Investigating Novel Proximity Monitoring Techniques Using Ubiquitous Sensor Technology

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On my honor as a University Student, I have neither given nor received unauthorized aid on this assignment as defined by the Honor Guidelines for Thesis-Related Assignments

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Abstract - **The goal of this work is to investigate novel proximity detection techniques by researching and testing various sensor technologies and investigate their feasibility in an athletic context. COVID-19 has challenged sports teams to come up with reasonable and easy-to-implement solutions to provide a safe training environment for their players and staff. For this reason, proximity data is more important than ever, as many teams are in need of a way to measure social distancing and maintain contact tracing of their athletes. Bluetooth has been widely used to detect colocation and monitor social distancing. However, there are many other sensing technologies that may prove to be more accurate, robust, and secure. Therefore, the focus of this work is to investigate how Bluetooth compares with ultra-wideband and ultrasound technologies when monitoring the distance between users. We have implemented and compared the three modalities in a controlled experiment to investigate their accuracy at detecting distance between users at various levels. Our results indicate that the UWB signals are the most accurate at monitoring co-location.**
This is in-line with previous research suggesting that Bluetooth cannot accurately measure the distance between fast moving objects and needs about 20 seconds to stabilize distance measurements; therefore, it is not feasible to use for sports. In addition, we recorded that UWB models yielded an accuracy of over 95%, while ultrasound correctly classified the observations over 80% of the time, and Bluetooth had an accuracy of less than 50% when predicting if a given signal is within 6 feet or not.

Keywords - sensors, co-location, wearable technology

Introduction

Due to the continuous advancements in smart phones and smart watches, biometric sensors and monitors have been incorporated into wearable technologies, allowing them to revolutionize the ways in which performance and training data can be evaluated [1]. Coupled with low prices and an increased social media presence, wearable devices have become popular tools for people to analyze their physical activities across the world. Wearable sensors have allowed athletics teams to constantly monitor the status of players' health and provide accurate data to assist in maximizing athletic performance and enhancing recovery [1]. The technological capabilities of personal fitness devices have advanced significantly in recent years which has led researchers to question if those health tracking measurements can be leveraged as tools to help combat COVID-19. Several companies have developed devices that monitor social distancing and contract tracing of individuals; however, how the distance tracking technologies compare with each other is still under-investigated.

In this work, we identify three sensor technologies within wearable devices that could be used to track distances including Bluetooth, ultrasound and ultrawide-band (UWB) and we evaluate their performance at monitoring colocation. The first sensor, Bluetooth, estimates distance between athletes through the received signal strength indicator (RSSI) between two devices [2]. Bluetooth combines sought after attributes such as widespread use, easy implementation, and energy efficiency. However, it tends to perform less accurately than other potential solutions. Ultrasound waves can similarly be analyzed to measure co-location. In an ultrasound sensor, distance is measured using the received signal from a reflected wave. While ultrasound sensors are cost effective and reliable, they can be disrupted by excess noise or impenetrable objects [3]. Recently, UWB technology has been the frontrunner of proximity detection. Sensors with UWB technology follow a similar process of measurement to that of Bluetooth, but differ in their communication via electrical pulses [4]. UWB is considered to be highly accurate and reliable, but more difficult to implement. Through this paper, these three technologies will be implemented and analyzed to determine the best combination of accuracy and effectiveness in the measurement of proximity between athletes.

Related Works

Many professional and college sports teams use wearable devices and sensors to track the performance and health of their athletes. For instance, a study conducted in 2016 leveraged smartwatch Bluetooth technology at a rehabilitation facility to monitor the location, posture, and movement of patients [5].

The smart device we used for this project is the Huawei Watch 2 smartwatch which contains an accelerometer, a heart rate sensor, geomagnetic sensor, Bluetooth, ultrasound capabilities, GPS, and Wi-Fi connectivity [6]. Bluetooth devices use RSSI values to estimate the distance between the beacon and the receiver. RSSI measures the power of the beacon's signal as seen by the smart device.

