Radio Tomographic Imaging-Based Fall Detection

ESE 498 Senior Design Project

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We affirm that this design was completed in compliance with the engineering code of ethics and the WUSTL Honor Code.

ABSTRACT

Amongst older adults, falls at home can be deadly. Fall detection systems are an important tool to quickly summon help in the event of a fall. Wearable devices such as help buttons have been a popular approach to the problem; however, studies show that they have a low efficacy in the event of a fall because they require the user to actively remember to use the device. In response to this issue, another branch of fall detection design has focused on environmental fall detection methods. Our literature research concluded that radio tomographic imaging was the best approach to fall detection based on criteria of reliability, user experience, and privacy concerns. In this project we implement radio tomographic imaging using ten National Instruments Universal Software Peripheral Radios (NI-USRP). Each USRP transmits a pure tone using amplitude modulation. The full duplex capabilities of the NI-USRP 2920s enable baseband frequency multiplexing, allowing for simultaneous transmit and receive. We measure received signal strength across each directional link between USRPs and implement kernel-based radio tomographic imaging to determine the relative attenuation in each pixel. Future work for this project would focus on using particle filtering for a track-before-detect approach to fall detection.

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Problem Formulation

Problem Statement and Formulation
Amongst older adults, falls pose a serious health risk. Thirty percent of people over the age of 65 fall each year; often they are alone in their homes [2]. Current fall detection systems focus on wearable help button devices. However, frequently people forget to wear the device or are unable to activate the device after they have fallen. Of those with wearable help button devices, 80% do not push the button, often because they are not wearing the device [10]. There exists a need for device-free fall detection systems for older adults for use in homes and residential care establishments.

Our sponsor, Dr. Arye Nehorai, conducts research on smart homes and has an interest in developing an environmental fall detection system to meet this need. The design should be able to detect falls without input from the user, and it should be reasonably unobtrusive within the person’s home.
Project Specifications

An environmental fall detection system must be able to detect falls without input from the user. The design should be adaptable in size and shape to standard room sizes and should be unobtrusive within a person’s home. The fall detection system should be able to detect all falls while minimizing the false alarms, though it is more important to detect all falls than it is to eliminate false alarms. The system should be able to easily connect to emergency services personnel in order to get rapid help for the fallen user.

After selecting radio tomographic imaging as the best technology for an environmental fall detection system based on the above criteria of user experience, this project focused on developing a radio tomographic imaging system, which is necessary for a radio tomographic imaging based fall detection system. For the initial proof of concept for radio tomographic imaging, the system should be able to image at least an area of 1 m x 1 m, the size of a small room. The proof of concept design should be scalable to the approximate size of the average American master bedroom 15 ft. by 15 ft. (4.572 m by 4.572 m). In this case, accurate imaging of an area means the system must be able to detect the pixel or pixels in which the person is located. The resolution of the design should involve a pixel size that is smaller than the size of the average person. To meet the eventual needs of a fall detection application, the system should be adaptable to non-rectangular rooms.

The imaging design must achieve a frame rate of at least 5 frames per second in order to be able to eventually image the room fast enough to detect a fall, which occurs in approximately two seconds [1]. For the simultaneous transmit and receive in our design, we need enough bandwidth that each USRP can transmit at a different frequency without its spectrum overlapping with that of other units. For our purposes, the USRPs should be separated by 5k Hz. With 10 URSPs, we need at least 50 kHz of bandwidth.

The carrier frequency and signal power should be chosen such that radio frequency signals from the environment, including those from Wi-Fi and cell phones, won’t disrupt the operation of the system and such that the emitted signals won’t interfere with other devices, such as Bluetooth, or with medical devices such as pacemakers and neurostimulators. The carrier frequency should attenuate well in the human body as radio tomographic imaging relies upon shadowing measurements.
The processing power required for the design should be such that a standard desktop computer can run the code. The imaging algorithm selected should be able to be fast enough to be run online in order to image the area in real time, and it should be compatible with tracking algorithms so that the design can be modified to a track-then-detect system for fall detection. The algorithm should be able to self-calibrate to the environment without input from the user, and it must be able to run for a long time without losing sight of the person. The algorithm should be resistant to multipath interference and capable of distinguishing between people and objects in the imaged area. In testing the algorithm, a visualization scheme selected or created with attention to its ability to clearly show the pixels of highest attenuation.

The physical layout of the design should be such that there are no wires impeding mobility within the imaged area. The design should be unobtrusive the central living space of the room and should pose no major safety concerns to its users. The power requirements of the design should be met with a couple standard 120-V wall sockets without tripping circuit breakers.
Concept Synthesis

Literature Review

There are two main approaches to fall detection: wearable devices and environmental monitoring. Wearable devices include help buttons that require the user to actively press a button in the event of a fall and devices such as accelerometers and gyroscopes that automatically detect falls. Help buttons are a poor approach to the problem as in the event of a fall the person must be conscious and holding the button in order to activate the device. Researchers at the University of Virginia and the College of William and Mary designed a combined gyroscope and accelerometer based system that detected posture using a gyroscope in order to distinguish apparent falls from activities such as jumping and sitting down quickly, which also generated fall-like accelerometer data [11].

Studies have shown that wearable devices fail to detect falls in 80% of users, often because the user has forgotten to wear their device at the time of their fall [2]. Entirely passive fall detection systems use environmental monitoring techniques that require no user input in order to improve the efficacy of fall detection systems. Approaches to environmental monitoring include the use of cameras, microphone arrays, and radio frequency waves. Camera-based approaches have looked at monitoring using cameras such as the Kinect camera to track moving objects in a room and detect falls [12]. Yun Li and Mihail Popescu from the University of Missouri [13] and Xiaodan Zhuang, Jing Huang, G. Potamianos, M. Hasegawa-Johnson of the University of Illinois at Urbana-Champaign [14] have both implemented acoustic fall detection systems using microphone arrays. When the system detects a sound, it amplifies and enhances the signal in order to characterize the signal as either a fall or a non-fall.

