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The Real-Time Classification of Competency Swimming Activity Through Machine Learning

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Abstract

Every year, an average of 3,536 people die from drowning in America. The significant factors that cause unintentional drowning are people's lack of water safety awareness and swimming proficiency. Current industry and research trends regarding swimming activity recognition and commercial motion sensors focus more on lap swimming utilized by expert swimmers and do not account for free-form activities. Enhancing swimming education through wearable technology can aid people in learning efficient and effective swimming techniques and water safety. We developed a novel wearable system capable of storing and processing sensor data to categorize competitive and survival swimming activities on a mobile device in real-time. This paper discusses the sensor placement, the hardware and app design, and the research process utilized to achieve activity recognition. For our studies, the data we have gathered comes from various swimming skill levels, from beginner to elite swimmers. Our wearable system uses angle-based novel features as inputs into optimal machine learning algorithms to classify flip turns, traditional competitive strokes, and survival swimming strokes. The machine-learning algorithm was able to classify all activities at .935 of an F-measure. Finally, we examined deep learning and created a CNN model to classify competitive and survival swimming strokes at 95% ac- curacy in real-time on a mobile device.

Keywords: swimming competency, machine learning, activity recognition, wearables

Introduction

Drowning and swimming-related injuries are a persistent and global issue. In 2000, a worldwide study estimated that 500,000 people die from drowning each year (Peden & McGee, 2003). From 2005 to 2014 in America, the average number of fatalities related to unintentional drowning was 3,536 as declared by the CDC (Disease Control & Prevention, 2021), which is approximately ten deaths a day. In that same article, among the people who die from drowning, 20 percent are children under 14. Historically in the early 20th Century, drowning had become such a severe issue in America that the Red Cross, a disaster relief organization, started educational courses and guidelines to help reduce people's risk of drowning (Feeney, 2021). Despite these efforts (American Red Cross, 2009, 2014a, 2014b), many people lack adequate means to learn how to swim due to socioeconomic and cultural inequality (Irwin et al., 2009b; Hastings et al., 2006; Irwin et al., 2009a; Irwin et al., 2008; Orlowski & Szpilman, 2001; Rahman et al., 2009).

Due to the traditional focus on competitive swimming during lessons by swimming organizations, most swim instructors and coaches focus on competitive swimming strokes. Competitive swimming consists of four strokes aimed at high movement speeds often used in competitions including events for backstroke, breaststroke, butterfly, freestyle, and flip turns (for transitions from one swimming lap to another). In contrast, survival swimming strokes and skills are intended to increase visibility, promote buoyancy, provide propulsion, and other factors that help people survive in swimming emergencies (Stallman et al., 2017). Stallman et al. proposed that propulsive swimming strokes, which consist of elementary (or survival) backstroke, breaststroke, sidestroke, and front crawl, are essential and help prevent drowning. The butterfly swimming stroke also is classified as a propulsive swimming stroke; however, it is not viewed as essential when reducing the risk of drowning and instead is specifically classified as a competitive swimming stroke and usually is taught later because of its difficulty to perform (Holub et al., 2021). Stallman et al. (2017) also determined that stationary buoyancy swimming skills such as treading water and floating are fundamental to reduce the risk of drowning because they allow a person to stop and rest and observe their environment spatially. Unfortunately, sidestroke and stationary buoyancy swimming skills are often neglected in training and for wearable tracking devices.

Commercially available wearable devices have implemented more water-based activity recognition in the past five years. Most commercial devices, like Garmin and the Apple Watch, focus on competitive swimming strokes and do not adequately measure survival swimming activities. These commercial devices recognize competitive swimming because the base group of users comprises elite swimmers and individuals tracking their swimming for exercise or competitions. In the research field, most studies have focused on expert and elite swimmers and the four competitive swimming strokes. Much research has tried to classify three out of the four swimming strokes due to the issues with breaststroke and butterfly swimming being very similar, which causes frequent misclassification. The most recent research has analyzed the starting and stopping positions when it comes to lap swimming, which is either the person pushing off or holding on to a wall or stationary object for rest. Beginner and novice swimmers would benefit from activity recognition of survival swimming styles and general swimming aptitude not currently covered by competitive swimming instruction. Recognizing and distinguishing a person's swimming technique and evaluating their motions would provide the individual with valuable feedback while learning to swim. Additionally, adding survival skills and all propulsion swimming strokes can help swimming instructors, water safety organizations, and parents evaluate the capabilities of swimming novices and provide more detailed instruction.

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We developed two Android applications for a mobile device capable of gathering sensor data and performing real-time recognition of survival skills and competitive swimming from various skill levels. We also have analyzed and developed the optimal wearable satchel that can store the mobile device for aquatic use and not cause distress to the person. This paper covers the development of the wearable device and the machine learning models used to classify swimming-related activities. The Method section covers the techniques for sensor placement, the development of the device, and how we collected the data from the user studies. We extracted features and built multiple machine learning (ML) models, which is found in the Discussion section. In the end, we evaluate each ML model at various time intervals and show the optimal features, time window, and ML model in the final section.

Related Work

Activity recognition researchers have created numerous wearable solutions to recognize various human activities, including fitness activities such as running, jogging, jumping jacks, sit-ups, pushups, and squats (Bao & Intille, 2004; Kwapisz et al., 2011; Bartley et al., 2013); ambulatory motions such as walking, running, standing, sitting, going upstairs, and pacing (Elizondo et al., 2016; Kwapisz et al., 2011); and mundane actions such as posture and getting up from a chair (Bao & Intille, 2004; Kwapisz et al., 2011). In addition, commercial devices like the Fitbit, Apple Watch, and Garmin watches can track people's steps, heart rate, and other physical activities such as running, hiking, and recently swimming (Diaz et al., 2015; Wada, 1982; Tang, 2009; Dervisoglu et al., 2021).

Gaps in Swimming Recognition

Current research in swimming activity recognition has concentrated on the major competitive swimming strokes: back crawl, breaststroke, butterfly, and front crawl (Slawson et al., 2009; Delgado-Gonzalo et al., 2016; Mooney et al., 2015; Siirtola et al., 2011; Marshall, 2013; Bachlin & Troster, 2009; Pansiot et al., 2010a). Research in swimming recognition has placed sensors on the wrists, lower back, upper back, chest, legs, and shoulders, producing excellent results for the four major swimming styles. Bachlin et al. (2009) placed sensors on the person's upper back, lower back, head, and wrists to collect data on the angle of the body, hand and arm motions, breathing patterns, rotation, and overall locomotion (Bachlin & Troster, 2012; Bachlin et al. (2009). The results of these papers showed that the four competitive swimming strokes had distinct patterns based on the location of the sensors on the person's body.

The other factor in recognizing water-based activities is the sensors used, such as gyroscope, accelerometer, and barometer. Choi (Choi et al., 2014) used lower back sensor placement of barometer, accelerometer, and gyroscope to detect the swimming activities of back crawl (i.e., the stroke commonly employed in backstroke competitive events), no movement, front crawl (i.e., freestyle events), breaststroke, butterfly, and flip turns. Choi recognized these forms of water activities at 96 percent precision through cross-validation. When they used their system among novice swimmers, they were barely capable of classifying at 50% accuracy (Choi et al., 2014).

The focus of this paper extends beyond the four competitive swimming strokes by including swimming competency among swimming skills and strokes that help reduce drowning (e.g., treading water, sidestroke) and includes greater accuracy classification with fewer sensors for both beginner, novice, and expert swimmers. Most research papers only focus on a few swim activities or try to concentrate on activity recognition and not in real-time measurement (Lecoutere & Puers, 2014; Slawson et al., 2010; Keskinen, 2000; Davey et al., 2005; Eng et al., 2008; Pan et al., 2016; Bachlin & Troster, 2012; Topalovic et al., 2014; Kon et al., 2015). We argue that technology needs to recognize survival swimming activities needed for competent as well as proficient swimmers, such as when treading water and performing flip turns. Many of these studies have focused on elite swimmers who perform with few flaws or idiosyncrasies in their form (Mullen, 2013). This advanced level of specialization prevents the technology from generalizing to the average or novice swimmer, decreasing the recognition accuracy if worn by anyone other than elite swimmers. Illustrating this is the Garmin waterproof watch, which is only accurate for those with advanced form because the watch is worn on the wrist (Mooney et al., 2017). Much of the research has focused on the four competitive swimming strokes (backstroke, breaststroke, freestyle, and butterfly).

