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# Radar Walk Detection in the Apartments of Elderly

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*Abstract* --- **Seniors want to live more independent lifestyles. This comes with some risks including dwindling health and major injuries due to falling. A factor that has been studied and seen to have a correlation to fall risk is change in gait speed. Our goal is to create a passive system that monitors the gait of elderly so that assessments can be given by caregivers if gait changes do occur. This paper will cover a method of using pulse-Doppler radar to detect when walks occur. In unscripted living environments, we are able to detect valid walks. The system does miss walks during the day, but when walks are detected, they are actually valid walks 91.8% of the time using a large data base of radar signals captured in living environments.**

## I. INTRODUCTION

As more and more people in America and the world are living longer and more fulfilling lives, they choose to live as independently as they possibly can [1]. However, as people get older, falls become the most common cause of injuries and hospitalizations for trauma in older adults and are the leading cause of death due to injury. 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 [2]. 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. Detecting and assessing problems while they are still slight can provide an opportunity for proper interventions to keep these problems from becoming major. Moreover, identification of small changes in health conditions is crucial for early interventions when treatment is the most effective and when prevention of major changes is still possible. Because of the severity that falls can have in older adults, a problem that could benefit from continuous assessment is fall risk. An approach that can be used for monitoring fall risk is to use passive sensors that can detect when a fall or a change in fall risk has occurred. These sensors do not have to be worn and would not impede on daily living activities. By having 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 that can be calculated is a change in gait or a change in walking speed [5]. 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 [3]. One of the best times to catch walks to be used for assessment is when they are naturally walking around in their own living area. These walks won't be influenced by someone changing their walk because they know that they are being tested. Instead, these would be their normal, everyday walks with their normal gait. A recent study has shown that a Pulse-Doppler radar system can be a feasible tool in gait characterization [6].The problem is figuring out when someone is walking in their own living environment so that a gait characterization from the walks can be extracted. To help solve this problem, we created a method of finding walks with Pulse-Doppler radar. By using radar, walks can be found throughout a normal day for a senior. Getting a daily look at a resident's gait information over a long period of time may help a health care provider see a better picture of the resident's gait changes and in return, may have the ability to assess the resident's fall risk much faster. More so, having this data could lead to earlier intervention so that the resident's fall risk can be kept to a minimal.

In this paper we demonstrate an algorithm for extracting walk segments from radar data. First, we will look at the method used to prepare the radar so that the data from it can be used for gait. The algorithm for finding the walks using radar will then be described. Finally, the algorithm is tested on both lab data and on data from seniors in their apartments. This latter data set demonstrates the feasibility of using the radar to capture walks every day over the course of normal senior living.

## II. METHODS

### A. Radar

For this study, Pulse-Doppler range control radars (RCR) were used for the detection of walks. They utilize a microwave carrier frequency of 5.8 GHz, and have a frequency of 10 MHz for pulse repetition [9]. The original

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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. In order to use these RCR's to detect walks and allow for proper gait extraction, some of the specifications had to be modified. The range of the radars is set to 20ft and the integrated passive infrared sensor is disabled. To reduce the effects of multi-paths that may saturate the signal, each of the radars are shielded using aluminum foil with a small opening in front of the antenna [6]. Due to the different layouts for each room, the shielding around the radar has to be calibrated. The size and shape of the opening is modified slightly for each setting until the optimal signal is received.

Collection of the radar signal is done using data acquisition (DAQ) units [10]. Each of the radars has its own DAQ unit for data collection. The sampling rate is set to 960Hz. For the connection, the radar has a signal wire that is put in one of the analog channel ports and a ground wire that is connected to the ground of the DAQ. There is also a drain wire connected to the ground to reduce interference on the signal being transmitted through the wire. Figure 1 shows the radar and DAQ setup for the Tiger Place apartments.

Figure 1 Radar unit placed in a non-hazardous position (left). The radar, DAQ and wireless inside of the box

## B. The Detection Algorithm

The algorithm used to detect walks looks at sliding 2 second windows of the data one window at a time, with the window incrementing by one second. At each window, features related to the signal are extracted. These features are given to the classifier that determines whether the given window has walking in it or not. If there are at least N consecutive windows that are determined to have walking in them, then that part of the signal is considered a walk. In the lab, N is set to 4 and N is set to 5 for the Tiger Place data. The starting time is considered the beginning of the first window of the set. The length of the walk in seconds is considered the number of consecutive windows with walking decisions.

Before extracting features from the radar signal, we first do some pre-processing of the signal. The first step is to smooth out the signal. By smoothing the signal, much of the high frequency noise will disappear from the signal. The smoothing is done by taking a sample point and averaging it with the point before and after it. The average becomes the new value for that given point. We do this for each point in the 2 second window from beginning to end. In order to allow each of the sample points to converge to a certain value, we run the smoothing on the window at least 10 times. After doing a complete smoothing of the window, we compute the Fast Fourier Transform (FFT) of the window. After smoothing the FFT, we compute the derivative.

