uF!t: A Framework for Monitoring Exercises

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ABSTRACT

Common reasons for the low motivation to exercise include the absence of an exercise partner and the large time investment required in traveling to the gym. Some responses to this issue have divulged possible solutions: joining an exercise support groups or focusing on exercises that can be done without gym equipment. While both suggestions are practical, studies show support groups are notable in that they have been known to be effective at keeping individuals adhere to a regular exercise routine. Furthermore, the modern evolution of social networking sites has allowed for support groups to form online. In our current iteration of uF!t, we are able to track situps. Before further improvement in the system, we completed an evaluation focused on the system's ability to count situps. After establishing the fact that uF!t is best placed on either the chest or the side of the chest, we were able to retrieve good results from tracking situps. At the moment, uF!t is good at tracking slower speed situps, with slower being defined as completing 1 situp in 3 seconds or more. From our evaluations, we believe that uF!t has great potential to become a system that is more than just situps.

1. INTRODUCTION

Currently, America's healthcare costs have been rising more and more each year. One of the most influencing factors in this phenomenal increase is due to obesity. In 2008, obesity healthcare costs account for at least 10% of total medical expenditures which amounts to approximately 147 million dollars a year [6]. In addition to the lack of control over how well a patient follows drug regiments, doctors cannot guarantee that their patients maintain a regular exercise schedule. In a case study involving 20 patients, on the first day all patients agreed that they would maintain their regiment, but after three months, only seven patients had continued their exercise regiment. In eight months, only five were consistent with their exercise regiment [12]. This case study reflects the same trend that is present in among the general populace joining exercise programs in America. Current studies show that 50% of Americans that join an exercise program, will drop out within the first six months [10]. In order to help the reduction of obesity issues, medical devices have been created such as body wireless sensor networks that are used to either provide body posture correction/monitoring or track daily activities. In many cases, body wireless sensor networks that are used to track an individual's activities attempt to motivate users to lead more healthy lifestyles [5],[13],[1]. The uF!T framework acts as a motivational tool that provides convenient exercise tracking on-the-go. By taking out the need to have a gym or time allotted for exercising an individual would be able to take advantage of small pockets of time to exercise. Therefore, uF!T intends to assist an individual with a busy lifestyle maintain a healthy lifestyle. Researchers have found that devices that monitors a person's vitals or exercise information is conducive to one's health [14]. Currently, people are able to track their exercises by recording it on paper or logging it in a spreadsheet. However, both of these methods are prone to human error, since you can easily forget the number of repetitions completed for each exercise in a workout. This can be especially difficult when completing exercises on the go, where paper or laptop access is not as easy. With uF!t, we will be able to eliminate the need of dedicating memory to exercise results, enabling user's to focus more on their workout at any time, thus maximizing the gains from a healthy exercise [14].

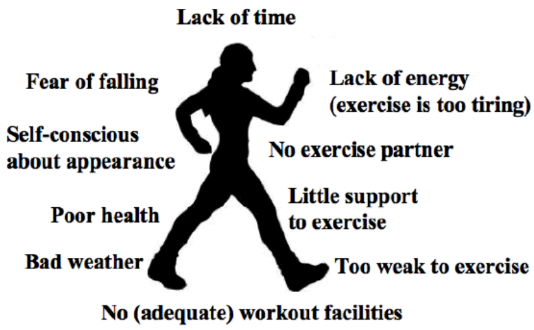

Figure 1: Some of the many reasons for not exercising.

1.1 Why don't people exercise?

While exercise is the main solution to help reducing obesity, people still choose to not exercise despite the health benefits. Some researchers believe that this is due to the increase in fast-paced lifestyles. In many cases, people just simply state that they do not have the time to maintain a regular exercise schedule, either due to long work hours or other schedules (*picking up kids, attending city meetings, taking care of family, etc.*) that make people generally unavailable.

Researchers claim that the general decrease in exercise in the US population is is mainly a consequence of technology replacing usual forms of exercising [6]. Previously, traversing long distances were completed by either walking or riding a bicycle, whereas now such distances are covered by either driving or use of public transportation (which generally involve an individual to be sitting). Following the advancement of technology, activities that involved physical activity are now being phased out. Even the household vacuuming can be replaced by purchasing a Roomba robot. In addition to fast-paced lifestyles and unavailable schedules, researchers attribute people's lack of motivation to workout to several different reasons as seen in figure 1 . Looking at the figure, we can see that lack of motivation is due to inability to obtain moral support from a partner or support group. It has been proven that people are more inclined to stick to an exercise regiment if they have a friend or family member that can assist them [17]. Following what is described in the article by Plante, having an exercise partner improves the amount of stress relieved during a regular exercise routine. Admittedly, we do not believe that uF!t is capable of solving every problem listed in the figure. However, we believe that uF!t has the possibility to solve two problems: *no exercise partner* and *lack of time*. in following pages, we will find results about being able to correctly detect peaks from the accelerometer and gyroscope. Additionally, we will test proper locations for the placement of uF!t to minimize the amount noise generated by a user's movement. Lastly, we wish to measure the accuracy of our system by doing trial runs with random individuals. By using random individuals, we will also be able to measure if our system is comfortable enough for users of various sizes. Through an evaluation of the system's current ability to measure situps, we believe that uF!t already has the groundwork that will allow it to track a multitude of various calisthenics.

