WALK DETECTION USING

PULSE-DOPPLER RADAR

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by

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and hereby certify that, in their opinion, it is worthy of acceptance.

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ABSTRACT

Seniors increasingly live more independent lifestyles. This can come with certain safety hazards including deteriorating health, and major injuries from falling. A factor that has been researched and observed to have a relationship to fall risk is changes in walking speed. In an ongoing interdisciplinary research effort at the University of Missouri, one goal is to provide a non-intrusive methodology to perform fall risk assessment on a daily basis for elders. As mentioned, an integral component of fall risk assessment is the determination of walking speed. This thesis will cover methods of using pulse-Doppler radar to detect when walks occur in an elder's apartment. In the future, these walks can then be used for gait analysis. The proposed method of finding walks was tested on data collected in a lab and in assisted living apartments at TigerPlace.

Chapter 1 - Introduction

More and more people in America, and around the world, are living longer and are having much more fulfilling lives. As part of a fulfilling life, they choose to live as independently as possible [1]. As people get older, living independently comes with some risks including weakening health that may be the result of insufficient care, and falls that could be debilitating. Actually, falls are the most common cause of injuries and hospitalizations for trauma in older adults and the leading cause of death due to injury[2]. To tackle these problems, researchers are developing ways to use sensor technologies so that residents can have their health automatically monitored in their own living environment [3]. There are also devices being developed that can improve residents' safety while living independently. Having these technologies in place can help reduce injuries and have health declines detected early.

One of the keys to indicating an initial decline in health and functional abilities is to have an ongoing assessment of physical function [4]. There is now more of an emphasis on detecting changes in someone's gait patterns in order to reduce their falling frequency [5].Detecting and assessing problems while they are still slight can provide an opportunity for proper interventions to keep these problems from becoming major. More so, identification of small changes in health conditions are crucial for early interventions when treatment is the most effective and when prevention of major changes are still possible. Because of the severity that falls can have in older adults, a problem that could also use continuous assessment is fall risk. There have been studies on falls, fall risk assessment and intervening to help prevent falls. The methods of assessing fall risk include research staff or clinicians doing a multi-factorial assessment of fall risk, maintaining logs of when falls occur, and wearing devices that detect and measure changes in position which could potentially indicate when falls have occurred so that an alarm can be activated when assistance is needed [2]. However, another approach that can be used for detecting fall risk is to use passive sensors that could detect when a fall occurred or parameters, such as walking speed, of an elder's physical functionality that can help in assessing fall risk. These sensors do not have to be worn and would not impede on daily living activities. Having falls or potential changes in fall risk detected earlier, these sensors can be used as a trigger for elders, family or health care providers so that physical functions can be improved, or illnesses that may cause falls could be better managed.

When assessing someone's fall risk, one thing to consider is the changes in gait or changes in walking speed. Studies have shown that elderly who fall or who have a high risk of falling will have slower walking speeds, shorter lengths between steps, and a big inconsistency in the length of each step [6]. One of the best times to catch walks for assessment is when people are naturally walking around in their living environment. These walks won't be influenced by someone changing their walk because they know they are being tested. Instead, these strolls would be their normal, everyday walks with their normal gait. A key component of a system to monitor gait parameters passively is the automated determination of when someone is walking in their own living facilities so that these walks can be used for assessing fall risk. To help solve this problem, we propose a method for finding walks that can be used for gait analysis with radar. By using radar, walks can be found passively throughout the day so that there is no interaction that may cause someone to change how they walk. Also, by getting a daily look at a resident's gait information, a health care provider can have a fuller picture of the resident's gait changes and will have to ability assess the resident's fall risk much faster. Moreover, having this data could lead to earlier intervention so that the resident's fall risk can be kept to a minimal.

Because of how the radar works, walks must have certain specifications so that the gait information from the walk can be extracted from the radar data. The walk must be straight and directly toward or away from the radar[7]. Walks that are across the radar will not provide good gait information. In order to get the best gait analysis from the radar, that walk must contain at least 5 steps. This gives the radar enough information to get a better walking speed average and to have a better look at the step information in the gait analysis. It is preferred that more than seven steps be taken just to be sure that the information comes out as accurate as possible. Our proposed method of finding walks using the radar will take these specifications into consideration in order to find the most usable walks in the radar data.

In this thesis, we will present some previous work that has been done in the area of assessing health risks using technology. We will then discuss the type and specifications of the radar used in this project. With that, we will give the necessary modifications that were made to the radar unit so that it is able to be used for walk detection and have the ability to collect cleaner gait information. Next, we will give complete details of the algorithm and features that we use to detect when walks happens using radar. Finally, we will show some results provide a discussion of the results found and a conclusion.

Chapter 2- Literature Review

2.1 Significance of Walking to Health

Many studies have been done on how someone's walking speed relates to their fall risk. One study explored the correlation between walking speed, physical function, and disability status [8]. The study also considered how age, gender, and body mass index (BMI) enhanced the prediction of physical function over just looking at walking speed alone. Balance tests, sit-to-stand tests, and a combination of both were used to measure physical function. The results show that there is significant correlation between walking speed and physical function, but the correlation was inadequate between walking speed and disability status. Age, gender, and BMI did not add any extra correlation.

Another research paperhas said that the variability in someone's walking speeds may help predict future falling more so than just looking at the person's average walking speed [9]. It is believed that slower average walking speeds in older adults may be more correlated to the person's fear of falling then it is to their actual fall risk. Another paper agrees with this assessment saying that decreased walking speed, decreased stride length, and a prolonged double support may actually be a person's adaptation for stabilization which comes from their fear of falling [10]. Being able to see how someone's gait varies day to day, instead of just looking for a decrease in gait speed and stride length, could lead to quicker and more efficient fall risk assessments.

2.2 Similar Studies

Other works have used webcams to extract gait and other fall risk features. One study uses two calibrated webcams to create silhouettes of the person that are used to create a 1x1x1 inch resolution voxel person [11, 12]. In order to extract the silhouette of the person, an accurate model of the background must first be acquired. Anything that is in subsequent frames that have significantly different characterizations from the background is considered the foreground. Foreground data that is moving is considered to be the person. From the voxel person, gait features such as step length, step length and walking speed can be extracted. The walking speed is extracted using the centroid of the voxel person, the distance travel, the frame rate (5 fps), and the number of frames. For step time and distance, the voxels that are within 4 inches from the ground plane are used to capture foot motion. As a person walks the number of voxels close to the ground increase and the decrease. The peak values for these voxels are considered to be the steps [12]. Average step time is calculated as the total walk time divided by the number of steps. The average step length is considered to be the distance traveled divided by the number of steps. Results show that this method is good for calculating walking speed and step length, but because of the frame rate, the step time showed a little less agreement with the ground truth.

Another research uses the same camera setup to find and analyze the sit-to-stand transition of elderly [14]. The sit-to-stand transition has been seen as a good indicator of health decline and balance deficits in elderly that may result in falling, so monitoring it could hopefully lead to care being provided quicker [13]. The sit-to-stand analysis is done using techniques of human motion analysis which uses body part analysis, tracking the person, and recognition of the sit-to-stand transitions [14]. Her results showed promising results for finding the sit-to-stand time using the camera system which could help with the measure of physical decline in the elderly.

Pulse-Doppler radar can be used to estimate the walking speed and stride rate of a person that is walking according to [7]. They were able to do this by using the short-time Fourier transform (STFT) and the spectrogram of the radar data. The reason for them using the STFT was to capture the dynamics of gait characteristics over short periods of time. To estimate the gait speed of the walker, they use the frequency with the highest peak energy level given by the spectrogram for a given time instant. They then take the mean of the gait speeds from each time instant over the course of the entire walk. For the estimation of the stride rate, they apply an averaging filter at each time instant and employ a peak selection to find the instances in time that corresponded to the leg swings. Experiments were done using 9 different types of walks that were simulated by one person. Each walk was done 3 times. A Vicon motion capture system was used for the ground truth. There results show that the gait speed and stride durations estimated from the radar were close to the results given from the Vicon for most cases. The case in which the results from the Vicon and the radar did not match up well was when the walk of a person that had a stroke was simulated. This result is believed to be because of the irregularity of this type of walk.

In [15], similar Pulse-Doppler radar to detect when falls occur. This study takes the radar signal and extracts the mel-frequency cepstral coefficients (MFCC) so that they can be used as features to classify falls and non-falls. Two different classifiers, the support vector machine (SVM) and K Nearest Neighbor, were used for the detection of falls. The results show that the MFCC features can be used to detect falls with very few false alarms. Most of the false alarms found had similar motions to falling such as kneeling down and bending over. They also show that the KNN classifier yields better results than the SVM for classifying falls.

Chapter 3 - Setup and Algorithm

3.1.1 Type and Specifications

For this project, we used Pulse-Doppler range control radar (RCR) (see Figure 3.1). The RCR's that were employed in this project have a height of 13 cm, a width of 7.1 cm, and a depth of 5.7 cm [16]. The original purpose for this type of radar was to detect any type of motion in a room so that it could be used as a security device. A RCR will not pick up items in its range that are stationary. This is due to the fact that the reflections from stationary items do not cause any frequency shifts in the signal. The radar has a range of 50 ft. with a 90 degree viewing angle (Figure 3.2). The range of the radar can be set to 20, 30, 40, or 50 ft. depending on which range is needed. It utilizes a microwave carrier frequency of 5.8 Ghz, and it has a frequency of 10Mhz for its pulse repetition. Also, the radars have passive infrared (PIR) sensors built in to them. The radar has two separate modes that allow for the PIR sensor to be on or off. There is a LED light at the bottom of the radar, which can be turned on or off, that will be lit when the radar is receiving power and will change colors when something is detected inside of its range. The maximum voltage that the RCR's can handle is 18VDC, and they can have a maximum current of 35mA [16].

Figure 3.1 A picture of a RCR radar that was used for collecting data.

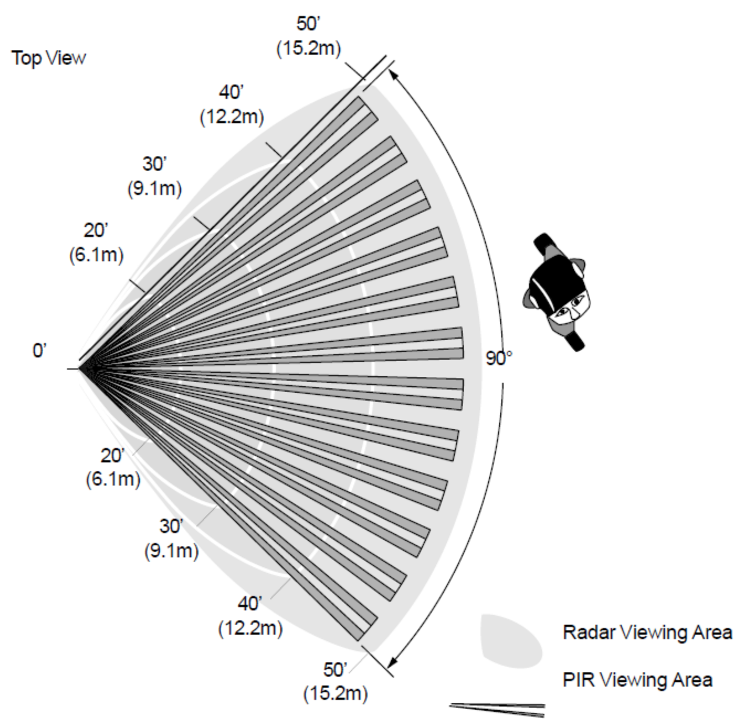

Figure 3.2 The viewing angle and viewing distances of the type of radar that was used [16].

3.1.2 Setup

In order to find walks and get the correct information and readings from the RCR's, some of the settings had to be adjusted for our purposes, and modifications to the radar had to be made. The range of the RCR was set to 20ft (Figure 3.4). This range was chosen because walks longer than 13ftwill usually have enough gait information for an analysis, and by setting the range of the RCR lower, the chance of other unwanted motion being picked up by the radar is lowered as well. Since the PIR information is not being used, the PIR detection is turned off. Figure 3.5 shows the jumper used for turning the PIR sensor on and off. For power, the radar is connected to a 12VDC external adapter. This adapter is connected to the +12V pin and the ground pin of the radar.

The external wire connection for sending the signal to our data acquisition unit (DAQ) is connected to the NC pin and the ground pin of the radar (Figure 3.3). The NC pin is an idle output pin that has a connection to the TP31 node so that the NC pin has the connection to the low gain baseband signal from the RCR [17]. The type of wire used for the external connection is a shielded wire that has a signal wire, a ground wire and a drain wire on the inside. The drain wire is connected to the ground of the DAQ to reduce noise as the signal passes through the wire. Also to reduce noise, the shielded wire is cut to about 1 ft. long. To ensure that the RCR is getting enough power and that motion is being detected, the LED indicator light is switched on (Figure 3.4).

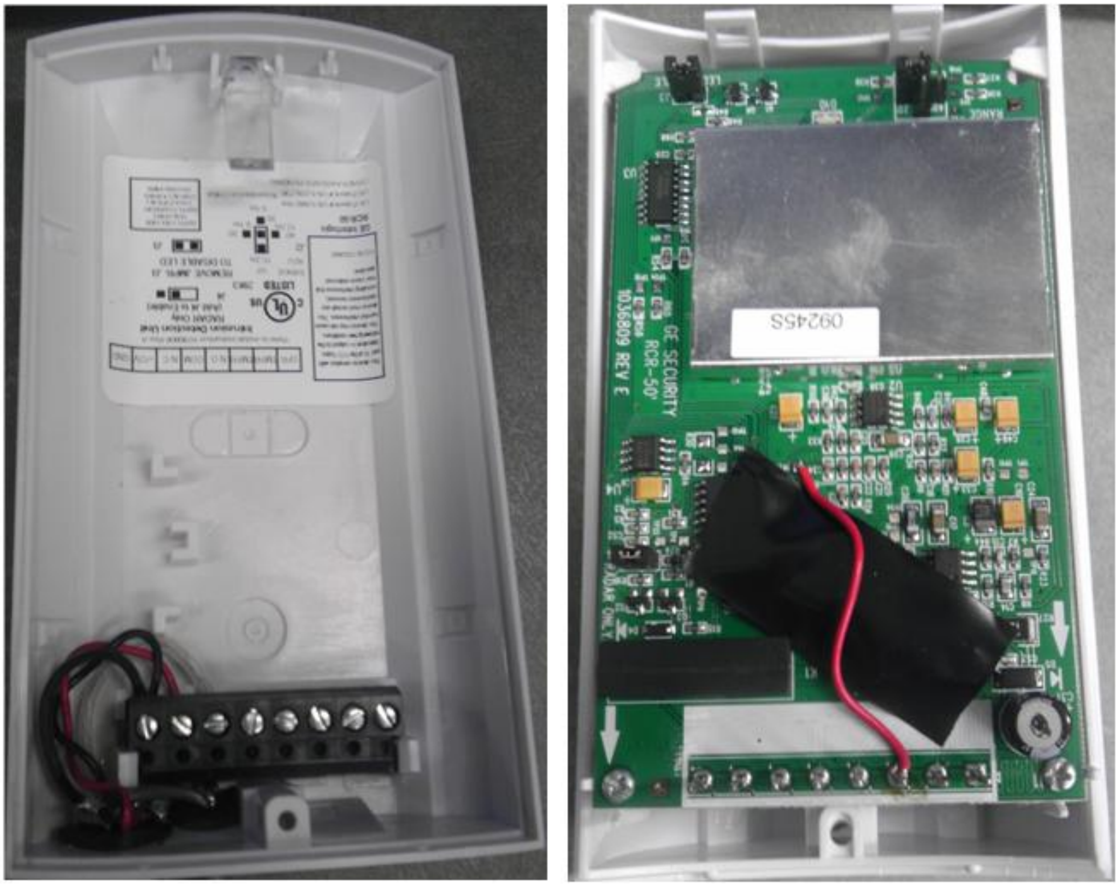

Figure 3.3 A picture of what the inside of a RCR Radar looks like. On the right is the red wire that is used to connect the TP31 node to the NC pin.

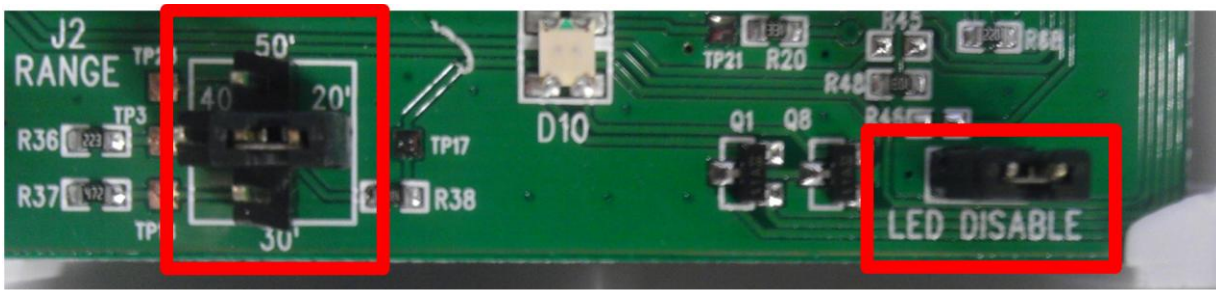

Figure 3.4 A close up look at the where to set the maximum distance of the radar (box on the left) and where to enable the LED (box on the right) inside of the radar.

