Fine-Grained Activity Detection in the Kitchen with UWB

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Contents

Chapter 1

Introduction

This thesis project investigates how to detect fine-grained action within the meal preparation activity of daily living (ADL) in the home without the use of privacy-intruding cameras. ADLs are common activities that an individual performs inside their homes. These include walking around, eating, dressing, personal hygiene, toileting, transportation, meal preparation, house cleaning, and managing medication. The meal preparation ADL was chosen as the main focus because cooking is a uniquely enjoyable activity while being procedurally dense. Meal preparation can include the following actions: opening the fridge, retrieving ingredients, cutting vegetables, and assembling the ingredients. Monitoring these actions may be used as part of a health monitoring program by enabling the assessment of the presence, duration, and correctness of each individual step in a goal-orientated activity. Missing or incorrect steps can be indicative of forgetfulness, and steps that take a long time can be indicative of low-efficacy or struggle that clinicians can address. Information obtained through the monitoring of the cooking task may help guide interventions and track the effectiveness of interventions in clinical populations such as people with dementia, frailty and Parkinson's disease. A further and more in-depth review of the background will be done in Chapter 2.

It is hypothesized that the combination of context, such as accurate indoor localization (down to 30 cm), and inertial data can accurate and reliable classification of fine-grained ADLs. The system used for indoor localization is the Pozyx Creator Kit which provides a wrist mounted wearable that can obtain data at a maximum of 60 Hz [1]. This data includes position relative to a floorplan, and inertial data from a BNO055 which outputs 3D Acceleration, 3D angular velocity, 3D Linear Acceleration, and the Heading, Pitch and Roll.

Prior to any experiments related to classification of these cooking actions, the optimal configuration of the system that provides reliable position data had to be investigated. Chapter 3 details the different attempts at changing the configuration of the Pozyx Creator Kit to obtain the most reliable positioning data in X, Y, and Z at a satisfactory sampling rate.

Chapter 2

Literature Review

2.1 Overview

In 2014, over 6 million Canadians (15.6% of the population) were 65 years old or older. The number of older adults (65+) continues to increase; and by 2030, Statistics Canada expects there to be over 9.5 million adults over the age of 65, comprising 23% of Canadians [2]. Frequently, older adults who wish to age-in-place or in the comfort of their own home must be able to perform their activities of daily living (ADLs) while bearing multiple diseases and syndromes that come with age, such as frailty, impaired cognition, gait and balance problems [3]. These ADLs may include cooking, bathing, getting into and out of bed, and toileting all of which require complex coordination of the older adult's cognitive, physical, visual, and perceptual abilities. Deficits in any of the categories mentioned can impair the older adult's ability to go about their day. Typically it is only after an incident or hospitalization that an older adult is assessed for their ability to perform ADLs [4].

The current system presents an opportunity for proactive and preventative medicine through the use of in-home monitoring. Data obtained through monitoring can be used to track functional decline. With this information, older adults, along with their clinician, can plan early interventions and prevent future incidents and hospitalization. The rest of the chapter will be organized as follows: first, an overview of the common diseases and conditions from aging that affect ADLs will be explored; next, current assessment tools for these conditions will discussed; finally, current attempts at in-home monitoring for ADLs will be investigated as well as what data and how the data is being used.

2.2 Background for Diseases and Conditions in Aging

This section reviews the current literature on the disease and conditions associated that affect the ability to perform ADLs as older adults age. In terms of functionally being able to perform one's ADLs, both physical and cognitive ability are required. Peter et al., in their exploration of ADLs, mention frailty and dementia as conditions limiting ADL performance [5]. In addition to physical and cognitive abilities, sensory decline with hearing, vision and vestibular function (associated with dizziness) occur [6]. Several chronic conditions may also be present in older adults such as cardiovascular disease including heart failure, ischemic heart disease, and atherosclerosis; diabetes mellitus; osteoarthritis; and osteoporosis [6].

2.2.1 Frailty

Frailty is a syndrome present in 20-50% of the middle and older aged population (ages 50+ years) [7] and is associated with ageing and co-morbidities, but not caused by them [8]. Individuals with frailty are at "higher risk for adverse health outcomes such as illnesses, hospitalization, disability and mortality" . To define frailty, there are 2 models: the frailty phenotype and the frailty index [9]. The frailty phenotype (also known as the Fried's Definition of Cardiovascular Health Study) defines frailty as meeting three out of five of the following criteria: "weakness, slowness, low level of physical activity, self-reported exhaustion and unintentional weight loss," whereas the frailty index uses a comprehensive geriatric assessment to determine cumulative deficits [9].

