Wrist-Based Survival Swimming Activity Recognition System

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Abstract
According to the World Health Organization, over 300,000 drowning deaths occur worldwide each year. One of the main contributors is lack of survival swimming knowledge; for example, the Redcross indicates that 50% of the population in the United States does not know how to swim. In this work, we explore the potential of using wearable technology to help address the lack of swimming training. Wearable technology like Fitbit or Apple Watch are smart devices that recognize people's activities and are increasingly integral to tracking one's health and well-being. When it comes to swimming or other aquatic activities, wearables have focused on professional and elite swimmers where devices support lap swimming strokes (backstroke, breaststroke, butterfly, freestyle) which are common in Olympic competitions. Our research expands lap swimming activity recognition by incorporating two survival swimming activities: treading water and sidestroke. We present a study which collects all six stroke types from a wrist-worn device, and we develop a machine learning algorithm that classifies activities with an F-measure of 0.94.

Introduction
Drowning is the leading cause of unintentional death worldwide, with over 300,000 drowning deaths every year, with most occurring in open water [1]. Many drowning deaths occur as a result of poor swimming skills [2]. Additionally, many deaths also occur due to an overestimation of one's swimming skills, indicating a disconnect between swimming skills taught by swimming education programs and the skills needed to survive in the water [3].According to the World Health Organization, drowning has been overlooked by governments and research bodies as a public health issue [4]. One in five drowning victims is a child under fourteen [5]. Over 50% of Americans do not know how to swim and 61% of American children cannot swim [6, 7]. Improving and further integrating swimming safety with education is thus of vital importance. With the rising popularity of water resistant smartwatches, we hope to explore ways to improve

swimming techniques and reduce the impact of poor swimming skills on drowning.

Water competency is difficult to define, and its very definition has changed in recent years. This means that creating a more unified curriculum for swimming education, particularly in children, has long been a complex subject. The American Red Cross creates a conceptual definition of water competency, where a competent swimmer can immerse his or herself in water completely, recover to the surface and tread water or float for at least a minute, be able to change orientation, moving in the water, and exiting from the water. Additionally, being able to adapt to different water conditions (e.g., variability in temperature, water clarity, calmness of the water) is an important characteristic to consider in classifying water competency [2, 8].

Swimming education programs have had more of a focus on teaching traditional swimming strokes used in competition (freestyle, backstroke, breaststroke, and butterfly), causing a disconnect between what constitutes water competency in those enrolled in such programs and the perceived versus actual swimming skills of swimmers [3, 9]. In particular, a study conducting a measurement of swimming skills using practical tests found that one-third of college students surveyed could not float for more than two minutes and around 48% could not float for more than six minutes, which are poor results in case of an emergency [9]. The use of technology to reduce drowning deaths has had some interest in recent years. One study prototyped a computer vision system that could differentiate between treading water and drowning [10]. Another study looked at using location information to keep track of swimmers in a pool and provide information on their current status (e.g., swimming stroke being performed, walking, not moving). Such a system could be used by lifeguards to help keep track of all swimmers in order to quickly notice a need for the lifeguard to step in [11].

Smartwatches have become popular in recent years, but could not offer more than the ability to keep time and view phone notifications, while being rather expensive. However, with the rise in popularity of smartwatch-producing companies such as Fitbit, Garmin, and Apple, there is a rising market for health tracking smartwatches. Health-tracking has become a subject of interest in industry application of activity recognition [12], and several companies, such as Samsung, Apple and Fitbit, have used activity recognition to track health statistics such as calorie-counting, distance-tracking and step-counting [13, 14]. Academic papers have also begun to track specific gym exercises [15, 16], sedentary lifestyles [17, 18] cleansing activities [19, 20], work actions [21, 22], and even road quality [23].

We first developed a data collection method using Pebble smartwatches and Android smartphones. Using data collected from participants at the Texas A&M Recreation Center, we focused on the identification of competitive swimming strokes (backstroke, breaststroke, butterfly, and freestyle), sidestroke, and treading water. Study participants wore smartwatches on both wrists, and swam for eight minutes at a time, with breaks as necessary. We classified this data using several machine learning algorithms with a variety of window sizes in order to determine the most optimal window size and most optimal algorithm. Classification results from wrist data were also compared to results from prior work using back-worn sensors in order to determine the effect of sensor placement on classification accuracy.

Related Work

The growing trend of using smartphone and smartwatch sensors in activity recognition has developed quickly, as the ubiquity and adaptability of smartphones and smartwatches has shifted research focus from using standalone sensors to using smart devices in activity recognition research. The ability to program smart devices and obtain raw sensor data allows for more complicated study design, and ubiquity allows for higher-quality research that is closer to mainstream usage [24, 25]. In particular, the trend of water resistant smart devices has increased the viability of swimming stroke recognition using these devices. In this section, we focus on prior work involving smart devices as well as prior work involving traditional sensors which paved the way for the research being done today in activity recognition with smart devices.