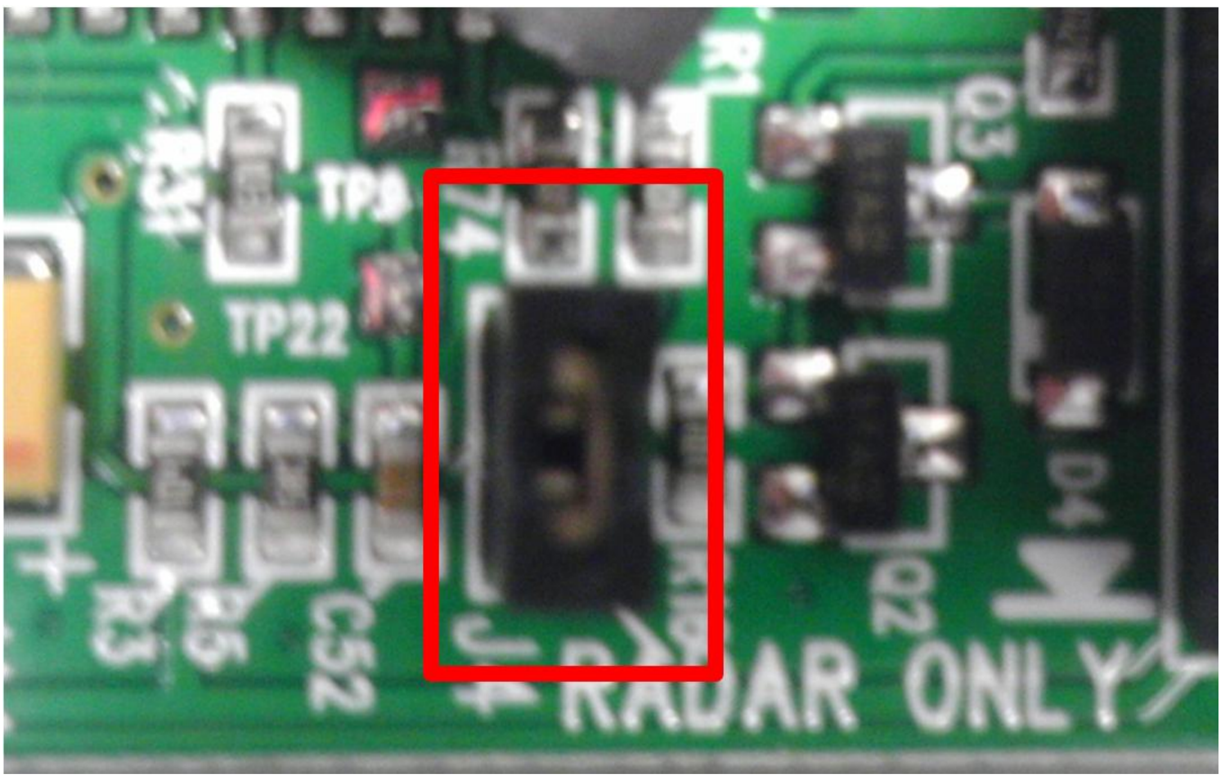

Figure 3.5 A close up look at where the radar’s built in PIR detector can be enabled or disabled.

Even though the radar was made to view in a certain direction, the antenna on the radar is still somewhat omni-directional. When indoors, the antenna may cause saturation in the radar signal due to multi-path. In order to solve this problem, the radar is wrapped in aluminum foil with a small opening in front of the antenna. Figure 3.6 shows what the radar looks like with the aluminum wrapping. This makes the antenna more directional so that the antenna can only send and receive signals through the opening in the foil. In so doing, the effects of multi-path are significantly reduced [17]. Adding the foil around the radar also reduces the amplitude level of the signal. By reducing the amplitude of the signal, there is a chance that some of the radar information could be lost. The signal amplitude level should still be large enough so that a good analysis can be made.

The foil around the radar has to be calibrated depending on the room that it is in, so when trying to get the best placement of the aluminum foil, there are certain aspects of the signal that require attention. The first part of the calibration was looking at the amplitude of the signal. When adjusting the foil, the amplitude of the signal should always be over 0.1V peak to peak. A signal with amplitude below this will result in lost gait information. To make sure that the signal saturation is being properly reduced by the foil, we view a spectrogram graph of the signal. By looking at the spectrogram, weare able to see if the power in the signal made by footsteps is too high or too low. If the power is high, there is still too much saturation in the signal, and if the power is too low, then the amplitude of the signal is probably too low.

Figure 3.6 Picture of a radar unit with the aluminum shielding around it.

To find the best placement and slot opening for the aluminum foil wrap around the radar, a calibration must be done. To calibrate, walks of 5-7 steps are collected by the radar with the wrap around it. The raw signal and the spectrogram of these walks are viewed to ensure that walking information can be extracted from signal. For the raw signal, the average amplitude should be above 0.1V peak to peak.If the amplitude is not high enough, the foil is moved up, or the opening for the antenna is opened up more. The slot should be opened along the height of the radar first, then along the width if the signal is still too weak. When looking at the spectrogram of the signal, the power at each of footsteps should be high enough that each footstep has a clear peak, but high enough that some of the power is being cut out of the spectrogram. If the power of the spectrogram is too high at the footsteps, then the opening in the foil should be closed some, and if the power is too low, the foil opening should be closed some. When opening and closing the slot in the foil, it should not be opened or closed more than 1 cm at one time.

The height of the radar should be between 3 to 6 inches off of the ground. This height off of the ground allows for the radar to be able to detect leg and torso motion so that they both can be used in the gait analysis. When placing the radar in a room, the radar should be in a position that allows for a walk of at least 13ftto be able to take place directly towards or away from it. It should also be placed in a position so that outside noise can be kept to a minimal. Hence, if at all possible, the radar should not be facing any walls or doors where there may be lots of motion on the other side. For the best results, the walking path should be as clear as possible. Even if objects are not in the way of the walking path, some objects around the path may still cause interference in the signal due to multipath reflections.

3.2 Data Acquisition Unit

To collect the radar data we used a DI-710 Series Data Logger from DATAQ Instruments. It comes equipped with 16 analog channels, 8 bidirectional digital ports, 2 digital and 2 analog grounds, and 2 +5V power ports. It has a maximum sampling rate of 4,800Hz when it is connected to the computer and a maximum rate of 10,000Hz when it is in stand-alone mode [18]. The analog to digital converter has a resolution of 14 bits. It can come with a USB interface for connecting to a computer and a SD card slot (2GB maximum) for stand-alone data collection. It can also come equipped with an Ethernet port instead of a USB port. Both types were used for this project. Figure 3.7 shows pictures of what the front and back of the DAQ with the USB port looks like.

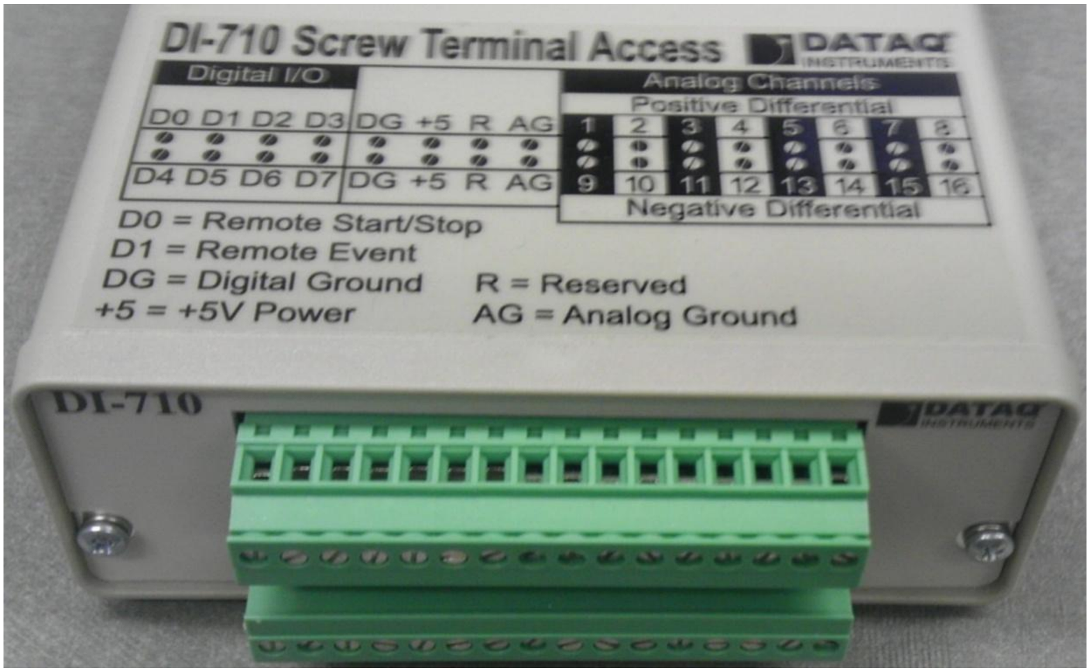

Figure 3.7 Picture of the front (top) and back (bottom) of a DATAQ unit with a USB interface and a spot for a removable SD card.

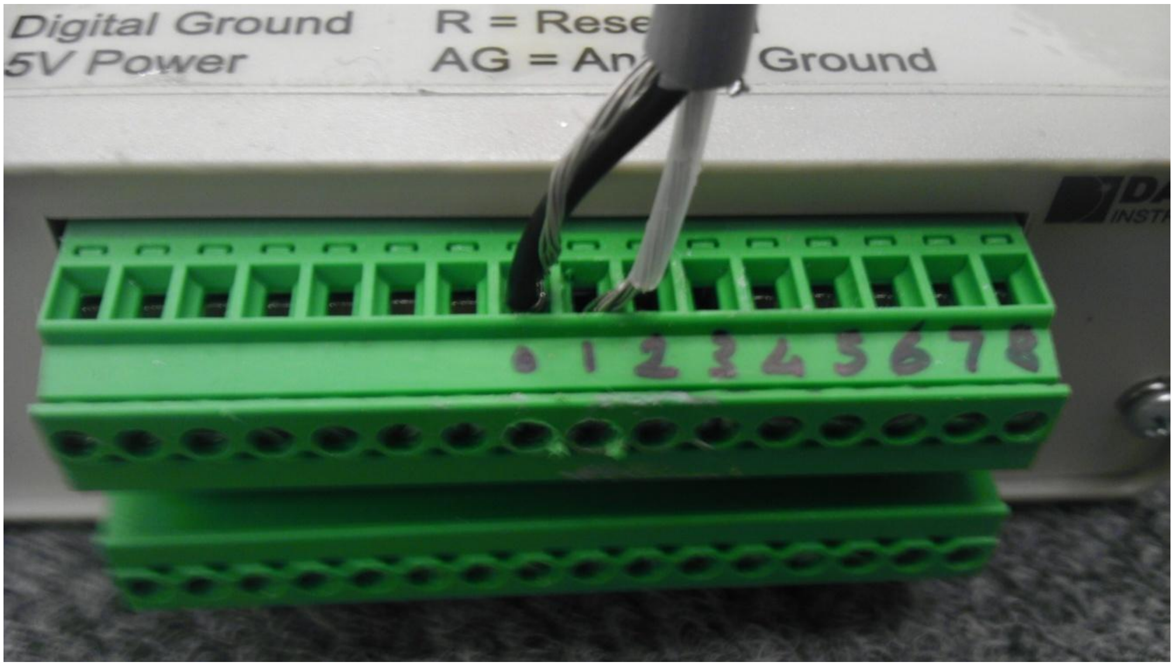

Figure 3.8 Shows the ground and drain wire connected to the analog ground of the DAQ and the signal wire going into the first positive analog channel of the DAQ.

For the purposes of this experiment, the sampling rate was set to 960Hz. This sampling frequency was used because we believed that frequency was high enough to get all of the gait information that was needed and not too high to cause excess noise.When connecting the radar to the DAQ, the signal wire was always put in first analog port and the ground and drain wires were connected to analog ground port (Figure 3.8). To ensure the best signal, one radar unit was connected to a DAQ at any given time, and all other analog ports were turned off. The shielded wire used to connect the radar to the DAQ was cut to about a foot long to reduce signal interference. The signal had a maximum voltage of +5V and minimum voltage of 0V.

3.3 Radar analysis software

All of the calibrations for the radar systems were done using General Electric's Radar Analysis Software (RAS) that is shown in Figure 3.9 [17]. RAS is a software interface created in Matlab that allows the raw signal and the spectrogram of the signal to be viewed at the same time. What the program does is take in a file made by the Dataq system. Once the file is selected, the RAS shows the beginning and ending times for the data that was collected. The RAS then allows a certain portion of the signal to be selected based on a beginning time and the time duration in minutes. The beginning time is the first time that will show on the graphs in the RAS interface. After this information is input into the system, the raw signal and the spectrogram appear in their respective boxes for the portion of the data selected. There are also some changeable variables that have to do with how the spectrogram is made. When we used the RAS for calibration, these variables are always left in their default settings. In addition to showing the different signal pictures, the RAR shows the calculated velocity of the walk, and the stepping cadence of the walker. Neither of these values were used during the calibration of the radar system.

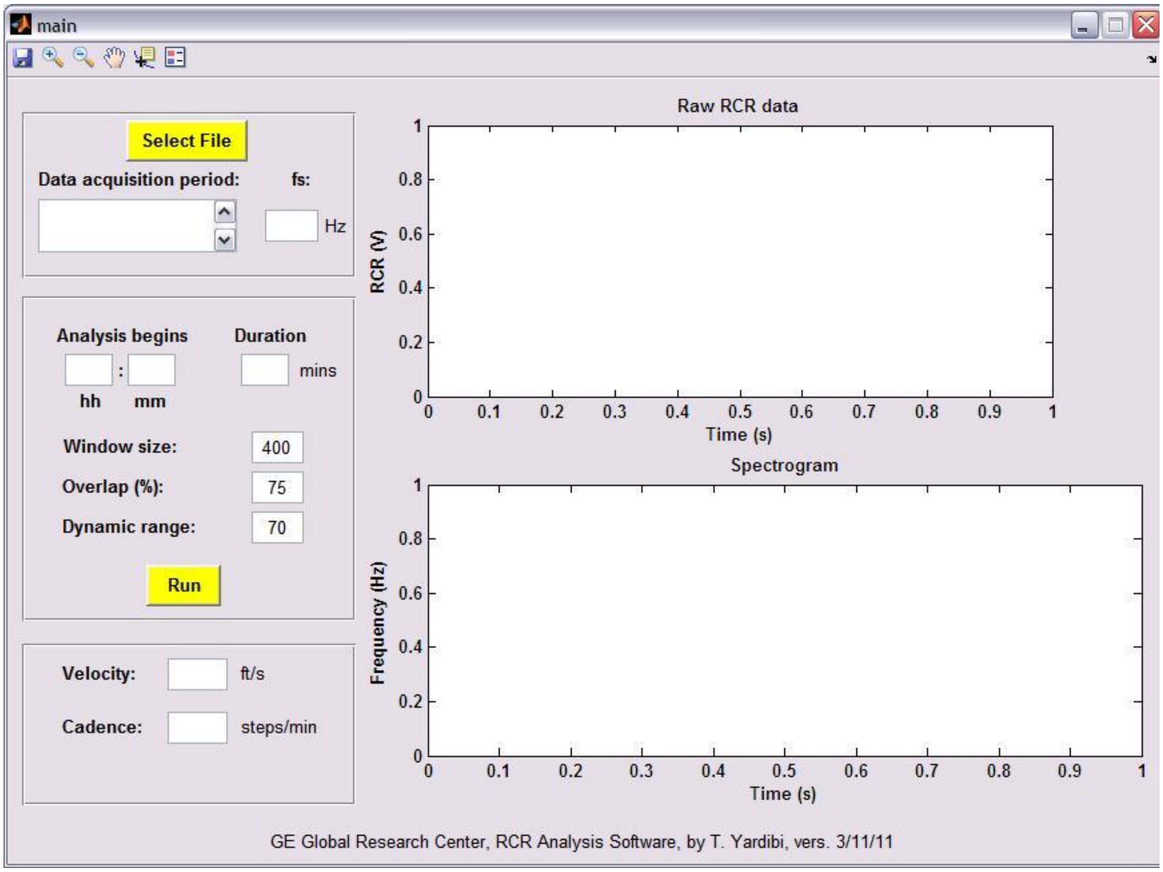

Figure 3.9 Screenshot of the Radar Analysis Software user interface. This software was written up by General Electric's Global Research Center [20].

3.4 Walk Detection Algorithm

The algorithm that we created to determine where walks happen in radar data was made to use different supervised learning techniques interchangeably. For this project, wepicked two of the many different classification techniques. We used the K Nearest Neighbor (KNN) classifier, and Bayes Decision Rule using the Maximum Likelihood Estimation (MLE) of a Gaussian distribution. For both of these methods to work as efficiently as possible, a largetraining set had to be collected. Thus, there were many radar sequences of walking and non-walking activities collected for training the algorithms. These activities will be covered in more detail in Chapter 4 of this thesis. After collecting the data for training, each activity is broken down into two second slices with the slices having a one second overlap. Each of the two second windows contain 1920 samples and will become a data point that is used in the training data.Therefore, there is one signal based feature vector for every second of an activity for both walks and non-walks.

Most of the training data that was collected was non-walk activities. There are two reasons for this. The first is that there are many more non-walk activities with variation than walk activities. With the walks, the only factors that can vary are how the person is walking and who is doing the walking. Non-walks are not bound to one certain activity therefore, there is a larger amount of data that should be collected. The other reason for having more non-walks is because of the fact that missing a walk is less important than misclassifying a non-walk activity as a walk. Most healthcare providers that were interviewed said that they would only need 1-3 good walks a day to be found to do an assessment. Since most walking residents that are active will walk around their living area many more times a day than that, it is okay to miss a few walks throughout the day. At the same time, it is worse for some other type of activity other than walking to be seen as a walk because if that data is used for gait analysis, the gait information will be wrong which may cause a false alert to happen. False alarmsmust be kept to a complete minimal.

