# Human Activity and Posture Classification Using Single Non-Contact Radar Sensor

by

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## Abstract

Radar has been proposed for monitoring the health of elderly patients in long term care because it is safe, non-contact and preserves the privacy of patients. Random body movements (RBM) obscure radar return signals making it difficult if not impossible to accurately estimate vitals. Activity classification is presented in this thesis as a preprocessing step for dealing with RBMs. Posture classification is presented in this thesis for assistance in preventing falls. Two popular radar architectures- continuous wave (CW) Doppler and ultra-wideband (UWB) are investigated in this thesis. Activity classification is performed with 92% average accuracy with CW and 86% with UWB. Posture Classification is performed with 64% average accuracy with CW and 85% with UWB. An occupancy detection algorithm was also developed for UWB and achieved 88% average accuracy. The contribution of this thesis is a proposed hierarchical processing approach for both radar types capable of dealing with moving subjects.

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## **Table of Contents**

| A  | bstract              |  | ii |  |  |
|----|----------------------|--|----|--|--|
| A  | Acknowledgementsiii  |  |    |  |  |
| T  | Table of Contents iv |  |    |  |  |
| Li | List of Tables vii   |  |    |  |  |
| Li | List of Figuresviii  |  |    |  |  |
| L  | ist of A             | ppendicesi                               | ix |  |  |
| 1  | Chap                 | ter: Introduction 1                      | 0  |  |  |
|    | 1.1                  | Motivation 1                             | 0  |  |  |
|    | 1.2                  | Problem statement 1                      | 4  |  |  |
|    | 1.3                  | Contributions 1                          | .6 |  |  |
|    | 1.4                  | Limitations of this thesis 1             | .6 |  |  |
|    | 1.5                  | Thesis overview1                         | 7  |  |  |
| 2  | Chap                 | ter: State of the art 1                  | 8  |  |  |
|    | 2.1                  | History of radar technology1             | 8  |  |  |
|    | 2.2                  | Breathing rate estimation                | 9  |  |  |
|    | 2.3                  | Heart rate estimation                    | 20 |  |  |
|    | 2.4                  | Moving subjects                          | 22 |  |  |
|    | 2.5                  | Posture classification                   | 23 |  |  |
|    | 2.6                  | Fall prevention                          | 24 |  |  |
|    | 2.7                  | Detection of room occupancy              | 24 |  |  |
|    | 2.8                  | Practical and commercial implementations | 26 |  |  |
|    | 2.9                  | Limitations and proposed solution2       | 27 |  |  |
| 3  | Chap                 | ter: Radar theory                        | :9 |  |  |
|    | 3.1                  | Radar fundamentals                       | 29 |  |  |

|   | 3.2   | Model of CW Doppler radar   |    |
|---|-------|---|----|
|   | 3.3   | Model of UWB radar  | 46 |
|   | 3.4   | Conclusion  | 48 |
| 4 | Cha   | pter: Experiment design and data collection                         | 50 |
|   | 4.1   | Data collection protocol for CW radar experiments                   | 50 |
|   | 4.2   | Protocol for data collection in UWB radar experiments               | 53 |
| 5 | Cha   | pter: Posture and activity classification with CW radar             | 55 |
|   | 5.1   | Proposed hierarchical classification approach for CW radar returns  | 55 |
|   | 5.2   | Preprocessing and feature extraction                                | 56 |
|   | 5.3   | Classifiers   | 59 |
|   | 5.4   | Activity classification   | 62 |
|   | 5.5   | Posture classification  | 64 |
|   | 5.6   | Feature evaluation  | 66 |
|   | 5.7   | Discussion of results   | 68 |
| 6 | Cha   | pter: Classification of radar returns using UWB radar               | 70 |
|   | 6.1   | Proposed hierarchical classification approach for UWB radar returns | 70 |
|   | 6.2   | Occupancy detection   | 72 |
|   | 6.3   | Feature extraction  | 78 |
|   | 6.4   | Activity classification   | 81 |
|   | 6.5   | Posture classification  | 83 |
|   | 6.6   | Feature evaluation  |    |
|   | 6.7   | Discussion of results   | 87 |
| 7 | Cha   | pter: Conclusion  | 89 |
|   | 7.1   | Limitations and future works  | 90 |
| A | ppend | lices   | 93 |

| Bibliography |                                       |    |
|--------------|---------------------------------------|----|
| B.3          | UWB feature extraction                |    |
| B.2          | Occupancy counter                     |    |
| B.1          | CW feature extraction                 | 97 |
| Appendix     | ς Β                                   | 97 |
| A.2          | Features extracted in UWB experiments | 95 |
| A.1          | Features extracted in CW experiments  | 93 |
| Appendix     | κ Α                                   | 93 |

## List of Tables

| Table 5.1: Confusion matrix for linear discriminant activity classifier              | 63 |
|--|----|
| Table 5.2: Confusion matrix for decision tree activity classifier                    | 63 |
| Table 5.3: Confusion matrix for naive Bayes activity classifier                      | 63 |
| Table 5.4: Confusion matrix for KNN activity classifier                              | 64 |
| Table 5.5: Strongest features for activity classification                            | 67 |
| Table 5.6: Strongest features for posture classification                             | 67 |
| Table 6.1: Confusion matrix for occupancy detection algorithm                        | 77 |
| Table 6.2: Confusion matrix for 3 class activity classification for UWB              | 81 |
| Table 6.3: Confusion matrix for KNN activity classification       8                  | 82 |
| Table 6.4: Confusion matrix for linear discriminant activity classification          | 82 |
| Table 6.5: Confusion matrix for naïve Bayes activity classification                  | 82 |
| Table 6.6: Confusion matrix for decision tree activity classification         Sector | 82 |
| Table 6.7: Confusion matrix for KNN posture classification       8                   | 83 |
| Table 6.8: Confusion matrix for linear discriminant posture classification           | 83 |
| Table 6.9: Confusion matrix for naïve Bayes posture classification                   | 84 |
| Table 6.10: Confusion matrix for decision tree posture classification         Sector | 84 |
| Table 6.11: Confusion matrix for decision tree posture classification at 3m          | 85 |
| Table 6.12: Confusion matrix for decision tree posture classification at 4.5m        | 85 |
| Table 6.13: Confusion matrix for decision tree posture classification at 6m          | 85 |
| Table 6.14: Strongest features for activity classification       8                   | 87 |
| Table 6.15: Strongest features for posture classification       8                    | 87 |

# List of Figures

| Figure 3.1: Demodulation and target motion for Ab= 0.1mm                                | 37         |
|---|------------|
| Figure 3.2: FFT of demodulated and target motion signals over 60s for $Ab = 0.1$ mm,    | fb =       |
| 0.2Hz, Ah = $0.08$ mm, fh = 1Hz, d0 = 1m  | 38         |
| Figure 3.3: Time domain of demodulated and target motion signals over 60 seconds.       | Ab         |
| = 1  cm,  fb = 0.2  Hz,  Ah = 0.08  mm,  fh = 1  Hz,  d0 = 1  m                         | 39         |
| Figure 3.4: FFT of demodulated and target motion signals over 60 seconds. $Ab = 1 cm$   | ı, fb      |
| = 0.2Hz, Ah $= 0.08$ mm, fh $= 1$ Hz, d0 $= 1$ m  | 40         |
| Figure 3.5: Time domain of demodulated and target motion signals over 60 seconds.       | Ab         |
| = 0, fb = 0.2Hz, Ah = 0.08mm, fh = 1 Hz, d0 = 1m  | 41         |
| Figure 3.6: FFT of demodulated and target motion signals over 60 seconds. $Ab = 0$ , fb | <b>)</b> = |
| 0.2Hz, Ah = $0.08$ mm, fh = 1 Hz, d0 = 1m   | 42         |
| Figure 3.7: FFT of demodulated and target motion signals over 60 seconds. $Ab = 1 cm$   | ı, fb      |
| = 0.33Hz, Ah $= 0.08$ mm, fh $= 1$ Hz, d0 $= 1$ m                                       | 43         |
| Figure 3.8: Continuous wave antenna   | 44         |
| Figure 3.9: Example of CW radar returns   | 45         |
| Figure 3.10: Novelda Xethru X4M03   | 48         |
| Figure 4.1: Mackenzie room number 4246  | 51         |
| Figure 5.1: Block diagram of hierarchical classification approach for CW radar return   | s 56       |
| Figure 6.1: Block diagram of hierarchical classification approach for UWB radar return  | rns        |
|   | 71         |
| Figure 6.2: First principal component for three different signal types [55]             | 74         |
| Figure 6.3: Occupancy detection algorithm block diagram [55]                            | 75         |

# List of Appendices

| Appendix A  |                                       |      |
|-------------|---------------------------------------|------|
| A.1         | Features extracted in CW experiments  | 93   |
| A.2         | Features extracted in UWB experiments | 95   |
| Appendix B. |                                       | 97   |
| B.1         | CW feature extraction                 | 97   |
| B.2         | Occupancy Counter                     | .100 |
| B.3         | UWB feature extraction                | .103 |

## **1** Chapter: Introduction

This chapter discusses the motivation for developing a system of non-contact monitoring using a single sensor radar and the inherent problems that must be overcome before a practical solution can be deployed. The contributions of this thesis are also discussed in this chapter. At the end of this chapter an overview of the rest of the thesis is given.

#### 1.1 Motivation

Breathing and heart rate are two important vital signs of life that need to be monitored. Monitoring of these vital signs can be done either using contact sensors or non-contact sensors. Ability to monitor these two vital signs reliably is an area of active research. Reliable monitoring of such physiological signs have several advantages. A physiological monitoring device in an intensive care unit in a hospital for instance can be trained to generate an alarm when it senses a cessation in respiratory activity. In addition to using respiratory activity as a sign of wellbeing, trends in respiratory rate can be used in medical diagnostics to indicate pathological conditions including chronic obstructive pulmonary disease (COPD), pulmonary embolisms, pneumonia, sepsis, systemic inflammation, low blood volume, malfunctions of the excretory system, and even some neurological disorders [1]. Obstructive Sleep Apnea (OSA), which is characterized by periodic cessations of breathing for more than 10 seconds at a time during sleep [2] is a serious medical condition that could also be detected using non-contact sensing technologies. Typically OSA is diagnosed by performing polysomnography tests, an expensive and time consuming process that could be mitigated by using low cost non-

contact sensors. Similarly, trends in heart rate as well as heart rate variability (HRV) can be analyzed by medical practitioners for diagnostic purposes.

Noncontact sensors offer a solution to many problems associated with contact or wearable sensors. Sensors requiring physical contact with the subject can be burdensome or uncomfortable making them impractical for 24/7 monitoring in long term care facilities, whereas noncontact sensors are capable of monitoring without the subject being aware of it. In some instances, contact sensors may compromise the health of patients such as burn victims or premature infants due to skin sensitivity. Noncontact sensing using video has been proposed, however video (infrared or visible spectrum cameras) requires an unobstructed view of the subject and privacy concerns can arise. Radar on the other hand is capable of monitoring subjects through barriers and does not record personal or identifying information.

Most works in literature deal with data recorded in very controlled environments. Subjects are typically stationary, very close to the radar or in a single posture for the duration of the tests. Current algorithms hat provide estimates of breathing and heart rate are only reliable when data is recorded for perfectly still subjects [3]. This means there is a need for classifying radar returns based on the activity levels of human subjects and ascertain if the subjects are stationary or not. When subjects are still, further analysis can be performed on the radar returns, and when subjects are moving analysis can be suspended until the subject is still. When systems are developed for monitoring patients in long term care facilities, information regarding activity levels could be useful for medical practitioners. Trends in activity levels can be tracked to determine if the subject or patient is becoming more active or less active with time. This could be used to predict

an improvement or decline in health. Activity classification using non-contact sensors should be able to detect whether the subject is sedentary and still, sedentary but moving their limbs (potentially corresponding to exercise) or walking around their home.

Posture classification using single non-contact radar sensors has had very little coverage in literature. For monitoring of patients who have an elevated risk of falling, posture classification could be used to generate alarms to staff when the patient stands up and gets ready to walk. Fall detection and fall prevention is an important area of research within the field of non-contact physiological monitoring for elderly care. Falls are the leading cause of death in seniors aged 65 and over, and the total cost worldwide related to these falls is estimated at \$30 billion (2010); one in every three seniors aged 65 or over fall each year [4]. Another important reason to perform posture classification of elderly patients is to potentially avoid bed sores and ulcers caused by long durations in which the subject remains in the same posture [5]. A benefit of radar solutions is that a single inexpensive radar sensor can cover a very large area as opposed to pressure mats for example which must be placed in all areas that the subject may be present.

In applications where a non-contact monitoring system is used to monitor people in their homes, room occupancy determination is essential so that when multiple people are present, the system is not tricked into recording physiological information of the wrong subject. The monitoring system may be trained to either stop recording when multiple people are present, or if it is able to differentiate and separate the people as independent targets then it could perform analysis on all subjects. Furthermore, the room occupancy data could be used in conjunction with smart home infrastructure to increase energy efficiency by turning off devices when nobody is present.

Contact-sensor based methods are already in place for monitoring of patients in long term care homes, including medic-alert pendants. The contact-based sensors requires co-operation from the home-care based patients. For instance, many senior citizens who would normally rely on wearable devices like medic-alert pendants may forget to wear them, or refuse to wear them because they cause discomfort or reduce their independence. Monitoring systems in home-care are integrated into a patient's everyday routine and so the sensors should be non-intrusive and not reduce the quality of life of individuals. Non-contact sensors are non-intrusive as the subjects can go about their daily activities as very minimal or no co-operation is needed from the subjects. Non-contact sensors can be implemented in a system that runs constantly and does not require any physical interaction with the subject. Wireless networks [6] have been used in breathing monitoring using the principles of receiver signal strengths. As a single wireless link is incapable of providing reliable detection and estimation of breathing frequency, a collection of wireless links were considered. Such active sensors, including radars, preserves privacy of the individual unlike passive sensors like video and hence may be a preferred way of monitoring in long term home-care environments. Radar does not capture personal information from subjects and can be used to monitor people even in places such as bedrooms and bathrooms. Unlike wireless sensor links, a single radar is capable of monitoring a large area (such as several rooms) at the same time. Radar is also able to penetrate objects so it does not require an unobstructed view of the subject. Furthermore, changes in ambient lighting that affects the performance of video based approaches for physiological monitoring has no effect on radar.

Patient care in long term home environments is one of the many applications that is currently being researched in the field of non-contact monitoring with radar. Radar sensors are used in search and rescue applications, as the transmitted radar waveforms are able to penetrate obstacles and provide location of trapped victims. In many medical applications, contact sensors are inappropriate because they have the potential to compromise a patient's health, such as with premature infants and burn victims. In polysomnographic sleep studies, using contact sensors may impede the subject's natural breathing patterns, biasing the results of the study. Use of noncontact sensors such as radars would circumvent these issues. These benefits have motivated physiological monitoring using radars in this thesis.

#### **1.2 Problem statement**

As will be shown in the survey of the current works done in the field of radar physiological monitoring (Chapter 2), there have been very few attempts at designing a system that can be implemented in a real environment. Other than a few key works in this area, majority of research has been done with data collected in very controlled situations. While this type of initial research is critical in the path to developing practical systems, there needs to be research done which deals with subjects behaving naturally, as they would in uncontrolled environments. The problem of large body movements manifests in uncontrolled environments. Large body movements obscure the smaller physiological signals reflected from the human body. Some research has been done with data fusion using video and radar for counteracting the effects of these movements [7], but there has been no reported research on single sensor radar that addresses dealing with large body movement, including walking, while estimating the vital signs. It is this issue that gives motivation for human movement classification (Chapters 7 and 8). Knowing whether or not a subject is stationary gives insight to the efficacy and confidence of breathing rate and heart rate algorithm outputs. For instance, if it is determined that a subject is moving, it may be best to withhold these estimates until the subject is stationary so as to not give erroneous results.

Posture detection has not been performed in a robust manner using a single noncontact radar sensor, nor has it been implemented into a system that also performs activity classification. Identification of a subject's posture is necessary for fall prevention; knowing that a subject who has a history of falling is standing may indicate that they are at a high risk of experiencing another fall. Hence in this thesis, posture detection using a single radar is studied.

The issue of multiple individuals being present in the field of the radar must also be solved for a practical system to be developed. Chapter 8 presents a potential solution to this issue which can easily be integrated into a system along with posture and activity classification.

Two radars, the continuous wave (CW) radar and the ultra-wideband (UWB) radar, are widely used in literature and are considered in this thesis. CW radar is typically designed to have a higher carrier frequency than UWB, meaning it has higher frequency resolution making it better suited for estimating breathing and heart beat frequencies. On the other hand, a UWB radar has much larger bandwidth which results in much higher spatial resolution making it better suited for posture classification and room occupancy (as will be discussed in later chapters).

