School of Computing
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UNIVERSITY OF LEEDS

The Robot Shopkeeper: An Integrated System for Robotic Manipulation and Perception

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The candidate confirms that the following have been submitted.
<As an example>

Items	Format	Recipient(s) and Date
Deliverable 1, 2, 3	Report	SSO (DD/MM/YY)
Participant consent forms	Signed forms in envelop	SSO (DD/MM/YY)
Deliverable 4	Software codes or URL	Supervisor, Assessor (DD/MM/YY)
Deliverable 5	User manuals	Client, Supervisor (DD/MM/YY)

Type of project: Exploratory Software

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Summary

The aim of this project is to produce a piece of software using the robotic operating system (ROS) that will allow Baxter to interact with people and give them sweets within a shop-like setting. The personal aim of this project is to learn the algorithms and software systems used in autonomous systems whilst doing this project. Practically, the aim is to allow the School of Computing to be able to use this system as an interactive shopkeeper demonstration on Open Days.

Acknowledgements

<The page should contain any acknowledgements to those who have assisted with your work. Where you have worked as part of a team, you should, where appropriate, reference to any contribution made by other to the project.>
Note that it is not acceptable to solicit assistance on 'proof reading' which is defined as the "the systematic checking and identification of errors in spelling, punctuation, grammar and sentence construction, formatting and layout in the test";
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Chapter 1

The Problem

1.1 The Problem

The initial problem that was stated was to develop a method for a Baxter robot to run a sweet shop to serve people. Ideally, there would be multiple steps in this interaction. Firstly a customer would walk up in front of Baxter and ask for a certain number and type of sweet. The robot would then go into a bowl of mixed sweets and retrieve the requested ones and give them to the customer. The robot would then ask for a certain amount of money for the sweets, take money from the customer and give them the correct change back. To further clarify this problem, we need to look into the different aspects of this project and how they can fit together to build up a coherent solution. In robotics, there are multiple different challenge areas, such as machine vision, machine learning, object manipulation and human-robot interaction. These areas can all be applied to the problem at different levels, which be explored further throughout the project.

1.2 Approach

The Herb 2.0 paper (2) separates the robot's architecture into several main components that make up the overall system: Robot Behaviour, Manipulation Planning, Planning Under Clutter and Uncertainty, Interacting with People and Perception. Initially, these sections can be used as a guide for developing the overall system architecture for Baxter.

Firstly, manipulation planning will be an important and complex task in the sweet shop. Baxter will have to be able to grasp a specified number and type of sweet and give it to a customer in some way or another. The manipulation of the sweets will be a key task in this project, allowing the robot to use some methods of separating the sweets from a bowl into the required amount. This could be done with multiple manipulation methods - picking the sweets up and dropping them on the table and separating them out (3), scooping some sweets up and looking at the sweets in Baxter's grasp at the time. This challenge will most likely have to test multiple methods and see which is the most efficient/most appropriate for the project. Further challenges could be met in manipulation if the project gets to a point where Baxter can manipulate money. Notes provide a manipulation challenge in the fact that they are soft, which means it will be hard to develop a method to grasp and separate notes. This manipulation could be

taken further and then taken into looking at the current areas of research here, such as the approach to robotic towel folding using cloth grasping (4).

Perception will be a key task in the project. Baxter will have to be able to look at his environment and eventually, be able to recognise a bowl, the individual sweets within a bowl, the table on which the objects are stored, the human purchasing sweets and some form of money/currency. Since Baxter uses a Kinect 2.0, object recognition will be attempted with point clouds initially, although there are some other methods that can be looked into (2D methods etc). There will be a challenge in learning how to analyse and manipulate 3D point clouds to perform vision tasks and getting Baxter to recognise the many different objects. This concept could further be expanded upon if there is time to include clutter in the environments and allowing Baxter to plan manipulation around the clutter using algorithms as this is a key area of robotics. The computer vision module from year 3 should be a good building block for this task, though working with 3D analysis was covered in very brief detail.

The complexity of the Human Interaction probably will depend on the time left at the end of the project (as it would first be key for Baxter to be able to recognise and manipulate sweets). For human interaction, methods could be implanted such as Kinect's gesture recognition for pointing at things or basic voice recognition commands. A nice implementation of the sweet shop would at least include the ability for Baxter to give the sweets or change directly to the person (5). This area could be expanded into many challenging areas, such as allowing Baxter to have basic conversations with the customer, understand more complex commands etc.

Chapter 2

Background And Literature Review

The idea of this project is to produce a fully functioning piece of software that allows Baxter to converse with customers in a sweet shop environment. To do this, background research was taken into the main areas I would need knowledge of in this project: robotic systems, machine vision, manipulation and human interaction. To develop a robotic architecture, it was necessary to look at some other robotics systems to see the main steps they took to plan and build them. The aspects discussed in the approach above were further researched below.

2.1 Robotic Behaviour

Robots use a behaviour engine to model their reactions to the environment in a logical way. This simple logic can be transferred to the shopkeeper project by Baxter having different behaviours to carry out in the shop. Those could be listening to a customer's command or picking up a particular sweet. All these behaviours and the logic along with them should be developed for make a robust set of behaviours for Baxter to use.

Two main architectures exist to develop robotic behaviour have been used in multiple robotic systems: a classical approach and a subsumption architecture [**REF**]. A classical architecture is based on a pipeline-like approach, where first perception occurs, building up a model of the world, then from that model, planning is made then tasks are executed. A subsumption architecture works in more of a layered model, where multiple tasks run at the same time, so the layers act in parallel. That means that tasks such as exploration and wandering would run together, both with access to the robot's motors.

The simplest approach to the shopkeeper's architecture seems to be a classical pipeline approach. It doesn't make sense for a subsumption architecture, since Baxter will need to re-analyse his environment before planning any manipulation tasks. Therefore a basic logical behaviour architecture could be theorised for a simple task of picking up sweets. In an example task, Baxter would want to pick up a sweet from a pile of sweets on the table. This could be split into a logical order of behaviours: recognise the sweets on the table, plan which sweet he wants to pick up, then pick up the sweet. This has to be done in this order, as Baxter will need to build up a model of his environment before he can pick the sweet up.

2.2 Machine Vision

Machine vision is the area of computer science where images can be analysed and understood. This is often used in robotics to help robots recognise and understand objects in their environment so they can react and respond appropriately. In the sweet shop, Many robotic vision systems are used in conjunction with manipulation and other aspect's of the robot's behaviour, so a robot will recognise and understand it's surrounding and interpret that in real-time to feed the information back to other processes. For example, this technique can be applied to Baxter looking at the table and then telling the manipulation process where the sweet is located to pick it up.

2.2.1 Image Processing Techniques

There have been multiple approaches to object detection in machine vision. The approaches analyse pixels by segmenting images into the desired edges/distinguishing features.

CONTOUR PARAGRAPH

TEMPLATE MATCHING

2.2.2 Pointcloud Analysis

Vision techniques used in a 3D Pointcloud have a slightly different approach. Instead of segmenting and processing the pixels in an image, object analysis is more concentrated around grouping of points that are close in orientation and colour.

RANSAC SEARCH METHODS

3D MODEL MATCHING

2.3 Manipulation Planning

Manipulation planning is a key aspect of robotic systems, where the hardware of the robot and the limitations need to be considered before integrating manipulation techniques. Manipulation tasks in the sweet shop include tasks such as picking up sweets, giving them to the customer, which will all require planning for the position and movement of the grippers.

2.3.1 Inverse Kinematics

Inverse kinematics is one of the common movement planning techniques in robotics. This involves a kinematic analysis of the current state of the robot's system, looking at the all of the joint positions and angles. Normal kinematics works out how and where to move the limbs with a specified range and then works out the endpoint of that limb. Inverse kinematics does the reverse of this where you specify a coordinate endpoint of the limb or specify joint angles, inverse kinematics will use some mathematics to calculate the limb movement from the initial position to the given one. Baxter's inverse kinematics requires an x, y, z coordinate for an endpoint, along with a quaternion for the rotation of the arm.

Some of the main issues with using inverse kinematics are that mainly, there are multiple solutions to get the limb to the specified position and one of those solutions has to be chosen. The most obvious solution to choose would be to select the one which contains the least overall movement to get to the right location. The problem with the multiple solutions is that sometimes, unexpected routes can be taken instead of the desired one. This usually tends to occur because a perceived human solution to a joint position will not be the closest solution in the joint's coordinate system, rather than the world coordinate system.[**REF**]

2.4 Planning Under Clutter

Planning under clutter could be an important aspect of the project depending on how the sweets are placed on the table. If they are grouped together, Baxter will have to plan to separate them from the clutter. Also other objects on the shop's counter could cause clutter issues with recognition and manipulation planning.

2.5 Interacting with People

Human interaction is going to be key to making the robot shopkeeper a realistic and comprehensive experience. By testing with human customers, this system could be made robust and efficient. This will be important once for Baxter to understand the customer's request and interact with them accordingly in the shop.

2.5.1 Voice Recognition

2.5.2 Skeleton Recognition

Chapter 3

Introduction

3.1 Aim

The overall aim of this project is to produce a piece of software using the robotic operating system (ROS) that will allow Baxter to interact with people and give them sweets within a sweet shop setting. The personal aim of this project is to learn the algorithms and software systems used in autonomous systems whilst doing this project. Practically, the aim is to allow the School of Computing to be able to use this system as an interactive demonstration on Open Days.

3.2 Objectives

The main objectives for the overall project are to:

- Develop a vision system to recognise the container that the sweets are in and a manipulation method to retrieve them from the container.
- Include a vision system to recognise the sweets in their environment and a manipulation method to separate/singulate sweets into the desired amounts.
- Integrate methods of human interaction between Baxter and a customer to allow them to order some sweets from the shop.
- Create a piece of software that would allow Baxter to implement all the previous steps into one integrated architecture. This would allow Baxter to interact with a customer in the sweet shop and give them whatever sweets they asked for.

