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Design and Implementation of Wearable Devices to Enhance Aquatics Physical Education

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The digital revolution has enhanced traditional in-class learning through countless hardware and software solutions that allow teachers and students to collaborate more effectively. However, physical education is still taught in the same way as hundreds of years ago, only using “small data” collected by coaches and teachers without technological assistance. This paper examines current solutions to aquatics physical education, proposes a unique wearable device for swimmers, and outlines the design process behind the creation of this device, as well as future steps and intended implementation of this product. The device presented in this paper is capable of gathering and processing biometric and motion data and generating recommendations that can benefit swim training at all competency levels. It combines the benefits of integrated hardware and management software solutions and is cost competitive against similar commercial products

Keywords: aquatics physical education ; machine learning ; artificial intelligence ; big data ; motion analysis; educational equality

1 Introduction

Aquatics training is a vital part of primary education, teaching children about maintaining physical fitness and safety in and around the water. Lack of proper water safety instruction can lead to injury and drowning. In fact, drowning is currently the “second leading cause of childhood unintentional death” (CDC 2012). The Canadian Red Cross learn-to-swim program is offered to 1.2 million children. The USA Swimming Foundation offers swimming classes at 800 nationwide centers, educating over 4 million students (American Red Cross, 2009). However, in less economically developed countries, lack of proper swim training is concerning (Brenner, 2009).

In addition to the safety benefits of learning to swim, more than 330,000 United States students pursue the sport competitively, racing for over 2000 clubs (USA Swimming, 2016). Swimmer enrolment in the United States has increased drastically since 2007, making aquatics education even more relevant in this decade.

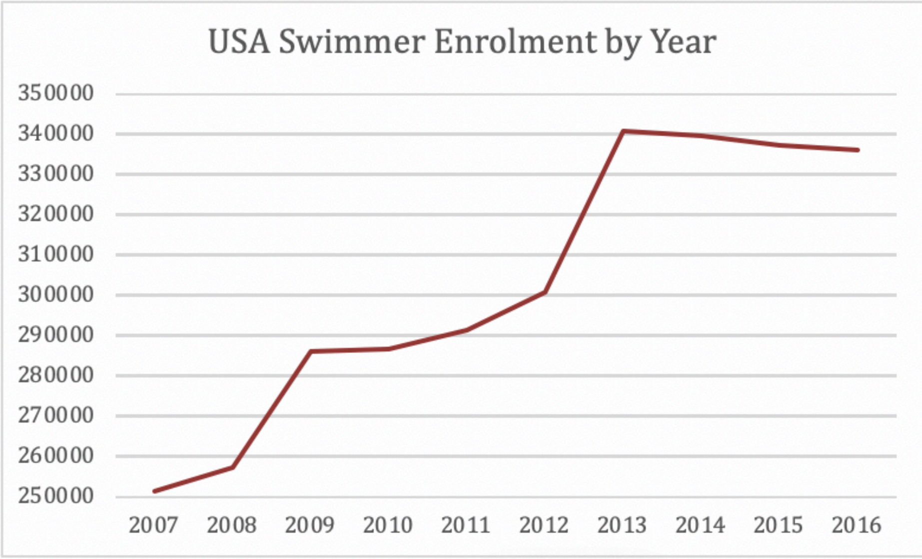


Figure 1: Competitive swimmer enrolment from 2007-2016. Source: adapted from USA Swimming 2016

However, traditional aquatics instruction is limited to "small data", the information instructors can collect by using their own senses. This primarily consists of visual information that the instructor uses to communicate areas for improvement to their swimmers. However, this method has two primary limitations: it requires focused attention on a single student, and it is difficult to make wider conclusions about students' improvements during a course. First, "small data" collection is highly inefficient. Most water safety classes have an average of five students per instructor, while competitive club training sessions might have a student to coach ratio of as high as 30. In such a setting, it becomes largely impossible for an instructor to give quality attention to each individual and make valuable comments to students. Second, since there is no way of synthesizing information over the course of a few lessons, it is difficult to gauge student progress and make adjustments accordingly. Most water safety learn-to-swim courses last for a duration of six to seven classes. Over this short period, instructors must rely solely on intuition and experience to understand how students are progressing through the course and whether adjustments are necessary. In club swimming, a competitive season can last up to three months, and in such an environment, swimmer-specific alterations are also nearly impossible.

Figure 2: Left: In most club settings in developed nations like the United States, it is impossible for a coach to give attention to all swimmers because there are too many swimmers in the pool at any given time. Right: Swimmers in poorer areas lack specialized coaches who are trained in proper technique and safety. There is a problem that needs to be

addressed in both developing and developed countries. Source: Poireier-Leroy and Farah Abdi Warsameh

2 Research background and competitive product analysis

Wearable devices are any technological device that "can be worn by individuals" and include the "ability to track information related to the individual wearer" (Sandall, 2016). These devices are often used to track the motions of the user and generate real-time feedback. Since 2014, the wearable technology industry has skyrocketed, with newer companies such as Fitbit creating fitness trackers that monitor the users step count, walking distance, and heart rate (Sandall, 2016). More recently, established high-tech companies such as Apple, Samsung, Google, and Huawei have developed smart-wearables that are more powerful with features such as integrated GPS and high-speed cellular connectivity. These devices are beneficial as fitness trackers that encourage users to be more active in their daily lives. They have a few primary purposes: 1) set exercise goals, 2) monitor user's activity, 3) share data with other users.