2. OVERVIEW

Our paper will be organized into the following sections: Initially, we will introduce the components that comprise uF!T's system architecture, the current implementation of uF!T, an evaluation of the uF!T sensor, related work and future plans for the uF!T.

3. SYSTEM ARCHITECTURE

Our system consists of an program that counts situps. Upon the completion of a situp, if uF!t properly detected the situp, it will communicate to a base station/gateway (laptop or desktop) wirelessly with a message describing how many situps have been completed so far. Once the workout has been completed, we want to upload the data to a social media application like Facebook or Twitter; Figure 2 describes the system that we are currently trying to achieve. Of course, the social media integration has not yet been implemented, you can find more information on this in the Future Works section. In this section, however, you will find information about the components about what is currently working in uF!t.

3.1 Exercise Counter

We have specifically defined features for our counter to look for: the counter will look for peaks and troughs by filtering sensor measurements through a complementary filter. In our current iteration, when a user is doing a situp, their body oscillates between two varying angles: the rest and the peak. We currently can count the amount of rest-peak pairs that have been completed, thus representing the amount of situps completed.

In order to recognize a peak in the measurement data, such as the angles found from our situp detector, we would like to set threshold values that would represent the minimum value to be considered a rest and the maximum value to be considered a peak. Each peak in the measurement readings would consist of data points that are above the peak threshold value. It is common to have multiple data points classify to be a peak value. The number of successive peak values indicate confidence that a peak is correctly observed. Typically, higher frequencies in a given would indicate a stronger confidence that a peak is indeed there while lower frequencies (one or two peak detections) might indicate some noise. In order to make our system more robust to misclassification due to noise we propose the following conditions:

1. In order to be classified as a peak there must be at least 3 consecutive peak classifications. Otherwise, the classification is assumed to be from noise.
2. If a peak is classified recently another peak classification would be counted toward the recent peak instead of classifying a new peak.

Furthermore, threshold values are initially chosen by hand. In order to account for the potential to have different forms of data for individuals, these threshold values will be user-specific. We hope to gain this information by dynamically updating these threshold values and store these in a user profile on the social media application.

3.2 Wireless Communication

Exercise counts are delivered wirelessly to a base station. Once a mote detects the completion of a situp, it will use a broadcast method called identified Best-effort local area broadcast. Messages that are sent to the base station are received through another mote connected to the base station. We chose to implement wireless communication as mote-to-mote communication because of the simplicity of construction. The structure of wireless communication code on both motes are basically identical.

Overall, the Best-effort broadcast will periodically broadcast about a completed situp until it receives an acknowledgment from the receiving end. Implicit in this form of wireless communication we have accounted form security: included in the message is a header that identifies the sender and the receiver is hard-coded with the address of the sender such that only messages sent from the specific sender will be accepted.

4. IMPLEMENTATION

We used the Tmote Sky for the basis of our project. The Tmote Sky can be powered by two AA batteries, however in our current implementation of uF!t, it is still wired, thus not requiring the use of batteries. Besides the electrical components, we have encased our device using a lightweight plastic container (similar to a soap bar case). The housing for our

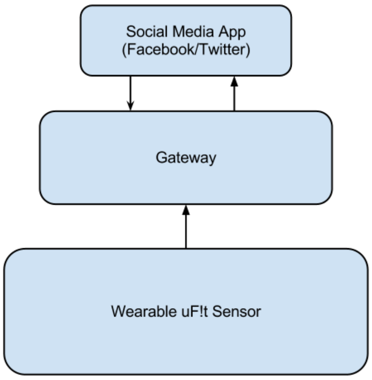

Figure 2: An overview of the system we are implementing.