Sensor Placement in Activity Recognition

Collecting data from subjects can be done with a variety of different sensors with varying placements, all of which impact the accuracy of the resulting activity recognition. A study conducted using a Samsung Galaxy smartwatch compared the difference in accuracy when collecting data using both accelerometer and gyroscope sensors versus just accelerometer data. While accuracy increased when both the accelerometer and gyroscope data was used, collecting data from just an accelerometer is nearly as useful, meaning the results from multi-sensor data collection may not justify the additional computational cost [26, 27].

Computational cost is important to consider in activity recognition involving smartwatches, as collecting data at high sampling rates likely limits the multitasking capabilities of smartwatches. Another study conducted using over twenty different sensors placed on different areas of the body in identification of common activities such as sitting or standing similarly concluded that accelerometers tended to be the most optimal sensor for activity recognition. Accelerometers react quicker to changes in activity, and it is easier to differentiate between activities. Perhaps more interesting is that in this study, Pärkkä et al. noted that accelerometers placed on the wrist could not distinguish between sitting and standing [28]. This discovery may indicate that attempting to classify swimming strokes may prove extremely difficult to perform. Swimming stroke motions tend to be full body movements, and because of this, only placing a sensor on the wrists likely has its limitations. As such, placement of sensors involves a more nuanced discussion.

In order to assess the optimal location for sensor placement, many studies have been conducted using various locations. The sensor placements of importance to this work are the wrists [26–39] and the lower back [37, 40, 41]. The wrists are of interest due to swimmers often swimming with watches (both analog and smart watches) to keep time as well as track other health statistics in the case of smart watches. On the other hand, the back is a good position to place a sensor as it is in an ideal position to observe motion occurring on any part of the body. Much of the work done in the field concludes that the best placement for any sensor varies wildly depending on the exercise type, but for high energy activities (e.g., running, walking) the most accurate sensor placements are on the head, behind the ear, on the waist, and on the back. Sensors placed on the wrist or other extremities were most accurate for low energy activities [34].

Bao et al. conclude that wrist sensor placements are better at identifying upper body and arm movements, and also determine that complex activities may benefit from both upper and lower body sensors [29]. Comparisons of sensor placement are difficult to make unilaterally, as such comparisons require using the same features for each sensor, which can skew the results. However, sensor placement on the wrists make it difficult to perceive actions on other parts of the body, particularly leg movements. On the other hand, the easiest place to put a sensor is on the wrist (e.g., Fitbits, smartwatches), at least for mainstream application. These complexities with sensor placement result in advantages and disadvantages that should be considered in mainstream applications of activity recognition.

Broader Usage of Smart Devices in Activity Recognition

Although few studies have been conducted using smartwatches and smartphones in swimming activities, smart devices have been used to a greater extent in recognizing other activities. Weiss et al. used an LG smartwatch and Android smartphone accelerometers to identify various hand motions such as handwriting and dribbling a basketball, considering both personal and impersonal models. This study had an overall smartwatch accuracy of 70% for impersonal models. Additionally, the smartwatch was able to identify various activities that are less hand-dependent, such as kicking, standing, walking, and jogging, though less accurate in comparison [38]. Another study used smartphones attached to the waist to identify common, everyday activities such as walking, going up and down the stairs, and sitting with an overall accuracy of 89% [42]. Bartley et al. developed World of Workout, a mobile RPG designed to encourage individuals to become more physically active based on recognition of physical activities such as push-ups, weightlifting, running, and biking [15].

Studies have also been conducted using Pebble smartwatches to successfully identify daily activities such as eating, brushing teeth, and working out [16, 20, 33] with high accuracy rates. As a result of work done using smart devices in activity recognition, it is now possible to pursue recognition of more complex activities and bridge the gap from academic research to the mainstream. In particular, gauging swimming stroke ability had to be done in-person or through video as there is currently no other way for users to evaluate their swimming skills. Work has been done in swimming stroke recognition, but focus has been limited due to recognition complexity and technological limitations.

Swimming Stroke Recognition

Swimming exercises are a very complex activity, as they require both upper and lower body movements. However, sensors are hard to place in locations such as the waist or back for mainstream usage, as swimmers will likely not carry even a water-resistant phone with them into the pool. But placing sensors on the wrist may result in complications, as swimmers may not perform exercises the same way (e.g., water polo players tend to avoid using their arms while treading water). Being able to balance or overcome the weaknesses in our sensor placement will dictate the course of our future work.

The complexity in extracting quantitative measures from swimming strokes has been explored more in recent years, with many studies being conducted on swimming stroke recognition using sensors [31, 43–51]. However, much of this work focuses on recognizing competitive swimming strokes as they are focused on applying their work to the competitive swimming industry (e.g., swim team coaching). We intend to focus on recognition of survival swimming strokes, and bring attention to issues pertaining survival swimming skills.