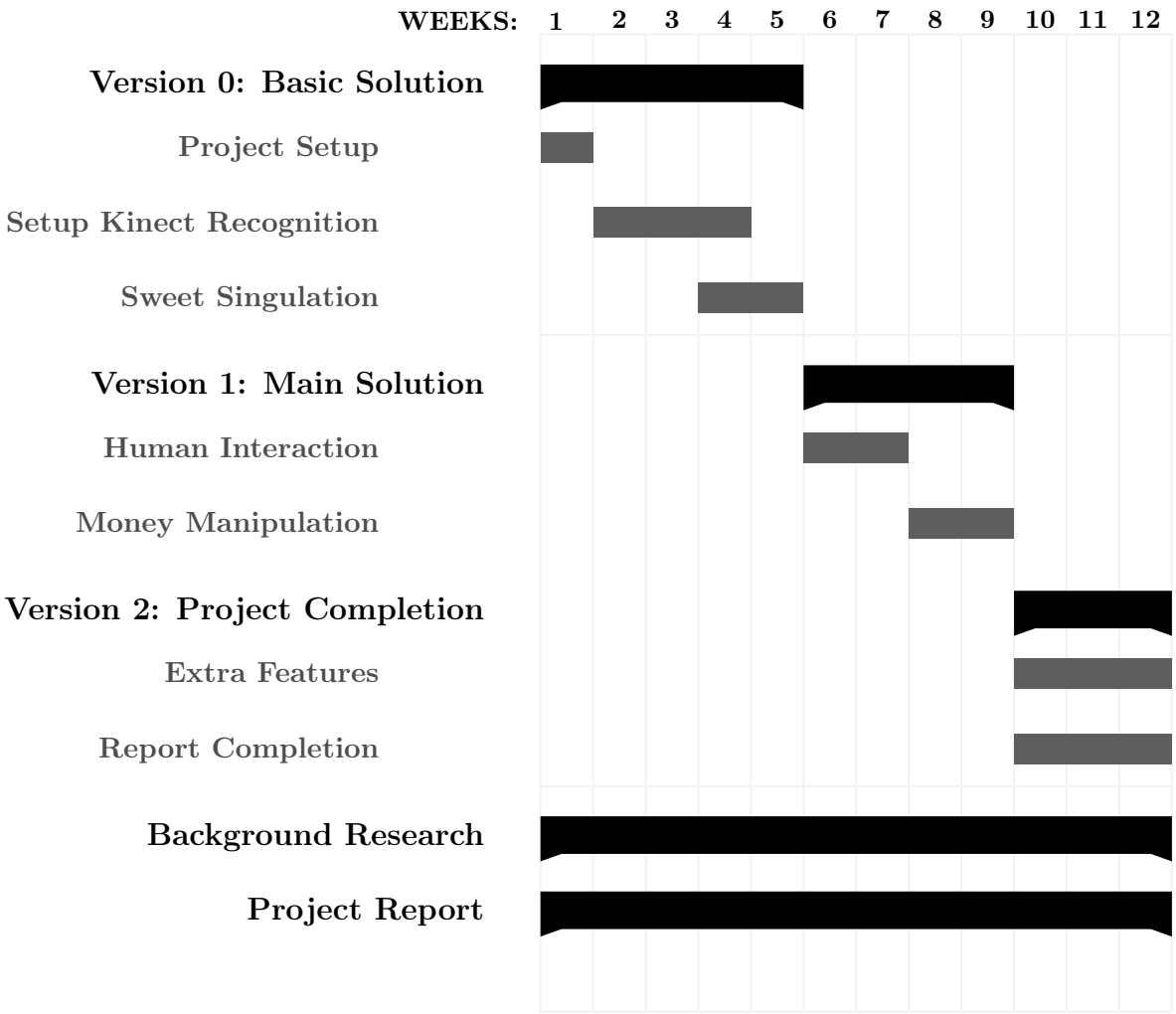
3.3 Methodology

Since this project involves a lot of different areas of robotics integrated into one system, a somewhat modular approach has to be taken. It was decided that each area (vision, manipulation, human interaction) would be developed in a sequence. The method therefore has a very testing-centric agile approach, where for a task, there would be planning for multiple approaches, development and then testing. Once an efficient solution has been found (determined with testing), the next task could then start being developed. Since the methodology was so linear, by looking at the large amount of tasks in the **Gantt chart** to complete, multiple contingencies had to be taken to make sure

that certain tasks didn't take too long or were too complex.

As you can see from the **Gantt chart**, there are multiple target versions for the project, in case some tasks run over their time limit. The basic solution was aimed to complete in 6 weeks, but tasks for version 1 and 2 could be seen as extra objectives if there isn't time to implement them all. Another contingency would also be the heavy planning and supervisor discussions before each task, meaning I would know what to read beforehand and the common methods of solving each problem.

3.4 Tasks, milestones and timeline



Here are each of the tasks explained in more detail:

- **Project setup** - Setup the ROS system and look learn the basics of the software. Complete ROS and Baxter tutorials and make some example programs to test and move Baxter in different ways.

- **Setup Kinect recognition** - Setup the Kinect with Baxter and look into different computer vision methods to recognise the bowl and sweets and their positions in 3d space.
- **Sweet singulation** - Trial multiple object manipulation algorithms to allow Baxter to grab and select specified sweet combinations.
- **Human interaction** - Create some form of human interaction between Baxter and a human to allow the human to ask for specific sweets. This could be gestures or voice control based.
- **Money Manipulation** - Develop some vision system to recognise paper money or change and then work on algorithms for Baxter to handle/count out money to give to a person.
- **Extra Features** - Allow time to further improve upon previous steps or pick one dedicated topic to further go into and develop.
- **Report Completion** - Allow the last three weeks to further improve upon the project report.
- **Project Report** - At each week, take a look at project report deadlines that need to be met. Make sure parts of the report are written at the time they are completed.

3.5 Deliverables

3.6 Determining the Quality of the Solution

Chapter 4

Materials and Logic

4.1 The Robot

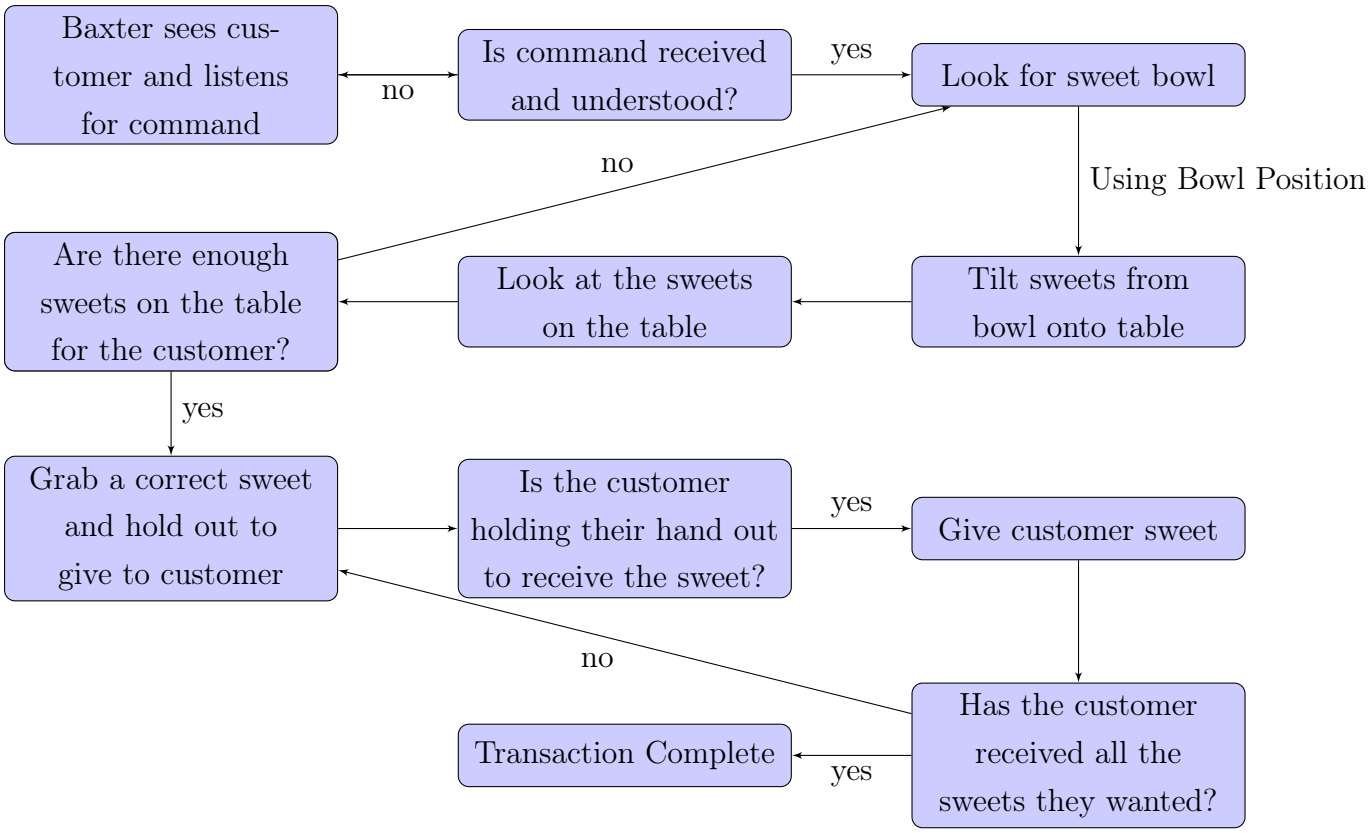
A Baxter robot is a programmable automaton which is already being integrated into workforces around the world (1). The Baxter robot is currently very popular to use at universities as a safe robot for research purposes and this project will use the one at Leeds. Baxter has three cameras to use, a right hand camera, a left hand camera and a head camera, each of which can output different resolution images for use in machine vision. He has two electronic grippers which can be customised to grip objects of different sizes, with pressure sensors to detect whether he has grabbed something. Seven joints are located on each arm, with humanoid movement, which can be controlled by specifying specific joint positions or torques at each joint.