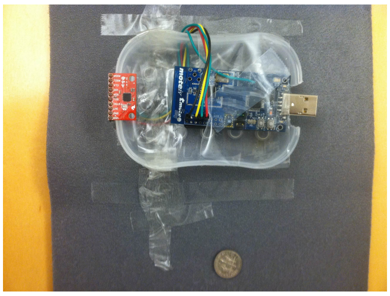

Figure 3: The current casing for our uF!t device, size compared to a dime.

device helps the sensor sit in a stable position. The data is already noisy, so it is important that the sensors are not given more opportunities to be mutated by noises induced by the sensor rocking carelessly.

To secure the device around a user's body, we have attached a neoprene corset to the uF!t's casing. The elastic qualities of the neoprene corset allows us to secure the device around big, as well as small, bodies. This versatility has allowed us to further reduce any noise produced from rocking the sensor and it has proven to be comfortable as seen in our evaluations.

4.1 Software: Contiki 2.6

Unlike a standard out-of-the-box Tmote Sky, we use Contiki 2.6, instead of using TinyOs. We chose to make this decision since our team was much more familiar with C, which made it much easy for us to quickly understand native functions in Contiki 2.6. Additionally, this allowed us to focus on understanding how to integrate the accelerometer and gyroscope's functionality into Contiki.

4.2 Hardware: mpu6050

We have connected the 3-axis Gyro/Accelerometer mpu6050. The gyroscope contains various degrees of sensitivity, which can be easily modified with Contiki functions that we have created. The mpu6050 sensor also contained a temperature gauge; for the time being, we did not incorporate the temperature gauge into our project, but we believe it may have later uses (for more info please look at future works).

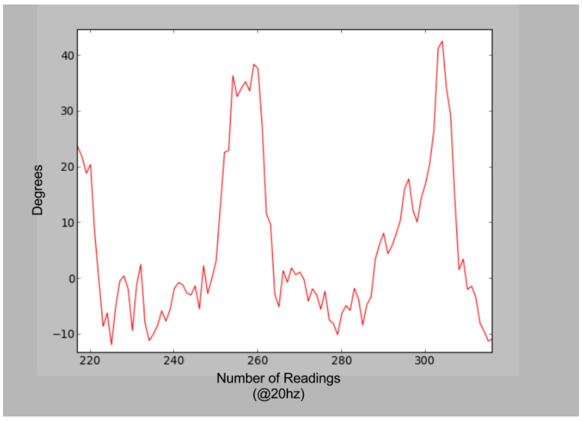

Figure 4: The results of the accelerometer.

To ensure that we could track a user's body while doing a situp, this required more work than just using the accelerometer and gyroscope raw data to do localization. As such, we ran through some equations that either used the accelerometer or the gyroscope. However, after running some tests separately on the accelerometer and gyrscope, we decided that we would need to use the measurements received from both devices in order to calculate the angle of user's body.

4.3 Accelerometer

In order to track simple movements like a push-up or situp, it was easy to determine by focusing on variation in the accelerometer's z (for the push-up) and the accelerometer's y (for a pull-up). However, in order to calculate the angle of the user's body with respect to our sensor, requires some trigonometry.

$$angle_{accel_x} = \arctan(accel_x, accel_z) + \pi \tag{1}$$

Using the equation above allows us to calculate the tilt angle for the accelerometer. Remember that arctan, known as atan2 in contiki, outputs between the range of $-\pi$ and π, so you must add π to the results of arctan to have the range converted to 0 to 2π. Having no initial knowledge in the usage of accelerometers or gyroscopes, we believed that the accelerometer would have served its purpose for calculating the wearer's body angle during a situp. However, if we look at figure 4 we can see that our initial assumption was clearly untrue. The accelerometer is great at calculating angles for stationary positions, but it is terrible at tracking the rapid movements experienced during a situp. After doing a realtime comparison of an actual situp and the data we recorded, it turns out that the accelerometer reports angles exceedingly lower than what is actually completed. In our initial tests, we only did situps up to angle of 60°, however when we look at figure 4, we can see that the highest recorded peak is about 40°. Additionaly, the data that we received was noisy, so this was unsuitable for accurately tracking a user's angle.

4.4 Gyroscope

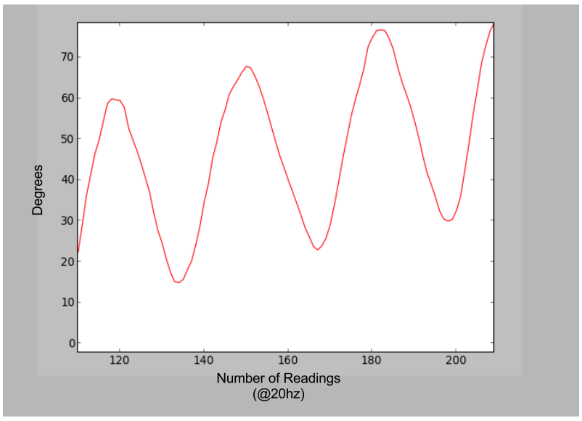

Figure 5: The results of the gyroscope, smoother than the accelerometer results.