Researchers at MIT developed a system, coined “WiTrack,” [15] that tracks a person’s motion based on information from radio signals reflecting off the person’s body. The system can track a person through walls or when the person is located in the line-of-sight of the radio units. The system transmits a narrowband RF signal which is ramped quickly across a 1GHz range of carrier frequencies, then measures the reflection of that same RF signal. The chirping carrier frequency allows the system to estimate time of flight based on difference in signal frequency.
between the transmitted and received signals. The distance and position of the person can be determined from the time it takes the reflected signal to travel to a receiving antenna, and rapid changes in a person’s elevation correspond to falls.

Radio Tomographic Imaging (RTI) [1, 3-7, 9] is another technique used for environmental fall detection. RTI measures changes in the received signal strength along links between radio units in a network of radio units positioned around the perimeter of the imaged area. Objects in the imaged area both attenuate and reflect radio frequency waves, leading to differences in the measured received signal strength based on a person’s motion across or near the line-of-sight between two communicating transceivers. Algorithms can then be employed to estimate the presence or absence of an attenuating object in a given pixel of the imaged area.

The paper that inspired this project is “Fall Detection Using RF Sensor Networks” [1] by Brad Mager, Niel Patwari, and Maurizio Bocca. The authors take the above approach to radio tomographic imaging and use a network of 24 radio frequency sensors in two square arrangements at torso and ankle height. The three-dimensional area inside between sensors is divided into 3D voxels, and the change in attenuation of a signal between each sensor pair is used to estimate the attenuation in each pixel, where sensor pairs contribute information only to pixels near to their line of sight. A regularized least-squares approach is used to reconstruct the attenuation in each pixel. The authors then use a hidden Markov model with three states (standing, mid-position, and lying down) in which quick transitions between standing and lying down indicate that a fall has occurred.
Figure 1: The three states of the hidden Markov model for 3D fall detection
We decided to use this paper as a guide for the initial direction of the project. Essential to the performance is a robust method of estimating pixel attenuation. For this we turned to Zhao, Patwari, Phillips and Venkatasubramanian’s “Radio Tomographic Imaging and Tracking of Stationary and Moving People via Kernel Distance,” [3] in which the authors propose a novel method for two-dimensional radio tomographic imaging. Essential to a good system is having a baseline measurement for RSS in each link. Since multipath, noise, and interfering in signal measurements are unpredictable and sporadic, it can also be difficult to accurately estimate RSS on each link at each point in time from a single measurement. To solve both these problems, for each link the authors construct a running long-term histogram (LTH), which weights each incoming RSS value evenly, only slightly favoring newer values, and short-term histogram (STH) which weights newer values much more heavily. The LTH serves as a running baseline for RSS values along each link, and allows us to measure the impact of changes in the STH. The authors use the distance between the Gaussian kernels of the STH and LTH as the estimation for the change in RSS along that link.

With this estimation for RSS change on each link as an input to an imaging algorithm, the authors use a weighting similar to [1] to reconstruct attenuation in each pixel and use Tikhonov regularization to deal with this ill-posed inverse reconstruction problem.

There are other proposed methods for radio tomographic imaging, such as variance-based RTI, as in [7] and RTI where change in RSS is measured by subtracting a previously measured baseline RSS from instantaneous RSS [9]. Additionally, there are (non-imaging) radio tomographic tracking methods used for similar aims, such as Li, Chen, Coats and Yang’s “Sequential Monte Carlo Radio-Frequency Tomographic Tracking” [8], in which they define a measurement model for RSS measurements based on radio wave propagation, and a particle filter is used to track a person in the area, which an expectation maximization algorithm finds estimators for the measurement parameters.

A visualization method from Patwari, Neal and Agrawal’s "Effects of correlated shadowing: Connectivity, localization, and RF tomography" [4] was incorporated into the final design in order to visualize the pixel attenuation. The visualization nonlinearly weights the pixel attenuation values. Values over a certain threshold are weighted more heavily, improving the resolution of that range. In the case of our pixel attenuation design, we have a baseline point and
a much higher threshold of attenuation caused by a person moving around in the area. The area between the baseline and threshold of human attenuation is not of interest for the purposes of the visualization. We therefore set the threshold so that there is greater visualization resolution in the range where a person might be attenuating the signal in a pixel, since the only attenuation of concern is where a person is present.

Figure 2: Subject standing in the 2D radio tomographic imaging test area

Figure 3: Output of imaging algorithm’s visualization
Our design was also supported by previous coursework. Since all the methods above only require information about RSS values, which is commonly available in commercial RF products, the authors mostly use inexpensive RF nodes to build a large sensor network. Due to practical considerations discussed below, we used NI USRP 2920 units for our network. We designed a scheme for simultaneous transmit and receive for each USRP to avoid issues related to round-robin timing. This design, which provides significant advantages, was built from knowledge gained in Washington University in St. Louis’ ESE 488 (Signals and Systems Laboratory) course, which was taught by Dr. Robert Morley.

We also incorporated information learned in ESE 433 (Radio Frequency and Microwave Technology for Wireless Systems) for understanding of transmit power required in the links. Informal independent study with Jichuan Li was crucial in understanding the above literature, incorporating elements of the designs above, and designing our system. An undergraduate research project using the USRPs undertaken by Daniel Lazar also contributed to the design choices and implementation. Some code for data acquisition with the USRPs was recycled into our system.