4.2 Kinect

The Kinect has two cameras to be used to detect objects with depth detection. It has been used in many areas of robotics as a more accurate vision method, creating 3D objects by looking at the Kinect's Pointcloud, an array of points with an x, y and z coordinate.

4.3 System Logic

To simplify the overall system logic, it was easier to look at the system as a whole and look at the simple interactions needed between a shopkeeper and their customer. Firstly, human interaction would determine what sweets the shopkeeper would need to get. Secondly, the shopkeeper would get some sweets from the bowl and individually pick out the ones the customer wanted. The shopkeeper would give those sweets to the customer and then ask for payment of some sort to complete the interaction. During the development of the project, more clear and precise logic steps came from development, shown in the flow chart below.



4.4 ROS

4.4.1 Inverse Kinematics

4.4.2 Fixed Frame Transforms

A key aspect of creating the integrated movement system was understanding the concept of fixed frames and transforms. In ROS, Baxter contains information for multiple transforms between every joint and sections of his body. These transforms are known at all times to help know where a point is relative to one part, say the hand, against Baxter's torso. This method works similarly for the Kinect, where Baxter's torso coordinate system, is linked to the Kinect's coordinate system via a transform, which can be accessed by certain methods in ROS.

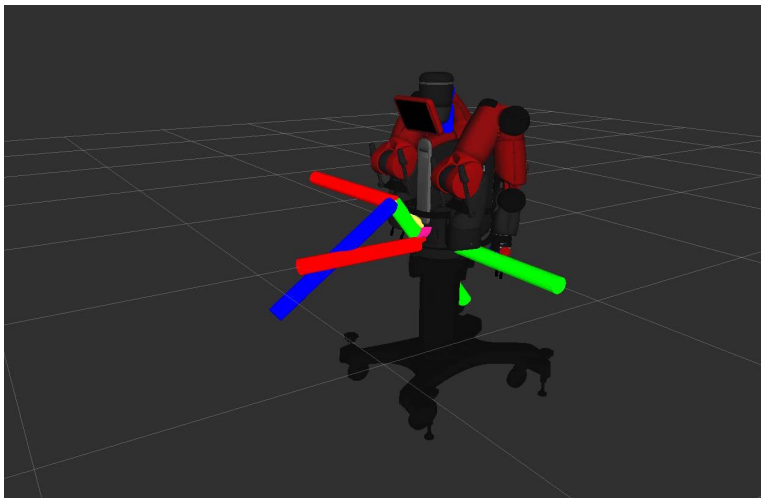


Figure 4.1: *Image showing axes transforms between the Kinect and Baxter's torso frame*

Fixed coordinate systems were constantly used in testing the vision systems in this project, mainly within rViz. Everytime a coordinate or shape was recognised within the vision system, they could be published to rViz using a PointStamped object, which can be published in a particular coordinate system. Therefore publishing in one frame, transforming then publishing it another, rViz can show whether a point is correctly detected and whether it is in the correct frame. This principle was used in the bowl recognition system, where after the centre of the bowl was obtained, Baxter needed to know where the centre of the bowl was in it's main body coordinate system before a movement command could be made. The system then looked up the transform between the Kinect and Baxter's torso to transform the 3D coordinate between coordinate systems.

4.4.3 Custom Service Requests

The idea that Baxter's movements would all be based on the current states of his vision system - depending upon where both the sweets and the bowl were, there needed to be a method developed for Baxter's movement system to be able to request information from the vision system. This was implemented via Services, which is a method in ROS that allows a custom message to be sent, and then received between two nodes.

Chapter 5

Methods

5.1 The Bowl

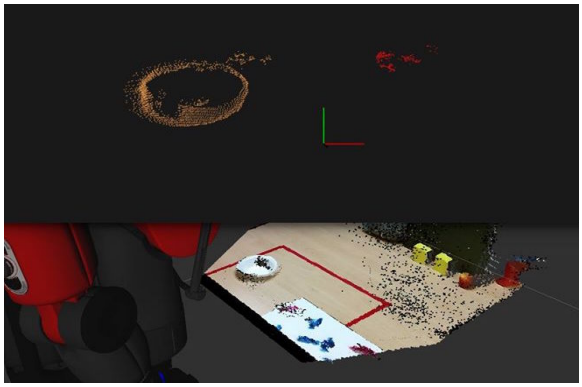
The bowl is a container Baxter uses to store his sweets in. The eventual aim of using the bowl was for Baxter to be able to recognise it on the table, scoop some sweets out and move on to giving them to the customer.

5.1.1 Recognition

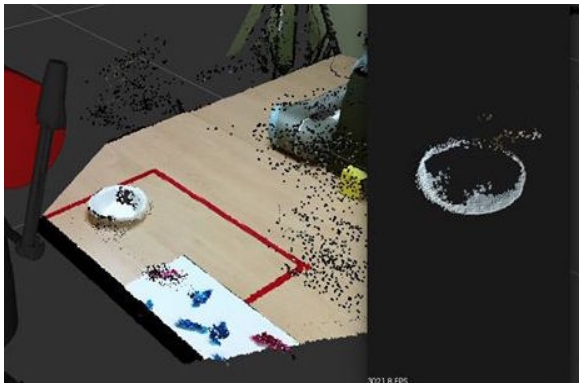
The first thing Baxter needed to do in his shop is to be able to recognise the bowl. This section shows how Baxter uses the Kinect to find the bowl on the table, identifying it from a range of other objects. The Kinect produces a Pointcloud, a set of 3D points in the Kinect's coordinates system. The first task to do when recognising the bowl, was to pick a type of bowl that would be easily visible in the Pointcloud. Multiple bowl types were trialled, until it was decided white polystyrene bowls would be a good overall choice. This is because, unlike other bowls, the rim was clearly visible in the cloud and polystyrene is an easy material to grab and manipulate. Plastic and foil materials were too reflective to show up in the cloud.

5.1.1.1 Segmentation and Recognition

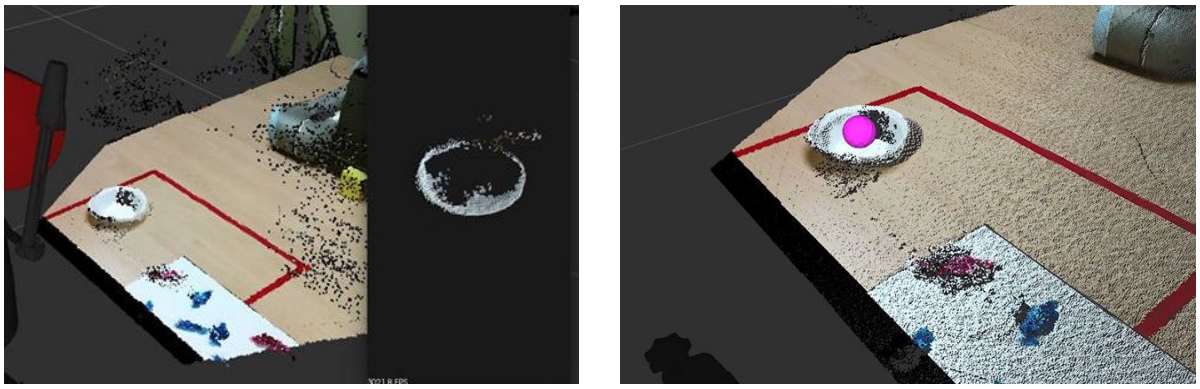
To recognise the bowl on the table, the vision system first separates objects from the table, then separates those points into individual clusters. To eliminate noise, a colour segmentation is performed to find only the white objects on the table. The bowl can then be found by looking for the rim as a circle in 3D space. The overall process is carried out by multiple algorithms, shown in the images and explained below.



(a) *Object clustering.*



(b) *RGB colour segmentation*



(a) *Circle detection in 3D* (b) *Bowl centre in rViz*

Figure 5.2: *Overall bowl recognition process*

1. Tabletop Object Detection/Segmentation - This method works by detecting the table in the Pointcloud by finding the dominant plane using RANSAC. Points above this plane are then considered to be objects on top of the table, which are then segmented from the points that belong to the table. This results in a Pointcloud without any interference from the table.

2. Object Clustering - The purpose of this algorithm is to separate the points in the Pointcloud into clusters, ones which are close enough to represent the individual objects on the table. The theory behind this algorithm is it takes in the indices and estimated normals of the Pointcloud and for each possible region, calculates a K-nearest neighbour search over the indices. During this search, it compares each point with another, checking first for a specified smoothness constraint, then if the deviation between normals is within a specified angle. If that is satisfied, then the difference in curvature is tested, allocating the points to the appropriately separated clusters. During the implementation of this algorithm, different values were tested. Variables such as number of neighbours, smoothness and curvature constraints were tested until the resulting cloud produced reliably clustered objects.

3. Colour-Based Segmentation - Whilst testing the bowl detection methods, it became clear that with the Kinect, there were clear noise issues caused by certain objects in the Kinect's view. Baxter's arms especially caused severe black noise to appear around them, making it harder to segment the bowl out from other objects. Therefore, a colour segmentation method was used to separate the white bowl from the black and other coloured clusters. This was done by looping over the points in each cluster and averaging the RGB values of each cluster. Then, only the clusters with a high enough R, G and B threshold were used, so that the Pointcloud contained only the points for the bowl and any other white object on the table. This method could be expanded to recognise other coloured bowls relatively easily, by finding the correct

thresholds for other colours.

4. Detection of the Bowl Rim - The most significant part of the bowl that tended to show up in the Pointcloud was the bowl's rim. From that information, it was decided that the simplest solution was to find the rim of the bowl by finding a specific sized circle within a plane of the 3D Pointcloud. This method was implemented by using the RANSAC algorithm to detect the points that best fit a circle shape within a plane in the cloud. This method in the PCL library is especially good at allowing variation in it's detection. By varying distance thresholds and minimum/maximum circle radius values, the bowl was able to be found successfully, even with gaps in the rim (which could occur when Baxter's hands went in front of the bowl). After the circle model had been found in the white Pointcloud, the x, y and z of the centre of the bowl's rim was then known in the Kinect's frame coordinates.