In one study considering the impact of sensor placement on swimming, standalone accelerometers were placed on the wrist and back to identify swimming strokes. Siirtola discovered that the back sensor was more accurate in stroke recognition but the wrist sensor had more success in stroke count and duration measurements. Siirtola also demonstrated that the loss in accuracy when down sampling from 25 Hz to 10 Hz is approximately 1% [31]. Looking to the future, it is important to consider the impact on battery life data collection might have in mainstream use, as the limited processing power of a smartwatch imposes restrictions on available computing resources. With a 25 Hz sampling rate, accelerometer data is collected every 40 milliseconds. Ideally, collecting accelerometer data from users would be done in the background, meaning the user should be able to use the smartwatch for other usages, such as checking and responding to text messages.

Another study looked into the possibility of using smart devices to identify more than just swimming strokes, and attempted to extrapolate beyond stroke classification. Bachlin prototyped a SwimMaster system which measured swimming related characteristics, meant for use in coaching and correcting swimming form [47]. The study was able to extract the body balance and rotation parameters successfully, as well as stroke count and velocity. However, the usage of standalone sensors has limited applicability in real world scenarios, where using commercially available equipment, such as smartphones and smartwatches, can have a broader impact.

Methodology

The purpose of this study is to examine the characteristics of swimming stroke recognition using smartwatches versus smartphones, considering the difference placement (wrist versus back) has on recognition. We also consider the impact of relative swimming skills on recognition accuracy by requesting information about each participant's overall swimming skills and skill level for each stroke they perform through our pre and post questionnaires.

User Studies

User studies were conducted as stated previously in the introduction. The researcher used three smartphones, one for each smartwatch and another to collect start and stop times for each activity. Activity timestamps are collected separately to avoid user error as well as provide greater control over labelling of data (i.e. reducing incorrect labeling). This also allows us to collect data for as long as possible without needing the user to do anything other than swim and take breaks when necessary. Conducting studies this way is also more naturalistic, as we can attach the devices and let them perform their routine as naturally as possible. However, they will need to stop for a little bit after eight minutes for data to get sent to the smartphone and written to a file, but participants will not need to exit the water. Watches can be removed from the participant while they are in the water for this syncing process to occur.

For instance, we can collect data from participants who are in swimming clubs or teams at Texas A&M while they are practicing. We only label the relevant information, and once data is collected, they can continue practice while data is synced from the watches to the phones. This can also be incorporated as regular breaks for the participant while swimming.

Pebble Smartwatch App

Initially, we tried to use Fitbit smartwatches to collect accelerometer data from participants. Unfortunately, we encountered several issues that made using Fitbits in data collection error-prone and unreliable. The Fitbit SDK is limited in the sense that it does not allow

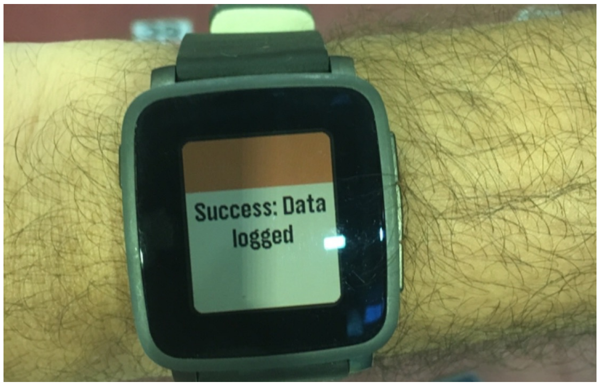

Figure 1: Custom Watch app Running on a Pebble.

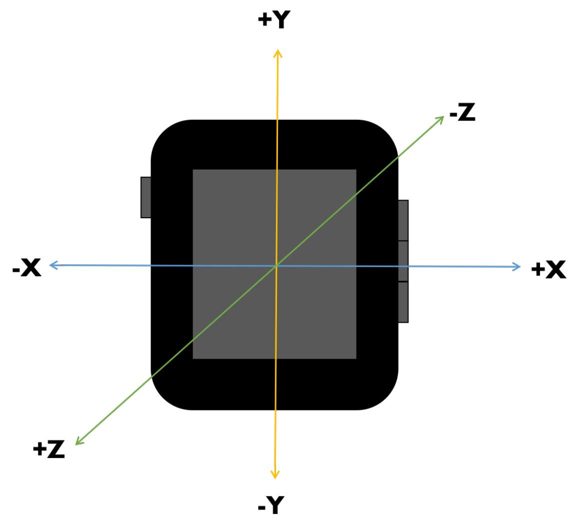

Figure 2: Pebble 3-Axis Accelerometer Axes

developers to develop custom third-party mobile applications to communicate with the Fitbit. It also does not provide any information about the current Bluetooth connection to the watch. This is difficult to use in a pool, as Bluetooth connections are often lost while in the water, and if data needs to be transmitted via Bluetooth, being able to verify connection status is required.

Additionally, data collected on the smartwatch is sent to the smartphone, but it cannot be stored on the smartphone. That is, the only way to collect data using Fitbits is to send data from the watch to the phone, and from the phone to a web server. We then decided that Fitbit smartwatches would not suffice for data collection currently. From this experience, we developed several criteria for choosing a smartwatch model for data collection.