Ultrasound waves are sound waves with frequencies greater than approximately 20 kHz, higher than the limit of human perception [7]. It has proved to be a very versatile solution to many technological applications in chemistry, food technology, materials science, and medicine [8, 9]. For example, a study from 2009 described a measurement system that used an ultrasonic transmitter, receiver, and microcontroller to be implemented in a robotic sewer inspection system [10]. This paper identified ultrasound technology as a low-cost, effective solution to the sewer system use-case. The technology performed quickly in both water and air. In this application, however, only small distances were necessary to be measured (5-20 cm). This paper intends to apply ultrasound at distances up to 6 feet and more, with social distancing protocols in mind.

UWB technology is similar to Bluetooth and Wi-Fi in that it is used for wireless communication; however, instead of using RSSI values to estimate distances, UWB devices emit several short electrical pulses that allow for wideband transmission bandwidths [4]. These devices can estimate the distance between two devices by measuring how long it takes for a pulse to move between the devices. Shortly after COVID-19 hit in the United States, the National Football League (NFL) and National Basketball Association (NBA) began monitoring social distancing and contract tracing of players by using Kinexon Safezone tags which employ UWB technology [11]. The NCAA employed the same devices to athletes participating in the 2021 NCAA tournament as they attempted to maintain a COVID-19-free "bubble" in Indianapolis [12]. Although the Safezone tags do not collect biometric data from individuals who wear the devices, other Kinexon products that incorporate UWB technology do have that capability and have helped revolutionize the way in which athlete performance can be maximized and injuries can be reduced.

Methodology

This study analyzes three technologies' distance measurement accuracy: Bluetooth, Ultrasound, and UWB. The models for each technology will be compared using statistics such as accuracy, F1 score, and root mean square error (RMSE) to investigate which performed the best at certain distances. A "best" model would be created that selects the model with the lowest error at any given distance in order to provide the most accurate prediction [13].

I. Bluetooth

The Bluetooth data was collected through a set of Huawei 2 smartwatches connected to an Android phone. These smartwatches collected RSSI values and their corresponding timestamps through an app called 'SixFeet'. The app is specially designed by a team at UVA to communicate between smartwatches in order to record ultrasound audio files and Bluetooth RSSI measurements. The app was built on top of SWear, a crowdsensing platform developed by the same team and available on the Google Play store for use by any android based smartwatch with the correct sensor capabilities [14, 15]. Figure 1 shows the graphical user interface of the app, including the Home page for activation of the sensor technology and the Status page indicating both the number of files available and the Amazon Simple Storage service (S3) bucket connection.

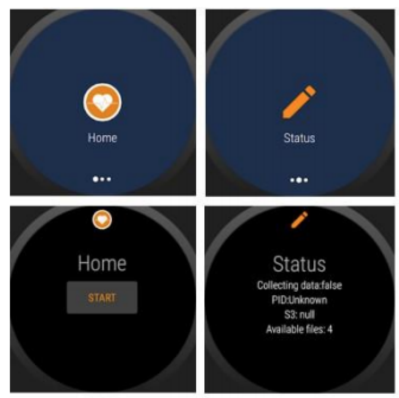

Fig. 1. User Interface of SixFeet App Used to Collect Data

After the data was collected, it had to be retrieved from the AWS server for further analysis. Figure 2 shows how the Bluetooth and ultrasound data is uploaded to an AWS S3 bucket connected to the watches through the app and downloaded via AWS Command Line Interface with a specified set of access keys. The data was then uploaded to a Box folder for shared access between team members for analysis. A python script was run to clean the raw encrypted and compressed files and output them as a CSV.