To help reduce the number of non-walk activities being seen as walks, the algorithm takes advantage of duration of the walk. Since each 2 second interval is classified as walk/non-walk, the algorithm uses the number of consecutive walk intervals in a potential walk sequence to reduce the number of non-walks that would be seen as walks. The number of consecutive windows of a walk needed before it is determined that walk found is a user-defined threshold. If at any time during an activity a window is not considered a walk and the threshold has not been met, then the beginning time and the length of the current walk sequence will be thrown away. This means that shorter walks and walks that have misidentified windows may get thrown away as well. As mentioned before, this is okay as long as too many parts of a walk are not being classified incorrectly.

3.4.1 Features

Before extracting features from the radar signal, we first do some pre-processing of the signal. The first step is smoothing. By smoothing the signal, most of the high frequency noise will disappear. Each sample point is averaged with the point before it and the point after it. The average becomes the new value of that data point. This is done for each point in the 2 second window from beginning to end with the first point only being averaged with the following point and the last point only being averaged with the previous point. In order to allow the sample points to converge to a certain value, we run the smoothing on a window at least 10 times. After doing a complete smoothing of the window, we take the Fast Fourier Transform (FFT) of the window. The FFT allows me to look at the frequency information of the signal. Wehave seen that different activities may have different frequency information in the signal, so from that, walks should look different from non-walks in the FFT information. The equation for getting the FFT from the raw signal is:

$$X_k = \sum_{n=0}^{N-1} x_n e^{-i2\pi k \frac{n}{N}} \qquad (1)$$

where N is the number of samples (N = 1920 for our purposes), x_n is the currents sample, and k is the number for the current FFT point [19]. For our purposes, the magnitude of the FFT is used.

The next step is to smooth out the magnitude of the FFT. This is done in the same way it is done for the raw radar signal. After smoothing out the FFT, we take the derivative of the FFT. When walking, a person's legs, torso and arms moves at different speeds. Therefore, each of these body parts should give the radar different frequency information with the information from each body part being closely related. The fact that the frequency information from the different body parts are related makes the slopes around their peaks in a FFT look different than the slopes around the peaks for non-walk activities. Using this reasoning, the derivative of the FFT would be useful in creating more separation between walks and non-walks in feature space. The derivative of the FFT goes through the smoothing process as well.

After pre-processing, the first feature that we extract from the radar data is the highest peaks of the FFT. We use both frequency where the peak occurs and the value of the smoothed magnitude of the FFT at the peak. We only look at the peaks that happen beyond 5Hz to eliminate the DC bias. This feature gives the frequency that has the most power in a given window. Since some walks may have similar frequency information to non-walks, the value of the FFT at the peak is used to give that extra dimension of separation in feature space.

Furthermore, if the frequency of a peak from a walk is the same as one from a non-walk, the chances of them having them having the same or a close FFT value at that peak is less likely.

The next feature that is extracted is the FFT power for the whole 2 second window. The complete FFT power is computed by taking the integral of the FFT from the zero to the sampling frequency divided by two. This feature gives a look at how much overall frequency information is in the radar signal for a given window. Since walks have considerable motion for different body parts, they should have more frequency information in the FFT, making the FFT power higher for walks than it is for most non-walks.

Similar to what we did with the FFT, we extracted the highest peaks of the FFT's derivative to be used as another feature. This feature gives us more separation in the feature space than just looking at the highest peak of the FFT alone. Since both the FFT and its derivative have been smoothed, high spikes due to noise should be non-existent and therefore, should not affect feature extraction from the derivative of the FFT.

The FFT peaks and the derivative of the FFT's peaks both give the 2 dimensions to each of the data points. The power of the FFT adds one more dimension giving the feature data points 5 dimensions.

3.4.2 Classifiers

As stated before, the classifiers that we used to detect when walks occur were the KNN and Bayes Decision Rule classifiers [20]. These classifiers are interchangeable in the algorithm and only one of the classifiers is in use when the algorithm is running at a given time. The purpose of using two different types of classifiers was to see which type was most efficient in finding walks in the radar data. For each of the classifiers, we will talk about how they work, what variables we change and how they may affect the outcome, and how we use them for the purposes of finding walks in the signal from the radar.

3.4.2.1 KNearest Neighbor (KNN)

The KNN classifier uses a distance or dissimilarity measure in order to classify the incoming data based on the training data. This classifier is good for determining how the training data is distributed directly around the incoming data point. Furthermore, it is able to tell which part of the training data has more training data points around the incoming data point that needs to be classified. It is also good for making concise choice when there are only to different groups in the training data.

KNN works by calculating the distance between the point that needs to be classified and all of the points in the training data. Once all of these distances are measured, the training data is sorted based on how close each of the training points is to the incoming data point that needs to be classified. The order of the points should go from closest to furthest away. After sorting, the classifier looks at the K closest training points to the data point being classified. If most of those K training points come from walking data, then the data point will be classified as a walk. If most of those training points come from non-walks, then it will classify the incoming point as a non-walk. In order to prevent a tie from happening with this data, K is selected as an odd number. This way either walk or non-walk will win out and no special choice has to be made.

A problem that can be ran into when using the KNN classifier is different features having different scales. When different features are not on the same scale, one of the features may have more control over the distance measurement than the other features. For example, let us say that there are 2 features being used to classify something. One of the features may have values between 1 and 1000, while the other feature has values between 0 and 1. If this is the case, the first feature may cause the distance measurement to change much more than the second feature. It may even be the case that the second case that the second feature has so little control that the actual classification of a data point is not affected this feature at all even though there is a relatively large separation of the groups with that feature. To prevent one feature from having more control than the other, there are certain distance measures that have to be used. There are two separate distance measures that we used for detecting walks.

One of the distance measures that handle features having different scales is the Mahalanobis distance. This distance measure uses the covariance of the training data in order to make the scales of the different features have very little effect on the distance measurement. The equation for the Mahalanobis distance is:

$$d(\vec{x},\vec{y}) = \sqrt{(\vec{x}-\vec{y})^T C^{-1}(\vec{x}-\vec{y})} \quad (2)$$

where$\vec{x}$ and$\vec{y}$ are two points in a dataset and C is the covariance of the entire dataset[20]. When using this measurement for our purposes, a covariance is found for the walking training data, and one is found for the non-walk training data. There is not a common covariance matrix that is used for all of the training data. By having two separate covariance matrices for each of the categories, the covariance will better represent the distribution of the category that it is being used for.

The other distance measure that was used is the standardized Euclidean distance. It is very similar to the Mahalanobis except that it does not use the covariance of the dataset. Instead it uses the variances at each of the different dimensions of the dataset. By doing this, the standardized Euclidean distance measure only looks at each of the dimension of the dataset separately. It does not look at all of the dimensions together as a whole. It has the equation:

$$d(\vec{x},\vec{y})=\sqrt{(\vec{x}-\vec{y})^{T}S^{-1}(\vec{x}-\vec{y})} \qquad (3)$$

where S is a diagonal matrix whose diagonal values are the variances of the dataset for each of the different dimensions [21].

3.4.2.2 Bayes Decision Rule

Using Maximum Likelihood Estimations for classifications is a statistical approach to classifying the datathat tries to determine what the optimal parameters are for a certain type of dataset based on the sample or training data points and the type of distribution that the data has or is assumed to have. The maximum likelihood estimation can do a good job of having the parameters converge to a certain value as the number of training points increase. For the purposes of this project, the distribution of the data collected is assumed to be Gaussian.

To find the solution to the estimation, a training set D is taken. All of the data points in D are assumed to have been gathered independently from one another. With that, the equation for the likelihood function would look like this:

$$p(D|\theta) = \prod_{k=1}^{n} p(x_k|\theta) \quad (4)$$

where θ is the unknown parameters that need to be estimated, and x_k is the is one of the data point in the dataset D [20]. The maximum likelihood estimation would be finding the parameters θ that maximizes p(D|θ). Since working with products is hard to do when trying to maximize, the natural log of the likelihood function is taken to simplify the derivations. Because of the properties of logs, taking the natural log, the parameters that maximize the likelihood will also maximize the natural log of the likelihood. By taking the log of the likelihood, we get

$$\mathrm{l}(\theta) = \ln p(D|\theta) = \ln \prod_{k=1}^{n} p(x_k|\theta) = \sum_{k=1}^{n} \ln p(x_k|\theta) \quad (5)$$

By using the log, the product gets changed to a summation and summation much easier to use for maximization.

The Gaussian distribution has two parameters that need to be estimated. They are the expected value of a data point, μ, and the covariance of the dataset, Σ. The equation for a Gaussian distribution given these parameters is

$$p(x_k|\theta) = \frac{1}{2\pi^{d/2}|\Sigma|^{1/2}} e^{-\frac{1}{2}(x_k-\mu)^t \Sigma^{-1}(x_k-\mu)} \quad (6)$$

where d is the number of dimensions for the data point x_k. Putting this equation into the log likelihood, we get

$$\mathrm{l}(\theta) = \sum_{k=1}^{n} \ln \frac{1}{2\pi^{d/2}|\Sigma|^{1/2}} e^{-\frac{1}{2}(x_k-\mu)^t \Sigma^{-1}(x_k-\mu)} \quad (7)$$

To find the maximum likelihood estimations for μ, and Σ, the partial derivatives of l(θ) with respect to μ and Σ are taken. Each of the partial derivatives are then set to equal zero and the corresponding parameter is solved for. The partial derivative with respect with to μ is

$$\frac{\partial l(\theta)}{\partial \mu} = \sum_{k=1}^{n} \Sigma^{-1}(x_k - \mu) \quad (8)$$

By setting this equation equal to 0 and solving for μ, we get the equation for estimating μ which is

$$\mu = \frac{1}{n}\sum_{k=1}^{n} x_k \qquad (9)$$

For the covariance, the partial derivative is

$$\frac{\partial l(\theta)}{\partial \Sigma} = \sum_{k=1}^{n}((x_k - \mu)^t \Sigma^{-2}(x_k - \mu) - \Sigma^{-1}) \qquad (10)$$

After setting it to zero and solving Σ, we get the equation

$$\Sigma = \frac{1}{n}\sum_{k=1}^{n}(x_k - \mu)(x_k - \mu)^t \qquad (11)$$

These estimation equations for μ and Σ are what we used for estimating the distributions of the walks and the non-walks. When looking at the data, it looked as though the non-walk data created two separate clusters because of the FFT peak feature. One of the clusters had most training data, but the other cluster was just large enough and far enough away from the cluster that it was throwing off the maximum likelihood estimations for the non-walks. For this reason, we decided to break down non-walk training data into two separate groups. After doing this, maximum likelihood estimation of the parameters looked to be much better.

Now that we know what the Gaussian distribution parameters look like for the walks and the non-walks, we need a way to classify the incoming data when it comes in. This is where Bayes decisions rules come into play. What the decision rules do is calculate the posterior probability of a data point being part of a certain class for all of the classes and then decides which class the point should classified by minimizing risk. To minimize the risk, it will simply choose the class that has the highest posterior probability. The posterior probability is calculated using Bayes formula which is

$$p(\omega_i|x) = \frac{p(x|\omega_i)p(\omega_i)}{p(x)} \quad (12)$$

where x is the data point that is being looked at and ω_i is one the i groups that the data point could be a member of [20]. Since p(x) is going to be the same for all of the groups, it is not needed or used when a decision on how to classify the point has to be made. This gives us a decision equation of

$$d_i(x) = p(x|\omega_i)p(\omega_i) \quad (13)$$

The equation used for $p(x|\omega_i)$ is the Gaussian equation using the estimated parameters μ and Σ base on which of the three groups from the training data is being looked at. The group that has the highest d_i for a point will be the group that point will be classified into.

To have some control over how strict the classifier is when it comes to classifying walks, we use the prior probability $p(\omega_i)$ for the different groups in the training data. The probability $p(\omega_i)$ is the prior probability that tells what the chances of an activity falling in a certain group based on prior knowledge. Even though prior knowledge tells us that non-walk activities happen more of the time, setting the prior probabilities of the training data to be even for walks and non-walks could yield better results from the classifier. They may be worse as well. For these reasons, wetest the prior probabilities at different values to try and obtain good working priors for the classifier.

3.4.3 Complete Algorithm

To start off, we need to determine the sampling frequency of the radar signal is. This information is important for finding the FFT which is used for finding some of the features. It also affects how much the window should slide in order to slide over one second at a time. For the purposes of this project, the sampling frequency in which the radar captures data is always set to 960Hz. After finding the sampling frequency, the next step is to import the training data. The training data will be different based on which of the classifiers is being used.

Once all the information need for processing and classifying is gathered, put a window around 2 second of the signal and do all of the processing needed to extract the features from the window. The features are then given to the classifier, and the classifier will determine whether it believes the window has walking in it or not. If it is determined that this window is one with walking in it, then the algorithm will determine whether this window is the beginning of a series of continuous walk windows. When it is the beginning, the time for the beginning of the window will be saved, and the number of consecutive walk windows in the series will be set to one. When it is not the beginning of the series, the number of consecutive walk windows is incremented by one. Only the time of the first window in the series is saved because that window is to be considered the beginning of the walk while all of the following windows are to be considered part of that same walk.

If the classifier looks at the current window and determines that the activity in that window is not a walk, then the algorithm will look at the information that was collected from the windows that were directly before it. If that information has a series of walk windows with the number of such windows greater or equal to a set threshold, the saved time from the beginning of that series will be put on a list of actual walk times and the number of windows in that series will be saved as well. The number of windows in the current series will then be set to zero. When the series' window amount is less than the threshold, the saved beginning time of that series will be thrown out and the number of windows in the series will be set to zero. If no walk information was before the current window, then the series information will remain blank. The window will then slide over by one second and the next part of the radar signal will go through the same process that has been stated above. The window will continue to slide over by one second until a desired ending time is met, or until there is no more radar data left to be processed. Once the wanted radar data has been fully processed, a there will be a list of walk times that are in chronological order, and there will be a list of the corresponding lengths of those walks in the same order.

Here is the pseudo-code for the algorithm:

```
Determine sampling frequency of the radar signal
Import the classifying data needed for the classifier
While there is still unprocessed radar signal
        read in next 2 second portion of data
        process the signal of the window
        extract the features
        classify this portion of data as a walk or non-walk
        if (walk)
                if(no iteration of walk right before this portion)
                        save the beginning time of this section
                        # of back to back walk windows = 1
                else
                        # of back to back walk windows  += 1
                end
        else
                if(# of back to back walk windows > min # of window for good walk)
                        add the beginning time of the walk to the walk list
                        save the # of windows back to back to the length list
                else
                        throw out the saved time for beginning of walk
                end
                        # back to back windows  = 0
        End
        Slide the window over by one second
end
```

Chapter 4 - Data Collected

All of the data collected from the radar was collected at a sampling rate of 960Hz. There are two main categories of data that was collected with the radar. They are walks and non-walking activities. The walks collected are varied by the speed of the walk and who is doing the walking. By collecting walks from different people, there will be different gaits in the data, giving the training data a wider array of walks. If the training data only had the gait of one person, the chances of that data working for multiple people would be much smaller. For non-walks, the variability is in the amount of different type of activities that were collected. Some of the activities, such as standing still, did not look like walks, while other activities, like swinging a leg back and forth while sitting, had motions in them that closely resemble the motions of a walk.

4.1 Lab Data

During a data collection, there were about 240 different walks collected with the radar. The walks were done by 15 different people. These people were of different ages and sizes. Each person did 15 or 16 walks which were divided into 8 walks at the person's normal speed and 8 slower walks. For both the normal speed walks and the slower speed walk, half of the walks were toward the radar, and the other half were walks going away from the radar. The length of each of the walks was about 13ft long. Each of the normal speed walks lasted between 4 and 7 seconds while the slower walks varied between 5 and 12 seconds.

Activities collected for non-walking data were activities that were likely to happen in most living arrangements of elderly people. There are activities of standing with some movement, normal motions and movements while sitting, sitting to standing, standing to sitting, swaying, swinging legs while sitting, dropping objects on the floor, and picking objects up from the floor. Collecting data while no one was in the room was also added to this group of data. Each of the activities was done at varying positions with respect to the radar and they were done at varying speeds with all of the activities being done in at least 3 different positions. Swaying and the swinging of legs were done in different directions as well. Some had motion going towards and away from the radar,while others were done going across the radar. All of the non-walk radar data was collected for at least 30 seconds for each of the activities in the different positions and directions.

4.2 TigerPlace Data

In some of the apartments at TigerPlace, a radar system was installed. They were placed where an optimal walk could be collected based on the arrangement of the apartment. Each of the radar systems was wirelessly connected to a separate data collecting computer in the apartment. To make sure that the radar systems were not as visible, less intrusive, and less likely to be tampered with, the systems were put in special made boxes that could hold the radar unit, the DAQ and a wireless router. Figure 4.1 shows what this box looks like. Through testing, we found that having the radar unit inside of the box did not change the signal coming from the radar. In most of the apartments, these boxes would sit out of the way of the residents next to a wall where it would be a tripping hazard.

This data was collectedcontinuously with the data being saved to a separate file for each day. It was used to verify that walks could be detected by the radar in actual living environments. In addition, this data was used to see if enough walks were being collected throughout the day and the level of false positives being picked up by the algorithm. Since it does not matter if some of the walks were missed, this data was not used to see how many walks were missed. We just wanted to make sure that a good number of the straight, long, and clear walks with respect to the radar were being picked up.