In order to collect data while a user is swimming, we felt that the smartwatch needed to support a Bluetooth API, which allows the researcher to communicate with the smartwatch from a custom mobile application as well as provide information about the smartwatch Bluetooth connection. Additional support for persistent storage on the smartwatch was also required, as Bluetooth is not reliable in water, and we also looked at cost and ease of use in making our decision.

The Pebble smartwatch, although somewhat outdated, met our needs for this study [52]. It is readily available in the Sketch Recognition Lab [1] [53], and prior work has already been done in developing data collection software with these watches. It allows third party applications to communicate with a paired smartwatch, and can store data on the watch until a smartphone is available to receive the data with its Datalogging API.

The Pebble watch app, built using C and the Pebble SDK, collects accelerometer data for eight minutes at a time with a sampling rate of 25 Hz, at which point accelerometer data is no longer being requested by the app. It also displays text notifying the user if data is not being logged for any reason (mostly used for testing purposes). The running Pebble watch app can be seen in Figure 1.

[1] `http://srl.tamu.edu`Sketch Recognition Lab Website

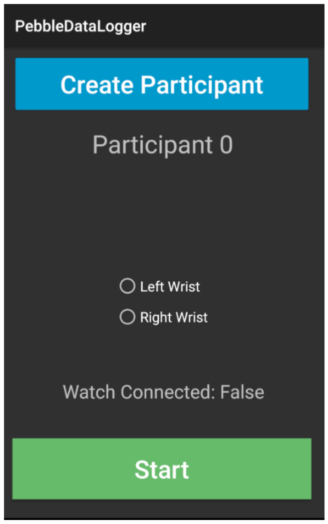

Figure 3: Android Pebble Companion App

Figure 4: Android Labelling App

Data is logged as an array of bytes, which must be translated by the corresponding Android app. Additionally, due to the amount of data being logged and the rate at which it is logged, data is sometimes cached in memory if the Datalogging session cannot be reached. This cached data will be logged to the watch after the eight minute timer ends.

Android Companion App

We chose to develop a third-party application to communicate with the Pebble smartwatch on the Android platform, as there are many resources to learn and develop for Android and very few limitations [54]. The graphical interface for the application can be seen in Figure 3.

The Android app has a GUI that allows the researcher to start the data collection smartwatch app without participant input, at which point data collection starts. The app also displays the current status of the smartwatch Bluetooth connection. Additionally, the app allows the researcher to display the current participant number, as well as add new participants. Data is received on the smartphone using an Android service, which segments the logic of receiving data from the main component of the app into a independent and separate component.

Data is converted into a Java class by using bitwise operators to convert the received byte array into x,y,z, and timestamp member variables of the corresponding class. Once all data has been received by the smartphone, the data is checked, removing duplicate entries and keeping data sorted by ascending timestamp. Data may need to be sorted as it may not arrive in order due to the caching process described above. This data is then saved to a file in .csv format, which allows us to use standard libraries for parsing .csv files, such as Microsoft Excel.

Android Labelling App

Using the graphical interface provided by the application seen in Figure 4 to label swimming strokes independently of accelerometer data collection, we can provide tighter bounds for the times in which swimming strokes are performed. For example, we can avoid labelling the ”push off” swimmers perform when they start a swimming stroke.

This app provides researchers a way to record the times at which a participant starts and stops swimming a certain swimming stroke. This method allows us to avoid labelling inactive data where the participant is not actually swimming any particular stroke. Prior methods of conducting studies would record some level of inactive data (e.g. participant walking to the pool), which would then have to be parsed and removed manually. We can also record flip turns with this app, which also allows us to avoid manually removing flip turns in order to preserve data integrity. This application was developed through prior work done with Powell [55].

Data Processing And Feature Extraction

In order to extract features and train a classifier using our accelerometer data, we first need to clean the data, extract features, and present it to our classifier(s) in a .csv file format, which is a file format that WEKA, a machine learning library, accepts as input for classifiers.

Data Stitching

Data collected from each wrist must be kept separate. This is because the orientation of accelerometer axes changes depending on the wrist the watch is on. The general orientation of Pebble smartwatch accelerometer axes can be seen in Figure 2. The gathered accelerometer data and the gathered label data must first be combined and split into folders for each participant, with files containing each swimming stroke performed. This process involves four major steps for each stroke:

1. Parse accelerometer data and label data.
2. Find the first timestamp in accelerometer data corresponding to the appropriate stroke start time.
3. Find the last timestamp accelerometer data corresponding to the appropriate stroke stop time.
4. Split the data between the first and last timestamps into a new file, named by stroke type.
5. Do this for every swimming stroke inside the label data.

Data Cleaning

After our data has been stitched, the next step is to manually look at each stroke for each participant and remove any inconsistencies, as well as make sure all flip turns have been removed from the swimming stroke files. Use of Python libraries allows us to visualize a large amount of data with little slowdown and also allows us to easily zoom in on certain sections, which makes it a perfect choice to examine such a large quantity of data.