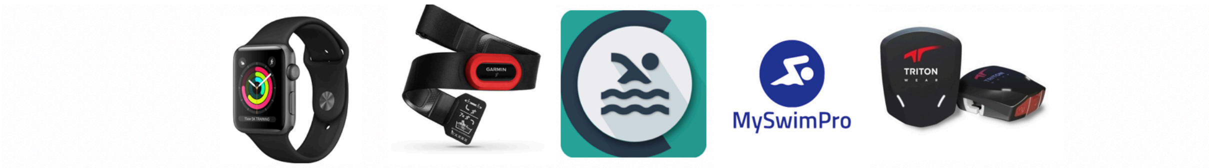
Some start-up companies are creating advanced products driven by artificial intelligence that use multiple sensors that can "classify which exercise the user is doing" and "correct the user's exercise pattern", two functions conventional fitness trackers cannot perform (Zhang, 2013). These devices are similar to the product functions this paper is outlining. Using accelerometer and gyroscopic data, the Microleap2 can detect common issues in running form that can cause injury or inflammation. It then notifies the user in real-time to correct their form. Currently, these devices are limited to running, basketball, golf, and baseball (Mardonova and Choi, 2018).

Recently, companies have incorporated aquatics features into their fitness trackers. However, all of the existing products have fundamental limitations.

For example, the Apple Watch contains an electrocardiogram (ECG) heart rate sensor that is accurate underwater, along with computer algorithms that can detect the type of stroke, and distance swam. Similar to their running functions, these devices fail to provide more specific swimming metrics or provide useful insights on form improvement.

Some professional clubs have adopted specialized hardware and software solutions to improve training efficiency. Team organization apps such as *CommitSwimming* can track training sets and athlete progression, but they require manual input of timing and set information. Biometric sensors such as heart rate straps, lactic acid monitors, and muscle oxygen monitors can gauge training intensity but are often bulky and impede the movement of athletes. "Integrated" software and hardware solutions are the current pinnacle of wearable technology in aquatics physical education, reducing the amount of data coaches need to collect. *MySwimPro* and *TritonWear* are two examples of this technology. *MySwimPro* is a software solution that can be paired with smartwatches from Apple, Garmin, Fitbit, and Google. It provides a personalized training schedule based on a user's ability and goals, using sensors in the smartwatch to generate data on stroke rate, stroke efficiency, and heart rate. *MySwimPro* is limited to personal use as it does not have team management features for coaches of large club or professional teams. *TritonWear* is a powerful ecosystem that monitors the swimming of up to 50 swimmers on a team. It generates profiles for each swimmer during a training session, giving coaches access to motion data such as acceleration and swimming specific metrics such as breath count and stroke efficiency. Each swimmer is equipped with a small "Triton Unit" containing basic motion sensors. The information collected by the unit is then transferred to a smart device via a "Triton Connect" hub for the coach to review.

While some professional teams do invest in products such as *TritonWear*, the cost of hardware solutions is prohibitive for non-professional club teams and learn-to-swim programs. For example, each “Triton Unit” and “Triton Connect” Hub costs $299 USD at the time of publication. Including the annual subscription cost of the program, the total initial investment for a 20-student swim program can be as high as $6500 USD. Even less powerful solutions, such as specialized sensors, e.g. heart rate, accelerometer, gyroscope, can cost hundreds of dollars and require a steep learning curve for operators and instructors.



Product	Apple Watch	Specialized Sensors	CommitSwimming	MySwimPro	TritonWear	Our Device
Type	Hardware	Hardware	Software	Software	Integrated	Integrated
Stroke Detection	Accelerometer	N/A	N/A	N/A	Accelorometer	Accelerometer referenced with IR sensors
Stroke Improvement	N/A	N/A	N/A	N/A	N/A	Under Development
Biometric Data	Heart Rate	One-type	N/A	N/A	N/A	Heart rate
Training program	Self Generated	N/A	Manual Input	Manual Input	Self Generated	Self Generated with motion and biometric data attached to each training set
Team management	N/A	N/A	Available	Available	Available	Available
Data output	6 axis accelerometer - gyroscope and Heart rate	One-type	N/A	N/A	6 axis accelerometer and gyroscope	9 Axis accelerometer - gyrosocope - compass with two IR bands and Heart Rate
Cost per Unit	400 USD (For 40mm model)	100 USD	N/A Subscription Service	N/A Subscription Service	299 USD	150 USD (Aim to reduce to 90 USD when manufacturing in bulk)
Cost for 20 person team	**8000 USD**	2000 USD	1200 USD	120 USD	**6500 USD**	**~3000 USD**

Figure 3: Function comparison chart. Source: Author

3 Design process and prototypes

3.1 Field Research

This project began in May 2018. A questionnaire was drafted and sent to swim coaches and swimmers. No coaches that were interviewed have used wearable devices for their swimmers, but a majority believed that a well-developed device can benefit their training. These coaches were then surveyed to determine the necessary features such a device should include.

Interviews were conducted with six athletes and three coaches of different calibres to determine the use case and proper implementation of features.

The consensus among elite swimmers and coaches including the Hong Kong national team head coach, former Chinese National Team directing coach of technique, and a Chinese national champion, was that a competitive, integrated solution for aquatics physical education in learn-to-swim programs, in a club setting, and at the professional level must include the following features:

1. A Comprehensive array of sensors that can measure motion and biometric data
2. Algorithms capable of analysing motion and stroke

3. Ability to synthesize and combine information that is easily accessible for coaches
4. An Easy-to-operate user interface for coaches and swimmers
5. Non-obtrusive for swimmers
6. Accessible to a broader audience with a non-prohibitive price

Table 1 Coach and Swimmer Questionnaire

	Coaches	Swimmers
Background	a. What information about the athlete during training would you like to know about that you currently cannot collect? (heartrate, stroke rate, breaths/length, turn speed, reaction time, blood oxygen) b. What sensors have you currently tried to collect data on the athlete during training? c. To what extent do those sensors affect your training in a positive or negative way? d. When do they become obtrusive, and how? e. What information would you like the athlete to know while training (HUD, recommended stroke rate) that will benefit their training? f. What equipment have you used to ensure this? g. To what extend do they affect the training in a positive/negative way? h. Have you tried using an all-in-one solutions for the above? i. If so, how well did they work? j. If not, would you consider beginning to use one?	a. How are your training sessions organized (e.g. private lessons, group setting, club or team setting)? b. How much attention does your coach give you during each training session? c. Do you wish your coach gave you more attention, if so in what aspects? d. Have you ever tried an sensors, under water earphones, or other accessories to complement your training? e. How well have these worked? Were they comfortable?
After Use	a. How has your training changed after using this device? b. What benefits does it bring you that are most significant and/or important? c. Would you consider using this system long term?	a. Did this device negatively affect your stroke and training? Was it comfortable to wear? Did it restrict your motion? b. Was there a change to how much individual attention your coach gave you after you started using this system and has his/her coaching style changed? c. Would you consider using this device long term? d. What changes would you make to this device? What else do you wish it did?