4.3 Training Data

Most of the data collected from the radar was used as training data. This was done in order to get a larger amount of training points in the training data for both walks and non-walks. Having more training data means that training data will be more diverse which should help with the classification of walks and non-walks. Also, with more training data, there is a higher chance of having a statistical significance of the training data.

The walks from 12 of the 15 people were used for the purposes of training the classifiers. This gave the training data about 192 walks to work with. For each of the walks, the 2 second window sliding at 1 second was used to get all of the data points for the training data. This means that for each of the walks, there are $t-1$ data points that are extracted, were t is time length of the walk in seconds. The time it took to finish a walk is rounded to the nearest second.

All of the non-walk data was collected in the lab for training. Since the activities for the non-walks were longer in time than any of the walks, each of the non-walks created more data vectors for the training than the walks. This resulted in the number of points in the training for the non-walk data being larger than the amount for the walking training data.

4.4 Testing Data

To test whether or not the algorithm is able to pick up walks, 3 of the 15 people's walks were used as testing data. The complete time interval that it took each of the people to complete all their walks was given to the program. This was to see if the program was able to pick out the beginning times and the length in time of each of the walks. Since there is no motion in the room when there is no walking during these time intervals, it is not a good test to make sure that non-walk activities are not being detected as walks. Web cameras were used to collect the ground truth determined the actual times of the walks. These cameras collected frames at about 7 frames per second and each of the frames had a timestamp.

The final data that was used for testing the algorithm was the data collected at TigerPlace. All of the TigerPlace data in our experiments was used for testing. Since the walkers in the lab were different from the walkers at TigerPlace, we wanted to see how well the walks from the lab data would coincide with detecting walks in the TigerPlace data. It also helped with testing how well the radar data in one type of environment coincided with another type of environment.

Figure 4.1 Pictures of the inside (left) and outside (right) of the special made boxes that housed the DAQ, radar and wireless router.

4.5 Ground Truth

During the data collection in the lab, all of the activities were recorded using webcams that were place on a wall in the lab about 8 ft. above the floor. The webcams collected frames at 7-8frames per second and were able to have all of the activities that happened in the lab in its view. Each of the frames had a timestamp that recorded the time to the nearest thousandth of a second. Using the frames collected by the webcam, weare able to see the times when walks and non-walks are happening.

To be able to see the type of activity when the algorithm believes that a walk was happening at TigerPlace, Microsoft Kinects that were installed in each of the apartments were used. The placements of the Kinects were usually near the front door of the apartment. Diagrams of the actual placement for each of the apartments used are given in Chapter 5. The Kinects collected depth images at a rate of 7-8frames per second when there is some type of motion in the room. These images are collected by the same computers that the radars are connected to. Each of the depth images are time stamped so that the radar times are synced with the image times. Depth images are used because the activity can be determined without being able to easily identify who the person is.

To test our algorithm with the TigerPlace data, we looked at a set amount of time on different days for different people. For each time sample we would run our algorithm on it and see what times our algorithm believes that it is collecting walks. We would also look at the time length of the walks as well. After getting the times, welooked the depth information to see if walks are actually happening at the times where the algorithm thought they were happening. If it is a walk, we would look to see if the walk picked up was a good walk for collecting gait information from the radar.

Chapter 5 - Results and Discussion

5.1 KNN

The first set of experiments was made to figure out what the best parameters for the KNN classifier for the radar data that was collected in February. In this experiment, the walks from the first 12 walkers are used for the training data. The walks from the last 3 subjects are used to test the classifier. The experimental sets are grouped based on which dissimilarity measure is being used. Each of the groups has times that were recorded using K with values of 3, 5, 7, and 9. Since the turnaround times are less than a second long in many cases (see Figure 5.1), a walking segment consists of a walk towards the radar, the turnaround, and a walk away from the radar. In order for a walk to be seen as a walk, the walk must have at least 3 consecutive windows that are classified as walks. The actual start and end times for these segments are compared to the start and end times from the classifier based on the parameter K and the dissimilarity measurement. All of the actual start and end times for the walk segments are rounded to the nearest second.

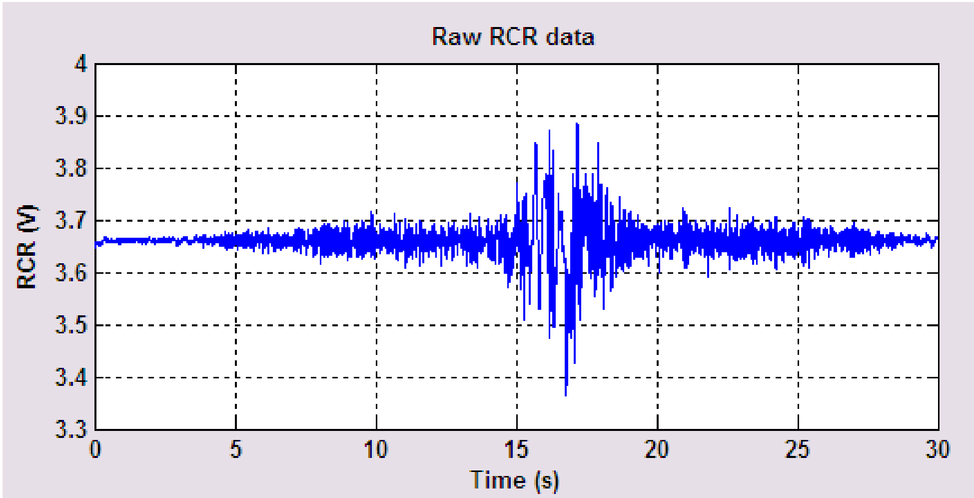

Figure 5.1 Raw radar signal of a walk towards and then away from the radar

5.1.1 Standardized Euclidean

Standardized Euclidean is first dissimilarity measured that is used by the classifier. The results are shown in Tables 5.1 – 5.8. There were times when the classifier was able to see the turnaround time as not being a part of the walk. Those time segments will be highlighted blue in the tables. There were also times where walk windows in the middle a walk were misclassified causing one walk to be separated into 2 walks. Those times will be highlighted red, and the number of dropped frames will be given. When windows during turnaround times are not classified as walks, the 2 walks during that segment were still classified as 1 segment.

When K was set to 3, one of the walk segments had a time when a walking window was misclassified in the middle of a walk. This was walk from subject o. During the walk away from the radar, a window was not classified correctly. It was the window that started at time

17:29:24. Figure 5.2 shows the spectrogram and the Number of Nearest Neighbors for this walk. There was also one time when a window with the walker turning around was not classified as a walk. During this walk, person m had a turnaround time that was slightly longer than most of the other times. The classifier was able to get all of the start times within 1 second of the actual start times. All but 2 of the calculated end times were within 1 second of the actual times. TABLE 5.1 shows the actual times versus the classifier times for each of the walking segments. TABLE 5.2 gives some the statistics for those times.

TABLE 5.1
FOUND VS ACTUAL TIMES OF WALKS SEGMENTS USING KNN
(STANDARDIZED EUCLIDEAN DISTANCE, K = 3)

Walk Sets		start	end	start	end	start	end	start	end
R-m-7-1	observed time	14:13:39	14:13:53	14:14:00	14:14:15	14:14:21	14:14:36	14:14:43	14:14:58
	segmented time	14:13:38	14:13:54	14:14:00	14:14:16	14:14:20	14:14:35	14:14:42	14:14:57
R-m-7-2	observed time	14:15:52	14:16:15	14:16:20	14:16:42	14:16:48	14:17:15	14:17:22	14:17:39
	segmented time	14:15:51	14:16:15	14:16:19	14:16:41	**14:16:47**	**14:17:15**	14:17:22	14:17:40
R-n-7-1	observed time	15:14:08	15:14:22	15:14:27	15:14:40	15:14:45	15:14:58	15:15:02	15:15:17
	segmented time	15:14:08	15:14:22	15:14:27	15:14:39	15:14:45	15:14:58	15:15:02	15:15:16
R-n-7-2	observed time	15:15:47	15:16:04	15:16:08	15:16:26	15:16:30	15:16:50	15:16:53	15:17:15
	segmented time	15:15:46	15:16:04	15:16:07	15:16:26	15:16:29	15:16:49	15:16:53	15:17:15
R-o-7-1	observed time	17:27:07	17:27:21	17:27:26	17:27:38	17:27:42	17:27:56	17:28:00	17:28:14
	segmented time	17:27:07	17:27:20	17:27:26	17:27:38	17:27:42	17:27:54	17:28:00	17:28:09
R-o-7-2	observedtime	17:29:14	17:29:29	17:29:32	17:29:48	17:29:52	17:29:08	17:30:13	17:30:27
	segmented time	**17:29:14**	**17:29:28**	17:29:33	17:29:48	17:29:52	17:30:07	17:30:13	17:30:26

TABLE 5.2
STATISTICS OF THE SEQUENCE CLASSIFICATIONS USING KNN
(STANDARDIZED EUCLIDEAN DISTANCE, K = 3)

Subject	#walk sequences	Dropped frames in the middle of a walk	Found start time is actual start time	Found end time is actual end time	start time within 1 sec of actual time	end time within 1 sec of actual time
m	8	0	2	2	8	8
n	8	0	5	5	8	8
o	8	1	7	2	8	6
total	24	1	14	9	24	22

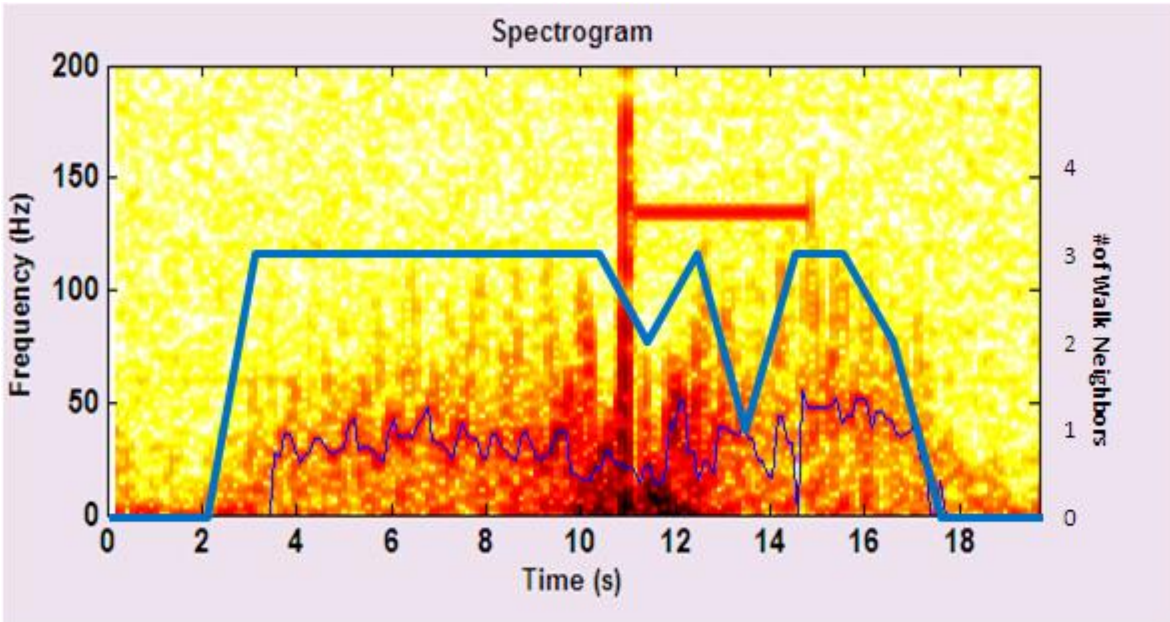

Figure 5.2 Spectrogram of the first walking sequence of R-o-7-2 with the number of nearest neighbors that are walks for each frame (blue line) with K = 3. In this case, a frame is misclassified in the middle of the walk away from the radar.

The results for when K was set to 5, shown in Tables 5.3 and 5.4, were pretty similar to the results from when K=3. It had the same problem of misclassifying walk for one of the walks from o. During the walk segment starting at 14:16:48, the classifier was able to not classify one of the turnaround times as walk similar to when K equaled 3 (see Figure 5.3). With K set to 5, the classifier was able to find one more exact start time then the classifier with K set to 3 (see TABLE 5.4), giving the setting of K=5 slightly better results.

TABLE 5.3
FOUND VS ACTUAL TIMES OF WALKS SEGMENTS USING KNN
(STANDARDIZED EUCLIDEAN DISTANCE, K = 5)

Walk Sets		start	end	start	end	start	end	start	end
R-m-7-1	Observed Time	14:13:39	14:13:53	14:14:00	14:14:15	14:14:21	14:14:36	14:14:43	14:14:58
	Segmented Time	14:13:38	14:13:54	14:14:00	14:14:16	14:14:20	14:14:35	14:14:42	14:14:57
R-m-7-2	Observed Time	14:15:52	14:16:15	14:16:20	14:16:42	14:16:48	14:17:15	14:17:22	14:17:39
	Segmented Time	14:15:51	14:16:15	14:16:19	14:16:41	**14:16:48**	**14:17:15**	14:17:22	14:17:40
R-n-7-1	Observed Time	15:14:08	15:14:22	15:14:27	15:14:40	15:14:45	15:14:58	15:15:02	15:15:17
	Segmented Time	15:14:08	15:14:22	15:14:27	15:14:39	15:14:45	15:14:58	15:15:02	15:15:16
R-n-7-2	Observed Time	15:15:47	15:16:04	15:16:08	15:16:26	15:16:30	15:16:50	15:16:53	15:17:15
	Segmented Time	15:15:46	15:16:04	15:16:07	15:16:26	15:16:29	15:16:49	15:16:53	15:17:15
R-o-7-1	Observed Time	17:27:07	17:27:21	17:27:26	17:27:38	17:27:42	17:27:56	17:28:00	17:28:14
	Segmented Time	17:27:07	17:27:20	17:27:26	17:27:38	17:27:42	17:27:54	17:28:00	17:28:09
R-o-7-2	Observed Time	17:29:14	17:29:29	17:29:32	17:29:48	17:29:52	17:29:08	17:30:13	17:30:27
	Segmented Time	**17:29:14**	**17:29:28**	17:29:33	17:29:48	17:29:52	17:29:07	17:30:13	17:30:26

TABLE 5.4
STATISTICS OF THE SEQUENCE CLASSIFICATIONS USING KNN
(STANDARDIZED EUCLIDEAN DISTANCE, K = 5)

Subject	#walk sequences	Dropped frames in the middle of a walk	Found start time is actual start time	Found end time is actual end time	start time within 1 sec of actual time	end time within 1 sec of actual time
m	8	0	3	2	8	8
n	8	0	5	5	8	8
o	8	1	7	2	8	6
total	24	1	15	9	24	22

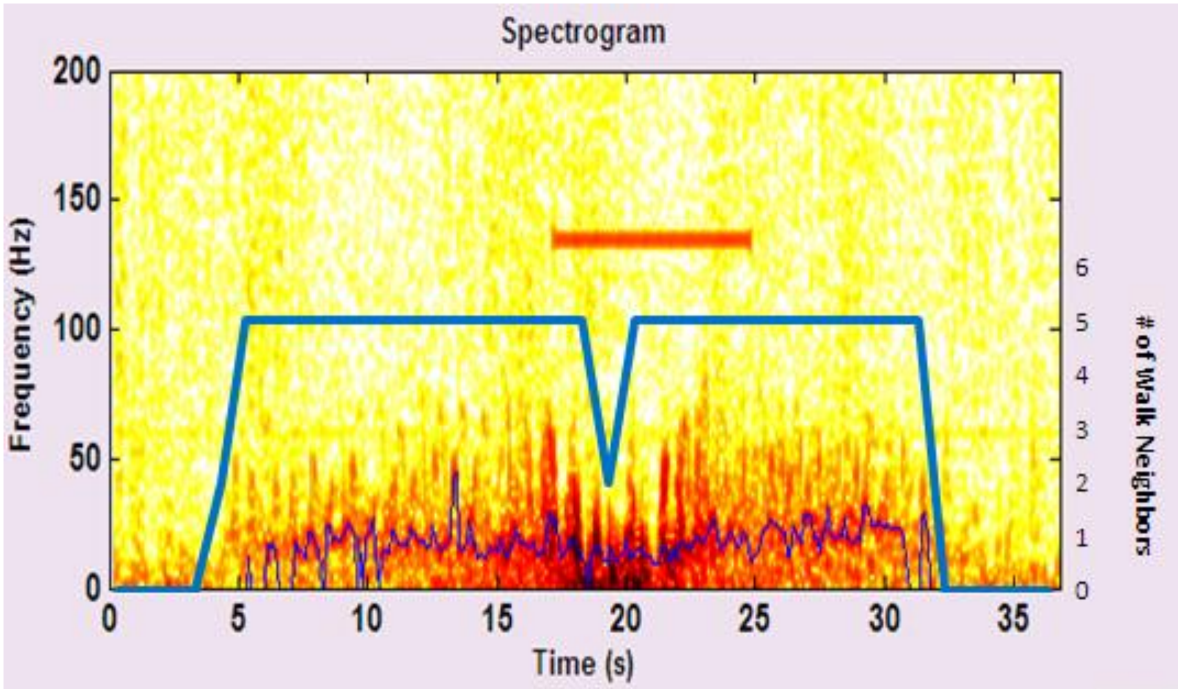

Figure 5.3 Spectrogram of the third walking sequence of R-m-7-2 with the number of nearest neighbors that are walks for each frame (blue line) with K = 5. In this case, the time that has the walker turning around is classified as a non-walk.