**Concept Generation**

Many of the design options are described in the literature review above. Before decisions related to RTI methods were made, we had to decide on a general method for fall detection. We considered wearable devices, such as accelerometers and gyroscopes, as well as environmental monitoring systems, such as microphone arrays, visible light/infrared cameras, and pressure sensors (diagram 1). We also considered various RF systems, including narrowband radar, a wideband body-reflection based system, and finally, radio tomography-based methods.
As discussed above, once within radio tomographic imaging, we had to choose a fitting algorithm. For the goal of fall detection, we had a choice between the 3D fall detection method outlined above [1] and a simpler, 2D method of our own design. This 2D fall detection uses a particle filter for track-before-detect [47].
We also face choices with regard to the hardware and setup of our RF network. The choices, described below, include using frequency synchronization and network communication schemes (diagram 3).
Concept Reduction
At each of the decision junctures we looked at theoretical advantages as well as practical considerations for our decisions. Paramount to our decisions was the user experience of the fall detection device. We wanted a method that was outwardly simple, reliable, easy for the user to operate, and unobtrusive within the user’s home.
We considered using an accelerometer or a radio frequency device on the person to detect position and falls. However, there is a glut of literature about accelerometer based systems. Additionally, while wearable devices may be easier to implement, in the event of a fall, if the user is not wearing the device, no fall will be reported. In fact, 80% of adults over the age of 90 who possess a fall report button do not activate it, often because they are not wearing it [10]. With this in mind, we choose to use a device-free method for fall detection.

We also chose from many environmental detection systems. We considered body reflection and traditional radar based approach, which we decided against because we did not have access to components that could support such an approach and fabricating them would take us far past the date required for the deliverables. It is possible to detect falls with a visible light/infrared camera combination, such as the one in the Xbox Kinect. In the Kinect, the infrared camera provides depth information about discrete points in the field of view to support the visible light camera. However, a Kinect is not able to image an entire room; it has viewing angles of 57.5 degrees horizontal, 43.5 vertical, and +/- 27 degrees of tilt [16]. In addition to the narrow field of sight of the camera, we ruled out a camera based approach since people are generally averse to cameras, even if the camera’s output is contained in an internal network. Furthermore, the presence of a camera can be disturbing to older adults, especially those with cognitive disorders such as Dementia.

Pressure sensors also stand as a possible solution to this problem, but this would require extensive overhaul of the area to be imaged by replacing the floor with one incorporating the sensors. Many sensors would be required, and they would need to be put into the floor, and the systems do not scale to multiple rooms as easily as radio tomographic imaging. Finally, we considered microphone arrays for acoustic sensing, but the concerns brought up about the presence of cameras in a residence also exist with microphones. We decided that should the accuracy of a radio tomography based system prove not as high as needed, we could incorporate a cheaper sensor type, such as a microphone array, to boost accuracy.

Having settled on radio tomographic imaging, we faced a decision between tracking and imaging. Imaging introduces error when it breaks the area into pixels, which is avoided in tracking. However, the tracking algorithms were much more computationally intensive, requiring a complex particle filter concurrently with expectation maximization. We ascertained that the
computer used for running the algorithm would likely not succeed in real-time detection, which
is a strong requirement. [3]

Once choosing imaging, we chose from the algorithms that exist. We ruled out variance-based
RTI, which cannot detect stationary targets. Based on our research, we determined that Kernel-
based RTI was the most accurate and robust system [3]. Having chosen our imaging
reconstruction algorithm, we faced a decision on whether to implement a dual-level 3D detection
system or a 2D system. Due to constraints on the number of radio units (the 3D method requires
nearly twice as many), as well as our desire to limit the complexity of the system, we chose 2D
fall detection. We subsequently designed an algorithm to do this, but due to time constraints,
were not able to implement it.

The choice of 2D detection algorithms was another opportunity for concept reduction. We
arrived at three options for 2D fall detection, including a hidden Markov model, a particle filter,
Kalman filter, and a more rudimentary design based on an attenuation threshold for determining
that someone is in the area. We chose particle filter with a track-before-detect algorithm since it
is proven to be effective and, in this case, the linearity assumption required for a Kalman filter
don’t hold. [47]

Once we decided upon radio tomography and fall detection methods, we face a choice about the
practical implementation of our sensor network. We had 10 NI USRP-2920 units available to us,
so we used those for our network. All literature we came across used a token passing timing
protocol, such as in [7], to prevent transmitted signals from interfering with each. Such a round
robin protocol allows only one transmitter at a time to transmit while all other units receive and
determine signal power. Switching off until each unit has a chance to transmit, RSS along each
link can be determined. Such a design poses some difficulties when implementing on the NI
USRPs. USRPs must be fed with identical clock signals in order to maintain synchronization and
prevent USRPs from transmitting over each other and creating ambiguity as to which signal is
being received. A clock source would significantly complicate the wiring of the system and care
would have to be taken not to obstruct the center of the room. Additionally, we used the Labview
interface with the USRPs, which made switching between transmit and receive on each unit
slow, slowing down the round-robin transitions to the point that we may not have been able to
maintain a fast framerate. Though a work-around was possible, it would have taken us past the date for the delivered final product.

Because of this issue, we designed a scheme in order to avoid dealing with complicated timing issues. We realized that if we had the capacity to simultaneously transmit and receive on each USRP, all timing conflicts could be resolved by transmitting a signal with differing frequency from each unit. In order to determine RSS, each unit would find the power spectral density (PSD) and separately sum the power the frequency range assigned to each transmitter. However, the issue remained as to whether we could simultaneously transmit and receive.

We ascertained that we were using XCVR 2450 2.4-2.5GHz, 4.9-5.9GHz [17] daughterboards, which are half duplex, and that we had access to WBX 50-2200 MHz [18], which are full duplex. We were originally transmitting at 2.4GHz, and therefore using the higher frequency daughterboard, because higher frequencies have greater attenuation in the human body.