A new form of research has covered the other steps that a person performs during lap swimming. Such steps are starting and stopping, which consists of interacting with land or an immovable object to start or stop swimming. The positions may look similar to treading water, a survival swimming activity. Treading water requires the person to move their arms and/or legs to keep their head above water constantly. The stop position allows the person to hold on to an object to rest the other body parts allowing them to be safe and get out if needed. Costa et al. (2021) have developed a wearable system that takes in an accelerometer, gyroscope, and magnetometer, among other sensors, and places them on the upper back of 10-year-old children. They could classify the start, stop, and different swimming styles; however, they did not define what specific swimming styles they classified. The paper specified an F-score of 95% but did not cover a confusion matrix of erroneously classified ones. Our system can also classify the four major competitive swimming strokes at 95% F-measure with only one accelerometer sensor in real-time. We also can classify the four major swimming strokes and two survival swimming skills. Our system also used older participants of various swimming skill levels from beginner to intermediate, with a larger group of 20 participants. This meant that the time the paper selected as most optimal was 1 second and could not fit an older person due to size, which we can show because we also analyzed 1.5 seconds and found out it was not the most optimal time window.

Overall, the previous papers mentioned focus on competitive swimming and ways to help with and support elite swimmers' desire to increase performance. The other spectrum of research has been related to the detection and classification of drowning. It is difficult to define drowning as an activity because previous papers have described the expected motions as sporadic/irregular movement and climbing motions to get air or access to land (Lu & Tan, 2002; Kam et al., 2002; Lu & Tan, 2004). Kam et al. presented papers that use a finite state machine which detected swimming, treading water, and drowning (Kam et al., 2002). The paper suggested that these three activities differ based on five categories: Speed, Posture, Submersion Index (sinking), activity index (distress vs. treading water), and splash index (Kam et al., 2002). Kam et al. and other papers separated treading water from drowning as activities because the papers said that treading water and drowning looked identical (Handalage et al., 2021; Lu & Tan, 2002; Kam et al., 2002). Among these papers, the current method for detecting drowning is through cameras and video data with validating their systems by having participants simulate drowning within their user studies. In this paper, we present competent swimming as an important skill set and with our work as a basis to prevent the need for drowning detection systems or provide a wearable method in detecting drowning individuals based on irregularity compared to water competent swimming skills and strokes.

Sensor Placement

Core aspects of activity recognition design include the collected metrics, the sensors used, and the location of said sensors. Sensor placement can be on the chest (Parkka et al., 2006; Olguın & Pentland, 2006; Gjoreski et al., 2011; Atallah et al., 2011), upper arm (Bao & Intille, 2004; Atallah et al., 2011), wrist (Mannini et al., 2013), ankle (Mannini et al., 2013; Atallah et al., 2011; Gjoreski et al., 2011), lower back (Bonomi et al., 2009; Sporri et al., 2017), upper back (Amft & Tr¨oster, 2008; Kunze & Lukowicz, 2014), or head (Ishimaru et al., 2014; Pansiot et al., 2010b; Bachlin & Troster, 2012b) depending on the activity. The location of the sensors plays an important role in the wearable's ability to recognize specific actions (Bao & Intille, 2004; Lester at al., 2006; Foerster et al., 1999; Maurer et al., 2006; Lester et al., 2005; Parkka et al., 2006). Bao and Intille's work with biaxial accelerometer placement showed that placing the sensor on the thigh, hip, and ankle works better for ambulation or postural activities. In contrast, sensors placed on the wrist and arm worked better for activities mainly involving the upper body (Bao & Intille, 2004). With swimming, Marc Bachlin used accelerometers on the wrist, upper / lower back, ankles, and head where they described that the sensor placement on specific body parts provided insight into the swimmer's current stroke (Bachlin et al., 2009). Bachlin examined the importance of sensor location on arm movement and body angle related to swimming strokes.

Machine Learning Classification

Classification is reliant on the implementation of the machine learning algorithm. Such algorithm researchers have used Decision Tree (Choi et al., 2014; Khan & Lawo, 2014), Random Forest (Fani et al., 2018), Bayesian Network (Wang & Ji, 2012), and Nearest Neighbor (Anjum & Ilyas, 2013) for classification of physical activities. Prior research has shown positive results when using these classification algorithms for activity recognition. Therefore, we plan to evaluate the value of these algorithms for accurately assessing our survival swimming activities.

For deep learning, researchers have implemented several neural networks for the classification of physical activities. There are multiple types of neural networks from Multi-Layer Perception (MLP), Convolutional Neural Network (CNN), Recurrent Neural Network (RNN), and Modular Neural Networks. Research (Viet et al., 2012; Pirttikangas et al., 2006; Wang et al., 2005) has focused on activity recognition systems that use MLP as their machine learning recognition system. Another reason researchers use MLP is that they do not require many input nodes to provide the best performance compared to CNN. With the advancements in technology, new deep learning classification models have become more applicable. Saez et al. (2016) reported that the use of CNN is possible with 280 nodes as input. These nodes were from six sensors: two accelerometers, one gyroscope, GPS, and one magnetometer. Each one provided a minimum of three features based on x,y,z-coordinates from each sensor system. CNN has also provided an increase in accuracy for activity recognition in medical health (DiPietro et al., 2016), physical activity (Saez et al., 2016), and genetics (Ijjina & Chalavadi, 2016).

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Data Collection

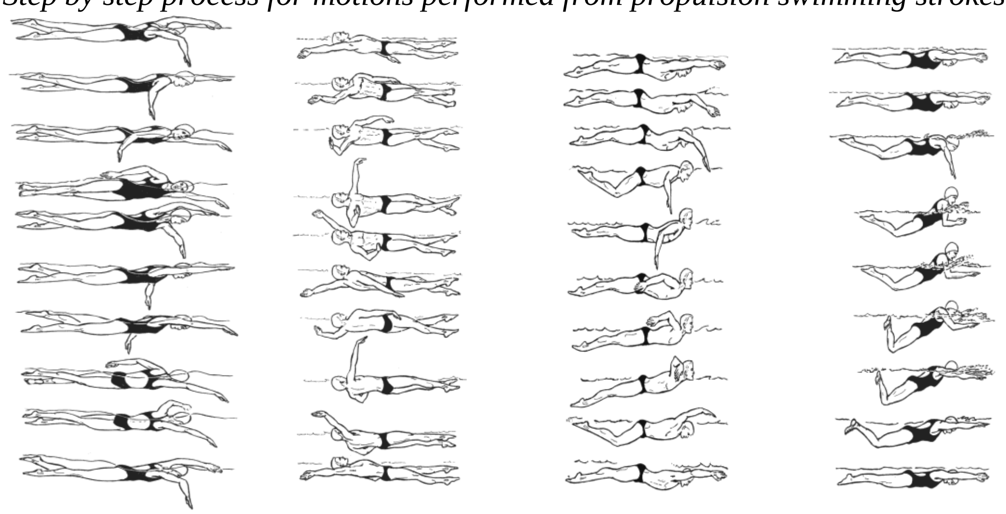
Our first step in building recognition for survival swimming skills was to collect a variety of swimming strokes using our wearable systems. We performed two user studies with participants of varying experience levels in different settings. Both of these user studies have been reviewed and approved by our university's Institutional Review Board (IRB). Typically, these 4 swimming strokes are associated with competitive swimming events and lap swimming activities.

Swimming Activity Being Analyzed

In a lap swimming environment, coaches teach their athletes a uniform method for propulsion swimming and lap transitioning (i.e., turns). The specific propulsion swimming strokes that coaches teach are back crawl (used in backstroke events), front crawl (used in freestyle events, butterfly and breaststroke (used in events by these same names). The pictorial depictions of these strokes are presented in Figure 1. These four strokes are associated with elite competitions (e.g., Olympics) and are also called competitive swimming strokes, where the athletes race for a specific distance using one of the swimming strokes. Breaststroke, front crawl, and back crawl have also been shown to be important for competent swimming and frequently have been used as a grading tool to determine if a person is a competent swimmer (American Red Cross, 2014b).

