Fine-Grained Activity Detection in the Kitchen with UWB

University of Alberta

Steven Phan

08 April 2023

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

By 2030, Statistics Canada expects there to be over 9.5 million adults over the age of 65, comprising 23% of Canadians [1]. Older adults (65 years or older), who want to live by themselves or age in the comfort of their homes (aging-in-place) must be able to perform their activities of daily living (ADLs) while facing declining physical and cognitive abilities [2]. Furthermore, older adults may need to face multiple comorbidities that include one or more of the following: multiple sclerosis, stroke, Parkinson's disease, dementia, traumatic brain injury and ataxia as they age [3]. One important factor in being able to perform these ADLs is the older adult's mobility, which Soubra et al. defines as the "[older adult's] ability to change [their] position or location or move from one place to another by walking and basic ambulation" [4]. Older adults with mobility limitations have a higher risk for falls, reduced access to medical services, and poorer psychological health and functional abilities [5]; all of which hampers an older adult's ability to age-in-place. Therefore, it is critical that the mobility of the older adult be assessed and tracked regularly to ensure that they have adequate mobility to perform all the necessary ADLs as they age [5]. If the older adult does not have adequate mobility, the assessments should have the role of highlighting areas of struggles in the older adult [4], [6] to a clinician who can suggest interventions or mobility aids.

Currently, mobility assessments take place in the clinic meaning that the older adult must travel to the clinic and be physically present with the clinician who instructs the older adults on what to do. Soubra et al. identified 31 pen-and-paper assessments that may be used to evaluate mobility in older adults [4]. In 2019, the top 5 most frequently cited mobility assessments were the Timed Up and Go (TUG), Short Physical Performance Battery (SPPB), Tinetti Performance Oriented Mobility Assessment (POMA), the Berg's Balance Scale (BBS), and the Six-Minute Walk Test (6MWT) [4]. These assessments can take up to 15 minutes and consist of simple tasks.

In the Timed up and Go test (TUG), the older adult starts from a seated position and is asked to walk 3 meters, turn 180 degrees, walk back to the chair, and sit down [7]. The process is timed and the time elapsed can be used as an indicator of functional capacity [7]. It is also used in the clinic as a screening tool that suggests patients with a TUG time 12 seconds or greater [8] receive further mobility investigation or recommendations for mobility aids [9].

In the Short Physical Performance Battery (SPPB), there are 3 categories of test: a test of standing balance by placing their feet side-by-side, semi-tandem and tandem for 10 seconds; walking across an 8-foot track; and finally 5 times sit-to-stand [10]. Each category is assigned a score of 0 to 4, which could be used to track the lower extremity function of the older adult as they age [9].

The original Tinetti Performance Oriented Mobility Assessment (POMA) consists of 2 assessment sections: balance and gait. The balance section contains 13 items that assess balance such as rising from a chair, turning balance, and standing with perturbation and the gait section contains 9 items that are assessed by asking the patient to walk down a hallway and back [11]. In practice, a modified POMA is used with 9 balance tasks and 7 gait tasks scored out of 2 or 3 and totalled to a maximum of 28 [4]. The total score can then be used to predict falls, measure mobility impairment, and study the effects of interventions [12].

The Berg Balance Scale (BBS) consists of 14 item that are scored from 0 to 4 with higher scores indicating better balance [9], [13]. Items include sitting tasks, standing tasks, and action tasks such as retrieving an object from the floor, stepping on a stool, and turning and reaching forward while standing [14]. For patients with stroke, a total BBS score of 0 to 20 indicates balance impairment, 21 to 40 indicated acceptable balance, and 41 to 56 indicates good balance [9]. Generally, scores from the BBS can be used to track changes in balance. However, there is a minimal detectable change (MDC) of 2.8 to 6.6 points (MDC changes based on the score range) that must be considered when concluding significant improvement or decline in balance [9].

Finally, in the Six-Minute Walk Test (6MWT), the patient is asked to walk as far as they can in 6 minutes [9], [15]. The distance is measured and can be used to assess the patient's aerobic capacity/endurance [9]. Also, a distance travelled less than 338m can indicate an increased risk of all-cause mortality [9].

Overall, these pen-and-paper mobility assessments generally seek to evaluate 3 things: fall-risk, need for intervention or mobility aids, and change in gait, balance, and transfer ability [4], [9].

In addition to pen-and-paper assessment, there is literature on the use of wearables containing inertial measurement units (IMUs) to quantify gait and balance as an alternative to scores, distances, or durations from the pen-and-paper assessments.

Zampieri et al. collected gait parameters including stride length, stride velocity, turning velocity, and cadence during a Timed up and Go (TUG) test [6]. Data was collected from an IMU on the chest as well as gyroscopes attached to the dorsum of each wrist, and each anterior shank (5 sensors in total) [6]. Gait parameters collected in the clinic compared to ones collected at home showed that older adults with PD performed worse in the home than in the clinic [6]. Furthermore, there was a significant difference in the gait parameters between PD patients and able-bodied controls [6] suggesting that the gait parameters proposed may be used as part of a mobility assessment and monitoring in older adults.

In another study, Noamani et al. objectively assessed standing balance by deriving center-of-pressure (COP) balance parameters [16] and body center-of-mass (COM) balance parameters [17] from data obtained by an IMU placed on the sternum, sacrum, and tibia of the dominant leg during a BBS assessment [18]. Balance parameters include root-mean-square distance from mean COP, mean velocity, sway area, median frequency in the anterior-posterior, mediolateral, and their resultant distance direction. These balance parameters were first compared between older adults and young adults and showed that the measures of COP were significantly different [18] indicating decline in balance can be tracked with IMUs. Then, the balance parameters were compared to scores from the BBS at admission and discharge for the older adult group. Both BBS and balance parameters suggested an improvement at discharge in the older adult group, but it was only the balance parameters that could explain what and where the underlying improvements were made (eg. reduced sway acceleration and jerkiness in the mediolateral direction) [18].