Accelerometer Data

We present a graphical visualization of the accelerometer axes for each swimming stroke using the matplotlib library in Python in Figure 5. These are all samples of data after data stitching and cleaning has been performed. Each visualization is a four second window of each stroke because at smaller windows it gets difficult for humans to perceive patterns in the visualization.

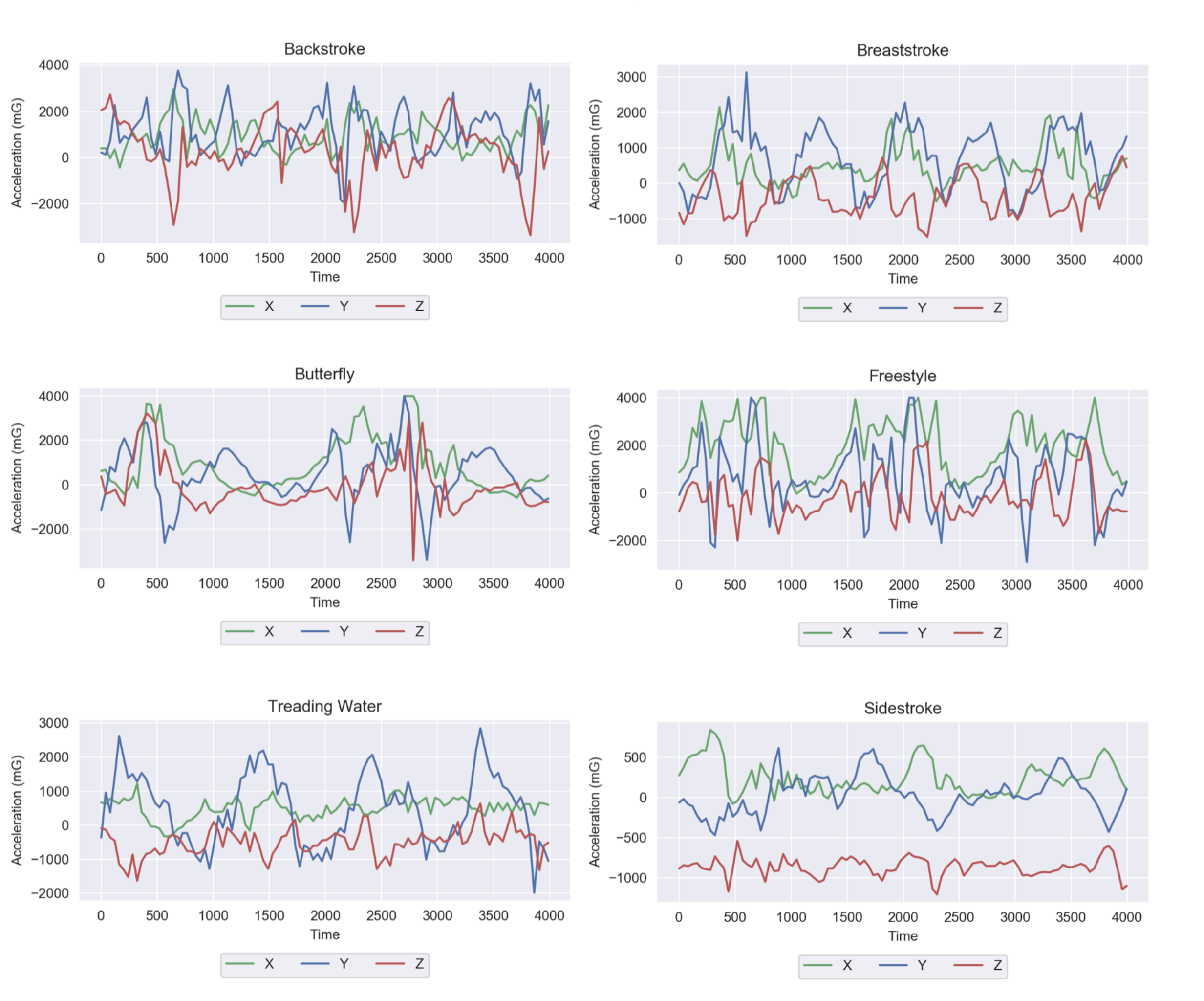

Figure 5: Visualization of Swimming Stroke Accelerometer Data

Once all data is appropriately cleaned, we can segment our data into sliding windows, where one window represents a discrete amount of time (e.g., four second windows). A sliding window has overlap between the previous and next window (e.g,. one second overlap). We test the impact of window size on classifier accuracy by extracting features from our data set with different window sizes and compare the results. In this work, we segmented our data into sliding windows with length 1500, 2000, 2500, 3000, 3500, and 4000 milliseconds each, and overlaps of 250 and 500 milliseconds.

Feature Types

In order to classify the obtained accelerometer data as a particular swimming stroke, we need to extract quantitative characteristics from the data that allow our classifiers to develop rules based on the most relevant characteristics. In this chapter, we focus on the mathematical generation of different features that are used generally within activity recognition, as well as ones that are more commonly used in swimming stroke recognition.