#### 1.3 Contributions

The intended goal of this work was to investigate the potential of using radar for non-contact physiological monitoring, and to develop algorithms that could be integrated into a system that is capable of performing monitoring in an uncontrolled environment. The following are the contributions of this thesis;

- A novel algorithm to detect occupancy and estimate the number of occupants in a room using UWB radar. This could enable separating the subjects as individual sources for further processing.
- 2. Classification of postures and activities using a single CW or UWB radar as a precursor to vital sign estimation. The posture classification for UWB is novel and is an improvement in classification accuracy compared to the only existing algorithm in literature [8].

This work lays the foundation for a robust non-contact monitoring system, for which research will extend past the scope of this thesis.

#### **1.4** Limitations of this thesis

The scope of this thesis is limited to data recorded in an indoor environment, with no obstructions between the radar and subject, and no known additional moving objects within the field of the radar (i.e. fan, water running through pipes). Additionally, the relative orientation between the subject and radar throughout data samples is limited- the subject faces the radar in all data recordings (with the exception of laying down posture in which the subject always has their side facing the radar). Data in which more than one subject is present in the field of the radar was only used for testing the occupancy detection algorithm; the data was not used for further processing.

### 1.5 Thesis overview

Chapter 2 is a survey of work that has been performed in the field physiological monitoring using radar, including the limitations of these works in practical applications. Chapter 3 details the fundamental principles of radar operation, signal characteristics of CW and UWB radar as well as the radars used in this work

Chapter 4 details the experimental protocol used for collecting the data for this thesis Chapter 5 includes activity classification and posture classification on data recorded with CW radar

Chapter 6 includes posture classification, activity classification, and room occupancy detection on data that was recorded with UWB radar.

Chapter 7 concludes the thesis by summarizing the contributions, explaining the limitations of the work presented in this thesis and providing directions for future work.

## 2 Chapter: State of the art

This chapter will provide a survey of the field of non-contact physiological monitoring. It will cover all work relating to breathing and heart beat measurements, gross body movements, posture classification, fall detection and occupancy classification. Finally, practical implementations will be discussed.

#### 2.1 History of radar technology

Radar and research applications of radar has gone through many changes during its relatively short existence. Research relating to radio wave transmissions began towards the end of the 19<sup>th</sup> century. Patents for metallic object detection using radio waves were filed early in the 20<sup>th</sup> century. WWII jumpstarted the development and proliferation of radar technology for defense applications. In 1975 James C. Lin conducted an experiment which placed an X-band continuous wave radar 30cm away from a 5.1kg albino rabbit, and then a seated human [9]. He found that the returns from the radar clearly showed the breathing pattern of both subjects. This initial finding was the catalyst for decades of research into the feasibility of using radar technology for monitoring human physiological signs. Different kinds of radar technology mostly based on continuous wave (CW) radar technology and its variants using different modulations to provide bandwidth for localization were considered for physiological processing [10]. In 2002 the Federal Communications Commission (FCC) allocated a frequency band for the use of ultra-wideband (UWB) radar. Since then UWB has become ubiquitous in noncontact sensing in numerous applications, including physiological monitoring.

#### 2.2 Breathing rate estimation

Respiratory activity, which was the first physiological signal to be recorded using radar, has been researched extensively for different purposes and using different radar architectures and configurations.

Initial findings have been presented using 60GHz V-band continuous wave radar. The benefit of using a higher frequency carrier wave is the increase in phase modulation resolution [11]. Respiration and heart beat signals were extracted using an algorithm that applies ensemble empirical mode decomposition (EEMD) and continuous wavelet transforms (CWT) for removing noise and separating the two source signals [12]. This was done using an IR-UWB radar, but was only tested on seated participants at 0.3m – 3m away with the radar mounted chest level. Nijsure et al. developed a hidden Markov model (HMM) based algorithm for chest wall tracking and breathing pattern change detection, however this algorithm required multiple UWB radars set up in an array around the subject for chest wall tracking and breathing pattern change detection [13].

Respiration motion tracking has use in cancer radiation therapy as it can be used for adaptive radiation administering. An adaptive DC-coupled CW radar was used by Gu et al. to track respiratory motion of radiation therapy patients with sub-millimeter accuracy [14].

A 2.34GHz quadrature CW Doppler radar was used to estimate the amount of energy that wearable devices would be able to harvest from human body motion caused by respiration [15]. In this work the test subject was seated only 1m away from the radar.

Using multiple radars it was shown that breathing patterns including normal breathing, chest breathing, and diaphragmatic breathing can be discriminated for supine

subjects [16]. Similarly, a system was presented by Kagawa et al. that used two 24GHz Doppler radars mounted underneath of a bed for detecting sleep apnea-hypopnea events based on decreased amplitudes of breathing signals as well as phase changes between thoracic and abdominal respiratory movement corresponding to respiratory disturbances [17].

Tidal volume, which holds valuable information for medical diagnostic purposes, was measured using a 2.4GHz Doppler radar [18]. This experiment was done on 8 healthy subjects in both seated and supine positions, 1m away from the radar. The radar returns only provided relative tidal volume estimates, so the data had to be calibrated with spirometry data.

Respiration monitoring was used by Kagawa et al. for classifying the sleep state of human subjects [19]. Multiple impulse Doppler radars operating at 24GHz were placed underneath a mattress and recorded data from subjects sleeping for an 8 hour period. The variation in respiration rate as well as the level of body movement was used to train a linear discriminant classifier. Singular Spectrum Analysis (SSA) was used to extract the breathing signal from the subject. Wakefulness, or sleep state of rats can also be determined using an impulse Doppler radar [20]. In Zeng et al. a support vector machine was trained to classify whether a rat was in one of these 3 states: a wakeful state, nonrapid eye movement sleep state, or rapid eye movement sleep state.

#### 2.3 Heart rate estimation

The major issue with estimating heart signals using radar is that the amplitude of chest motion due to respiration is on the order of 10mm whereas for cardiac motion it is only on the order of 0.1mm [21]. This means that power of the signal corresponding to

heart motion can be negligible in the presence of heavy respiration and signal noise. Furthermore, heart rate and breathing signals can have overlapping spectra making it difficult to separate the signals in the frequency domain.

Several methods have been presented in literature to overcome the difficulties of monitoring small heart signals in the presence of larger physiological signals. Singular Spectrum Analysis (SSA) has been shown to be able to localize heart sounds in respiratory data recorded using a stethoscope [22]. A model based approach was presented by Boryssenko et al. which used predefined difference signals to estimate the blood volume in the heart, corresponding to the different states of the heart's pump cycle [23]. That work however used a UWB radar sensor mounted on a human subject which makes it impractical for many applications.

Monitoring of cardiac activity other than just for estimating heart rate has also been attempted in recent years. Heart rate variability (HRV), which is the variation in beat to beat periods of heart motion, is an indicator of cardio-vascular health. HRV monitoring has been performed using a direct conversion quadrature continuous wave Doppler radar in stationary (seated and supine) positions [24]. Yavari et al. estimated HRV on a supine subject using a synchrosqueezing transform approach [25]. In another work HRV was measured using an algorithm that filtered radar returns using a continuous wavelet transform (CWT) then extracted the heart signal using EEMD [26]. This experiment used a 5.8GHz quadrature CW Doppler radar, and the subjects were seated and remained stationary 0.5m away from the radar. Xu et al. showed that a 2.4GHz Doppler radar was able to measure with sub-millimeter accuracy the movement of a mechanical oscillator acting as a surrogate for a human chest [27]. This work however was just a feasibility study- it was not used on a human subject, and did not include a respiration signal. Heart motion imaging has also been performed using an UWB radar fitted with an eight element antenna array and placed close to a supine subject [28].

#### 2.4 Moving subjects

One major limitation in the current research is the inability to accurately estimate vital signs during periods of gross body movements [24]. At most, small movements such as typing on a laptop or smart phone while the subject is sedentary is admissible for a radar physiological monitoring system to obtain reliable estimates [3]. Hence, a vital sign monitoring system in real life must be able to provide reliable vital sign estimates irrespective of whether the subject is sedentary or moving.

Current state-of-the-art non-contact physiological monitoring systems provide reliable vital sign estimates only in sedentary conditions. Large body movements can obscure the micro-Doppler variations caused by chest wall and abdominal movements. An autocorrelation based approach was used by Sun et al. for a 10GHz CW Doppler radar to remove the effect of random body movements (RBM); however, the data was recorded for subjects' seated 0.2-0.3m away and remaining still [29]. An algorithm was developed by Khan et al. to detect RBMs by computing the width of the autocorrelation function of the signal and using a threshold to classify the amount of movement [30]. If the subject is classified as stationary, then the algorithm computes the respiration rate and heart rate from peaks in the Fourier transform, whereas if the subject is classified as nonstationary the estimate for respiration and heart rate is not computed. This system reduces estimation error by only computing estimates when the estimates are expected to be accurate. The issue with this work by Khan et al. was that it only dealt with a seated subject. A random body movement cancellation (RBMC) algorithm that fuses data from video and radar was proposed by Gu et al. [7]. The phase data from the video was used for removing the RBMs in the radar returns so that the respiratory signals were preserved during periods of body movement.

Rather than trying to estimate breathing rates in the presence of random body movements (RBM), one work exploited the existence of these movements by proposing a 24GHz CW radar array system, to detect victims trapped in building rubble based solely on RBMs [31].

RBMs effect accuracy of other physiological estimation algorithms as discussed in Sections 2.2 and 2.3, however there has not been an algorithm proposed in literature which has been shown to be capable of dealing with RBMs in a robust manner.

#### 2.5 **Posture classification**

An algorithm for detecting postural changes while lying down was presented by Nguyen et al. [5], however it was not tested in any other posture. A radar-video fusion system was presented which used radar for initial location of the subject, but video processing alone was used for posture classification [32]. Classification of posture using an IR-UWB radar was performed by Ahangar-Kiasari et al. with 86% accuracy for standing, 83% accuracy for sitting and 80% accuracy for lying postures [8]. This work extracted statistical features from the first 10 principal components of the radar return signals and used them for training a neural network. Data was collected for subjects at 1, 3 and 5 meters from the subject, but the orientation of the subjects relative to the radar was not explained.

#### 2.6 Fall prevention

Preventing falls, or mitigating risks of falling for at risk seniors is a very important task that is currently being researched. Gait is a term used to refer to the characteristics of a subject's movements while walking. It has been found that changes in gait over time can be representative of failing health and be used as predictors for increased risk of falling in senior citizens. Reduced walking speeds and higher variability in gait parameters were found to be good predictors for those who have an elevated risk of falling [33]. Gait analysis was performed by extracting features such as torso velocity, limb acceleration and period of limb movement from the short-time Fourier transform (STFT) of radar returns while subjects walked in a radial direction towards and away from a CW radar [34]. Differences in gait were found between men and women, as well as between healthy subjects and those suffering from neuro-muscular diseases. Gait analysis was also performed by Wang et al. within the context of fall prevention using two pulse Doppler radars: one at the torso level and the other at the foot level [4]. Furthermore, gait parameters were used to differentiate human subjects from other moving targets such as dogs, bicycles and automobiles [35].

#### 2.7 Detection of room occupancy

Several methods have been used to determine room or building occupancy. Sensors used for these methods fall into three categories; infrared (IR), video, and radio frequency (RF) [36]. Infrared technology performs poorly in sunlight due to signal interference and requires the space between the IR sensor and the human target be free of obstructions. Video suffers from the same problems as IR sensors. Furthermore, video has implications regarding privacy.

RF occupancy detection can be further broken down into two methods: systems that require the target to carry a passive or active tag, and systems that do not require the target to carry a tag. The first method works on the principle of measuring signal strength in an array of wireless links, where each link is between the target and another RF sensor or RF tag located in a different part of a building. This method was used by Bahl et al. for occupancy detection of subjects that were stationary or moving [37]. Subjects were located and tracked with a resolution of 2-3m. A major drawback with this method is that it requires cooperation from the subject- they must wear the passive tag. This type of system may detect occupancy in office type applications where all employees are required to carry a badge. Tag-based systems may not be suited for monitoring patients in long term care homes as the requirement of carrying a monitoring tag at all times would be burdensome or cannot be guaranteed in cases with seniors with dementia.

Non-contact occupancy detection using radars mounted in the room and not requiring subjects to wear a tag is a relatively new area of research. Occupancy detection and localization of a human subject was performed using a dual-band Doppler radar by detecting signal components in the radar returns corresponding to human breathing and heartbeat [38]. Data was collected from only one subject in that experiment. Similarly, Yavari et al. used a 2.405GHz offset quadrature phase-shift keying (O-QPSK) Doppler radar to extract the breathing signal of a single subject using cubic spline interpolation for determining the presence of a subject [39].

Yavari et al. used a 2.4GHz continuous wave (CW) Doppler radar to detect human occupancy based solely on the root mean square (RMS) value of the radar returns [40]. Yavari et al. used a mechanical device moving at 0.2Hz to mimic breathing motion

of a single human subject and reported an average accuracy of 93%. The energy levels recorded from a commercially available 3.1-5.3GHz UWB were used by Brown et al. to determine room occupancy, and the occupancy data was aggregated with power consumption in the household for analyzing the correlation of occupancy with energy consumption [41].

A 5.46GHz to 7.25GHz frequency modulated continuous wave (FMCW) radar was used by Adib et al. to detect occupancy of a room for up to 3 subjects [3]. With this radar, estimation of breathing and heartbeat of three individuals simultaneously as well as detection of occupancy by two individuals while one was moving within the room (while staying at least 1.5m away from the other individual) was reported. The system proposed by Adib et al. was limited in range to 8m due to low SNR and was only able to separate two individuals as long as they were 1-2m apart. The details of the algorithm for occupancy determination and the number of occupants or location of the occupants and location accuracy was not available.

#### 2.8 Practical and commercial implementations

There are a few research teams that have proposed or demonstrated a system for monitoring human physiological movements with non-contact radar sensors. A team from the Massachusetts Institute of Technology has developed a system called Vital-Radio which they claim is capable of estimating breathing and heart rate with 99% median accuracy up to 8m away unobstructed, and 4m behind a wall [3]. The system is also claimed to be capable of identifying and analyzing the radar returns for up to 3 subjects with at least 0.8m separation between subjects. Technical information regarding

the system including aspects about the hardware and signal processing algorithms were not presented.

Norwegian radar manufacturer Novelda has a product on the market which is designed to monitor respiration and movement of customers while they sleep. The system is capable of monitoring subjects up to 5m away [42].

Panasonic has teamed up with Kyoto University for the development of a millimeter-wave radar capable of monitoring physiological signs [43]. Similarly, TES Electronic Solutions has demonstrated a 60.5 GHz radar system for monitoring respiration and heartbeat up to 2m away, designed to be implemented in personal vehicles [44]. Details of the system and the algorithm used in these commercial systems are not publicly available yet.

#### 2.9 Limitations and proposed solution

The main limitations in the current state of the art of non-contact monitoring using a single RF sensor are the following: being able to deal with moving subjects, detecting posture and determining room occupancy. There has been work done in each of these three areas, however there has not been a single work that has attempted to implement a solution to all of these three problems in a single system using only a single RF sensor.

In the remainder of this thesis, algorithms are developed to deal with these problems, and a hierarchical processing approach which integrates all of these algorithms is proposed. The point of this approach is to be able to deal with data from subjects in uncontrolled situations, and provide estimates of posture and breathing only when

appropriate. This work is a step towards realization of a practical sensing system that can be implemented in uncontrolled environments for senior care applications.

## **3** Chapter: Radar theory

Two distinct radar types are used in this thesis. Continuous wave (CW) Doppler radar and ultra-wideband (UWB). Both of these radar types are used widely within the field of non-contact human monitoring, so it is important to understand the advantages and disadvantages of using those two radars.

In this chapter, the CW and UWB radar models used in this thesis will be introduced as well as an explanation of the signal characteristics of each. An explanation of radar fundamentals will be given first.

#### 3.1 Radar fundamentals

Radar, which is an acronym for **Ra**dio **D**etection **and Ranging**, operates by transmitting an electromagnetic signal and analyzing the signal returns or echoes. From these echoes a target can be detected via its range and velocity. A radar transmits a signal with power  $P_t$  (W) and receives an echo signal of power  $P_r$  (W) which are related by the following equation [1]

$$P_r = \frac{P_t G^2 \sigma \lambda^2}{(4\pi)^3 R^4} \tag{3.1}$$

where G is the gain of the antennas (assuming the antennas for transmission and receiving are identical),  $\lambda$  is the wavelength of the radar carrier frequency, R is the distance to the reflecting target, and  $\sigma$  is the radar cross section (RCS) which is defined as the ratio of echo power returned to the transmitter to the power that would be reflected by a perfectly conducting sphere with  $1m^2$  cross sectional area, or

$$\sigma = \frac{4\pi R^2 |E_r|^2}{|E_i|^2}$$
(3.2)

where  $E_r$  is the echo field strength at the receiving antenna and  $E_i$  is the field strength incident on the target [1]. RCS can also be defined as the cross sectional area of a uniformly scattering target located at the same distance away that would produce the same reflecting power. With equation 3.2 one can determine the distance from a target or calculate the maximum range of target detection given a minimum received power required.