The gyroscope is able to calculate angular velocity in degrees per second, which lead us to think that the gyroscope would provide more promising results. For the gyroscope, we used this simple equation to calculate the angle.

$$angle_{gyro_x} = angle_{gyro_x} + gyro_x * dt \tag{2}$$

Gyro is the degrees per second ($°/s$) recorded from the gyroscope, while delta t is the sample period calculated from the sample speed. Multiplying the gyro by sample period, gives us the angle calculated within one cycle, which can be accumulated in our total angle. Successfully being able to calculate the angle using the gyro, we were certain that our results would be promising. Looking at figure 5, however, the gyroscope's measurements are constantly increasing by a fixed amount as time goes on, this is called *drift*. From our gryoscope analysis, the gyro not only experiences drift (about $5°/s$), but it also is not centered properly. Currently, when the gyroscope is stationary, it returns an angular velocity of $34°/s$. in motion.

4.5 Complimentary Filter

From our analysis, we can see that both accelerometers and gyroscopes have their own pros and cons. The accelerometer is really good at detecting static positions, however whenever it is moving very quickly, it returns very noisy data. In contrast, the gyroscope is really good at detecting rapid movements, however its data drifts over time, making it increasingly inaccurate the longer you monitor the gyroscope.

Now the solution to our predicament is to try using a combination of the accelerometer and gyroscope data. A lot of the research we found involving body movement detection utilized either the Kalman Filter or other variations of it (Extended Kalman Filter, Fast Kalman Filter, etc.). However, in our research we were not able to find any articles about utilizing the Complimentary Filter to analyze data. Since the Complimentary Filter is computationally cheaper than the Kalman Filter, we decided to begin our research here [2].

$$angle_x = (a) * (angle_x + gyro_x * dt) + (1 - a) * (angle_{accel_x}) \tag{3}$$

With the knowledge that we cannot rely on the gyroscope for long periods of time, it is important to calculate a good time constant. The time constant helps determine the coefficients used in the filter.

$$\tau = \frac{a * dt}{1 - a} \tag{4}$$

The time constant may vary from user to user depending on the reliability of the gyroscope's data and the sample rate. The time constant defines the boundary between trusting the gyroscope and trusting the accelerometer. In our time constant, we used a time constant of *.5 seconds*. We had chose this time constant due to our results from the gyroscope. It is important to choose a time constant that will work with the amount of drift generated from the gyroscope. This means that for any measurement that is lower than half a second, the algorithm will take the gyroscope's measurements into consideration. However, for any measurements that take longer than half a second, the accelerometer will have more weight, allowing it to take precedence over the gyroscope. Remembering that the gyroscope drifts over time, so for the results that are recorded short periods, such as a quick rise during a situp, it is very reliable. However, consider a user that has already risen and is waiting at the peak of their situp. In this situation, the gyroscope will become unreliable as time continues to expire, so it is better to trust the accelerometer's data because it is suited for recording angles in stationary positions. Using the complementary filter in this style, allows us believe that we will be able to record situps at varying speeds.

5. EVALUATION

In order to estimate how well our uF!t system is working, it will require the evaluation of two things: Peak Detection and Proper Sensor Placement. Peak Detection allows us to determine whether the user has successfully completed a situp or not. This algorithm is important in being able to correctly detect a situp. Without good recognition of a simple situp, we would be unable to trust our system, which means that we would not able to further implement new exercises on our system. Proper Sensor Placement is important for making sure that the data we record is consistent. By placing uFit in neg- lible areas, the data may suffer from additional unwanted noise, which would make it more difficult to detect good exercises.

5.1 Peak Detection

There are two important terms that we use for our Peak Detection algorithm: *peaks* and *rests*. Peaks are moments where the user has effectively slowed their angular velocity to 0, while also being above a threshold value. Rests are the complete opposite, they are moments where the user's angular velocity is close to 0, while also being below a threshold value In our current implementation, we have designated zones to represent ”good” areas for peaks and ”good” areas for rests. These ”good” areas are set by threshold values that has been determined by us for our studies. 50° or higher represents the threshold value for peaks, while 10° or below represents the threshold value for rests. We have chosen these threshold values based upon monitoring other people who were doing situps. Of course, we admit that currently having static threshold values is not the best implementation for detecting situps. However, we found threshold values provided us a quick and simple way to begin detecting situps without having to use anything that is computationally heavier. Looking at Figures 6, 7, and 8, we already have results from the threshold values that we selected. The upper blue dots, represents detected peaks, while the lower green dots represent detected rests. Like our competitors, we too have provided in-sensor calculations, allowing us to minimize the amount of data that will be sent once we begin working on wireless communication support.