3.2 Device Objectives

A smart, wearable device must be comfortable for the wearer and placed in an optimal location for data collection. In order to maintain balance, keep a hydrodynamic form, and collect data on head-position and the position of the user's arms, the hardware should be placed in a compact wedge on the wearer's head, parallel to the elastic goggle straps.

A primary concern with smartwatches, sensor bands, and other traditional data collection hardware is that they affect the swimmer's natural movement through the water. Since smartwatches are only worn on one hand, they slightly imbalance the swimmer, affecting their stroke. Uncomfortable heart rate bands can restrict an athlete's breathing and movement. These concerns also apply to less experienced swimmers who are still perfecting their stroke. A smart wearable device should be placed on the axis that traverses the athlete's center of buoyancy. It should be slim, limiting the resistance it enacts on the swimmer's movement. It should be in a comfortable, easily accessible location.

To accurately measure motion and biometric data, sensors must be strategically placed. A swimmer's motion can be measured by several important variables: the movement of the athlete's head, the arm position relative to the axis of rotation, and the swimmer's acceleration, velocity, and rotation. The sensors must also be able to detect a swimmer's heartbeat to collect data on training intensity.

3.3 Physical Design

The athlete's head is an optimal location for sensors. In each competitive swimming stroke, both arms pass over the ears in a single stroke cycle. In the short axis strokes (butterfly and breaststroke), both arms pass this point simultaneously, while in the long axis strokes (backstroke and front crawl), the arms alternate. By placing sensors on the sides of the athlete's head, distance data on both arms can be collected. Second, while swimming, an athlete's head remains relatively stationary; the head only moves when the swimmer breathes or turns at the end of the pool. Placing motion sensors on the head streamlines data output and reduces the need for advanced data processing to eliminate noise generated when sensors are placed on a swimmer's hand or chest. In both of these locations, subtle movements such as breathing or rotations of the hands can cause data to be unreliable. Third, heart rate sensors must be placed near large arteries where heartbeat is easier to detect. Since both movement and distance sensors are on the swimmer's head, a single unit is sufficient to collect all necessary data.

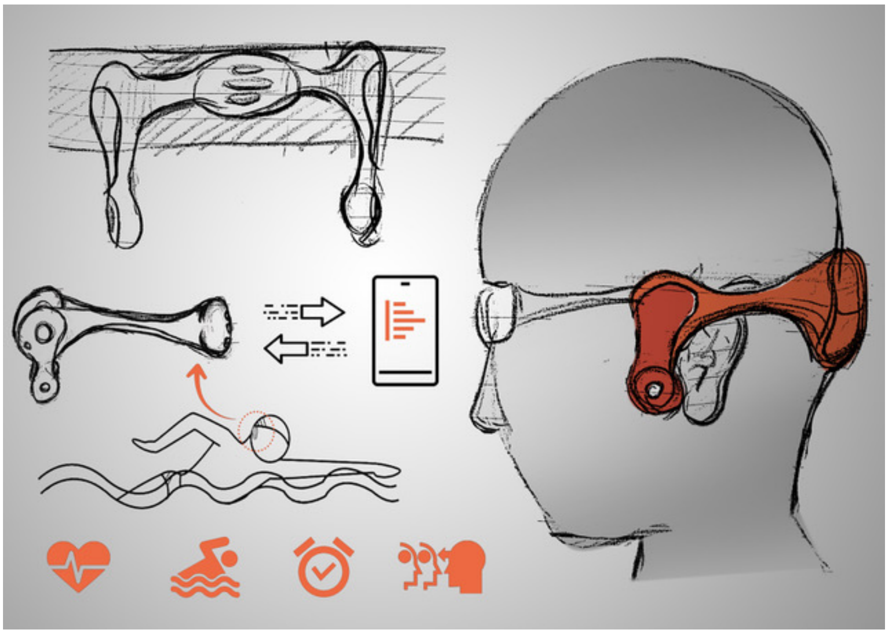


Figure 4: Initial product design concept drawings reveal a form factor that can accurately determine biometric data, swim stroke and other metrics, timing, and allow coaches to communicate with swimmers in real time. Source: Author

Sensors are laid out in a horseshoe on half of the back of the user's head as shown in Figure 5. Motion sensors are placed near the base of the swimmer's skull while two distance sensors and the heart rate sensor are placed on the sides of the athlete's head.

1 – Battery
2 – Power Delivery
3 – Bluetooth Antenna
4 – IMU
5 – SD Card Reader
6 – Curie SOC
7 – Power input
8 – Left Infrared
9 – Right Infrared
10 – Heart Rate Sensor

