SWING TECH

Project Documentation

Cindy Xuan, Jason Bian

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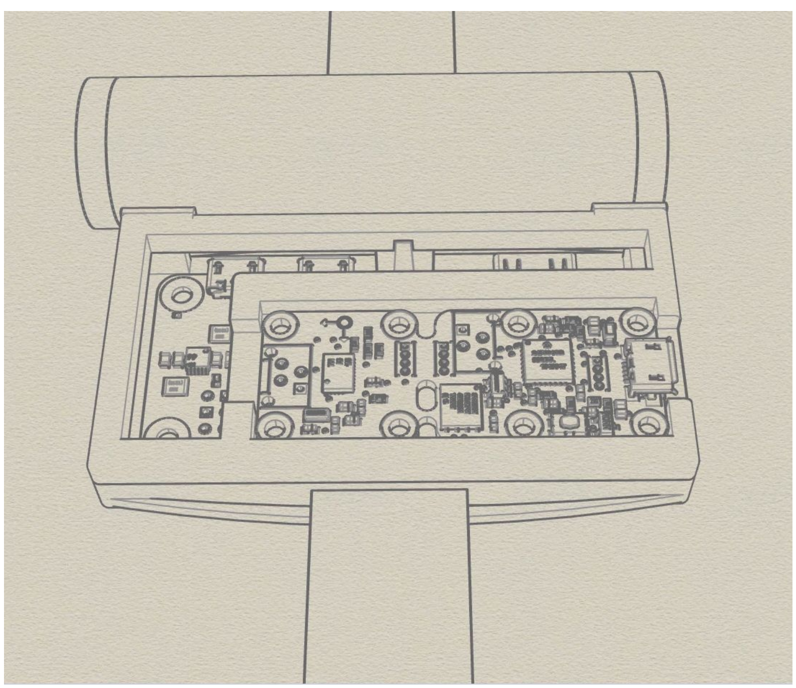

I. OVERVIEW

Swing Tech is a smart sensor project that analyzes sensor data from a wrist wearable to helps users improve their swing movements in racquet sports such as tennis, pickleball and squash. With the combined knowledge from a group of Michigan alumni and current graduate students, we aim to deliver value using existing and collected sensor data sets through machine learning. The final product will be a wrist wearable with high precision acceleration, gyroscope, and magnetometer sensors. Accompanying the wearable is proprietary software that transforms the movements in real time to provide performance analytics. The software is supported by swing classification algorithms developed in-house and a suite of 3d spatial visualization tools.

II. SYSTEM STRUCTURE

The high level structure of our product is shown below in Figure 1. The product uses a Yoctopuce 3d v2 sensor to record auto calibrated tilt, compass, and acceleration. The recorded values are then calibrated to the orientation of the court and processed using a raspberry pi w. After processing, the data is transmitted to a desktop app and analyzed through proprietary machine learning algorithms to provide post game analytics to the player.

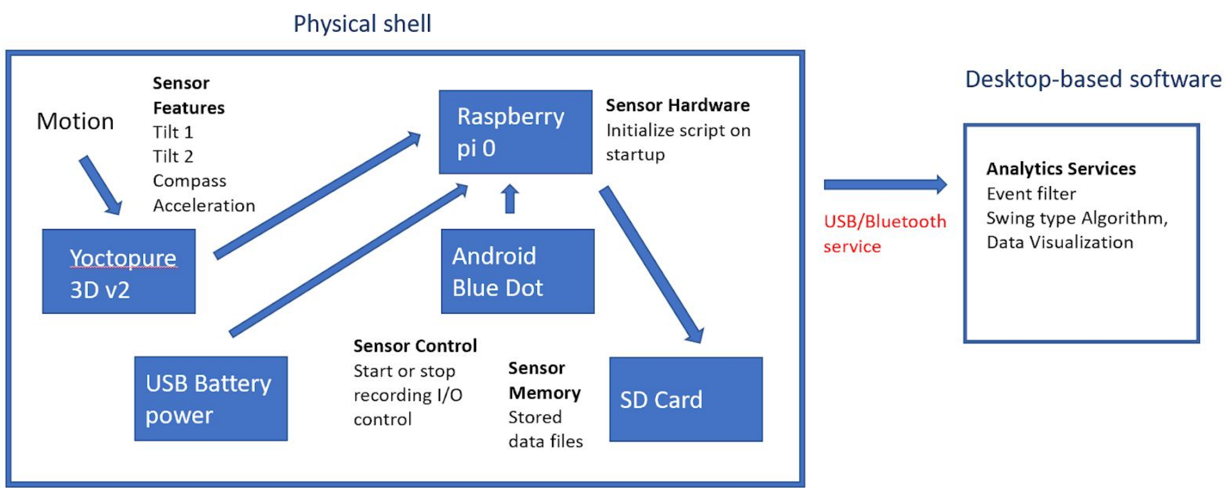

Figure 1: High level Diagram

Figure 2 shows our mockup app. The app is currently in development for desktop, but will be available on mobile in the future. The app allows the user to see a summary of all their swings. Users can also analyze individual swings over time and feedback is provided on swing quality through a comparison to professional swings.