After setting K to be 7, the classifier was no longer able to classify the turnaround as a non-walk. The results in TABLE 5.5 show that the classifier is still classifying a walking window of the segment starting at 17:29:14 as a non-walking window. Looking at TABLE 5.6, the classifier was able to find more of the actual end times but it faired a little worse the actual start times of the segments. The results for K equal 9 were pretty similar to the results for K equal to 7 except that with K set to 9, it had one less end time that was calculated correctly. Tables 5.7 and 5.8 show these results.

TABLE 5.5

FOUND VS ACTUAL TIMES OF WALKS SEGMENTS USING KNN

(STANDARDIZED EUCLIDEAN DISTANCE, K = 7)

Walk Sets		start	end	start	end	start	end	start	end
R-m-7-1	observed time	14:13:39	14:13:53	14:14:00	14:14:15	14:14:21	14:14:36	14:14:43	14:14:58
	Segmented time	14:13:38	14:13:54	14:14:00	14:14:15	14:14:20	14:14:35	14:14:42	14:14:47
R-m-7-2	observed time	14:15:52	14:16:15	14:16:20	14:16:42	14:16:48	14:17:15	14:17:22	14:17:39
	Segmented time	14:15:51	14:16:15	14:16:19	14:16:41	14:16:47	14:17:15	14:17:22	14:17:40
R-n-7-1	observed time	15:14:08	15:14:22	15:14:27	15:14:40	15:14:45	15:14:58	15:15:02	15:15:17
	Segmented time	15:14:08	15:14:22	15:14:27	15:14:39	15:14:45	15:14:58	15:15:02	15:15:16
R-n-7-2	observed time	15:15:47	15:16:04	15:16:08	15:16:26	15:16:30	15:16:50	15:16:53	15:17:15
	Segmented time	15:15:46	15:16:04	15:16:07	15:16:26	15:16:29	15:16:49	15:16:53	15:17:15
R-o-7-1	observed time	17:27:07	17:27:21	17:27:26	17:27:38	17:27:42	17:27:56	17:28:00	17:28:14
	Segmented time	17:27:07	17:27:20	17:27:26	17:27:38	17:27:42	17:27:56	17:28:00	17:28:09
R-o-7-2	observed time	17:29:14	17:29:29	17:29:32	17:29:48	17:29:52	17:30:08	17:30:13	17:30:27
	Segmented time	**17:29:14**	**17:29:28**	17:29:33	17:29:48	17:29:52	17:30:07	17:30:13	17:30:26

TABLE 5.6

STATISTICS OF THE SEQUENCE CLASSIFICATIONS USING KNN

(STANDARDIZED EUCLIDEAN DISTANCE, K = 7)

Subject	#walk sequences	Dropped frames in the middle of a walk	Found start time is actual start time	Found end time is actual end time	start time within 1 sec of actual time	end time within 1 sec of actual time
m	8	0	2	3	8	8
n	8	0	5	5	8	8
o	8	1	7	3	8	7
total	24	1	14	11	24	23

TABLE 5.7
FOUND VS ACTUAL TIMES OF WALKS SEGMENTS USING KNN
(STANDARDIZED EUCLIDEAN DISTANCE, K = 9)

Walk Sets		start	end	start	end	start	end	start	end
R-m-7-1	observed time	14:13:39	14:13:53	14:14:00	14:14:15	14:14:21	14:14:36	14:14:43	14:14:58
	segmented time	14:13:38	14:13:54	14:14:00	14:14:14	14:14:20	14:14:35	14:14:42	14:14:47
R-m-7-2	observed time	14:15:52	14:16:15	14:16:20	14:16:42	14:16:48	14:17:15	14:17:22	14:17:39
	segmented time	14:15:51	14:16:15	14:16:19	14:16:41	14:16:47	14:17:15	14:17:22	14:17:40
R-n-7-1	observed time	15:14:08	15:14:22	15:14:27	15:14:40	15:14:45	15:14:58	15:15:02	15:15:17
	segmented time	15:14:08	15:14:22	15:14:27	15:14:39	15:14:45	15:14:58	15:15:02	15:15:16
R-n-7-2	observed time	15:15:47	15:16:04	15:16:08	15:16:26	15:16:30	15:16:50	15:16:53	15:17:15
	segmented time	15:15:46	15:16:04	15:16:07	15:16:26	15:16:29	15:16:49	15:16:53	15:17:15
R-o-7-1	observed time	17:27:07	17:27:21	17:27:26	17:27:38	17:27:42	17:27:56	17:28:00	17:28:14
	segmented time	17:27:07	17:27:20	17:27:26	17:27:38	17:27:42	17:27:56	17:28:00	17:28:09
R-o-7-2	observed time	17:29:14	17:29:29	17:29:32	17:29:48	17:29:52	17:30:08	17:30:13	17:30:27
	segmented time	**17:29:14**	**17:29:28**	17:29:33	17:29:48	17:29:52	17:30:07	17:30:13	17:30:26

TABLE 5.8
STATISTICS OF THE SEQUENCE CLASSIFICATIONS USING KNN
(STANDARDIZED EUCLIDEAN DISTANCE, K = 9)

Subject	#walk sequences	Dropped frames in the middle of a walk	Found start time is actual start time	Found end time is actual end time	start time within 1 sec of actual time	end time within 1 sec of actual time
m	8	0	2	2	8	8
n	8	0	5	5	8	8
o	8	1	7	3	8	7
total	24	1	14	10	24	23

5.1.2 Mahalanobis Distance

For the most part, the classifier performed well no matter what the value of K was. When K was set to 3 and 5, the classifier was able to find a pause in the walk for one of the walking sequences, with the classifier doing slightly better with finding the start times when K was set to 5. The classifier seemed to do the best with determining the starting and ending times when the value of K was 7. At the same time, the classifier was no longer able to see the pause in the one walk during the turnaround when K had a value of 7 or 9. It seems that if pauses in walks are wanted be found with the classifier still having good accuracy, using a value of 5 for K gives the best results.

Mahalanobis

The following results will be from the KNN classifier using the Mahalanobis distance and the dissimilarity measure between the features. The same values of 3, 5, 7, and 9 were used for K as in the previous experiment. The data used for testing and training is the same as well. When K was set to 3, the results showed 5 different segments in which a window from the segment containing the turnaround was classified as a non-walk. One of these times is shown in Figure 5.4. That is 4 more times that this classifier was able to this than any of the classifiers using the standardized Euclidean dissimilarity measure. Looking at Tables 5.9 and 5.10, this classifier was also slightly better at determining the actual start times of the walking segments. At the same time, it was slightly worse at determining the ending times. For the walking sequence starting at 17:29:28, this classifier was able to determine that the turnaround was not a walk, but it also misclassified 2 consecutive windows that contained walking.

TABLE 5.9

FOUND VS ACTUAL TIMES OF WALKS SEGMENTS USING KNN

(MAHALANOBIS DISTANCE, K = 3)

Walk Sets		start	end	start	end	start	end	start	end
R-m-7-1	observed time	14:13:39	14:13:53	14:14:00	14:14:15	14:14:21	14:14:36	14:14:43	14:14:58
	segmented time	14:13:38	14:13:53	14:14:00	14:14:14	14:14:20	14:14:35	**14:14:42**	**14:14:57**
R-m-7-2	observed time	14:15:52	14:16:15	14:16:20	14:16:42	14:16:48	14:16:15	14:17:22	14:17:39
	segmented time	14:15:52	14:16:13	**14:16:19**	**14:16:41**	**14:16:48**	**14:17:15**	14:17:22	14:17:40
R-n-7-1	observed time	15:14:08	15:14:22	15:14:27	15:14:40	15:14:45	15:14:58	15:15:02	15:15:17
	segmented time	15:14:08	15:14:22	15:14:27	15:14:39	15:14:45	15:14:58	15:15:02	15:15:16
R-n-7-2	observed time	15:15:47	15:16:04	15:16:08	15:16:26	15:16:30	15:16:50	15:16:53	15:17:15
	segmented time	15:15:46	15:16:04	15:16:06	15:16:26	15:16:29	15:16:49	15:16:53	15:17:15
R-o-7-1	observed time	17:27:07	17:27:21	17:27:26	17:27:38	17:27:42	17:27:56	17:28:00	17:28:14
	segmented time	17:27:07	17:27:20	17:27:26	17:27:38	17:27:42	17:27:54	17:28:00	17:28:09
R-o-7-2	observed time	17:29:14	17:29:29	17:29:32	17:29:48	17:29:52	17:29:08	17:30:13	17:30:27
	segmented time	**17:29:14**	**17:29:28**	**17:29:33**	**17:29:47**	17:29:52	17:30:07	**17:30:13**	**17:30:26**

TABLE 5.10

STATISTICS OF THE SEQUENCE CLASSIFICATIONS USING KNN

(MAHALANOBIS DISTANCE, K = 3)

Subject	#walk sequences	Dropped frames in the middle of a walk	Found start time is actual start time	Found end time is actual end time	start time within 1 sec of actual time	end time within 1 sec of actual time
m	8	0	4	2	8	7
n	8	0	5	5	7	8
o	8	2	7	1	8	6
total	24	2	16	8	23	21

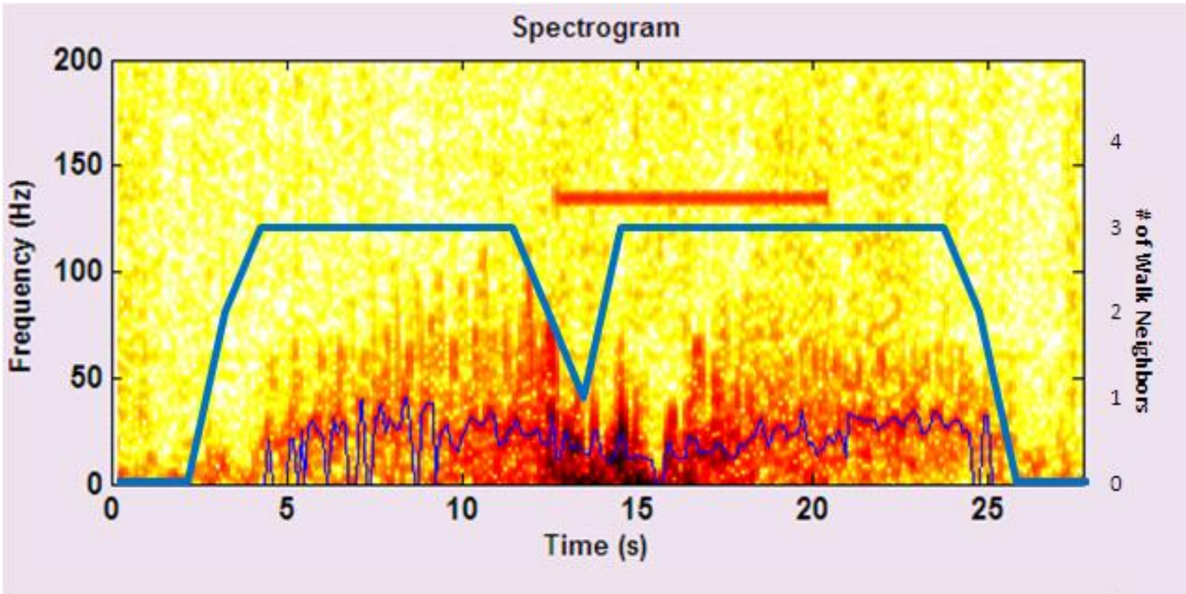

Figure 5.4 Spectrogram of the second walking sequence of R-m-7-2 with the number of nearest neighbors that are walks for each frame (blue line) with K = 3. In this case, the time that has the walker starts turning around is classified as a non-walk.

After changing the value of K to 5, the number of turnaround times that were considered non-walks dropped from 5 to 1. The one turnaround time that it didn't classify as a walk was the same time that found using the standardized Euclidean distance with K equaled to 3 and 5. It did, however, do a marginally better job of obtaining the correct start times for the walks. Tables 5.11 and 5.12 show that the rest of the results were similar to what was found when K was set to 3. For K equal to 7, Tables 5.13 and 5.14 show that the results were pretty much the same as they were for K=5. When K was set to 9, the classifier did slightly better with determining the starting times, but it did a little worse when determining the end times (see Tables 5.15 and 5.16). The rest of the results were pretty much the same as when K was equal to 5 and 7.

TABLE 5.11
FOUND VS ACTUAL TIMES OF WALKS SEGMENTS USING KNN
(MAHALANOBIS DISTANCE, K = 5)

Walk Sets		start	end	start	end	start	end	start	end
R-m-7-1	observed time	14:13:39	14:13:53	14:14:00	14:14:15	14:14:21	14:14:36	14:14:43	14:14:58
	segmented time	14:13:38	14:13:53	14:14:00	14:14:14	14:14:20	14:14:35	14:14:42	14:14:47
R-m-7-2	observed time	14:15:52	14:16:15	14:16:20	14:16:42	14:16:48	14:17:15	14:17:22	14:17:39
	segmented time	14:15:52	14:16:13	14:16:19	14:16:41	**14:16:48**	**14:17:15**	14:17:22	14:17:40
R-n-7-1	observed time	15:14:08	15:14:22	15:14:27	15:14:40	15:14:45	15:14:58	15:15:02	15:15:17
	segmented time	15:14:08	15:14:22	15:14:27	15:14:39	15:14:45	15:14:58	15:15:02	15:15:16
R-n-7-2	observed time	15:15:47	15:16:04	15:16:08	15:16:26	15:16:30	15:16:50	15:16:53	15:17:15
	segmented time	15:15:46	15:16:04	15:16:07	15:16:26	15:16:30	15:16:49	15:16:53	15:17:15
R-o-7-1	observed time	17:27:07	17:27:21	17:27:26	17:27:38	17:27:42	17:27:56	17:28:00	17:28:14
	segmented time	17:27:07	17:27:20	17:27:26	17:27:38	17:27:42	17:27:54	17:28:00	17:28:09
R-o-7-2	observed time	17:29:14	17:29:29	17:29:32	17:29:48	17:29:52	17:30:08	17:30:13	17:30:27
	segmented time	**17:29:14**	**17:29:28**	17:29:33	17:29:47	17:29:52	17:30:07	17:30:13	17:30:26

TABLE 5.12
STATISTICS OF THE SEQUENCE CLASSIFICATIONS USING KNN
(MAHALANOBIS DISTANCE, K = 5)

Subject	#walk sequences	Dropped frames in the middle of a walk	Found start time is actual start time	Found end time is actual end time	start time within 1 sec of actual time	end time within 1 sec of actual time
m	8	0	4	2	8	7
n	8	0	6	5	8	8
o	8	2	7	1	8	6
total	24	2	17	8	24	21

TABLE 5.13

FOUND VS ACTUAL TIMES OF WALKS SEGMENTS USING KNN

(MAHALANOBIS DISTANCE, K = 7)

Walk Sets		start	end	start	end	start	end	start	end
R-m-7-1	observed time	14:13:39	14:13:53	14:14:00	14:14:15	14:14:21	14:14:36	14:14:43	14:14:58
	segmented time	14:13:38	14:13:53	14:14:00	14:14:14	14:14:21	14:14:35	14:14:42	14:14:57
R-m-7-2	observed time	14:15:52	14:16:15	14:16:20	14:16:42	14:16:48	14:16:15	14:17:22	14:17:39
	segmented time	14:15:51	14:16:13	14:16:19	14:16:41	**14:16:48**	**14:17:15**	14:17:22	14:17:40
R-n-7-1	observed time	15:14:08	15:14:22	15:14:27	15:14:40	15:14:45	15:14:58	15:15:02	15:15:17
	segmented time	15:14:08	15:14:22	15:14:27	15:14:39	15:14:45	15:14:58	15:15:02	15:15:16
R-n-7-2	observed time	15:15:47	15:16:04	15:16:08	15:16:26	15:16:30	15:16:50	15:16:53	15:17:15
	segmented time	15:15:46	15:16:04	15:16:07	15:16:26	15:16:30	15:16:49	15:16:53	15:17:15
R-o-7-1	observed time	17:27:07	17:27:21	17:27:26	17:27:38	17:27:42	17:27:56	17:28:00	17:28:14
	segmented time	17:27:07	17:27:20	17:27:26	17:27:38	17:27:42	17:27:54	17:28:00	17:28:09
R-o-7-2	observed time	17:29:14	17:29:29	17:29:32	17:29:48	17:29:52	17:29:08	17:30:13	17:30:27
	segmented time	**17:29:14**	**17:29:28**	17:29:33	17:29:47	17:29:52	17:30:07	17:30:13	17:30:26

TABLE 5.14

STATISTICS OF THE SEQUENCE CLASSIFICATIONS USING KNN

(MAHALANOBIS DISTANCE, K = 7)

Subject	#walk sequences	Dropped frames in the middle of a walk	Found start time is actual start time	Found end time is actual end time	start time within 1 sec of actual time	end time within 1 sec of actual time
m	8	0	4	2	8	7
n	8	0	6	5	8	8
o	8	1	7	1	8	6
total	24	1	17	8	24	21

TABLE 5.15

FOUND VS ACTUAL TIMES OF WALKS SEGMENTS USING KNN

(MAHALANOBIS DISTANCE, K = 9)

Walk Sets		start	end	start	end	start	end	start	end
R-m-7-1	observed time	14:13:39	14:13:53	14:14:00	14:14:15	14:14:21	14:14:36	14:14:43	14:14:58
	segmented time	14:13:38	14:13:53	14:14:00	14:14:14	14:14:21	14:14:35	14:14:42	14:14:57
R-m-7-2	observed time	14:15:52	14:16:15	14:16:20	14:16:42	14:16:48	14:16:15	14:17:22	14:17:39
	segmented time	14:15:51	14:16:13	14:16:20	14:16:41	**14:16:48**	**14:17:15**	14:17:22	14:17:40
R-n-7-1	observed time	15:14:08	15:14:22	15:14:27	15:14:40	15:14:45	15:14:58	15:15:02	15:15:17
	segmented time	15:14:08	15:14:22	15:14:27	15:14:39	15:14:45	15:14:58	15:15:02	15:15:16
R-n-7-2	observed time	15:15:47	15:16:04	15:16:08	15:16:26	15:16:30	15:16:50	15:16:53	15:17:15
	segmented time	15:15:46	15:16:04	15:16:06	15:16:26	15:16:30	15:16:49	15:16:53	15:17:15
R-o-7-1	observed time	17:27:07	17:27:21	17:27:26	17:27:38	17:27:42	17:27:56	17:28:00	17:28:14
	segmented time	17:27:07	17:27:20	17:27:26	17:27:38	17:27:42	17:27:54	17:28:00	17:28:09
R-o-7-2	observed time	17:29:14	17:29:29	17:29:32	17:29:48	17:29:52	17:29:08	17:30:13	17:30:27
	segmented time	**17:29:14**	**17:29:28**	17:29:33	17:29:47	17:29:52	17:30:07	17:30:13	17:30:26

TABLE 5.16

STATISTICS OF THE SEQUENCE CLASSIFICATIONS USING KNN

(MAHALANOBIS DISTANCE, K = 9)

Subject	#walk sequences	Dropped frames in the middle of a walk	Found start time is actual start time	Found end time is actual end time	start time within 1 sec of actual time	end time within 1 sec of actual time
m	8	0	5	2	8	7
n	8	0	6	5	7	8
o	8	1	7	1	8	6
total	24	1	18	8	23	21

5.2 Bayes Decision Rule

The next set of experiments was used to test how well the classifier using Bayes' decision is able to segment out the walks in the radar data. The same February data used to test the KNN classifier with the same walking segments was used for this experiment. We ran tests with this classifier with the prior probabilities of both the walks and non-walks being equal, the prior of the walks being higher (60%) than the non-walk prior, and the prior of the walks being lower (40%) than the non-walk prior.