Using sensors have the advantage over pen-and-paper assessments in providing objective data that answer why pen-and-paper mobility assessment scores, distances or times were low or high.

Though in-clinic assessments (pen-and-paper or sensors) can provide information on the mobility of older adults, results from the in-clinic assessment may be influenced by the white-coat bias (being in the clinic affects performance), the Hawthorne effect (being observed affects performance), and day-of fatigue, pain, and stress [19] leading to a misrepresentation of performance in unsupervised environments such as the home—from Warmerdam et al's systematic review, it was found that performance was overall lower (slower gait speeds, and longer transfer durations) in unsupervised settings compared to supervised, clinic, environments [19]; they are time-consuming (commute to the clinic and administration of the assessment); and they provide only snapshots of the older adult's mobility meaning that clinically relevant in-home events that may include response to dopaminergic treatment in Parkinson's Disease, falls, and freezing [19], [20] may be overlooked. Thus, to assess an older adult's mobility for the purpose of ageing-in-place, unsupervised data collection and analysis are essential [19], [21].

To collect data on mobility in unsupervised settings, usage of smart homes, or wearable sensor suites have been implemented at various institutions. The Center of Advanced Studies in Adaptive Systems (CASAS) created multiple smart homes instrumented with item sensors, motion sensors, and door sensors [22]. Kaye et al. placed a series of passive infrared (PIR) sensors 61 cm apart in a single hallway to automatically collect trigger events that could be used to calculate the participant's gait speed [23]. Schooten et al. used an accelerometer placed at the L5 level on the trunk to obtain gait quality characteristics such as walking speed, stride length, stride frequency, intensity, variability, smoothness, symmetry, and complexity. These gait quality characteristics were shown to be moderately to highly correlated (r ¿ 0.4) with fall incident during monthly check-in with the participant for six to twelve months [24]. Sprint et Al. used 3 inertial measurement units (IMUs) placed on the patient's center of mass, and both ankles to assess a "standardized ambulation [created during the study] performance task called the ambulatory circuit (AC)" [25]. The ambulatory circuit consists of rising from a seated position in a chair, walking to the vehicle, transferring into the vehicle, and walking back to and sitting in the chair. 16 parameters including walking speed, cadence, shank range of motion, step length, step regularity, stride length and step symmetry were calculated. Additionally, duration of events such as sit-to-stand, stand-to-sit, and straight walking were calculated, graphed and presented to the clinicians [25]. Newland et al. used a 3D depth imaging system to collect stride time, stride length, gait velocity in Multiple Sclerosis patients and correlated them to daily symptoms and found that pain and fatigue decreased stride length and gait velocity [26]. Finally, Tiger Place uses a sensor suite that consists of depth cameras (Microsoft Kinect [27]), motion detectors, and bed sensors to detect activity as well as vitals (during sleep) [28]. The depth camera is used to collect gait parameters such as stride length and gait speed [27].

The studies in literature have demonstrated that it is possible to collect and analyze data in an unsupervised setting with the purpose of monitoring mobility. However, some of the methods require many sensors placed on the body [29], [30] and are impractical for long-term implementation in unsupervised settings (the older adult will need to put on and take off many sensors everyday). In terms of ambient patient mobility monitoring, sensor suites that include cameras may be undesirable due to concerns with privacy [26]. Placing motion sensors in series to estimate walking speed may be feasible in a small area of the home, but may be impractical if required to be placed around the entire home [31]. Additionally, motion sensor systems may have difficulty distinguishing between each person in a multi-resident tracking situation without habitual pattern recognition or machine learning [22]. Thus, although data may be collected and analyzed in an unsupervised setting, practicality, privacy, acceptance, and adherence to the sensor system must be considered. For body-worn sensors, a survey by Noury et al. discovered that individuals prefer to have sensors on the wrist the most, followed by trunk (chest), belt, ankle, and armpit [32]. A further consideration is integration of data collection and analysis into wearables containing sensors that are already available on the market such as the Fitbit, Apple Watch, Garmin Watch or sensors can be integrated into accessories that people already wear (belts, necklaces, rings). For example, sensors on necklaces and wrist are seen as locations with heightened acceptability [33].

In addition to limitations with scalability, privacy, multi-resident tracking, adherence, and acceptance with current systems, Warmerdam et al. state that one critical limitation is that data from unsupervised environments is challenging to interpret [12]. Misclassification can occur from similar IMU signals that occur in situations such as bending over to pick something up and a sit-to-stand event; or tremors and teeth brushing [19], [21]. Furthermore, there is not yet a standardized way of validating the unsupervised data [19]. Post-analysis of video capture can aid with validation, but it is estimated that it will take 1.5h-2h to process and label 20 minutes of video data [34], [35], which may be hard to implement in studies at scale. All mobility parameters are a product of both intrinsic (physiological) and extrinsic (environmental) factors. Thus, the context in which the measures of mobility, such as gait asymmetry, are assessed in must be considered [19], [21], [36]–[38]. Considering all the limitations with current methods of unsupervised mobility data collection and analysis, indoor localization combined with wearables sensors may be a scalable solution for capturing context-rich and interpretable mobility data in unsupervised settings without compromising privacy.