5. Averaging and Transformations - After the bowl was found in the Kinect's frame, when publishing in RVIZ, it was clear that whilst the centre point was always within the bowl, it wasn't a reliable bowl centre. Therefore, a new ROS node was created that took in the previous result, averaged the centre value over 20 frames and then outputted a new averaged centre point. This point was a lot more stable for Baxter to use. Then, using the averaged bowl centre, that point was transformed into Baxter's torso frame and published, so the values could be used for bowl manipulation.

6. Improvements - The basic approach to recognising the bowl is described above. However, as the system began more rigorous testing, when the basic shop system was being put together, the detection was not accurate enough for Baxter to always be able to grip the edge of the bowl. Therefore, a few improvements and changes were added to the system.

Due to increased noise in the Kinect's Pointcloud recordings, the averaging over 20 frames was not reliable enough to keep a fixed centre. To counteract this, a cumulative average was taken instead, meaning that if there was interference, the recognised bowl centre would not be affected as much. Another improvement was to reduce noise at the segmentation stage. To do this, a larger minimum clustering size was used when clustering the objects, so less areas of noise included in the bowl rim detection. This resulted in a stable centre for the bowl in multiple positions on the table, as shown in the testing below.

5.1.1.2 Testing

To determine whether the recognition was reliable enough, multiple tests were taken for the bowl recognition and noted down in **Appendix A**. The main method of testing whether a bowl recognition was accurate enough was devised by getting Baxter to grab the edge of the bowl using the bowl's centre coordinate found through the vision system. Since grasping the bowl is a key aspect in getting the sweets from the bowl, it made sense that the recognition system would have to be accurate enough for Baxter to be able to reliably repeat this feat.

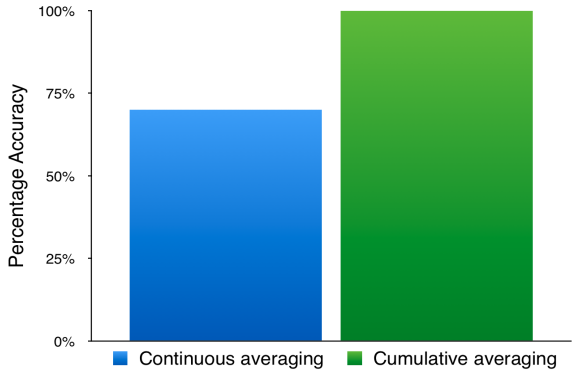


Figure 5.3: Comparison of repeated grasps using different techniques over time

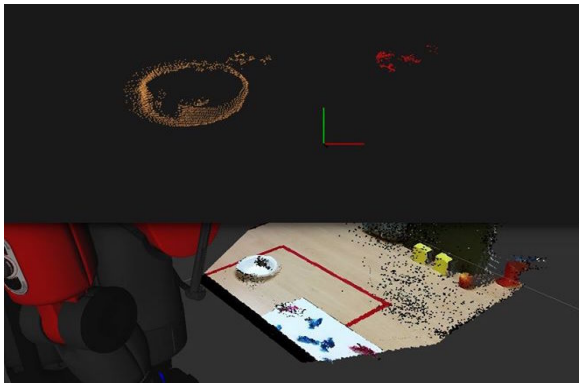
For the initial rolling average over 20 frames and the cumulative averaging methods (mentioned in the sections above), Baxter was tasked with grasping the edge of the bowl 10 times with each method. The efficiency was then calculated as a percentage of the bowl grasping accuracy, shown above in **Figure 5.3**. As you can see, the cumulative averaging obtained a 100% accuracy over 10 tests and therefore seemed the more reliable and sensible choice to use in the overall system. The only issue with the cumulative average method is after the bowl has been moved, if the bowl had previously been in place for a long time, the centre will end up being a mixture of the two positions. Therefore, a reset option had to be implemented so that when Baxter moves the bowl, a new cumulative average was taken before looking for the bowl again.

5.1.2 Manipulation

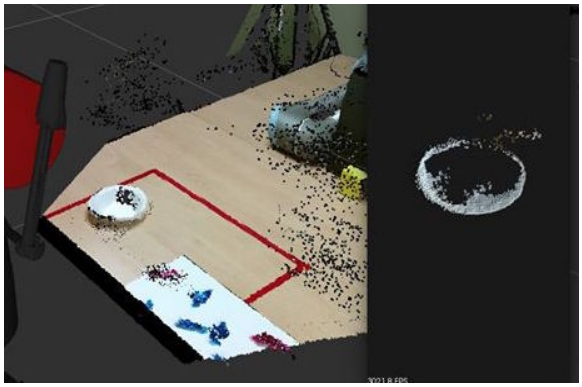
With the bowl having been recognised, the next step is for Baxter to get sweets out of the bowl so he can separate them out on the table. Two main methods for this were trialled, first scooping methods were tested, trying different ways of Baxter scooping out sweets with his grippers. Secondly, Baxter tipped the bowl onto the table at different angles to get the sweets out. Both methods are explained in more detail here:

5.1.2.1 Scooping Methods

Firstly, several methods of scooping were trialled for Baxter to scoop sweets out of the bowl with his gripper. These methods were developed through theories and trials and then tested to see which methods were the most efficient. Different variables to consider were things like gripper distance - the distance between the grippers when closed, angle of entry to the bowl and gripper movement before grasping. Testing for the reliability of these methods are shown in the **Scooping Tests** section and videos on all of the different scooping methods are located on the **Github repository**.



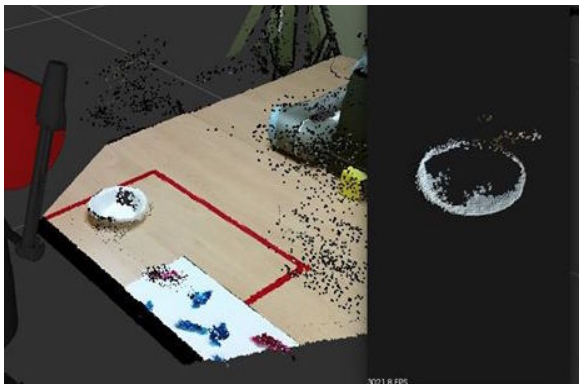
(a) *Grasp from above.*



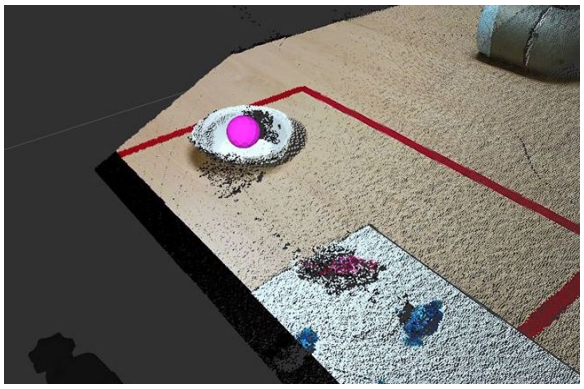
(b) *Grasp and shake.*

Grasp from Above - The grasp from above method was the simplest, first approach taken, where Baxter retrieves the centre of the bowl, goes slightly above the bowl at a fixed height, then moves slowly down into the bowl and closes his gripper. To an extent, this method was one of the best at gripping individual sweets from a full bowl however, the problem was the approach to the bowl. During this method, Baxter would try and go to a fixed depth and then grab sweets. Unfortunately, without analysing the sweet's orientation in the bowl first, the end of Baxter's grippers would get caught on sweets before reaching the specified depth. Then the sweets underneath the grippers would be crushed, which was seen as a problem for a shopkeeper.

Grasp and Shake - A second version of the grasp from above method uses a slightly adapted method of bowl entry, where Baxter goes near the rim of the bowl, then lowers his hand moving from side to side. In theory, that would reduce the likelihood of hitting and crushing sweets on the way into the bowl as the hand would be able to shake itself in. However, yet again, if the grippers approached on top of sweets, they would be crushed and then moved from side to side, staying stuck. Another fault of this method came from trying to empty the bowl. Due to the position being approached at the centre, only sweets in the centre could be retrieved, pushing other sweets to the side of the bowl. That spawned the idea for creating a scooping method that tilted the bowl in future trials. **Scoop from the Side** - The scoop from the side method worked very



(a) *Scoop from the side.*



(b) *Tilt and scoop.*

much how it sounds, using Baxter's gripper to come in at an angle to the bowl to try and scoop up some sweets. The downside to this approach came apparent when after multiple trials, Baxter ended up pushing sweets to once side of the bowl so on repeated grasp attempts, it could no longer reach them after pushing them all away. This method did however improve Baxter's ability not to crush sweets, as a more angled entry meant that he was less likely to get stuck on a sweet, as he could just push it to the side.

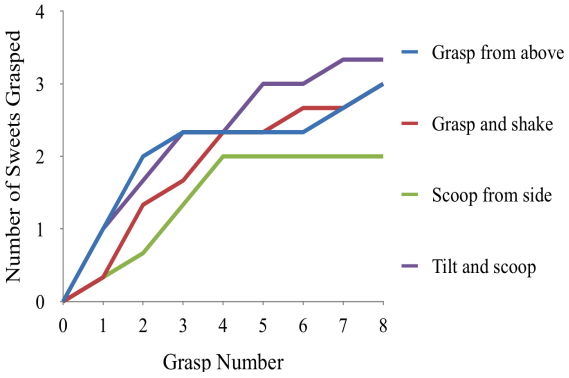
Tilt and Scoop - This method came by combining ideas from the previous methods to develop a more reliable method of scooping sweets. Firstly the left hand would grip the side of the bowl and tilt it so sweets fall down to one side, then the right hand gripper would come in and try and scoop some sweets up. This process, while reliable on tilting the sweets, was unreliable on it's consistency, as the approach sometimes managed to pick up one or two sweets, but most often it missed them on a random approach.