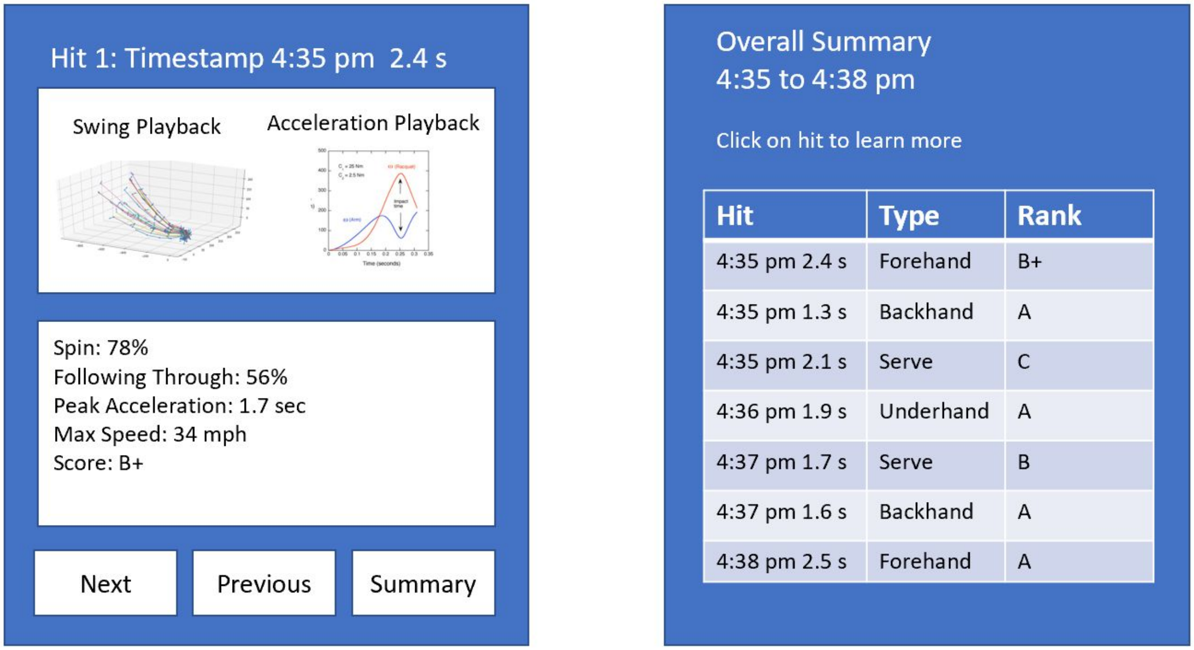

Figure 2: App Service Mockapp

III. HARDWARE AND DESIGN CHALLENGES

The hardware for each wearable is composed of one raspberry pi 0 w, one yoctopuce sensor, one 3d printing enclosure, one light-weight battery bank, adjustable straps, and soldered short cables to connect the raspberry, sensor and battery. We aim to reduce the total weight to 1 kg and the size (without strap) to 7.5 cm (L) * 6.3 cm (W) * 1.5 cm (H) for the final prototype, mainly by reducing the weight and size of the battery bank. The target size is based on the fact that the average wrist circumference can vary from 13 cm to 25 cm[1] (from smallest female wrist to extra large male wrist).

The first iteration is shown below in Figure 3. It is mainly for testing purposes and so the bottom enclosure for raspberry and the top enclosure for sensor are mostly open. Space is left for attaching and detaching cables easily. It can be worn either by straps or in a sports sleeve pocket. Our first data collecting session was achieved by using the two first iteration prototypes.

[1] https://wbracelet.com/average-wrist-size-men-women-ultimate-bracelet-wrist-size-guide/

Figure 3: First iteration prototype

Shown below in Figure 4 is the first iteration with a strap based connection. As seen it comfortably rests on the space above the user's wrists through two elastic straps.

