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 [2]. 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 [9]. 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 [17]. 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 [18].

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 ths 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 [8]. In addition to physical and cognitive abilities, sensory decline with hearing, vision and vestibular function (associated with dizziness) occur [10]. 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 [10].

2.2.1 Frailty

Frailty is a syndrome present in 20-50% of the middle and older aged population (ages 50+ years) [24] and is associated with ageing and co-morbidities, but not caused by them [25]. Individuals with frailty are at "higher risk for adverse health outcomes such as illnesses, hospitalization, disability and mortality" [26]. To define frailty, there are 2 models: the frailty phenotype and the frailty index [27]. 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 [27]. There have been several indices for assessing frailty that have been developed including the frailty index (FI), the Survey of Health, Ageing and Retirement in Europe frailty index (SHARE-FI), and the Groningen Frailty indicator. Applications of Smart Homes include encouraging exercise, and proper nutrition. There is also the potential for monitoring of the symptoms of frailty and tracking the progression of the syndrome as outlined in Lin et al.'s study [28].

2.2.2 Dementia

Dementia is an umbrella term describing a gradual decline in cognitive abilities in several domains to the point of impairing social or occupational function [32]. Dementia involves a slow onset and gradual loss of memory, typically paired with the inability to retain new information [32]. 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 [32]. When diagnosing dementia, a common assessment 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. [33]. Physical exercise, cognitive stimulation, and a healthy diet are some ways to positively affect cognitive function. Smart Homes may have a role in encouraging exercise, performing cognitively challenging tasks such as crossword puzzles and a healthy diet prior to dementia. For patients already with dementia, Smart Homes may have a role in helping the patient remember things such as reminding the patient to take medication, and helping the patient find misplaced items.

2.2.3 Hearing Loss

2.2.4 Vision Loss

2.2.5 Vestibular Function

2.2.6 Cardiovascular Disease

Heart Failure

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 [1]." HF is a clinical syndrome caused by structural and functional defects in myocardium resulting in impairment of ventricular filling or the ejection of blood [2]. The most common cause for HF is reduced left ventricular myocardial function; however, dysfunction of the pericardium, myocardium, endocardium, heart valves or great vessels alone or in combination are also associated with HF [2]. Heart failure (HF) is affecting at least 26 million people worldwide and is increasing in prevalence [3]. Currently 5.7

million people in the US have HF, but the projections are worrisome since it is expected that by 2030 more than 8 million people will have this condition, accounting for a 46% increase in prevalence [3]. The major goals of treatment in heart failure are (1) to improve prognosis and reduce mortality and (2) to alleviate symptoms and reduce morbidity by reversing or slowing the cardiac and peripheral dysfunction [2]. For in-hospital patients, in addition to the above goals, other goals of therapy are (1) to reduce the length of stay and subsequent readmission (2) to prevent organ system damage and (3) to appropriately manage the co-morbidities that may contribute to poor prognosis [2]. 'In-patient' management of HF: It is advised to admit the patient in the telemetry bed or in ICU and the treatment is based on the following points [2].

- Monitor oxygen, whether PaO2 ¡ 60% or SaO2 ¡ 90% [2].
- Provide noninvasive positive pressure ventilation (NIPPV) in the few cases with respiratory distress for respiratory support to avoid subsequent intubation [2].
- Use pharmacological agents depending on the precipitating factors and symptoms/signs for congestion [2].

Ischemic Heart Disease

Artherosclerosis

2.2.7 Diabetes Mellitus

Diabetes occurs when the body cannot control its blood sugar levels [13]. People who have diabetes are at risk of damaging blood vessels in their eyes, kidneys and nerves [13]. Diabetes mellitus can come in two main subtypes: type 1 diabetes mellitus (T1DM) or type 2 diabetes mellitus (T2DM) [13]. 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 [13]. 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 [13]. Signs of diabetes include the following:

- overweight/obese [13]
- acanthosis nigricans [13]
- blurry vision [13]
- yeast infections [13]
- numbness [13]
- neuropathic pain [13]

Management of type 2 diabetes depends on the hemoglobin A1c levels of the person. The higher the A1c, level the greater the intervention. From an A1c level of 5.7%-6.5% management involves encouraging lifestyle changes, weight loss and increased exercise. For levels of 6.5% to 9.0% metformin is added in, and as the A1c levels increase, a second antihyperglycemic drug is added. Finally, once the A1c increases past 9.0%, a basal insulin or prandial insulin is added to the prescription [14]. Smart homes (SH) can be used to monitor blood glucose and make intelligent decisions, such as alerting a physician and providing the physician with blood glucose data when the SH detects blood glucose levels that are not normal [15]. Another use of SH in diabetes is to remind the patient to take their insulin and medication [16].

2.2.8 Osteoarthritis

Osteoarthritis is the most common type of joint disorder. It is a disease characterized by the mechanical destruction and failure of a synovial joint [19]. High-risk factors or factors that greatly increase the chance of having osteoarthritis include obesity and previous joint injury [20]. Osteoarthritis affects approximately 27 million Americans [21] and onsets in a third of adults during the typical working age of 45-64 years [22]. 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 [20]. Osteoarthritis is accompanied by pain and stiffness, which is a driver in the clinical management of osteoarthritis [19]. Strategies recommended by the American College of Rheumatology begin with slowing the progression of the disease. For instance, if an individual is overweight, they can decrease the progression of osteoarthritis by decreasing their weight. If an individual's joint is misaligned, then braces can be used to improve alignment and reduce joint loads [20]. If an individual has muscle weakness, then strength training may be beneficial for slowing down osteoarthritis. In the case that these methods do not appreciably slow the progression of osteoarthritis or improve the symptoms of osteoarthritis, pharmacologic intervention can begin with simple over-the-counter pain relievers such as Tylenol [20]. Vitamins and supplements can also be considered; although the side effects are under investigation, chondroitin sulphate and strontium ranelate have promising results in improving the quality of bone and slowing the progression of osteoarthritis [20]. Nonsteroidal anti-inflammatory drugs (NSAIDS) or opioids can be administered to alleviate symptoms. However, in cases where symptoms are too severe, the last line of defense for managing osteoarthritis is surgery and may involve a total joint replacement. Since obesity is a high-risk factor for causing osteoarthritis [19], Smart Homes can have a role in promoting lifestyle changes such as reminding the patient to exercise or eat healthy. Also, wearables that can measure gait may be used to track the progression of the disease and provide data to clinicians to assist with management of osteoarthritis [23].