The features extracted from each of the window are the highest peak of the FFT, the FFT's power and the highest peak of the FFT's derivative. For the peaks, the frequency where the peak happens and the value of the peak are both used as features. With the FFT, only the peaks that are beyond 5Hz are considered. This is done to cut out the DC component of the signal, i.e., where the highest peak happens around 0Hz.

For classifying the windows, the K Nearest Neighbor (KNN) classifier was used [11]. The training data for the classifier was collected in a lab. There are two categories for the training data, walks and non-walks. The activities used for training data, and examples of these activities will be given later. The number of neighbors, K, was experimentally set to 5. For measuring the distance between points, the normalized Euclidean distance measure calculated using the equation

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

where $\vec{\mathbf{x}}$ and $\vec{\mathbf{y}}$ are feature vectors and S is a diagonal matrix whose diagonals are the calculated standard deviations for each feature.

# III. DATA COLLECTION

## A. Lab Data

In the lab, walks were collected from 15 different people. Each person did 16 walks. Each of the walks was about 20ft. in distance. Of these walks, 8 of them were normal walks, and 8 were walks with a slower speed. The normal walks lasted between 4 and 7 seconds while the slower walks varied between 5 and 12 seconds. Half of the total walks were walks towards the radar and the other half were walks away from the radar. The walks from 12 of the 15 people were for training data for the classifier. The walks from the other 3 people were used for testing.

The walks were scripted so that the person walked towards the radar, turned around, walked away from the radar, and then stopped. There was little to no pause between walking toward and walking away from the radar (see Figure 2). Because of this, each sequence of walking toward and away from the radar is considered one walk for testing purposes.

Non-walks were collected in the lab as well. The activities for non-walks included standing with some movement, normal motions 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. A room without any motion in it was collected as well. These were activities that were thought to resemble activities that may happen in a senior's living area. All of the activities are include in the training data for non-walks. Figure 3 shows an example of what the raw radar signal of raw radar data would look like.

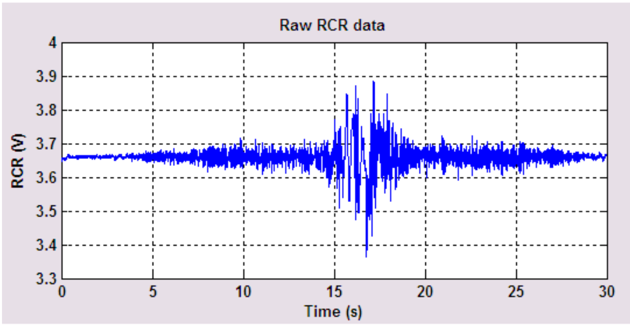

Figure 2 Raw radar signal of a walk towards and then away from the radar

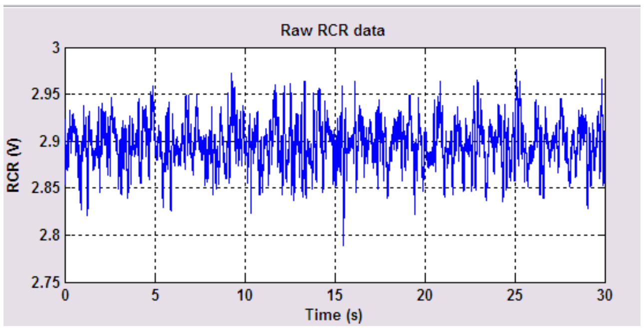

Figure 3 Raw radar signal of the non-walk activity of swaying towards and away from the radar

### B. *Radar at Tiger Place*

At Tiger Place, an assisted living facility, residents have signed up to be a part of the research for the University of Missouri whose ages range from 67-98. In 10 of the apartments, radar systems were 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. 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. 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 not be a tripping hazard (Figure 1).

The radar signals were collected continuously with the data being saved to a separate file for each day. It was collected to verify that walks can indeed be detected by the radar in actual living environments. In addition, this data was used see if walks were being collected throughout the day with little to no false positives being picked up by the algorithm. Since it does not matter if some of the walks were missed, our objective was not to see how many times a day walks were missed. We just wanted to make sure that a sufficient number of the straight, long, and clear walks with respect to the radar were being picked up.

### C. *Microsoft Kinect*

To be able to see what type of activity is happening when the algorithm believes that a walk is happening, Microsoft Kinects that were also installed in each of the apartments were used. The Kinects collect depth images at a rate of 15 frames per second when there is some type of motion in the room [7, 8]. 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 that is happening can be seen without being able to easily identify the person.

The Kinects were usually placed by the front door where it could see most of the living room in the apartment. It is also set up near the ceiling looking down on the room, as shown in Figure 4. This allows for most of the floor in the living rooms to in the viewing area of the Kinect. This also allows for most of the person's body to be captured throughout the living area. Having most of the body viewable by the Kinect makes determining the activities in the room a little easier.