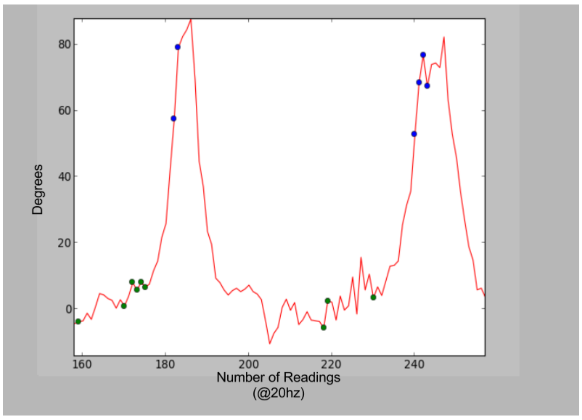

Figure 6: The results of the complimentary filter with sensor placed on the center of the chest.

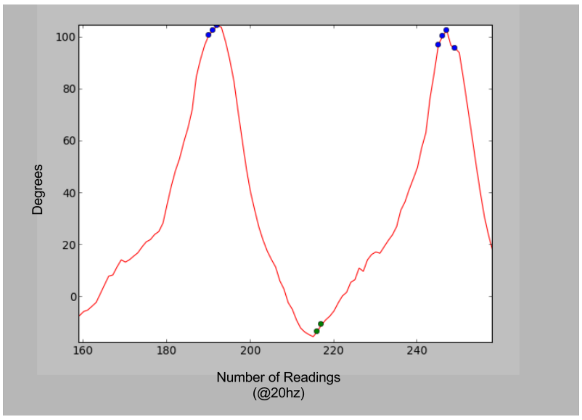

Figure 7: The results of the complimentary filter with sensor placed on the side of the chest.

5.2 Proper Sensor Placement

For testing proper sensor placement, we tested several areas where the sensor could be placed on a user's body. As stated earlier, it is important to choose a good location for the system since it may affect the overall quality of the data. Additionally, we must consider whether or not if the placement of the sensor is comfortable for the user. In our preliminary tests, it seems that it was acceptable to place the device on the following three places: *the arm, center of chest, and the side of the chest.* We assumed that the center of the chest would provide us with the most accurate data, since it is centered at the body and it should not affect any of the data since the chest area is generally an even area for people of most sizes.

Looking at the graphs depicted in Figures 6, 7, and 8 , we see that our initial assumption was actually incorrect. It seems that the sensor obtained the best results when it was placed on the side of the chest. Of course, we expected that the arm would not be the best place since depending on the user, they may either do a situp with their arms placed on the side of their body, or they may do it with their arms crossed across their chest.

These results were nice for our initial attempts, however, we believe that it lacks the diversity of different sized bodies for the test results. We believe that if we can get more people for our analysis, we can see if the positions that we have provided are universally good for different sized people. So far our preliminary results have been tested on average-sized males, which currently is a limited scope of view considering that we wish this device to be used by many people.

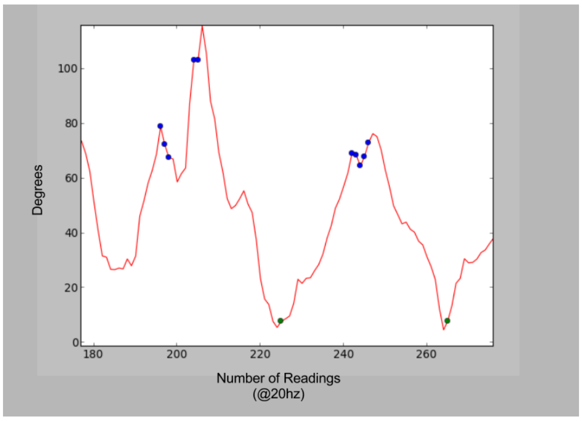

Figure 8: The results of the complimentary filter with sensor placed on the arm.

5.3 Accuracy

Remembering the last section, we determined that it is important that we are able to detect the correct amount situps with individuals of varying body types. For our next tests, we used four random individuals to do situps while wearing our uF!t device. Each user was properly informed about what our device is capable of, and they were given the choice to decline if necessary. Our test comprised of three different situp speeds: *fast, normal,* and *slow.* Fast is equivalent to completing a situp every second, while normal is completing a situp every two seconds and slow is completing a situp every three seconds. The objective of each testing speed was to complete ten situps.