There are many radio frequency (RF) technologies that can be used to localize an object including GPS, WiFi, Bluetooth, and RFID [39]–[42] that requires a tag to placed on the person or thing being tracked, and static anchors that use trilateration to determine position or returns the position of the anchor as the tag passes by. However, localization used with these methods achieves accuracies on the order of meters [39], [42]. An accuracy on the order of meters means that the person could be anywhere in a room (2.74m – 4.87m [43]); the system will be able to tell that a person is in a room, but not where. Ultra-wideband (UWB) technology, however, can have a positioning accuracy of less than 30 centimeters [39] which allows the system to tell what furniture or appliance an individual is interacting with within a room. Furthermore, each user receives a tag for tracking so multi-resident tracking will be a feature that is included with the technology. The context provided by UWB is expected to enhance validation of data from wearable IMU. In relation to the situations provided in [19], [21], if it is known the older adult is at a static piece of furniture, it is not likely that they are bending over to pick something up. Similarly, if it is known that the older adult is at the sink in their washroom, then there is a higher chance they are brushing their teeth instead of experiencing tremors.

In line with the goal of continuously assessing mobility at home, this project seeks to fuse UWB indoor positioning data with data obtained by a consumer smart watch to assess the feasibility of validating unsupervised data and using the system for remote mobility monitoring. As part of the feasibility assessment, system-specific algorithms to extract gait and balance parameters found previously in literature will also be developed. To address practicality, acceptability and adherence, the smartwatch will be worn on the non-dominant wrist, and the tag for the UWB system will be worn as a necklace. Current smart watches can measure heart rate, steps, and wrist acceleration; and the UWB system can measure position and acceleration at the chest.

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.

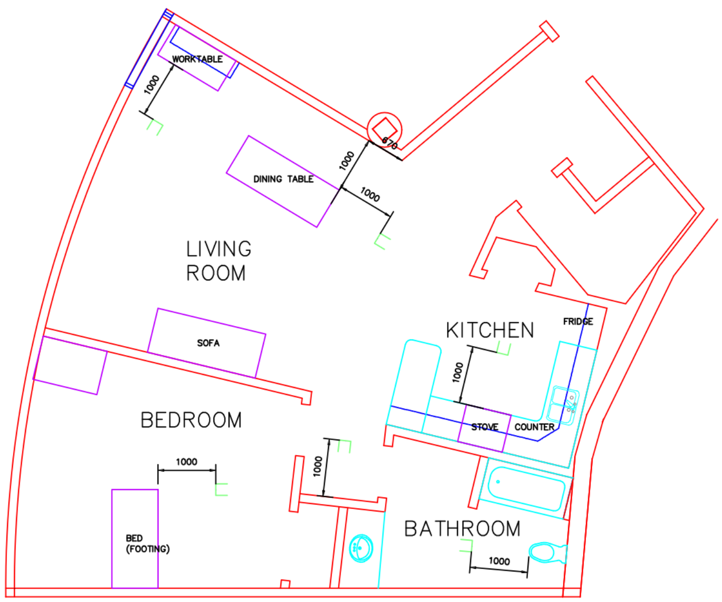


Figure 3.2: Floor plan of the ILS. Positions where the participant stood 1 meter from appliances or furniture are marked in the green "open" box on the floorplan.

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

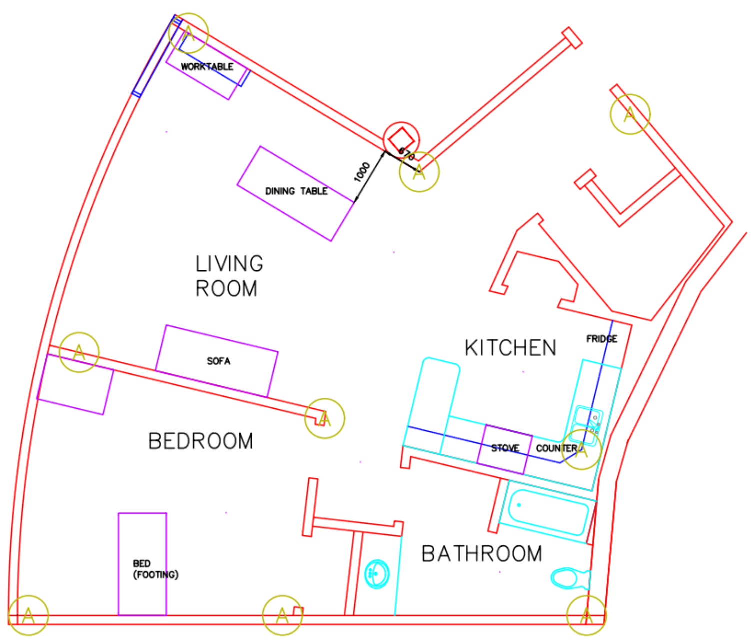


Figure 3.7: ILS Floorplan with the 9 anchors all high.

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.