2.2.2 Dementia

Worldwide, 47 million people live with dementia, and the number is only expected to increase. By 2050, it is projected that 131 million individuals will be living with dementia [10]. In the US, the prevalence of dementia in older adults above the age of 68 is 15% [10]. Dementia is an umbrella term describing a gradual decline in cognitive abilities in several domains to the point of impairing social or occupational function [10]. It involves a slow onset and gradual loss of memory, typically paired with the inability to retain new information and ability to perform daily activities [10]. Prior to diagnosing dementia, there is typically a long history of cognitive decline combined with mention of cognitive decline from close friends and family [10]. When diagnosing dementia, a common tool that is used is the Mini Mental State Examination (MMSE): a paper test that lists several simple tasks such as spelling a word backwards, and asking about the day of the week, etc. [11].

2.2.3 Hearing Loss

The prevalence of hearing loss increases with age and at around 85 years or older, about half of all older adults experience hearing impairments [12]. Hearing loss is associated with a decreased quality of life and impairs speech processing. Reduced conversational ability may lead to social isolation which is associated with depression and cognitive decline [6].

2.2.4 Vision Loss

Similar to hearing loss, the prevalence of vision loss increases with age. In the UK, it was found that 23% of older adults ages 85-89 had severe vision loss and this increases to 37% for older adults older than 90 years [13]. Older adults with vision loss are reported to have slower walking speeds and have difficulty doing physical activities [14]. Vision loss can also "predict cognitive decline and risk of dementia" [14].

2.2.5 Vestibular Function

2.2.6 Cardiovascular Disease

Heart Failure

Heart Failure affects at least 26 million people worldwide and the number of people affected continues to grow [15]. The American College of Cardiology (ACC) Foundation and American Heart Association (AHA) define Heart failure (HF) as "a complex clinical syndrome that results from any structural or functional impairment of ventricular filling or ejection of blood

[16]." There are two types of HF: HF with reduced ejection fraction and HF with preserved ejection fraction. HF with reduced ejection fraction occurs at an ejection fraction $\leq$40% and and HF with preserved ejection fraction occurs at an ejection fraction $\geq$50% [16]. Though patients with HF present with a variety symptoms, some include shortness of breath, lethargy, fatigue, reduced exercise tolerance, wheezing, and ankle swelling [17].

Ischemic Heart Disease

Artherosclerosis

2.2.7 Diabetes Mellitus

Diabetes occurs when the body cannot control its blood sugar levels [18]. People who have diabetes are at risk of damaging blood vessels in their eyes, kidneys and nerves [18]. Diabetes mellitus can come in two main subtypes: type 1 diabetes mellitus (T1DM) or type 2 diabetes mellitus (T2DM) [18]. T1DM occurs due to the destruction of insulin producing beta-cells from an autoimmune process, while T2DM appears when cells develop a resistance to insulin and fail to use insulin that is being produced. The full extent of T2DM occurs when a cell's resistance to insulin overtakes the body's ability to produce insulin [18]. Diabetes affects 1 in 11 adults. 90% of adults have T2DM and the remaining 10% have T1DM. Onset for people with T1DM gradually increases from birth and peaks at ages 4 to 6 years and again from 10 to 14 years [18]. Signs and symptoms of diabetes include being overweight/obese, blurry vision, yeast infections, numbness, and neuropathic pain [18]. T1DM is diagnosed based on a history of "fasting glucose over 126 mg/dL, random glucose over 200 mg/dL, or hemoglobin A1C exceeding (HbA1C) 6.5%" [18]. The early stages of T2DM uses fasting glucose and HbA1C as well, but Sapra and Bhandari do not provide a specific level. A precursor to T2DM, prediabetes can be diagnosed with a glucose level of 100 to 125 mg/dL or a 2-hour post-oral glucose tolerance test (testing blood sugar levels one hour after ingesting 75 g of glucose dissolved into 250 ml to 300 ml of water [19]) glucose level of 140 to 200 mg/dL [18].