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 [14]. 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 testretest reliability of 89%-90%; and an inter-observer agreement of 96%-97% [6] 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 [5] but fraught with risks [19]. Older adults also cook frequently, with 53% of older adults ages 65-80 reported to cook at home 6-7 days a week [12]. 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 [19].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 [14]. 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 [11]. 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 [16]. 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 [13]. 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" [20].

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" [7]. 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 [13]. 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 [15]; 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 [4].

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 [3, 1] 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.

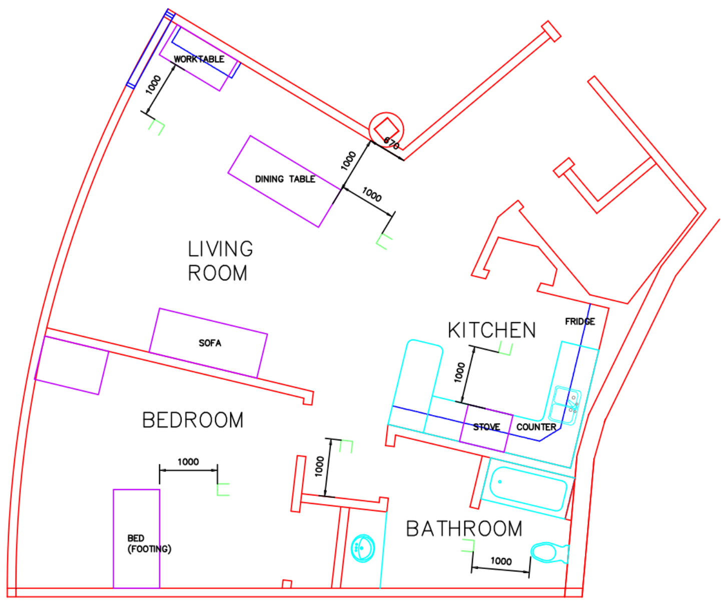


Figure 3.2: Floor plan of the ILS. Positions where the participant stood 1 meter from appliances or furniture are marked in the green "open" box on the floorplan.

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 [1] 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

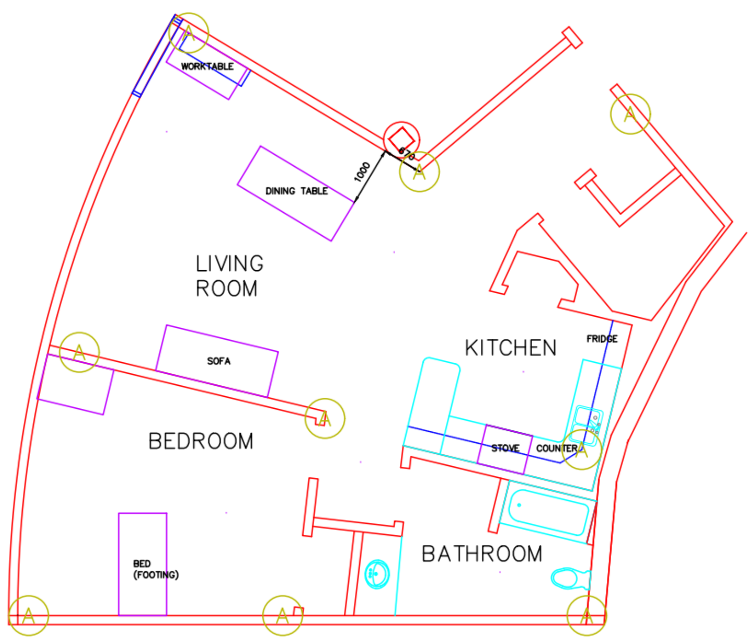


Figure 3.7: ILS Floorplan with the 9 anchors all high.

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

Continuing from the findings in Chapter 2, the 9H anchor configuration was used to perform a preliminary classification of activities in the kitchen. Steps performed in making a sandwich were broken down and organized into Setup, Preparation, Cooking, and Finishing steps, Figure 4.1.

From the actions shown in Figure 4.1, actions with distinct location or patterns were selected as classes for classification. OPENFRIDGE, OPENFREEZER, and GETPLATE were selected as classes from the Setup category, washing hands/vegetables/fruits/using the kitchen sink were grouped into a WASHHANDS category, and SLICETOMATO were selected as a class. Finally, All intermediary transitions or motionless segments were grouped into a UNDEFINED category. Single trials were performed to collect data for each of these classes.