When the prior probabilities for both the walks and the non-walks were equal, there was only one time when frames were misclassified in the middle of a walk (see TABLE 5.17). However, the classifier did not do as good of a job determining the end of the walks when compared to the KNN classifiers. TABLE 5.18 shows that eight of the 24 walks did not have the end times calculated within 1 second of the actual end times. Of those times, 5 were off by more than 2 seconds. The classifier did do a better job with the start times than it did with the end times. Three of the start times were calculated more than a second off.

TABLE 5.17

FOUND VS ACTUAL TIMES OF WALKS SEGMENTS USING BAYES DECISION RULE

(WALK PRIOR = 0.5, NON-WALK PRIOR = 0.5)

Walk Sets		start	end	start	end	start	end	Start	end
R-m-7-1	observed time	14:13:39	14:13:53	14:14:00	14:14:15	14:14:21	14:14:36	14:14:43	14:14:58
	segmented time	14:13:39	14:13:53	14:14:01	14:14:14	14:14:21	14:14:35	14:14:42	14:14:58
R-m-7-2	observed time	14:15:52	14:16:15	14:16:20	14:16:42	14:16:48	14:16:15	14:17:22	14:17:39
	segmented time	14:15:52	14:16:12	14:16:20	14:16:41	14:16:47	14:17:14	14:17:22	14:17:41
R-n-7-1	observed time	15:14:08	15:14:22	15:14:27	15:14:40	15:14:45	15:14:58	15:15:02	15:15:17
	segmented time	15:14:09	15:14:21	15:14:27	15:14:39	15:14:46	15:14:57	15:15:02	15:15:16
R-n-7-2	observed time	15:15:47	15:16:04	15:16:08	15:16:26	15:16:30	15:16:50	15:16:53	15:17:15
	segmented time	15:15:46	15:16:04	15:16:06	15:16:26	15:16:30	15:16:49	15:16:53	15:17:15
R-o-7-1	observed time	17:27:07	17:27:21	17:27:26	17:27:38	17:27:42	17:27:56	17:28:00	17:28:14
	segmented time	**17:27:08**	**17:27:21**	17:27:26	17:27:35	17:27:44	17:27:53	17:28:02	17:28:09
R-o-7-2	observed time	17:29:14	17:29:29	17:29:32	17:29:48	17:29:52	17:29:08	17:30:13	17:30:27
	segmented time	17:29:14	17:29:24	17:29:33	17:29:44	17:29:52	17:30:03	17:30:13	17:30:26

TABLE 5.18

STATISTICS OF THE SEQUENCE CLASSIFICATIONS USING BAYES DECISION RULE

(WALK PRIOR = 0.5, NON-WALK PRIOR = 0.5)

Subject	#walk sequences	Dropped frames in the middle of a walk	Found start time is actual start time	Found end time is actual end time	start time within 1 sec of actual time	end time within 1 sec of actual time
m	8	0	5	2	8	6
n	8	1	4	3	7	8
o	8	0	4	1	6	2
total	24	1	13	6	21	16

After setting the priors to .6 for the walks and .4 for the non-walks, the overall performance of the classifier dropped. TABLE 5.19 shows more times when windows were misclassified in the middle of the walks. Less of the end times were calculated correctly as shown in TABLE 5.20. With these settings, the classifier did find one more start time that was correct to within one second of the actual time, but it found one less start time that was the actual start time.

When the priors were set so that the non-walks had a prior of .6 and the walks had a prior of .4, the results seemed to have overall improvements. Looking at Tables 5.21 and 5.22, the classifier improved with finding both the start times and the end times. It also improved over the previous results in misclassifying frames that are in the middle of a walk, but it was not better than with the priors being equal. There were walks with windows in the middle of a walk being misclassified as opposed to one with the first settings for the priors.

This classifier seemed to have the best results for the starting and ending times when the prior for the non-walks was set to .6. However, with this setting, the classifier also had an extra time when frames were dropped during a walking sequence. The setting with the priors being equal showed the best results for not misclassifying walk windows in the middle of walks. With that being said, there may be a setting for the prior of the non-walks between .5 and .6 that will have good results for the starting and ending times while maintaining the lowest rate of not misclassifying the window in the middle of walks.

TABLE 5.19
FOUND VS ACTUAL TIMES OF WALKS SEGMENTS USING BAYES DECISION RULE
(WALK PRIOR = 0.6, NON-WALK PRIOR = 0.4)

Walk Sets		start	end	start	end	start	end	Start	end
R-m-7-1	observed time	14:13:39	14:13:53	14:14:00	14:14:15	14:14:21	14:14:36	14:14:43	14:14:58
	segmented time	14:13:39	14:13:51	14:14:01	14:14:14	14:14:21	14:14:35	14:14:42	14:14:57
R-m-7-2	observed time	14:15:52	14:16:15	14:16:20	14:16:42	14:16:48	14:16:15	14:17:22	14:17:39
	segmented time	14:15:53	14:16:12	14:16:20	14:16:41	**14:16:48**	**14:17:14**	14:17:22	14:17:41
R-n-7-1	observed time	15:14:08	15:14:22	15:14:27	15:14:40	15:14:45	15:14:58	15:15:02	15:15:17
	segmented time	15:14:09	15:14:21	15:14:28	15:14:39	15:14:46	15:14:57	15:15:02	15:15:16
R-n-7-2	observed time	15:15:47	15:16:04	15:16:08	15:16:26	15:16:30	15:16:50	15:16:53	15:17:15
	segmented time	15:15:46	15:16:04	15:16:07	15:16:25	15:16:30	15:16:49	**15:16:53**	**15:17:15**
R-o-7-1	observed time	17:27:07	17:27:21	17:27:26	17:27:38	17:27:42	17:27:56	17:28:00	17:28:14
	segmented time	**17:27:08**	**17:27:21**	17:27:26	17:27:35	17:27:44	17:27:53	17:28:02	17:28:09
R-o-7-2	observed time	17:29:14	17:29:29	17:29:32	17:29:48	17:29:52	17:29:08	17:30:13	17:30:27
	segmented time	17:29:14	17:29:24	17:29:33	17:29:44	17:29:52	17:30:03	17:30:13	17:30:26

TABLE 5.20
STATISTICS OF THE SEQUENCE CLASSIFICATIONS USING BAYES DECISION RULE
(WALK PRIOR = 0.6, NON-WALK PRIOR = 0.4)

Subject	#walk sequences	Dropped frames in the middle of a walk	Found start time is actual start time	Found end time is actual end time	start time within 1 sec of actual time	end time within 1 sec of actual time
m	8	1	5	0	8	5
n	8	1	3	2	8	8
o	8	1	4	1	6	2
total	24	3	12	3	22	15

TABLE 5.21

FOUND VS ACTUAL TIMES OF WALKS SEGMENTS USING BAYES DECISION RULE

(WALK PRIOR = 0.4, NON-WALK PRIOR = 0.6)

Walk Sets		start	end	start	end	start	end	Start	end
R-m-7-1	observed time	14:13:39	14:13:53	14:14:00	14:14:15	14:14:21	14:14:36	14:14:43	14:14:58
	segmented time	14:13:38	14:13:53	14:14:01	14:14:14	14:14:21	14:14:35	14:14:42	14:14:58
R-m-7-2	observed time	14:15:52	14:16:15	14:16:20	14:16:42	14:16:48	14:16:15	14:17:22	14:17:39
	segmented time	14:15:52	14:16:13	14:16:20	14:16:41	**14:16:47**	**14:17:15**	14:17:22	14:17:41
R-n-7-1	observed time	15:14:08	15:14:22	15:14:27	15:14:40	15:14:45	15:14:58	15:15:02	15:15:17
	segmented time	15:14:08	15:14:21	15:14:27	15:14:39	15:14:45	15:14:57	15:15:02	15:15:16
R-n-7-2	observed time	15:15:47	15:16:04	15:16:08	15:16:26	15:16:30	15:16:50	15:16:53	15:17:15
	segmented time	15:15:46	15:16:04	15:16:06	15:16:26	15:16:30	15:16:49	15:16:53	15:17:15
R-o-7-1	observed time	17:27:07	17:27:21	17:27:26	17:27:38	17:27:42	17:27:56	17:28:00	17:28:14
	segmented time	**17:27:08**	**17:27:21**	17:27:26	17:27:35	17:27:44	17:27:54	17:28:01	17:28:09
R-o-7-2	observed time	17:29:14	17:29:29	17:29:32	17:29:48	17:29:52	17:29:08	17:30:13	17:30:27
	segmented time	17:29:14	17:29:24	17:29:32	17:29:44	17:29:52	17:30:03	17:30:12	17:30:26

TABLE 5.22

STATISTICS OF THE SEQUENCE CLASSIFICATIONS USING BAYES DECISION RULE

(WALK PRIOR = 0.4, NON-WALK PRIOR = 0.6)

Subject	#walk sequences	Dropped frames in the middle of a walk	Found start time is actual start time	Found end time is actual end time	start time within 1 sec of actual time	end time within 1 sec of actual time
m	8	1	4	3	8	6
n	8	0	6	3	7	8
o	8	1	4	1	7	2
total	24	2	14	7	22	16

5.3 TigerPlace Data

The final experiment was check to see if walks could be detected in actual living environments. To test this, the data that was collected at TigerPlace from 4 different days in 3 different apartments. For each day, the classifier was run on the data that was collected between the hours of 9:00 and 17:00. Since there will be lots of time when non-walks occurred in an apartment, this experiment is a good check to make sure that not too many false alarms are occurring. After running the classifier on the data, we checked only the times where the classifier believed there were walks against the Kinect depth image data. This means some walks may be missed during the course of the day. This test is to make sure that something that is being detected as a walk is actually a walk. Since the KNN classifier had better results in lab, the TigerPlacedata was classified using the KNN classifier. For the standardized Euclidean distance measure, a K of 5 was used. K was set to 3 for the Mahalanobis distance measure. In order for the walks to be saved, they must have 5 consecutive windows that are classified as walking windows.

The first room considered was that of subject 3004. We looked at 2 days for this room. The first day was September 1, 2011, and the second day was January 11, 2012. In this room, the radar system was placed to the right of the front door on the ground. The Kinect was placed above and to the left of the front door. In the second apartment (3047), the radar was placed to the right of the kitchen’s bar that was a few feet in front of and to the left of the front door. The Kinect was above and to the left of the front door. September 15, 2011 was the day that was used for this room. The last apartment that we used was the apartment of 3038. There, the radar system was placed in the bedroom between the nightstand and the dresser and the Kinect was above and to the right of the front door. The layouts of the three rooms are shown in Figures 5.5, 5.6, and 5.7.

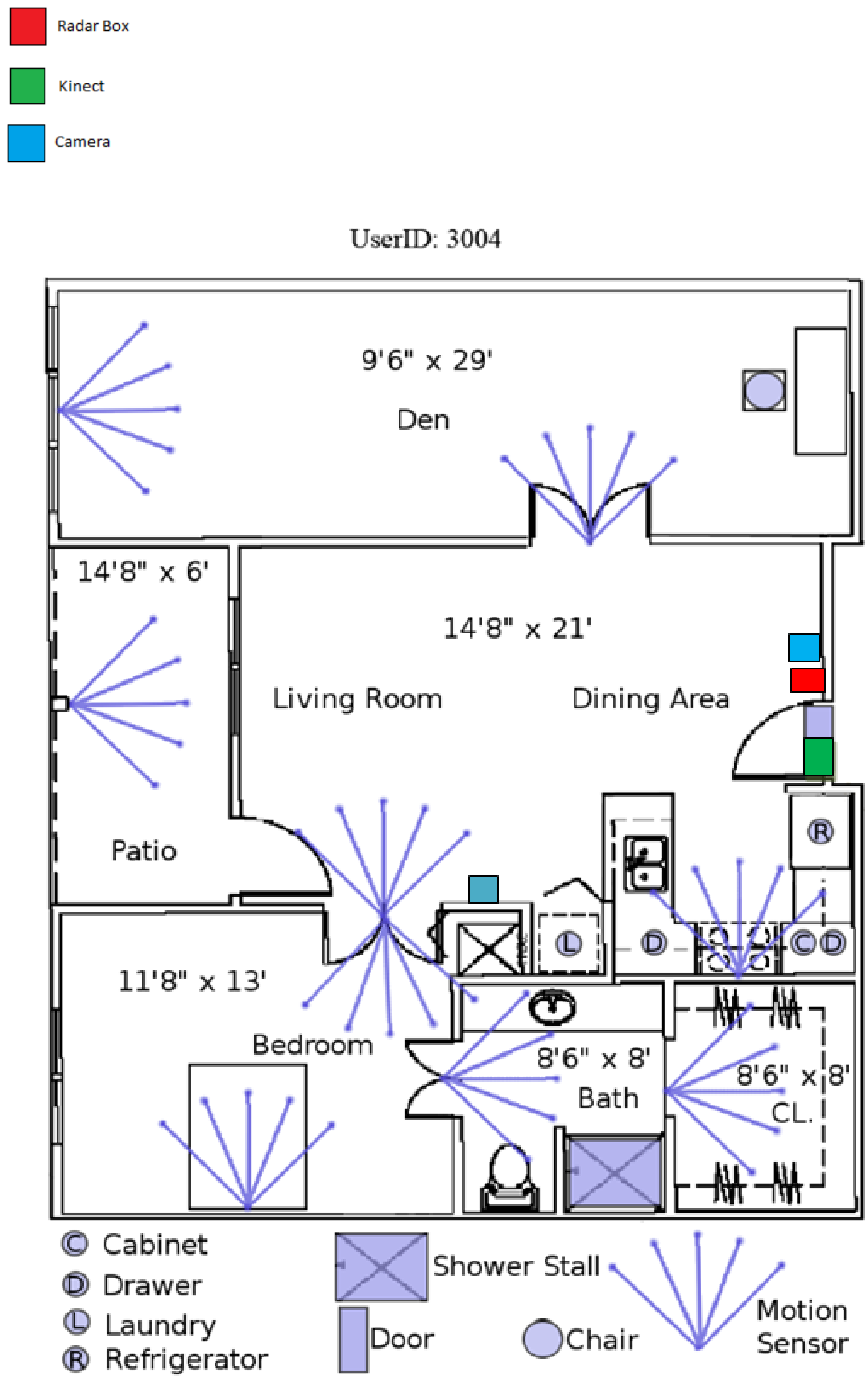

Figure 5.5 Diagram of 3004's apartment with the placement of the different sensor. The Key is as the top.