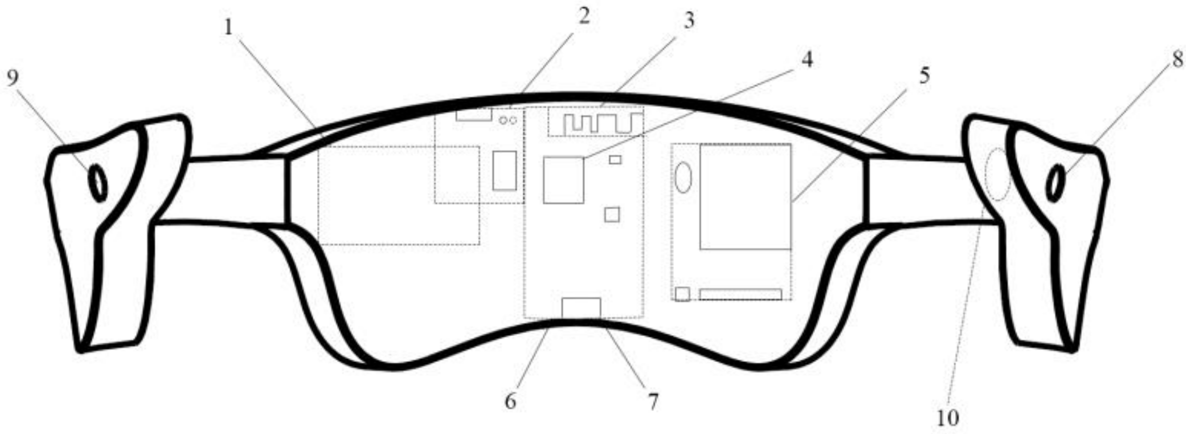


Figure 5,6: Technical drawing and render of the product casing. Source: Author

3.4 Hardware Implementation

To be competitive with existing solutions, effective hardware must be highly accurate, reliable, and low-cost. The initial model implements a modular system with good compatibility, using The Arduino ecosystem with Intel libraries for the first prototypes.

When measuring the effectiveness of training sessions, it is important to consider the following variables:

- Motion data including position, velocity, and acceleration on 3 axes
- Rotation (3 axes) and heading of the swimmer's head
- Arm position in relation to head
- Heart rate (measured from the head)

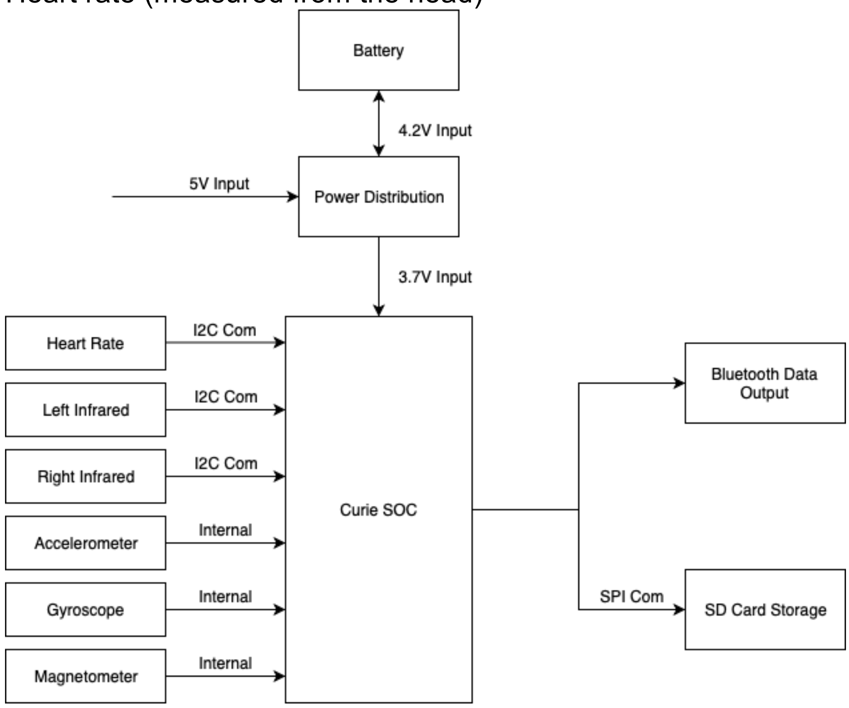


Figure 7: Hardware Configurations. Source: Author

First, an Intel Curie SOC was used for data processing and motion data collection. This board includes various functionalities such as a built-in digital compass, accelerometer, and gyroscope. Raw data from the digital compass can determine a swimmer's heading. The integral of accelerometer data fused with other metrics for orientation calculates a swimmer's position and velocity at any given time. All other sensors and equipment are connected through the Curie Nano chip, which is placed at the center of the device, sitting above the base of the swimmer's head. This location's symmetry also allows accurate headings to be calculated since the board stays parallel to the ground during exercise.

Second, a pair of infrared sensor modules were used to determine the location of the swimmer's arms. The sensors were symmetrically placed on the side of the athlete's head so that the infrared beams were perpendicular to the swimmer's motion.

Third, a single heart rate sensor was placed on the inside of the horseshoe-shaped exterior in order to be in contact with the swimmer's skin. This allows it to receive reasonably clean heart rate data from the large arteries near the temples. This prevents the noise that is generated from placing sensors on high-movement areas of the body such as the neck or the wrists.

Fourth, a single microSD (tf) card reader is used to write and store data. The current capacity of the drive is 16 gigabytes. The device outputs approximately 30 bytes of data every 20 milliseconds, and the sd card can store approximately 2 hours of data.

Finally, the device is powered by a single 1200 mah battery. The battery and protection boards are located adjacent to the Curie Nano for easier wiring and cable management.

All electrical components within the casing were applied with a waterproof resin. Special attention was given to the battery and protection board which were entirely sealed. The microSD card slot is also completely sealed as future data transfer will happen via Bluetooth or USB. Micro USB ports for charging and data transfer were replaced by magnetic induction contact points. Finally, the entire plastic outer casing is wrapped for insertion into the casing.

4 Data Processing

4.1 Models of Swim Ability

The main goal for swim training is to reduce the time needed to complete a specific event through improved reaction time, start time, velocity, and turn time. Therefore, the time to complete an event can be modelled by the following:

$$t_{total} = t_{reaction} + \frac{d}{v} + t_{turn}$$

Where the total time taken is the sum of the reaction time, turn time, and the swim time. The swim time can be calculated by calculating the quotient of total distance and swim velocity. The swim velocity at any time t is equal to the integral of a function of acceleration as follows:

$$v = \int_0^n a(t)\ dt$$

However, in the real world, a Riemann sum of each outputted acceleration point will be used as no smooth curve can be easily approximated. A left bound Riemann sum will be calculated using the following formula:

$$v = t_{interval}(\sum_{t=0}^{n-1} a(t))$$

and

$$d = t_{interval}\left(\sum_{t=0}^{n-1} v(t)\right)$$

With an identified initial position and orientation.