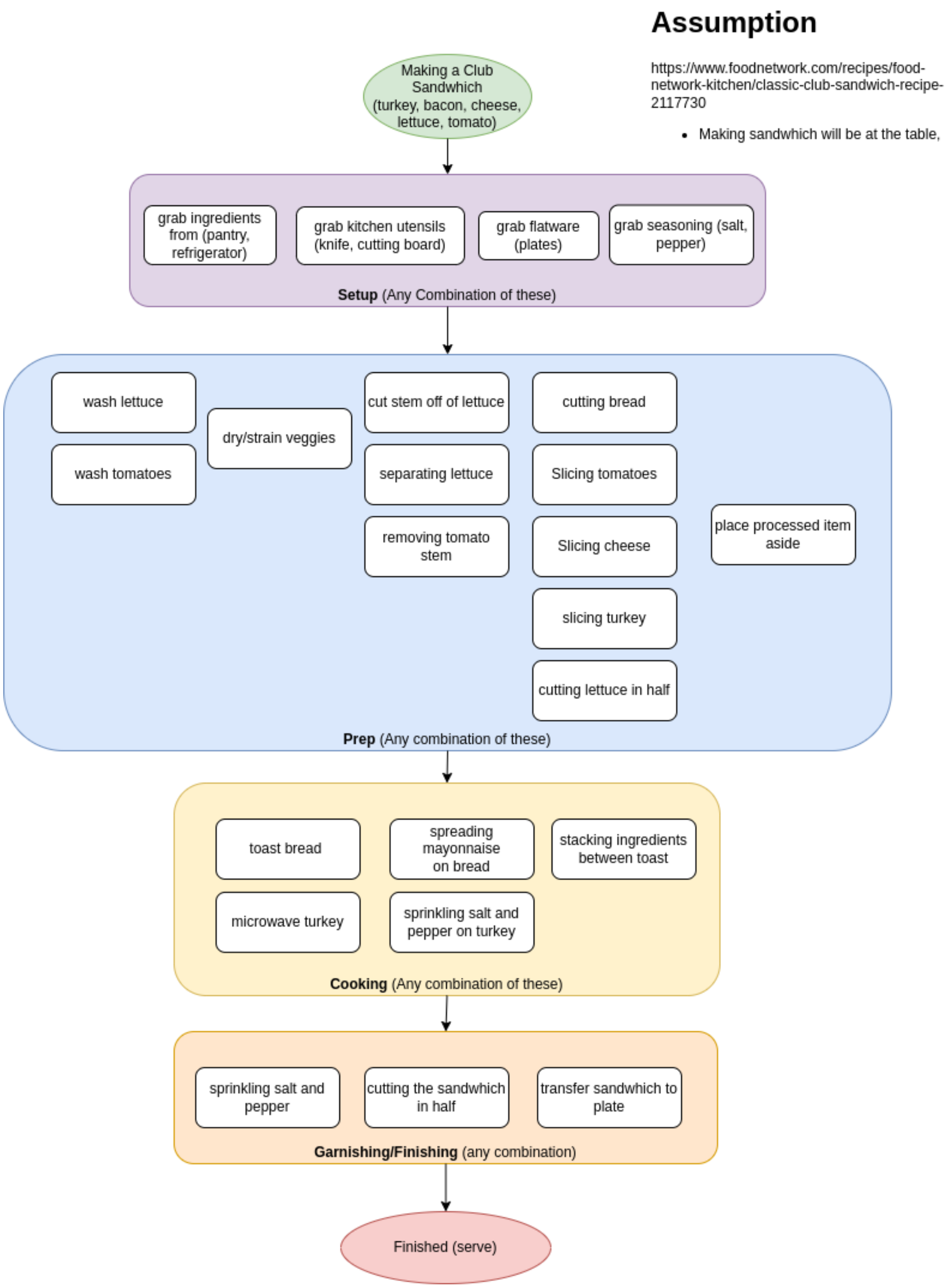


Figure 4.1: Task decomposition of making a sandwich.

4.1 Experimental Protocol

4.1.1 Setup

Several points were enforced to ensure that the training dataset captures the variation in action sufficiently when classifying data from right-handed individuals.

- Pozyx Tag is mounted on the right wrist (Figure 4.2).
- Initial position for each of the single trials are not marked. Participant will be able to choose a location from which they can perform the action comfortably without moving their feet.
- An action starts when the individual contacts the appliance or furniture. For SLICETOMATO the action starts when an individual starts slicing the tomato and ends when they stop slicing the tomato. Motions such as picking up the knife and getting in position to slice were considered transitions and labelled as UNDEFINED.

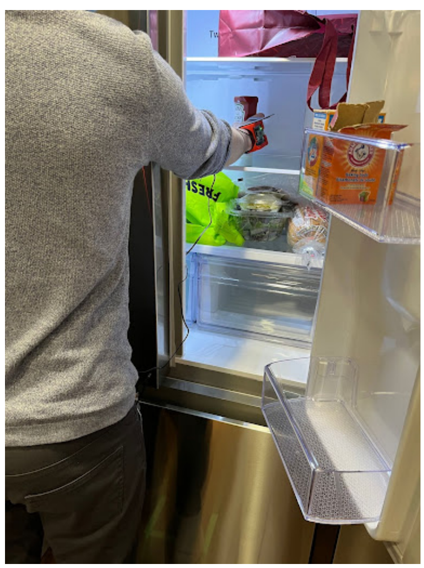


Figure 4.2: Pozyx tag mounted on the wrist. The participant is performing the OPENFRIDGE task

4.1.2 Data Collection

Custom Python stopwatch scripts were created to accurately label periods of transitions (quiet standing + getting into position for the action) and the action. An example of the data collected is shown in Figure 4.3. For each action there is a quiet standing period at the beginning and end. OPENFRIDGE, OPENFREEZER, OPENPLATE, WASHHANDS each had 5 repetitions for each trial. SLICETOMATO contained 3 slices to conserve the amount of tomato. Each action had a total of 5 trials.