When the target RCS is unknown or when there are reflections from multiple targets as is the case in any practical implementation of a radar, the range must be determined not by comparing transmitted and received power levels but by analyzing the time delay between the received signal and the transmitted signal.

Target velocity can be found by exploiting the Doppler shift observed in the return echoes. A signal reflected from a moving target will undergo a frequency shift proportional to the velocity of the moving target. This frequency shift is known as the Doppler shift. When a radar signal is reflected off of a moving target the received signal has a Doppler shift given by

$$f_d = \frac{2f_t v_r}{c} \tag{3.3}$$

where  $f_d$  is the Doppler shifted frequency as seen at the receiver,  $f_t$  is the frequency of the transmitted signal, or carrier frequency,  $v_r$  is the radial velocity of the target, and c is the speed of light in free space [1].

#### **3.2 Model of CW Doppler radar**

The simplest type of radar is pure continuous wave (CW) which transmits and receives a narrow bandwidth signal of fixed frequency simultaneously (in the case of a bistatic, or two antenna configuration) or intermittently (in the case of a monostatic, or single antenna configuration with a duplexer or circulator). A pure CW radar cannot unambiguously detect the range to a moving target since there is no way to time stamp the transmitted signal. Pure CW radars work very well for detecting target velocity due to the narrow bandwidth of the transmitted signal; the velocity is found by measuring frequency derivations of the received signal. The maximum range of target velocity that can be detected is based solely on the bandwidth of the receiving antenna and circuitry.

Frequency Modulated Continuous Wave (FMCW) radars can detect both the range and the velocity of a moving target. The transmitted signal is frequency modulated by a triangular function (typically) which sweeps the frequency between an upper and lower bound (called the frequency excursion). This allows the range to be determined by comparing the phase delay of the returned signal, as the distance to the target is directly proportional to half of the time delay. The Doppler frequency is found by comparing the average frequency of the returned signal to the average (carrier) frequency of the transmitted signal. FMCW radars have larger bandwidths than pure CW radars, which can limit the range of target velocity that the radar can detect. The maximum range to a target that an FMCW radar can unambiguously detect is related to the period of the modulation function. The range resolution of a FMCW radar is defined by

$$\Delta R = \frac{c}{2\Delta f} \tag{3.4}$$

where  $\Delta f$  is the bandwidth, or frequency excursion of the transmitted signal [1].

Other types of radars use a coding technique for time stamping the transmitted signal for comparison with the received signal to detect range of targets. The CW radar that is used for the experiments in this thesis is a Binary Phase Coded Continuous Wave Doppler Radar. Binary phase coding splits the transmitted signal into equal length

segments (called chips) which correspond to distance ranges (range bins) and applies a phase shift of either 0 or  $\pi$  radians. Barker codes are used to reduce time side-lobes to a minimum [45].

There are many configurations that radars can be used in, including monostatic, bistatic, pseudo-monostatic, and multi-static. Monostatic refers to the use of a single antenna for both transmission and receiving. The antenna is switched using either a duplexer or circulator (similar to a commutator in a DC motor). The issue with a monostatic configuration is that there is little to no spatial separation of the transmitter (tx) and receiver (rx) circuits. For this reason, the radar can suffer from self-injection which results in high DC components in the demodulated baseband signal that saturate or damage the circuit. Self-injection obscures weak signals from distant targets. Bistatic refers to the use of spatially separate antennas for transmission and. Bistatic configurations can increase circuit isolation to improve SNR. Antennas in a bistatic configuration can be located at any distance apart and thus the radar configuration can be used in special applications such as detecting stealth aircraft or semi-active missile guidance. Pseudo-monostatic refers to a bistatic configuration in which the antennas are located close enough together that they can be considered to be in the same place for long range targets. The CW radar used in this thesis would fall into this category since there are four pairs of antennas (only one pair active at any point in time) that are located close to one another. Pseudo-monostatic radar configurations have higher circuit isolation than monostatic configurations because the circuits are separated. Multi-static refers to the use of more than two antennas. This may include two or more receiving antennas with only one transmitting antenna, two or more transmitting antennas with only one receiving

antenna, or multiple transmitting and multiple receiving antennas. Using multiple antennas (therefore multiple paths) can allow for greater localization of targets from noise and clutter because the noise and clutter in each channel is considered uncorrelated with one another, therefore the correlated components in each channel relate to moving targets. Using multiple antennas that are spatially separated also allows for obtaining information about targets from different angles which can be especially important for environments with a lot of occluding objects.

A CW radar transmits a continuous wave signal of frequency  $f_c$  (carrier frequency) and receives a reflected version of the transmitted signal. The received signal carries information about the environment in its frequency, phase, and amplitude. Frequency variations are induced in the signal when it is reflected off a target moving in the direction of wave propagation. This is called the Doppler shift and it is defined as

$$f_d = \frac{2f_c v_t}{c} \tag{3.5}$$

where  $f_d$  is the Doppler shifted frequency,  $v_t$  is the velocity of the target in the direction of wave propagation (positive when moving towards the radar) and c is the speed of light in free space in m/s [1]. If the target moves away, then  $f_d$  is considered as a negative frequency.

The transmit signal of a CW radar can be defined as

$$S_t = \cos(\omega_o t) \tag{3.6}$$

where  $w_o$  is the carrier frequency (in radians/second). [1]

The transmit signal is reflected off N number of objects in the environment covered by the antenna beam width and received at the receiving antenna as

$$S_r = \sum_{t=1}^N A_t \cos\left(\omega_o t + \frac{2\pi}{\lambda} \left(2d_{o_t} + 2d_t(t)\right)\right)$$
(3.7)

where the subscript t is the target in the environment that is reflecting the signal,  $d_o$  is the nominal distance to the target, d(t) is the time varying displacement of the target from the nominal distance (in the axis of signal propagation) [1]. In this thesis a target is defined as a point source capable of reflecting a portion of the incident radar signal back to the receiving antenna. For targets that are stationary the time varying component will be zero meaning their total contribution to the received signal will simply be a constant (resulting in a DC bias after demodulation). The number of targets (N) is very large for any environment save an anechoic chamber, however the purpose of this study is to analyze a moving human subject in an otherwise stationary environment. Therefore only time varying targets need to be considered- leaving only targets located on the human body (moving organs). After the signal is received at the receiving antenna it enters a mixer and is demodulated by a delayed version of the transmitted signal

$$S_r S_t = \sum_{t=1}^N A_t \cos \omega_o t \cos \left( \omega_o t + \frac{2\pi}{\lambda} \left( 2d_{o_t} + 2d_t(t) \right) \right)$$
(3.8)

Using the following trigonometric identity

$$\cos a \cos b = \frac{\cos(a-b) + \cos(a+b)}{2}$$
 (3.9)

the demodulated received signal is

$$S_r S_t = \sum_{t=1}^N \frac{A_t}{2} \left[ \cos\left(\frac{2\pi}{\lambda} \left(2d_{o_t} + 2d_t(t)\right)\right) + \cos\left(2\omega_0 t + \frac{2\pi}{\lambda} \left(2d_{o_t} + 2d_t(t)\right)\right) \right]$$
(3.10)

The second term in the square brackets when filtered out by a low pass filter provides the following

$$S_r S_t = \sum_{t=1}^N \frac{A_t}{2} \cos\left(\frac{2\pi}{\lambda} \left(2d_{o_t} + 2d_t(t)\right)\right)$$
(3.11)

Using the following trigonometric identity

$$\cos(a \pm b) = \cos a \cos b \mp \sin a \sin b \tag{3.12}$$

the demodulated received signal from one target reflection can be rewritten as

$$S_r S_{t_1} = \frac{A}{2} \cos(\frac{4\pi d_0}{\lambda}) \cos(\frac{4\pi d(t)}{\lambda}) - \frac{A}{2} \sin(\frac{4\pi d_0}{\lambda}) \sin(\frac{4\pi d(t)}{\lambda})$$
(3.13)

or

$$S_r S_{t_1} = a \cos(\frac{4\pi d(t)}{\lambda}) - b \cos(-\frac{4\pi d(t)}{\lambda} + \frac{\pi}{2})$$
(3.14)

where

$$a = \frac{A}{2}\cos(\frac{A}{2}\sin(\frac{4\pi d_0}{\lambda})) \quad b = \frac{A}{2}\sin(\frac{4\pi d_0}{\lambda}) \tag{3.15}$$

The two signals can thus be thought of as having two quadrature related components. To simplify the signal in baseband, a trigonometric 'rule of thumb' called the small angle approximation can sometimes be used to reduce the above equation to a simple linear equation. The small angle approximation [46] states that

$$\cos\theta \approx 1 - \frac{\theta^2}{2}, \theta < 0.664 \text{ rad} (38^o)$$
 (3.16)

To check if the small angle approximation would hold,  $\frac{4\pi d(t)}{\lambda}$  must be less than 0.664. In the case of this work the radar being used is a CW Doppler with center frequency of 24.125GHz. The wavelength at 24.125 GHz is 0.0124m, so the maximum amplitude of target motion (d(t)) should be within 6.571\*10<sup>-4</sup>m or 0.6571mm in order to apply the

small angle approximation. Chest displacement due to heart motion is approximately 0.08mm while displacement due to breathing is 0.1mm to several mm [47]. This means that during periods of no breathing (or light breathing) the heart beat can be obtained through a simplified version of the received signal by applying the small angle approximation, but during normal breathing the large displacements of chest and abdominal motion causes non-linear harmonic distortion.

Assuming there are only two independent sources within the human body causing periodic motion- namely the heart and lungs- we can expect that all moving targets found on the human body will oscillate with the frequency of breathing rate, heart rate, or a combination of both. In this case, a point source reflecting target may be modelled as

$$d(t) = A_b \cos(2\pi f_b t) + A_h \cos(2\pi f_h t)$$
(3.17)

where  $A_b$  is the amplitude of chest/abdominal displacement due to breathing,  $A_h$  is the amplitude of chest displacement due to hear beat and  $f_b$  and  $f_h$  are breathing and heart rate frequency respectively.

A simulation was performed in MatLab to help understand the effect of changing distance to target, frequency of motion of target, and relative amplitudes of motion sources. For small breathing displacements ( $A_b = 0.1 \text{ mm}$ ) the spectrum as obtained by performing a 2<sup>16</sup> point FFT with a Blackman window shows little harmonic distortion. For large breathing displacements ( $A_b = 2 \text{ cm}$ ) that may be witnessed at the abdomen of a subject during deep breathing the spectrum has a lot of harmonic distortion.


Figure 3.1: Demodulation and target motion for Ab= 0.1mm



Figure 3.2: FFT of demodulated and target motion signals over 60s for Ab = 0.1mm, fb = 0.2Hz, Ah = 0.08mm, fh = 1Hz, d0 = 1m



Figure 3.3: Time domain of demodulated and target motion signals over 60 seconds. Ab = 1cm, fb = 0.2Hz, Ah = 0.08mm, fh = 1 Hz, d0 = 1m



Figure 3.4: FFT of demodulated and target motion signals over 60 seconds. Ab = 1cm, fb = 0.2Hz, Ah = 0.08mm, fh = 1 Hz, d0 = 1m

As seen in Figures 3.1-3.4 the relative weights of the harmonics in the spectrum are dependent on the amplitude of displacement of the target. Since the heart motion only results in a very small displacement of the chest, its motion is obscured by the motion of the abdomen resulting from breathing. When the breathing signal is removed (i.e. Ab = 0) which is an analog for the case that the subject stops breathing but is still alive. The heart rate can be clearly seen in the spectrum (Figures 3.5 and 3.6).



Figure 3.5: Time domain of demodulated and target motion signals over 60 seconds. Ab = 0, fb = 0.2Hz, Ah = 0.08mm, fh = 1 Hz, d0 = 1m



Figure 3.6: FFT of demodulated and target motion signals over 60 seconds. Ab = 0, fb = 0.2Hz, Ah = 0.08mm, fh = 1 Hz, d0 = 1m

Linear signal processing techniques, such as Fourier analysis, are not well suited for this signal because of its highly non-linear nature. For instance, under some permutations of breathing displacement amplitude and breathing frequency the fundamental breathing frequency is not even seen in the spectrum (Figure 3.7) which could lead to incorrectly estimating breathing frequency as its second or third harmonic.



Figure 3.7: FFT of demodulated and target motion signals over 60 seconds. Ab = 1cm, fb = 0.33Hz, Ah = 0.08mm, fh = 1 Hz, d0 = 1m

In the case of Figure 3.7, the inter-peak separation of the frequency is the fundamental frequency of the signal. This can be used to estimate the breathing frequency in the model; however in a real signal it is expected that there will be noise which could obscure the peaks of the harmonics.

The nominal distance between the radar and the target does not have an effect on the harmonic distortion of the spectrum, however it is expected that the further away the target is from the radar, the more the SNR will decrease due to the lower signal strength from  $R^4$  losses as well as increased baseband phase noise due to range correlation [1].

A binary phase coded frequency modulated continuous wave Doppler radar built by K&G Spectrum (Gatineau, QC) is used for collecting the data. The carrier frequency of the radar is 24.125GHz and the sampling rate is 905 samples per second. The radar has four antenna pairs that are each 20° x 70° beam-width, mounted adjacent to one another. The transmission antennas are all transmitting simultaneously while only one receiving antenna is receiving at any point in time. This means the radar is operating as a single input single output radar, but with unequal beam-width transmitting and receiving antennas. The reason for this architectural design was to allow the entire room to be flooded with the transmitted radar signal while still allowing narrow receiving beamwidth for locating the subject within specific regions of the room. The antennas are labelled antenna 1-4, which cover corresponding room regions. The receiving antennas are switched using solid state Macom SP4T switch with low insertion loss and high isolation between channels.



Figure 3.8: Continuous wave antenna

The received signal is arranged in a matrix format for signal processing purposes, where one dimension is indexed by the samples in slow time (temporal dimension) and one is indexed by samples in fast time (spatial dimension). The spatial dimension is indexed by 'zones' which are 0.75m wide and overlapping. The room is adequately covered by 9 zones.

To better visualize the structure of the received signal, Figure 3.9 represents the radar returns after demodulation of a subject walking toward and away from the radar in a single antenna beam path. The rows in the graph represent each zone, numbered 1 to 9 where zone 1 is closest to the radar. The signal energy can be seen to change in zones 3 to 9 as the subject walks through them, starting in zone 9 at t=0 and walking towards zone 3 at t=5, reaching zone 3 at approximately t=10 and then turning around and walking back at t=13.



Figure 3.9: Example of CW radar returns

### 3.3 Model of UWB radar

Continuous wave radar has a very narrow bandwidth, which means its ability to locate a subject is limited. Ultra-wideband on the other hand has a bandwidth of at least 25% of its center frequency. This allows UWB to locate a subject with better accuracy than CW. Ultra-wideband radar works on the basic principal of sending very short impulses, on the order of Nano or even Pico seconds, at high pulse repetition frequencies. Because the duration of these pulses is so short, the range resolution is very high.

In UWB radars, the pulse length, denoted by  $c\tau$ , where c is the velocity of light in free space and  $\tau$  is the length of the pulse in time, is typically much smaller than the antenna aperture L. Therefore, antenna radiation pattern varies with time because there is a delay for the pulse to traverse the entire length of the antenna. Also the electromagnetic field at any point in the field of the radar is dependent on time and angle. This addition of angle dependence is unique to UWB radars- it is not present in CW [48].

UWB radiation patterns are modelled by treating an antenna as a series of elementary Hertzian dipole radiators with length  $\Delta$ Li or c $\tau$ . The electric field of a Hertzian dipole excited by current i(t) is

$$E(\theta, t) = \frac{Z_0 \sin \theta}{4\pi R} \frac{d}{dt} \left[ i \left( t - \frac{R}{c} \right) \right] \Delta L$$
(3.18)

where  $\theta$  is the angle between the dipole axis and point in space, Z<sub>0</sub> is the impedance of free space, and R is the distance from the dipole to the point in space [48].

Since the antenna is being modelled as a series of these simple dipoles, the value of  $E(\theta,t)$  will be the superimposition of the field radiated from each dipole. As the pulse i(t) tracks along the antenna, there will be a time delay. The following equation represents the total field  $E_T(\theta,t)$ .

$$E_T(\theta, t) = \frac{Z_0 \sin \theta}{4\pi R} \int_0^L \frac{d}{dt} \left[ i \left( t - \frac{L}{c} - \frac{R - L \cos \theta}{c} \right) \right] dL$$
(3.19)

This equation shows the dependency of the electric field about the UWB radar antenna with not only distance but angle as well [48].