Swim velocity is related to the product of stroke rate and stroke efficiency in the following relationship:

$$v = f * \eta$$

Stroke rate is calculated using the number of strokes per second; efficiency is calculated using distance per stroke. Stroke efficiency can be maximized through technical improvements to reduce drag and improved strength to power through each stroke. Velocity in all four competitive strokes is maximized with a unique combination of a high stroke rate and consistent but lower stroke efficiency (Craig and Pendergast, 1979).

The final data output of the device must allow swimmers to optimize this model and improve their time in the target event.

4.2 Software Implementation

The software's primary purpose is processing raw data to generate useable information that can be easily viewed by coaches and swimmers. The data processing is done in two parts. First, raw motion and biometric data is read from the SD card and processed to give swimming information. Next, using the outputs from the previous step, algorithms identify areas of improvement for coaches and swimmers to focus on.

The first step of data processing is done with a lightweight Python script. Using functional programming, raw data is converted to data that reflects efficiency of training by the subsequent steps: first, reading the CSV file and creating data structures that sort information by lap; second, processing each swim variable per lap and saving it to a separate list; and third, combining all data and writing to a separate file. The data structures are displayed in Figure 9.

Time

$$\begin{pmatrix} t_1 & r_1 \\ \vdots & \vdots \\ t_n & r_n \end{pmatrix}$$

Accelerometer

$$\begin{pmatrix} t_1 & Ax_1 & Ay_1 & Az_1 \\ \vdots & \vdots & \vdots & \vdots \\ t_n & Ax_n & Ay_n & Az_n \end{pmatrix}$$

Gyroscope

$$\begin{pmatrix} t_1 & Gx_1 & Gy_1 & Gz_1 \\ \vdots & \vdots & \vdots & \vdots \\ t_n & Gx_n & Gy_n & Gz_n \end{pmatrix}$$

Infrared

$$\begin{pmatrix} t_1 & l_1 & r_1 \\ \vdots & \vdots & \vdots \\ t_n & l_n & r_n \end{pmatrix}$$

Heading

$$\begin{pmatrix} t_1 & h_1 \\ \vdots & \vdots \\ t_n & h_n \end{pmatrix}$$

Figure 9: Sensor type data structures for head and relative arm positions

Thirteen data channels are outputted at a rate of approximately 10 hertz. Data is imported into the processing script as a csv file and conclusions are outputted as a csv file with all focused metrics for data visualization. This process can be done in real time via a low energy Bluetooth connection. The final output of the script separates each lap that a swimmer has swum, with swim-specific metrics including stroke rate, distance per stroke, average velocity and breath count, along with a classification label for the type of stroke swum. Please refer to the appendix for a more detailed description of the methodology.

4.3 Machine Learning Algorithm for Stroke Improvement

An optional advanced data processing package allows the device to generate conclusions on technique and possible areas of improvement by identifying common mechanical errors. By collecting data on athletes doing the correct and incorrect movements, an algorithm can be trained to identify incorrect technique and provide the necessary feedback to the swimmer. Currently, the following common errors are being trained; these mistakes can be identified with data that the sensors on the device output:

1. Front Crawl:
   a. Shoulder over-rotation: Occurs when the swimmer rotates his arms past his center of rotation, causing arms to reach in front of the opposite shoulder. This increases the risk of shoulder injury and causes additional drag.

   b. Head misalignment during breathing: Occurs when the swimmer shifts his head off the streamline position, causing body position in the water to suffer, increased frontal area and greater drag.
2. Backstroke:
   a. Incorrect head position: Occurs when the swimmer tilts his head forward too much during the backstroke, harming body position and causing the lower body to sink in the water, increasing drag.
   b. Incorrect arm position: Occurs when the swimmer's arms are too close or too far away from the ears when the arms are raised above the swimmer's head. Can cause shoulder strain and decreased stroke efficiency.
3. Breaststroke:
   a. Improper head movement during breathing: Occurs when an inexperienced swimmer throws his head up and down during the stroke, negatively impacting the body's streamline in the water and increasing drag.
   b. Weak streamline: Occurs when the swimmer's arms are not tightly tucked during the recovery portion of the stroke, causing increased frontal area and drag.
4. Butterfly:
   a. Late breaths: Occurs when the swimmer breaths at an incorrect time in the stroke.
5. All
   a. Late stroke or incorrect rhythm: Occurs when the swimmer pauses at incorrect positions during his stroke, decreasing stroke efficiency, and stroke rate, especially in butterfly.
   b. Mismatched kick and pull: Occurs when the kick is not done in conjunction with the pool so that the body is not able to return to a natural position in the water. This causes increased drag and lower speed in the water.

5 Applications

5.1 Application in Learn-to-Swim Programs

In many learn-to-swim programs, coaches may not have the proper training to use the processed data from the sensors. The device will be able to provide feedback on technique with very little human guidance. Incorrect posture or poor stroke mechanics while swimming can often lead to injuries. These are especially prominent in a club setting with inexperienced coaches who do not pay proper attention to correct technique.

Table 2 Common Swimming Injuries

Injury	Cause and Solutions
Neck and Shoulder Injuries: Inflammation, tendonitis and rotator cuff tears, shoulder impingement syndrome.	Extended periods of competitive swim training can wear out the rotator cuffs (Dischler, 2017). The primary causes of shoulder and neck injuries are poor breathing and shoulder rotation (UPMC Sports Medicine). The device will be able to detect the rotating motions of the head and match it with accelerometer data to determine if breathing is done at the appropriate time to prevent stress in the shoulders and neck. Second, over-rotation of the shoulders when the arms cross the center of rotation can cause inflammation or shoulder impingement syndrome in the long term.
Knee injuries: MCL tear, tendonitis, inflammation	Excessive breaststroke kick training puts extra pressure on the insides of the knees, leading to possible injury. If the device detects a large amount of breaststroke swam combined with sudden decreases in a swimmer's kick strength it can generate recommendations that allow a swimmer to recover

After analysing the data, the device can provide feedback that is displayed in the companion app to remind the swimmer. The app can then guide the swimmers to online resources on injury prevention and proper technique. In addition, the data from these swimmers can be sent to high-level coaches remotely, matched with video footage, allowing swimmers to be coached remotely by a specialist. This device will be a resource for students in rural or poorer areas who aim to swim competitively and promote equality in aquatics education.