5.1.2.2 Scooping Tests

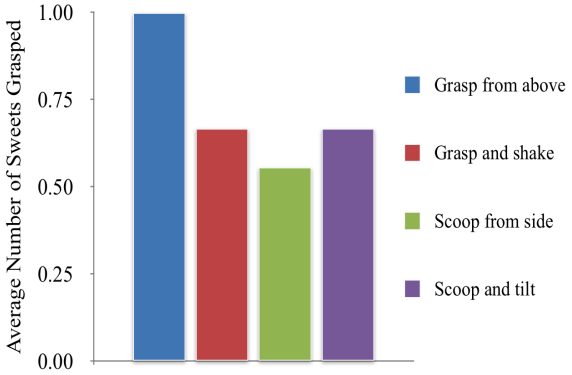
In **Appendix B**, there is a spreadsheet showing trials of each type of scooping method mentioned above. For each method, there was a trial regarding it's efficiency from grasping sweets from a full bowl (the less grasps Baxter can get the customer's sweets in the better) and repeated trials were carried out, to see how well they performed when some sweets had already been retrieved. **Figure 5.18b** shows that the tilt and scoop method was the most reliable grasping method over time. This means that the tilting added to the method and meant that it prevented sweets from being pushed to one side after initial grasps. The problem with all grasping methods in this figure however, is that sweets were not grasped particularly efficiently. There was a maximum of around 3 sweets retrieved after 8 attempts, meaning the customer would have to wait a very long time if they wanted 3 or more sweets.

In **Figure 5.7b**, you can see that, on average from a full bowl, the grasp from above method was the most effective, averaging one sweet grasped over ten attempts. The

(a) Comparison of repeated grasps using different techniques over time



(b) Comparison of the average sweet number grabbed from a full bowl



main thing to point out here is that the maximum average grasped from a full bowl was only one sweet. In a shop-like scenario, a customer will most likely want more than one sweet, so if Baxter had to grasp one at a time, it could take a very long time for him to grab the right sweets.

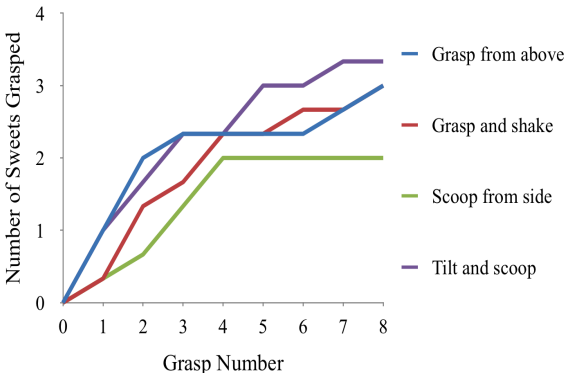
After testing these grasping methods, it was determined that no one scooping method would be efficient enough for Baxter to use to retrieve multiple sweets for a customer. This is due to the reliability of these methods was not sufficient enough for Baxter to get multiple sweets from the bowl each time. By taking inspiration from the tilt and scoop method, it was decided that tipping sweets from the bowl onto an area on the table would be a possible solution to get more sweets in a shorter number of attempts. This was trialled in the next section.

5.1.2.3 Tipping Methods

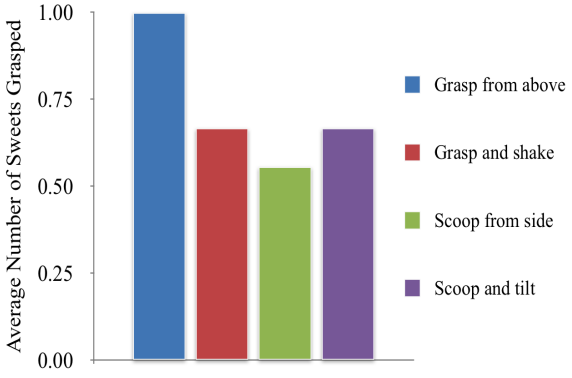
After determining scooping the sweets was not a reliable enough method, some bowl tipping methods were trialled to attempt to get a better efficiency. Each method was again developed through manipulation trials. In each trial, the sweets were attempted to be tipped and dropped onto a rectangular area designated for sweet singulation. This brought in several new factors to consider such as whether the sweets landed successfully in the area, how many sweets fell next to each other (the more often that happened the harder for Baxter to separate them later) and where in the area should the sweets be tipped.

Different variables considered in these methods included factors such as tipping height, tipping angle, tipping location and tipping speed. Tipping added another issue to the manipulation because once sweets had been tipped out of the bowl, it was harder to get the last ones out, meaning an incremental approach had to be taken, increasing angles and speed to retrieve them. Testing for the tipping method are shown in the **Tipping Tests** section and videos of the methods are located on the **Github repository**.

(a) Vertical Tilt **Placeholder**



(b) Horizontal Tilt **Placeholder**



Vertical Tilt - A vertical tilting method was the first tipping method trialled, where Baxter would grasp the bowl from the side, then raise the 'elbow' of his arm so that the bowl was tilted at an angle. Then Baxter would move up and down, shaking the sweets out of the bowl onto the table. The optimal number found through testing was for Baxter to tip the sweets out once in the right-centre of the sweet area and once in the left-centre so there was a reasonably even spread of tipped out sweets on the table. This method caused issues in reliability over multiple tilts. Sometimes, when there were sweets down in the bottom of the bowl, no matter how high the tilt angle was, they were hard to shake out without completely tipping the bowl upside down. The horizontal tilt method was developed from the flaws in this method, hopefully to gain some extra control over the tilting angle and shake by using Baxter's gripper rotation instead of the 'elbow' movement.

Horizontal Tilt - This method was similar to the vertical tilt as mentioned above but instead, Baxter tilts the bowl using his gripper so there is more control over the tipping. Another factor added to this method is that instead of shaking the bowl up and down, Baxter now shakes it in a upward diagonal motion, shaking sweets upwards and out of the bowl at the same time. Whilst this technique does add a worry of throwing sweets too far out of the bowl, it does help get the sweets at the bottom of the bowl. The efficacy of this method against the vertical tilt is discussed in testing.

5.1.2.4 Tipping Tests

- FINISH DOING THE TIPPING TESTS AND DETERMINE WHICH ONE IS BEST - HORIZONTAL TILT SEEMS LIKE THE BEST ONE AT THE MOMENT

- PRODUCE A GRAPH/ANALYSIS OF THE RESULTS

5.2 The Sweets

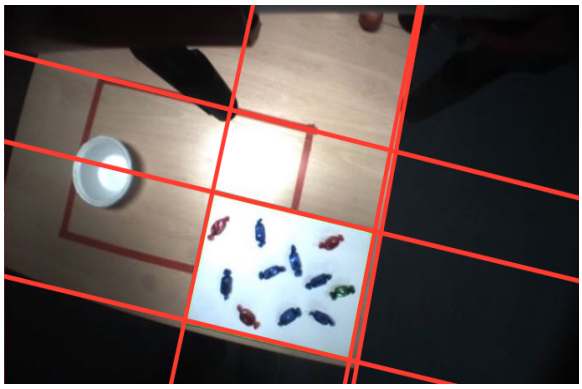
5.2.1 Recognition

The task of Baxter recognising the sweets involved him being able to look at an area of the table with sweets retrieved from the bowl and determine how many sweets there were in that area along with what type/colour each sweet was. The problem with recognising the sweets using the Kinect is that the sweets were such small objects, that the noise in the Kinect meant that a significant number of sweets weren't picked up after segmenting objects on the table. Therefore an alternative method was proposed using OpenCV. The idea behind this method was for Baxter to capture an image of the table with the sweets on using his hand camera. Then from that image, OpenCV image processing techniques could be applied to separate the sweets into individual objects, from which the shapes, centres and colours could be obtained.

5.2.1.1 Sweet Background Detection

The first task in separating the sweets was to have Baxter to only look in the area the sweets were placed on the table, so the sweets remaining in the bowl would not interfere. It was decided that the easiest way to segment this area out was to use a white piece of paper as the background, making it easier to segment out the rest of the image. The piece of paper used was A3 in size and had a black edge drawn on, to help detect the border of the page. Multiple vision methods were trialled to try and recognise this sweet placement area, explained here:

(a) An example of opening after Gaussian blurring and Canny Edge detection.



(b) An example of the Hough line transform used on the edge image.

Image Pre-processing - Before the image from the camera could first be used, some pre-processing was taken place to reduce noise and make it easier to detect the area on the table. A Gaussian Blur was performed with a small kernel to firstly blur the image to reduce possible noise. Then, Canny Edge Detection was used to detect edges within the image, along with dilation and erosion to close any incomplete edges, resulting in a

reasonably successful edge detection for the entire image.

Hough Line Transform - Firstly, to find a rectangle in the image, Hough Line Transform was attempted to be used to find the individual edges of the paper. This technique was somewhat successful when attempting to distinguish between the edges however, by varying and optimising the line detection threshold, it was difficult to detect all four edges of the paper constantly. Either one or two edges kept being detected then undetected or too many edges were found. Due to the inaccuracy of this edge detection, the four edges could not always be found to form the rectangle. Therefore other methods were explored.