Given that higher frequency signals attenuate more in a person’s body, which is desired, we faced a dilemma between possible accuracy (higher attenuation) and simplicity of design (no timing wiring). In our research, we determined that frequencies above 1GHz attenuate well in water, and therefore a body, so we decided to pick a frequency on the lower frequency daughterboard as close to the upper limit of 2.2GHz as possible. We first attempted to use our 2.4GHz antennas, but using a vector network analyzer, determined that the voltage standing wave ratio (VSWR) of the 2.4 GHz antenna at 2.2 GHz was too high. We found the VSWR to be 4, which lead to 60% of the transmitted power to be reflected from the antenna back to the transmitter. This would greatly hamper our design and could possibly even damage the transmitter.

With this in mind, we bought 1.4GHz antennas, which were the closest commercially available antennas we could find to 2.2GHz. We conducted tests and determined that 1.4GHz attenuates satisfactorily in the body.

Though we eliminated the clock reference, we still connected the USRPs to a frequency reference so the internal oscillators would be synchronized for demodulation. In the absence of a
frequency reference, the received signal frequencies spread significantly, as during
demodulation, the frequency difference between the internal oscillators translates into
differences in the demodulated signal. Though this existed in the presence of a frequency
reference, it was significantly worse without one.

![Baseband Power Spectrum](image)

**Figure 4: Frequency spread of received signals**

To face this problem, we changed our design to widen the frequency range (number of bins in
the PSD) over which receivers summed each transmitter signal power. Due to computer speed
limitations, our USRP sampling rate was limited to 200kHz, so we had 100kHz of bandwidth in
which to multiplex. However, signals under 10kHz would show up garbled, so we chose to send
signals starting from 20kHz. We found that the frequency spread in the absence of an oscillator
was approximately 3kHz, so we assigned each transmitter 5kHz of bandwidth in which to
transmit. For each transmitter, the receivers would sum the PSD over a total of 4.5kHz, centered
on the assigned transmitter frequency. Once again, facing the decision between simplicity and
accuracy, we chose simplicity and modified our design so that it would meet specification.

One potential downside of the simultaneous transmit/receive is that if units are separated by a
great distance, on a USRP, the large power transmitted by its transmit antenna (separated by 2cm
from the receive antenna) could overshadow faint received signals from afar. Though the signals
are separated on the frequency domain, the danger remains the transmitted signal could bleed
internally and clip, leading to harmonic distortion. However, within ranges tested this was not an issue, and experiments discussed below showed that this would remain a non-issue for a distance between radio units of up to 10 meters.
Engineering Analysis and Design Presentation

Design Overview

Below we summarize the major subsystems and aspects of our design.

**Fall Detection:** In order to detect falls we chose to use radio tomographic imaging to image the area with future work to be focused on applying a track-before-detect algorithm to the design in order to detect falls within a 2D area.

**Sensor Network:** We use 10 NI Universal Software Peripheral Radios (USRPs) with full duplex daughterboards to simultaneously transmit and receive. The USRPs transmit a pure tone using amplitude modulation. The baseband signal is frequency multiplexed so that each USRP unit transmits at a unique baseband frequency. Radio Tomographic Imaging measures received signal strength along links between the radio units. No standard exists for received signal strength, so we elected to measure total power for received signal strength because it will reflect the change in the signal’s strength as it is attenuated and reflected off a person.

**Radio tomography algorithm:** We implement a kernel-based radio tomographic imaging algorithm to image the area. The algorithm takes long-term and short-term histograms of the RSS values. More recent values are weighted more heavily in the short-term histogram and less heavily in the long-term histogram. The algorithm then computes the kernel distance between the histograms and applies a least-squares formulation to the equation \( d = Wx + n \) (where \( d \) is the kernel distance, \( n \) is the noise (assumed to be Gaussian), and \( W \) is a weighting matrix) to solve for the estimation of pixel attenuation [3].

**Tracking/fall detection algorithm:** After imaging the area, a particle filter could be applied to track an object within the imaged area. A detection algorithm could then be applied to determine whether it is likely that a person left the area, laid down, or fell. [47]
Figure 5: Illustration of how the algorithm’s histograms change in the presence of an attenuating signal in the line-of-sight of a link. The distance between the short-term histogram and the long-term histogram is used to estimate attenuation on that link.
Description of Design:

**Figure 6: Radio Tomographic Imaging Experimental Setup**

**Experimental Protocol:** In order to get reproducible results, we settled on a specific experimental setup so that we could tune parameters to meet our needs.

Our experiments involved using 10 USRPs as shown by the red dots in figure 3. The centers of each unit along the horizontal line were placed 0.5 m from one another. The two units placed on the vertical line were placed with centers 0.6 m from the horizontal lines. These 2 USRPs were placed 0.05 m offset on the x-axis from the two lines of USRPs in order to allow the 0.2 m x 0.2 m pixels to be split evenly for a 1.6 x 1.2m space.
Figure 7: Experimental Setup. USRP antennas are at the red dots. Pixels are of size 0.2 and bordered up by green lines.

Our experiments used the same test subject for reproducible results. This person was approximately 0.4 m wide and 0.25 m in length. This meant that her body could be modeled by approximately 4 pixels. In order to test data obtained quantitatively, we only used one test subject. However, we did test other subjects qualitatively and found that the imaging system worked with every subject tested.