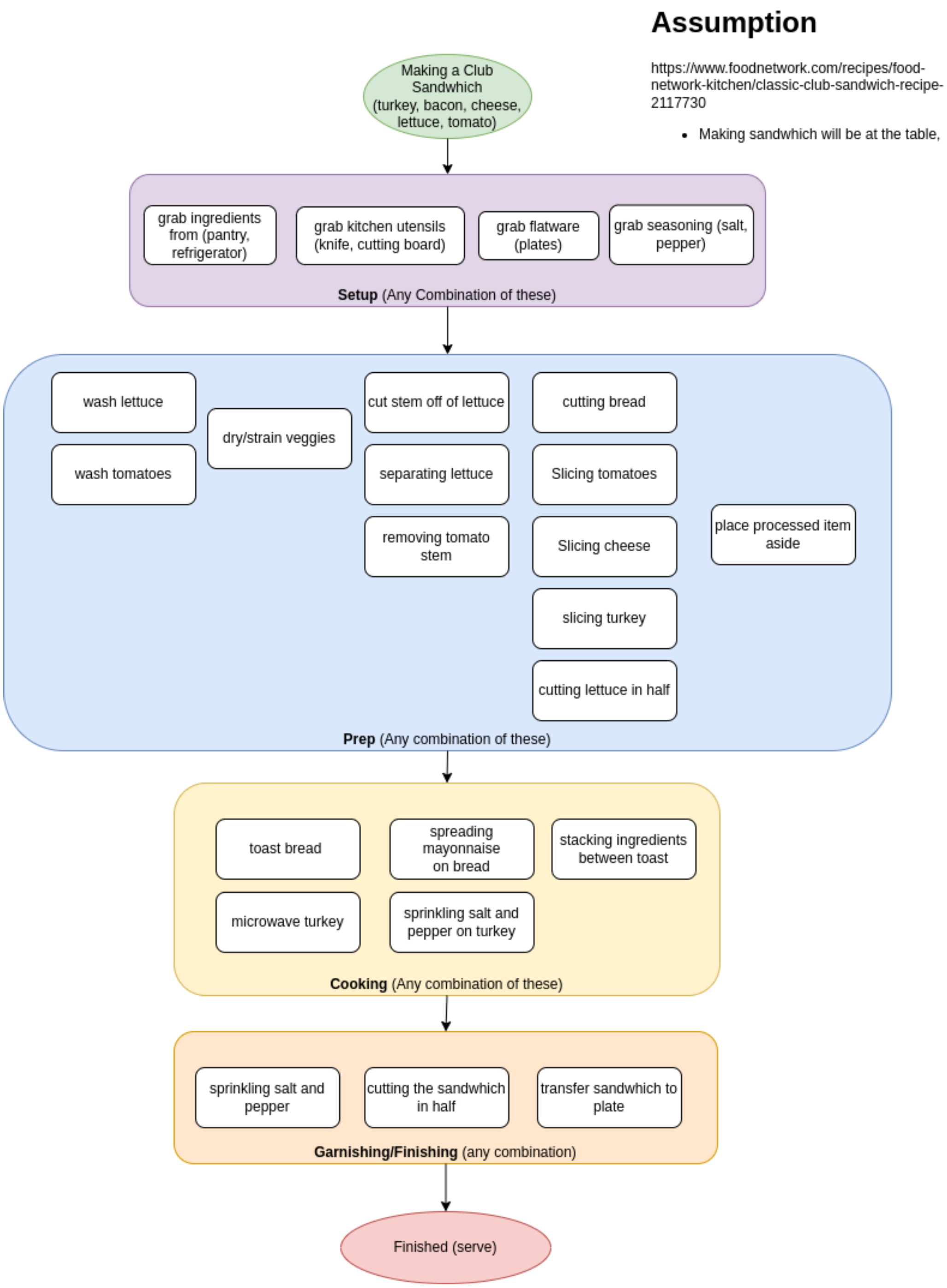


Figure 4.1: Task decomposition of making a sandwich.

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.

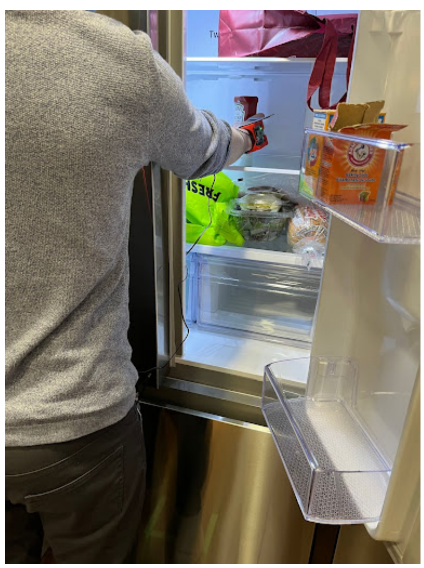


Figure 4.2: Pozyx tag mounted on the wrist. The participant is performing the OPENFRIDGE task

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.

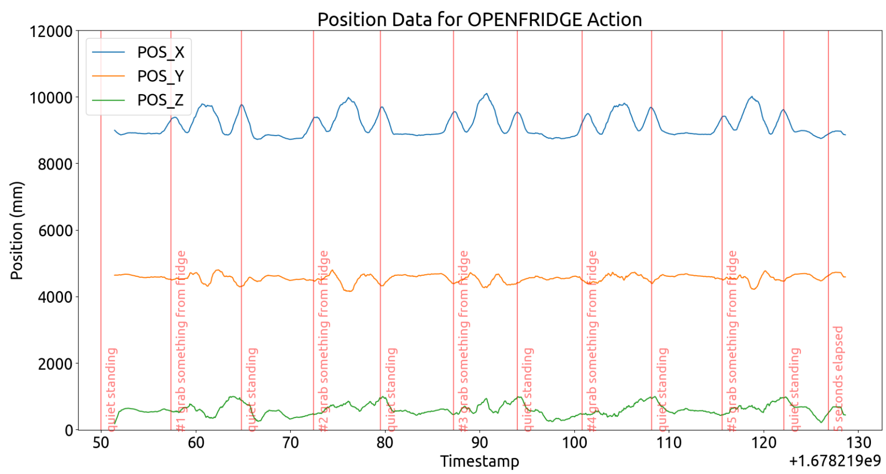


Figure 4.3: Labelled position data of the OPENFRIDGE action. Note that the "quiet standing" periods do not consist entirely of quiet standing, but also include traces of transitions from getting into the correct position to perform the action.