Traditional Features
Activity recognition has been a long studied topic in machine learning, and as a result, features commonly used in many activity recognition studies have become a gold standard [20, 56]. Here we split our discussion of these "gold standard" features into separate sections based on type: time domain features, and frequency domain features.

Time domain features refer to a subset of commonly used features that are dependent on all data in the current window (e.g., the maximum x accelerometer value in the window). These features are good at providing contextual information about each window but cannot be used to extrapolate on patterns that may exist within subsets of windows. For each axis, we compute the mean, standard deviation, correlation, and root mean square values in each window. We also use the skewness, kurtosis, peak value threshold, and valley value threshold as defined in [55].

Frequency domain features refer to a set of features calculated with respect to frequency rather than time. This requires a conversion from time-based data, which can be done using a Fast Fourier Transform (FFT) or Fast Time-Frequency Transform (FTFT). We use features calculating entropy, whose formula can be seen in equation 1.

$$\begin{gathered} FrequencyDomainEntropy = \frac{\sqrt{a_i^2+b_i^2}}{\sum_{k=0}^{N-1}\sqrt{a_i^2+b_i^2}} \\ a_i = x_i cos(\frac{2\pi f_i}{N})\, and\, b_i = x_i sin(\frac{2\pi f_i}{N}) \end{gathered} \tag{1}$$

Swimming-Related Features
Although traditional features provide a good starting point for recognition, features more related to the unique characteristics of swimming are needed to improve accuracy. In prior work using back-worn sensors, novel features were extracted and compared with traditional features in stroke recognition. Usage of novel features in recognition improved classifier performance [55]. Again, we use features in both time and frequency domains. For time, these consist of cross correlation, zero crossing count, and peak and valley angles, and for frequency, we use the power spectral density and discrete frequency in a window, all drawn from [55]. Specifically, these features focus on breathing and movement patterns that users display while swimming, as they vary by person and by swimming stroke.

Results
Prior to running our classifiers, we determined the optimal feature subset and removed any sub optimal features. The resultant feature subsets are listed below in Table 1. Out of the 60 features evaluated, nineteen features were selected. Out of these nineteen features, eleven were traditional features, and eight were swimming-specific. The highest performing window size and classifiers are listed below for both wrists in Figure 6.

Table 1: Selected Features

Feature Type	X-Axis	Y-Axis	Z-Axis
Average	✓	✓	✓
Root Mean Square	✓		
Standard Deviation	✓	✓	✓
Kuritosis			✓
Entropy	✓	✓	✓
Average Peak Angle			✓
Max Valley Angle			✓
Min Valley Angle	✓	✓	
Zero Crossing	✓		
Power Spectral Density	✓		
DC Component	✓		
Axis Average			✓

Considering our results, we felt that one potential reason for low performance could be because certain features have a high range of values, causing them to be implicitly weighted [57]. In order to test this hypothesis, we applied a standardize filter to our data after selecting the most optimal feature subset. This filter standardizes each feature to have a mean of zero and unit variance. This improved classifier performance, as can be seen below in Figure 7.

In order to determine the effectiveness of wrist-worn sensors, we compared these results to that of other work using back-worn sensors. Using data collected through a back-worn sensor, the same features used here were extracted and used as input to several different classifiers. Using Multilayer Perceptron and a 3000 window, with 500 ms overlap, a back-worn sensor can achieve an F-Score of 0.94 when attempting to classify all swimming strokes, as seen in Table 5. Comparing this result to those obtained from wrist-worn sensors (Tables 2, 3, 4) illustrates the difference in accuracy between wrist and back-worn sensors.

Table 2: Wrist Sensor 2250 Size Window With 250 ms Overlap, All Swimming Strokes

Total / Percent	Backstroke	Breaststroke	Freestyle	Treading Water	Sidestroke	Butterfly
Backstroke	115/0.88	9/0.07	2/0.02	0	4/0.03	0
Breaststroke	7/0.05	131/0.85	2/0.01	12/0.08	2/0.01	0
Freestyle	10/0.04	5/0.02	189/0.84	0	3/0.01	17/0.08
Treading Water	0	10/0.06	3/0.02	162/0.90	6/0.03	0
Sidestroke	6/0.09	11/0.17	6/0.09	17/0.26	25/0.38	1/0.02
Butterfly	0	0	13/0.24	0	0	42/0.76

Figure 8 also demonstrates the increase in performance that occurs when considering the various subsets of features used in back-worn sensor classification. The variation in performance between traditional, novel, and combined features indicates that novel features provide useful information when identifying patterns within windows, as described in Chapter . However, this information is