Figure 1

Step by step process for motions performed from propulsion swimming strokes



(a) Freestyle (b) Backstroke (c) Butterfly (d) Breaststroke

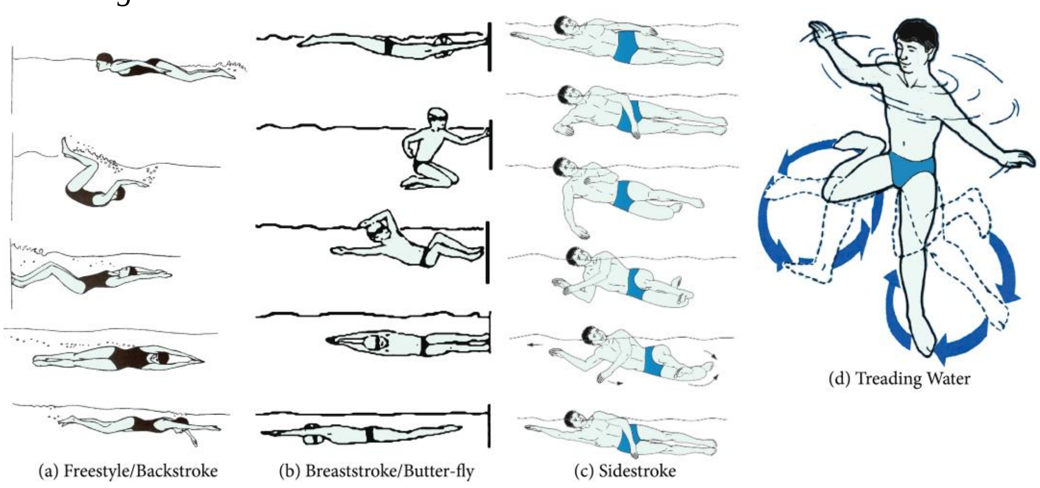
Note. (Figures used with permission from Colwin, C.M. (2002). *Breakthrough Swimming*. Human Kinetics; pp. 50-70.

The second essential swimming technique taught for lap swimming is the transitioning between laps, defined as turns, specifically flip turns. Swimmers use the flip turns to switch between laps to keep the swimming motion continuous. There are official rules for flip turns during competition. If not followed according to competitive rules, athletes may be disqualified from their race. Montgomery and Chambers (2008) presented two types of turns (backstroke/freestyle flip turn and breaststroke/butterfly open turn) which are depicted in Figure 2a and 2b.

Lap swimming is essential, but there are survival skills that the average person needs to learn how to do to reduce their risk of drowning. These swimming strokes are a great way to move around in the water; however, a long-distance sidestroke may be the most efficient when needing to swim for an extended distance. Stallman et al. (2017) proposed that side stroke offers endurance swimming because sidestroke gives the individual the ability to use the least amount of energy and provides easier breathing which is shown in the steps found in Figure 2c. Stallman et al. also proposed that stationary surface competency swimming skills which are floating and treading water allow the individual to have a 360 view in a stationary position with their head above the water (Stallman et al., 2017). The movement patterns of treading water reinforce the breathing and stationary skills as shown in Figure 2d. Stallman et al. (2017) claimed that treading water is the most versatile and essential stationary water competence skill needing to be learned.

Figure 2

*Step by step process for motions performed for flip turns **A/B** and survival swimming strokes **C/D***



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Wearable Device

The HTC6500LVW (Moto7) was the wearable device used to collect data. We went with a mobile (cellular) device because it contains the sensors and internal memory that best suited our studies. The device holds a BOSCH BMA250 3-axis accelerometer, which is capable of 39.2266 m/s^2 and runs on 0.1 mA of power (Specs, 2021). The Android operating system has three settings (Fastest, Normal, and UI) to gather data. For the studies, we used the fastest setting, which gathers sensor values at a sampling rate of 100Hz.

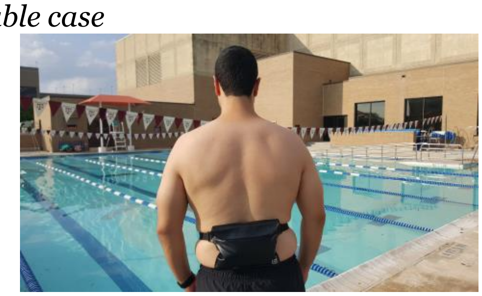
Water Pack System Design and Sensor Placement

We developed a single strap waterproof pack for our first wearable device (Figure 3a) to hold the mobile smartphone. As discussed earlier, sensor type and placement on the body determine effectiveness and accuracy in recognizing activities. To avoid impeding the wearer or causing discomfort, the device uses a single sensor placed on the lower back because a device placed on the lower back impedes swimmer's motion to the least degree. The location is classified as an intuitive location, meaning it will not distract or cause discomfort when worn.

When testing this system, we found that the single strap design was insufficient to hold the device to the person's body. During the pilot study, the pack had the freedom to rotate, flapping while the user swam, which ruined the data. The other complaint was that the strap was not elastic, causing discomfort to the swimmer, as shown in Figure 3b. We developed an improved storage system with a more secure fit via a new case design to address these flaws. The second wearable case uses three elastic straps shown in Figure 4a that secure the pack on the upper, lower, and middle portions of the lower back shown on the user in Figure 4b. The completed pack and system improved the data collection during testing and users felt less restricted by the pack design.

Figure 3

Version 1: First Design of device wearable case



Initial prototype design, involving a waterproof pack, an HTC Android phone, and harness

Time Window

When swimming, there are repetitive motions executed as part of the activity. For example, when a person swims from one side of a pool to another, they take multiple, repeated stroke cycles. For classifying these motions, activity recognition uses segmented data. The data segments are separated based on a time duration, which is called the time window. We overlap time windows to maintain flow and not remove motion segments.

The time it takes to perform a single motion when completing a breaststroke, compared to a backstroke, is different. Since the time it takes to complete gestures varies, the length of the time window affects the accuracy in classifying the physical activities. To determine the optimal window for classifying propulsion swim styles, we used a window size range of 1500–4000ms. As mentioned before, the flip turn is performed once per lap, as shown in Figure 7b; causing the window range to be reduced to 1500–3000ms.

User Study 1

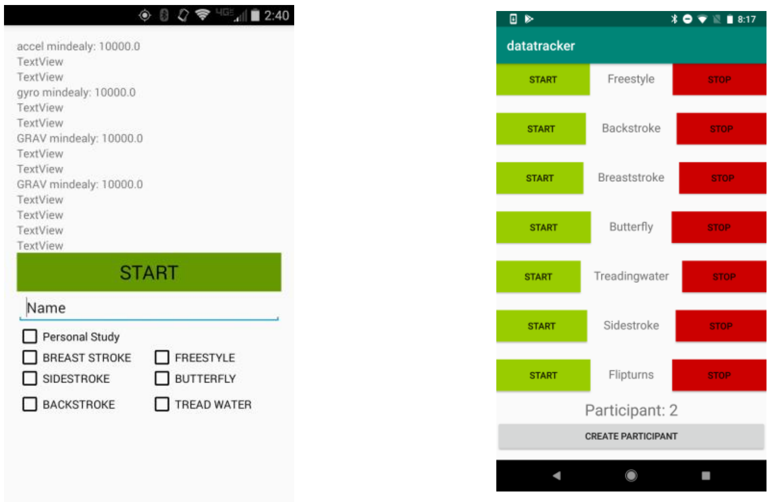
We needed labeled data associated with each swimming stroke from various proficiency levels (beginner, intermediate, expert). The study we developed comprised 15 participants, with half being intermediate/beginner and the other half being expert. These participants were recruited through a direct request from swimmers at university’s student recreation center or with the swim classes. Each participant performed backstroke, breaststroke, freestyle, butterfly, treading water, and sidestroke. Each participant could opt-out of a swimming stroke if they did not feel confident in performing it. The distance they were required to go is a total of 2 laps or 50 meters, giving us the ability to record the flip turns. We used 60 seconds time window to record treading water data because it is a stroke specific to spatial awareness and not locomotion.

Figure 4

Version 2: Second design of device wearable case; Screen shots of user study 2 UI

Figure 5

Study 1 UI: User interface (a) was used in first study; Study 2 UI: Both user interface (a) and (b) were used in second study

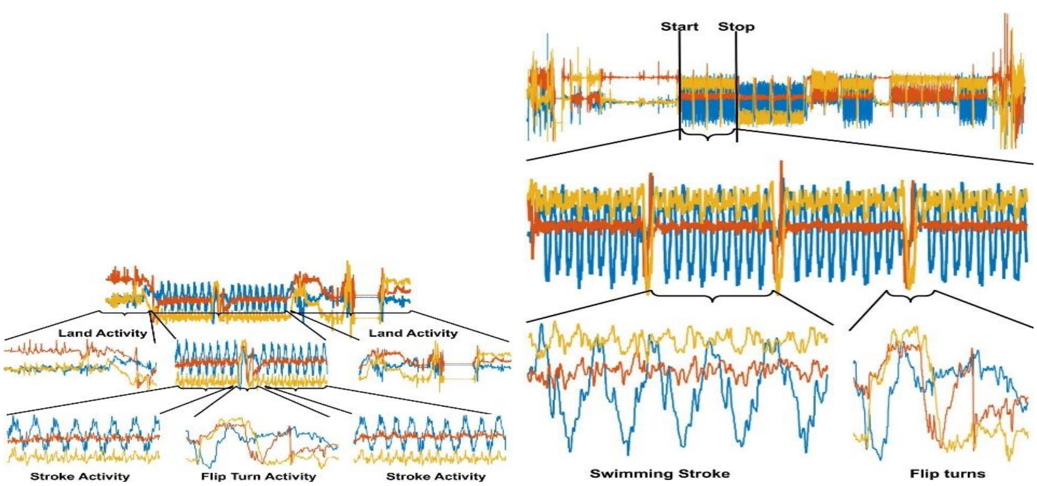


(a) Swimmer's UI for Multiple Strokes Data Collection

(b) Proctor's UI for Multiple Strokes Data Collection

Figure 6

Study 1 Processing: extracting activities and labeling them was used in first study; Study 2 Processing: extracting activities and labeling them was used in second study (Blue=X axis, Red=Y axis, Yellow=Z axis)



(a) Visual method to processing data from user study 1

(b) Visual method to processing data from user study 2

To collect data for each swim stroke, the proctor interacted with the application we developed. Before participants would swim, the experimenter set up their ID through the UI (Figure 5a). Participants selected the swimming stroke they performed within the UI, then clicked the start button to start a 2-minute timer in the background. Once the timer began, the proctor inserted the device into the satchel and attached it to the participant, similarly shown in Figure 4b. We repeated the last two steps for each swim stroke the participant performed. While the background timer was running, the accelerometer collected data at 100 hertz. The timer prevented communication and interaction difficulties while the device was in the waterproof satchel. Later, the participant's data was filtered to separate the activities performed (Figure 6a).