As the UWB radar pulses have a wide frequency band, the pulse shape cannot be expected to be the same after it has been reflected off a target. The frequency response of each point target will distort the pulse shape. This means that the circuitry connected to the receiving architecture cannot use a simple correlator or matched filter as is done in CW radars. The relationship between the incident and reflected signal spectrum after target reflection is represented in the following equation:

$$U_r(\omega) = U_i(\omega)K(\omega) \tag{3.20}$$

where  $K(\omega)$  is the complex frequency characteristic of the target [48].

Furthermore, because there is spatial separation between the transmitting and receiving antennas resulting in a difference in angle of arrival, the receiving antenna will have a different radiation pattern than the transmitting antenna.

This exploration into the signal characteristics of UWB radar shows that the phenomena governing short duration and large bandwidth pulses makes model based approaches for designing algorithms far more difficult than for CW radar. There are many unknowns that factor into the received signal such as relative angle, distance, and the frequency response of the target. This also makes the signal processing of UWB return echoes more challenging than that of CW radar.

The ultra-wideband radar used in this experiment is the Xethru X4M03 development kit manufactured by Novelda (Oslo, Norway), which uses the X4 chip operating at a center frequency of 7.29 GHz. The radar is equipped with 6-8.5 GHz

directional patch antennas with a beam width of 65° in both azimuth and elevation axes. The radar sampling rate is 23 GS/s in fast time and up to 20 S/s in slow time. The chips range is programmable up to 25 m.



Figure 3.10: Novelda Xethru X4M03

The output data is in the form of a matrix where the rows represent observations, or samples, in slow time and the columns represent samples in fast time (corresponding to range bins). The range resolution of the X4 radar is approximately 5.35cm. During experiments the radar was programmed to record data from a range of 9.75m away from the radar which resulted in 187 columns in the data matrix. The sampling rate in slow time was set to 17 S/s.

#### 3.4 Conclusion

CW radar utilizes a very simple architecture to transmit and receive RF signals. This means that a model based approach can be used in designing algorithms for detection of targets and estimation of target motion. Furthermore, CW radar typically transmits and receives at a much higher frequency than UWB meaning frequency resolution of the return signals are much higher.

UWB radar has a very high spatial resolution due to the extremely short duration of its pulses. A downside to short duration pulses however is the complexity of mathematical models describing signal propagation and reflection. This makes model based approaches very difficult.

CW radar is a better candidate for estimation of breathing and heartbeat frequency due to its high frequency resolution, whereas UWB is a better candidate for posture classification due to its high spatial resolution. The following chapters will utilize both of these radars for classification purposes.

# 4 Chapter: Experiment design and data collection

In this chapter the data collection protocol for the experiments performed in this thesis are discussed.

#### 4.1 Data collection protocol for CW radar experiments

The data collection was performed in Mackenzie Building Room 4246 at Carleton University (Ottawa, ON). The testing protocol was approved by the Carleton Research Ethics Board. The room measured 3.35x3.15x2.95 m and contained a bed constructed of a cushion overlaying a chip board supported by 6 cinder blocks, a stainless steel toilet and sink unit, a plastic chair (not a fixed location) and a metal table located in one of the radar's blind spots. The radar was mounted 2.70m above the floor in one of the room's corners. A Bosch NEI368 vandal proof wide-angle camera was also located in the room to record video data in conjunction with the radar for later processing. The walls of the room were brick (typical construction bricks) which should not be transparent to electromagnetic signals at the operating frequency of the radar used in this experiment (i.e. there should not be motion artefacts in the signal whose source is outside of the room). A picture of the room can be seen in Figure 4.1. Marks A, B, and C are 1.5m, 2.5m and 3.5m from the corner of the room that contains the radar respectively. During data acquisition only one antenna was operating and only one human was present in the radar field (other experimenters were in a corner of the room that was not within the path of the radar).



Figure 4.1: Mackenzie room number 4246

During radar measurements the subjects' heart and breathing activity were monitored using 3 ECG adhesive sensors (mounted on the left and right wrists and left ankle) and a Braebon piezo-electric respiratory effort sensor belt (strapped around the chest near the sternum). The sensors were connected to a BioCapture data acquisition module which streamed data via Bluetooth to a PC located on the table. These measurements were recorded so that baseline breathing and heart rate measurements could be obtained for later evaluating the performance of signal processing algorithms applied to the corresponding radar returns.

There were five different types of test protocols for this experiment-

- Lying on the bed in the left lateral recumbent position facing the radar. One minute of normal breathing followed by one minute of holding breath (or as long as comfortable) finished with one minute of normal breathing with arm/head movements. (3 minutes)
- Sitting on the bed facing the radar, back straight and hands resting on knees. One minute of normal breathing followed by one minute of holding breath (or as long as comfortable) finished with one minute of normal breathing with arms/head movements. (3 minutes)
- 3. Standing at mark C on the floor facing radar. One minute of normal breathing followed by one minute of holding breath (or as long as comfortable) finished with one minute of normal breathing with arms/head/knees movements. Repeated twice at marks B and A on the floor. (9 minutes)
- 4. Standing at mark A on the floor with back to radar. One minute of normal breathing followed by one minute of holding breath (or as long as comfortable) finished with one minute of normal breathing with arms/head/knees movements. Repeated twice at marks B and C on the floor. (9 minutes)
- 5. Walking slowly back and forth between marks C and A on the floor, normal breathing for three minutes. (3 minutes)

These test protocols (totaling 27 minutes) were performed by four subjects (3 male and 1 female) of varying ages.

The data was synchronized (time aligned) and segmented and saved into one minute files. Synchronization was done by starting both radar and breathing belt and ECG data acquisition processes simultaneously. Each 1 minute segment of radar data (which consisted of 54300 samples in each of the 9 zones) was saved into a CSV file. Each 1 minute segment of ECG and breathing belt data (which consisted of 15360 samples for each signal) was also saved in a CSV file. 214 CSV files were saved and stored on a PC as well as on a Google Drive to be accessible by other teammates. The subjects' personal information was stored in a referencing CSV file and their names were replaced with a numeric code. The 214 data files contained no identifying information about the subjects. All data was password protected, and the only file that contained the coding scheme which could link the data to the subjects was a text file that was password protected and accessible only to team members. The zone in which the subject was present was estimated by finding the highest energy zone (after the mean of the signal was removed). 10 second samples were taken from the data, in total 642 samples were extracted.

A MatLab code was written to import the referencing CSV (which contained the labels of all samples- including posture, zone, antenna, activity, breathing rate, heart rate, start and stop sample points, file names, subject number, weight, height, and age) and parse through every sample of data for feature extraction and breathing and heart rate estimation.

#### 4.2 Protocol for data collection in UWB radar experiments

Data was collected in a laboratory in SITE5077 at the University of Ottawa (800 King Edward Avenue, Ottawa). The laboratory measured 12.6x4.1m, and had a desk at one end of the room, on which the radar was fixed 1.5m above floor level. The testing protocol was approved by the University of Ottawa Research Ethics Board. The test protocol was developed to ensure proper controls and avoid any biasing for classification of activities and postures. The test protocol required the subject to perform varying levels of activity while sitting, standing and lying down. Tests were performed in different locations throughout the room so that the algorithms could be developed invariant to location and relative angle.

The following protocol was performed at three position in the room which were 3m, 4.5m and 6m from the radar.

- 1. Stand facing the radar breathing normally and remaining still. (1 minute)
- 2. Stand facing the radar breathing normally and move limbs and head. (1 minute)
- 3. Lie down on the floor with left side facing radar breathing normally and remaining still. (1 minute)
- 4. Lie down on the floor with left side facing radar breathing normally and move limbs and head. (1 minute)
- 5. Sit facing the radar breathing normally and remaining still. (1 minute)
- 6. Sit facing the radar breathing normally and moving limbs and head. (1 minute)

After the data in the three positions was recorded, a recording was made in which the subject walked radially (from the radar to the back of the room and back). (3 minutes)

Data from 5 subjects were recorded, totaling 105 minutes. Data was labelled with subject information (subject number, age, weight, and height), activity level, location, posture, and orientation. Data samples of 10 seconds in duration were extracted from the data set with 30% overlap between the adjacent 10 second data samples resulting in a total of 816 samples.

# 5 Chapter: Posture and activity classification with CW radar

This chapter contains classification algorithms that were developed and tested for the CW radar used in this thesis. A proposal for a hierarchical processing approach which integrates algorithms for classification of activity and posture is provided in the first section, and the remaining sections discuss each step in this proposed approach.

## 5.1 Proposed hierarchical classification approach for CW radar returns

When radar returns are collected in real time, there is no information available to the system regarding the state of the subject being monitored. As discussed in previous sections, the level of movement of the subject has implications for further processing including breathing and heart beat estimation. Therefore it is essential that radar returns are first passed through a trained classifier so that the activity level of the subject can be determined. Once it is confirmed that the subject is non-moving, other information such as vital sign estimation or posture information can be extracted as posture information is key for preventing falls and bed sores. Figure 5.1 shows a block diagram of the proposed approach for classification of radar returns based on a CW implementation.



Figure 5.1: Block diagram of hierarchical classification approach for CW radar returns

The remainder of this chapter discusses the activity and posture classification steps, as well as a discussion of the results and the limitations encountered using CW radar for this application.

#### 5.2 Preprocessing and feature extraction

The data from the radar is recorded in an M x N matrix where M represents the number of radar returns and N represents the number of zones. For this experiment, 10 seconds of data are used for each sample, and 9 zones were captured. The sampling rate was 905 S/s. This means each data sample (10 seconds long) is 9050x9. For all processing, only the data corresponding to one zone is used. To determine which zone the subject is present in, the mean of each column is removed for clutter suppression and the

energy is calculated. The zone corresponding to highest energy is selected for further processing.

43 features (listed in Table A.1 in Appendix 1) were extracted from the data samples. The code used for extracting these features can be found in Appendix B. The features can be categorized as time domain features and frequency domain features. In time domain, the correlation of the signal was calculated. First, the signal's auto-mutual information was calculated for the first 50 lags. The lag corresponding to the first local minimum in the auto-mutual information was taken as the signal for computing correlation. This was performed on the original time series data as well as on two separate band passed versions corresponding to the range of breathing and heart beat (0.2-0.333 Hz and 0.667-3Hz respectively). Next, the original raw data was band pass filtered between 0.08-20 Hz (for clutter and high frequency noise removal), and the following statistics were computed: RMS, zero-crossing rate, turns count, variance, skewness, kurtosis, mobility and form factor.

For the frequency domain features, the data was standardized and a 2<sup>16</sup> point welch-periodogram was computed for the original signal as well as the signal band pass filtered in the breathing and heart beat frequency ranges. The energy of each of these spectra was computed and used as a feature. The mean and median frequency of the whole signal spectrum was calculated as well as the second and third spectral moments and used as features. The energy contained in the following frequency bands were also calculated: 0.2-0.667 Hz (first and second breathing harmonics), 0.667-3Hz (heart beat), 3-5Hz (low frequency noise), 5-11Hz (mid frequency noise) and 11-20Hz (high frequency noise). Each possible energy ratio from those bands were also calculated. The

57

energy from the first and second breathing harmonic frequency (0.08-0.35Hz and 0.37-0.7Hz respectively) bands were calculated as well as their ratio. Finally, the energy of the whole spectrum as well as the spectrum in the breathing and heart beat ranges were calculated for the final features. Table A.1 in Appendix A lists the extracted features.

Many of the aforementioned features were either taken from the works of Nejadgholi et al [49] or Forouzanfar et al. [50] or are variations of features from that work. Table A.1 contains notation of which features were taken those works. The main difference between the work presented in this thesis and the work in those two papers is the data collection protocol. In this work, data was collected for subjects in different areas throughout the room and in all three postures.

Statistical features extracted from the time domain signal are used because they contain information about the randomness of the underlying sources present in the signal. For instance, when many random body movements are contained in the data is assumed that the distribution of the signal is closer to being Gaussian than when there is a single dominant narrow bandwidth breathing signal.

Similarly, statistical features extracted from the signal spectrum should contain information about the sharpness and modality of the spectrum. Signals in which the breathing signal is dominant should have a significant peak at the breathing frequency and its harmonics. Signals which contain random body movements should have many peaks throughout the spectrum, showing that the signal is multimodal or contains more than one source of movement.

Because random body movements are faster than the movement of the chest and abdomen due to breathing, the Doppler shift should due to these movements should be

58

higher than the breathing and heartbeat range. Hence the spectrum is split into 6 sections and the energy of each is used as a feature along with all possible ratios. Similarly for posture classification, body sway should affect the relative energy contained in each band.

### 5.3 Classifiers

Machine learning is a very broad field hence there have been countless algorithms and variations of algorithms developed for classification. Like any other type of algorithm, classifiers offer a tradeoff between complexity and performance. Furthermore, some advanced classifier types require large data sets for training (such as in deep learning). For the purpose of this thesis, four classifiers were chosen for comparison. Two parametric models- naïve Bayes and linear discriminant, and two non-parametric models-K-nearest neighbors and decision tree. Parametric models require fewer data samples since they infer or assume information about the population distribution whereas nonparametric models learn solely from the data. Parametric models may make assumptions that are incorrect and lead to poor fitting, but non-parametric models can lead to overfitting.

Naïve Bayes classifiers work by computing the conditional probability of an observation belonging to a particular class using Bayes' theorem

$$p(c|x) = \frac{p(c)p(x|c)}{p(x)}$$
(5.1)

where x is the feature vector of a data sample or observation and c is the class type [51]. Naïve refers to the fact that the classifier assumes independence between all features. The training data is used to construct the probability model, and class is assigned to new data based on maximum likelihood. Linear discriminant classifiers compute the axes of highest class separability. The feature set is projected onto a lower dimension space that best captures the separability between classes. The linear discriminants are solved using the function

$$S_B v_k = \lambda_k S_w v_k \tag{5.2}$$

which is essentially an eigenvector computation, where  $v_k$  and  $\lambda_k$  are the eigenvector and eigenvalues of the between class and within class scatter matrix'  $S_B$  and  $S_w$  respectively.  $S_B$  is defined as

$$S_B = \sum_{i=1}^{c} \sum_{x_k \in \ class \ i} (x_k - \mu_i) \ (x_k - \mu_i)^t$$
(5.3)

and  $S_w$  is defined as

$$S_w = \sum_{i=1}^{c} (\mu_i - \mu) (\mu_i - \mu)^t$$
(5.4)

where  $x_k$  is the feature vector,  $\mu_i$  is the sample mean of class *i*,  $\mu$  is the total mean of all samples, and *c* is the number of classes [52]. The first k eigenvectors, where k < c, are used for projecting the feature space onto a smaller subspace where the classes can be linearly discriminated. Linear discriminants assume that features belong to a population that follows a normal distribution and that they have equal class covariance.

K-nearest neighbors is a very simple classifier model that assigns classes based on the most similar data from the training set. When a new data sample is passed to the classifier, the K nearest data points in the feature space are found and the class that the majority of the data points belong to is assigned to the new data point. Because it is a majority rules classifier, K must be an odd integer. In this thesis the value of K is 3.

A decision tree is a hierarchical set of rules for splitting data into categories. In this thesis, the tree classifiers are trained using the classification and regression trees (CART) method which finds optimal rules for each node of the tree, and stops adding nodes once no further gain in classification accuracy is made for node additions [53].

The performance of a classifier is evaluated in the validation stage. Initially the data set is partitioned into a training and validation set. The training set is used solely for training the classifier model. The validation set is then used to validate the classifier by performing classification on each sample within the validation set using the trained classifier. A confusion matrix is initialized as a square matrix of zeros, and when a validation sample is classified the result is added to the confusion matrix. The row and column number of the confusion matrix corresponds to the 'actual' class of the sample and class 'predicted' by the classifier, respectively. Each sample contributes an equal weight *w* to the confusion matrix;

$$w = \frac{1}{N} \tag{5.5}$$

where N is the number of instances in each class in the validation set. All classifiers in this thesis are trained and validated on class balanced sets hence N is equivalent for each class. This results in each row of the confusion matrix summing to 1, or 100%. The value in each element of the confusion matrix represents the percentage of samples classified either correctly or incorrectly as a particular class. The values along the diagonal of the confusion matrix define the class accuracy or percentage of correctly classified samples in each class (denoted by the row). To compute the overall or average accuracy of the classifier, the diagonal is summed and divided by the number of classes. It is important to note the difference between class accuracy and average accuracy. The type of accuracy, average or class, should be stated explicitly when discussing classifier performance or understood unambiguously in context.