5.2 Application in Competitive Programs

By using big data and machine learning, this product can improve the swimming capabilities of students at any level.

At the competitive level, the data collection device described has benefits for team management and individual feedback. First, all key information is saved to an easily accessible document. Coaches can keep track of all training plans that were written and whether deviations were made during the actual training session. Second, in many professional clubs, coaches will no longer have to spend so much their time measuring their swimmers' splits. An automated timing system will reduce their workload and allow coaches to concentrate on stroke and technique improvement instead. Finally, this data collection device can give coaches and swimmers access to swim metrics that are otherwise impossible to obtain, such as heart rate, stroke efficiency, and stroke rate. Data processing algorithms can then determine trends in these and other variables enabling targeted feedback for swimmers. For athletes, the device is non-obtrusive, allowing them to swim normally while learning from specific data about their performance.

This device can give athletes higher quality coaching by providing conclusions on stroke and technique. The stroke recognition function can also determine if strokes were done correctly. By matching sensor data of inexperienced swimmers with those of experienced ones the algorithm has learned, the device can notice errors and communicate them to swim instructors. For example, in a short axis stroke, if the program registers an extremely high count of non-zero outputs, it can conclude that the swimmer's stroke is asymmetrical and provide the necessary feedback. Similarly, the acceleration graphs of learn-to-swim students can be compared to those of professional athletes. Using this comparison as well as video analysis, areas of improvement can be identified.

Figure 10: On-land testing using first low-fidelity working prototype. Source: Author

6 Market Feedback Analysis

Between December 2018 and April 2019, two rounds of testing were conducted using this device with 6 swimmers and 3 club-level coach. Recommendations were taken into account for future development. Feedback after testing was as follows:

1. Comfort: Swimmers who used this device for training said it did not impact their training in a negative way and got used to the device on their heads quickly. Only one swimmer complained of too much clamping pressure on the sides of his head and downwards pressure on his ears. When worn correctly, additional drag was not noticeable even during high-intensity sets where the swimmer was swimming with great speed.
2. Effectiveness: Most coaches were impressed by the amount of data that this device could generate. However, they requested a more elegant method to visualize the data through an app instead of through a text output. This will be a primary area of improvement. One coach asked for audio feedback to be integrated either as a beeping sound for swimmers or voice feedback that is linked either to the program or to a microphone that the coaches can use.
3. Price: The current price is acceptable for most of the elite teams that were interviewed (details on price reduction are mentioned in the "Improvements" section).

7 Summary

7.1 Current Development

Currently, multiple low fidelity prototypes have been created for beta testing with a few athletes at an international high school in Shanghai, China. Hardware and firmware development is mostly finished with the software capable of outputting all eleven channels of data accurately. Stroke identification software and basic swim metric outputs are complete with software and the stroke improvement package under development.

The latest medium fidelity prototype improves upon the existing form factor, allowing for better usability. First, the total volume of the device was decreased. Second, components were shifted to reduce the clamping force on swimmers' and also remove obstructions present in previous models that prevented swimmers from achieving the best streamline position. Figure 11 shows a side-to-side comparison of the two models.

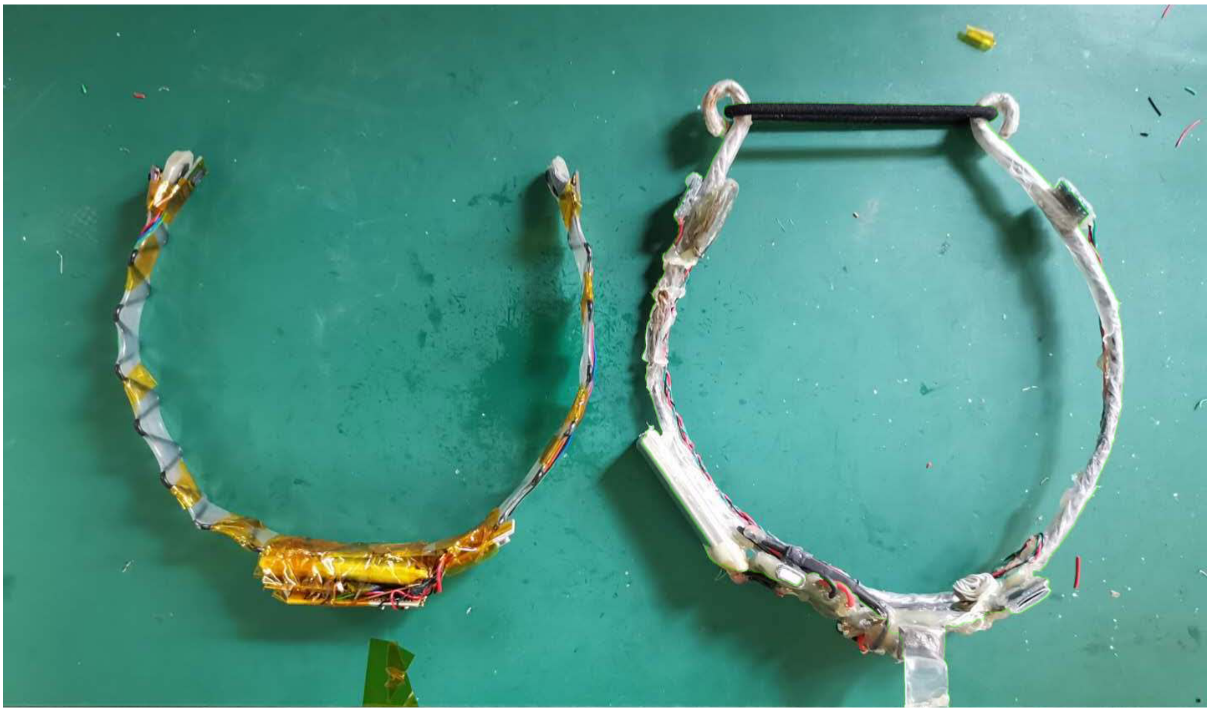


Figure 11: Medium fidelity prototype (left) and low fidelity prototype (right). Source: Author