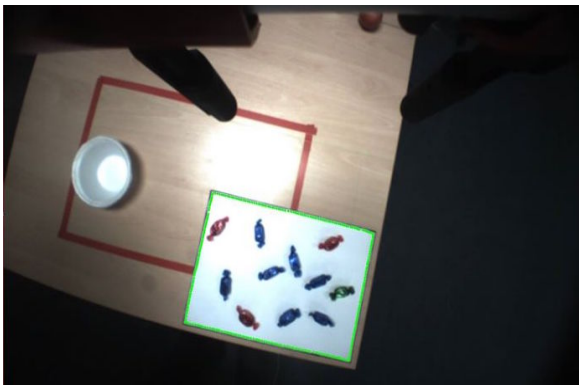
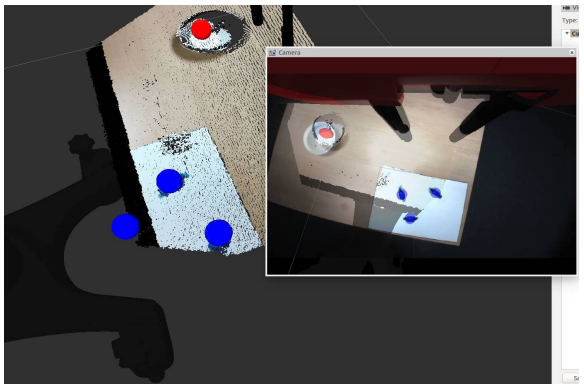


Figure 5.9: Image showing green contour wrapping round the sweet area.

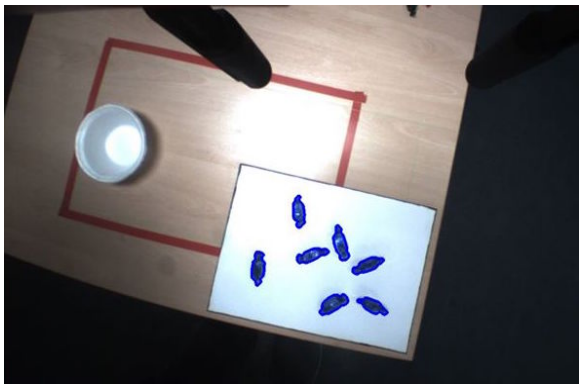
Contour Detection - Once the black border on the area was defined enough to be consistent during canny edge detection, a contour successfully managed to detect the four edges of the paper. Due to there being many contours detected in the image, certain constraints had to be put on the detection to segment out the sweet area. The main method of segmenting out the rectangular area then was to first eliminate the smaller contours by size (using the in-built OpenCV countourArea method) and then approximate a polygon for the countours to detect which countour was a rectangle. This contour then produced a mask, which could segment out the rest of the image from the sweet area.

5.2.1.2 Sweet Recognition

Once the sweet placement area was reliably segmented out from the image, multiple methods were used to attempt to try and identify the individual sweets. These methods are explained below:



(a) Round sweets detected using the Hough circle detection.



(b) Correct contours found for the sweets on the table.

Hough Circle Transform

For the simple, round sweets initially used in trials, a Hough Circle detection algorithm seemed like a sensible way to detect the simpler, round sweets. However, like the Hough Line detection used earlier, it was hard to get a constant solution, with circles being detected and then undetected throughout various received image frames, therefore other methods needed to be tried to get a more reliable vision system.

Contour Detection

A better method was to do some image processing, Gaussian blurring, closing and opening to produce a lot better results, producing a mask of a white background with some black sweets in front. The problem with using this method is due to reflections on the sweets wrappers, this caused an issue of multiple broken contours within an individual sweet, whereas a preferred method would have been to capture the whole sweet with one contour, as Baxter needs to be able to count each sweet once.

HSV Colour Segmentation with Contour Detection

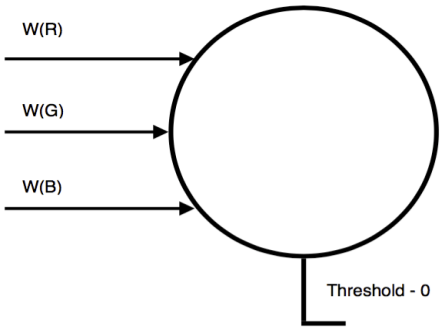
A more accurate method was found by using an existing tool called objectfinder. This tool uses multiple sliders to segment an image and produce a mask using lower and upper bounds for RGB values. Since each sweet wrapper had different identifiable colours and they were placed onto a separatable white background, using a scale of possible HSV values could be used to identify main sweet wrapper colours - blue, green, red etc. The only limitation of this approach was that similar colours under light could be mixed up, for example, red and pink wrappers had overlapping HSV RBG ranges, and therefore could not be both separated and identified by this method. It did however result in very clear contours for the significantly different colours so this method was used for the sweet recognition. Possible improvements could be made with shape recognition then colour analysis, which may have been able to identify a typical sweet shape and then separate by colour after.

Improvements on Colour Detection

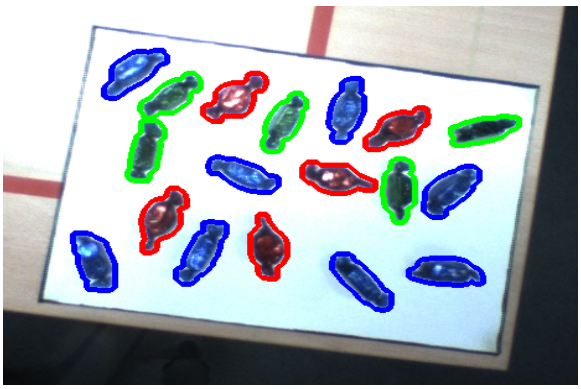
Whilst the HSV detection method was reasonably accurate, there were issues, which often occur in vision techniques, when the lighting changed. At different times of day, the HSV colour recognition failed, as the blue//green and green/red colourspaces overlapped in light or dark conditions. A couple of solutions were proposed as improvements on the colour detection to rectify this:

Euclidean Distance - Since the HSV range method varied in the light, an attempt was made to capture some of the light variation. Instead of detecting a range of HSV values, an averaged HSV value was calculated using multiple samples of each colour. By analysing the mean colour of the contour multiple times for each colour, an average RGB value for red, blue and green was calculated. Then, when trying to check what colour a sweet was, the RGB value with the smallest Euclidean distance to the average colour value would be the detected colour value.

Neural Networks - Neural networks are a relatively new development in AI, used to learn certain tasks by knowing the needed results, training the network to produce a set of weights to produce the desired results. Since the RGB colourspaces of the green, blue and red sweet wrappers overlapped in their values, it was decided a neural network could take some example values of the sweet's RGB values, learn them, and produce a more reliable colour recognition method.



(a) An example perceptron of the neural network with a threshold of 0.



(b) An image showing the correct classification of sweet colours using a neural network.

This was done by first collecting a sample of 50 of each coloured sweet's RBG values. 10 images were taken of five green, red and blue sweets respectively with sweets in different positions respective to the light source and at different times of day. Then the RGB values from within each sweet contour was written to a text file along with the desired result, for example: "R: 75, G: 80, B: 100, blue". This colour dataset was then used to

train a simple neural network. The simple neural network design was based on the basic perceptron learning algorithm, which uses a basic perceptron design, shown in **blah**. This perceptron would ideally train using the dataset by finding four weights that would give a less than zero value if the sweet RGB values matched a colour and above zero if it didn't match. After training the perceptron weights on the dataset for each colour (ie. green vs non green values), three sets of weights were returned to classify the colours. These weights could then be applied to any RGB average value to determine whether a sweet was red, green and blue. In neural networks, there can be some convergence issues, meaning there would be no weights to classify all three datasets however, seeing as the weights converged without any errors, that meant that red, green and blue sweets could be classified using the neural network with no overlap in classification. The neural network worked very well in classifying the colours, as it took into account variations in light for classification. It is seen working above in **Figure blah**.

5.2.1.3 Testing

After testing multiple colour detection methods, the best method was decided by testing between the three main ones: HSV colour segmentation, Euclidean distance and neural networks. The testing consisted of using each of the three methods on the sweet area and seeing which one had the most efficient colour detection. Five red, five green and five blue sweets were laid on the page in ten different orientations and tested with each method and the results are shown below.

5.2.2 Manipulation

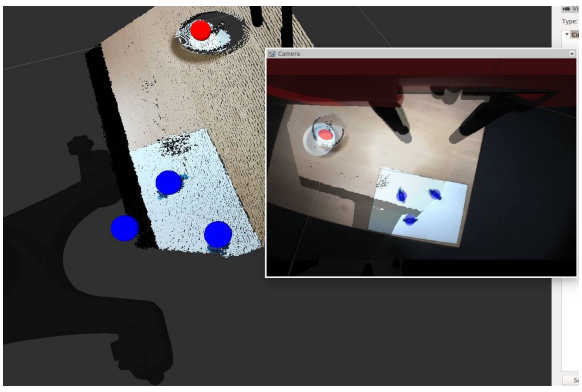


Figure 5.12: RViz showing the transformation between the detected sweet centres and the actual coordinates.

Now there was a method for the sweets to be detected, by extracting moments from the sweet contours, the 2D pixel coordinate could be retrieved from the 2D image. The problem then was converting the 2D points in that image into 3D world coordinates. This was done using an altered version of a pinhole camera method, where the u, v

coordinate within the 2D image could be converted to a 3D world coordinate using Baxter's in-built calibrated camera matrix. The equation uses the x and y camera offset values, with the focal lengths to scale the initial point. Then using the distance from the camera to the table (which is fixed), the points can then be converted into 3D world coordinates. This was tested using rViz and Baxter to make sure it worked.

5.2.2.1 Grabbing Methods

5.2.2.2 Testing

5.2.3 Singulation

A major problem with the tipping sweets from the bowl is that it can result in sweets which are too close together to be recongised properly by Baxter's recognition system. Without them being properly recognised, Baxter ignores them and therefore can't include them in the overall system. This results in problems say, if the customer wants three red sweets and there are only four in the bowl. If two red sweets are overlapping when tipped onto the table, Baxter could only possibly recognise the other two. This section explains methods used to recognise overlapping sweets and methods to separate them/pick them up from a pile to rectify this problem.

5.2.3.1 Detecting Overlaps

Since the previous sweet recognition system only recognised sweets which were separated from each other on the table via a contour method, large contours of two or more sweets could not be recognised. The main problem here was that, due to the sweets not being separable by colour reliably (the colour spaces overlapped), there needed to be a custom vision method developed to separate them. This section discusses the multiple approaches on trying to analyse these larger contours and split them into the respective separate sweets.