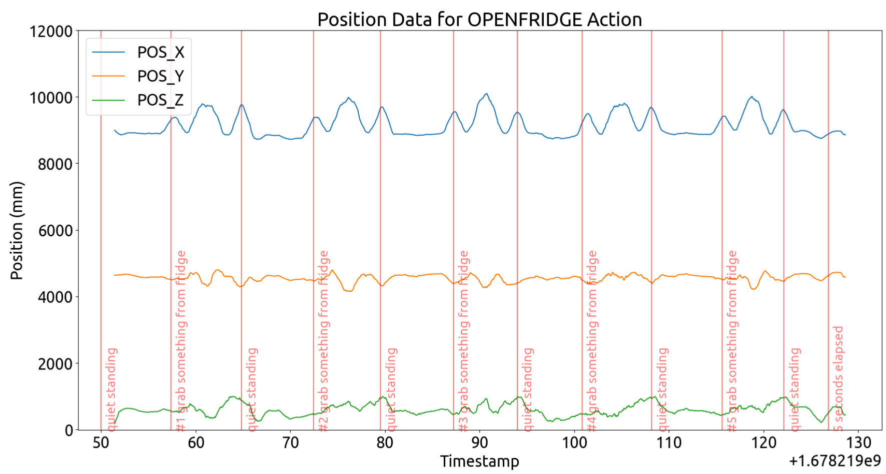


Figure 4.3: Labelled position data of the OPENFRIDGE action. Note that the "quiet standing" periods do not consist entirely of quiet standing, but also include traces of transitions from getting into the correct position to perform the action.

Since the Pozyx Tag contained a BNO055 chip, in addition to 3D Position data, the tags were able to capture inertial data including Accelerometer Data, Linear Accelerometer Data, Angular Velocity Data, and the orientation.

Data for each of the actions that relate to making a sandwich were collected from 2 participants.

4.2 Feature Extraction

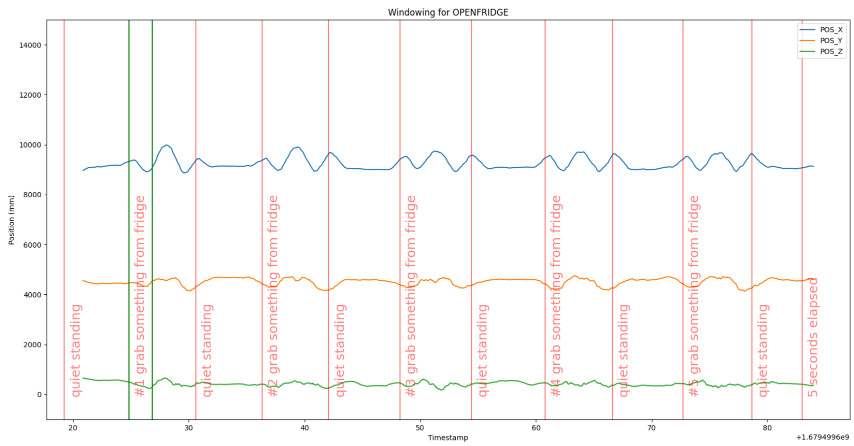
An initial sliding window with a width of 2 seconds and a stride length of 1 second was used to ensure that enough feature vectors could be extracted from the SLICETOMATO dataset. An example of a windows taken for the OPENFRIDGE action and UNDEFINED action are shown in Figure 4.4.

From each window, basic statistical measures over the entire window were taken. These measures include the MEAN, MEDIAN, MODE (to 5cm for position), MAX, MIN, and STD of the entire window. From each window of data, there were a total of 3 (axes) * 5 (types of data) * 6 (statistical measures) = 90 Features

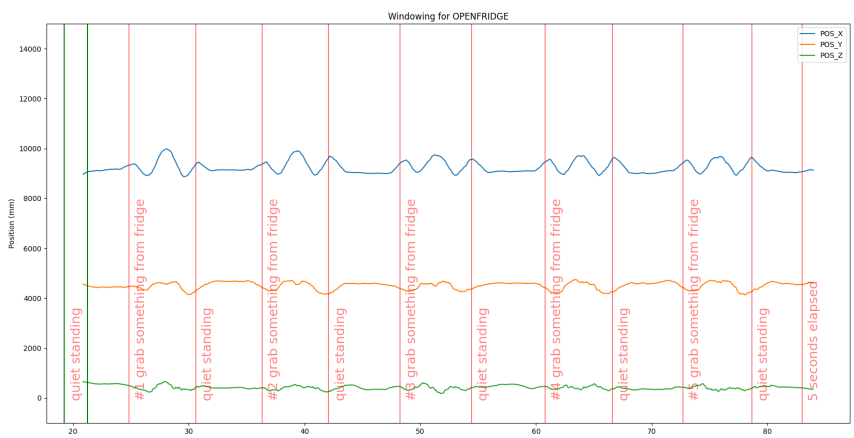
From the entire timeseries dataset, 2773 feature vectors were extracted. Refer to Table 4.1 for the breakdown of counts for each label.

Table 4.1: Count of the occurrences of each action.

Action	Count
UNDEFINED	1518
SLICETOMATO	197
WAHSHANDS	316
OPENFRIDGE	239
OPENFREEZER	203
GETPLATE	300



(a)



(b)

Figure 4.4: Obtaining windows from the OPENFRIDGE dataset. The green vertical lines section off a 2-second window. (a) A window labelled OPENFRIDGE. (b) A window labelled UNDEFINED.