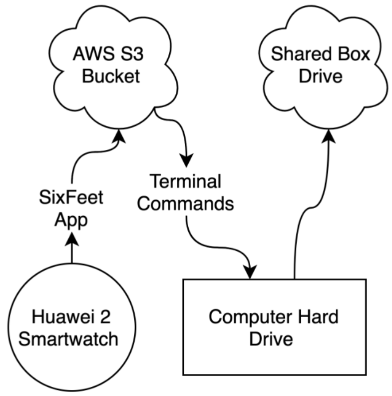

Fig. 2. Collection of Bluetooth Data

A preliminary experiment was run with the Huawei 2 smartwatches in which 2 smartwatches were held constant for 50 seconds at various distances: from 1 to 6 feet with increments of 1 foot, from 6 to 15 feet with increments of 3 feet, and from 15 to 90 feet with increments of 15 feet. Since Bluetooth data needs about 20 seconds to stabilize [16], we discarded the first 20 seconds and averaged the remaining RSSI values for each distance measurement. The average RSSI values for each watch and each distance measurement were then inserted into a power regression model as predictors [17]. The average RSSI values at each distance were then divided by the reference RSSI at 1 meter to obtain a ratio to insert into the predicted distance equation. The independent and dependent regression variables were set as the ratio values and the distances in meters, respectively. The variable values were then pasted into a power regression calculator that output values for the A and B constants [17].
Predicted distance values were then calculated using Equation 1:

$$y = A * (r/t)^B \qquad (1)$$

where $y$represents predicted distances, $A$and $B$are constants, r is the RSSI value and t is the reference RSSI value at 1 meter, which is -59 for both watches. We chose to optimize distance measurements to 6 feet, due to the minimum social distancing requirements, and the constant C was calculated by subtracting the predicted distance from the actual distance at the 6 foot measurement. The addition of the C constant is necessary because an assumption for power regression is that the intercept value is 0 [17]. Updated distance predictions were then calculated using Equation 2:

$$y = A * (r/t)^B + C \qquad (2)$$

Figure 3 shows a plot of the actual and the predicted distances obtained from the calibration model.

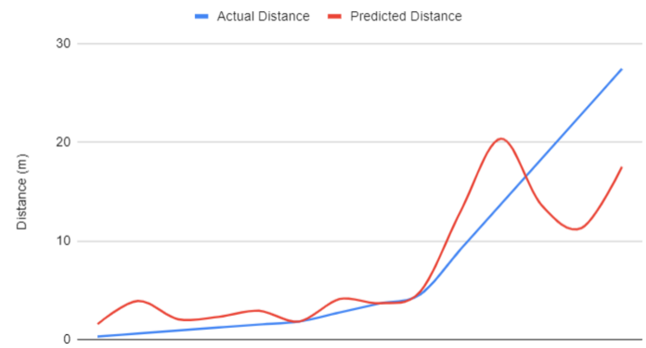

Fig. 3. Actual vs. Predicted Distances for Calibration Model

Additional experiments were then run with the Huawei smartwatches that included one person holding a watch and walking away from the other watch at various speeds (slow, medium, and fast) to a distance of 30 feet. The other experiment involved two people walking 20 feet in the same direction with the watches being held at various distances apart: 3, 6, 9, and 12 feet. For the experiment involving walking at different speeds, average RSSI values were calculated for the slow, medium, and fast paces and for the experiment involving the watches moving in the same direction, average RSSI values were calculated for 3, 6, 9, and 12 feet. These average RSSI values were then inputted into the distance equation from the calibrated regression model. To assess prediction errors for the predictor models, the RMSE was calculated for each distance.

II. Ultrasound

Data Collection

Ultrasound data was also collected by the Huawei smartwatches in the same preliminary experiments discussed above. The data was again uploaded to AWS via the SixFeet app and then extracted to the shared Dropbox. Each file was saved in one-minute segments in the .m4a format, with the UTC timestamp in the file name. These timestamps were then compared to the recorded times of the experiments to match the audio data to specific experimental times.

Data Manipulation

The .wav file associated with the experiment was then imported into Python with the Librosa package [18]. The audio loads as an array of floats with a sampling rate of 44,100 Hz. Using the experiment's timestamps, this array was then divided into segments associated with the controlled distances. Then, rolling time windows were created for each of these distances with a frame length of 500 ms and 50% overlap. These were then transformed into a DataFrame in preparation for feature extraction and analysis.