User study 1 is a controlled user study where the participant performed every activity individually with rest or a break between activities, as previously mentioned. In user study 1, the participants wore a wearable mobile device placed on their lower back that collected sensor data. 2.6 hours of the overall amount of sensor data was collected from this controlled study. Separating the data based on each activity varied in minutes for all the swimming strokes: freestyle (32.86), backstroke (19.71), breaststroke (25.37), butterfly (35.65), sidestroke (19.56), and treading water (21.75).

User Study 2

The purpose of conducting a second user study was to gather data from a non-controlled environment focusing on the average swimmer's daily workout routine. For this study, we communicated with the university's swim classes to recruit participants that could provide consecutive swimming routines for about 30 minutes, the average swimmer's workout time (Kostich, 2021). The classes' instructors provided background information on the participant's swimming proficiency levels (beginner, intermediate, experts). The study gave us a realistic workout environment of swimming data that contained fatigued participants.

The plan of this second study was to gather the swimmer's data for a constant 30 minutes. We had to adjust the methods of how we collected and labeled the sensor data. We accomplished this by using two devices. One for attaching to the participant and gathering the swimming data. The second for the research proctor (observer) to record what swim stroke the participant was per- forming. We reused the interface designed for user study 1 to collect data, which is shown in Figure 5a. The only actions allowed were setting the participant's ID and initiating the 30-minute time for collecting data. The secondary device contained an application for the proctor to keep track of the participant's swimming stroke. The proctor’s device used a UI app, Figure 5b, that allowed the proctor to press the start and stop button when the swimmer started and ended each swimming stroke. The back end of the proctor’s observation app stored the swimming stroke’s text, the labeled start and stop, and the timestamp. We used these timestamps to filter and label the data, as explained in Section 3.7. User study 2 is an experimental user study that collected participants’ data in a naturalistic setting. The participants were requested to wear the sensor device and swim for 30 minutes. A researcher observer would monitor and record the participants swimming strokes based on the six swimming strokes presented. For this user study, we collected sensor data from among 5 participants, which produced 2.06 hours of sensor data.

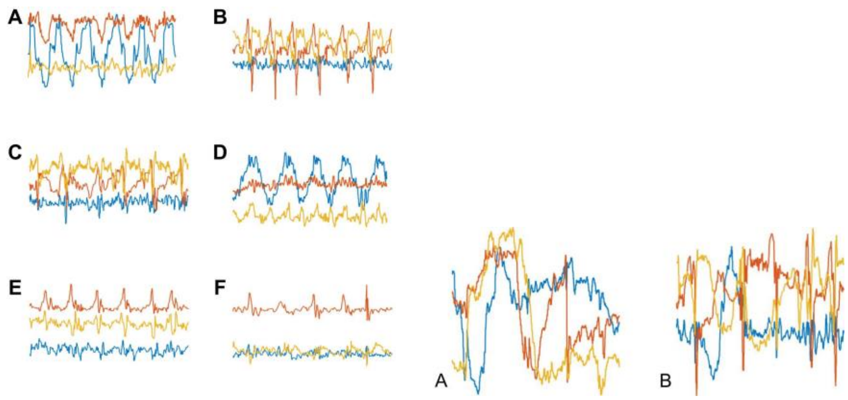
Raw Data Filtering

The raw data from both user studies contained a conglomeration of multiple activities. Those activities consisted of swimming, flip turning, or land activities (standing, sitting, walking). To pull and label the activities from the data, A researcher used observations on time window to filter and separate each activity. Study 1 contained data from a controlled setting where the participant performed three specific actions: Swimming, flip turns, and getting in/out of the water. Figure 6a illustrates the researcher’s methods in selecting and labeling the data for a single swim stroke performed. Based on previous papers and patterns of the data, we could visualize each swim stroke and flip turn. Figure 7a shows that the propulsion swimming styles have a pattern to them because they are repetitive. In contrast, flip turns do not show that that repetitive pattern which can be seen in Figure 7b. The repetitive motions of the swimming activity are visually overloaded; we scaled down the data to a single motion as visualized in Figure 8. Figure 8 shows that most of the swimming styles are different except for butterfly and breaststroke. One can only see a slight difference when looking at its single motions.

Study 2 was more difficult to filter because the participants had free range in deciding what activities they performed as well the length of time for each participant was a constant 30 minutes of sensor data. We benefited from having observations timestamped labels containing what activity they were performing with a start and end time. Since we did not want to rely on the accuracy of the observer, the data went through a second review to fine-tune the filtering and separating of activities. Figure 6b demonstrates the way that each activity is pulled when dealing with longer lengths of data.

Figure 7

(a)/top: A = freestyle, B = butterfly, C = breaststroke, D = backstroke, E = sidestroke, and F = treading water; (b)/bottom: A/Left = backstroke/freestyle flip turn, B/Right = breaststroke/butterfly flip turn

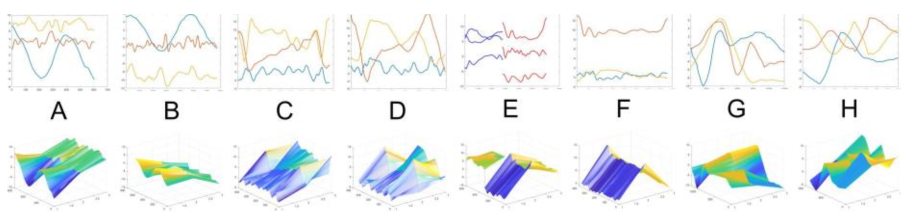


(a) propulsion Swim Styles (b) Flip turns

Note: (Blue=X axis, Red=Y axis, Yellow=Z axis)

Figure 8

Single motion of each swimming stroke: A = freestyle, B = backstroke, C = breaststroke, D = butterfly, E = sidestroke, and F = treading water, G = backstroke/freestyle flip turn, H = breaststroke/butterfly flip turn



Note: (Blue=X axis, Red=Y axis, Yellow=Z axis)

Feature Extraction

Traditional Features

Prior research uses time-domain and frequency-domain features that already show positive results regarding physical activity classification. For the different feature types, the time-domain features are formulas that focus on the sensor's values. In contrast, frequency-domain features use signal processing formulas associated with the values during the change of time. Both feature groups use a time window of segmented data. We grouped these features as traditional features when it comes to our evaluation in Section 6.

Time-domain features use data from a single axis or multiples axes from the sensor's data within a time window. One of the features that uses multiple axes is the correlation coefficient, where the formula takes the static relationship between data sets from two axes. Another specific feature is peak count. Sezgin et al. (2007) present the peak and valley detection through a recognition of sketches. We expand on Sezgin's formulas 1 and 2 to add peak and valley count features.

The frequency-domain features focus on the waveform produced by the data for a period of time. Formula 6 used Fast Fourier Transformation (FFT) to process the time windows signal. Features that use FFT was the Frequency Domain Entropy feature calculated by the formula in Equation 6 based on the methods presented in articles (Attal et al., 2015; Bao & Intille, 2004).

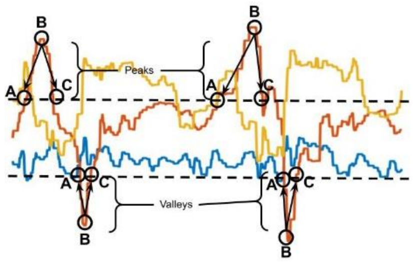
Novel Features

We developed novel feature sets focusing on recognizing swim strokes by using angles and time variation equations. Compared to traditional features, the novel features emphasize the data's peaks and valley angles. Peaks and valleys are detected based on whether the data points are above or below a respective threshold, using Sezgin's Formulas 1 and 2 based on sketch recognition (Sezgin et al., 2007). Figure 9a is a visual representation of the threshold when it comes to peak and valley detection.