4.3 Model Selection

A 60:40 split was used to train and test the model selected. Several models were chosen including Linear Support Vector Machine, Radial Support Vector Machine, K-Nearest Neighbors, Decision Trees and Random Forests. As this was a pilot study in determining the feasibility of classification of the fine-grained actions involved in making a sandwich, rigorous parameter tuning and feature selection were neglected and the defaults from the sklearn Python package were used.

4.4 Results

The confusion matrices from each model are output in Figures 4.5-4.10. Total accuracy was reported as well as the sensitivity, specificity, and precision of each class were reported. These measures are calculated as follows:

$$\text{Accuracy} = \frac{\text{All}\, TP}{N} \tag{4.1}$$

$$\text{Sensitivity} = \frac{TP}{TP + FN} \tag{4.2}$$

$$\text{Precision} = \frac{TP}{TP + FP} \tag{4.3}$$

$$\text{Specificity} = \frac{TN}{TN + FP} \tag{4.4}$$

Where N is the number of samples TP are True Positives, TN are true negatives, FP are false positives and FN are false negatives.

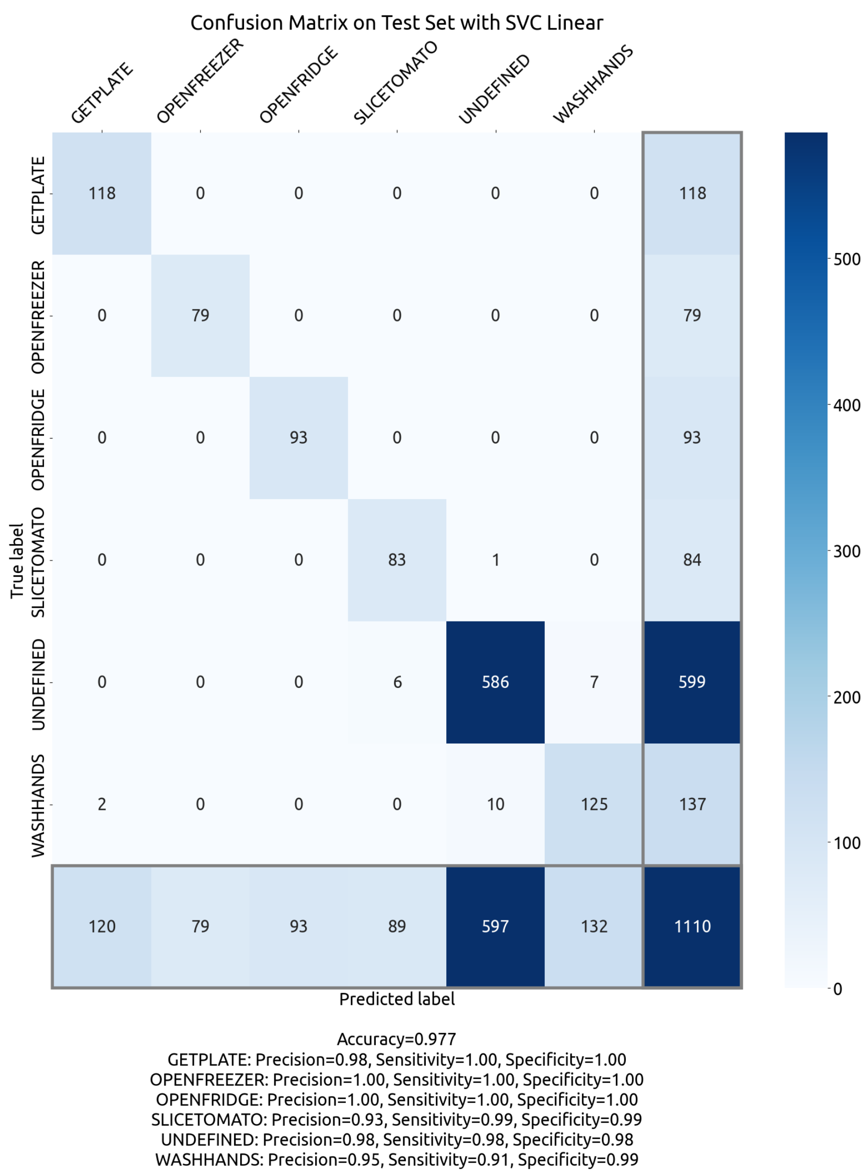


Figure 4.5: Test confusion matrix using the Support Vector Classifier with a Linear Kernel