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

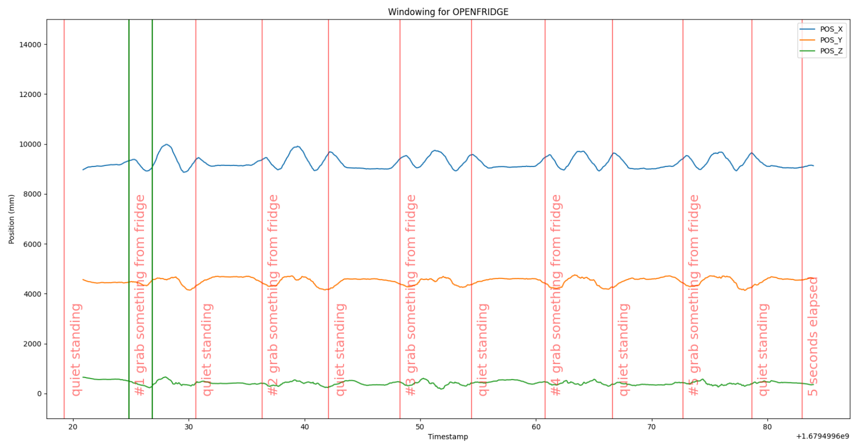
An initial sliding window with a width of 2 seconds and a stride length of 1 second was used to ensure that enough feature vectors could be extracted from the SLICETOMATO dataset. An example of a windows taken for the OPENFRIDGE action and UNDEFINED action are shown in Figure 4.4.

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

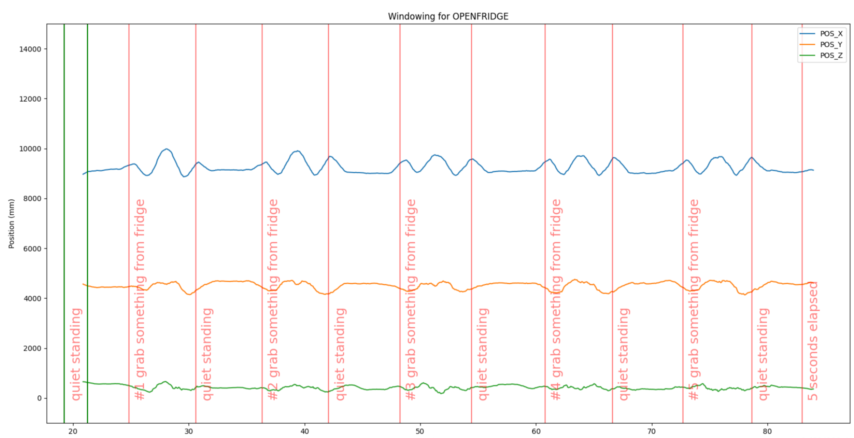
From the entire timeseries dataset, 2773 feature vectors were extracted. Refer to Table 4.1 for the breakdown of counts for each label.

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.

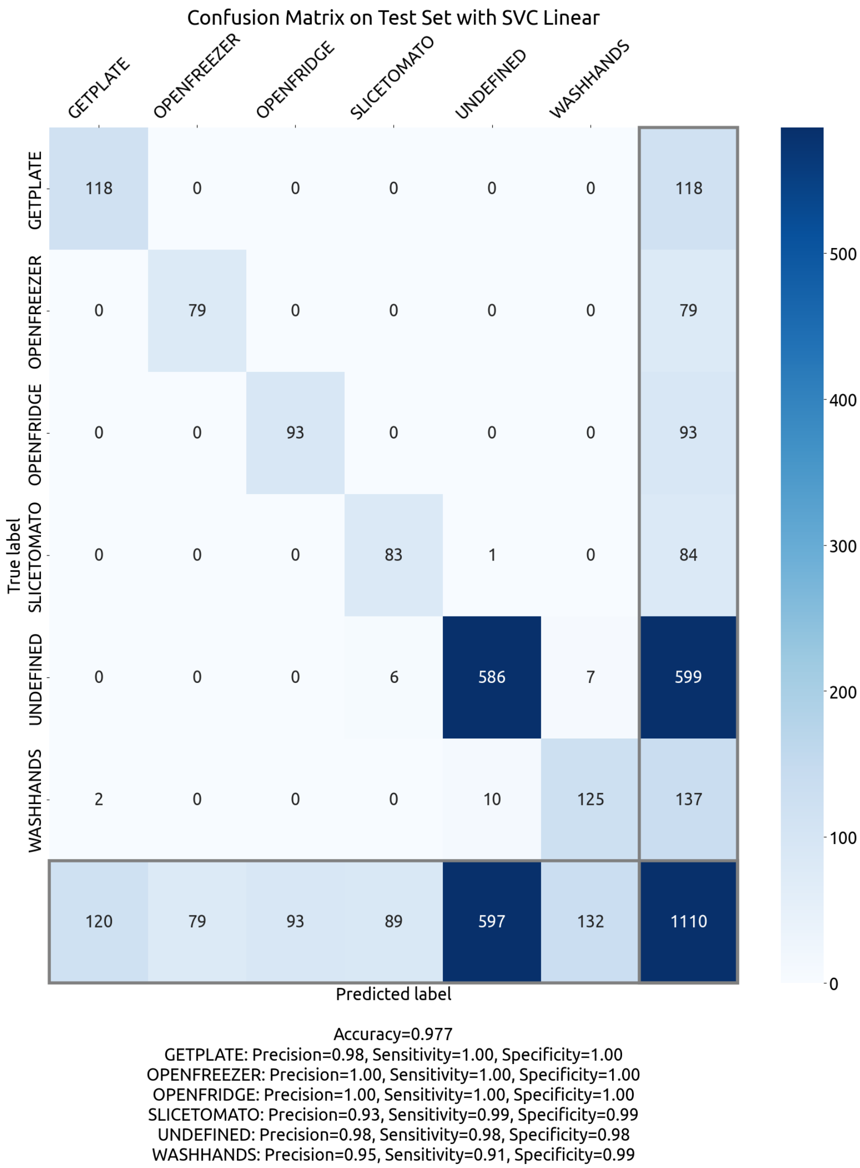


Figure 4.5: Test confusion matrix using the Support Vector Classifier with a Linear Kernel