To ensure that each set of situps was completed in the same fashion, participants were given a 10 minute break to allow them to recuperate if they were feeling fatigued. Determining the accuracy of each setup involving the comparison between the amount of situps that uF!t detected and

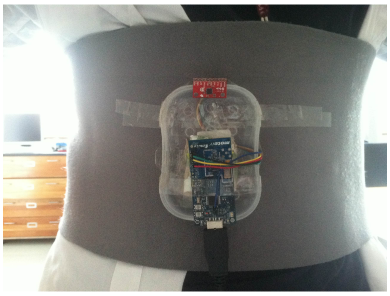

Figure 9: Example of participant wearing uF!t device.

the amount situps counted. As stated earlier, the stress of workout can impact a person's ability to record situps. To avoid the human error of our participants, we allowed third parties to count the amount of situps being done for each subject.

For our sampling speed, we chose 20hz for our measurements. As seen in some related works, there have been tests using higher sampling speeds to record data [8]. However, when reading about the SATIRE device, their group was able to achieve decent readings with using only 25hz [13]. In accordance with our future works for uF!t, we wish our device to be usable on the go. We will not be able to accomplish this goal if our device consumes too much energy. Higher sampling speeds means that our device will have higher power consumption. In our initial design of uF!t, we found that 20hz was the lowest sampling speed possible while still producing reasonable results; lower sampling speeds were unable to keep up with the slowest situp speed.

If we look at the table 1, it seems that our device is highly accurate when the user is utilizing a slow situp speed (average of .7875). Unfortunately, as the user completes sit-ups at a normal speed, the device's accuracy drops by a factor of 1.88 (average of .425). This accuracy drops even further when the user is completing situps at a fast speed, dropping by a factor of 5.3 when compared to the slow situp speed (average of .15).

5.3.1 *Participant's Comments*

Considering that we intend uF!t to be used by different people, it is important to record our participants initial thoughts about our device. After the completion of the test, each participant was allowed to see the results of their situps and were asked a small questionnaire with the following questions:

1. Do you consider yourself a casual or hardcore exerciser?
2. Did you like using the uF!t device? Was it comfortable?
3. Any additional comments?

Out of the eight test subjects, five identified their-selves as casual exercises saying that they enjoyed that the device was able to track their situps when they were completing a slow set. However, the other three participants that classified as hardcore did not appreciate that the device was unable to detect a fast set of situps. The hardcore exercises said that they needed to do a larger quantity of faster situps to reap any benefits. Some participants commented that the important part of recording the situp is the rise. This confirms some of our observations during the tests where a participant's situp would not be detected until a proper rest-peak pair was confirmed on the situp device. There were also comments about the device still being comfortable, despite it being worn by participants of vary sizes. As we described in Proper Sensor Placement, it is important to gauge the comfortability of doing the situps with the device, since its placement can provide unnecessary noise into our data sets.

6. RELATED WORKS

Unlike uF!t's use of the accelerometer and gyroscope, one of our main competitors rely on the raw measurements received from using only 3-axis accelerometers [1] . However, unlike our design, they use multiple accelerometers. This allows their system to have more versatility than the amount of exercises that we are attempting to track. So far, our exercises are limited to calisthenics, whereas myHealthAssistant can do resistance and weight training exercises. The ability to do more of these exercises come at a cost. In their paper they do not cover the amount of power consumed by using multiple sensors. This can make or break the effectiveness of myHealthAssistant since it is not useful to record multiple exercises with only a short amount of battery life. In our current design, we admit that we have not provided results for uF!t's battery life, too. However, we have not reached the phase where we can focus on analyzing uF!t's battery life. For these reasons, we make note of myHealthAssistant's lack of battery life discussion because it is important reminder for a device that is marketed to be used by people that are on the go.