#### 5.4 Activity classification

Three classes were used for this classification experiment, namely 'sedentary', 'sedentary with movements' and 'walking'. 'Sedentary' means the subject remains still in one location. 'Sedentary with movement' means the subject moves their limbs or head freely while remaining in one location. 'Walking' means the subject moves about the room. It should be noted that each activity class is independent of posture and location within the room, except for 'walking' class which is only represented by standing posture for obvious reasons. This means that the relative angle and distance between the subject's thorax and the radar varies from sample to sample. This was done so that the samples represent as closely as possible what would be encountered in a real environment where the subject is not following ideal test cases.

Classification was attempted on the data using multiple classifiers so that the relative accuracies could be compared. The data was first under-sampled so that all classes would have equal representation. The total number of samples used to train and validate the classifier was 284 from the original 642. Some samples from the original recorded data were removed because they were corrupted with noise. The random under sampling was done in each iteration of training/validating so the pool of possible samples was larger- 575 in total. Classifiers were trained and validated in 200 iterations of 70% random partitioning with stratified sampling; 149 training samples and 64 validation samples.

The confusion matrix for each classifier can be seen below.

|                  | Predicted Sedentary | Predicted Sedentary | Predicted Walking |
|------------------|---------------------|---------------------|-------------------|
|                  |                     | with Movements      |                   |
| Actual Sedentary | 85.40               | 14.04               | 0.54              |
|                  |                     |                     |                   |
| Actual Sedentary | 4.20                | 95.79               | 0.00              |
| with Movements   |                     |                     |                   |
| Actual Walking   | 2.56                | 1.93                | 95.50             |
|                  |                     |                     |                   |

# Table 5.1: Confusion matrix for linear discriminant activity classifier

Table 5.2: Confusion matrix for decision tree activity classifier

|                  | Predicted Sedentary | Predicted Sedentary | Predicted Walking |
|------------------|---------------------|---------------------|-------------------|
|                  |                     | with Movements      |                   |
| Actual Sedentary | 90.06               | 9.93                | 0.00              |
|                  |                     |                     |                   |
| Actual Sedentary | 10.04               | 88.79               | 1.15              |
| with Movements   |                     |                     |                   |
| Actual Walking   | 0.09                | 0.81                | 99.09             |
|                  |                     |                     |                   |

Table 5.3: Confusion matrix for naive Bayes activity classifier

|                  | Predicted Sedentary | Predicted Sedentary | Predicted Walking |
|------------------|---------------------|---------------------|-------------------|
|                  |                     | with Movements      |                   |
| Actual Sedentary | 88.02               | 10.88               | 1.09              |
|                  |                     |                     |                   |
| Actual Sedentary | 5.31                | 94.54               | 0.13              |
| with Movements   |                     |                     |                   |
| Actual Walking   | 0.31                | 5.18                | 94.50             |

|                  | Predicted Sedentary | Predicted Sedentary | Predicted Walking |
|------------------|---------------------|---------------------|-------------------|
|                  |                     | with Movements      |                   |
| Actual Sedentary | 67.31               | 27.04               | 5.63              |
| Actual Sedentary | 18.79               | 78.77               | 2.43              |
| with Movements   |                     |                     |                   |
| Actual Walking   | 3.77                | 10.09               | 86.13             |

Table 5.4: Confusion matrix for KNN activity classifier

# 5.5 Posture classification

Like activity classification, posture classification is also presented in this thesis as a three class problem; 'sitting', 'lying', and 'standing'. Posture classification was tested using 4 different classifiers; linear discriminant, KNN, naïve Bayes, and decision tree. Data in which the subject was walking was withheld from this experiment because as seen in the previous section, walking is easily discriminable from other activity classes. The inclusion of walking into the standing class would likely optimistically bias the accuracy of detecting standing. Similarly, since the lying class was only recorded at a single point in the room (on the bed), only the sitting and standing data recorded at mark C (near the bed) in the room were included. This resulted in fewer data samples than were used in the activity classification experiment, so in order to estimate the accuracy values of the classifiers 90% stratified partitioning was used instead of 70%, with 1000 randomized tests rather than 200. The results of this experiment can be seen in Tables 5.7-5.10.

|                 | Predicted Sitting | Predicted Lying | Predicted Standing |
|-----------------|-------------------|-----------------|--------------------|
| Actual Sitting  | 60.23             | 24.25           | 15.51              |
| Actual Lying    | 28.65             | 60.88           | 10.46              |
| Actual Standing | 10.43             | 16.70           | 72.86              |

Table 5.7: Confusion matrix for linear discriminant posture classifier

## Table 5.8: Confusion matrix for KNN posture classifier

|                 | Predicted Sitting | Predicted Lying | Predicted Standing |
|-----------------|-------------------|-----------------|--------------------|
| Actual Sitting  | 44.08             | 27.11           | 28.80              |
| Actual Lying    | 25.21             | 63.53           | 11.25              |
| Actual Standing | 28.75             | 11.18           | 60.06              |

Table 5.9: Confusion matrix for naïve Bayes posture classifier

|                 | Predicted Sitting | Predicted Lying | Predicted Standing |
|-----------------|-------------------|-----------------|--------------------|
| Actual Sitting  | 5.85              | 32.91           | 61.23              |
| Actual Lying    | 4.00              | 61.96           | 34.03              |
| Actual Standing | 3.80              | 5.51            | 90.68              |

# Table 5.10: Confusion matrix for decision tree learning posture classifier

|                 | Predicted Sitting | Predicted Lying | Predicted Standing |
|-----------------|-------------------|-----------------|--------------------|
| Actual Sitting  | 53.55             | 26.93           | 19.51              |
| Actual Lying    | 28.50             | 59.13           | 12.36              |
| Actual Standing | 22.85             | 12.48           | 64.66              |

### 5.6 Feature evaluation

In order to gain more knowledge about the underlying phenomena of this classification problem, the extracted values were evaluated based on their relative class separations. The metric used was the Bhattacharyya distance [50].

The Bhattacharyya distance is a measure of separation between two distributions. It can be used to evaluate a feature based on its class separability. A higher Bhattacharya distance means larger separation between distributions (i.e. less overlap between classes). The following equation defines the Bhattacharya distance for two class (w) distributions of a single feature with mean  $\mu$  and standard deviation  $\sigma$  [50].

$$D_B(w_i, w_j) = \frac{1}{8} (\mu_i - \mu_j)^T \left[ \frac{\sigma_i - \sigma_j}{2} \right]^{-1} (\mu_i - \mu_j) + \frac{1}{2} \ln \left| \frac{(\sigma_i - \sigma_j)/2}{\sqrt{|\sigma_i||\sigma_j|}} \right|$$
(5.6)

Often, only average  $D_B$  is used in literature when discussing features. The average Bhattacharyya distance for each feature is calculated by averaging the  $D_B$  for each possible pair of classes. For  $D_B > 0.8$  a Bayes classifier should achieve an error rate below 10% [50]. Since the average Bhattacharyya distance does not represent the separability of a feature for all pairs of classes, Table A.1 in Appendix A was constructed to show how each feature performs in separating each class.

Bhattacharyya distance assumes a normal distribution, however  $D_B$  can still be used to evaluate the feature set without the knowledge of the true distribution as it still contains information about the 'difference' between the two class distributions for each feature.

The features were sorted in descending order of largest Bhattacharyya distance, and the top ten features for each class pair were highlighted in green in Table A.1. The strongest features, their corresponding  $D_b$  and the average  $D_b$  across the entire feature set for each class pair for activity classification can be seen in Table 5.5, and for posture classification in Table 5.6.

| Class pair        | Strongest feature | Db of strongest | Average D <sub>b</sub> for |
|-------------------|-------------------|-----------------|----------------------------|
|                   |                   | feature         | entire feature set         |
| Sedentary vs      | F2/F5             | 1.24            | 0.57                       |
| Moving            |                   |                 |                            |
| Sedentary vs      | ZCR               | 7.29            | 2.12                       |
| Walking           |                   |                 |                            |
| Moving vs Walking | Energy in 0.667-3 | 7.13            | 1.96                       |
|                   | Hz band           |                 |                            |

Table 5.5: Strongest features for activity classification

Table 5.6: Strongest features for posture classification

| Class pair          | Strongest feature | D <sub>b</sub> of strongest | Average D <sub>b</sub> for |
|---------------------|-------------------|-----------------------------|----------------------------|
|                     |                   | feature                     | entire feature set         |
| Sitting vs Lying    | Median Frequency  | 1.96                        | 0.27                       |
| Sitting vs Standing | Energy in 0.667-3 | 6.07                        | 1.33                       |
|                     | Hz band           |                             |                            |
| Lying vs Standing   | Energy in 3-5 Hz  | 5.15                        | 1.35                       |
|                     | band              |                             |                            |

The results of this experiment show that the spectral features are the most valuable features in the set. The relative energy contained in specific bands of the spectra hold information about the activity and posture of the subject.

It can also be seen that the features that were extracted for this experiment had the least amount of class separation for the class pair 'sedentary vs moving' and 'sitting vs lying'. This is likely because 'walking' is easily separable due to the higher frequency movements and the fact that the subject moves in and out of the zone during each sample. Similarly, 'standing' is different from the other two posture classes because it is the only posture that does not have the subject's back supported. This means the subject sways slightly as they maintain their balance.

#### 5.7 Discussion of results

Activity classification using CW radar yielded very high average accuracy (92.64% for decision tree) and high sensitivity [54] of predicting 'sedentary and still' (89.88% for decision tree). Posture classification on the other hand performed poorly in average accuracy (64.66% for linear discriminant) and sensitivity of identifying 'standing' (73.72% for linear discriminant). Standing is the most important posture to detect for this classifier because one of the reasons for performing posture classifications is to aid in fall prevention, and it is assumed that if a subject is standing they are at an elevated risk of falling. The continuous wave radar used in this experiment had 0.75m overlapping zones, meaning the reflected signals from the human subject are superimposed into a single time series signal. This means that information from the limbs, thorax, and abdomen are all contained in the signal being analyzed, resulting in high average activity classification accuracy. The downside of this however, is the lack of

68

spatial resolution in the radar returns. Without any spatial information, no information regarding the shape of the human target cannot be obtained. This means posture classification must be performed using only spectral and time series features. This is likely the reason why posture classification resulted in very low average accuracy for all classifiers tested.

## 6 Chapter: Classification of radar returns using UWB radar

As seen in the results of the posture classification section of the previous chapter, it is difficult to perform posture classification with CW radar. This is due to the fact that CW radar has very low spatial resolution due to the narrow bandwidth of the carrier wave. UWB radar signal has low power, can penetrate obstacles, and has low probability of intercept. Furthermore, there are many low cost on chip solutions on the market making it a strong candidate for this application.

UWB radar is used for the remainder of the work in this thesis so that the benefits of high spatial resolution afforded with this radar can be explored.

### 6.1 Proposed hierarchical classification approach for UWB radar returns

There are many unknowns in non-contact sensing, including most importantly the number of subjects within the field of the radar and the activity level of those subjects. A simple hierarchical approach is proposed which classifies the incoming radar returns and applies estimation algorithms based on the class of the radar returns. The first stage of the approach is to determine whether or not the room is occupied, and if so estimate the number of occupants. Occupancy detection was done for UWB only because the high spatial resolution allows for easier identification of individual subjects. If multiple subjects are present in the field of the radar, then the next step is to separate them as individual sources and then classify their corresponding activity levels. Once this has been done, if a subject is found to be stationary, posture classification and breathing and heart beat monitoring algorithms are applied in parallel. Figure 6.1 shows this approach in a block diagram.





The remainder of this chapter deals with each classification step shown in the above diagram. First the occupancy detection algorithm will be described, then the feature extraction process and corresponding activity and posture classification steps will be explored.

### 6.2 Occupancy detection

An algorithm for detecting and counting occupants in the field of the radar was developed based on the first principal component (PC) of the radar returns. The work in this section was presented at the 2017 IEEE Midwestern Symposium on Circuits and Systems in Boston, Massachusetts [55]. Principal Component Analysis (PCA) is an orthogonal linear transformation which defines a new basis for a data set. Each new axis, or PC, is aligned in a direction corresponding to the largest variance of the data, starting with the first PC. PCA is an effective way of suppressing clutter and separating time varying sources, making it an attracting signal processing technique.

In order to perform PCA, the mean is first removed from each column of the m x n data matrix *X*,

$$X = [x_1[i], x_2[i], \dots, x_n[i]], 1 \le i \le m$$
(6.1)

$$\hat{X} = \left[\hat{x}_1[i], \hat{x}_2[i], \dots, \hat{x}_n[i]\right], 1 \le i \le m$$
(6.2)

where,

$$\hat{x}_1[i] = x_1[i] - mean(x_1[i]), 1 \le i \le m$$
(6.3)

where m is the number of observations and n is the number of range bins. The zero mean data matrix is then used to construct the auto-correlation matrix *R*:

$$R = \hat{X}^T \hat{X} \tag{6.4}$$

The first principal component is found as follows:

$$w_1 = \arg\max\{\frac{w^T R w}{w^T w}\}\tag{6.5}$$

where w is a weighting vector [55]. This is a maximization of a Rayleigh quotient. The value of w that maximizes the equation will be the Eigenvector (principal component) corresponding to the largest Eigenvalue (principal values).
Ahangar-Kiasari et al. used PCA to classify human postures using a neural network classifier [8]. They computed the first 10 PCs from each sample. Mean, variance, and kurtosis were calculated from each of the 10 PCs and used as features.

The algorithm developed and discussed in this thesis only makes use of the first PC, which corresponds to the greatest variance in the data.

To first determine if the room is empty or occupied by a human subject, the energy of the zero mean data matrix is calculated by

$$E_{ij} = \sum_{i=1}^{n} \sum_{j=1}^{m} (\hat{x}_i[j])^2$$
(6.6)

If the value of the energy is above a certain threshold then the algorithm decides that the room is occupied, otherwise it decides that the room is vacant. If the room is decided to be occupied, the algorithm proceeds to determine the number of subjects in the room. The energy threshold was determined by calculating the max energy value that is encountered in the empty room data.

Once the algorithm determines that the room is not vacant then the algorithm computes the first PC using the MatLab function princomp(). Figure 6.2 shows the first PC (vector  $w_1$ ) for data in which the room is vacant, for data in which there is one subject sitting approximately 3m away from the radar, and for data in which there is one subject sitting approximately 3m away from the radar and another subject standing approximately 5m away from the radar. As seen from the three plots, when there is a subject present in the field of the radar, the first PC has a sharp peak centered at the location in which the subject is present. The algorithm searches for the largest peak of the PC, and then a window around that peak is constructed where the bounds of the window are defined by the first point that falls below 5% of the peak value. This window represents the area within the field of the radar that the subject occupies. As previously stated, the first PC is a vector that lies along the axis of highest variance in the data matrix. To determine if the room has only a single subject occupying it, the proportion of variance in the first PC that the first subject contributes to is computed by integrating the window and dividing that value by the integral of the entire PC. If the proportion of variance is below a threshold value then the algorithm begins searching for another subject by repeating the above process while omitting the window of the first subject in its search for the next largest peak and corresponding window. This process is repeated until the sum of the variance in all windows surpasses the threshold value.



Figure 6.2: First principal component for three different signal types [55]

The value of the threshold for proportional variance contained within the windows as well as the threshold which defines the bounds of the window were determined by optimizing the algorithm by varying the two threshold values and finding the point at which the average accuracy was maximized for all samples. Average accuracy was optimized for a proportional variance threshold of 0.5 and window bounds of 5% peak value. The proposed algorithm is represented in Figure 6.3 as a flow diagram.



Figure 6.3: Occupancy detection algorithm block diagram [55]

To further boost average accuracy of the algorithm, the outputs are filtered through a voting process which considers the current and previous two outputs and changes the output to the mode of the three estimates. This ensures that there are fewer abrupt changes in the occupancy determined or predicted by the algorithm. This means that for the filtered output the amount of data required to compute an estimate of room occupancy is extended to 15.8 seconds.

This algorithm was tested on 17 minutes of data, with the data acquired by the following protocol:

- Empty room (5 minutes)
- One subject sitting on a couch 3m from the radar (5 minutes)
- One subject sitting on a couch 3m from the radar, another subject standing 5m from the radar directly behind the seated subject (5 minutes)
- Two subjects standing, one subject 2m away from the radar, the other subject 3.2m away from the radar and directly behind the first subject both facing the radar. At each 30s interval the second subject steps towards the first subject in 40cm steps (2 minutes)

To test the algorithm the data from the first 15 minutes is separated into 101 data windows with 10 second samples for each 5 minute file, with 70% overlap between adjacent windows. The results from running the samples through the algorithm can be seen in Table 6.1.

|           |   | Predicted Number of Occupants |    |    |   |
|-----------|---|-------------------------------|----|----|---|
|           |   | 0                             | 1  | 2  | 3 |
| Actual    | 0 | 101                           | 0  | 0  | 0 |
| Number of | 1 | 0                             | 82 | 19 | 0 |
| Occupants | 2 | 0                             | 15 | 84 | 2 |

Table 6.1: Confusion matrix for occupancy detection algorithm

As can be seen in the above Table, the algorithm is able to classify accurately 100% of the time if the room is vacant (row 1 and column 1), and is able to determine when there is one subject and two subjects 81.2% and 83.2% of the time respectively.