7.2 Improvements

Future improvements for the device should focus on increased usability, functionality, and accessibility. Regarding hardware, next generation prototypes will use a more flexible material for additional comfort and more effective waterproofing. A replacement for the Curie platform will be used as it has been discontinued by Intel. Since the current firmware already outputs all necessary raw data, very little improvement is necessary. Only slight revisions may be required for compatibility with new hardware modules.

The second stage of data processing must be addressed: identifying areas of improvement for swimmers. A deep learning algorithm will be incorporated, combining swimming videos and motion data to give recommendations on stroke. This requires data collection from professional and amateur swimmers of all age levels. To improve usability, both recommendations and processed swimming metrics must be presented in a readable format through data visualization techniques. The current document output only consists of a table of values with category headers. It is difficult to gauge trends throughout a training session or season. Cumulative graphs and tables will be used to display data in a more user-friendly way.

Next, a mobile app and cloud ecosystem will be established. A mobile app will allow coaches to access data in real time via Bluetooth connection with the device. Coaches can use this information to give timely feedback to swimmers. Users can then opt to upload their training data to the cloud where it can be compared to datasets from high-level athletes. All data on the cloud can then be used to train and improve algorithms.

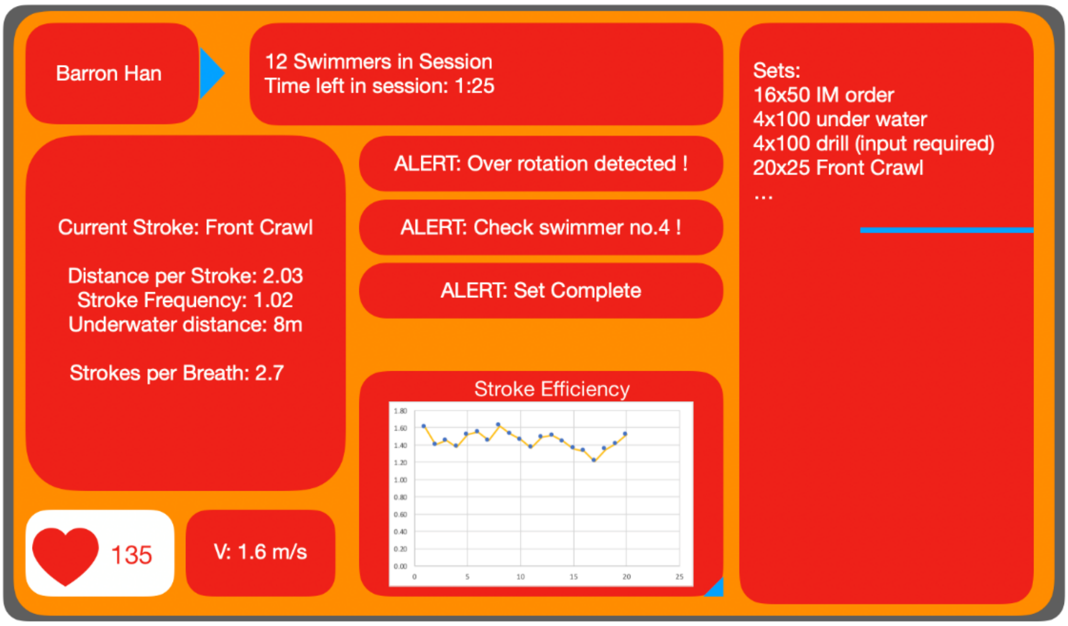


Figure 11: Sample App Interface. Source: Author.

Finally, the price of the product must be reduced to make it viable for learn-to-swim clubs and students in economically developing nations. A primary concern when designing this device is price. This device uses only off-the-shelf components making broken parts easily replaceable. Currently, the market price of a single prototype is around $150 USD, which is already considerably less than other high-tech aquatics education solutions valued at around $300 USD. While this is already appealing to many competitive institutions, the price can be further decreased to less than $100 USD per unit when a larger quantity of product casings are ordered at once.

The vision is to create a tool that can provide high-quality aquatics physical education for all students, from a learn-to-swim level to the professional level. This device will first be pushed to competitive swimmers and professional teams for development and feedback. Ultimately, it has the capacity of transforming physical education on a basic level, changing the vague, inaccurate "small data" ideology to incorporate the benefits of big data and machine learning for all swimmers.

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Appendix

Summary of Data Processing

Laps were sorted using the “heading” variable outputted by the electronic compass. The script uses a running sum on the change in heading of the swimmer to determine when a 180-degree turn is made. It then uses the “time” variable of these points as an index value to split the data into separate lists per lap. This allows future functions to reference specific intervals (laps), calculating the necessary swimming metrics for each lap. A simple filter removes slight changes in a swimmer’s head position while breathing to increase the accuracy of turn detection. The indexes outputted by this function can also be used to calculate lap count and distance in a given session.

The following functions were calculated on a lap to lap basis using the outputs from the first lap separation function: heart rate, stroke detection and count, stroke rate and efficiency, and breath count.

Heart rate is calculated using turning point detection. The raw data from the heart rate sensor is mapped on an interval from 0 to 1023. The data is first filtered for irregularities that could be registered as false maximums. Then, the algorithm compares adjacent points to locate turning points, counting the number of maximums within a single lap interval. Using the time stamps and the calculated number of turning points, the heart rate can be calculated.