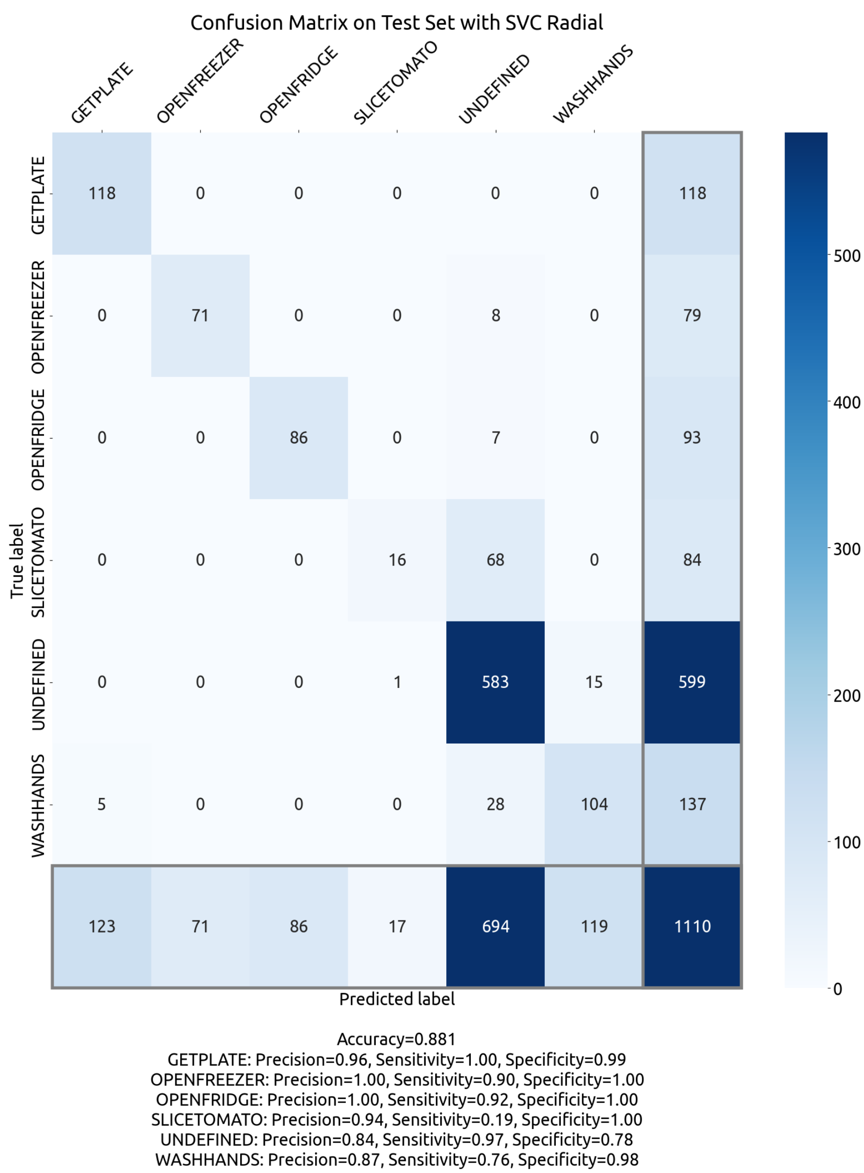


Figure 4.6: Test confusion matrix using the Support Vector Classifier with a Radial Kernel