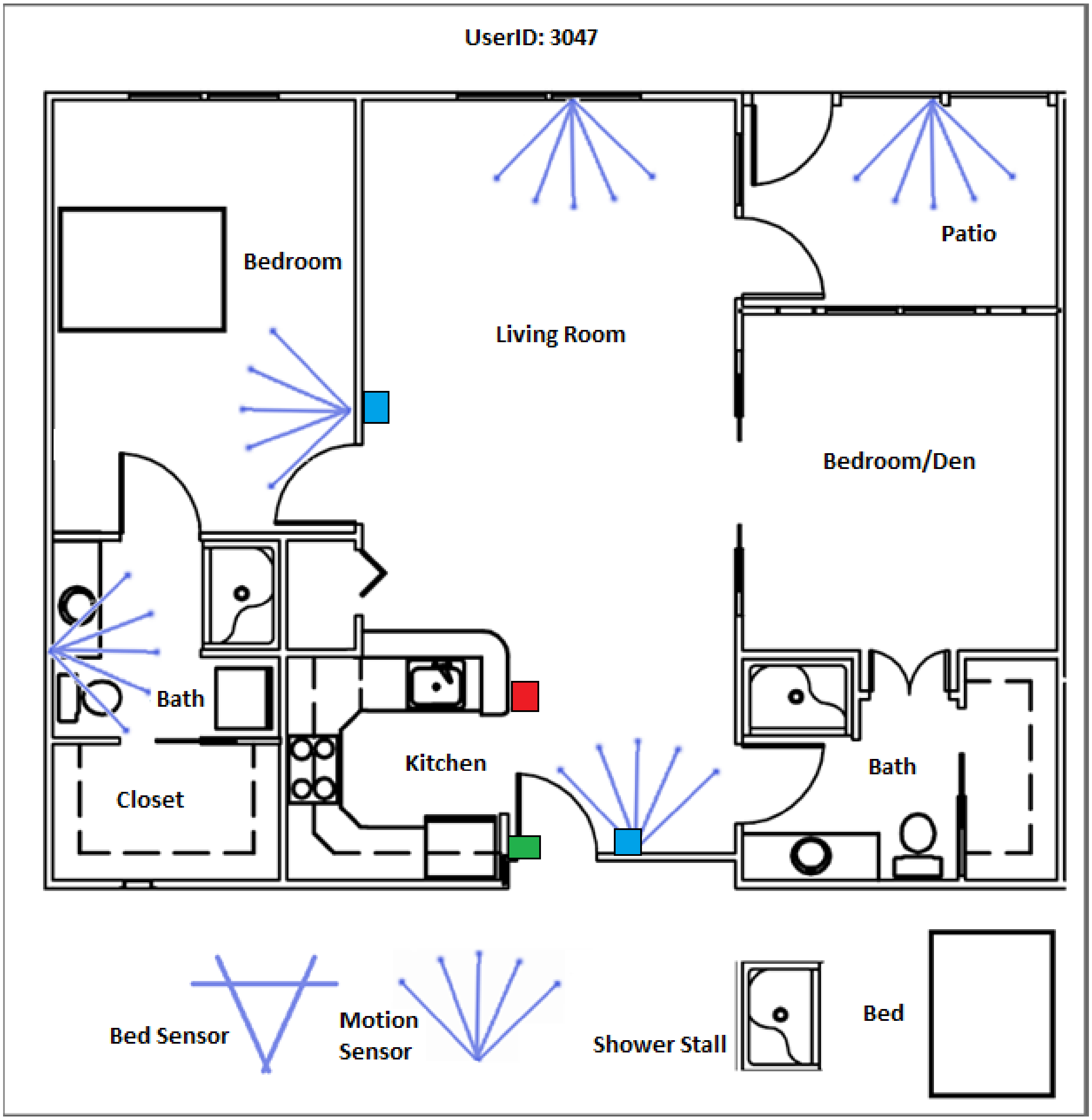

Figure 5.6 Diagram of 3047's apartment with the placement of the different sensor.

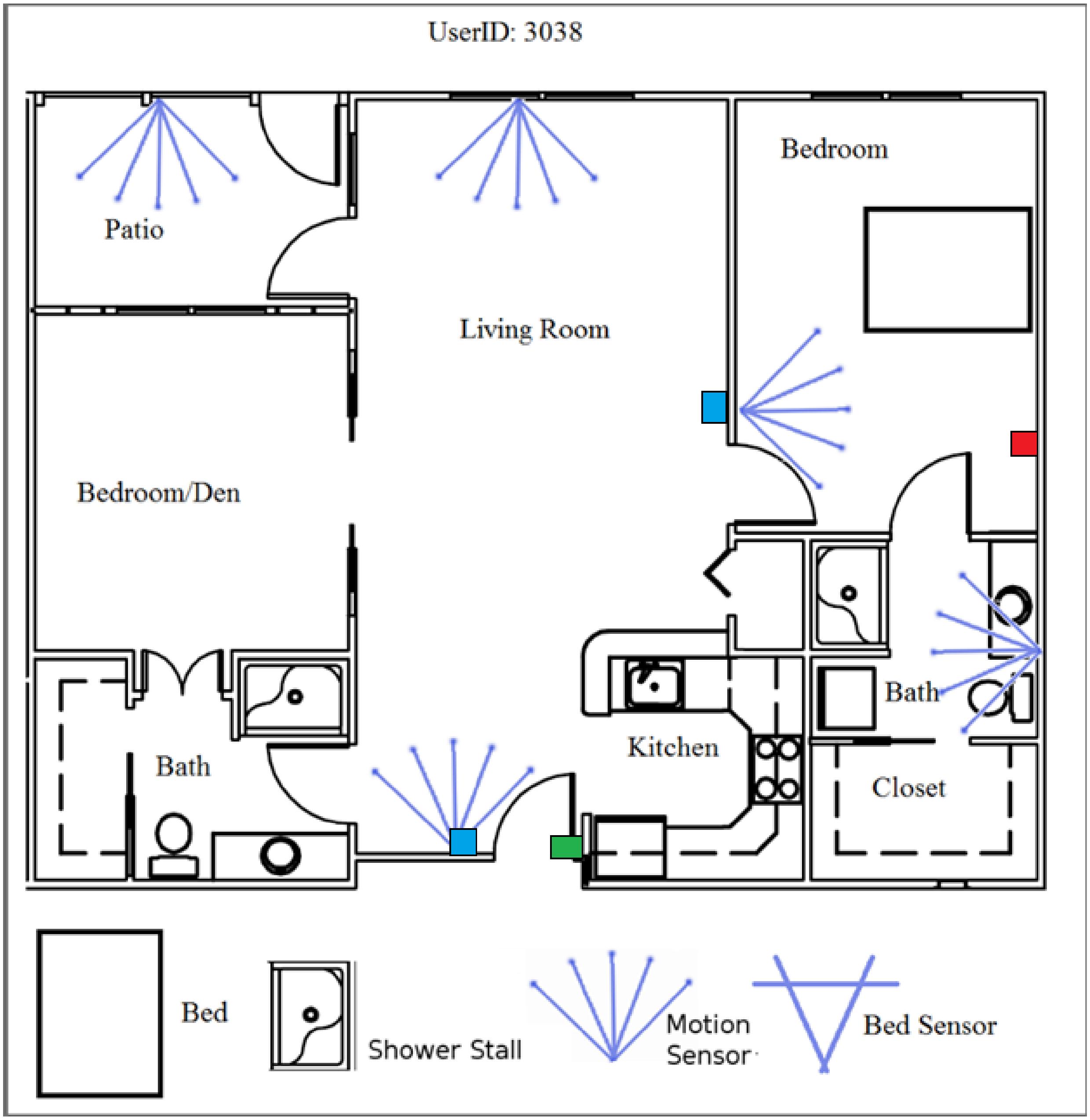

Figure 5.7 Diagram of 3047's apartment with the placement of the different sensor.

5.3.1 Standardized Euclidean

During the first day for 3004, 31 walk times were found by the classifier. Of those times, 29 of the times were times of actual walks. TABLE 5.23 shows that there was a variety of different types of walks that were found. These walks include walks toward the radar, away from the radar, across the radar, multiple people walking, walks not in a straight path, and walks with small pauses in them. For some of the walks, the whole walk was not collected by the Kinect because the walks started in a separate room. For this reason, the 2 walks that were not confirmed by the Kinect could possibly still be walks in a different part of the apartment.

For the second day collected from 3004, as shown in TABLE 5.24, the classifier found 37 walk times. Five of those walks were not confirmed to be walks looking at the Kinect video data. The walks found for this day were similar to the walks that were found during the first day. For some of the unconfirmed walks, a person was in the kitchen area which is not in the view of the Kinect camera. For these times, it could be possible that the person is moving back and forward in the kitchen which is causing the classifier to see it as a walk. Since the kitchen is small, these would still not be walks, but instead leg movements back and forth for maneuvering around the kitchen area.

In the apartment of 3047, 114 walks were found during the 8 hour period, and 107 of those times were the times of actual walks. Some of these walks are shown in TABLE 5.25. Since this was a larger apartment, it had many longer walks that were detected. Some of the non-walks that were seen as walks were movements around the couch area and swaying back and forth near the radar. There were also classified walk times were there seemed to be no movements and the residents were sitting down on a couch. There may, in fact, be some interference from movements outside of the room, but based on the place of the radar in the apartment, this is unlikely.

The apartment of 3038 had 14 walk times found during the day (see TABLE 5.26). Two of those times were not confirmed by the Kinect. In both of those cases, the resident was in the bedroom, out of the view of the Kinect. With that, it is a strong possibility that those times could indeed be walks. Most of the walks found in this room were walks going in and out of the bedroom.

TABLE 5.23
WALKS FOUND IN 3004'S APARTMENT USING KNN DAY 1
(STANDARDIZED EUCLIDEAN DISTANCE, K = 5)

Time	Length (s)	Description
9/1/2011 09:02:01	14	walks in with someone else
9/1/2011 09:35:48	5	walking outside the door
9/1/2011 09:50:28	6	side room to front door
9/1/2011 10:14:17	6	walks in and right back out
9/1/2011 10:35:40	9	walks from side room to the bed room
9/1/2011 10:37:12	6	walk from bedroom to side room
9/1/2011 10:38:08	6	walks from side room to outside the apartment
9/1/2011 11:13:45	5	2 people take a few steps, then stop
9/1/2011 11:13:59	5	2 people walk into the bedroom
9/1/2011 11:14:28	8	two people walk from bedroom to front door
9/1/2011 11:14:57	6	walks from front door to outside door
9/1/2011 11:20:57	10	walks in to middle of the room, stops for 1 sec, then walks to side room
9/1/2011 11:21:13	7	nothing in the video
9/1/2011 11:23:05	8	walks from room to outside the front door (best so far)
9/1/2011 13:13:30	6	walks in and walks into the kitchen area
9/1/2011 13:17:12	7	walk from side room to bedroom
9/1/2011 13:18:27	8	bedroom to front door
9/1/2011 13:19:15	7	walks in from door to the bed room (good walk as well)
9/1/2011 13:19:23	7	nothing in the video
9/1/2011 13:23:48	6	from bedroom to sideroom
9/1/2011 13:32:49	13	walks from side room to outside the door
9/1/2011 13:33:20	6	walks in the door to kitchen area, and then right back out
9/1/2011 14:36:26	7	walk from side room to bedroom
9/1/2011 14:37:54	6	walk from bedroom to side room
9/1/2011 15:51:23	8	walks from side to outside back door
9/1/2011 15:53:18	9	walks from outside back door to the bar outside kitchen area
9/1/2011 15:54:07	9	walks from bar area to outside back door
9/1/2011 15:55:18	10	walks from outside back door to the bedroom
9/1/2011 15:57:16	5	walk from bedroom to side room
9/1/2011 16:47:26	8	side room to bedroom

TABLE 5.24
WALKS FOUND IN 3004'S APARTMENT USING KNN DAY 2
(STANDARDIZED EUCLIDEAN DISTANCE, K = 5)

Time	Length (s)	Description
01/11/2012 11:48:08	15	walk from back to front of room then back
01/11/2012 11:49:24	7	walk from back to front of room
01/11/2012 11:49:33	5	walk from front to back of room
01/11/2012 11:49:44	5	nothing
01/11/2012 11:50:40	6	walk from back side to front
01/11/2012 11:58:48	10	walk from front door to the back
01/11/2012 11:59:55	14	walk from the back room to the front door
01/11/2012 12:04:38	5	walk from front door to right side room
01/11/2012 12:04:56	7	walk from bar area to the back of the room (side room)
01/11/2012 12:05:29	14	walk from back left to the front door
01/11/2012 12:12:28	5	moving around in the kitchen
01/11/2012 12:14:06	5	nothing
01/11/2012 12:15:53	7	walk from kitchen to the side room
01/11/2012 12:29:29	7	walk from the side room to the bar area
01/11/2012 12:31:55	5	nothing might be in the kitchen
01/11/2012 12:34:05	9	walking from kitchen to the side room
01/11/2012 12:57:21	7	nothing
01/11/2012 13:00:03	5	nothing
01/11/2012 13:00:57	5	walk from out of the kitchen and round the bar
01/11/2012 13:02:01	7	walk from the bar to the side room
01/11/2012 14:10:22	8	nothing
01/11/2012 14:26:26	8	walk from side room to the back of the room
01/11/2012 14:46:05	7	walk from the back to the side room
01/11/2012 15:48:40	8	walk from side room to the back of the room
01/11/2012 15:50:06	9	walk from back of the room to the side room
01/11/2012 16:04:27	8	walk from side room to the back of the room
01/11/2012 16:06:35	7	walk from back of the room to the side room
01/11/2012 16:16:55	11	walk from side room to the back of the room
01/11/2012 16:17:28	10	walk from back of the room to the side room
01/11/2012 16:23:53	7	walk from the side room to the back of the room
01/11/2012 16:27:52	6	walk from back room to couch in the back then back in to the back room
01/11/2012 16:28:46	6	walk from the back room to the couch
01/11/2012 16:29:05	9	walk from the back couch to the bar area
01/11/2012 16:46:06	10	walk from the front door to the back room
01/11/2012 16:46:47	19	walk from the back room to the front door
01/11/2012 16:48:49	8	moving around at the front door

TABLE 5.25
WALKS FOUND IN 3047'S APARTMENT USING KNN DAY 1
(STANDARDIZED EUCLIDEAN DISTANCE, K = 5)

Time	Length (s)	Description
9/15/2011 9:04:28	10	walks from side room toward and across radar
9/15/2011 9:10:25	5	walk from side room to side room
9/15/2011 9:20:00	9	walks from in front of radar to the back
9/15/2011 9:20:56	12	walks from back to front along the right wall
9/15/2011 9:24:47	5	side room to side room
9/15/2011 9:26:33	5	walks just outside of right side room, then stops
9/15/2011 9:26:59	8	walks from just outside of the room to the kitchen
9/15/2011 9:30:05	6	walks from left room to the back and out the patio door
9/15/2011 9:31:47	12	walk from behind radar to the back of the room
9/15/2011 9:32:07	16	walk from back to in front of radar
9/15/2011 9:33:14	5	walk from back right to just in front of the couch
9/15/2011 9:36:30	9	walk from kitchen to the back of the room
9/15/2011 9:37:13	5	walk from the couch to the kitchen
9/15/2011 9:40:14	11	walk from kitchen from side room (right)
9/15/2011 9:44:35	7	walks out of the right side room
9/15/2011 9:44:46	5	walk from the middle of the room to the back
9/15/2011 9:50:42	10	walk from back of the room to the kitchen
9/15/2011 9:59:21	5	walks from the side of the couch to the front of the couch
9/15/2011 10:02:53	**7**	could not tell
9/15/2011 10:25:34	10	walk from side room to the middle of the room
9/15/2011 10:25:56	5	walks into the right side room
9/15/2011 10:27:05	**6**	could not tell
9/15/2011 10:35:28	5	walks from right side to the front of the couch, and then back between the couch and left side
9/15/2011 10:55:47	5	walks on the right side from in front of the right side room towards the front
9/15/2011 10:55:54	6	walk from the couch to to the middle of open area, then stops
9/15/2011 10:57:34	9	multiple people walking
9/15/2011 10:59:09	7	walks from the kitchen to the left side room
9/15/2011 10:59:52	7	2 people walk from the open area to the back. One stops closer to the front then the other
9/15/2011 11:00:47	5	takes a few steps to the back of the room
9/15/2011 11:01:52	7	one person walks from the left to the middle while one walks one the right side towards the patio and then back
9/15/2011 11:02:52	6	walk from the left side room to the back of the room
9/15/2011 11:03:00	5	walk from the back of the room to the left side room
9/15/2011 11:03:58	7	walks from the middle of the room to the left side room
9/15/2011 11:04:37	6	walk from the middle of the room towards the bar

TABLE 5.26
WALKS FOUND IN 3038'S APARTMENT USING KNN
(STANDARDIZED EUCLIDEAN DISTANCE, K = 5)

Time	Length (s)	Description
2/5/2012 11:54:05	7	walk
2/5/2012 11:56:34	8	can not tell
2/5/2012 13:09:55	9	walk
2/5/2012 13:16:24	6	can not tell
2/5/2012 13:16:49	7	walk
2/5/2012 13:30:36	10	walk
2/5/2012 13:31:37	7	walk
2/5/2012 14:27:40	7	walk
2/5/2012 14:28:46	8	walk
2/5/2012 14:29:09	7	walk
2/5/2012 14:29:33	10	walk
2/5/2012 16:02:40	6	walk
2/5/2012 16:11:32	7	walk
2/5/2012 16:38:10	5	walk

TABLE 5.27
TOTAL WALKS FOUND FOR EACH OF THE APARTMENTS
(STANDARDIZED EUCLIDEAN DISTANCE, K = 5)

Room	**# of Days**	**Walks detected**	**Actual Walks**
3004	2	68	61
3047	1	114	107
3038	1	14	12

The overall performance of the classifier using the standardized Euclidean distance was pretty good with 91.8% of the walks found being confirmed as walks. TABLE 5.27 shows the performance of the classifier for each room. Some of the times found were confirmed to not be walks while other times could not be confirmed as walks. This means that the accuracy of the classifier may be better than 91.8%. There are times where the classifier missed walks. Since it is okay that walks are missed during the day, the accuracy is based on when the classifier determines that a walk has occurred.