2.2.8 Osteoarthritis

Osteoarthritis affects approximately 27 million Americans [20] and onsets in a third of adults during the typical working age of 45-64 years [21]. There are about 315 million visits to the doctor, and 744 000 hospital admissions per year in the US for osteoarthritis. These figures add up to a total of 68 million days off work [22]. Osteoarthritis is the most common type of joint disorder. It is a disease characterized by the mechanical destruction and failure of a synovial joint [23]. In order of the most common location, the knee ranks first, followed by the hand and the hip [23]. High-risk factors or factors that greatly increase the chance of having osteoarthritis include obesity and previous joint injury [22]. Osteoarthritis typically presents as debilitating pain, and is accompanied by stiffness, reduced range of motion, joint instability, swelling, muscle weakness, and fatigue [23]. Clinical diagnosis is based on the symptoms that the patient presents with such as pain, and functional limitations [23]. Additionally, diagnostic criteria such as those from the American College of Rheumatology may also be used [23, 24].

2.2.9 Osteoporosis

2.3 Assessing Conditions and Diseases

There is an abundance of assessments that may be used to pinpoint problems with the patient's ADLs. One of these assessments is the Performance Assessment of Self-Care Skills (PASS) where patients are asked to perform select activities and are assessed by their healthcare provider on their ability to perform each task.

PASS assesses an individual's ability to perform ADLs by judging 3 parameters: independence, safety and adequacy. There are concrete guidelines and identifiers mentioned for scoring each parameter in Performance Assessment of Self-Care Skills [25]. For instance, the safety category has a maximum score of 3. At a score of 3, there are no risks observed; at a score of 2, there are minor risks observed, but no assistance is needed; at a score of 1, there are obvious risks to safety and assistance is required to complete a task; Finally, at a score of 0, there are risks to safety of such severity that the task had to be stopped. PASS is used around the world; has been translated to multiple languages including Spanish, Hebrew and Mandarin; has a test-retest reliability of 89%-90%; and an inter-observer agreement of 96%-97% [26] making it a reliable tool for assessing ADLs.

Of the ADLs that PASS assesses, cooking was identified to be critical in terms of sustaining a healthy lifestyle in older adults [27] but fraught with risks [28]. Older adults also cook frequently, with 53% of older adults ages 65-80 reported to cook at home 6-7 days a week [29]. Despite the health benefits and enjoyment gained from cooking, cooking is a dangerous ADL and older adults with comorbidities may have difficulty cooking safely (older adults with cognitive impairments may forget about a stovetop or oven that is on, improper knife use can result in injury and unsafe kitchen environments may exacerbate injury from falls or increase the risk of falls); the kitchen is in second place for the location of most domestic accidents [28].PASS assesses the independence, safety and adequacy of the cooking ADL by splitting the cooking task into categories of oven use, stovetop use, use of sharp utensils, and cleanup after meal preparation each with a list of its own subtasks [25]. The concrete classification framework provided by PASS allows for Smart Home (SH) interventions through monitoring and assessment with internet of things (IoT) devices.

Devices that have been used in literature cover a wide range of sensors. Logan and Healy used a modified form of AdaBoost with simple linear weak learners to distinguish meal preparation and eating through accelerometer, video capture, and audio capture data [30]. Sarma et al. used Long short-term memory (LSTM) to determine various ADLs from datasets containing motion sensors, door closure sensors and temperature sensors data [31]. Chibaudel et al. detected cooking by noting the physical location of the participant and their refrigerator usage through door sensors placed in the refrigerator and motion sensors in the kitchen [32]. Yordanova et al. used Decision Trees (DT), Computational Causal Behavior Models (CCBM), and Hidden Markov Models (HMM) to process data from the full-scale SPHERE Smart Home system consisting of temperature sensors, humidity sensors, luminosity and motion sensors, water and electricity usage sensors, cameras, and door contact sensors to classify the preparation of a wide range of recipes as "cooking" [33].

Although there have been many studies involving the detection of the cooking ADL, few studies assess the quality of cooking and provide feedback to the user. The closest attempts at assessing quality involve quantifying the number of departures from a given task. Cook and Schmitter-Edgecombe used motion sensors, analog sensors for water and stove usage, open/shut sensors for the status of cabinets, and load sensors for the absent/present status of items to assess the quality of ADLs including meal preparation. If a correct sequence of tasks was done and if the task was done efficiently, then an activity is considered as normal. Any significant departures from this "correct sequence" and normal time required to complete each step was only left with a tag of "anomalous" [34]. There is no further information with respect to how much of an anomaly the error was or what to do about it. Similarly, in Menghi et al.'s study, errors were identified in a series of tasks, but nothing was done to evaluate the severity of the error and no feedback was given to the user [32]. There is no impact on the user because errors were only identified. The user does not receive feedback about what areas need improvement and how to improve, because there was no evaluation using standardized assessments such as PASS.

