters in length. Simply putting a camera overviewing the entire field limits the spatial resolution to the order of several centimeters. Furthermore, most of the pixels/bandwidth are being wasted because players occupy a small portion of the field. A network of cameras focused on individual players does not have this problem but requires a real-time inference of game events to follow the players.

We designed our sensors to be closely focused on a single player. This maximizes signal-to-noise ratio which we define as the fraction of pixels corresponding to a player over the total image resolution. There is also bandwidth available to use higher frame rates for tracking fast game events, such as a baseball pitch or a bat swing.

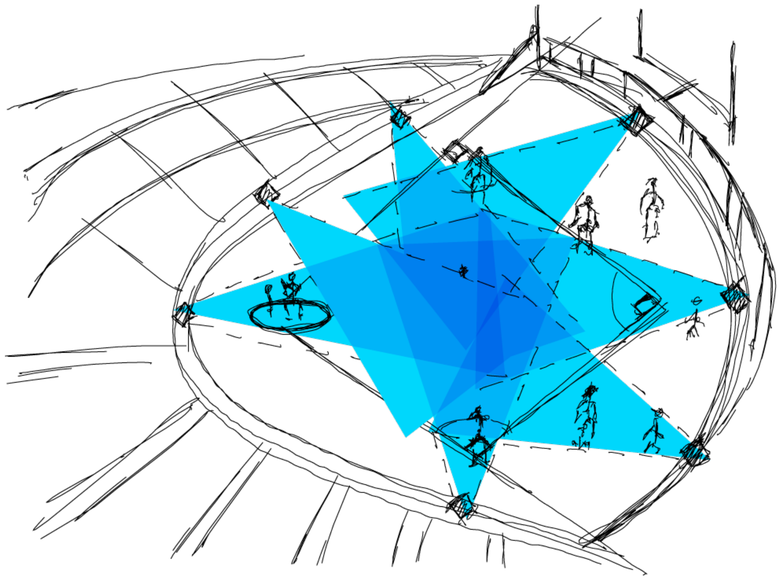

Figure 1: *A network of independent sensors that work together to reconstruct a sports game (e.g., baseball).*

System Overview

Tracking units are placed on the ground plane of the field and zoomed cameras are motorized in horizontal direction to follow the players. We are using the NVIDIA Jetson as computing platform for real-time player detection directly on each unit. This minimizes the latency in the feedback loop of the camera and simplifies the infrastructure needed to operate the system, making it accessible at a lower price.

Tracking units are synchronized with error less than 100 µs for sensor fusion across different modalities and automatic reconstruction of high-level game events which is currently done by a human operator in alternative systems. For instance, the start of pitcher movement can be detected from pose estimation, but it is easier (and more accurate) to measure the time when the ball was hit by a batter from the loud "pop" sound.

The differences between movements of professional players are subtle and richer player

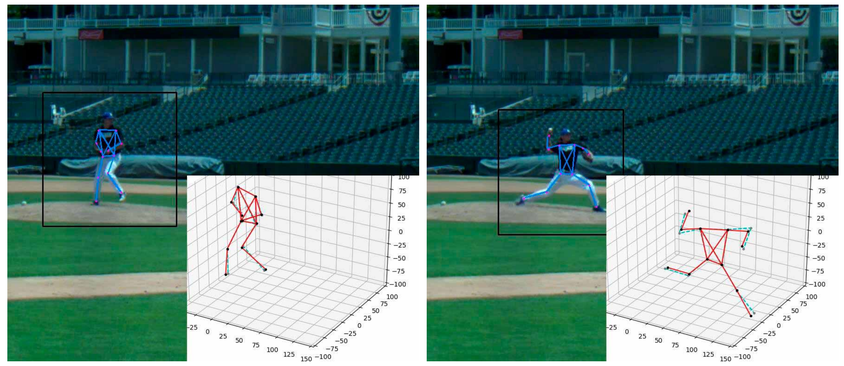

Figure 2: *Deep learning based algorithms detect players and their joints. 3D skeleton is then reconstructed from single view.*

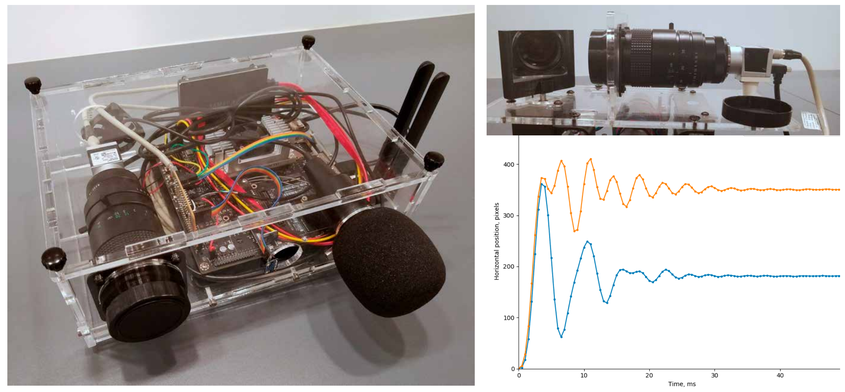

Figure 3: *An early sensor prototype based on NVIDIA Jetson. Motorized mirror enables fast changing of viewing direction.*

tracking can reveal details of player behavior and game patterns that will change the way coaches manage players and plan strategy.

Future Directions

One of the main challenges is to understand when and how (note that we intentionally omit why) the object detection and pose estimation algorithms fail. Output of these algorithms is used to guide data acquisition and processing, so they have to be fast and reliable. A higher speed motorized camera could also provide the ball trajectory between passes.

Works Cited

1. Major League Baseball Advanced Media (MLBAM). Statcast, 2015. http://m.mlb.com/glossary/statcast.