The algorithm was then tested for determining how close in proximity two subjects can be standing for the algorithm to still be able to discriminate both subjects. At 0.8m subject separation the algorithm correctly estimated an occupancy of 2 subjects with 86% accuracy. At 0.4m subject separation however, the accuracy dropped to 24%. When both subjects were standing beside one another, the accuracy was 0%. The reason for this last result was that the algorithm separates the subjects spatially, therefore if the subjects are both in the same radii from the radar they will be superimposed in the radar returns.

The results of this test are promising; when the subjects are stationary the algorithm correctly identified the room occupancy with up to 86% accuracy, and is able to identify a vacant vs occupied room with 100% accuracy. This algorithm could be integrated into a larger system so that processing of radar returns can be adaptive to the number of subjects present in the field of the radar.

The main limitation of this algorithm is that it is unable to identify multiple subjects in close proximity to one another with respect to radial distance from the radar. To overcome this issue, the algorithm could be updated to store historical data, such as room occupancy and the locations of the subjects over. For instance, if two subjects are identified in the room, the locations of the two subjects could be tracked. If those subjects, or 'peaks' in the first principal component suddenly merged, it may be a good indication that both subjects are still in the room. Rather than claim that the occupancy dropped to 1, keep the previous estimate of 2. Similarly, information about the room layout could be fused with the data from the radar so that points of egress could be known. This could be used to reduce errors by constraining the algorithm to only allow for changes in room occupancy estimates if a new subject is discovered near a point of egress, or if a subject is lost near a point of egress.

#### 6.3 Feature extraction

Because the radar returns of the UWB is much different than the returns from the CW radar, the features extracted in this experiment are different. One main difference between the two signals are the sampling frequency- CW radar samples at 905 S/s whereas UWB samples at only 17 S/s meaning the highest frequency encountered in the UWB returns is 8.5 Hz. Additionally, UWB radar has significantly higher range resolution meaning spatial information can be exploited.

33 features (given in Table A.2 in Appendix A) were extracted from the radar returns. First, the power of the entire signal prior to any signal processing was computed. Next, PCA was performed on the data sample. The maximum point in the first PC was found and a window was constructed around the peak (in the same manner as done in the

occupancy detection algorithm). This window represents the region of the room containing the source of largest variance in the radar signal returns. This window was normalized to sum to 1, and the width, mean value, median value, skewness, kurtosis end entropy were computed and taken as features. The second through tenth eigenvalues (sorted in descending order) as computed from PCA were taken as features after being normalized by the value of the first (and largest) eigenvalue. Next, the range bin corresponding to the point of maximum variance in the first PC was used for the computation of the remaining features. The remaining features were extracted either in the time domain or frequency domain. In the time domain, the mean value of the signal was calculated, and then the mean was removed and the signal was normalized by dividing by the maximum value. Next the RMS, zero crossing rate, turns count, variance, skewness, kurtosis, mobility and form factor were computed and used as features [50]. A  $2^{16}$  point Welch-Periodogram was computed from the signal and then the following features were extracted from the Periodogram. The features included the energy of the spectrum, the mean frequency, median frequency, entropy of the spectrum, the energy contained in the range of the fundamental breathing frequency (0.2Hz < f < 0.333Hz), the energy contained in the range of the second harmonic of breathing frequency (0.334Hz <f < 0.667Hz), the ratio of the fundamental to the second harmonic power, and the values of the fundamental and second harmonic breathing frequency ranges normalized by the energy contained in the entire spectrum.

The reason for extracting statistical features from the first PC is that it contains spatial information about the movement of the target (or subject). The window taken around the maximum point is treated as a distribution, so the statistics from that

distribution describe the spatial distribution of the target (subject) motion. The assumption is that posture information should be contained in these features since the human body will be situated or distributed among the range bins in the radar returns differently for each posture.

In order to fully characterize the distribution of the time domain signal, higher order statistical features are considered. Higher order statistics such as skewness and kurtosis may help in measuring the deviation from Gaussian distribution.

Similarly, the statistics extracted from the spectrum should hold information about the activity level of the subject. For instance if the subject is stationary and breathing normally, it is assumed that the spectrum will have defined peaks near the breathing and heart beat frequencies, whereas if the subject is moving, the spectrum will be flatter (fewer peaks), or more noisy. The energy bands and corresponding ratio for the first and second breathing harmonics are assumed to hold information about the subject's posture, as changes in posture affect the amplitude of movement of the abdomen and chest due to respiration.

The first ten Eigenvalues are taken as features because they represent the strength and number of separate sources of variation. If the subject is highly active, the movement of their body may show up in multiple eigenvectors because they appear to be separate sources of movement. In this case, the amount of eigenvalues with high amplitude will be larger than if the subject were stationary, and the only sources of movement were respiration and heartbeat.

#### 6.4 Activity classification

Initially, activity classification was approached as a three class problem-'sedentary and still', 'sedentary with movements' and 'walking'. Four classifiers were tested on this data and results were obtained using 200 randomized training and validation iterations with 70% partitioning between data sets with class balanced samples (154 samples per class before partitioning). The four classifiers tested were K-nearest neighbors, linear discriminant, naïve Bayes and decision tree. All four classifiers yielded low average accuracy, the highest performing of the four was the decision tree. The confusion matrix for the decision tree can be seen in Table 6.2.

|                  | Predicted Sedentary | Predicted Sedentary | Predicted Walking |
|------------------|---------------------|---------------------|-------------------|
|                  | and Still           | with Movements      |                   |
| Actual Sedentary | 66.06               | 8.11                | 25.81             |
| and Still        |                     |                     |                   |
| Actual Sedentary | 7.72                | 70.24               | 22.03             |
| with Movements   |                     |                     |                   |
| Actual Walking   | 25.76               | 22.58               | 51.64             |
| 1                |                     |                     |                   |

Table 6.2: Confusion matrix for 3 class activity classification for UWB

The accuracy values of the decision tree is quite low, especially compared to the activity classifier developed for the CW experiment.

The purpose of the activity classification step is to isolate data samples in which the subject is still for further processing. Therefore it isn't crucial to discriminate types of movement but rather identify whether or not movement is present. The 'walking' and 'sedentary with movements' classes were grouped in order to test the average accuracy of a two class classifier. The results of two way classification using all four proposed classifiers can be seen in the Tables 6.3-6.6.

|               | Predicted Still | Predicted Moving |
|---------------|-----------------|------------------|
| Actual Still  | 73.38           | 26.61            |
| Actual Moving | 23.82           | 76.17            |

Table 6.3: Confusion matrix for KNN activity classification

#### Table 6.4: Confusion matrix for linear discriminant activity classification

|               | Predicted Still | Predicted Moving |
|---------------|-----------------|------------------|
| Actual Still  | 91.00           | 8.99             |
| Actual Moving | 19.06           | 80.93            |

#### Table 6.5: Confusion matrix for naïve Bayes activity classification

|               | Predicted Still | Predicted Moving |
|---------------|-----------------|------------------|
| Actual Still  | 91.24           | 8.75             |
| Actual Moving | 21.82           | 78.17            |

#### Table 6.6: Confusion matrix for decision tree activity classification

|               | Predicted Still | Predicted Moving |
|---------------|-----------------|------------------|
| Actual Still  | 81.79           | 18.20            |
| Actual Moving | 19.46           | 80.53            |

The top performing classifier for activity classification was the linear discriminant with 85.96% average accuracy. The sensitivity however is only 82.68%. Sensitivity is a

measure of how well the classifier can correctly identify when the subject is still. This is an important metric for this classifier because if a radar return sample is incorrectly identified as still, the results from further processing may be inaccurate.

#### 6.5 Posture classification

For posture classification using UWB radar, data in which the subject was moving or walking was withheld from training and validation sets. After class balancing the samples there were 94 samples per class. Four classifiers were tested, using 70% partitioning between training and validation with class balanced samples (observations of each class). Results were averaged over 200 randomized tests. The results of this can be seen in the following four Tables.

|                 | Predicted Sitting | Predicted Standing | Predicted Lying |
|-----------------|-------------------|--------------------|-----------------|
| Actual Sitting  | 34.22             | 27.27              | 38.50           |
| Actual Standing | 32.62             | 52.53              | 14.84           |
| Actual Lying    | 40.10             | 11.60              | 48.29           |

Table 6.7: Confusion matrix for KNN posture classification

Table 6.8: Confusion matrix for linear discriminant posture classification

|                 | Predicted Sitting | Predicted Standing | Predicted Lying |
|-----------------|-------------------|--------------------|-----------------|
| Actual Sitting  | 64.98             | 13.50              | 21.52           |
| Actual Standing | 18.47             | 77.93              | 3.60            |
| Actual Lying    | 22.48             | 3.03               | 74.48           |

|                 | Predicted Sitting | Predicted Standing | Predicted Lying |
|-----------------|-------------------|--------------------|-----------------|
| Actual Sitting  | 63.47             | 9.79               | 26.74           |
| Actual Standing | 30.43             | 68.10              | 1.47            |
| Actual Lying    | 35.76             | 3.02               | 61.22           |

Table 6.9: Confusion matrix for naïve Bayes posture classification

Table 6.10: Confusion matrix for decision tree posture classification

|                 | Predicted Sitting | Predicted Standing | Predicted Lying |
|-----------------|-------------------|--------------------|-----------------|
| Actual Sitting  | 62.21             | 7.38               | 30.41           |
| Actual Standing | 8.00              | 90.31              | 1.69            |
| Actual Lying    | 28.29             | 2.71               | 69.00           |

The highest performing classifier based on accuracy was the linear discriminant with 73.84% average accuracy. Since data was recorded at three different distances from the radar, a distance specific classifier scheme was tested. The data was separated into three categories corresponding to distance of the subject from the radar, and the four classifier types were trained and validated for each of the three data sets. At 3m, the highest performing classifier based on accuracy was decision tree, at 4.5m naïve Bayes and at 6m the highest performing was naïve Bayes. For this test there were fewer observations since the data set was divided by three. After under sampling for class balance, there were 33 samples per class at 3m, 33 samples per class at 4.5m and 30 samples per class at 6m. Since fewer samples were available for training and validation the data partitioning was changed to 90% and 1000 randomized tests were performed instead of 200. The confusion matrices for those classifiers can be seen in the following three Tables.

|                 | Predicted Sitting | Predicted Standing | Predicted Lying |
|-----------------|-------------------|--------------------|-----------------|
| Actual Sitting  | 82.93             | 3.63               | 13.45           |
| Actual Standing | 3.88              | 94.73              | 1.40            |
| Actual Lying    | 13.10             | 3.63               | 83.28           |

Table 6.11: Confusion matrix for decision tree posture classification at 3m

Table 6.12: Confusion matrix for decision tree posture classification at 4.5m

|                 | Predicted Sitting | Predicted Standing | Predicted Lying |
|-----------------|-------------------|--------------------|-----------------|
| Actual Sitting  | 73.13             | 10.95              | 15.93           |
| Actual Standing | 12.43             | 85.85              | 1.73            |
| Actual Lying    | 13.78             | 3.38               | 82.85           |

Table 6.13: Confusion matrix for decision tree posture classification at 6m

|                 | Predicted Sitting | Predicted Standing | Predicted Lying |
|-----------------|-------------------|--------------------|-----------------|
| Actual Sitting  | 81.17             | 2.43               | 16.40           |
| Actual Standing | 2.80              | 96.97              | 0.23            |
| Actual Lying    | 16.13             | 0.20               | 83.67           |

When location specific classifiers were used, the average accuracy for each posture increased; 79.07% for sitting, 92.51% for standing, and 83.26% for lying. The average posture classification accuracy is therefore 84.94%. Because one of the uses for posture classification is fall prevention, 'standing' is an important class to correctly identify. The

overall sensitivity of the three distance specific classifiers with respect to 'standing' is 91.97%. When compared to the results obtained by Kiasari et al, the posture classification algorithm presented in this section has higher average accuracy (85% compared to 83%), and is recorded at greater distances from the radar [8].

#### 6.6 Feature evaluation

Because of the high spatial resolution of the UWB radar returns, it is necessary to examine how correlated each feature is with distance from the radar. For robust classification, features should be uncorrelated with distance, so that the trained classifiers perform well with radar returns from subjects located anywhere in the room. In order to determine which features were invariant to distance from the radar, the Spearman rank coefficient was computed for each feature in each posture. The Spearman rank [56] was computed by comparing each observation of the feature to the distance that the subject was from the radar. The results of this can be seen in Table A.2 in Appendix A. Values close to  $\pm 1$  indicate high correlation with distance, meaning the classifier trained using these features may be distance specific.

The Bhattacharyya distance of each feature distribution compared over all classes (posture and activity) was also calculated for analyzing the strengths of each feature. These results are also in Table A.2 in Appendix A.

This data in Table A.2 shows that there are many features that are highly correlated with distance and have strong class separation. This indicates that it may be a better option to integrate multiple location specific classifiers in the real time system as opposed to a single classifier which is trained on data from all distances. The results of the distance specific classifiers tested in Section 6.5 validate this. When distance specific classifiers are implemented, the average accuracy for the same data set was boosted by 11.10%.

The strongest features as calculated using Bhattacharyya distance can be seen in Tables 6.14 and 6.15.

| Class Pair             | Strongest Feature                           | D <sub>b</sub> of Strongest<br>Feature | Average D <sub>b</sub> for<br>entire feature set |
|------------------------|---|--|--|
| Sedentary vs<br>Moving | Median of Window<br>from 1 <sup>st</sup> PC | 0.4425                                 | 0.1468   |

Table 6.14: Strongest features for activity classification

| Class Pair          | Strongest Feature | Db of Strongest | Average D <sub>b</sub> for |
|---------------------|-------------------|-----------------|----------------------------|
|                     |                   | Feature         | entire feature set         |
| Sitting vs Standing | Power of Signal   | 1.7348          | 0.1767                     |
| Sitting vs Lying    | Eig9/Eig1         | 0.2311          | 0.0846                     |
| Lying vs Standing   | Power of Signal   | 1.750           | 0.2638                     |

#### Table 6.15: Strongest features for posture classification

#### 6.7 Discussion of results

Both activity classification and posture classification performed very well with UWB radar – 85.96% and 84.94% accurate respectively. It was shown that many of the 33 extracted features had high correlation with distance and hence the initial results from posture classification were poor. From the results it may be inferred that posture classification performance could be boosted by implementing distance specific classifiers. This also indicates that in a practical application, a lot of training data may need to be collected and labelled on order to develop a robust location invariant system. The inability to classify activity with high accuracy when the 'walking' class was included is likely because when the subject is walking they do not remain in a single bin ling enough to extract valid statistical features from the time domain. In Chapter 5, 'walking' is highly separable from other classes. This is likely because the range bins (called zones) for CW are much wider than in UWB so the subject remains in a single bin for a much longer duration.

### 7 Chapter: Conclusion

Monitoring of patients in long term care facilities is important for mitigating health care costs, ensuring peace of mind of the patient's loved ones, and most importantly ensuring the wellbeing of the patient being monitored. Radar is an attractive solution to this problem since it is non-contact, relatively inexpensive, safe and preserves the privacy of individuals being monitored. As of the present day there are no products on the market that use a single radar sensor for monitoring of human subjects and capable of performing robust analysis during normal daily activities. In academic literature there have been very few demonstrations of single RF sensor radar systems capable of adapting to various human activity levels and changing room occupancy. No systems have been demonstrated or proposed that combine occupancy detection, activity classification, posture classification and breathing and heartbeat estimation using a single radar sensor.

In this thesis, the problems encountered in developing a system capable of each of these feats using both continuous wave radar and ultra-wideband radar were presented. Algorithms were developed for activity classification and posture classification using CW and UWB radar, and a novel occupancy detection algorithm was developed for UWB radar. Activity classification achieved 92.64% average accuracy for CW and 85.96% for UWB. Posture classification achieved 64.66% average accuracy for CW and 84.94% for UWB. Occupancy detection was performed with 88.13% average accuracy for UWB radar. Posture classification with UWB radar performed with higher average accuracy than the only other instance of posture classification using single sensor UWB radar in literature.

Based on findings presented in this thesis, UWB radar is a more attractive candidate than CW Doppler radar for posture and activity classification. UWB radar emits low power signals, has low probability of intercept, is capable of penetrating solid obstacles, has high spatial resolution and is a low cost solution. While activity classification results are slightly lower for UWB than for CW (6.7% lower), posture classification results are significantly higher for UWB than for CW (20.3% higher). Furthermore, high spatial resolution in UWB radar returns enables occupancy detection to be performed with relative ease and high average accuracy.