The literature cites using AI techniques on data collected from IoT devices, from which two issues arise: a huge amount of data will be necessary to produce reliable classification models [35]; and, to facilitate collection of these large datasets, data from various IoT device vendors must be easily extractable. To solve these two issues, this project will be part of a recent joint initiative between several Universities across Canada gave rise to the Program to Accelerate Technologies for Homecare (PATH) which will unify SH devices and their various communication protocols (including Bluetooth, Zigbee, and Wi-fi) into a plug-and-play cloud-based system. As the platform matures, PATH will collect data from both home-like labs and at least 350 homes across Canada by partnering with companies in the SH industry. Collecting from this many sources will lead to a huge database of real-world data that will be used to develop and improve AI algorithms for use in monitoring and detection of abnormalities present in the home or the user [36].

The potential to rapidly collect data on various cooking scenarios provided from PATH, along with concrete classifiable items assessing the quality of cooking provided by the PASS framework can be used to create a novel and robust cooking quality assessment SH system that doubles as a tool for ensuring the safety of older adults in the kitchen and automation of cooking functional assessments for clinicians.

Objective and Methodology: The research project proposes the development of a cooking-focused SH monitoring system on the PATH platform for older adults to ensure that cooking is done safely and to automate cooking assessments for clinicians. This will involve selecting and testing commercially available devices to testing the entire system on patients at the Independent Living Suite (ILS) in the Glenrose Rehabilitation Hospital (GRH). To create a system that is easy to use for older adults and clinicians, they will be consulted at every step in the process. The research project can be broken down into 5 phases:

1. Research the usability and acceptability of SH devices among older adults with a focus on how the usability and acceptability may be affected by the design of the devices. A UTAUT2 focus group study involving older adults (65+), care providers and clinicians will be conducted to obtain feedback for usability and acceptability;

2. Research common data analytic tools and frameworks that are relevant for monitoring cooking through the PASS's criteria. Keywords from the sub tasks outlined in PASS + "Machine Learning, Detection, Assessment" will be searched on the academic databases Scopus, PubMed, Cinahl, IEEE Explore, ISI Web of Sciences, and ACM Digital Library; and on the general web on StackOverflow, TowardsDataScience and TowardsAI;

3. Select and validate commercially available SH devices tailored to the preferences from the usability study and clinical relevance from the literature review. This step involves searching for previous validation of the devices on Scopus, PubMed, Cinahl, IEEE Explore, ISI Web of Sciences, and ACM Digital Library along with any necessary validation of the devices in-lab by comparing to gold standards such as ECG for Heart Rate;

4. Apply data analytics methodologies from the literature review to devices selected to assess cooking safety and function. The bulk of these algorithms will be written in Python and any other additional languages deemed necessary from the literature review will be used;

5. Conduct a clinical pilot-study at the ILS with real-world participants to determine the sensitivity and specificity of devices when detecting the cooking activity and evaluate if users are cooking safely. The developed system will be installed into one living suite at the ILS and a single user will be monitored for the remaining duration of research project. Key outcomes investigated throughout the pilot-study involve cooking ADL detection F-score, cooking safety evaluation compared to clinicians' judgement and effectiveness of automated SH interventions by comparing independence, safety and adequacy scores before and after.

The outcomes of this research project are four-fold: the development of a SH cooking safety system, an automated cooking assessment tool for clinicians, testing and further development of the PATH system, and contribution of data to the PATH system for other researchers.

Chapter 3

System Tuning at the Independent Living Suite

3.1 System Tuning Review

The Pozyx Creator Kit comes with anchors and several tags. Anchors are mounted on the walls and are used to position the tags. Multiple tags may be positioned at the same time. The Pozyx Creator kit uses ultrawideband (UWB) signals with the two-way ranging protocol to localize the tag. The tag is mounted on custom 3D printed wearables which the participant can wear as a wrist-watch or a necklace. Through trial-and-error and consultation with the Pozyx Creator Documentation [37, 38] it was determined that the accuracy of the system depends on factors listed below:

- Number of anchors
- Position of anchors

These variables were modified to achieve satisfactory actual position error and standard deviation below the expected error of 30 cm for UWB systems. The protocol for obtaining data and evaluating the actual position error and standard deviation is described in the next section.

3.2 Methodology

This protocol tests the X, Y, and Z positional accuracy of the Pozyx Creator system in the Independent Living Suite (ILS) at the Glenrose Rehabilitation

Hospital by having a participant stand at a specific location in each room. Permanent appliances or furniture such as the stove or dining table were used as much as possible to ensure that the experiment is repeatable.