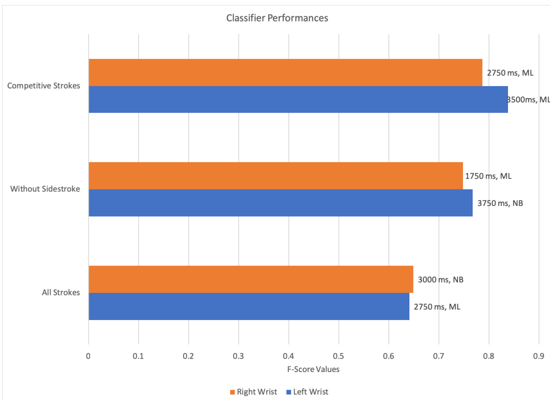

Figure 6: Classifier Performances, Left & Right Wrists; ML = Multilayer Perceptron, NB = Naïve Bayes

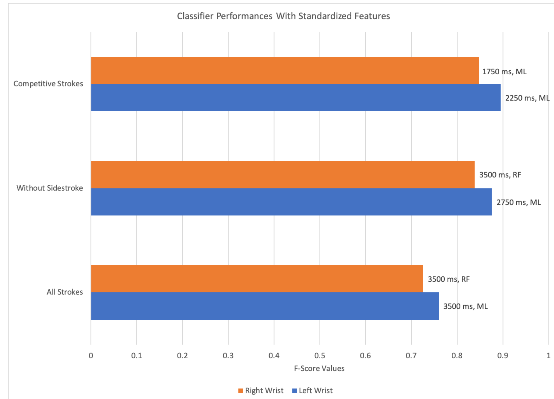

Figure 7: Classifier Performances, Left & Right Wrists; ML = Multilayer Perceptron, RF = Random Forest

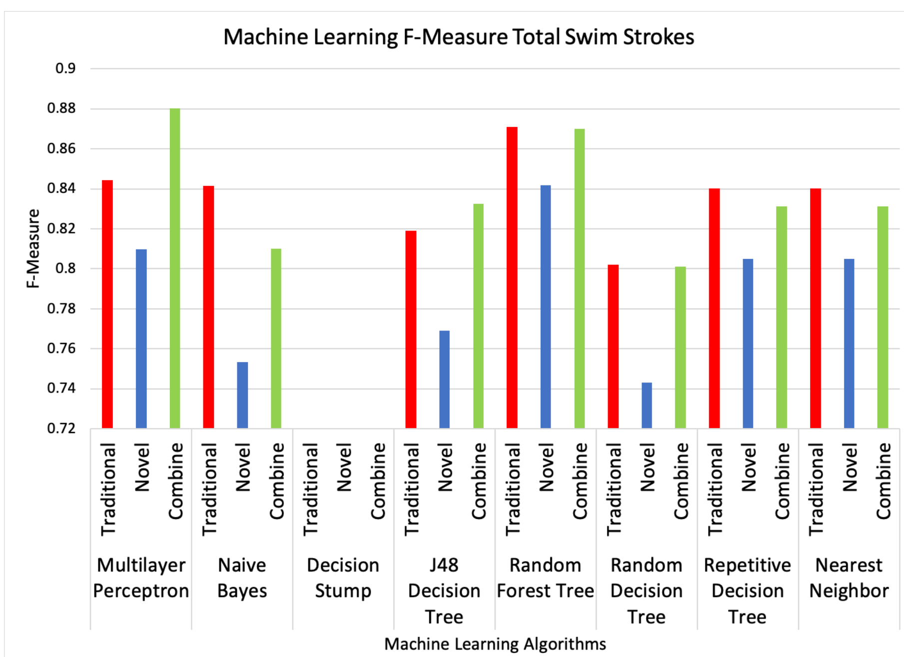

Figure 8: Classifier Performances for Various Feature Sets Using a Back-Worn Sensor, [55]

Table 3: 2250 Size Window With 250 ms Overlap, Without Sidestroke

Total / Percent	Backstroke	Breaststroke	Freestyle	Treading Water	Butterfly
Backstroke	94/0.88	8/0.07	2/0.02	3/0.03	0
Breaststroke	17/0.12	105/0.75	4/0.03	9/0.06	5/0.04
Freestyle	0	1/0.01	165/0.96	0	5/0.03
Treading Water	0	7/0.05	3/0.02	137/0.93	0
Butterfly	0	0	14/0.25	0	41/0.75

Table 4: 3500 Size Window With 500 ms Overlap, Competitive Strokes

Total / Percent	Backstroke	Breaststroke	Freestyle	Butterfly
Backstroke	68/0.85	11/0.14	1/0.01	0
Breaststroke	2/0.02	84/0.82	16/0.16	0
Freestyle	1/0.01	0	127/0.95	5/0.04
Butterfly	0	0	11/0.26	32/0.74

less useful without the contextual information about the window provided by traditional features, which is the likely cause of lower F-Scores for novel feature sets.

Discussion

Most notably, we found that sidestroke was consistently the most difficult to predict, as when sidestroke is removed from the picture, accuracy is much higher. This was contrary to our belief that treading water would be the most difficult to classify due to its more varied movements. Sidestroke is likely more difficult to classify because each arm is consistently performing a different motion. This makes it difficult to classify as a result. Results are highest when we only consider competitive swimming strokes, but they are still not quite high enough for mainstream usage. This is due to breaststroke and butterfly being difficult to differentiate.