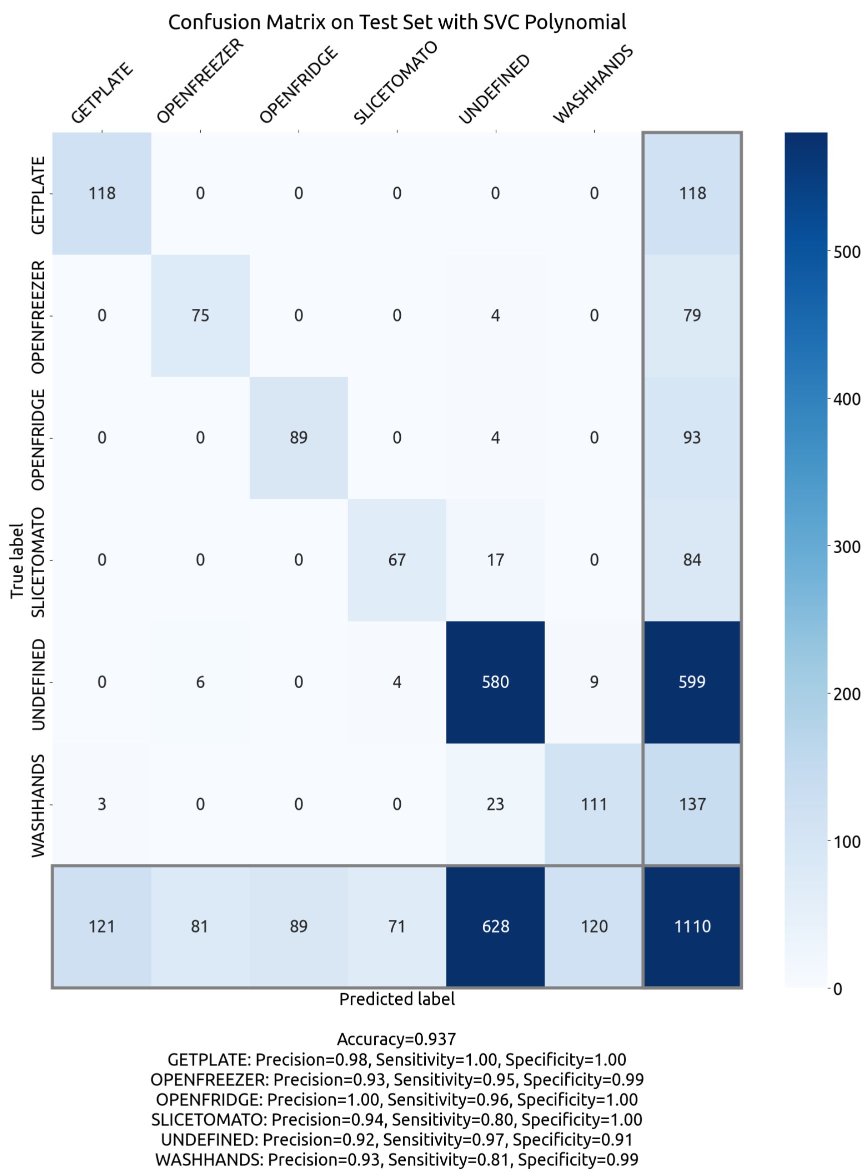
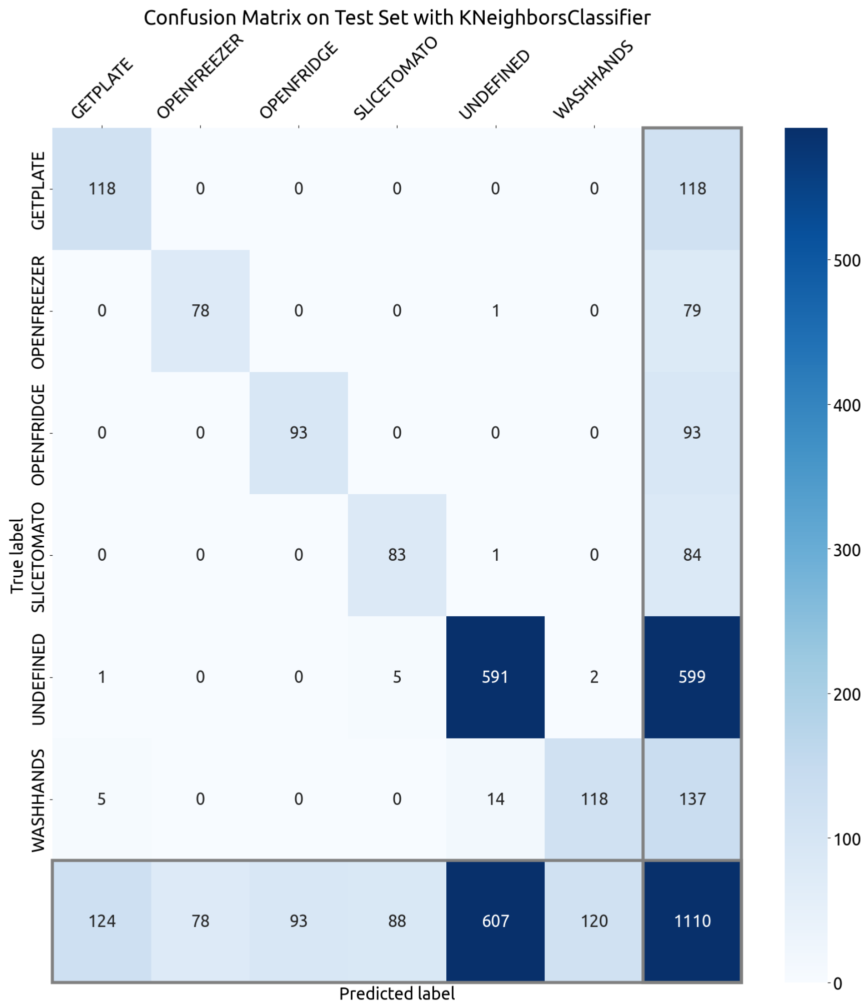


Figure 4.7: Test confusion matrix using the Support Vector Classifier with a Polynomial Kernel



Accuracy=0.974
GETPLATE: Precision=0.95, Sensitivity=1.00, Specificity=0.99
OPENFREEZER: Precision=1.00, Sensitivity=0.99, Specificity=1.00
OPENFRIDGE: Precision=1.00, Sensitivity=1.00, Specificity=1.00
SLICETOMATO: Precision=0.94, Sensitivity=0.99, Specificity=1.00
UNDEFINED: Precision=0.97, Sensitivity=0.99, Specificity=0.97
WASHHANDS: Precision=0.98, Sensitivity=0.86, Specificity=1.00