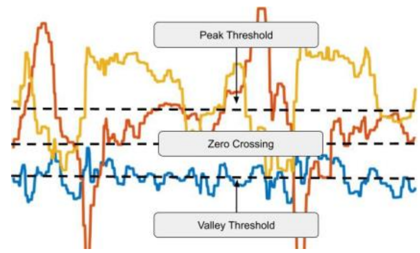
Other features that we use are calculated based on the change in the axis positions over time. The cross-correlation feature described in Equation 7 enhances fluctuations in the accelerometer data. The zero crossing feature detects if the accelerometer axis data changes in numeric sign. Figure 9a illustrates the implementation of zero-crossing on the butterfly swim stroke.

Figure 9

Zero Crossing: demonstration of thresholds used for finding peaks, valleys, and points crossing the zero axis; Peak/Valley Angles: demonstrates the angle calculations from the peak and valley thresholds



(a) Total angles for peak and valleys: A is first point past threshold, B is the point that is either peak or valley, C is the final point after crossing threshold again



(b) Zero crossing and Peak/Valley threshold

Time-Domain Features: These formulas use a list of x, y, z axis of sensor data based on a given time window

- Peak Threshold (X,Y,Z)

Peak_threshold = media(a) = ((median(a)-max(a))*threshold% (1)

- Valley Threshold (X,Y,Z)

Peak_threshold = media(a) = ((median(a)-min(a))*threshold% (2)

- Standard Deviation(X,Y,Z)

$$\sigma = \sqrt{\frac{\sum(a-\bar{a})^2}{n-1}} \qquad (3)$$

- Skewness (X,Y,Z)

$$\gamma = \frac{\sum\frac{(a-\bar{a})^3}{n}}{\sigma^3} \qquad (4)$$

- Kurtosis (X,Y,Z)

$$K = \frac{\sum\frac{(a-\bar{a})^4}{n}}{\sigma^4} \qquad (5)$$

Frequency-Domain Features: These formulas use a list of x-, y-, and z axes of sensor data based on a given time window:

- Entropy (X,Y,Z)

$$Entropy = \frac{\sqrt{a_i^2+b_i^2}}{\sum_{k=0}^{N-1}\sqrt{a_i^2+b_i^2}} \quad (6)$$

$$a_i = x_i \cos\left(\frac{2\pi f_i}{N}\right) and\ a_i = x_i \sin\left(\frac{2\pi f_i}{N}\right)$$

- Cross correlation (XY,XZ,YZ)

$$Cc(a,b) = max_{d=1}^{n-1}\left(\frac{1}{n}\sum_{i=1}^{n} a_i * b_{i-d}\right) \quad (7)$$

- Power Spectral Density (X,Y,Z)

$$PSD = \frac{1}{n}\sum_{i=0}^{N-1} a_i^2 + b_i^2 \quad (8)$$

- DC (X,Y,Z)

$$DC = \frac{1}{n}\sum_{i=0}^{N-1} a_i^2 \quad (9)$$

- Angle calculation From Thresholds

$$A = cos^{-1}\left(\frac{ba*bc}{2ba*bc}\right) \quad (10)$$

- Max peak angle X,Y,Z

$$v_i = max_{1\to i-1}(PeakA_i, PeakA_{i+1}) \quad (11)$$

- Max peak angle X,Y,Z

$$v_i = min_{1\to i-1}(PeakA_i, PeakA_{i+1}) \quad (12)$$

- Average peak angle X,Y,Z

$$v(n) = \frac{\sum_{i=1}^{n} PeakA_i}{n} \quad (13)$$

- Max valley angle X,Y,Z

$$v_i = max_{1\to i-1}(ValleyA_i, ValleyA_{i+1}) \quad (14)$$

- Max valley angle X,Y,Z

$$v_i = min_{1\to i-1}(ValleyA_i, ValleyA_{i+1}) \quad (15)$$

- Average valley angle X,Y,Z

$$v(n) = \frac{\sum_{i=1}^{n} ValleyA_i}{n} \quad (16)$$

- Total angle average X,Y,Z

$$v(n,k) = \frac{\sum_{i=1}^{n} PeakA_i + \sum_{i=1}^{k} ValleyA_i}{n} \quad (17)$$

Like traditional features, we used frequency-domain features that expand on Fast Fourier Transformation (FFT). We added two new equations: the **power spectral density** (Equation 8), which measures the signal's power compared to the usual frequency and **DC component** (Equation 9), which is the measurement of the Discrete Frequency of the signal based on 0 Hz.

Machine Learning Implementation

To implement the best machine learning algorithms, we separated the development into three steps. The first step was the subset selection method, which selects relevant features needed for the machine learning algorithm. Next was understanding and evaluating the types of machine learning algorithms used. The final step was the validation of the model's performance. This section will cover the subset selection of features, types of machine learning algorithms examined, and the validation methods for proving the model's competencies.

Subset Selection

The features used and activities being classified affect the performance of the machine learning algorithm. The relevance of the features used can reduce overfitting and produce faster and simplified machine learning algorithms. The selection process is called subset selection. The subset selection method uses techniques that examine the sample of labeled featured data sets—comparing each feature to each specific labeled data extracting the most relevant features. We used is the best-first subset selection technique, which uses forward evaluation on sub-feature paths, selecting the highest correlation paths capable of distinguishing between activities.

Machine Learning Algorithms

The machine learning algorithms we implemented were grouped into several categories. The first category is the Decision Trees, which are algorithms that classify through if/then statements based on values determined from a correlation formula. There are many decision tree classifiers; the ones we evaluate are Random Forest, Random Tree, J48 Decision Tree, Decision Stump, and Reduced-Error Pruning Tree (REPTree).

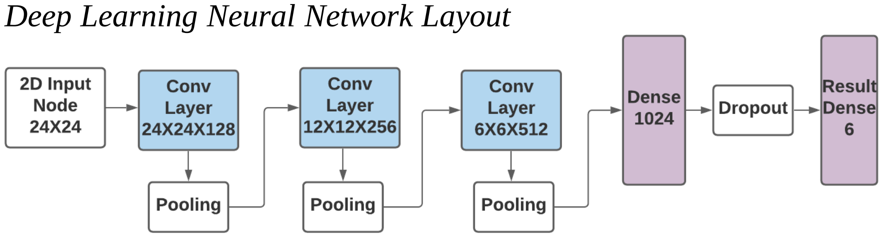
Other classifiers we reviewed emphasize a straightforward algorithm. The Naive Bayes classifier uses probability function from Gaussian Distribution for classification. Another classifier used is the nearest neighbor, where the classification method compares data sets based on the Euclidean Distance. Both the nearest neighbor and naive Bayes benefit from its simplicity and ability to classify based on similarity in data sets. The final category we evaluated was neural networks.

Deep Learning

Utilizing deep learning, we developed a convolutional neural network (CNN) classifier that can recognize locomotive swimming styles. The reason for choosing CNN is that CNN uses fewer neurons than other neural network layers and can extract features from the data. Compared to a general fully connected neural network which works best with already defined features instead of raw data. CNN models are meant to be used with 2D arrays such as images, but A recent paper presented a 1D convolutional neural network that showed positive results when classifying land-based activities (Gupta, 2021). However, the CNN model in the paper, also combined with a Recurring Neural network, would use more layers. We plan to stick with a CNN and modify the data to fit the 2D array and reduce the number of layers. The CNN that we built can be seen in Figure 10, in which the output of the final layer is to a binary classifier based on the six locomotive swimming styles.

Figure 10

Deep Learning Neural Network Layout



We converted our single-layer dataset into a 2D array by taking advantage of a resample algorithm discovered by Sezgin et al. (2007) P$ (Vatavu, Anthony, & Wobbrock, 2012). The reason is that the resampling will smooth the data and reduce the amount of noise. It will also resize the data so that it can be a constant value for the 2D array. We needed to build a 2D array capable of down sampling evenly when passing through the CNN and its max-pooling layers for our data. We went with a 24X24 array which is 576 total data points. The reason for 576 point array is because it is also divisible by three, which equals 192. Having the 2D array divisible by three means that the X, Y, Z data points can be evenly distributed among the 2D array. Now that we had decided the size of the data, we had to determine the best time window. As previously mentioned, the device produces 100 data points per second and with the 2D array needing 192. We went with a 2.5 second window of data which produced 250 data points so it can be resampled to 192 data points. The resampling reduces the amount of data by only 25%, which is an optimal size compared to a smaller or larger window that may cause enhancing noise or over smoothing out the data points.