For recognition, Multilayer Perceptron tends to perform the best, with Random Forest often a close second. Naive Bayes also performs well in certain situations, but Perceptron performs exceptionally well once data is standardized. One drawback of the Perceptron is still its complexity, as Random Forest is easier to implement and more space efficient. Both Perceptron and Random Forest benefit from large feature sets, as large feature sets need more nodes and more trees, respectively.

When comparing to other sensor placements, we see that the ability of wrist-worn sensors to identify swimming strokes is limited when compared to back-worn sensors. Wrist-worn sensor results indicate a maximum F-Score of 0.76 while a back-worn sensor results achieve an F-Score of 0.94 using the same features, though different subsets are used [55]. This indicates that the back is a better position to place a sensor with the current feature set. With additional features, performance may improve for wrist-worn sensors, though the amount of possible improvement is unknown.

As previously indicated, treading water is easier to classify than sidestroke, but this also indicates that treading water motions are distinct and have enough hand movements to discern the motion,

Table 5: Back Sensor Classification Confusion Matrix, [55]

Total / Percent	Freestyle	Backstroke	Breaststroke	Butterfly	Treading Water	Sidestroke
Freestyle	172/1	0	0	0	0	0
Backstroke	0	69/1	0	0	0	0
Breaststroke	0	0	103/1	0	0	0
Butterfly	0	0	23/0.37	38/0.63	0	0
Treading Water	0	0	0	0	107/1	0
Sidestroke	0	0	0	0	6/0.09	59/0.91

at least in general populations that are not familiar with treading water techniques used by water polo players.

Overall, results illustrate the difficulty of identifying full-body motions using only one sensor placed on an extremity. While recognition of some swimming strokes is possible with fairly high F-score, recognizing all six swimming strokes is incredibly difficult. Further improvements to the model would need to be made, particularly to aide in identifying between breaststroke and butterfly, and classifying sidestroke.

One possible source of improvement is to consider the direction the wrist is moving, and extract additional features based on the current direction of the watch. The current feature set being used does not consider the current velocity of the sensor, as the feature set was originally developed for back sensors, which remain stationary.

Some of the results may also have been influenced by noise in the datasets. This can be addressed through resampling to reduce noise and establish a consistent sampling rate. Applying a standardization filter to our datasets after selecting an optimal feature subset improves results, likely due to implicit weighting of features with large ranges.

Study Limitations

Data was collected in a semi-naturalistic setting, as participants were asked to perform swimming strokes but were not obligated to do them in any order. But this study is still a laboratory study, as researchers were required to be present to perform labelling and facilitate data collection.

Another limitation is in the usage of smartwatches. Data was collected at a sampling rate of 25 Hz, but due to smartwatch sensor limitations, any window with a sampling rate not between $\pm$ 10% of the sampling rate (22.5 - 27.5 Hz) was excluded from data analysis.

Being limited to data collection for eight minutes at a time does not allow us to collect data from participants for the entire duration of their swim, and also can make participants more aware of the watches themselves, as researchers will have to remove the watches from participants in order for data to sync from watch to phone.

This synchronization time is also significant, as data cannot be collected, and the time it takes for the watches to sync collected data to the phone is often erratic, and takes anywhere from one to four minutes.

CONCLUSION

This work focuses on comparing the identification of swimming strokes using smartwatches on the wrist to results from prior work using back-worn sensors. Our results illustrate that sensors placed on the wrist have difficulties identifying sidestroke, and differentiating between breaststroke and butterfly.

We achieved an F-Score of 0.76 with Multilayer Perceptron when differentiating between all swimming strokes. In comparison to sensors placed on the back, wrist-worn sensors are less performant in identification, as an F-Score of 0.94 can be achieved with a back-worn sensor when identifying all swimming strokes. While accuracy of wrist-worn sensors is lower in comparison to back-worn sensors, no past studies have valued treading water and sidestroke enough to study its effect in swimming stroke recognition for either sensor placement. In particular, treading water not only has immense value in dangerous situations, it is also one of the most common activities swimmers will perform in the water.

User Studies

With the usage of modern technology, user studies can be performed without requiring swimmers to get out of the water. Additionally, because labelling of activities is done by the researcher present during the study, there is less manual pre-processing that needs to be done. Prior iterations of the system developed in Chapter labelled data on the smartwatch itself, requiring manual splicing of turns. With further improvements to the system, collecting data for a longer period of time is also possible.

Data Collection

In order to perform this work, a system needed to be developed that could collect accelerometer data from swimmers. We developed a system that performs this activity and can be used without buying specialized equipment meant for swimming stroke recognition. All that is needed are Android devices and Pebble smartwatches, which are all commonly available and can be used for more than just swimming stroke recognition.

Accelerometer Sensor Features

Usage of features traditionally used in recognition and additional features related to peaks and valleys improved results significantly. Furthermore, standardizing feature subsets to have zero-mean and unit variance improved our results, indicating that paying attention to the distribution of data for each feature may improve recognition.

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