Separation by Case - An initial attempt to split these contours into separate sweets was to code the contour splitting manually by analysing the position and angle of the contours and splitting them the correct way. This method was attempted by first looking at the shape of the contours, the area of them and the ratio between the height at width.

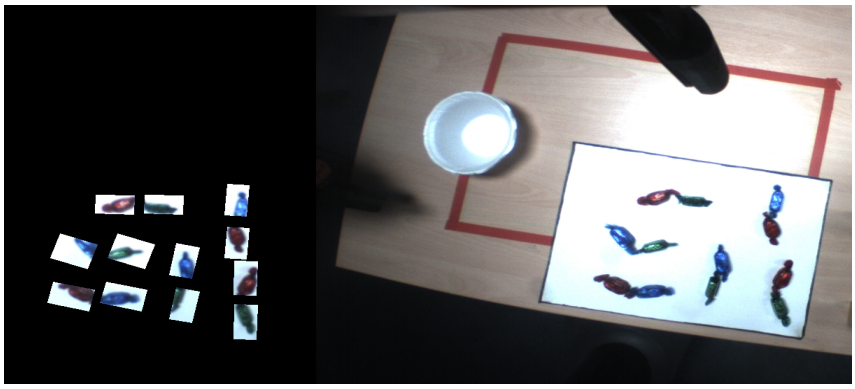


Figure 5.13: An example of splitting contours using a simple case

Initially, the first case attempted to solve was the one in **FIGURE**, where the sweet contour had a rectangular shape with an area the size of two sweets. As you can see in the image, this case was easily separable and therefore the sweets were recognisable. However, the problem came when attempting to apply this technique to multiple cases. The number of different separable cases were too large and varied to use this technique, so other techniques had to be developed.

Morphological Analysis

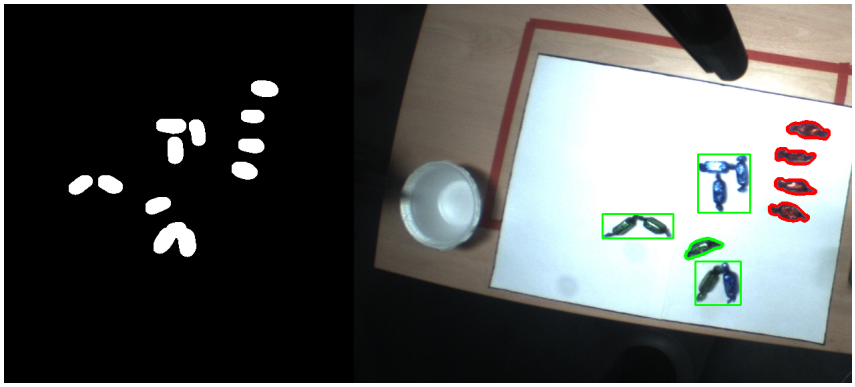
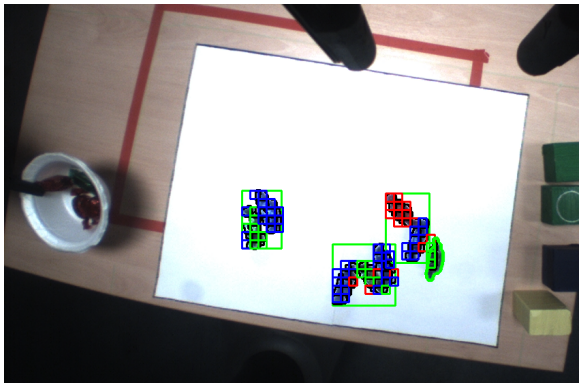


Figure 5.14: An example of a failed morphological analysis on groups of sweets

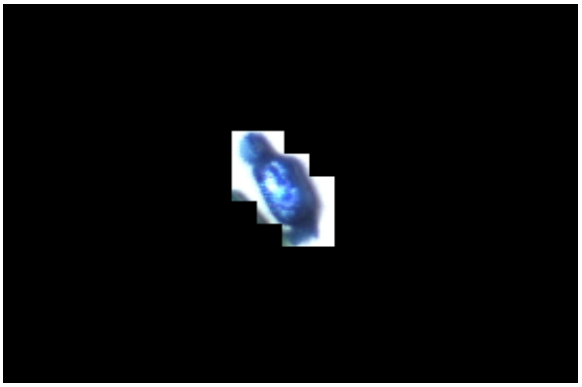
Another attempt to do this was to try and split the sweet contours via morphological analysis. This was done by a few processing methods to dilate and erode the masked sweet images to split them apart into separate elliptical shapes. The problem worked for the most part aside from when two sweets fell next to each other, touching with their shared horizontal side. This situation could not be split using this method as the sweets were too close to each other to split via this method. An example of this method failing is shown above.

Rectangular Search Method

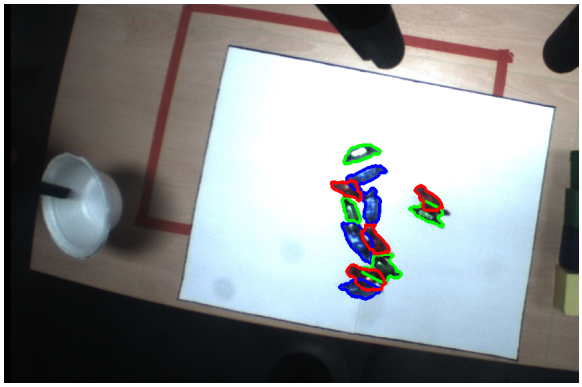
The main method used in the final version of the software was the rectangular search method. This method uses a combination of vision techniques to process the sweets and separate them within the grouped contour. This process has multiple steps, explained below:



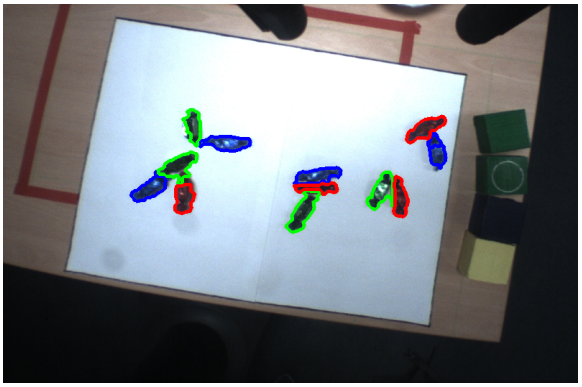
(a) An example of detected colours within sweet groups.



(b) A sweet mask retrieved from the detected coloured squares.



(a) Detected sweets using convex hulls to expand the detection area.



(b) A working example of the vision system detecting overlapping sweets.

1. Splitting into coloured squares - Firstly, an algorithm splits the whole contour up into small squares and looks at the colour of each square using the neural network developed in **subsubsection: Neural Network Recognition**. Due to the fact the green, blue and red colourspace has some overlaps in the RBG values, these square colours are not always accurate, but this method is accurate enough to recognise the majority of the sweet's correct colour values (shown above in **figure blah**).

2. Region Growing Algorithm - Secondly, a custom region growing algorithm was developed to loop over the coloured squares to grow out the regions. This algorithm checked the horizontal, vertical and diagonal neighbours of each colour and determined the colour was correct if it had two or more of the same neighbours of the same colour. This meant that any anomalous colour recognition was not included in further analysis.

3. Masking and Recognition - After the region growing, the individual sweet areas can be converted to a mask, which can then be detected as a whole sweet using the regular image processing techniques normally used for the existing vision system.

4. Convex Hull/Non Convex Hull Recognition - Occasionally, the sweet mask missed some of the edges of the sweets, due to the colours not being properly recognised. In this case, convex hulls could be taken of the mask, to slightly expand the mask allowing for the whole sweets to be detected. However, convex hulls did have a downside, overlapping the detected sweets as shown in image **blah**.

5.2.3.2 Singulation Methods

5.2.3.3 Testing

5.3 Human Interaction

After the main sweet manipulation and recognition methods, the final system to implement was human interaction methods. Since the human interaction methods were the least important aspect of the overall system (Baxter could get sweets via the command line without any interaction), the human interactions were the least developed at the end of the project, due to time restraints.

5.3.1 Voice Recognition

Voice recognition was a feature that seemed key to implement.within the system. The idea of this feature was for a customer be able to approach Baxter, speak a voice command for the requested sweets and then Baxter would get those sweets for them. A couple of approaches were taken to voice recognition, to get the valid accuracy required for an order. The idea was for program to eventually recognise a complex command such as "I would like two green sweets, three blue sweets and one red sweet" and parse the command appropriately.

5.3.1.1 Python's NLTK

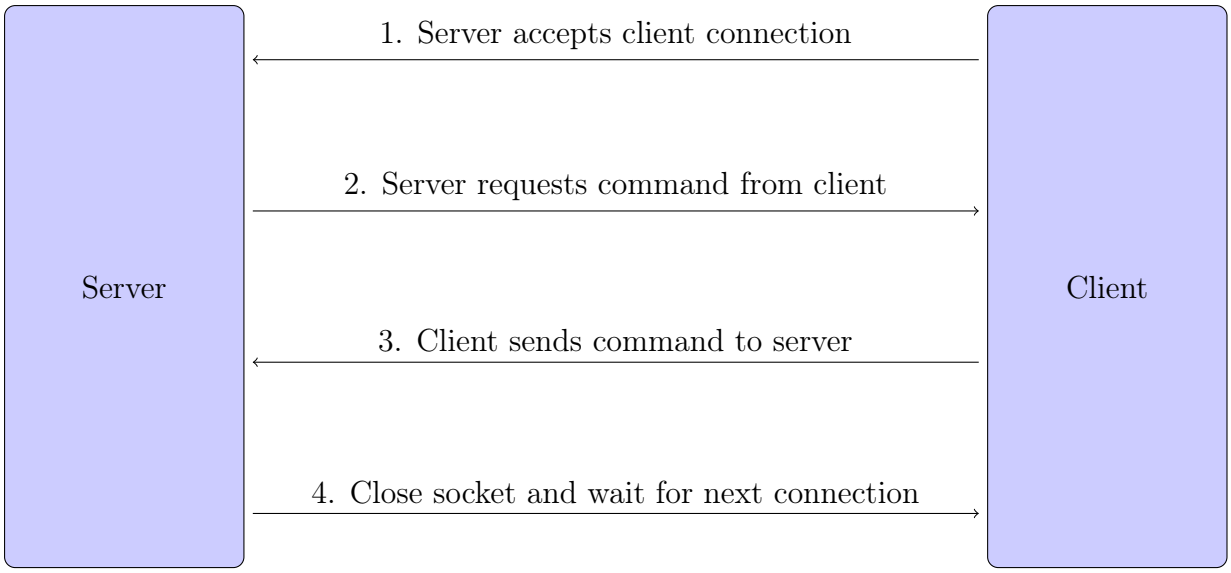
Firstly, Python's NLTK module was proposed to be used to analyse voice commands. An in-department microphone was used to record voice commands using some in-built Python microphone recognition/recording modules (alsaaudio module amongst others). This method proved to be difficult to set up and depends on the linux machine and the currently installed audio drivers. When the microphone drivers were set up, a ROS node was set up so that the microphone first averages the background noise to cancel it out. Then the microphone will record until a timed period of no speech occurs.