Converting the data to a 2D array is by preprocessing the data to its 192 data points and then using a reshaping function to convert it to the 24 by 24 array. The selected window of time is 2.5 seconds, and the original dataset contains 3x250 data points where each column is the X, Y, and Z axis. The down sampling of the data converted the 250 points to 192. Next is the reshaping step, a function that splits the data into eight groups of 3X24 datasets. The function then appends each grouping by its rows producing a 24X24 dataset. . When it came to integration and having it classified in real-time, there were some obstacles we had to deal with, such as RAM space, computation capability, and storing of classification. A mobile device has a small RAM space and cannot hold large neural networks. Using Tensorflow, we can compress the neural network into a file, read by a mobile device using the Tensorflow API. For loading the data and processing it, we used threads. When the data reached 2.5 seconds, we sent it using a thread to be processed and classified. Once classification is done, the thread would then write it to a specific file. We tested our application in a realistic setting, and it was capable of classifying in real-time.

Validation Methodology

We used two methods to validate the machine learning models. The first method was through cross-validation, which divided the data randomly into (K) equally-sized splits called folds. Each fold of data is either used to train or test the ML model. Cross-validation helped verify the effectiveness of our features in the model's classification. If the accuracy is high, then we know that the features can distinguish between labels. The second method, leave-one-out validation, evaluates the system further and simulates a naturalistic setting. Leave-one-out validation involves storing a single participant's data as a test and using the rest as training for the model. Both validation methods used F-measure over accuracy. Using F-measure, we can validate the models even without a balanced data set of classifications. The formula of F-measure, equation 18, is the measurement of accuracy through the combination of recall, equation 19, and precision, equation 20.

- F_measure = $2(\frac{precision*recall}{precision+recall})$ (18)
- Recall = $\frac{tp}{tp+fn}$ (19)
- Precision = $\frac{tp}{tp+fp}$ (20)

For evaluating our machine learning algorithm, we performed both cross-validation and leave-one-out validation. Cross-validation has the issue with the data split for training and test datasets containing a participants datasets giving a higher accuracy. The cross-validation method only shows the max possible accuracy with the most correct conditions for our results. The result of our system relied on leave-one-out validation, which separated the data based on participants giving accurate measurements of the machine learning algorithm to control the information leakage when developing a machine learning model. For the second part of our analysis, we classified with realistic swimming data. The data provided in User Study 1 was from a controlled setting with the participants being at their top physical condition. User study 2 is a longer study that collected sensor data from participants swimming for 30 minutes. The machine learning model developed from the previous study's data will be used to classify the second set of data, accurately representing a realistic setting.

Results

In this section, we evaluate the performance of several machine learning algorithms as mentioned in section 5.2. The classifications are separated into three groupings: propulsion (backstroke, breaststroke, butterfly, freestyle, sidestroke, treading water), flip turns (backstroke/freestyle flip turns, breaststroke/butterfly flip turns), and combination of propulsion and flip turns. We separated classification because propulsion swimming styles are repetitive motions and are most common when swimming. Flip turns are performed once, and the purpose is to transition between lanes when swimming in a lap pool. We did not have enough room to show all subset features selected from various time windows. The features presented are based on subset selection from the optimal time window and machine learning algorithm.

Propulsion Swimming Styles Evaluation

We have six labeled sets of propulsion swimming styles (backstroke, breaststroke, butterfly, freestyle, sidestroke, treading water). In the performance of propulsion swimming styles the leave-one-out validation in Table 2, both novel and traditional features had the same f-measure of 0.901 and, when combined, produced the highest of 0.923. While among the features selected presented in Table 1, more novel features were selected compared to traditional ones. When examining the realistic setting of swim styles, the traditional features confusion matrix's performance in Table 3 was perfect among freestyle, backstroke, breast- stroke, and treading water. That was noticeable when it came to combining the features with Table 3, showing similar results. The novel features in the confusion matrix Table 3 found that backstroke was the only similar swim stroke with perfect classification. The other strokes' performances had a reduced performance of about 0.05.

Flip Turns Evaluation

The type of flip turn performed is reliant on what swimming stroke the per- son was performing at the time. There are two types of flip turns (back- stroke/freestyle and breaststroke/butterfly). Meaning we have only 2 labeled classifications for our machine algorithm. We also shortened the time window to a range of 1500–3000ms because the flip turn performance is a single action. There were little features selected in Table 4. With the action not being repetitive we removed the cross-validation and relied on a leave-one-out validation, as shown in Table 5. The results showed similar f-measures among combined and traditional at 0.935 which based on the features selected, the combined had no features used among novel features. In reviewing Table 6, the confusion matrix showed higher classification among both flip turn types for novel features than traditional.

Evaluation of Total Swimming Styles

Previously we reviewed locomotion styles and flip turns separately. We wanted to evaluate the performance of all the expected total swimming styles for lap swimming. In Section 6.2, we evaluated flip turns at a smaller time window of 3000ms. We kept this time window to evaluate combined swim groups to include flip turns data sets under 4000ms.

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Table 1

Feature selection for propulsion swimming styles: The features selected among several time windows are from the highest f-measure produced by the leave-one-out validation. Traditional Features: 4000ms time window with 500ms overlap Novel Features: 4000ms time window with 250ms overlap Combined Features: 3000ms time window with 500ms overlap

	Traditional			**Novel**			**Combined**		
	X	**Y**	**Z**	**X**	**Y**	**Z**	**X**	**Y**	**Z**
Average	✓		✓						✓
Standard Deviation	✓	✓	✓				✓	✓	✓
Root Mean Square	✓	✓	✓				✓		
Peak Count								✓	
Valley Count	✓								
Skewness							✓		✓
Kurtosis								✓	
Correlation Coeff							✓	✓	✓
Entropy	✓	✓	✓				✓	✓	
Max Peak Angle				✓					
Min Peak Angle					✓		✓		
Average Peak Angle						✓			✓
Max Valley Angle				✓				✓	
Min Valley Angle				✓					
Average Valley Angle					✓	✓			
Axis Angle Average				✓		✓	✓		
Cross-Correlation				✓	✓	✓	S✓	✓	✓
Zero Crossing				✓	✓		✓		
DC Component				✓	✓	✓	✓	✓	✓
Power Spectral Density				✓	✓	✓			

Table 2

Cross-validation(C) of propulsion swim styles with optimal time windows: Traditional 3500ms time window with 500ms overlap, Novel: 4000ms time window at 500ms overlap, and combined features: 4000ms at 500ms overlap;
Leave-one-out(L) validation of propulsion swim styles with optimal time windows: Traditional: 3500ms time window with 500ms overlap, Novel: 4000ms time window at 500ms overlap, and Combined features: 4000ms at 500ms overlap

	Traditional		Novel		Combined	
	C	L	C	L	C	L
Multilayer Perceptron	0.960	0.900	0.988	**0.901**	0.945	**0.923**
Naive Bayes	0.936	0.890	0.936	0.820	0.969	0.901
Decision Stump	0.431	0.311	0.447	0.311	0.990	0.424
J48	0.932	0.862	0.993	0.845	0.995	0.865
Random Forest	**0.972**	**0.901**	**0.998**	0.894	**0.998**	0.914
Random Tree	0.949	0.853	0.989	0.834	0.991	0.873
REPTree	0.941	0.889	0.991	0.862	0.993	0.900
Nearest Neighbor	0.941	0.889	0.991	0.862	0.993	0.900

In Table 7, the selection of traditional, novel, and combined groups was most comparable to propulsion and flip turns individually separated, which is expected with the increased number of classifications needing to be performed. When it came to cross-validation, even though the window was shortened, the f-measure in Table 8 shows no change in the results. The reason is the increased features used for classification, with Random Forest being the top algorithm for all three featured sets. With the high f-measured values in cross-validation, we examined leave-one-out validation. The results in Table 8 show a 0.09 difference in combined compared to traditional. The machine learning algorithms used are the same compared to Table 1 from the locomotion swim styles analysis. The only difference is that novel moved from multilayer perception to Random Forest. The change in algorithm and features selected affected when evaluated in a realistic environment.

When testing the algorithms in a realistic setting, there was a pattern in the confusion matrix for classification. Similar to Tables 3 and 4 in propulsion swim styles, freestyle, backstroke, treading water, and breaststroke provided perfect accuracy in the classification of those four swim styles. The reason is that each of those swim styles had significant differences when it came to the activity. Backstroke is performed on one's back which distinguishes it from the others; similarly treading water is performed with the person vertically positioned in the water. At the same time, the front crawl method of locomotion relies on relies on rotation around the x-axis. Other than backstroke, no other stroke uses a rotary motion around the longitudinal axis. Many research papers that distinguish the butterfly stroke from breaststroke by using lower back sensors have had difficulty. Swimming butterfly is a rhythmic fluid motion that relies on the person's legs and arms to act synchronously to have the speed to get the arms out of the water. Most beginner and intermediate swimmers have not had the practice to get the right rhythm. The other issue is that the butterfly is the most physically demanding swim stroke leading to faster exhaustion and difficulty in keeping efficient form, making it look similar to breaststroke due to their similar forward breathing techniques.