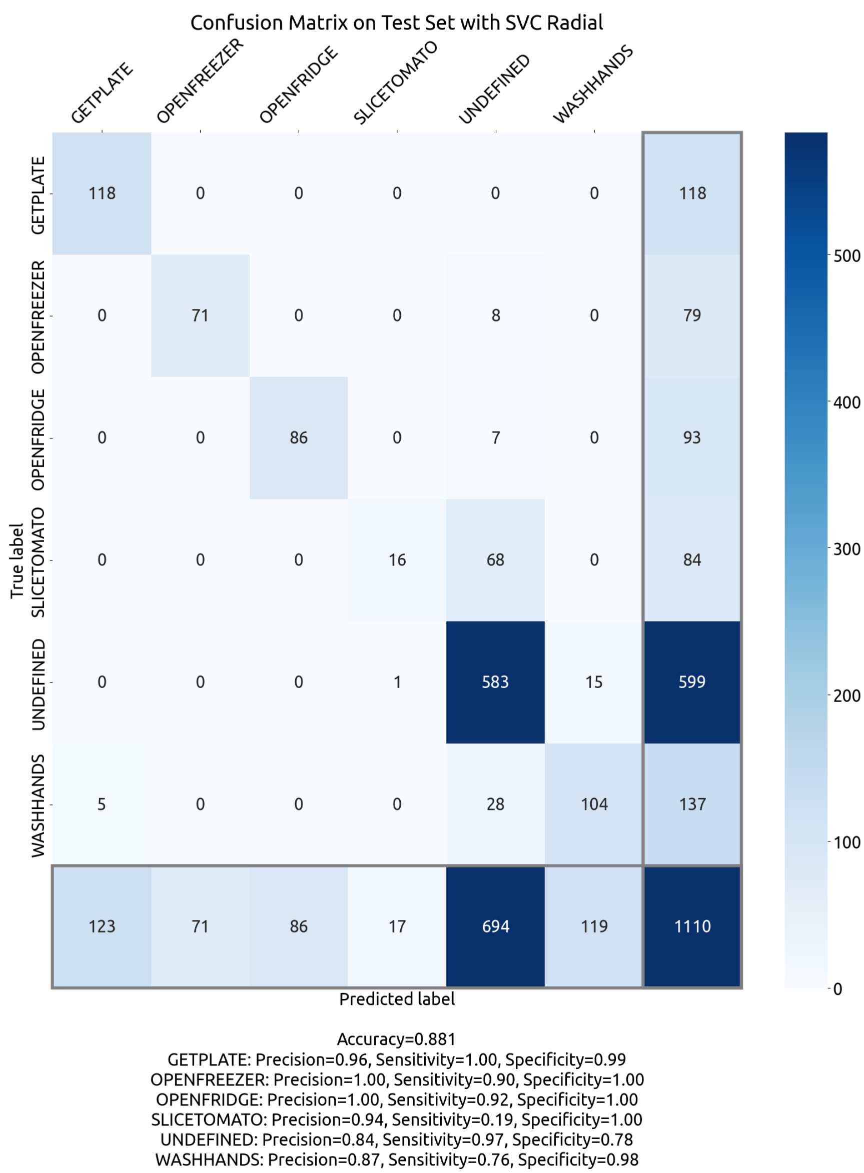


Figure 4.6: Test confusion matrix using the Support Vector Classifier with a Radial Kernel

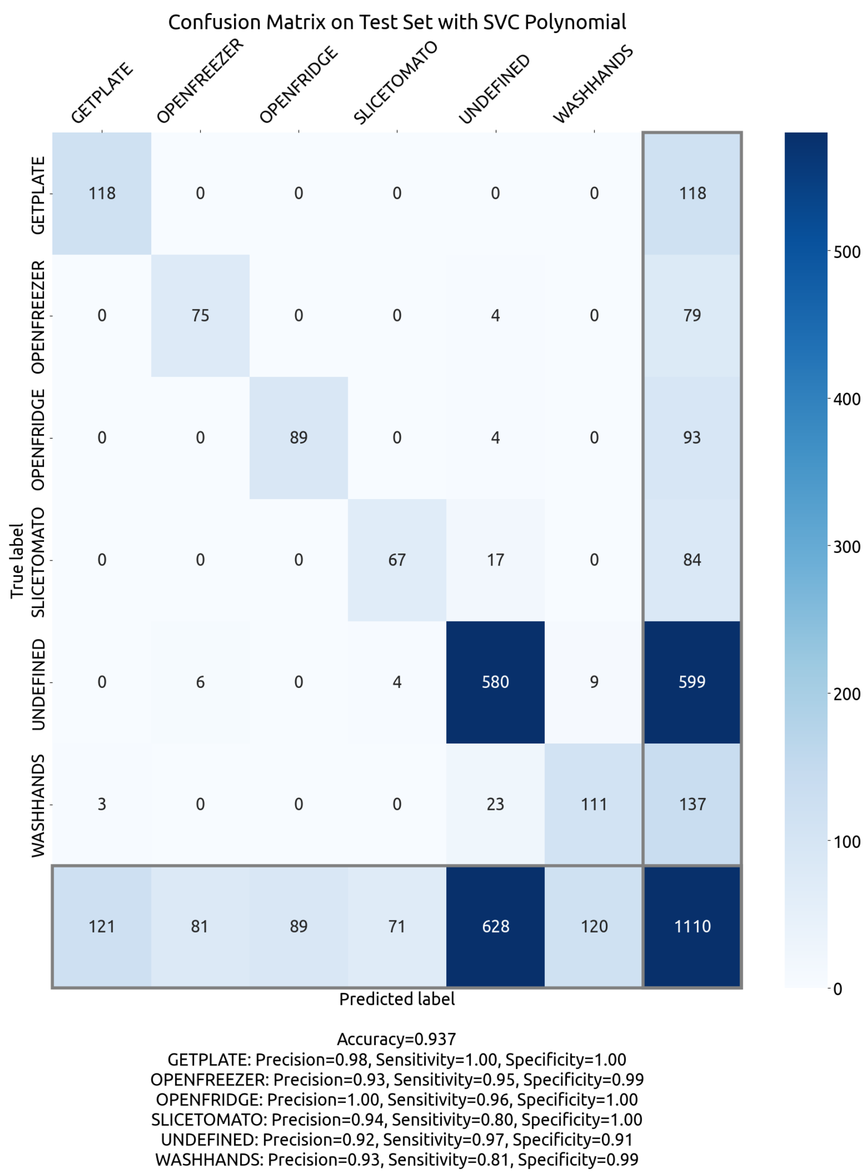


Figure 4.7: Test confusion matrix using the Support Vector Classifier with a Polynomial Kernel