**Hardware Selection:** Our design uses 10 NI 2920 USRPs (full duplex) positioned 0.5 m apart from each other in a rectangle, which yields a suitable link line-of-sight density in the imaged area for our algorithm. Image frames of the area are taken using simultaneous transmit and receive for reasons discussed above, and because it allows for a higher frame rate than having one USRP transmit at a time while the others listen. With this design we can achieve an arbitrarily fast frame rate, which provides very fine time resolution. A group at Washington University implemented time-switching between USRPs and found that a frame rate of 3 frames
per second was achievable. By contrast, baseband frequency multiplexing allowed for a frame rate of 20 frames per second, and is only limited by the computing power of the computer, since the algorithm is run on each iteration. For the eventual goal of fall detection, a higher frame rate would allow for more precise timing of the transitions between falling and non-falling states and can therefore lead to a more accurate fall detection system.

Figure 8: Hardware Setup

**Engineering Analysis**

**Carrier Frequency:** The 2920 USRPs can operate in a frequency range of 50 MHz to 2.2 GHz. A frequency above 1 GHz is required so that the RF waves attenuate effectively in the human body. A frequency of 1.4 GHz was selected to meet this criterion. Additionally, 1.4 GHz does
not interfere with cell phone frequency bands (700-900 MHz or 1700-2500 MHz), Wi-Fi (2.4GHz or 5 GHz), or medical devices such as pacemakers (32-175 kHz) [19, 20, 21].

**Baseband Frequency:** We used baseband frequency multiplexing to simultaneously transmit and receive. We discovered experimentally that the USRPs transmit unreliably at baseband frequencies below 10 kHz. The internal oscillators in the USRPs are not synchronized, leading to frequency spreading about the baseband frequency. Without a GPS-disciplined oscillator, the frequency accuracy of the USRP-2920 is 2.5 ppm, which at a carrier frequency of 1.4 GHz gives a frequency accuracy of 3.5 kHz [22]. Since the frequency is spread over 3.5 kHz, we space the baseband signals 5 kHz apart to ensure the frequency spectrums are clearly separable. We measure the power over a band of 4.5 kHz centered at each baseband frequency to account for the frequency spread and for the potential differences in the internal clocks of the USRPs.

![Baseband Power Spectrum](image)

**Figure 9:** Frequency spread of received signals

**Power:** As discussed in the concept reduction, our design involves simultaneous transmit and receive, with each transceiver transmitting at a different baseband frequency, with the same carrier frequency. However, there are limitations to the output power of a USRP, quoted in the specifications as 50-100mW. Additionally, since each USRP is both transmitting and receiving, and the two channels are not isolated, there is significant bleed between the two. Furthermore,
due to the physical characteristics of the USRPs, the transmit and receive antennas are separated only by 2cm. These factors contribute to a significantly elevated noise floor for each receiver.

Therefore, there are two constraints facing our design. Each transmitter must be able to transmit enough power such that each other unit can detect the signal above the noise floor, even in the presence of multipath and attenuating objects. Furthermore, with each USRP transmitting at this necessary level, they must be able to receive all the other transmitted signals above their noise floor, without and distortion that may be cause by clipping due to a very large received signal from its own transmitter.

To test this, we transmitted a 50kHz tone on one USRP, on a second USRP transmitted a 55kHz tone, with its receiver activated. We then found the maximum distance we can separate two transceivers while the second USRP can see the signal of the first USRP above the noise floor. Each USRP can be assigned a gain for transmit and receive, so for this experiment, we assigned the transmit gain to be 0dB and the receive gain to be 1dB.

We found the distance necessary for the second USRP to lose the signal from the first to be very large, so we tested the same setup with a 30dB attenuator between transmitter 1 and its antenna and incorporate this known attenuation into our distance estimates.

We found that, with transceiver 2’s transmit and receive antenna separated by the small distance of 2cm, it lost transceiver 1’s transmitted signal at a distance of 30cm.
Using the Friis transmission equation [22] in decibels,

\[ P_r = P_t + G_t + G_r + 20 \log_{10} \left( \frac{\lambda}{4\pi R} \right) \]

each doubling of the distance between transmitter and receiver yield a 6dB change in the received power, equivalent to \( \frac{1}{4} \) of the original power. Therefore, an imposed 30dB attenuation on the transmitted power is equivalent to a distance factor of

\[ 10^{(30\text{dB}/20)} = 31.6228 \]

Therefore, without the attenuator, and with 0dB gain on the transmitter and 1dB gain on the receiver, the maximum receive distance is \( 31.6*(20\text{cm}) = 6.32 \text{ meters} \).

This takes into account the ambient noise, but does not incorporate the attenuation of a signal passing through a person and objects in the area to be imaged. Furthermore, indoor areas are multipath rich, which can destructively interfere with a transmitted signal.

The Amtel *Range Calculation for 300MHz to 1000MHz Communication Systems* document adds a variable exponent for distance between transmitter and receiver. (Though the guide is for a
slightly lower frequency range, we extend it to apply to our system, with allowances for inaccuracies as described below). The guide proves an exponent of 3 for an office with hard walls, which is similar to a residential room in density of people and objects. This exponent accounts for multipath in the room and attenuation due to obstructions, including people.

With an \((1/d)^3\) term, each 9dB of gain is equivalent to doubling or halving the distance between transmitter and receiver. In the test cast, 30dB of attenuation is equivalent to \(10^{(30\text{dB}/30)} = \text{distance factor of 10}\). Therefore, our maximum distance is \(10^*(20\text{cm}) = 2\text{m}\). However, the USRPs allow for up to 25dB of transmitter gain, which is equivalent to a distance multiple of \(10^{(25/30)} = \sim7\). Therefore, we can theoretically successfully transmit and receive a signal at a distance of 14m, which is much larger than required for our system. The above calculations involve significant approximation, but the large margin of the resulting value provides certainty that the design is robust for up to 10m.