Table 3

(T) Traditional features with 4000ms time window with 500ms overlap using random forest; (N) Novel features with 4000ms time window with 250ms overlap using multilayer perception; and (C) Combined features with 3000ms time window with 500ms overlap using multilayer perception. Column and row labels are freestyle (Fre.), backstroke (Bac.), breaststroke (Bre.), butterfly (But.), treading water (Tre.), sidestroke (Sid.)

	Fre.	Bac.	Bre.	But.	Tre.	Sid.	
T	**1.00**	0.00	0.00	0.00	0.00	0.00	
N	**0.97**	**0.01**	**0.02**	0.00	0.00	0.00	Fre.
C	**1.00**	0.00	0.00	0.00	0.00	0.00	
T	0.00	**1.00**	0.00	0.00	0.00	0.00	
N	0.00	**1.00**	0.00	0.00	0.00	0.00	Bac.
C	0.00	**1.00**	0.00	0.00	0.00	0.00	
T	0.00	0.00	**1.00**	0.00	0.00	0.00	
N	0.00	0.00	**0.95**	**0.05**	0.00	0.00	Bre.
C	0.00	0.00	**1.00**	0.00	0.00	0.00	
T	0.00	0.00	**0.24**	**0.76**	0.00	0.00	
N	0.00	0.00	**0.41**	**0.59**	0.00	0.00	But.
C	0.00	0.00	**0.37**	**0.63**	0.00	0.00	
T	0.00	0.00	0.00	0.00	**1.00**	0.00	
N	0.00	0.00	0.00	0.00	**0.98**	**0.02**	Tre.
C	0.00	0.00	0.00	0.00	**1.00**	0.00	
T	0.00	0.00	0.00	0.00	**0.10**	**0.90**	
N	0.00	0.00	0.00	0.00	**0.08**	**0.90**	Sid.
C	0.00	0.00	0.00	0.00	**0.09**	**0.91**	

Table 4

Feature selection flip turns swimming styles: The features se- lected among several time windows are from the highest f-measure produced by the leave-one-out validation. Traditional Features: 3000ms time window with 500ms overlap Novel Features: 3000ms time window with 250ms over- lap. Combined Features: 3000ms time window with 500ms overlap.

	Traditional			**Novel**			**Combined**		
	X	**Y**	**Z**	**X**	**Y**	**Z**	**X**	**Y**	**Z**
Average			✔					✔	✔
Standard Deviation			✔						✔
Root Mean Square							✔	✔	
Skewness									✔
Cross Correlation					✔				

Table 5

Leave-one-out validation of flip turns swimming styles: The features selected among several time windows are from the highest f-measure produced by the leave-one-out validation. Traditional Features: 3000ms time window with 500ms overlap. Novel Features: 3000ms time window with 250ms overlap. Combined Features: 3000ms time window with 500ms overlap

	Traditional	**Novel**	**Combined**
Multilayer Perceptron	0.885	0.779	0.918
Naive Bayes	0.882	0.740	0.896
Decision Stump	**0.935**	**0.838**	**0.935**
J48	0.872	0.825	0.856
Random Forest	0.863	0.801	**0.935**
Random Tree	0.867	0.724	0.846
REPTree	0.916	0.735	0.914
Nearest Neighbor	0.916	0.735	0.914

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Table 6

(T) Traditional features with 3000ms time window with 500ms over- lap using decision stump; (N) Novel features with 3000ms time window with 250ms overlap using decision stump; (C) Combined features with 3000ms time window with 500ms overlap using decision stump; Column and row labels are freestyle/backstroke flip turn (Fre./Bac. FT), and breaststroke/butterfly flip turn (Bre./But. FT).

	Fre./Bac. FT	Bre./But. FT	
T	0.57	0.43	Fre./Bac. FT
N	0.77	0.23	
C	0.57	0.43	
T	0.13	0.87	Bre./But. FT
N	0.05	0.95	
C	0.13	0.87	

Table 7

Subset selection for major swim strokes and flip turns Swimming Styles: The features selected among several time windows are from the highest f-measure produced by the leave-one-out validation. Traditional Features: 3000ms time window with 500ms overlap Novel Features: 2500ms time window with 500ms overlap. Combined Features: 3000ms time window with 500ms overlap

	Traditional			**Novel**			**Combined**		
	X	**Y**	**Z**	**X**	**Y**	**Z**	**X**	**Y**	**Z**
Average	✔		✔				✔		✔
Standard Deviation	✔	✔	✔				✔	✔	✔
Root Mean Square	✔	✔	✔				✔		
Peak Count	✔	✔	✔					✔	✔
Valley Count	✔	✔	✔						
Skewness									✔
Kuritosis							✔		
Entropy	✔	✔	✔				✔	✔	
Max Peak Angle				✔	✔	✔	✔		
Average Peak Angle									✔
Max Valley Angle				✔	✔	✔			✔
Axis Angle Average						✔	✔		
Cross Correlation				✔	✔	✔	✔	✔	✔
Zero Crossing				✔	✔	✔	✔		
DC Component				✔	✔	✔	✔	✔	✔
Power Spectral Density				✔	✔	✔			

Table 8

Cross-Validation(C) of major swim strokes and flip turns Swimming Styles: The features selected among several time windows are from the highest f-measure produced by the leave-one-out validation. Traditional Features: 3000ms time window with 500ms overlap. Novel Features: 2500ms time window with 500ms overlap. Combined Features: 3000ms time window with 500ms overlap

	Traditional		Novel		Combined	
	C	L	C	L	C	L
Multilayer Perceptron	0.986	0.844	0.966	0.801	0.986	**0.880**
Naive Bayes	0.944	0.841	0.889	0.753	0.941	0.810
Decision Stump	0.394	0.272	0.409	0.265	0.354	0.248
J48	0.987	0.819	0.976	0.769	0.986	0.833
Random Forest	**0.995**	**0.871**	**0.990**	**0.842**	**0.994**	0.870
Random Tree	0.984	0.802	0.968	0.743	0.981	0.801
REPTree	0.981	0.804	0.964	0.805	0.980	0.832
Nearest Neighbor	0.981	0.804	0.964	0.805	0.980	0.832

Note. Leave-one-out (L) of major swim strokes and flip turns Swimming Styles: The features selected among several time windows are from the highest f-measure produced by the leave-one-out validation. Traditional Features: 3000ms time window with 500ms overlap. Novel Features: 2500ms time window with 500ms overlap. Combined Features: 3000ms time window with 500ms overlap.

Table 9

(T) Traditional features with 3000ms time window with 500ms overlap using random forest; (N) Novel features with 2500ms time window with 500ms overlap using Random Forest; (C) Combined features with 3000ms time window with 500ms overlap using multilayer perceptron; Column and row labels are freestyle (Fre.), backstroke (Bac.), breaststroke (Bre.), butterfly (But.), treading water (Tre.), sidestroke (Sid.), freestyle/backstroke flip turn (F/B FT), and breaststroke/butterfly flip turn (B/B FT)

	Fre.	Bac.	Bre.	But.	Tre.	Sid.	F/B FT	B/B FT	
T	**1.00**	0.00	0.00	0.00	0.00	0.00	0.00	0.00	
N	**1.00**	0.00	0.00	0.00	0.00	0.00	0.00	0.00	Fre.
C	**1.00**	0.00	0.00	0.00	0.00	0.00	0.00	0.00	
T	0.00	**1.00**	0.00	0.00	0.00	0.00	0.00	0.00	
N	0.00	**1.00**	0.00	0.00	0.00	0.00	0.00	0.00	Bac.
C	0.00	**1.00**	0.00	0.00	0.00	0.00	0.00	0.00	
T	0.00	0.00	**1.00**	0.00	0.00	0.00	0.00	0.00	
N	0.00	0.00	**1.00**	0.00	0.00	0.00	0.00	0.00	Bre.
C	0.00	0.00	**1.00**	0.00	0.00	0.00	0.00	0.00	
T	0.00	0.00	**0.35**	**0.65**	0.00	0.00	0.00	0.00	
N	0.00	0.00	**0.52**	**0.48**	0.00	0.00	0.00	0.00	But.
C	0.00	0.00	**0.23**	**0.77**	0.00	0.00	0.00	0.00	
T	0.00	0.00	0.00	0.00	**1.00**	0.00	0.00	0.00	
N	0.00	0.00	0.00	0.00	**1.00**	0.00	0.00	0.00	Tre.
C	0.00	0.00	0.00	0.00	**1.00**	0.00	0.00	0.00	
T	0.00	0.00	0.00	0.00	**0.09**	**0.91**	0.00	0.00	
N	0.00	0.00	0.00	0.00	**0.08**	**0.92**	0.00	0.00	Sid.
C	0.00	0.00	0.00	0.00	**0.09**	**0.91**	0.00	0.00	
T	**0.08**	**0.06**	**0.02**	0.00	0.00	**0.02**	**0.74**	**0.08**	
N	**0.08**	**0.06**	**0.02**	0.00	0.00	**0.02**	**0.74**	**0.08**	F/B FT
C	**0.08**	0.00	0.00	0.00	0.00	0.00	**0.85**	**0.06**	
T	**0.06**	0.00	**0.10**	**0.13**	0.00	0.00	**0.10**	**0.61**	
N	**0.22**	0.00	**0.30**	**0.02**	0.00	**0.05**	**0.17**	**0.24**	B/B FT
C	**0.13**	0.00	**0.10**	**0.03**	0.00	0.00	**0.07**	**0.67**	