#### 7.1 Limitations and future works

Because there are many possible variations in the orientation of a human subject relative to the radar, it is very difficult to design a test protocol that ensures good representation of data that would be encountered in an uncontrolled. In order to improve the robustness of classification algorithms, a 3 month long period of uncontrolled data collection is planned to take place in an Ottawa senior care facility. A single radar unit will be placed in each participant's room along with a 3D depth sensor camera. Residents will be monitored 24 hours a day performing their daily routines. The data collected during this period will be used to develop and train classifiers which are more robust to variations in subject posture, orientation and activity. The major challenge for this experiment will be to label the massive amount of data. The 3D depth sensor will allow for automatic labelling of posture information.

Feature space reduction techniques can be explored in future works. Techniques such as PCA or mapping using a kernel function can be used to reduce the feature space. A reduction in feature space would reduce the complexity of the classifiers, and may be

able to improve average accuracy by removing features that only contribute noise to the data set. Additionally, in this thesis time and frequency domain features were extracted independently of one another. Future work could involve extracting time-frequency features using a short time Fourier transform (STFT) or wavelet transform. These time-frequency features could help in discriminating activity classes which involve changes in frequency over short periods of time.

Receiver operator characteristic (ROC) curves can be used for analyzing the performance of a classifier when decision thresholds are changed. In this thesis ROC curves were not used for optimizing classification accuracy. Future works could include optimizing classifier performance using ROC curve diagnostics.

Data fusion using both CW and UWB radar could be explored in future works, since it is understood that these two architectures have complementary strengths. CW could be used for activity classification and vital sign estimation whereas UWB radar could be used for occupancy detection and posture classification

While it is known that UWB radar is capable of penetrating solid obstacles, the algorithms presented in this thesis have not been tested on data obtained by placing subjects behind solid objects. The effect of subject occlusion must be studied in the future and occupancy detection, posture classification and activity classification must be performed when the subject is occluded by a solid object.

During all data recording sessions there were no known sources of physical movement other than the subject being monitored. In uncontrolled environments it is assumed that there will be other sources of movement present in the field of the radar such as fans, pipes with running water or stereo speakers. The effect of these additional

sources of movement on the algorithms developed in this thesis should be considered as part of the future study.

Data in which two subjects are present in the field of the radar was only used for testing the occupancy detection algorithm for UWB radar. This data was not used for testing of any of the classification algorithms. Future work should involve separating the returns from multiple subjects and classifying the activity and postures of the individual subjects. Time domain decomposition techniques such as empirical mode decomposition (EMD) may be used to identify the number of individual sources in a particular area of the room. This may lead to improvement in occupancy detection when there are entry or egress of subjects.

The contribution of this thesis is the development of activity and posture classification algorithms for CW and UWB radar as well as an occupancy detection algorithms for UWB. A hierarchical approach for processing radar returns using these algorithms was proposed for both CW and UWB radar. This approach can be integrated into a real time system along with breathing and heartbeat estimation algorithms for wellness monitoring in senior care applications.

# Appendices

# Appendix A

## A.1 Features extracted in CW experiments

| Feature Name                             | Bhattacharyya Distance (Posture) |   |        | Bhattacharyya Distance |        |         |  |
|--|----------------------------------|---|--------|------------------------|--------|---------|--|
|  | 1 v 2                            | $\frac{1 \text{ v}^2}{1 \text{ v}^2} = \frac{1 \text{ v}^3}{1 \text{ v}^3} = \frac{2 \text{ v}^3}{2 \text{ v}^3}$ |        |                        |        |         |  |
|  | 0.1594                           | 0.2108  | 0.0078 | 0.0777                 | 1.1757 | 1.26748 |  |
| Correlation of whole signal <sup>1</sup> |                                  |   |        |                        |        |         |  |
| Correlation of breathing signal          | 0.0061                           | 0.0450  | 0.0218 | 0.0228                 | 0.0352 | 0.00138 |  |
| Correlation of heart signal              | 0.1202                           | 0.4193  | 0.7378 | 0.5909                 | 1.3444 | 0.71727 |  |
| RMS <sup>2</sup>                         | 0.2409                           | 0.0053  | 0.2881 | 0.0569                 | 0.2488 | 0.22570 |  |
| ZCR <sup>2</sup>                         | 0.0039                           | 0.2884  | 0.3411 | 0.6912                 | 7.2858 | 3.57729 |  |
| Turns Count <sup>2</sup>                 | 0.0478                           | 0.0351  | 0.1534 | 0.5641                 | 0.0226 | 0.53489 |  |
| Variance <sup>2</sup>                    | 0.6008                           | 0.0127  | 0.7008 | 0.0907                 | 0.6053 | 0.36685 |  |
| Skewness <sup>2</sup>                    | 0.0491                           | 0.0075  | 0.0197 | 0.1222                 | 0.1006 | 0.03222 |  |
| Kurtosis <sup>2</sup>                    | 0.1003                           | 0.3623  | 0.1194 | 0.1043                 | 0.8241 | 1.06479 |  |
| Mobility <sup>2</sup>                    | 0.0028                           | 0.2818  | 0.3266 | 0.6541                 | 3.9260 | 2.24502 |  |
| Form Factor <sup>2</sup>                 | 0.0040                           | 0.0072  | 0.0219 | 1.1141                 | 1.7705 | 0.53556 |  |
| Total Power                              | 0.6136                           | 6.0731  | 5.1444 | 0.8028                 | 6.0000 | 7.13092 |  |
| Mean Frequency <sup>2</sup>              | 0.3472                           | 0.2001  | 0.6951 | 0.4837                 | 1.1329 | 0.44276 |  |
| Median Frequency <sup>2</sup>            | 1.96089026316501                 | 0.4767  | 2.7271 | 0.2479                 | 1.2187 | 0.68732 |  |
| Spectral Variance <sup>2</sup>           | 0.2611                           | 0.5773  | 1.0729 | 0.8377                 | 1.9727 | 0.92448 |  |
| Spectral Skewness <sup>2</sup>           | 0.0439                           | 0.0001  | 0.0392 | 0.4172                 | 0.5207 | 0.00773 |  |
| F1 (0.2-0.667 Hz) <sup>2</sup>           | 0.6133                           | 6.0729  | 5.1445 | 0.8025                 | 6.0001 | 7.1306  |  |
| F2 (0.667-3 Hz) <sup>2</sup>             | 0.6146                           | 6.0737  | 5.1440 | 0.8045                 | 5.9996 | 7.1320  |  |
| F3 (3-5 Hz) <sup>2</sup>                 | 0.1973                           | 5.6010  | 5.1508 | 0.1101                 | 5.9108 | 6.1693  |  |
| F4 (5-8 Hz) <sup>2</sup>                 | 0.2085                           | 5.6041  | 5.1243 | 0.2366                 | 5.9195 | 6.2117  |  |
| F5 (8-11 Hz) <sup>2</sup>                | 0.1333                           | 5.5018  | 5.1242 | 0.3082                 | 5.8941 | 5.9856  |  |
| F6 (11-20 Hz) <sup>2</sup>               | 0.1671                           | 5.5304  | 5.1054 | 0.2007                 | 5.9330 | 5.9149  |  |
| FB1 (0.2-0.333 Hz)                       | 0.6132                           | 6.0728  | 5.1445 | 0.8024                 | 6.0001 | 7.1305  |  |

| FB2 (0.334-0.667 Hz))     | 0.6134 | 6.0730  | 5.1445 | 0.8026 | 6.0000 | 7.1307 |
|---------------------------|--------|---------|--------|--------|--------|--------|
| F1/F2 <sup>2</sup>        | 0.3909 | 0.0876  | 0.1446 | 0.0422 | 1.5555 | 1.3555 |
| F1/F3 <sup>2</sup>        | 0.0245 | 0.0329  | 0.0010 | 0.5197 | 0.1322 | 1.0724 |
| F1/F4 <sup>2</sup>        | 0.0536 | 0.0321  | 0.0081 | 0.8253 | 0.0053 | 0.8911 |
| F1/F5 <sup>2</sup>        | 0.0463 | 0.0153  | 0.0134 | 1.1647 | 0.0803 | 0.7746 |
| F1/F6 <sup>2</sup>        | 0.0175 | 0.0098  | 0.0152 | 1.0131 | 0.4439 | 0.2004 |
| F2/F3 <sup>2</sup>        | 0.0229 | 0.03021 | 0.0009 | 0.5283 | 0.1253 | 1.0739 |
| F2/F4 <sup>2</sup>        | 0.0074 | 0.0022  | 0.0065 | 0.8741 | 0.0067 | 0.8476 |
| F2/F5 <sup>2</sup>        | 0.0055 | 0.0003  | 0.0084 | 1.2447 | 0.1572 | 0.6811 |
| F2/F6 <sup>2</sup>        | 0.0892 | 0.0200  | 0.0326 | 1.0049 | 0.5594 | 0.1402 |
| F3/F4 <sup>2</sup>        | 0.4252 | 0.0111  | 0.3390 | 0.7675 | 1.3471 | 0.2950 |
| F3/F5 <sup>2</sup>        | 0.3488 | 0.0559  | 0.5543 | 1.1726 | 1.6343 | 0.2022 |
| F3/F6 <sup>2</sup>        | 0.4823 | 0.2033  | 0.9194 | 1.2387 | 2.5959 | 1.0732 |
| F4/F5 <sup>2</sup>        | 0.0608 | 0.2048  | 0.4139 | 0.5693 | 0.4100 | 0.0399 |
| F4/F6 <sup>2</sup>        | 0.2053 | 0.5913  | 1.0449 | 0.8374 | 1.7675 | 0.7847 |
| F5/F6 <sup>2</sup>        | 0.3433 | 0.0726  | 0.5741 | 0.1578 | 1.0065 | 0.8833 |
| FB1/FB2                   | 0.8325 | 0.3101  | 0.2646 | 0.1647 | 1.6311 | 1.2069 |
| Shannon Entropy           | 0.3053 | 0.0248  | 0.1725 | 0.1744 | 0.1006 | 0.0215 |
| Shannon Entropy Breathing | 0.0146 | 0.0144  | 0.0532 | 0.0953 | 0.0301 | 0.0173 |
| Shannon Entropy<br>Heart  | 0.0168 | 0.0314  | 0.0878 | 1.0461 | 1.6548 | 0.3090 |

1 - Features that are identical or variations of features from [49]

2 - Features that are identical or variations of features from [50]

| Feature Name  | Spearman Rank<br>(correlation with distance) |          |         | Bhattacharyya Distance (Posture) |        |        | Bhattacharyya<br>Distance<br>(Activity) |  |
|---|--|----------|---------|----------------------------------|--------|--------|---|--|
|   | Sitting                                      | Standing | Lying   | 1 v 2                            | 1 v 3  | 2 v 3  | 1 v 2 & 3                               |  |
| Power of Signal   | -0.5773                                      | -0.5674  | -0.4467 | 1.7348                           | 0.0187 | 1.750  | 0.3233                                  |  |
| Width of Window from 1 <sup>st</sup><br>PC                    | 0.2081                                       | -0.0401  | 0.1914  | 0.0227                           | 0.0086 | 0.0582 | 0.0520                                  |  |
| Mean of Window from 1 <sup>st</sup><br>PC                     | -0.0873                                      | 0.1638   | -0.0684 | 0.0181                           | 0.0123 | 0.0391 | 0.0168                                  |  |
| Median of Window from 1 <sup>st</sup><br>PC                   | 0.0857                                       | 0.0524   | 0.2052  | 0.1987                           | 0.1876 | 0.5967 | 0.4425                                  |  |
| Skewness of Window from<br>1 <sup>st</sup> PC                 | 0.0683                                       | 0.0294   | -0.1227 | 0.0108                           | 0.0405 | 0.0455 | 0.0131                                  |  |
| Kurtosis of Window from<br>1 <sup>st</sup> PC                 | 0.2415                                       | 0.1308   | -0.0879 | 0.0425                           | 0.0078 | 0.0152 | 0.0083                                  |  |
| Entropy of Window from<br>1 <sup>st</sup> PC                  | 0.2504                                       | -0.02100 | 0.1929  | 0.4755                           | 0.0155 | 0.3633 | 0.0450                                  |  |
| Mean Value in Time<br>Domain                                  | -0.6781                                      | -0.1099  | -0.0140 | 0.0480                           | 0.1123 | 0.0244 | 0.0040                                  |  |
| Root Mean Square Value in<br>Time Domain                      | 0.0698                                       | 0.6119   | -0.1822 | 0.0295                           | 0.0281 | 0.1013 | 0.0568                                  |  |
| Zero Crossing Rate  | 0.5023                                       | -0.1476  | 0.0936  | 0.0243                           | 0.0059 | 0.0215 | 0.4104                                  |  |
| Turns Count   | 0.6515                                       | -0.2969  | 0.3331  | 0.0620                           | 0.0074 | 0.0545 | 0.0718                                  |  |
| Variance in Time Domain                                       | 0.0698                                       | 0.6119   | -0.1822 | 0.0237                           | 0.0367 | 0.1127 | 0.0690                                  |  |
| Skewness in Time Domain                                       | -0.0566                                      | -0.4712  | 0.3793  | 0.0965                           | 0.0401 | 0.1060 | 0.0721                                  |  |
| Kurtosis in Time Domain                                       | -0.0307                                      | -0.4717  | 0.3183  | 0.3986                           | 0.0279 | 0.3933 | 0.2998                                  |  |
| Mobility  | 0.6711                                       | -0.3337  | 0.0205  | 0.2009                           | 0.0207 | 0.2906 | 0.2255                                  |  |
| Form Factor   | -0.3312                                      | 0.5000   | 0.1933  | 0.0807                           | 0.0535 | 0.2519 | 0.1648                                  |  |
| Energy of Welch-<br>Periodogram                               | 0.1254                                       | 0.6012   | -0.1790 | 0.0243                           | 0.0329 | 0.1102 | 0.0639                                  |  |
| Mean Frequency  | 0.3555                                       | -0.3922  | 0.1996  | 0.3209                           | 0.0189 | 0.4375 | 0.2145                                  |  |
| Median Frequency  | 0.1028                                       | -0.2391  | -0.1316 | 0.4876                           | 0.0495 | 0.6038 | 0.2492                                  |  |
| Entropy of Welch<br>Periodogram                               | 0.4017                                       | -0.2998  | -0.1293 | 0.2056                           | 0.0626 | 0.3500 | 0.2963                                  |  |
| Energy of Welch<br>Periodogram, 0.167Hz < f <<br>0.33Hz (FB1) | 0.1551                                       | 0.3976   | -0.2920 | 0.2058                           | 0.1733 | 0.5687 | 0.0807                                  |  |
| Energy of Welch<br>Periodogram, 0.33Hz < f <<br>0.67Hz (FB2)  | 0.4979                                       | -0.0017  | 0.0082  | 0.3143                           | 0.0986 | 0.5876 | 0.4238                                  |  |
| Ratio of Energy FB1/FB2                                       | -0.3173                                      | 0.4533   | -0.2384 | 0.0027                           | 0.0150 | 0.0285 | 0.3097                                  |  |
| FB1 normalized with energy of entire spectrum                 | 0.1286                                       | -0.1040  | -0.2242 | 0.1970                           | 0.1462 | 0.5064 | 0.1708                                  |  |
| FB2 normalized with<br>energy of entire spectrum              | 0.4554                                       | -0.2722  | 0.0972  | 0.2614                           | 0.0946 | 0.5375 | 0.3299                                  |  |
| Eig <sub>3</sub> /Eig <sub>1</sub>                            | 0.0023                                       | -0.3361  | 0.3749  | 0.0571                           | 0.0360 | 0.0704 | 0.0334                                  |  |

### A.2 Features extracted in UWB experiments

| Eig <sub>4</sub> /Eig <sub>1</sub>  | 0.2429 | -0.3589 | 0.4797 | 0.0970 | 0.1414 | 0.0327 | 0.0390 |
|-------------------------------------|--------|---------|--------|--------|--------|--------|--------|
| Eig5/Eig1                           | 0.3602 | -0.4302 | 0.4964 | 0.0635 | 0.1891 | 0.0523 | 0.0433 |
| Eig <sub>6</sub> /Eig <sub>1</sub>  | 0.4721 | -0.4767 | 0.5066 | 0.0447 | 0.2117 | 0.0759 | 0.0510 |
| Eig7/Eig1                           | 0.5406 | -0.4693 | 0.5172 | 0.0347 | 0.2189 | 0.0926 | 0.0575 |
| Eig <sub>8</sub> /Eig <sub>1</sub>  | 0.6330 | -0.4718 | 0.5265 | 0.0232 | 0.2181 | 0.1116 | 0.0640 |
| Eig9/Eig1                           | 0.6725 | -0.4653 | 0.5342 | 0.0129 | 0.2311 | 0.1483 | 0.0675 |
| Eig <sub>10</sub> /Eig <sub>1</sub> | 0.6844 | -0.4560 | 0.5370 | 0.0083 | 0.2298 | 0.1647 | 0.0727 |