SATIRE is another system that rivals some of the functionalities that uF!t provides. In SATIRE, they create a body sensor network that is integrated into a simple winter coat [13]. Their work is related to uF!t since the system they create involves determining the activity being performed by the wearer. They use simple actions such as walking, sitting, climbing stairs, typing, and reading. To monitor these actions they use an *exponential weighted moving average* (EWMA) filter. We find this paper very interesting, since they use it as a way to figure out basic repetitive actions (they provide 4 labels: stillness, typing, walking, fall). With the uF!t device, instead of monitoring day to day activities like SATIRE, we wish to focus on calisthenic exercises. Even though SATIRE is only for tracking normal activities, it allows them to maintain records on the wearer's health. uF!t provides flexibility, considering that it is not only good for maintaining the user's health, but useful for improving one's health as well. Our uF!t device, once fully completed, can be used for people and patients who wish to be healthier through doing simple calisthenics. As stated before, uF!t will be able to track your progress by storing results from daily workouts, whereas SATIRE is not necessarily an exercise device, but only a device that monitors your current health and activity. Similar to SATIRE, we have found other researchers who have attempted specific movement recogni-

Table 1: Accuracy of Situps

Participants	Accuracy (Slow)	Accuracy(Normal)	Accuracy(Fast)
1	.8	.4	.2
2	.9	.7	.1
3	.5	.1	.1
4	.8	.5	.2
5	.7	.5	.2
6	.9	.4	.1
7	.8	.5	.1
8	.9	.3	.2
Average	.7875	.425	.15

tion. The system provided by John Varkey et al, focused on classifying different movements, such as the following: standing, walking, smoking, jogging, and writing [7]. Unlike SATIRE, however, they used a machine learning approach by implementing a support vector machine (SVM), to recognize the different activities. Although their results are not useful to the current iteration of uF!t, we believe their research will be conducive to our efforts to recognize different calisthenic exercises.

Wireless Body Area Network (WBAN), is another device that has gait/motion detection [4]. However, WBAN, unlike the other research we found, is capable of measuring your "fitness level" while exercising. Beyond the accelerometer for gait detection, WBAN has several additional components such as: Temperature/Humidity monitor, Electrocardiogram sensor, motion sensors, and SpO2 (Oximeter). Following a model similar to ours, WBAN can forward this information to a gateway, which in their case is a PDA. From the PDA, the information is forwarded to various servers, which can either be a medical official's server, your home computer, or your emergency contact's computer.

Many mobile application developers have sought to provide creative solutions that complement a packed schedule and low interest in exercising. Mobile devices such as smartphones, ipods, and chips built-in shoes now are equipped with considerable computational power and are very portable. Some notable examples of mobile devices are as follows: Nike fit (an ipod application that is available on most ipod devices) is available on many Ipod devices as an application that encourages users to run by logging the distance run, calories burned and time of an individual's runs. Another application is *Zombies, Run!* which has sought to encourage individuals to exercise by introduce a gaming aspect to the routine as well as the ability to share results via social media. The *Zombies, Run!* application has shown to be successful by popular account and has therefore involved encouraged many people to exercise more [18]. Zombies, Unfortunately, the *Zombies, Run!* application is extremely limited in its variety exercises. Researchers believe that there is some correlation between exercising and social media applications. Believing that there are plenty of benefits, such as increased motivation for exercise, but there also drawbacks, such as increased sedentary behavior from staying connected to the network instead of exercising [15, 16]. As seen with *Everywhere Race!*, they also believe that you can promote better health through the use of famous social networking applications [5, 3]. In *Everywhere Race!*, people were allowed to connect with other users in a virtual run. This virtual run would allow multiple connected users to run a specified distance in different locations while still being able to compete in a virtual race with each other. However, all of these fitness apps share one thing in common: they only measure running data; as explained, *Zombies, Run!* and *Everywhere Race!* is only capable of encouraging a user to run; furthermore, the researchers data did not involve applications that do more than just tracking running exercise data. UF!t offers a variety exercises, so that a user will not have to stick to the same routine. Being able to change your routine has been proven to provide better health benefits, than a routine that is always the same.

7. FUTURE WORKS

Currently, UF!T is limited in its capabilities to provide portable exercise tracking and counting However, in order to extend the number of features available to its users, we plan to add functionality using the temperature sensor, a workout classifier and dynamic peak detection.

As stated earlier, the mpu6050 contains a temperature sensor. In future designs of uF!t, we believe that we can incorporate the temperature sensor to monitor the amount of heat being generated during a workout session. With this data, we want to be able to determine if the user has been working out for too long. This would be idealistic for situations where the wearer is exercising in undesirable conditions, such as a small stuffy room. Given our initial research, we believe that by monitoring the temperature, we can prevent uF!t users from suffering from severe illnesses such as dehydration and hypothermia [9]. This degree of security would be enticing for new people that are interested in excerciing.