Feature Extraction

In order to create a meaningful model that predicts distance using ultrasound, sound features were extracted from the audio frames. It was determined that the Fast-Fourier-Transformation (FFT) and Mel-frequency cepstral coefficients (MFCCs) were the most applicable to this application [19, 20]. The Fast-Fourier-Transformation is a commonly used algorithm to convert sound data in the time domain to the frequency domain [19]. This means the transformation outputs an array of amplitudes corresponding to a certain frequency. The FFT feature of audio is important for this paper's scenario. Each smartwatch emits a unique frequency (above 19,000 Hz). In theory, the amplitude of this frequency would be directly related to the watches' distance from one another. In order to account for error, however, only frequencies from 18,000 - 22,050 Hz were considered as features for the machine learning models. Figure 4 below shows the FFT of the audio data collected at different distances from preliminary experiments.

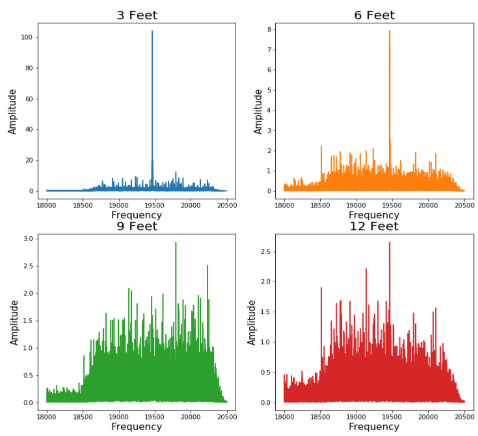

Fig. 4. FFT Plot of Watches at Different Distances

Due to the large amplitude spike present at lower distances, there appears to be strong potential in using ultrasound as a proximity sensor. This frequency spike was much more confounded by noise at larger distances, which was kept in consideration moving forward.

The Mel-Frequency Cepstrum represents the linear cosine transformation of a short-term, log power spectrum, based on a non-linear Mel scale of frequency [20]. MFCCs collectively make up this cepstrum and are often used for speech recognition. Through cross-validation techniques, it was determined practical to use 20 coefficients in the feature space and effectively represent the time windows.

Therefore, FFT amplitudes associated with 18,000 – 22,050 Hz and 20 MFCC coefficients were extracted for each time window and formatted in a data frame. The corresponding distance between the watches at the time was then added to each window feature DataFrame as a final column.

Predicting Distance From Ultrasound Signals

Two different prediction models were created: a regression model predicting distance and a classification model predicting whether or not two users were within 6 feet of one another. Several model types were considered, but it was determined that random forest was the most applicable due to the dataset's vast size, the algorithm's insensitivity to outliers, and ease of interpretation [21]. The algorithm is particularly powerful for classification, and a primary interest of this study is to determine whether or not an interaction within 6 feet occurred.

Next, dimension techniques were considered due to the dataset containing 2045 features. It was determined that principal component analysis (PCA) may be effective, and the number of components used in the model would depend on their explained variance.

III. Ultra-Wideband

Hardware Setup

To be able to measure co-location distance with UWB sensor technology, we implemented a custom setup using a set of UWB sensors manufactured by Decawave (DWM1001) [22]. To set up the devices, each had to be configured as either a gateway, a tag, or an anchor for the system. In a typical network of DWM1001 sensors, anchors are stationary nodes with a known location and tags are mobile nodes of which distances between tags and anchors are calculated periodically. A gateway node can be used within the network in order to view the location of the nodes using an included online web application, but is not necessary and was not used in this study. An overview of the system is in Figure 5 below [22].

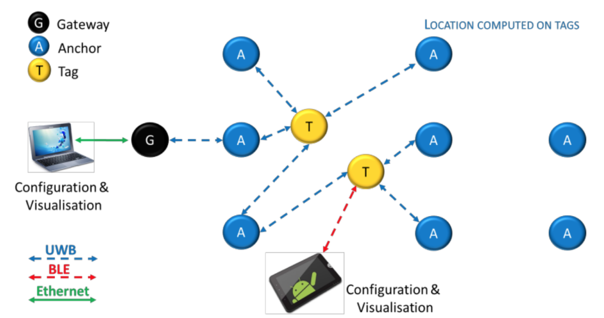

Fig. 5. Typical DWM1001 System Architecture

For the purposes of this study, two DWM1001 sensors were configured such that one was a tag and one was an anchor. This was done in order to achieve ranging between the two devices, as shown in Figure 6 below. Additionally, the sampling rate was set on each device to be 10 Hz.