Figure 4 Placement of the Microsoft Kinect sensor in an apartment

## IV. RESULTS

### A. *Experiment Scope*

The segment in the lab started 5 seconds before beginning of the subject's first walk and ended 5 seconds after the end of the final walk from that subject. Between each of the toward and away walk sequences, there were natural body motions as the subject waited to be instructed on to start the next walking sequence. These motions are what's used to test and whether the algorithm is picking up non-walks correctly. The starting and ending times are rounded to the nearest second.

From the Tiger Place data, three of the apartments with the radar system in place, whose ages ranged from 82-89, were used to test if walks can be detected using radar in an actual living environment. These apartments were chosen because they all had people who could walk unassisted. For each of the rooms, 8 hour segments from one or two days of the radar data were examined. The segments for each of the days are from 9a.m. to 5p.m. The days were chosen at random. All of the apartments contain walking on the days that were chosen, as verified by the Kinect imagery.

### B. *Results from Lab Data*

Using the algorithm on the test data, all of the walks from all of the subjects were found. There were no false positives, i.e., non-walks that were seen as walks. For the test cases, 15 of the 24 calculated start times perfectly matched the actual start times. All 24 computed starting times were within one second of the actual starting time. For the ending times, 3 of the 24 times calculated were not within one second of the actual time. In all three cases, the computed ending time was shorter than the actual time. Table I shows the results for each of the subjects.

TABLE I. LAB WALKS DETECTED IN THE RADAR SIGNAL

| Subject # | #walk sequences | walk found | start time within 1 sec of actual time | end time within 1 sec of actual time |
|---|---|---|---|---|
| 13 | 8 | 8 | 8 | 8 |
| 14 | 8 | 8 | 8 | 8 |
| 15 | 8 | 8 | 8 | 5 |
| total | 24 | 24 | 24 | 21 |

### C. Results from Tiger Place Data

In all of the rooms, there were a total of 196 times that the radar system thought it detected a walk. In Table II, 180 of the times were actual walks, giving the system an accuracy of 91.8% for the times when walks are believed to be detected. When actual walks were detected, the time lengths of the walks were usually within 2 seconds with the actual walk time lengths being longer than the calculated values. The radar would miss the beginning seconds of the walks in most of those cases. In some instances, the last second of the walks would not be detected. Some of walk segments being missed may be due to walks starting or ending outside of the radar's view. Some of the non-walk activities that were detected as walks were moving around in the kitchen, swaying while standing in front of the radar, and body movements near the radar.

TABLE II. WALKS DETECTED THROUGHOUT NORMAL DAYS IN DIFFERENT ROOMS

| Room | # of Days | Walks detected | Actual Walks |
|---|---|---|---|
| 1 | 2 | 68 | 61 |
| 2 | 1 | 114 | 107 |
| 3 | 1 | 14 | 12 |

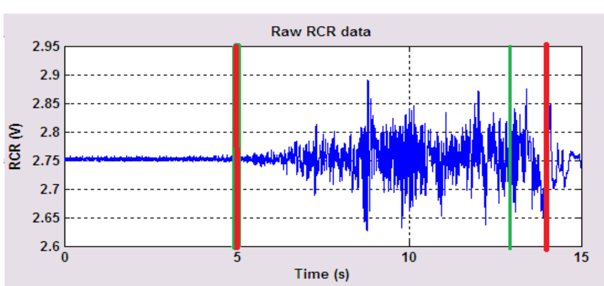


Figure 5 Radar signal of a detected walk in room #1 with the locations of the detected (green) and actual (red) beginning and ending of the walk

## IV. CONCLUSION

The results show promise in being able to extract useful walk segments from normal daily activity using radar. We were able to put the radar in actual living environments and to detect walks with very few false alarms. Our results from the lab show that we are able to detect all of the walks within one second of the actual start time. Most of the walk time lengths were within a second as well.

The results from the Tiger Place senior apartments show that walks that are detected by the radar system have a 91.8% accuracy. There still needs to be more work done figure out why the beginning and ending of some of the walks are missed. Throughout the day, some of the walks may have been missed. This is okay since only a few walks a day would be needed to do a gait analysis for the given person. In future work, the classifier should be adjusted so that the number of false positives goes down to zero even if that means losing additional walks.

The next step in the development is to improve the algorithm so that only walks that are useable for gait analysis from the radar system are detected. This means that any walks that are across the radar and walks that are not directly toward the radar should not be detected. We also need to devise an algorithm to determine whether each walk is likely to have been performed by the person of interest. Walks from visitors or pets should be discarded. In the future, we believe that finding walks daily may lead to trends of the person's gait being collected over a long period of time. These trends may become useful in alerting caregivers of an increasing fall risk for the resident which could lead to quicker treatment or intervention.

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