Figure 4: First iteration worn with straps

Shown below in Figure 5 is the first iteration with a sleeve attachment. This places the sensor higher at the point of the users upper forearm. In initial testing, there was less breathability and adjustability in this design.

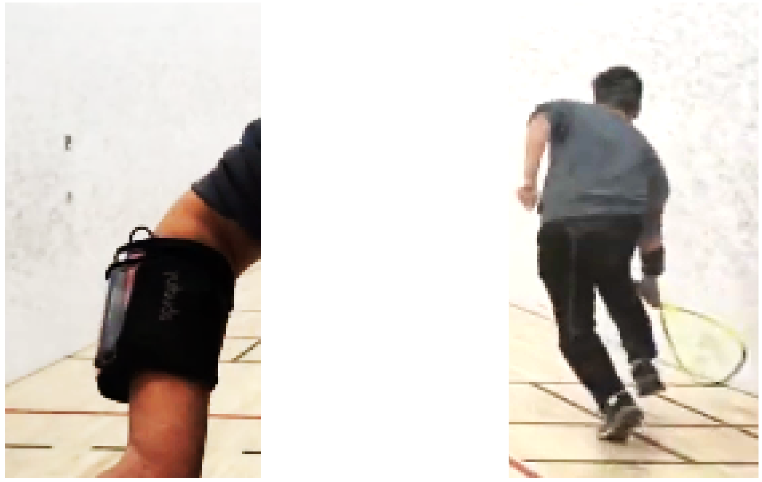

Figure 5: 1st iteration worn with a sleeve pocket

In the second iteration, snap fit was added to the design. However, snap fit were not printed accurately as PLA is not a very rigid plastic material. We will continue testing with stronger 3D printing plastic, such as ABS and Nylon infused PLA. However, these materials are much more expensive. Therefore, we will continue exploring other options, including laser cutting seperate pieces from acrylic sheet and then combining them into an enclosed box with slots for parts and cables. No matter which design we finally adopt and develop on, we want users to be able to see the LED lights on both raspberry and sensor. At the same time, the enclosure especially the electronic parts should be covered and cannot be accessed directly. This will avoid improper operations and sweat falling into the device to prevent unsafe situations. Shown below in Figure 6 is the second iteration design.

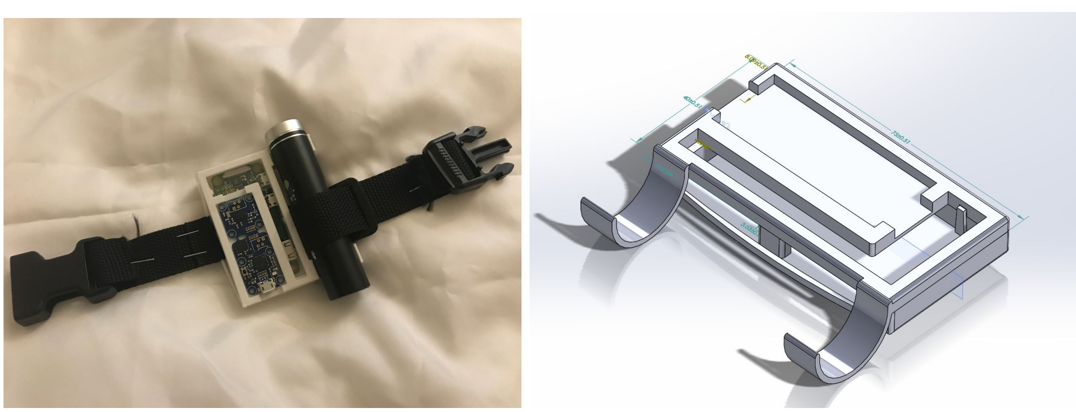

Figure 6: 2nd iteration and CAD model

The parameters for the future iterations will be judged on the following criteria:

Parameters	L*W*H (cm) (without strap)	Weight (g)	Battery Duration (hr)	Cost ($)	Total
Weighting	4	3	1	2	
Value	?	?	?	?	= ?

Future iterations will also be based on test users' suggestions and the dimensions of the procured materials/parts. Since the device is only for stroke events, it will not be waterproof.