3.2.1 Setup

Masking tape was used to mark the locations where the participant should place their feet. The following procedure was followed to place the tape:

1. Using a measuring tape, measure 1 meter out from the middle of the appliance or furniture and place a 20 cm piece of tape centered on, perpendicular to and underneath the measuring tape (the tips of the participant's toes should be 1 meter away from the appliance).

2. Place parallel tape on the sides of the tape placed in Step 1 to constrain the feet to a box. (The participant should have their toes on the tape perpendicular to the measuring tape and usually facing the appliance or furniture). Figure 3.1 outlines some examples of tape placements.

Following the tape placement guidelines outlined at the beginning of this section, tape was placed at or near the following locations. Refer to the AUTOCAD floor plan for the location of the rooms (Figure 3.2):

- The Hallway between Living Room and Kitchen facing the Dining Table.

- The Living Room facing the Desk.

- The Bedroom facing the bed.

- The Hallway between the bedroom and the bathroom, facing away from the wall.

- Bathroom facing the toilet.

- Kitchen facing the stove.

Figure 3.1: Box tape placement at the stove, fridge, and dining table. Participant's toes and sides of feet should touch the tape.

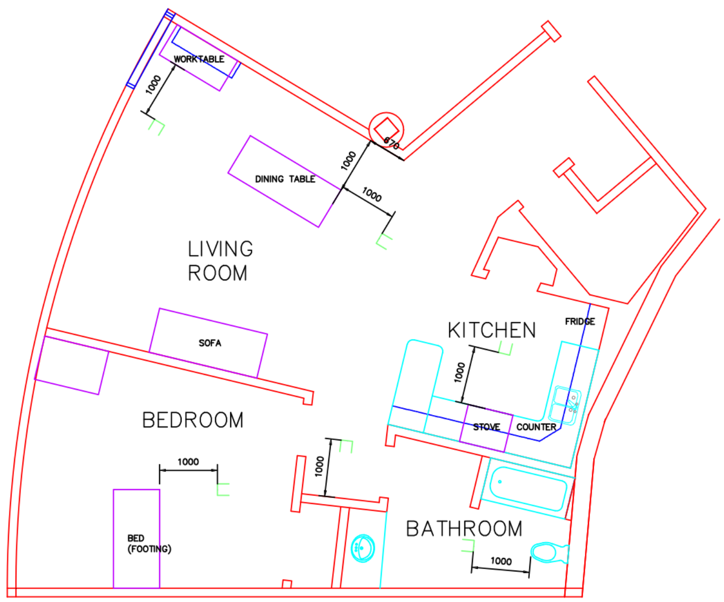

Figure 3.2: Floor plan of the ILS. Positions where the participant stood 1 meter from appliances or furniture are marked in the green "open" box on the floorplan.

3.2.2 Protocol

A stopwatch python script was created with predetermined labels and used as the ground truth for positions. A single participant wore the tag on a 3D printed necklace mount (Figure 3.3). The measuring tape was used to measure the height from the ground and height when squatting. For this participant, the standing height was **144cm** and the squatting height was **68.5cm**.

Figure 3.3: The Pozyx tag mounted in a custom 3D printed necklace mount.

The protocol had the following steps:

1. At the first location (Hallway Between Living Room and Kitchen) stand still for 10 seconds
2. Squatt still for 10 seconds.

3. Move to next position.

4. Repeat steps 1-3 until all of the positions have been reached.

5. Finally return to the first position (Hallway Between Living Room and Kitchen)

There were 3 trials for each configuration. Following the guidelines from the Pozyx Creator Setup [38] anchors were staggered at heights of 1.4m and 2.4m (ceiling height) for 4, 5, 6, 8, and 10 anchors. A configuration where anchors were all low (10cm) were tested for 8 anchors and configurations where anchors were all high (2.4m) were tested for 8 and 9 anchors.

3.3 Results

Trials for each configuration were aggregated, transition periods were removed, data of interest was time normalized and the error and standard deviation of each location while standing and squatting were calculated. An as-built AUTOCAD file of the ILS was used to obtain the real position and used in the calculation of the error between measured versus the actual position. The results of the experiment are summarized in the heatmap tables (Figures 3.4, 3.5 and 3.6) with a minimum darkness set at 30cm and a maximum darkness set at 60cm.

