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Smart Tennis Racquet

Machine Learning for Smart Tennis Sensors

Introduction

Tennis is a sport with a relatively high barrier to entry – it requires equipment, access to a court, and most importantly specialized coaching for teaching proper game mechanics. Coaching is extremely expensive and can be prevent many players from seriously pursuing the sport. Smart tennis sensors aim to level the playing field by giving players personalized feedback about their game. A smart tennis sensor is a device that is either built-in or attached to a tennis racquet, that tracks data about the player's game. This data can include but is not limited to swing speed, swing type (backhand, slice, forehand…etc.) and ball contact location. The primary way to collect this data would be in the form of an IMU to capture motion or a piezo-electric sensor to capture vibration data. After the data has been collected via sensors attached to the racquet, it can be transmitted either via Bluetooth or wi-fi to a user's phone where it's presented in an app. This makes it easy for the user to get a detailed summary of relevant statistics during their game, allowing them to make improvements to their technique or style of play as necessary. This technical review summarizes some commercially available devices and explains the machine learning algorithms that can be used to enable these devices.

Commercial Applications of Smart Tennis Sensors

With 87 million tennis players around the world, tennis is widely accepted as one of the most popular sports in the world [1]. Any product that can be marketed to such a large and actively growing player base has huge potential for commercial success. The ideal consumer for a sensor device would be an intermediate tennis player that would benefit from a more nuanced improvement to their style of play. Such a device would have to satisfy certain criteria, such as not interfering with the physical racquet, being able to attach to any racquet, being accurate, lightweight, relatively cheap, and possessing a battery long enough to last an entire session of play. Many products have been launched by different companies but none satisfy all these criteria and have not been met with much success. In the middle of the bracket is the Koospur by Coollang, a Chinese hardware and IoT company that produces smart sport sensors. The Koospur costs $55 and attaches to the bottom of any racquet and connects to smartphones via Bluetooth 4.0. It claims to accurately collect metrics such as swing speed, strength and angle, and has a 6-hour battery life. Upon closer inspection we see that not only is it missing key metrics such as swing type and contact location, but it's not even accurate with the data it does collect. 52% of the Amazon user reviews are 1-star, and users complained that it failed to log the vast majority of their swings.

Another device, this time at the higher end of the spectrum, is the Zepp Tennis Analyzer. The Zepp device was designed to track all the previously mentioned stats and even some more stats such as ball spin and sweet spot detection. It offers similar battery life to the Koospur (~5.5 hours) [2] but comes in at a price point of $220. Common customer complaints include the sensor flying off the racquet, and once again, the device failing to log most user strokes.

Sony also attempted to break into this market with it's own smart sensor. Sony's device had the most features, as well as the easiest to use IOS and Android apps, however it was plagued by poor sensor quality, and a terribly low battery life of two to three hours. The product has since been discontinued, however it still serves to demonstrate the importance of a device meeting all the key requirements – data quality, battery life, ease of use, price point and overall product quality.

Using Machine Learning for Smart Tennis Sensors

To implement algorithms to accurately detect common tennis metrics, two types of machine learning algorithms can be used – classification models and regression models. To classify shot type, a deep neural network (DNN) can be utilized. The input to this network would be sensor data from an IMU and the output would be one of four to five different shot types. DNN's have been proven to effectively classify tennis shot types when using data from an IMU attached to the player's wrist [3]. This same methodology can be easily extrapolated for use in device that attaches to the racquet. There are different kinds of DNN's that can be leveraged for continuous motion detection – including convolutional based neural networks [4], long-short-term memory models (LSTMs) [5], and residual networks. To estimate swing and serve speed, a regression model can be used based on the data from the IMU [6]. Regardless of model type, an effective model must be robust to different player types, must be able to clearly detect when the racquet is being swung vs. when the player is idle, and have low latency in order to enable real-time implementation.

Implementation

To successfully deploy this product to satisfy all the constraints we must consider both software and hardware challenges. First a location must be determined for where the physical sensor will be placed. Options include under the handle, on the dampener, inside the handle, or even a wearable band on the wrist of the athlete [7]. After a location has been determined, we have to collect real-world data with the sensor in this location. Ideally this data will be collected on a variety of different users and racquets to be more robust. Next, a model must be designed to accurately measure all the relevant metrics. Not only does this model have to be accurate, but it has to be small enough to fit on a microcontroller. This will most likely be done with the use of TensorFlow Lite – an optimized version of TensorFlow meant specifically for deploying to microcontrollers. We must then choose a target hardware based on the memory constraints of our model, and the battery life we hope to obtain. A communication protocol must also be selected for data transfer between the device and a smartphone. Finally, a hardware enclosure and battery management system must be designed. An effective tennis sensor must have many working parts to be successful, but if such a device can be engineered it will serve a clear need in the market.

Sources

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