**Antenna:** We used a 1.4 GHz quarter-wavelength monopole whip antenna in our design. The antenna is sufficiently wideband for our application. Monopole whip antennas have omnidirectional radiation patterns, which radiate equal energy in perpendicular directions. This is a desired pattern for imaging a broad area. The frequency of 1.4 GHz is widely available with an SMA attachment, which is needed to attach the antenna to the USRP.

**Selection of Algorithm Parameters**

We selected the long-term histogram weighting parameter so that the long-term histogram adapted slowly to changes in the RSS along the links and did not adapt to the presence of a person along the link. For user convenience, we want the long-term histogram to reach baseline within a half-hour of empty room calibration. By contrast, the short-term histogram weighting parameter was selected so that the short-term histogram adapted quickly to changes in the RSS along the links. Experimental testing found that a long-term histogram weighting parameter of 0.002 and a short-term histogram weighting parameter of 0.3 met these requirements.

**Pixel Size**

The received signal strength is measured along the links between USRP units. The number of directional links between ten USRPs is calculated from the permutation formula:
nPr = n!/(n-r)!

The number of links between two of the ten USRPs is therefore

10P2 = 90 links

The imaged area is divided into pixels. In order to image a pixel, at least one of the ninety links must pass through the pixel so that the presence of an attenuating object will affect the signal strength in that pixel. We chose to space the USRPs equally around the imaged space to allow for even imaging coverage throughout the area. A smaller pixel size improves resolution; however, at least one link must pass through each pixel to prevent blind spots. We selected a pixel size of 0.2 m x 0.2 m because at least one of the ninety links crossed each of the pixels the imaged area. The size of a pixel should also be smaller than the width of a person.

Figure 11: Ellipse modeling Line of Sight between two USRPs. Shaded pixels are the pixels whose centers are contained within the ellipse. The pixels are weighted according to the weight equation in the section Link Modeling.
**Link Modeling**

The directional links between USRP units are mathematically modeled by a narrow ellipse. An ellipse is chosen as an approximation of line of sight because it is computationally cheaper than determining line of sight and incorporated scattering caused by a person very close to a link. Pixels are weighted according to whether their centers are in this line of sight as shown in figure 6. This figure shows each pixel with its center; the shaded pixels are those that have their centers encompassed by the ellipse. The equation to determine weighting is fairly simple because of the ellipse approximation:

\[
W(i,j) = 1, \text{ if } d_1 + d_2 < ld + \lambda
\]

0, otherwise

\(d_1\) is the distance from the pixel center to 1 USRP

\(d_2\) is the distance from the pixel center to the other USRP

\(ld\) is the link distance - the distance between the two USRP

\(\lambda\) is the ellipse parameter

Lambda helps to determine the width of the ellipse. It is selected to be a small value so that it closely approximates a line. We chose to use .007 as our value for lambda. This is the value used in [9].

**Imaging Accuracy**

In order to determine the accuracy of the system, we used a test subject that moved around in the test area.

The test subject was modeled as 4 pixels based on her size as can be seen by the 4 red pixels in figure 7. The center pixel of the 4 is the pixel that the test subject had her feet in, however, due to the size of the pixel vs. the size of the test subject, her body would not be fully contained in just this pixel, hence the choice of 4 pixels to model. The algorithm used to determine accuracy is
purely based on the most attenuated pixel. We measured the accuracy of detecting the test subject in each pixel. The accuracy obtained with this model of 4 pixels was 77.72%. In addition, we measured the accuracy of detecting the test subject in pixels that were not on the edges, which are where most inaccuracies occur. These inaccuracies likely occur because the test subject has more of her body in other pixels because she cannot physically center herself over the pixel she should be in. The accuracy gained by taking away the edge pixels increased the accuracy to 92.29%.

![Radio Tomography Contrast Plot](image)

**Figure 12:** Radio Tomography Contrast Plot modeling the test subject as the 4 red pixels.

In every case of an inaccuracy, the estimated location was only 1 pixel away (either horizontally, vertically, or diagonally) from the pixel that the test subject was centered over. This means that there is never so much noise that the algorithm cannot detect the general area that the person is in.
This is great for potential future work for the tracking algorithm. Given more time, we would implement a particle filter in order to track which would help to take away some of the noise that occurs in this accuracy test.

**Distance**

Our original setup was chosen because with, 10 USRPs, all pixel centers would be crossed by at least 1 ellipse, which gives good accuracy. Figure 8 shows this. Each pixel has a color corresponding to the number of ellipses that pass through its center; all of these pixels centers are contained within at least 1. This size was also chosen for testing purposes to avoid the hazards and extra cost of using more extension cords that could be tripped on.

![Figure 13: Grid of pixels. Colors correspond to the number of ellipses that cross each pixel center.](image)

As the distance between USRPs changes, keeping all else constant, the eccentricity of the ellipses changes. The eccentricity for our system is the ratio of the distance between the USRPs to the distance between the USRPs plus lambda. This means that as the distance increases, this
ratio gets closer to 1, thereby narrowing the ellipse. Figure 9 shows the effect of doubling the width and length of the area (increasing the area to 3.2 x 2.4 m) that is imaged by the system in terms of how many of the pixels are covered by ellipses. 8 of the 192 pixel centers are not contained within an ellipse yielding 95.8% coverage.

Figure 14: Setup of area that is 3.2 m x 2.4 m with 0.2 m pixel size. X’s show pixels not crossed by ellipses.
Figures 14 and 15 show the effect of doubling the size of the pixels to .4 x .4 m with this 3.2 x 2.4 m area. Now only 4 pixels are left uncovered. However, this is a larger percentage because the number of pixels has decreased back to 48, yielding 91.7% coverage.