X Position Error at Each Location (cm)

	POS_X_A4	POS_X_A5	POS_X_A6	POS_X_A8	POS_X_A10	POS_X_A8H	POS_X_A8L	POS_X_A9H
Go Hallway between kitchen and living	40.1	41.5	42.2	47.9	33.0	11.8	3.5	28.0
Go Hallway between kitchen and living(sit)	18.6	11.7	7.4	44.2	20.6	29.2	21.9	41.4
Living Room	50.4	57.8	48.3	7.7	34.5	20.0	31.3	41.8
Living Room(sit)	44.6	30.2	20.0	28.8	23.7	5.2	6.5	11.0
bathroom	49.1	39.8	33.0	65.3	15.4	111.9	120.6	52.0
bathroom(sit)	29.2	19.6	22.9	23.2	39.0	64.5	24.6	61.1
bedroom	24.1	2.5	39.4	58.3	55.8	99.8	78.3	49.2
bedroom(sit)	26.9	12.8	4.1	103.8	45.9	53.5	27.0	37.5
hallway between bedroom and bathroom	2.7	14.9	5.3	5.4	7.6	6.6	3.7	36.1
hallway between bedroom and bathroom(sit)	2.8	13.9	26.5	0.1	3.4	1.7	51.3	22.2
kitchen	23.7	26.8	18.5	30.1	31.5	37.3	29.1	7.7
kitchen(sit)	8.2	22.2	8.8	41.9	31.2	43.7	44.1	28.0

(a)

X Standard Deviation at Each Location (cm)

	POS_X_A4	POS_X_A5	POS_X_A6	POS_X_A8	POS_X_A10	POS_X_A8H	POS_X_A8L	POS_X_A9H
Go Hallway between kitchen and living	105.9	56.5	62.1	39.2	42.2	43.8	29.1	28.2
Go Hallway between kitchen and living(sit)	9.8	19.2	12.7	24.5	13.7	12.3	20.0	15.6
Living Room	5.4	7.9	6.4	18.7	19.1	17.3	12.0	12.9
Living Room(sit)	11.6	24.9	19.2	18.0	20.2	17.4	16.2	13.2
bathroom	44.4	27.3	19.6	82.5	43.4	65.3	90.6	39.1
bathroom(sit)	13.8	12.6	9.7	68.0	39.7	44.5	80.2	23.1
bedroom	17.7	17.3	17.6	21.0	21.6	36.3	30.5	24.7
bedroom(sit)	7.9	20.7	28.1	28.3	14.6	29.5	29.1	14.4
hallway between bedroom and bathroom	10.2	12.5	6.9	24.6	18.1	16.0	13.6	19.3
hallway between bedroom and bathroom(sit)	14.6	4.8	10.8	13.0	13.4	10.1	12.3	12.9
kitchen	16.7	7.8	10.3	5.1	5.0	7.9	7.9	7.8
kitchen(sit)	20.7	6.6	16.4	14.4	9.6	8.5	9.7	5.1

(b)

Figure 3.4: The positional error in X (a) and the standard deviation in X (b) at each location and body position

Y Position Error at Each Location (cm)

	POS_Y_A4	POS_Y_A5	POS_Y_A6	POS_Y_A8	POS_Y_A10	POS_Y_A8H	POS_Y_A8L	POS_Y_A9H
Go Hallway between kitchen and living	20.5	28.7	38.8	95.4	62.3	58.2	8.6	28.5
Go Hallway between kitchen and living(sit)	46.5	58.2	57.9	65.5	49.5	63.4	31.7	42.7
Living Room	11.6	6.2	3.2	62.3	63.5	47.1	37.4	38.0
Living Room(sit)	7.8	0.7	3.7	47.8	35.6	25.8	32.7	15.1
bathroom	27.9	0.4	7.8	44.4	56.1	47.3	10.3	38.2
bathroom(sit)	54.7	39.2	37.7	53.7	29.7	5.1	15.1	1.0
bedroom	22.8	14.5	9.2	39.5	16.1	71.7	58.4	5.7
bedroom(sit)	20.2	5.3	33.9	60.9	5.0	34.6	1.8	8.7
hallway between bedroom and bathroom	4.6	7.8	24.8	7.1	9.4	23.5	2.0	19.4
hallway between bedroom and bathroom(sit)	56.2	67.0	44.4	31.0	7.7	28.3	8.8	13.8
kitchen	16.8	2.8	10.8	28.5	33.7	39.0	38.0	31.3
kitchen(sit)	17.5	4.0	9.0	21.9	31.1	15.5	28.6	22.2

(a)

Y Standard Deviation at Each Location (cm)