5.3.2 Mahalanobis Distance

The classifier found 32 walks in 3004's apartment using the Mahalanobis distance measure on September 01, 2011. Two of the times for this classifier were different from the times given by the classifier using the standardized distance. For one of the times, nothing was seen in the video while the other time was of two people walking into apartment from the front door. There are times when the beginning and ending times of the two classifiers did not match up. In most of those cases, the classifiers were within one second of each other.

For the second day used in 3004's apartment, 40 walks were found. From this day, 30 of the walk times could be confirmed by the Kinect video data (see TABLE 5.29). This classifier picked up more false alarms than the previous classifier did for this room.

TABLE 5.28
WALKS FOUND IN 3004'S APARTMENT USING KNN DAY 1
(MAHALANOBIS DISTANCE, K = 3)

Time	Length (s)	Description
9/1/2011 9:02:01	14	walks in with someone else
9/1/2011 9:35:48	5	walking outside the door
9/1/2011 9:50:28	6	side room to front door
9/1/2011 10:14:17	6	walks in and right back out
9/1/2011 10:16:04	5	Nothing in video
9/1/2011 10:35:40	8	walks from side room to the bed room
9/1/2011 10:37:12	6	walk from bedroom to side room
9/1/2011 10:38:08	6	walks from side room to outside the apartment
9/1/2011 11:13:19	5	2 people walk into the door
9/1/2011 11:13:45	5	2 people take a few steps, then stop
9/1/2011 11:13:59	5	2 people walk into the bedroom
9/1/2011 11:14:28	8	two people walk from bedroom to front door
9/1/2011 11:14:57	6	walks from front door to outside door
9/1/2011 11:20:57	9	walks in to middle of the room, stops for 1 sec, then walks to side room
9/1/2011 11:21:14	6	nothing in the video
9/1/2011 11:23:05	8	walks from room to outside the front door (best so far)
9/1/2011 13:13:30	10	walks in and walks into the kitchen area
9/1/2011 13:17:12	7	walk from side room to bedroom
9/1/2011 13:18:27	8	bedroom to front door
9/1/2011 13:19:15	7	walks in from door to the bed room (good walk as well)
9/1/2011 13:19:23	7	nothing in the video
9/1/2011 13:23:47	7	from bedroom to sideroom
9/1/2011 13:32:49	13	walks from side room to outside the door
9/1/2011 13:33:20	6	walks in the door to kitchen area, and then right back out
9/1/2011 14:36:26	7	walk from side room to bedroom
9/1/2011 14:37:54	6	walk from bedroom to side room
9/1/2011 15:51:22	9	walks from side to outside back door
9/1/2011 15:53:18	9	walks from outside back door to the bar outside kitchen area
9/1/2011 15:54:08	8	walks from bar area to outside back door
9/1/2011 15:55:18	10	walks from outside back door to the bedroom
9/1/2011 15:57:16	5	walk from bedroom to side room
9/1/2011 16:47:26	8	side room to bedroom

TABLE 5.29
WALKS FOUND IN 3004'S APARTMENT USING KNN DAY 2
(MAHALANOBIS DISTANCE, K = 3)

Time	Length (s)	Description
1/11/2012 9:03:56	5	nothing in video
1/11/2012 10:21:06	5	nothing in video
1/11/2012 11:48:08	5	walk from the back to the front of the room
1/11/2012 11:48:14	9	walk from the front to the back of the room
1/11/2012 11:49:23	8	walk from the back door to the kitchen bar
1/11/2012 11:49:33	5	walk from front to back of room
1/11/2012 11:49:44	5	nothing
1/11/2012 11:50:40	6	walk from back side to front
1/11/2012 11:58:48	10	walk from front door to the back
1/11/2012 11:59:55	14	walk from the back room to the front door
1/11/2012 12:04:56	7	walk from bar area to the back of the room (side room)
1/11/2012 12:05:29	14	walk from back left to the front door
1/11/2012 12:12:28	5	moving around in the kitchen
1/11/2012 12:12:36	5	bends over then walks from just outside to inside the kitchen
1/11/2012 12:13:26	5	nothing in video
1/11/2012 12:14:06	5	nothing
1/11/2012 12:15:53	7	walk from kitchen to the side room
1/11/2012 12:29:27	7	walk from the side room to the bar area
1/11/2012 12:31:55	5	nothing might be in the kichen
1/11/2012 12:34:05	8	walking from kitchen to the side room
1/11/2012 12:57:21	7	nothing
1/11/2012 13:00:03	5	nothing
1/11/2012 13:02:01	7	walk from the bar to the side room
1/11/2012 14:10:22	8	nothing
1/11/2012 14:26:26	8	walk from side room to the back of the room
1/11/2012 14:45:21	5	nothing in video
1/11/2012 14:46:04	8	walk from the back to the side room
1/11/2012 15:48:40	8	walk from side room to the back of the room
1/11/2012 15:50:06	9	walk from back of the room to the side room
1/11/2012 16:04:27	8	walk from side room to the back of the room
1/11/2012 16:06:35	7	walk from back of the room to the side room
1/11/2012 16:16:55	10	walk from side room to the back of the room
1/11/2012 16:17:27	12	walk from back of the room to the side room
1/11/2012 16:23:53	7	walk from the side room to the back of the room
1/11/2012 16:27:52	6	walk from back room to couch in the back then back in to the back room
1/11/2012 16:28:46	6	walk from the back room to the couch
1/11/2012 16:29:06	8	walk from the back couch to the bar area

1/11/2012 16:46:06	10	walk from the front door to the back room
1/11/2012 16:46:47	8	walk from the back room to the front door
1/11/2012 16:48:50	7	moving around at the front door

During the data collection day for 3047, 101 walks were found in the apartment. Some of these walk times are shown in TABLE 5.30. Of those times, 3 of them were not confirmed to be walks and 1 of those times was confirmed to be a non-walk. This classifier missed more walks than the previous classifier, but it also has less than half of the times where walking was not confirmed. Most of the times using the Mahalanobis distance classifier were found using the standardized Euclidean classifier.

For 3038, the classifier using the Mahalanobis distance found the same walksthat were found by the classifier using the standardized Euclidean Distance, except the classifier using the Mahalanobis distance missed one. TABLE 5.31 shows the results from room 3038. The classifier did not find any different walks with this setting as well, but some of the starting times and lengths did vary between the two sets of results from the classifier.

Overall, the classifier had an accuracy of 90.3% for the walks that it found when using the Mahalanobis distance. In comparison to the results from the standardized Euclidean distance classifier, this classifier missed more of the walks overall. TABLE 5.32 shows the overall results for each room. In 3004's apartment, the Mahalanobis classifier seemed to pick up more times when there were not walks, but in the apartment of 3047, the classifier seemed to pick up fewer times when there wasn't any walking.

TABLE 5.30
WALKS FOUND IN 3047'S APARTMENT USING KNN
(MAHALANOBIS DISTANCE, K = 3)

Time	Length (s)	Description
9/15/2011 9:01:41	5	walk from side room to the side of the bar
9/15/2011 9:04:28	8	walks from side room toward and across radar
9/15/2011 9:10:25	5	walk from side room to side room
9/15/2011 9:18:23	5	walk from right side close to the door, to the bar
9/15/2011 9:20:00	9	walks from in front of radar to the back
9/15/2011 9:20:56	12	walks from back to front along the right wall
9/15/2011 9:24:47	5	side room to side room
9/15/2011 9:26:33	5	walks just outside of right side room, then stops
9/15/2011 9:26:59	6	walks from just outside of the room to the kitchen
9/15/2011 9:30:05	5	walks from left room to the back and out the patio door
9/15/2011 9:31:49	10	walk from behind radar to the back of the room
9/15/2011 9:32:08	15	walk from back to in fron of radar
9/15/2011 9:33:14	5	walk from back right to just in front of the couch
9/15/2011 9:36:30	8	walk from kitchen to the back of the room
9/15/2011 9:37:13	5	walk from the couch to the kitchen
9/15/2011 9:40:13	12	walk from kitchen from side room (right)
9/15/2011 9:44:35	7	walks out of the right side room
9/15/2011 9:44:46	5	walk from the middle of the room to the back
9/15/2011 9:50:43	10	walk from back of the room to the kitchen
9/15/2011 10:02:55	5	could not tell
9/15/2011 10:25:34	10	walk from side room to the middle of the room
9/15/2011 10:25:56	5	walks into the right side room
9/15/2011 10:27:06	5	could not tell
9/15/2011 10:55:55	5	walk from the couch to to the middle of open area, then stops
9/15/2011 10:57:34	8	multiple people walking
9/15/2011 10:59:08	8	walks from the kitchen to the left side room
9/15/2011 10:59:53	6	2 people walk from the open area to the back. One stops closer to the front then the other
9/15/2011 11:00:47	5	takes a few steps to the back of the room
9/15/2011 11:01:53	6	one person walks from the left to the middle while one walks one the right side towards the patio and then back
9/15/2011 11:02:03	5	walks around the front of the couch from the right of it to the left of it
9/15/2011 11:02:52	6	walk from the left side room to the back of the room
9/15/2011 11:02:59	6	walk from the back of the room to the left side room
9/15/2011 11:03:58	7	walks from the middle of the room to the left side room
9/15/2011 11:04:12	6	two people walk in from left side room to the middle of the room
9/15/2011 11:04:37	6	walk from the middle of the room towards the bar

TABLE 5.31
WALKS FOUND IN 3038'S APARTMENT USING KNN
(MAHALANOBIS DISTANCE, K = 3)

Time	Length (s)	Description
2/5/2012 11:54:05	7	walk
2/5/2012 11:56:34	8	can not tell
2/5/2012 13:09:55	9	walk
2/5/2012 13:16:24	6	can not tell
2/5/2012 13:16:49	7	walk
2/5/2012 13:30:37	9	walk
2/5/2012 13:31:38	6	walk
2/5/2012 14:27:40	7	walk
2/5/2012 14:28:46	8	walk
2/5/2012 14:29:09	6	walk
2/5/2012 14:29:33	10	walk
2/5/2012 16:02:40	6	walk
2/5/2012 16:11:31	8	walk

TABLE 5.32
TOTAL WALKS FOUND FOR EACH OF THE APARTMENTS
(MAHALANOBIS DISTANCE, K = 3)

Room	**# of Days**	**Walks detected**	**Actual Walks**
3004	2	72	59
3047	1	101	98
3038	1	13	11

Chapter 6 – Conclusion

The results show promise in being able to extract useful walk segments from normal daily activity using radar. In both the lab and in actual living environments, walks were detected with very few false alarms. Results from the lab data show that walks are able to be detected within one second of their actual start time. Most of the walk time lengths were within a second as well. This one second time differences may be due to the fact that a two second time window is being used. Even though the whole window does not have walking data, there may be enough walk information in it so that the whole window is seen as a walk. Also, with the lab data, there were not many false alarms that were picked up by the radar. This is a promising result that shows that if non-walk activities do not have movements resembling walking motions, it is very unlikely that it will be seen as a walk.

Of the two different types of classifiers that were used on the lab data, the KNN classifier did a better job of determining the beginnings and the lengths of the walks. The classifier using Bayes decision rule had more times when windows in the middle of a walk would be misclassified as non-walking windows. When testing the KNN, the classifier using the Standardized Euclidean distanced got the best results when K was equal to 5 or 7. When K was equal to 5, the classifier had a slightly better chance of being able to see small pauses in walks, while the classifier had better performance in determining the actual start and end times when the value of K was 7. When using the Mahalanobis distance for the KNN classifier, the best performance happened when K was set to 3. Some of the other values of K showed slightly better performance with getting the correct starting and ending times, but when K was set to 3, the classifier did a much better job of classifying the turnaround and pauses during the walk sequence. The classifier was able to see the turnaround time for 5 of the walks as non-walks when K was 3. With any other value of K, the number of times that happened dropped down to one.

The results from the TigerPlace senior apartments show that walks that are detected by the radar system have 91.8% accuracy when using standardized Euclidean distance and setting K equal to 5. When the classifier used the Mahalanobis Distance and a K of 3, the accuracy of the system became 90.3%. Most of the non-walks that were detected as walks did have some leg motions or movements. Throughout the day, some of the walks were not detected no matter which distance measure was used. In all of the rooms, the classifier using the Mahalanobis distance missed more of the walks. Recall that it is okay that some walks are missed since only a few walks a day would be needed to do a good gait analysis for the given person. In future work, the classifier should somehow be adjusted so that the number of false positives goes down to zero even if that means losing additional walks.

Overall, the KNN classifier using the standardized Euclidean distance and a K of 5 showed the best results. These settings had the better accuracy for the walks that it found in TigerPlace, and the classifier was able to pick up more walks. The classifier using the standardized Euclidean distance also showed marginally better results in finding the correct end times with the lab data. The classifier with both of the distance measures showed similar results for the starting times.

The next step in the research and development of the system is to enhance the algorithm so that only walks that are useable for good gait analysis are detected. Any walks across the radar and walks that are not straight toward the radar should not be detected. Walks that are shorter in time length should be dismissed as well. Also, an algorithm needs to be developed to determine whether each found walk is likely to have been completed by the person of interest. Walks from visitors, pets or other family members should be discarded. When looking at the daily analysis over a longer period of time, the trends of the person's gait can then be collected. These trends can be used to alert caregivers of an increasing fall risk for the resident which could lead to quicker treatment or intervention. A system like this could be promising in reducing falls and fall risk in elderly.

BIBLIOGRAPHY

[1] M. Skubic (2008) *HCC: Elder-Centered Recognition Technology for the Assessment of Physical Function.* [Online]. Available: http://eldertech.missouri.edu/hccelder.htm

[2] M. Rantz (2009) Technology to Automatically Detect Early Signs of Illness in Senior Housing. [Online]. Available: http://eldertech.missouri.edu/docs/Rantz%20AHRQ.htm

[3] M. Rantz. (2009) Technology to Automatically Detect Falls and Assess Fall Risk in Senior Housing. [Online]. Available: http://eldertech.missouri.edu/R21_Early_Illness_2009.htm

[4] M. Skubic (2009) CPS: Medium: Active Heterogeneous Sensing for Fall Detection and Fall Risk Assessment. [Online]. Available: http://eldertech.missouri.edu/cps_2009.htm

[5] F. Prince, H. Corriveau, R. Hebert, D. Winter ,"Review Article Gait in the elderly" Gait and Posture, pp 128-135, May 1997.

[6] RM Guimaraes, B. Issacs, "Characteristics of the gait in old people who fall." Int Rehabil Med 1980; 2:177–180.

[7] T. Yardibi, P. Cuddihy, S. Genc, C. Bufi, M. Skubic, M. Rantz, L. Liu, and C. Phillips, "Gait characterization via pulse-Doppler radar", ;in Proc. PerCom Workshops, 2011, pp.662-667.

[8] J. Yu, "The Significance of Walking speed in Physical Function among a Group of Community Dwelling Older Adults", Ph.D. thesis, University of Missouri-Columbia, 2008.

[9] Hausdorff, Jeffrey M. "Gait variability: Methods, modeling and meaning." Journal of NeuroEngineering and Rehabilitation 2005; 2: 19

[10] Maki BE, "Gait changes in older adults: predictors of falls or indicators of fear." J Am GeriatrSoc 1997, 45: 313-320.

[11] Wang F, Stone E, Dai W, Banerjee T, Giger J, Krampe J, Rantz M, Skubic M., "Testing an In-Home Gait Assessment Tool for Older Adults" ConfProc IEEE Eng Med Biol Soc. 2009;2009:6147-50

[12] Fang Wang; Stone, E.; Wenqing Dai; Skubic, M.; Keller, J.; , "Gait analysis and validation using voxel data," Engineering in Medicine and Biology Society, 2009. EMBC 2009. Annual International Conference of the IEEE , vol., no., pp.6127-6130

[13] S. Allin, and A. Mihailidis, “Sit to Stand Detection and Analysis”, AAAI in Eldercare: New Solutions to Old Problems, Washington DC, November 7-9, 2008.

[14] T. Banerjee “Activity Segmentation With Special Emphasis On Sit-To-Stand Analysis,” M.S. thesis, Dept. Comp. Eng., University of Missouri, Columbia, MO, 2010

[15] Liang Liu, Mihail Popescu, Marjorie Skubic, Marilyn Rantz, Tarik Yardibi, Paul Cuddihy, “Automatic fall detection based on Doppler radar motion signature.” Pervasive Health 2011: 222-225

[16] PrecisionLine RCR-50 Dual Technology Motion Sensor Installation Instructions [Online]. Available FTP: http://www.homecontrols.com/homecontrols/pdf/GERCR50install.pdf File: GERCR50install.pdf

[17] Yardibi, T.; Cuddihy, P.; Genc, S.; Bufi, C.; Skubic, M.; Rantz, M.; Liang Liu; Phillips, C.; , "Gait characterization via pulse-Doppler radar," Pervasive Computing and Communications Workshops (PERCOM Workshops), 2011 IEEE International Conference on , vol., no., pp.662-667

[18] (2011) DI-710 Series [Online]. Available: http://www.dataq.com/support/documentation/pdf/datasheets/710ds.pdf

[19] Wikipedia (2012) Fast Fourier Transform. [Online]. http://en.wikipedia.org/wiki/Fast_Fourier_transform

[20] R. Duda, P. Hart, D. Stork, Pattern Classification, 2nd ed., New York, NY: John Wiley & Sons, Inc., 2001, p.

[21] MathWorks (2011) pdist2 - Pairwise distance between two sets of observations. [Online]. http://www.mathworks.com/help/toolbox/stats/pdist2.html