Determining how changing the size of the area and changing the pixel size will affect the coverage is a complex problem. It is greatly affected by where exactly the pixel centers are compared to the ellipses that make up each link and therefore are difficult to mathematically model to make predictions of the best size. The most practical way to determine a good size is to run a simulation that can change parameters and determine the size that will be able to ascertain the highest coverage percentage that can obtained that is within the allowable error threshold.
Scalability

In order to model how our system would be able to perform on a room of this size of 15ftx15ft, we approximate this size to be 4.8 x 4.8 m (15.748 x 15.748 ft) with 0.2 m per side pixel size. As shown in figure 9, this creates an area of 576 pixels with 64 centers left uncovered, yielding 88.89% coverage.

In order to increase coverage, thereby increasing the accuracy, we consider adding in more units to cover this area. The new layout using these 12 units can be seen in figure 12. When we increase the number of units to 12 while covering the same area, we decrease the number of pixels left uncovered to a mere 4 pixels as shown in figure 13. This increases the percentage coverage to 99.31%.

Figure 16: Experimental Setup with 10 USRPs. 4.8x4.8 m room with 0.2 m pixels.
Figure 17: Grid of pixels. Colors correspond to the number of ellipses that cross each pixel center.

Figure 18: Experimental Setup with 12 USRPs. 4.8x4.8 m room with 0.2 m pixels.
Figure 19: Grid of pixels for 12 USRPs. Colors correspond to the number of ellipses that cross each pixel center.

Having the coverage accuracy as high as possible is important for the accuracy of the complete system because as was discussed in the Imaging Accuracy section, the object cannot be found in the correct pixel 100% of the time.

**Practical Implementation**

Our design assumes that the eventual implementation would be in a home. In all likelihood, one would not want USRPs hung on the walls of the room, and therefore it would be preferable to have them within the wall. According to [3], the KRTI algorithm should be able to be implemented in a through wall implementation.

For practical implementation, it would be cheaper to use USRP B200s. These USRPs are full duplex but are not NI proprietary and so would use a different software interface. Once programmed, the software could be put on a special purpose computer that would not need a screen. It would only need to connect to a landline and the USRPs.
One limitation in terms of practical implementation is a limit on the data throughput to the computer. The USRP B200 communicates with a computer via USB 3.0, which has a data transfer capability of 5Gbit/second. Considering that we sample our signals at 200kS/s both transmit and receive for each USRP, and each B200 has a 12 bit analog to digital converter, the data transfer required for each USRP is

$$200\text{kS/s} \times 12\text{bit/S} \times 2 (\text{Tx and Rx}) = 4800\text{kbit/s}.$$  

With a USB transfer rate of 5Gbit/s, we can support $$5\text{Gbit/s} / 4.8 \text{Mbit/s} = 1041$$ USRPs. The reality is that due to overhead, we will not be able to support this many units. Ettus Research, which manufactures the B200, provides documentation on the streaming rate benchmarks for these USRPs. With an Intel Corporation 7 series USB controller, Ettus has achieved a sampling rate of 20MS/s with successful data transfer. At 200kS/s for each channel (transmit and receive), this corresponds to

$$20\text{MS/s} / (2\times200\text{kS/s}) = 50$$ USRPs.

This will be more than enough for our intended implementation especially as our intended room size can be well covered with 12 USRPs.

**Cost Analysis**

Based on the bill of materials analysis, the cost of the 10 unit radio-tomographic imaging prototype system is $29,913.34. If implemented on a larger scale, the price per system could decrease even if the number of radio units used increased. The implemented system would use GNU-based software instead of proprietary software such as LabVIEW and MATLAB, lowering the total cost by $1049. A practical implementation of the system could purchase USRPs directly from the manufacturer, Ettus Research, instead of through National Instruments. This would lower the per unit cost of a USRP unit from $2,746 to $710. Even if scaling the design required an additional two USRP units, the total cost of the design would still be greatly reduced. The laptop would be replaced with a special-purpose computer; further reducing the system’s cost. The design might be compatible with less expensive radio units than the USRP. Further market research would be required to conclusively decide on the USRP as the radio unit of choice for
this system. The lifetime operational costs would be low. With a 10 year lifespan comparable to that of other electronic systems, maintenance would be periodically required in the event of a hardware malfunction. The long-term maintenance costs should however be relatively low.