	POS_Y_A4	POS_Y_A5	POS_Y_A6	POS_Y_A8	POS_Y_A10	POS_Y_A8H	POS_Y_A8L	POS_Y_A9H
Go Hallway between kitchen and living	103.7	53.5	62.1	115.5	79.0	137.9	25.8	24.7
Go Hallway between kitchen and living(sit)	10.3	13.7	10.7	23.6	17.8	21.1	27.6	16.0
Living Room	5.7	8.3	4.8	13.7	16.1	17.4	20.8	14.2
Living Room(sit)	11.1	14.7	11.0	21.3	12.2	16.3	13.1	7.5
bathroom	35.1	25.1	21.9	50.8	24.8	36.2	39.8	23.4
bathroom(sit)	29.8	42.1	29.3	19.1	23.4	20.3	38.9	17.8
bedroom	15.6	17.7	14.2	18.9	12.2	18.4	23.7	9.5
bedroom(sit)	9.5	12.4	14.3	24.9	14.9	16.8	17.5	6.2
hallway between bedroom and bathroom	15.2	9.0	12.2	23.0	13.6	13.4	9.5	13.0
hallway between bedroom and bathroom(sit)	12.7	10.5	16.7	8.0	12.9	12.3	12.1	8.2
kitchen	17.6	9.1	6.2	9.9	7.1	14.0	9.0	9.8
kitchen(sit)	24.4	16.0	17.2	15.3	11.0	12.7	16.1	5.9

(b)

Figure 3.5: The positional error in Y (a) and the standard deviation in Y (b) at each location and body position

Z Position Error at Each Location (cm)

	POS_Z_A4	POS_Z_A5	POS_Z_A6	POS_Z_A8	POS_Z_A10	POS_Z_A8H	POS_Z_A8L	POS_Z_A9H
Go Hallway between kitchen and living	132.3	56.9	47.9	180.1	87.6	7.5	58.2	3.2
Go Hallway between kitchen and living(sit)	137.0	207.8	184.0	232.3	104.7	7.6	22.8	16.0
Living Room	121.5	36.7	41.7	99.4	88.5	58.1	54.8	57.0
Living Room(sit)	79.1	177.1	197.1	224.9	16.7	30.8	97.0	17.2
bathroom	84.0	66.7	114.7	64.2	27.3	43.6	147.6	80.3
bathroom(sit)	43.2	10.2	11.2	211.1	66.4	26.3	4.6	66.2
bedroom	57.5	65.8	121.6	192.9	233.5	155.3	234.6	37.1
bedroom(sit)	39.7	1.3	54.8	305.5	3.5	80.9	142.5	20.6
hallway between bedroom and bathroom	74.0	103.4	4.1	208.3	48.6	30.8	72.3	71.7
hallway between bedroom and bathroom(sit)	33.4	26.2	59.1	84.2	2.8	61.1	54.4	65.2
kitchen	70.5	117.0	40.5	0.1	38.7	33.5	73.8	31.5
kitchen(sit)	119.0	3.9	25.9	216.1	70.6	38.5	139.6	20.5

(a)

Z Standard Deviation at Each Location (cm)

	POS_Z_A4	POS_Z_A5	POS_Z_A6	POS_Z_A8	POS_Z_A10	POS_Z_A8H	POS_Z_A8L	POS_Z_A9H
Go Hallway between kitchen and living	93.9	80.0	89.6	68.1	69.9	58.7	110.3	33.8
Go Hallway between kitchen and living(sit)	84.8	110.0	123.2	151.2	108.1	21.0	77.3	9.0
Living Room	46.7	36.1	23.5	92.1	25.6	20.0	144.2	17.1
Living Room(sit)	53.1	118.1	112.8	107.5	106.7	13.2	87.2	22.0
bathroom	89.9	105.2	69.6	99.9	77.3	79.4	151.9	40.7
bathroom(sit)	107.7	18.3	35.4	90.0	115.6	119.0	93.6	63.7
bedroom	65.4	109.7	67.8	142.2	58.5	24.2	246.9	20.0
bedroom(sit)	15.1	28.4	66.1	154.6	130.0	25.6	144.2	12.1
hallway between bedroom and bathroom	37.2	50.0	21.1	51.5	98.9	31.1	150.1	30.2
hallway between bedroom and bathroom(sit)	104.2	13.2	24.7	176.0	112.5	14.1	57.9	15.7
kitchen	75.2	62.0	64.5	61.8	13.2	24.4	26.3	17.0
kitchen(sit)	149.3	46.5	95.5	172.8	119.5	15.9	42.7	7.2

(b)