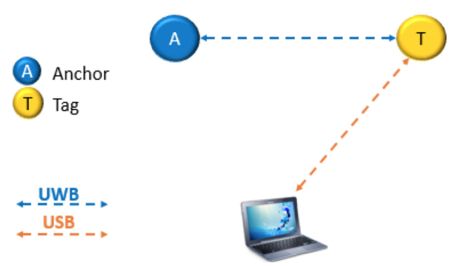

Fig. 6. The 1 Anchor, 1 Tag DWM1001 System Architecture Used

As this study, we measured the distance between two DWM1001 sensors with one in a stationary node, the most straightforward configuration of a DWM1001 for this purpose was chosen. As each node can be accessed through a universal asynchronous receiver-transmitter (UART) shell, the tag node was configured through a Python script to output calculated distances at the 10 Hz refresh rate. As this can be only done with a DWM1001 sensor configured as a tag, the other anchor node was used as the mobile node in this experiment design.

Data Collection

After configuring all the necessary DWM1001 UWB sensors, we had to be able to access the data that was being generated. To do this effectively, a Python script was created that would configure the devices upon set up, establish a connection with the UART shell, and then output distance calculations based on an x, y, and z position. To go along with the outputted distance, there was an attached timestamp. The data was outputted to the terminal of a team member and then compiled into a spreadsheet for further analytics as explained below.

Evaluation

I. Study Design

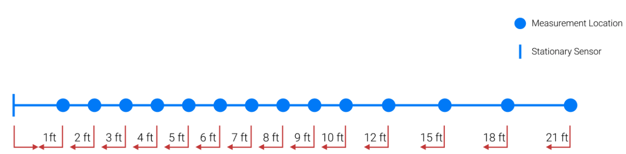

Fig. 7. Design of Final Trial Experiment

After analyzing the results and building models from the preliminary experiments, a final experiment was run for each of the sensor types: Bluetooth, Ultrasound, and UWB. The experiment setup, shown in Figure 7 below, involved the measurement of stationary distances at 1-10 feet with increments of 1 foot and 12-21 feet with increments of 3 feet. All of the sensors were measured with attempts to control for sound in order to minimize potentially disruptive conditions.

II. Comparative Analysis of Results

Regression statistics were used to compare the performance of each technology at predicting distance. Similarly, binary classification was used to determine the accuracy of all three sensors by calculating the F1 score (precision), the accuracy, and the sensitivity. A positive result is defined as the real or measured value having a distance of less than or equal to 6 feet. A negative result is defined as the real or measured value having a distance greater than 6 feet.

TABLE IV. Overall Results For Each Sensor Type

Sensor	RMSE	RMSE (6ft)	Accuracy	F1 Score
Bluetooth	10.2347	7.5434	0.4803	0.3854
Ultrasound	2.9252	2.3137	0.8109	0.7438
UWB	0.44198	0.04573	0.9595	0.9542

The results in Table IV above show that UWB performed the best across all metrics, while Bluetooth performed the worst in the overall and 6 feet models. RMSE, a standard regression metric used to evaluate performance of multiple models, was compared, and the results show that UWB has the lowest RMSE at 0.44198 whereas Bluetooth has the highest RMSE at 10.2347. The UWB model's RMSE within 6 feet was calculated to be 0.04573, significantly lower than any other mode. This proves that UWB is very effective at predicting distance, especially when in closer proximity. As shown by the lower RMSE value for the 6 foot model, the RMSE has a positive relationship with distance, meaning that the models yield higher error at increasing distances.

UWB performed the best with regards to accuracy in the classification models. The UWB model yielded an accuracy of over 95%, while ultrasound correctly classified the observations over 80% of the time, and Bluetooth had an accuracy of less than 50%. An accuracy of 95% is strong, but could be improved further when classifying an "interaction" in context of 6 feet social distancing and contact tracing.