**Bill of Materials**

<table>
<thead>
<tr>
<th>Item</th>
<th>Price</th>
</tr>
</thead>
<tbody>
<tr>
<td>NI USRP 2920 (10) 50MHz to 2.2 GHz Software Radio. National Instruments</td>
<td>$2,746 per unit</td>
</tr>
<tr>
<td><em>includes</em>:&lt;br&gt;- Universal Software Radio Peripheral&lt;br&gt;- 20MHz-2.2GHz Full Duplex Daughterboard&lt;br&gt;- Ten (10) 6-ft Gigabit Ethernet cables&lt;br&gt;- Power Adapter, 0.6A</td>
<td>$2,746 per unit</td>
</tr>
<tr>
<td>Rubber Feet (40) 3M SJ5003-8-ND Bumpon Hemisphere Rubber Foot (0.440” diameter, 0.197” thick), Digikey</td>
<td>$0.06268 per unit</td>
</tr>
<tr>
<td>60 ft Gigabit Ethernet Cable (1)</td>
<td>$3.69 per unit</td>
</tr>
<tr>
<td>8 Port Gigabit Ethernet Switch (2) Trendnet GREENnet EGS80G 8-port Gigabit Ethernet (SKU: 975169), Microcenter</td>
<td>$29.99 per unit</td>
</tr>
<tr>
<td>1.4GHz Monopole Swivel Antenna (20) Linx Technologies ANT-1.4-CW-HWR-SMA-ND, Digikey</td>
<td>$10.04 per unit</td>
</tr>
<tr>
<td>Cable ties (1 package of 100 cable ties) Gardner Bender 4 in. Cable Ties <a href="http://www.homedepot.com/p/Gardner-Bender-4-in-UV-Resistant-Cable-Ties-100-Pack-295780/202520063">http://www.homedepot.com/p/Gardner-Bender-4-in-UV-Resistant-Cable-Ties-100-Pack-295780/202520063</a></td>
<td>$4.28 per package</td>
</tr>
<tr>
<td>Gaffer’s Tape Adorama Gaffer Tape 8 yards x 1” -- Black</td>
<td>$5.20 per role</td>
</tr>
<tr>
<td>Extension Cord (4) Workforce 50ft. 16/3 Extension Cord. Home Depot</td>
<td>$11.97 per unit</td>
</tr>
<tr>
<td>Power Strips (8) LPT-2-1S 6-Outlet, 6-ft Cord 15A Power Strip</td>
<td>$10.00 per unit</td>
</tr>
<tr>
<td>Dell Latitude E6410 Laptop (1) Dell Latitude E6410 Laptop (14.1-Inch). Dell</td>
<td>$1000 per unit</td>
</tr>
<tr>
<td>Labview Software (LabVIEW Base)</td>
<td>$999</td>
</tr>
<tr>
<td>Matlab Software for student use</td>
<td>$50</td>
</tr>
</tbody>
</table>

Table 1: Bill of Materials [24-35]
Hazards and Failure Analysis

The device requires a number of wires and cables to connect all of the components to each other. These wires and cables can pose a tripping and falling hazard if not neatly organized at the edges of the design. The system was designed so that the cables could be placed at the perimeter of the room away from the area being imaged, and ideally within the walls. The cables and wires should be in good condition to reduce the risk of electrical sparks or fires. A power supply connected to a circuit breaker should be used to protect against electrocution and the power supply should be grounded. The system should be placed so that direct contact with liquids is unlikely. Surge protectors should be used to protect the USRPs against damage and failure due to electrical surges.

The radio tomographic imaging design will fail if the design loses access to electricity. The system could fail if there were other devices transmitting at the same carrier frequency (1.4 GHz) in the area. We considered the carrier frequencies of common devices such as cell phones, Wi-Fi, and biomedical devices. Cell phones typically transmit at 700-900 MHz or 1700-2500 MHz. Wi-Fi uses carrier frequencies in either the 2.4 GHz or 5 GHz ranges. The chosen carrier frequency (1.4 GHz) avoids commonly used frequency ranges to reduce the potential of failure due to frequency interference.

The algorithm will fail in the case where many pixel centers are not contained within ellipses. This will occur especially when there are many pixels next to one another that aren’t contained within an ellipse. Figure 14 shows the problem that occurs when this happens. The oval is the model of a person. If this person stands in that location, he or she will not be detected because these x’s indicate pixels that don’t have ellipses going through their centers. This means that the person will not attenuate across any link. This issue is prevented through advance analysis and optimization of the setup.
Figure 20: Blind Spots. The person is modeled by an ellipse. The x’s show pixels that are not covered by ellipses

**Conclusions**

Fall Detection using Radio Tomographic Imaging is a new field that plays an important role in allowing older individual to maintain freedom and independence while allowing for fast response time in the event of a fall.

This project allowed us to delve into many new concepts while having the opportunity to make informed design decisions that guided our progress through this experience. In formulating the concepts for this project, throughout the research into algorithms, and in testing our system, we used concepts learned in previous classes, especially ESE 488. The radio tomography projects completed by the group at the University of Utah were incredibly helpful in providing us with algorithms that were used as the basis for this project.

We further develop our implementation to use the full duplex nature of the daughterboards of the USRPs. We use baseband frequency multiplexing to determine which USRP was transmitting each signal. This allows us to have a very high frame rate which could be helpful in future work, when the fall detection portion is fully implemented.
The system we created was 92% accurate in an area of 1.6 m by 1.2 m using 2 USRPs, a pixel size of 0.2m while excluding the edge pixels for reasons as discussed above. Some future extensions to this project are as follows: testing the system in a larger area, using particle filtering in order to track the person more accurately, and finally, implementing the 3D fall detection algorithm.

Our process came with many complications along the way. We learned a great deal about debugging and the different issues that can come about when hardware and software interact, not to mention some issues with the interaction between LabVIEW and MatLab. We learned interpersonal skills of working constructively in an engineering team and the value of teamwork. In addition, having multiple mentors with a variety of expertise enabled us to learn about and design different aspects of our system and the design process.
References


Appendices

USRP 2920 Block Diagram


[41-42]

USRP B200

http://www.ettus.com/content/files/kb/b200-b210_spec_sheet.pdf
http://www.ettus.com/kb/detail/usrp-b200-and-b210-faq

[43-45]

Terminology

Daughterboard-- A circuit board that is an extension of the motherboard

KRTI-- Kernel-based radio-tomographic imaging

Link-- The path between a radio transmitter and a radio receiver.
LTH-- Long-term histogram

Node-- A radio device, in this case a USRP

Pixel-- A subdivided square piece of the imaged area

PSD-- Power spectral density

RF-- Radio Frequency

RSS-- Received signal strength

RTI-- Radio-tomographic imaging

STH-- Short-term histogram

Tikhonov Regularization-- A method of regularization for ill-posed problems

USRP-- Universal Software Peripheral Radio

Voxel-- A three-dimensional pixel

VRTI-- Variance-based radio-tomographic imaging

VSWR-- Voltage standing wave ratio

*Used Interchangeably*: USRP, transceiver, transmitter/receiver, node, unit