Figure 3.6: The positional error in Z (a) and the standard deviation in Z (b) at each location and body position

3.4 Discussion

3.4.1 X Position

Visually, the heatmap of error in the X position shows different spots where the system struggled to obtain the location based on the AUTOCAD as-builts depending on the configuration selected. For 4, 5 and 6 anchors, the errors seemed to be larger in the living room and the hallway between the kitchen and the living room. 8, 10, 8 (L)ow, 8 (H)igh, and 9H anchors seemed to struggle most around the bathroom and bedroom area. The standard deviation in X position seems to follow a similar pattern where 4, 5 and 6 anchors have higher standard deviation in hallway between the kitchen and living area and 8, 10, 8 (L)ow, 8 (H)igh, and 9H seems to struggle the most in the bathroom. Out of all of the configurations the 9H configuration has the most locations where the standard deviation is acceptable.

3.4.2 Y Position

For 4, 5, and 6 anchors, the error seems to increase in the seated position meaning that there may be some dependence on the Z position. This occurs in the hallway between the kitchen and the living room, the bathroom and the hallway between the bedroom and bathroom. There seems to be a large struggle for 8, 10 and 8H anchors to pinpoint the Y position in the hallway between the kitchen and the living, the living room and the bathroom. The 8L anchor configuration struggled when the in the bedroom, but was overall within or near the acceptable threshold of 30cm. 9H anchors overall seemed to be the best at determining the Y position with mild errors at the hallway between the kitchen and the living room, the living room and the bathroom.

In terms of standard deviation, anchor configurations 4, 5, 6, 8, 8H, and 10 had trouble at a height of 144cm, but otherwise had low standard deviation. 8L had minor issues regarding standard deviation in the bathroom but was otherwise low. The 9H configuration seemed to yield the lowest standard deviations in the Y Position.

3.4.3 Z Position

The Z position at many of the locations and all configurations seem to deviate from the measured heights and have high error. Only the 8H and 9H configurations have acceptable standard deviations for most of the rooms (there is still some struggle in the bathroom). Considering the inaccuracies in the Z positioning, it is recommended that the Z not be used as a absolute source of truth for height. Rather Z position should be used relative to another reference tag with the 9H configuration. For example, a necklace tag may be combined a wrist tag. When standing, the position of the wrist may be compared with the position of the necklace to determine if the wrist is above, below or at chest height.

3.4.4 Overall

The 9H configuration seems to provide the most reliable data when observing the standard deviations of the X, Y, and Z positions. With this configuration, each room had around 4 anchors surrounding it Figure 3.7

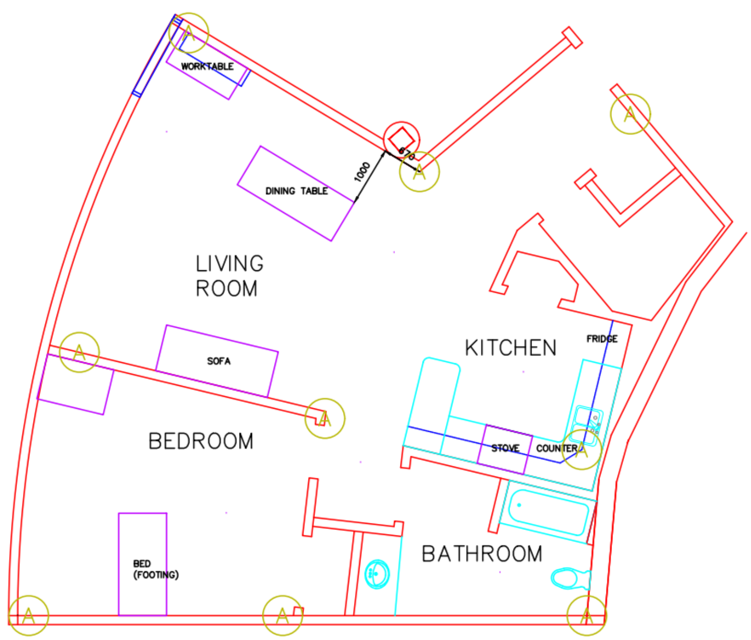

Figure 3.7: ILS Floorplan with the 9 anchors all high.

Though the inaccuracies in the hallway, living room, bathroom and bedroom may prevent the 9H configuration from using heuristics for classification at these locations, the inherent repeatability evident in the low standard deviation in each axes of the position can make the position data from the 9H configuration a candidate for machine-learning based classification.

Chapter 4

Pilot Testing of Detecting Activities to make a Sandwich

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