The evaluation of traditional features in a realistic setting Table 9 confusion matrix shows similar propulsion results even though the time window was shorter by 500ms. The significant difference is the butterfly which performed worse. Because the swimmers swam for 30 minutes, causing exhaustion which leads to the reduced form. Making some of the strokes look similar to a butterfly. With the smaller window, fewer repetitive strokes are examined, meaning the deviations in form affect results. For the flip turns, there was not much of a change. One stroke went up, and the other went down.

The novel features selected, as shown in Table 7, show from the confusion matrix that all propulsion swim styles performed much better in classification. The reason is the increased features and the change in the machine learning algorithm. Multilayer perceptions performed better when there was more data being input. When reviewing the flip turns, however, the values were much lower in classification. The reason was that flip turns are discrete actions, and with the time window being smaller to 2500ms, there is much less of the action being evaluated.

When we combined the novel and traditional features set, the classification of butterfly and flip turns increased. Within Table 9, both algorithms' most significant issues were flip turns and butterfly swim styles. Table 9 confusion matrix shows an increase of 0.12 for butterfly and an increase of 0.11 for back/free turns and a 0.06 increase in butterfly/breaststroke turns. Though compared to the novel features classification of flip turns, they were higher. The reason why there is a difference is the added labels of propulsion swim styles. That causes both flip turns to be misclassified.

Applied Deep Learning Model in Real-Time Test

We developed and trained a deep learning model that uses a convolutional neural network to classify all propulsion swimming styles. For training the neural network, we used all the data sets produced from user study 1. After training the neural network model was able to produce an accuracy of 0.95. We then integrated it within the mobile application to classify in real-time. As proof of concept to test the real time classification system we had a single participant wear the device and swam all strokes for 50 meters in a 25-meter pool forcing flip turns. The classification was able to recognize the majority of swimming styles, as shown in Table 10. The total classification based on each swimming stroke (correct/total classified): freestyle (20/20), backstroke (20/20), breaststroke (20/20), butterfly (17/20), sidestroke (40/40), treading water (20/20). It has shown that butterfly was the only swimming stroke that was misclassified when using it in real time with the swimmer.

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Table 10
Confusion matrix for convolutional neural network. Column and row labels are freestyle (Fre.), backstroke (Bac.), breaststroke (Bre.), butterfly (But.), treading water (Tre.), and sidestroke (Sid.)

Fre.	Bac.	Bre.	But.	Tre.	Sid.	
1.00	0	0	0	0	0	Fre.
0	1.00	0	0	0	0	Bac.
0	0	1.00	0	0	0	Bre.
0	0	0.15	0.85	0	0	But.
0	0	0	0	1.00	0	Tre.
0	0	0	0	0	1.00	Sid.

Discussion

Wearable System and Pack

We performed two studies with the first study focused on gathering specific swimming styles in a controlled environment and the second allowed the participants to swim recreationally in a lap pool. When developing a wearable system, we had to consider the storage pack placed on the person's body and the device. A 3-strap pack with elastics was non-obstructive to the person and it allowed the device to fit snug on the person's body. Waterproofing and attachment to the person for the wearable storage system were important. The mobile phone had to be programmed and contain an interactive app for the device. The final app could hold a convolutional neural network capable of classifying swimming styles in real-time and provide high accuracy.

Feature Set Comparison

Swimming styles are structured to allow the swimmer's breathing pattern to coexist with the swimming stroke's motion rhythm. Each swimming stroke breathing method is different; except breaststroke and butterfly, noticeable in the y-axis peaks found in Figure 7a. We believe that is why it is tough to classify the difference between breaststroke and butterfly. Because butterfly is such a problematic swimming technique, beginner and intermediate swimmers have trouble getting the flow right, causing the motions to look similar to the breast- stroke. The traditional and novel features classification from the participants of user study 2 found in Table 3 helps support the notion with butterfly having the lowest accuracy from the confusion matrix. Though both swimming styles' peaks had differences in their pattern, the novel features were expected to exceed the traditional ones in classification. The novel features' classification provided similar F-measure results to the traditional ones in a smaller time window. Traditional features rely on the entire data set within the window, while the novel features rely on the peak and valley detected locations.

The motions to perform the two types of flip turns are noticeably different, as presented in Figure 7b. However, the initial actions for when the flip turn starts and ends are nearly identical. The reason is that for flip turns, the swimmer must visually see the wall before it starts to make sure that they do not collide with it. With flip turns, the body position does not require the swimmer to follow a specific motion meaning they have free range to twist and move in a three-dimensional space before they push off from the wall and start the next lap. Those motions while performing the flip turns cause issues with the traditional and novel features in classification. One method to fix this is to focus on the peaks of the actual turning action and move the range from that point.

Future Work

Peak Analysis

We discovered that the peak and valley detection method could be optimized to better fit multiple swimming proficiency levels for our system. When analyzing the data, the x -axis for breaststroke/butterfly flip turns erroneously display as designated swim strokes. With the ability to resample the data, we can eliminate noise and increase the accuracy of distinguishing between all swimming styles. We plan to implement better complex algorithms related to data between peak sets by understanding and finding exact peaks. Swimmers maintain vary- ing distances between peaks because swimmers possess various levels in their ability to hold their breath. If we analyze the data between peaks, we may recognize the swimmer's proficiency level, with the bonus of recognizing the swimmers' breathing capacity and physical stress the workout is providing.

Education and Sports

The user studies we conducted examined the distinctions between professional swimming and beginner or inexperienced swimming among the various strokes and skills. With more data, we plan to expand on the proficiency classification and provide feedback to the user. This enhanced classification could allow our system for real-time recognition and feedback to correct the swimmer's stroke proficiency. Additionally, recognition can be implemented as a testing system to evaluate a person's swimming capability. We would be able to provide people with the ability to assess their capabilities when they consider swimming in more dangerous environments.

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Drowning

Many factors can reduce the risk of drowning for individuals. The main reasons that papers have presented which increase a person's risk of drowning are lack of supervision and water safety knowledge (Szpilman et al., 2012; Turgut & Turgut, 2012). Previous research has focused on using cameras as a supporting tool to increase supervision in pools (Lu & Tan, 2002; Kam et al., 2002; Lu & Tan, 2004). These systems are specific to a swimming pool-like environment and will be difficult to implement for natural bodies of water such as lakes, reivers, and oceans. Expanding our work, we believe we can develop a monitoring system that can recognize swimming activities and provide a wearable life system that can recognize drowning and distress personally. The system will augment lifeguards' surveillance while keeping individuals safe. This work in relation to water safety knowledge by using our system as a basis can increase the activity recognition of swimming competency in non-competitive swimming strokes. We can develop a personal swimming proficiency examination to help people understand their skill level.

Conclusion

This paper focused on understanding competitive, and survival swimming activities of diverse skill level swimmers collected data. Most previous research studies have focused on the three swimming strokes (back crawl, front crawl, and breaststroke) used in competitive Olympic swimming events. We evaluated the locomotive swimming styles and flip turns related both to survival and to Olympic swimming. The goal was to understand all actions related to the education of water safety and effective and efficient survival swimming, so we incorporated treading water and sidestroke among the swimming recognition classifications. We have provided a novel insight into the classification of aquatic locomotor styles (a.k.a., strokes) and flip turns while evaluating all time windows, machine learning algorithms, and feature selections related to each swim stroke classification. With the ability to recognize a swimmer's stroke, we discovered other avenues of research to expand upon. We believe the recognition algorithm can restructure the education, sports, health, and safety fields with the current results.

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