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

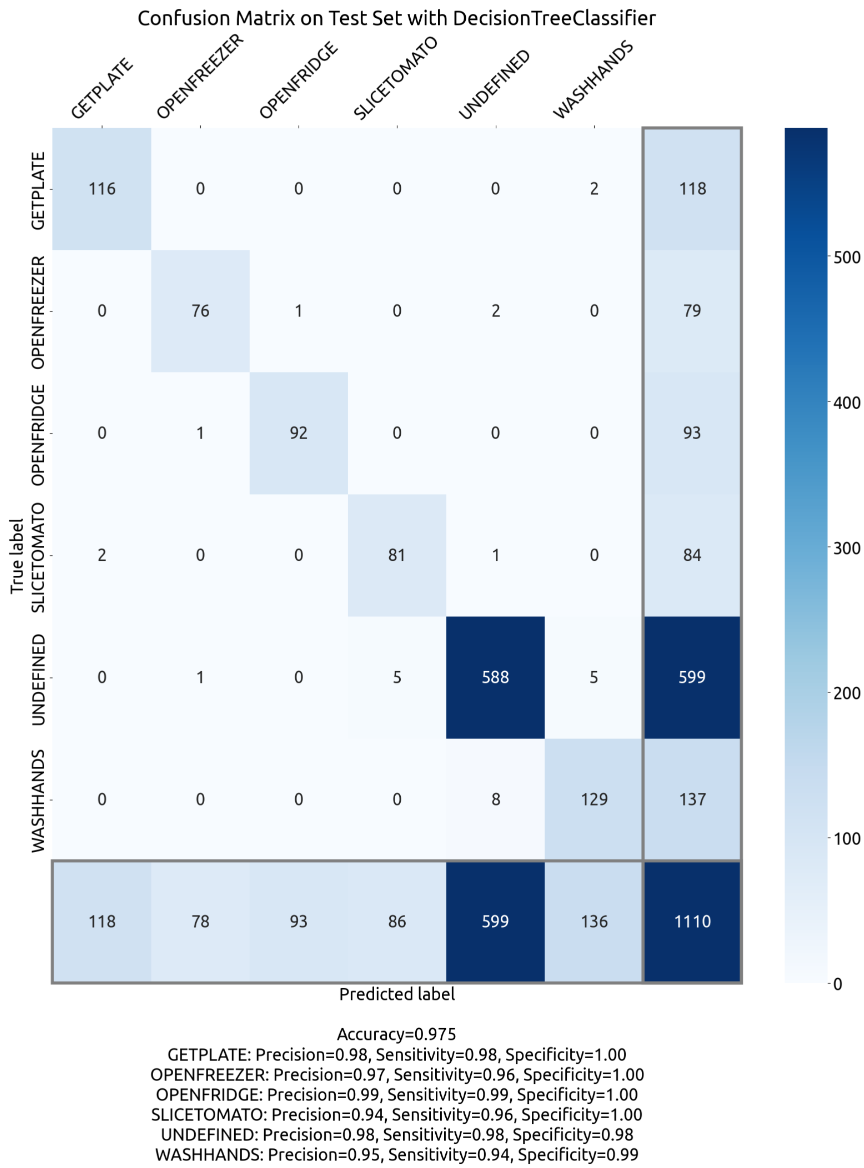


Figure 4.9: Test confusion matrix using the Decision Tree Classifier

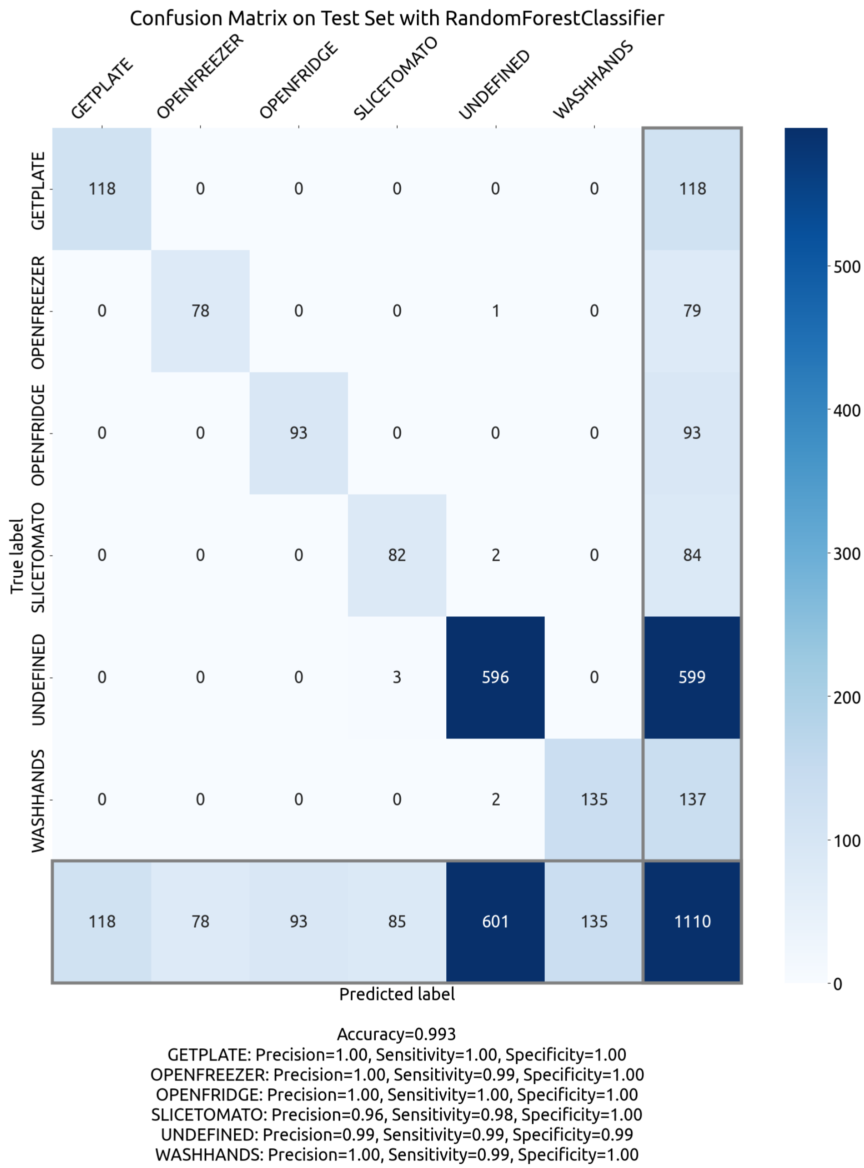


Figure 4.10: Test confusion matrix using the Random Forests Classifier

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.

Bibliography

[1] Configuration of the UWB parameters (Arduino).

[2] Creator One Kit for research and prototyping - Pozyx.

[3] Hardware setup.