The F1 score is another performance metric of classification models. It takes into account the number of true positive, false positive, and false negative realizations to output a score on a scale of 0 to 1 to measure precision. A value closer to 1 indicates high precision while those closer to 0 show irregularities and lack of fit [23]. Adhering to the results of the rest of the evaluation metrics, UWB outperforms both ultrasound and Bluetooth by a significant margin. With an accuracy and F1 score of 0.48 and 0.39 respectively, Bluetooth continued to prove its ineffectiveness as a proximity sensor.

The residuals of the three regression models were analyzed to see how the errors of each technology compared as distance increased. Figure 8 shows the results of this analysis.

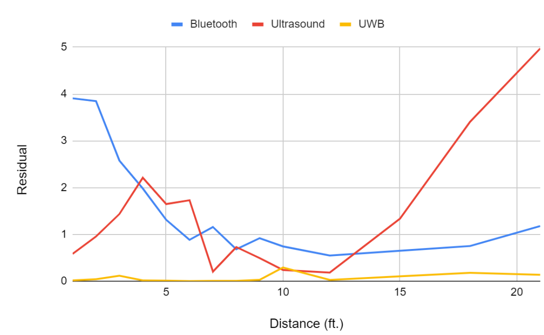

Fig. 8. Model Errors across Distances

Ultimately, UWB configuration outperformed the other two modes of technology in predicting distance. UWB had the lowest prediction error at essentially all distances, making it the best model, and it only strayed from the best model at 10 feet, where ultrasound was slightly more accurate. The UWB model's performance was particularly impressive at large distances, with its average error barely increasing with distance, even up to 21 feet. The ultrasound model's errors seemed to be random at distances up to 10 feet, but then steadily increasing at distances past 10 feet. Bluetooth had very high error at low distances but became constant as distance increased. We hypothesize that this is due to the fact that we recorded significantly less Bluetooth observations during longer distance because the watches couldn't sense Bluetooth signals when originating from farther sources.

Discussion and Conclusion

Limitations of this project included external noise, differing transmission abilities, and physical barriers. External noise can skew data by disrupting the signals that are measured via Bluetooth and ultrasound waves. Due to the COVID-19 pandemic, we were limited to where these experiments could be run and the only option we had was to run them on an outdoor field that was open for public use. We attempted to control for external noise as much as possible by being silent while conducting measurements; however, noises from other people using the field or from the nearby road could have caused some disturbances in the data.

Overall, UWB significantly outperformed ultrasound and Bluetooth in all metrics at almost every measured distance; therefore, UWB would be the optimal solution for measuring co-location proximity between college athletes during the COVID-19 pandemic. The technology combines high accuracy under 6 feet with the ability to predict distance in real time. Although UWB sensors are not integrated into most wearables and smartphones, they could be adapted to be used as wearable technology in the athletics field.

However, it's worth noting that UWB and Bluetooth signals have the ability to transmit through walls and other physical barriers while ultrasound devices do not [23]. This means that UWB and Bluetooth devices could potentially record false positives if another device is identified behind a barrier even if it is not a direct interaction. This can also indicate that ultrasound methods are less prone to security and privacy concerns, given that ultrasonic signals are confined by the physical space that the user is embedded in.

Future studies using the three technologies could be designed to consider a greater set of participants and account for various external conditions and scenarios. These scenarios could be designed to emulate sports environments, with one or more devices in motion to imitate real interactions between athletes. This would help test the accuracy in a realistic setting and ensure that the technologies will perform at a high level with fewer variables controlled. Similarly, running several trials with the three technologies at the same time and under the same conditions would help provide a stronger comparison of the accuracy and performance of the three modes. Future work with UWB technology could include the development of a system that does not use any anchors. Finally, all three of these sensors could be implemented in one wearable technology, where data from each could be analyzed together in a singular prediction model. This would likely improve performance greatly across all evaluation statistics and eliminate some of the variance in prediction error.

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