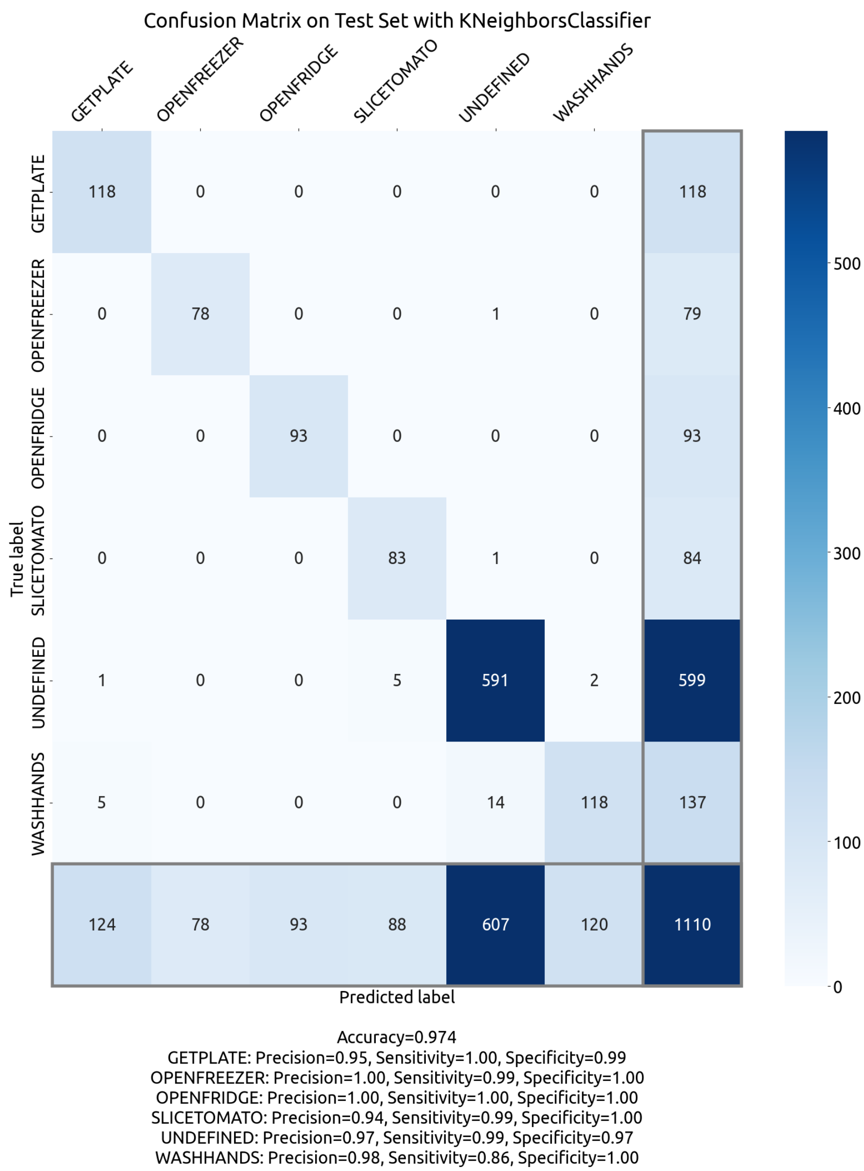


Figure 4.8: Test confusion matrix using the K-Nearest Neighbors Classifier

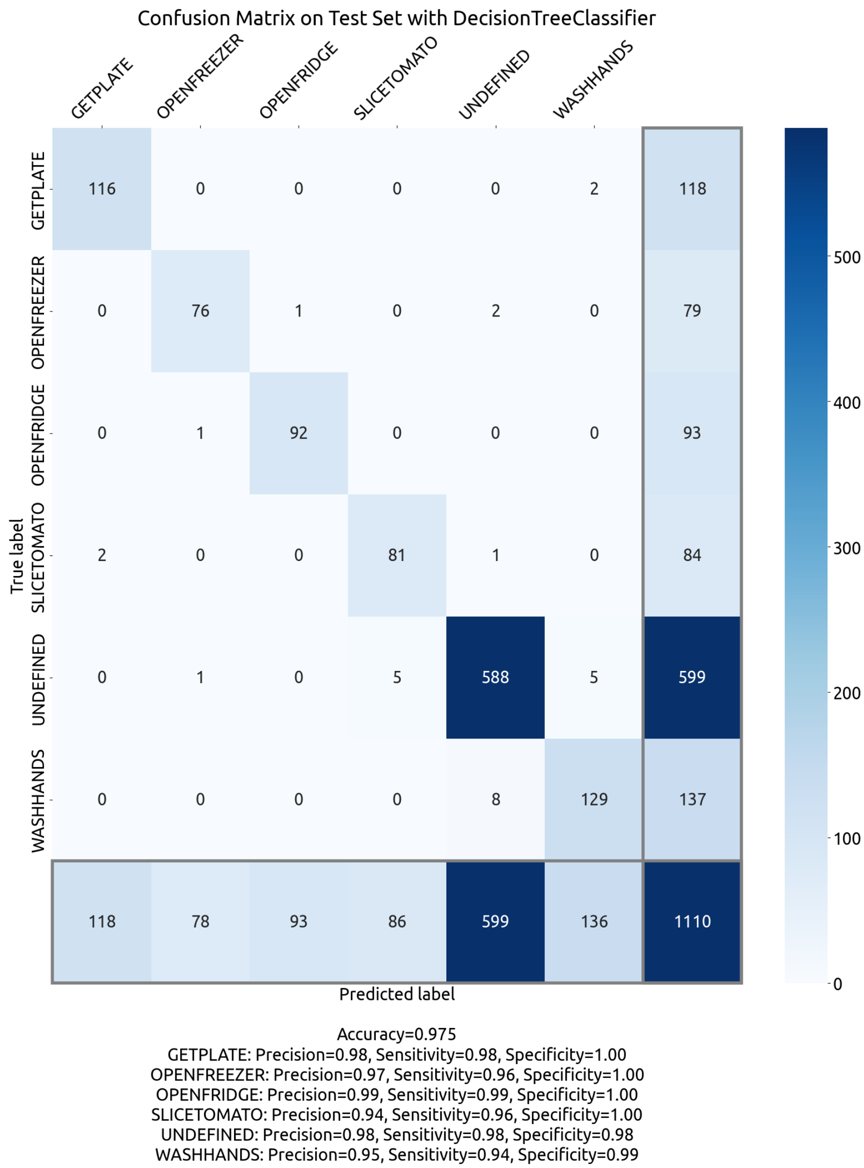


Figure 4.9: Test confusion matrix using the Decision Tree Classifier

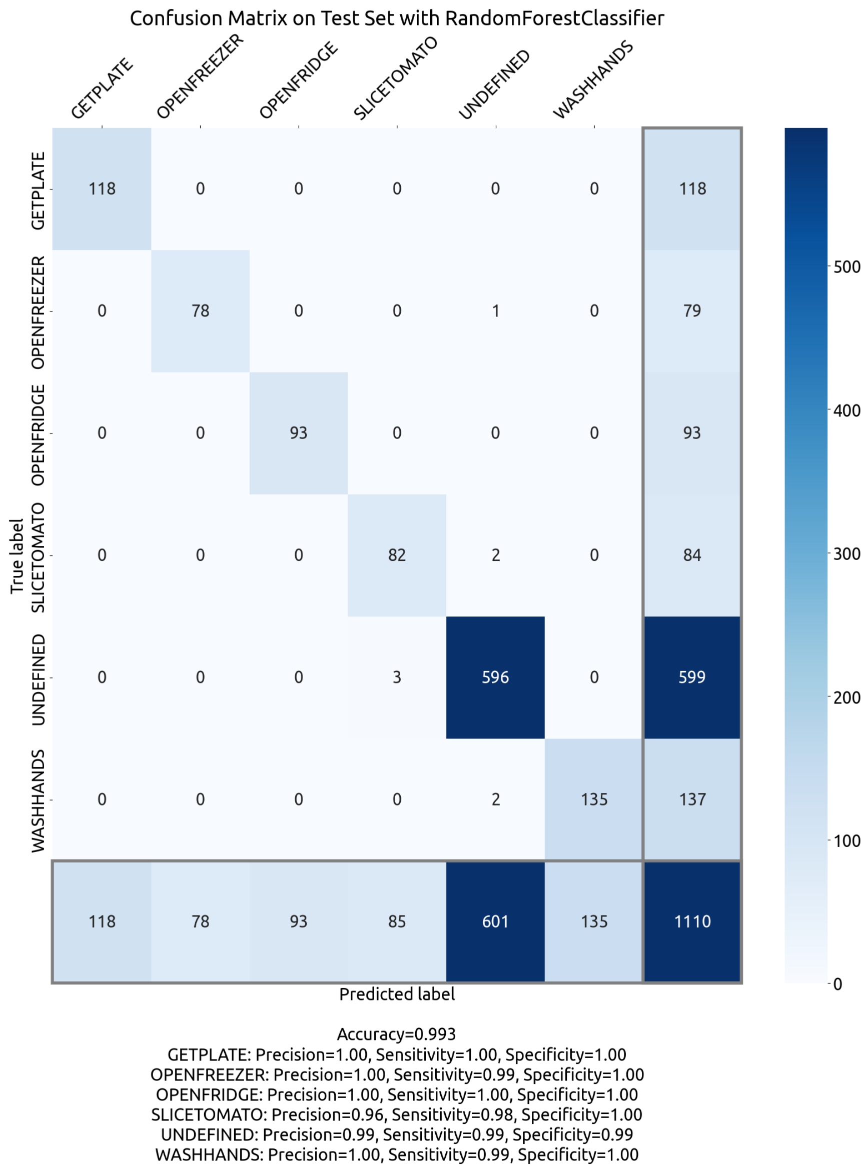


Figure 4.10: Test confusion matrix using the Random Forests Classifier

4.5 Discussion

Table 4.2 summarizes the accuracies obtained from each model.

Table 4.2: Accuracy of each Model

Model Name	Accuracy (%)
SVM Linear	97.7
SVM Radial	88.1
SVM Polynomial	93.1
kNN	97.4
Decision Tree	97.5
Random Forests	99.3

With the exception of the Radial SVM, all of the models perform well achieving an accuracy of somewhere in the high 90s. In day-to-day activities, there is a disproportionately higher number of the UNDEFINED class compared to the other "action" classes signifying the presence of class imbalance. If a classifier guesses all UNDEFINED it can obtain an accuracy of $599/1110 = 54\%$. Thus, accuracies taken around 54% should be interpreted with caution. Other metrics such as the Sensitivity, Precision and Specificity have been provided to address this class imbalance. Sensitivity is the rate at which the classifier predicts a TP, Precision is the fraction of predictions that are actually true, and Specificity is the rate at which the classifier predicts a TN. Of all the models, the Random Forests Classifier at the default settings seem to the best in terms of Accuracy and Precision, Sensitivity, and Specificity for all classes.

The performance of these models in the real-time will need to be tested and quantified before any conclusions can be made. A high accuracy is promising, but may also be indicative of overfitting which means that the model will not be able to generalize variation experienced in the real world. In later sections, more fine-grained actions will be considered, models will be more rigorously tuned, and the performance in real-time will be investigated.

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