IV. PROBABILITY BASED CLASSIFIER

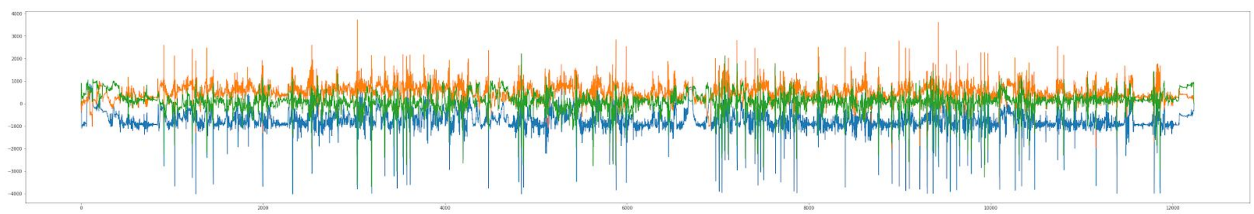

Figure 7: Acceleration Plot of Recorded Swing Events

We have run several trials to collect sensor data from multiple players and recorded videos to keep track of different swing types, whether the swing is a serve or return, and whether the player hits or misses the ball. By matching the sensor data with the events identified in videos, we are able to label all swing events and train our machine learning models.

We currently have 3 layers of classifiers. The first layer is simply finding acceleration larger than 2g and with noticeable change of wrist orientation. The orientation is calculated from the gyroscope through the following matrix multiplication:

$$R = R_z(\alpha)\, R_y(\beta)\, R_x(\gamma)$$

Each matrix is defined as follows:

$$R_x(\theta) = \begin{bmatrix} 1 & 0 & 0 \\ 0 & \cos\theta & -\sin\theta \\ 0 & \sin\theta & \cos\theta \end{bmatrix}$$

$$R_y(\theta) = \begin{bmatrix} \cos\theta & 0 & \sin\theta \\ 0 & 1 & 0 \\ -\sin\theta & 0 & \cos\theta \end{bmatrix}$$

$$R_z(\theta) = \begin{bmatrix} \cos\theta & -\sin\theta & 0 \\ \sin\theta & \cos\theta & 0 \\ 0 & 0 & 1 \end{bmatrix}$$

According to the reference papers and our own dataset, a ball contact will always have an acceleration magnitude of at least 2g in force (and can be as high as 5g for fast/heavy hits), so this is a suitable threshold for detecting candidate strokes.

The second layer is to categorize serve/return and type of swing (underhand, overhand, forehand and backhand). Currently we are still tuning and comparing different classifiers, but we believe that Support Vector Machine or Random Forest Classifier will give us relatively higher accuracy of prediction as they perform better than other classifiers (logistic regression, KNN, CART, GBM) in both serve/return classification and type classification. A successful second layer will give player effective summary statistics about a match by simply showing them the number of serves and returns, and the percentage of different types of swings. With these numbers in mind, they can choose to practice one specific swing type more.

The third layer is to rate the quality of each swing. It is suggested that good swing happen "only if you relax your arms enough to allow the swing and that you swing more sideways than backward.[2]" Also, forehand is usually the most explosive swing type and so players can improve on forehand first, then move on to other swing types. Therefore, by inviting professional players to record their wrist movements and reconstructing their swing curves, it is possible to find universal traits in good swings. In addition, different pro players have different habits. For example, Roger Federer's forehand swings have been analyzed frequently but these swings might not be copied easily as he does not use much side swing in most cases.

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[2] https://www.optimumtennis.net/tennis-forehand-swing.htm

Figure 8. Comparison of Sideways Swing from Two Players

Instead of directly using acceleration and orientation during swings as predictors, we need to carefully study the data and find the most representative traits. We have been using Generalized Procrustes Analysis to align the same type of swings into a single hyperplane and extracting features from the aligned data. Our ultimate goal is to develop algorithms so that by comparing the current player's swing curve to the average from pro players' curves, he/she can get feedback on how to improve the swing. "Practice makes perfect" will then become "guided practice makes even more perfect".

We hope that by interviewing more players and collecting more data, we will keep improving the accuracy and robustness of all three layers.

V. PUBLICITY AND ADVERTISING

According to the current progress, we plan to launch the kickstarter at the end of April. To further investigate the potential market and attract potential customers, we will establish our website, Facebook page and Instagram platform no later than the end of March. Meanwhile, we will outreach different types of key opinion leaders, including alumni, youtubers, and tech and sports enthusiasts. By tracking the number of followers to our platforms and making adjustments for post contents accordingly, we aim to reach at least 1000 followers combined before starting the kickstarter.

VI. CURRENT FUNDING SOURCES

We hope to launch our initial product through kickstarter with a $25,000 target. Depending on the success of our campaign, we might scale up for increased production using venture capital sources. We are also seeking industry sponsorship to fund our product.