#### **Appendix B**

#### **B.1** CW feature extraction

```
for R1=1:642
M = csvread(filename,R1,C1,[R1 0 R1 21]);
s1='C:\Users\Zach\Desktop\GradDegree\Radar
Project\Data\CW MAY25\labelledData\'; % folder location
s2 = num2str(M(15)); % number of radar file
s3='.dat'; % file extension
filename R=strcat(s1,s2,s3); % Name of Radar data file
Data = csvread(filename R); % Import Radar Data
Zone=M(14);
if Zone==0
for j = 1:9
        xx1 = Data(:,j);
        xx1 = xx1-mean(xx1);
        xx1=detrend(xx1);
        nfft1 = length(xx1);
        window1 = hamming(length(xx1));
        [p11,f11] = periodogram(xx1,window1,nfft1,fs);
        E1(j) = sum(p11.^2);
end
[dontneed Zone] = max(E1);
end
Data=Data(M(17):M(18), Zone);
POSTURE=M(7);
ACTIVITY=M(8);
if M(6) == 3 || M(6) ==4
    LOCATION=1;
else
    LOCATION=0;
end
%% Embedding Space
for i=0:50 % First 50 lags
DataShift=circshift(Data,i); % Apply lag
ind=i+1;
mu(ind)=mutInfo(DataShift,Data); % Auto Mutual Information
end
% Find first local minimum
der=diff(mu);
for z=1: length(der)
if der(z) > 0
    lag=z;
    break
end
end
```

```
% Standardized Version
m=mean(Data);
Data1=(Data-m) / (sqrt(var(Data)));
%% Filter Data
[b,a] = butter(2,0.16/fs, 'high'); % 0.08Hz highpass
Data = filter(b,a,detrend(Data));
[b,a] = butter(2,40/fs,'low'); % 20Hz lowpass
Data = filter(b,a,Data);
% To find periodicity of breathing range (4.8-20bpm)
[b,a] = butter(2,0.4/fs, 'high'); % 0.08Hz highpass
DataB = filter(b,a,detrend(Data));
[b,a] = butter(2, (4/6)/fs, 'low'); % 0.333Hz lowpass
DataB = filter(b,a,Data);
% To find periodicity of heart range (50-180bpm)
[b,a] = butter(2,(8/6)/fs,'high'); % 0.833Hz highpass
DataH = filter(b,a,detrend(Data));
[b,a] = butter(2,6/fs,'low'); % 3Hz lowpass
DataH = filter(b,a,Data);
%% Time Features
CORR = Data1\circshift(Data1, lag); % Correlation
CORRB = DataB\circshift(DataB, lag); % Correlation of breathing only
CORRH = DataH\circshift(DataH,lag); % Correlation of heart only
RMS=sqrt(mean(Data.^2)); % Root Mean Square
ZCR= sum(abs(diff(Data>0)))/length(Data); % Zero Crossing Rate
TC= sum(abs(diff(diff(Data)>0)))/length(diff(Data)); % Turns Count
V= var(Data); % Variance
SKEW=skewness(Data); % Skewness
KURT= kurtosis(Data); % Kurtosis
MOB= sqrt(var(diff(Data))/V); % Mobility
FF= sqrt(var(diff(diff(Data)))/var(diff(Data)))/MOB; % Form Factor
%% Frequency Features
Data=(Data-m) / (sqrt(var(Data)));
pxx=pwelch(Data,[],[],2^16,fs); % Welch Periodogram of signal
pxxB=pwelch(DataB,[],[],2^16,fs); % Welch Periodogram of Breathing
Signal
pxxH=pwelch(DataH,[],[],2^16,fs); % Welch Periodogram of Heart Signal
%EX= sum(abs(pxx).^2)/length(pxx); % Power of Signal
EX=sum(pxx); % Total power of signal
PofF=pxx/EX;
EXB=sum(pxxB); % Total power of Breathing signal
PofFB=pxxB/EXB;
EXH=sum(pxxH); % Total power of Heart signal
PofFH=pxxH/EXH;
FMEAN=meanfreq(Data); % Mean Frequency
FMED=medfreq(Data); % Medin Frequency
kbar=FMEAN*length(pxx)/fs; % index of FMEAN (not Feature)
```

```
M2=(fs*2/(length(pxx)*EX))*sum(((linspace(0,length(pxx)/2-
1, length (pxx) /2) -kbar) .^2) .*pxx(1:length(pxx) /2) '); % Second Spectral
Moment (Variance)
M3=((fs*2/(length(pxx)*EX))*sum(((linspace(0,length(pxx)/2-
1, length (pxx) /2) -kbar).^3).*pxx(1:length(pxx) /2) ')) / (sqrt(M2)^3); %
Third Spectral Moment (Variance)
F1=sum(pxx((0.2/fs)*length(pxx):(0.667/fs)*length(pxx))); % Breathing
F2=sum(pxx((0.667/fs)*length(pxx):(3/fs)*length(pxx))); % Heart
F3=sum(pxx((3/fs)*length(pxx):(5/fs)*length(pxx))); %
F4=sum(pxx((5/fs)*length(pxx):(8/fs)*length(pxx)));
F5=sum(pxx((8/fs)*length(pxx):(11/fs)*length(pxx)));
F6=sum(pxx((11/fs)*length(pxx):end));
FB1=sum(pxx((0.2/fs)*length(pxx):(0.333/fs)*length(pxx)));
FB2=sum(pxx((0.334/fs)*length(pxx):(0.667/fs)*length(pxx)));
F1F2=F1/F2;
F1F3=F1/F3;
F1F4=F1/F4;
F1F5=F1/F5;
F1F6=F1/F6;
F2F3=F2/F3;
F2F4=F2/F4;
F2F5=F2/F5;
F2F6=F2/F6;
F3F4=F3/F4;
F3F5=F3/F5;
F3F6=F3/F6;
F4F5=F4/F5;
F4F6=F4/F6;
F5F6=F5/F6;
FB1FB2=FB1/FB2;
ShannonEnt=-sum(PofF.*log2(PofF));
ShannonEntB=-sum(PofFB.*log2(PofFB));
ShannonEntH=-sum(PofFH.*log2(PofFH));
win = window(@hamming,length(Data));
m=2048; % number of sample points to calculate for chirp transform
f1 = 0; % lower frequency bound of chirp transform
f2 = 4; % upper frequency bound of chirp transform
w = exp(-li*2*pi*(f2-f1)/(m*fs)); % arc in unit circle of z domain is
defined by w and a
a = \exp(1i*2*pi*f1/fs);
z = czt(Data.*win,m,w,a); % chirp transform
fn = (0:m-1)'/m; % normalized frequency vector
fy = fs*fn; % un-normalized frequency vector
fz = (f2-f1)*fn + f1; % adding back f1 (in case f1 is not zero)
%% Feature Vector
FEATURES(R1,:)=[CORR CORRB CORRH RMS ZCR TC V SKEW KURT MOB FF ...
    EX FMEAN FMED M2 M3 F1 F2 F3 F4 F5 F6 FB1 FB2 ...
    F1F2 F1F3 F1F4 F1F5 F1F6 F2F3 F2F4 F2F5 F2F6 F3F4 F3F5 F3F6 F4F5
F4F6 F5F6 FB1FB2 ShannonEnt ShannonEntB ShannonEntH
    POSTURE ACTIVITY LOCATION];
```

```
end
```

#### **B.2** Occupancy counter

```
clear
clc
addpath('C:\Users\Zach\Desktop\GradDegree\Radar
Project\Functions\entropy')
addpath ('C:\Users\Zach\Desktop\GradDegree\Radar
Project\RealTimeDataFilesForCSCProject')
Data = csvread('C:\Users\Zach\Desktop\2017-05-31\2017-05-31-13-09-
30 ZAC-SIT-FR-STATIONARY UWBX4.csv');
Data=Data(:,21:end);
phase=atan(imag(Data)./real(Data));
%Data=phase;
[row col]=size(Data);
samp=0;
test no=3;
V thresh=0.5;
W thresh=0.05;
for i=1:100:row-170
   samp=samp+1;
Data sample=Data(i:i+169,:);
energy (samp) = 0;
%Ent(samp)=entropy(Data sample);
for e=1:col
   energy(samp)=energy(samp)+sum(abs(detrend(Data sample(:,e))).^2);
end
if energy < 0.19
Number of people(samp)=0;
else
%% PCA
    [COEFF, SCORE, Latent] = princomp(Data sample, 'NumComponents', 1);
    first PC=COEFF(:,1);
%% First Person
if samp==10
   keep1= COEFF(:,1);
end
if samp==5
  keep=COEFF(:,1);
end
[M, I]=max(COEFF(2:end,1)); % Find maximum in principal component
f(1+20)/18.7);
Loc1(samp) = (I+20)/18.7;
% Find lower bound of human
mini=abs(M);
counter mini=1;
while mini > W thresh*abs(M) && I-counter mini > 2
  mini=abs(COEFF(I-counter mini,1));
    counter mini=counter mini+1;
end
```

```
% Find upper bound of human
maxi=abs(M);
counter maxi=1;
while maxi > W thresh*abs(M) && I+counter maxi < col</pre>
  maxi=abs(COEFF(I+counter maxi,1));
    counter maxi=counter maxi+1;
end
% Statistics about person 1
Percent_variance=sum(abs(COEFF(I-
counter mini:I+counter maxi,1)))/sum(abs(COEFF(:,1)));
width 1(samp)=counter mini+counter maxi+1;
Number of people(samp)=1;
Total Percent variance=Percent variance;
%% Check if there are more people
while Total_Percent_variance < V_thresh</pre>
    Number of people(samp)=Number of people(samp)+1;
    [M1, I1]=max(abs(COEFF(2:I-counter mini,1)));
    [M2, I2]=max(abs(COEFF(I+counter maxi:end,1)));
    II=[I1 I2+I+counter maxi];
    [mm, I]=max([M1,M2]);
    I p2=II(I);
    if I p2==1
        I p2=2;
    end
    if I p2>=166
        I p2=165;
    end
    frintf(Person 2 is \fm away from radar \n', (I p2+20)/18.7);
    Loc2(samp) = (I p2+20)/18.7;
    mini=abs(mm);
    counter mini=1;
    while mini > W_thresh*abs(mm) && I_p2-counter_mini > 1
        mini=abs(COEFF(I p2-counter mini,1));
        counter mini=counter mini+1;
    end
    maxi=abs(mm);
    counter maxi=1;
    while maxi > W thresh*abs(mm) && I p2+counter maxi < col-1
        maxi=abs(COEFF(I p2+counter maxi,1));
        counter maxi=counter maxi+1;
    end
    % Statistics about person 1
    Percent variance 2=sum(abs(COEFF(I p2-
counter mini:I p2+counter maxi,1))/sum(abs(COEFF(:,1)));
    Total Percent variance=Total Percent variance+sum(abs(COEFF(I p2-
counter mini:I p2+counter maxi,1)))/sum(abs(COEFF(:,1)));
    width 2(samp)=counter mini+counter maxi+1;
end
end
```

```
if samp > 2
    Number of people filt(1:2)=Number of people(1:2);
    Number of people filt(samp)=mode(Number of people(samp-2:samp));
end
end
figure(1)
% subplot(3,1,test no)
%plot(linspace(1,3,length(COEFF(:,1))),abs(COEFF(:,1))/sum(abs(COEFF(:,
1))))
% ylabel('two people')
plot(linspace(1,180,length(Number of people)),Number of people,'r*')
% figure(2)
% plot(linspace(1,10,length(first PC)),abs(first PC))
figure(2)
plot(linspace(1,180,length(energy)),energy)
figure(3)
plot(linspace(1,180,length(Number of people filt)),Number of people fil
t,'g*')
%figure(4)
%plot(linspace(1,180,length(energy)),Ent)
figure
plot(abs(keep));
hold on
plot(abs(keep1));
acc=[0 0 0 0];
for i=1:length(Number of people)
    acc(Number_of_people(i)+1) = acc(Number_of_people(i)+1)+1;
end
accuracy=acc(2)/length(Number of people)
acc f=[0 0 0 0];
for i=1:length(Number of people)
acc f(Number of people filt(i)+1)=acc f(Number of people filt(i)+1)+1;
end
accuracy f=acc f(2)/length(Number of people)
errors=Number of people filt-1;
acc 1(1) = sum (errors (101:150))/50;
acc 1(2) = sum (errors (151:200))/50;
acc 1(3) = sum(errors(201:250))/50;
acc 1(4) = sum(errors(251:299))/49;
```

#### **B.3** UWB feature extraction

```
function [FEATURES]=FeatureExtraction(Data)
%% Author: Zach Baird
% Date: June 26, 2017
% This function takes input data and returns a feature vector
[row, col]=size(Data);
fs=17;
% Take absolute value
Data=abs(Data);
%% Energy
% Calculate energy of entire signal
ENERGY=0;
for e=1:col
  ENERGY=ENERGY+sum(abs(detrend(Data(:,e))).^2);
end
POWER=ENERGY/row;
%% PCA features
W thresh=0.05;
% Compute Principal Components
[COEFF, SCORE, Latent] = pca(Data);
[M, I]=max(COEFF(:,1)); % Find maximum in first principal component
%% EIG
EIG=abs(Latent(1:10))/abs(Latent(1));
%% Maintain bounds
if I < 3
    I=3;
end
if I > col-1
    I=col-2;
end
% Construct Window around maximum point in first principal component
% find lower bound of window
mini=abs(M);
counter mini=1;
while mini > W thresh*abs(M) && I-counter mini > 1
   mini=abs(COEFF(I-counter mini,1));
    counter mini=counter mini+1;
end
% Find upper bound of window
maxi=abs(M);
counter maxi=1;
while maxi > W thresh*abs(M) && I+counter maxi < col</pre>
  maxi=abs(COEFF(I+counter maxi,1));
```

```
counter maxi=counter maxi+1;
end
% Statistics about person 1
%% WIDTH
WIDTH=counter mini+counter maxi+1;
%% MEAN
window=COEFF(I-counter mini:I+counter maxi,1);
window=window/sum(window); % normalize to sum to 1
MEAN=mean(window);
%% MEDIAN
MEDIAN=median(window);
%% SKEWNESS
SKEW=skewness(window);
%% KURTOSIS
KURT=kurtosis (window);
%% ENTROPY
ENTROPY=0;
for z=1:length(window)
    ENTROPY=ENTROPY-window(z) *log10(window(z))/log10(2);
end
%% Single Dimension Data
Data V=Data(:,I); % from max variance column
%% MEAN T
MEAN T=mean(Data V);
%% Filter Data and normalize
[b,a] = butter(2,0.16/fs, 'high'); % 0.08Hz highpass
Data V = filter(b,a,(Data V));
Data V=Data V-mean(Data V);
Data V=Data V/max(Data V);
%% RMS
RMS=sqrt(mean(Data V.^2)); % Root Mean Square
%% ZCR
ZCR= sum(abs(diff(Data V>0)))/length(Data V); % Zero Crossing Rate
%% TC
TC= sum(abs(diff(diff(Data V)>0)))/length(diff(Data V)); % Turns Count
88 V
V= var(Data V); % Variance
%% SKEW T
SKEW T=skewness(Data V); % Skewness
%% KURT T
KURT T= kurtosis (Data V); % Kurtosis
%% MOB
MOB= sqrt(var(diff(Data V))/V); % Mobility
%% FF
FF= sqrt(var(diff(Data V)))/var(diff(Data V)))/MOB; % Form Factor
%% Frequency Domain
pxx=pwelch(Data_V,[],[],2^16,fs); % Welch Periodogram of signal
%% EX
EX=sum(pxx); % Total power of signal
%% FMEAN
FMEAN=meanfreq(Data V); % Mean Frequency
%% FMED
FMED=medfreq(Data V); % Medin Frequency
```

```
%% SHANNON
PofF=pxx/EX;
SHANNON=-sum(PofF.*log2(PofF));
%% FB1
lower bound=(0.4/(fs/2))*2^16;
upper bound=(0.66/(fs/2))*2^16;
FB1=sum(pxx(lower bound:upper bound));
%% FB2
lower bound=(0.67/(fs/2))*2^16;
upper bound=(1.33/(fs/2))*2^16;
FB2=sum(pxx(lower_bound:upper_bound));
୫୫ RFB
RFB=FB1/FB2;
%% FB1N
FB1N=FB1/EX;
%% FB2N
FB2N=FB2/EX;
%% Feature Vector
FEATURES=[POWER, WIDTH, MEAN, MEDIAN, SKEW, KURT, ENTROPY, MEAN T, RMS,
ZCR, TC, V, SKEW T, KURT T, MOB, FF, EX, FMEAN, FMED, SHANNON FB1 FB2
RFB FB1N FB2N EIG(2:9)'];
end
```

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