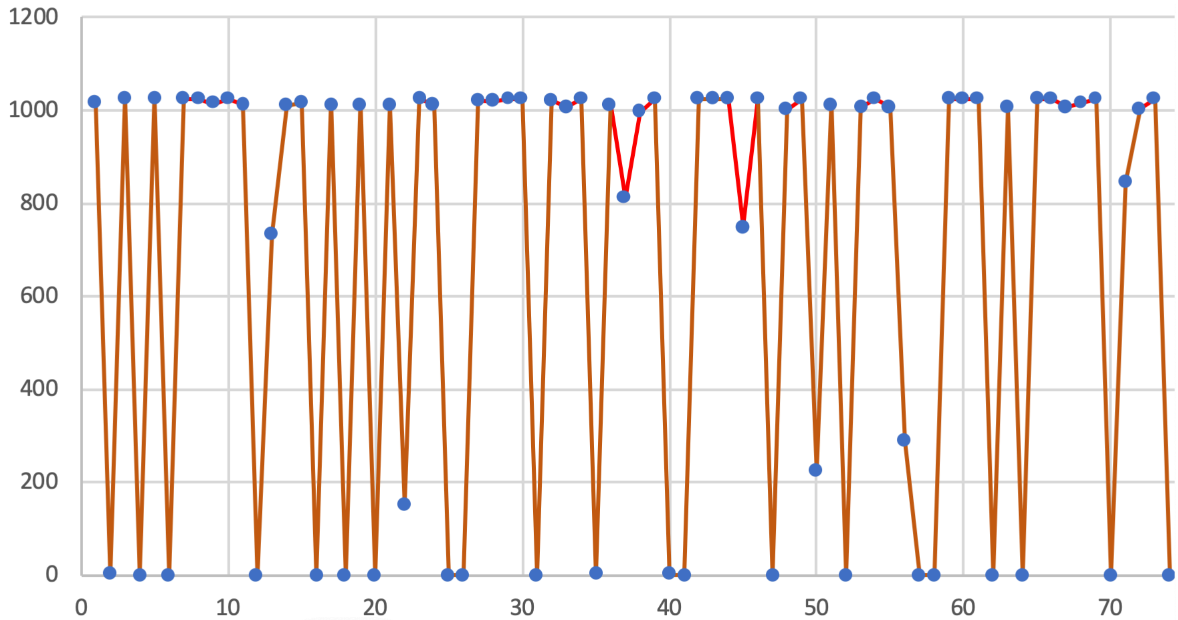

Figure 10: Sample Underwater Heartrate Data with false maximum detection (red segments were judged as inaccurate and eliminated from the total heart-beat count)

Stroke recognition is done in two parts. First, the algorithm detects whether the swimmer’s stroke is a “long-axis” or “short-axis” stroke. The long-axis strokes (front crawl and backstroke) involve alternating arm rotation while the short-axis strokes (breaststroke and butterfly) are symmetric. The data from the infrared sensors have a range of 0 to 4494 millimetres. For the purpose of stroke recognition, this data must be standardized for the algorithm to process it more accurately. The distance variable from the left and right sensors are combined and standardized through a comparison function. This function compares the distance between the left and right arm. If the difference is statistically significant, and not the result of a slight imbalance in a swimmer's stroke, the function outputs an integer of either "1" or "-1" depending on which value is larger. If the difference is not statistically significant, a "0" is outputted. Using this method, each raw data value is determined to be part of a short-axis stroke, where the output is "0", or a long-axis stroke, where the output is either "1" or "-1".

A separate filter determines sudden changes between short and long axis strokes that are most likely the result of data collection errors, concluding whether the stroke is short or long axis during a given target lap. Using this output, a separate algorithm distinguishes between the two strokes for each type. The distinction between backstroke and front crawl is straightforward. The acceleration value in the z-axis is retrieved to determine whether the gravitational acceleration is positive or negative. A positive gravitational acceleration indicates that the Curie Nano module is reversed and the swimmer is facing upwards. A negative gravitational acceleration indicates the opposite. Using this method, the orientation and thus the type of long-axis stroke can be determined. The two short-axis strokes are more similar so the distinction algorithm is more complex. There are two possible approaches. First, a guided algorithm can be used to determine the difference in the y-axis acceleration graphs of the two strokes. The acceleration graph for butterfly should have two maximums per stroke cycle that are created by the two kicks done per stroke. Breaststroke only has one maximum generated by a continuous pull-and-kick motion for each stroke cycle. Second, a machine learning algorithm can be used without human guidance to distinguish the difference using classification. However, the first approach is preferable since it does not require resource-intensive python machine learning libraries such as *sci-kit learn*. This will be beneficial for the final application which will be installed on mobile devices that must process data in real time at roughly 50 times a second.

Stroke detection is used to determine when a stroke cycle is completed—as the swimmer's arms return to the streamline position next to the head. Only the left infrared data output is used for this purpose. When the hand crosses the sensor, the data is at its minimum, usually at a distance between 0 and 20 millimetres. A turning point detection algorithm (similar to the one used for heart rate) is used to determine the number of minimums and thus the number of strokes. The time indexes are used to calculate related metrics such as stroke rate. Acceleration data can also be used to calculate distance per stroke, a unit to measure stroke efficiency.

The breath count algorithm utilizes the output of the stroke recognition program and utilizes a specific function based on stroke type. For backstroke, no breath count is outputted. For front crawl, the gyroscope is used to determine when a significant head rotation occurs. By integrating the accelerometer data, the zeroes of the angular velocity function can be determined. These points indicate when a breath was taken. This function allows metrics such as breath count and strokes per breath to be calculated.

About the Author:

Barron Han: A junior at Shanghai American School, Barron is a competitive swimmer who's interest in engineering, computer science, and product design inspired him to create a wearable device to enhance training for all swimmers.

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