7.1 Workout Classifier

uF!T will interpret accelerometer and gryoscope data in order to determine what exercise is being performed. Our current classifier distinguishes exercises according to sensor measurement values along the x, y and z axes. Sensors measurements would include angular velocity around each axis and acceleration along each axis and be stored in a 6-tuple. The k-means classification algorithm would be used to group these measurements into motion features (such as movements around the principle axis, i.e. yaw for gyroscope and thrust for accelerometer movements) which would consequently be grouped into clusters which assist our exercise classifier. Each exercise would be described by a series of cluster for example, a situp would consist of clusters describing the positive and negative pitch rotations based off positive gyroscope values. As an exercise is being conducted, we would provide templates for each exercise in order to serve as a comparison. Each template would provide the coordinates of the cluster centers that describe an exercise.

We note that we have not classified the characteristics of many exercises besides a situp. Furthermore, it is possible to have an individual do an exercise that is currently not defined. In this case, this exercise would be classified as an unknown exercise and still be tracked and counted. For each unknown exercise, the user would be given the option of specifying a name for this exercise so that it could be tracked in the future.

Furthermore, we note that k-means is a naïve solution that is heavily dependent on the initial placement of the cluster centers as terrible initial placements could introduce inaccuracies that are not completely eliminated by moving the center. We look to implement a more advanced dynamic version of k-means that is touted to be more accurate "K-Harmonic Means" [19].

7.2 Dynamic Peak Detection

For dynamic peak detection would implement "general" peak detection that would search for inflection points in the data

We also take into account the fact that threshold values could be driven to values too low that noise would cause mis-classification.

In order to upload data to a social networking application the motes will communicate with a base station and transmit the exercise counts when ever the opportunity arises. Once a mote has transmitted its data, it will idle its radio for a idling time period that is configurable by the user, given then it is unlikely that there will be much more data to transmit soon after a transmission. After the specified period of time, the radio will return to its original state of listening. A default value that the mote's idling time period would be 15 minutes (which is arbitrarily chosen as a reasonable time period that is short enough that a user is not likely to do a significant number of exercises before the mote attempts to transmit again). It is noted that much of the lifetime of the mote is dependent on efficient use of the radio since much of the radio will be used to constantly listen for a beacon. It would then be advantageous to transmit data as rapidly as possible and return to a idle state in order to reduce the use of radio as much as possible. It is possible to obtain energy savings by implementing X-MAC which provides a solution to the excess latency of the long preamble that prefaces data transmissions [11]. Therefore, by avoiding the use of long preambles X-MAC's approach the mote can complete its transmission of data rapidly. In order to initiate data transmission the beacon must discover the presence of the mote and establish a connection. We will attempt to implement an active architecture for mote discovery. This architecture calls for the beacon to periodically transmit its location such that motes that are within in range can query the beacon with a transmission request. Consequently, the beacon can send an ack and begin receiving data. Our wireless protocol will likely increase the lifespan of the mote given that the radio is guaranteed to remain idle for the sum of the configured idle times.

7.3 Social Media Application

Our framework plans to have a base station connect to a server for storage of user profiles. Users would be able to login into a Facebook application in order to view and share their exercise history with friends. A primary feature of the Facebook application would be the game component of the application. Users would be rewarded for completing exercise goals and in turn use their rewards to their advantage in an online game. The game would involve a system where cumulative progress is visible (i.e. building a fortress with upgraded turrets to defend against barbarian hordes). Researchers have stated that one of the causes for not exercising is that the routine is very boring. By integrating a video game into our uF!t Facebook application, it would provide the user with an incentive to continue exercising through the form of constant entertainment. Furthermore, the Facebook application would also serve to store user-specific information that would allow for dynamic exercise classification. Each user would have posses their own profile which would be able to contain unique values, such as personal threshold values (More information on this in future works), the highest angle achieved during a situp, and the average speed of a situp (more information in evaluations). By allowing the Facebook application to store unique information about a uF!t user, it will allow the user to see the more technical details of their exercises. These details can be shared with other uF!t users, so that they may provide critique on using the device. Even further, they could share the data with healthcare experts if they are concerned about the way they do specific exercises. In the case of the situp detector, if a healthcare expert sees that the average completion time for one situp is around five seconds, they may ask the uF!t user if they were fatigued while doing the situps, or if there was any pain experienced during the workout.

8. CONCLUSIONS

We believe that we have provided the necessary groundwork to start implementing the rest of the components as we described in the System Architecture system. If we continue to work on uF!t, we think that it has great potential to incorporate numerous exercises beyond the simple situp. Given our evaluations, we notice that uF!t has considerable room for improvement. Since situps are only reliably detected at a time of 3 seconds or more, we wish to run more tests to see if we can achieve faster response times. This will allow our system to be more versatile for users with various degrees of expertise in doing situps. Additionally, we yet to implement our social media application side, so we will begin integrating Facebook and Twitter with uF!t. With these promising results, we believe we are capable of further improving uF!t.

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