After the recording was made, the Google API was queried with the recording, to convert the speech to a line of text. Unfortunately, with noise issues and microphone efficiency issues, there was some difficulty in recognising some words due to the person needing to be a very specific distance from the microphone (otherwise varying noise levels from different distances would interfere with the voice to speech detection). After the speech has been converted to text, the text can be analysed to determine the person's command. Since the voice recordings weren't too reliable, the text could be parsed for numbers to have a reliable command. The Python module therefore listened three times - for a number for blue, red and green sweets respectively. However, since this didn't recognise full sentences very well, it was decided an Android device could be used to provide a better recording device for more complex commands.

5.3.1.2 Android's Google Voice Recognition

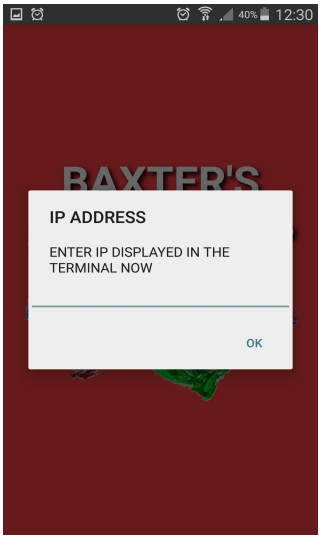
Due to complications with the microphones detecting longer commands, it was decided that an Android device with built-in voice recognition could be a more accurate approach. The only problems with the Android approach is the fact that it assumes an Android device would be available to use alongside Baxter and a small server-client application would have to be developed to run this. Here are some details for the development of this application:

Server-Client Application - The easiest way to connect an Android app with the computer running Baxter's software was to connect a ROS node written in Python to a Java by means of a server-client architecture. The idea being that the Python node would run a server via a Python socket on the uni's wireless network and then when a user needs to provide a command, the server would send a command to the client prompting the user to speak or enter a touch command. The client-server logic is seen below:

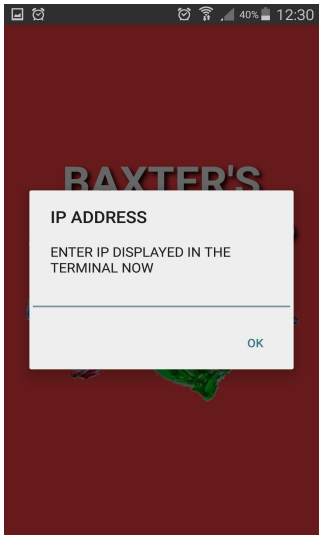


The application client was set up so that it only asks the user for a sweet command when the Python server prompts the client for it. The Python server uses an open '0.0.0.0' IP address on the machine running it and then the client uses the specified wireless IP for the server machine. This is inputted into the app on first opening to ensure that the correct IP address is being used for socket connections between the two devices.

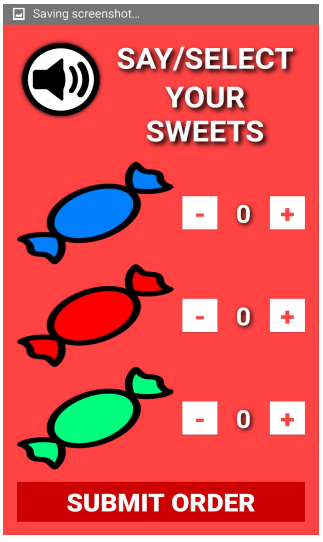
User Interface - The user interface was designed to be simply understood by the user and only require a small amount of setup for the person running the software. The idea of the app is that it would connect to the server on opening, show the main menu and then when Baxter wants a command, the server would send a request to the Java app client, the app would open up the command page, which would prompt the user to record a voice request or enter the sweet numbers they want via touch arrows. The main menu and sweet command page are shown in the images below.



(a) Enter IP page.



(b) Main menu page.



(c) Choose sweets page.

When the app is opened, the IP address is entered from the command line printed by the server node. Then the main menu page is viewed until the server wants to receive a customer's command.

Analyse Command - After the speech has been converted to text using the Google voice recognition API on the device, the text needed to be parsed for a command. The parsing works in a relatively simple way, where it first looks for whether someone has said the words 'blue', 'green' or 'red'. There is also a basic fuzzy search method where it also looks for other words that sound very similar to them. Then after that, the locations of those words are found and then the words before the colours are analysed, to see what number they are. If they are recognised as 'one', 'two', or 'three', then the parser knows how many of each colour the customer wants. This approach works reliably enough and the more people that tested the system, the more changes and extra anomalies were caught in the voice recognition.

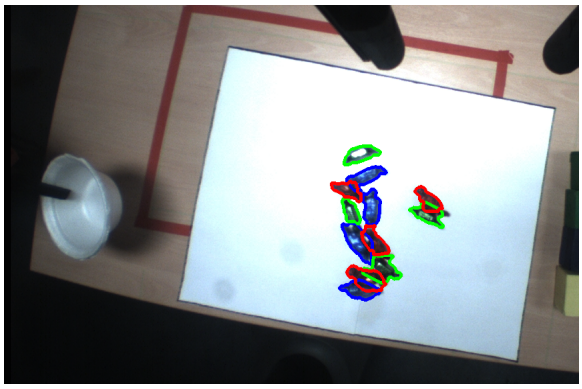
5.3.1.3 Testing

5.3.2 Customer Recognition

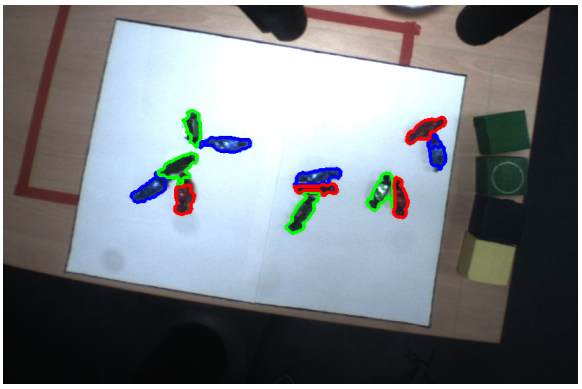
The next implementation of human interaction was to recognise whether a customer has approached Baxter or not. Then if the customer has approached Baxter for some sweets, Baxter will know and can therefore start the conversation and other aspects of the interaction. The initial idea for the approach was to know when a customer enters and exits the scene, to ideally be further expanded to recognise certain actions, like reach for the sweet bag and exchange money.

5.3.2.1 Detect Person

The first method to detect a person was a very simply devised method, based around background subtraction without any shape recognition on the person whatsoever. Firstly, Baxter would request a ROS node to look for a person. Then Baxter would move his arms out of the way so the head could turn and see a customer enter. The current frame would then be used as the background frame for subtraction. A person would be considered to have entered the scene when a large contour was found entering the scene, seen in **figure blah**.



(a) Background person contour.



(b) Detected contour in image.

After the person was found, a key part of the recognition would be to make sure the person was in front of Baxter for a set period of time. After the person existed in front of the camera for 40 frames, the node recognised the person as wanting sweets and sent a message back to Baxter to start the interaction. However, if a person did not exist for 40 frames, the program would recognise the contour exiting the scene and therefore carry on waiting for another customer.

5.3.2.2 Skeleton Recognition

Due to time constraints, a working implementation of skeleton recognition could not be implemented by the end of the project. This was partially due to technological issues. To get a skeleton recognition system working, the system would need to implement a second Kinect depth camera. The problem with a second Kinect is that it was difficult to find a place to put the Kinect, due to one Kinect already being on the torso of Baxter looking at the table. This meant that the only place to put a second Kinect was on a tripod away from Baxter, meaning that if Baxter was moved at all on open day, that Kinect would have to be recalibrated each time. The decision to not implement skeleton recognition was then made from a time perspective, as it takes a long time to set up an extra Kinect and calibrate it to work with the system. Due to only having 4 weeks left at the point of discussing this, it was decided it was better to focus on other key features of the project.

5.4 System Integration

5.4.1 Node Communication and Custom Service Requests

5.4.2 Control of Vision Processes

5.4.3 Roslaunch Files

5.4.4 System Logic

[3] [2] [4] [1]

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Appendices

Appendix A

Bowl Recognition Tests

A table showing the tests of the bowl recognition system and the method's respective accuracies.

	Continuous Averaging	**Cumulative Averaging**
Trial Number	**Successfully grabbed bowl? (1 for yes 0 for no)**	
1	1	1
2	1	1
3	1	0
4	1	1
5	1	1
6	1	1
7	1	0
8	1	1
9	1	0
10	1	1
Percentage Accuracy	1	0.7

Appendix B

Bowl Scooping Tests

Appendix C

Bowl Tipping Tests

Appendix D

Ethical Issues Addressed