MRSD Project Course Team D
Pantrybot for Amazon Picking Challenge

October 2, 2015

Abhishek Bhatia
Alex Brinkman
Feroze Naina
Lekha Mohan
Rick Shanor

Table of Contents

1. Project Description

Pantrybot is about maintaining independence. The need for in-home assistance will grow alongside the gracefully aging senior population in America and will further strain elderly care services. Currently, senior citizens comprise approximately 14.1% of the U.S. population but that number is projected to increase to 21.7% by 2014 [1]. The goal of Pantrybot is to improve the quality of life of the users in their homes by autonomously storing and retrieving groceries and other items. Such a system should reduce the physical strain on the user and help reduce the risk of injury in the kitchen, further enabling the user to live independently with confidence.

In order to be useful in home assistance, Pantrybot will require highly-sophisticated features to operate in the dynamic home environment and perform the core functions of item retrieval and item stowage. A commercially viable offering of Pantrybot would be out of the scope for a two semester student project so the 2015 implementation will focus only on the task of item retrieval. Specifically, this involves interpreting a user request to locate and fetch items from a cluttered pantry. By breaking the Pantrybot into the sub tasks of item retrieval and item stowage, we hope to limit the scope so we can deliver to realistic expectations and at the same time allow for the possibility of additional MRSD development in years to come.

Additionally, the goals and timeline of this semester aligns well with the Amazon Picking Competition (APC) planned to be held at International Conference on Robotics and Automation (ICRA) in 2016. This competition aims to stimulate academic and industry interest in more generalized pick-and-place robotic systems with the ultimate of goal of automating the item retrieval task in Amazon's order fulfilment process. The contest promises high public visibility and this will be leveraged to gather industrial sponsorship, public support for Quality of Life Technology Center at CMU, and demonstrate the Pantrybot project. In many ways, the picking challenge is a subset of the goals of the Pantrybot project and for this reason we feel success in the Amazon Picking Competition would translate to success for the Pantrybot system.

2. Use case

2.1. Narrative

Amazon customers place about 3 million orders online everyday [2]. Within hours, products are delivered to their doorstep, all without human intervention. The order is dispatched to a collection of robots in the warehouse where Kiva shelves autonomously drive from storage to their place in the order queue. This is where Pantrybot comes into play.

Robots then perform the mundane task of grabbing items off shelves and boxing them for customers. The packing robot receives a packing list from a central server. Once the shelf drives up to the packing station, the robot begins the boxing process. Perceptive sensors determine the position and orientation of a desired item on the shelf. A robotic arm strategically grabs the item and places it in the customer's box.

Later down the line, more robots label the box and tape it up for delivery. Autonomous cars pick up the packages and drop them off for the customer to enjoy.

2.2. Graphical Representation

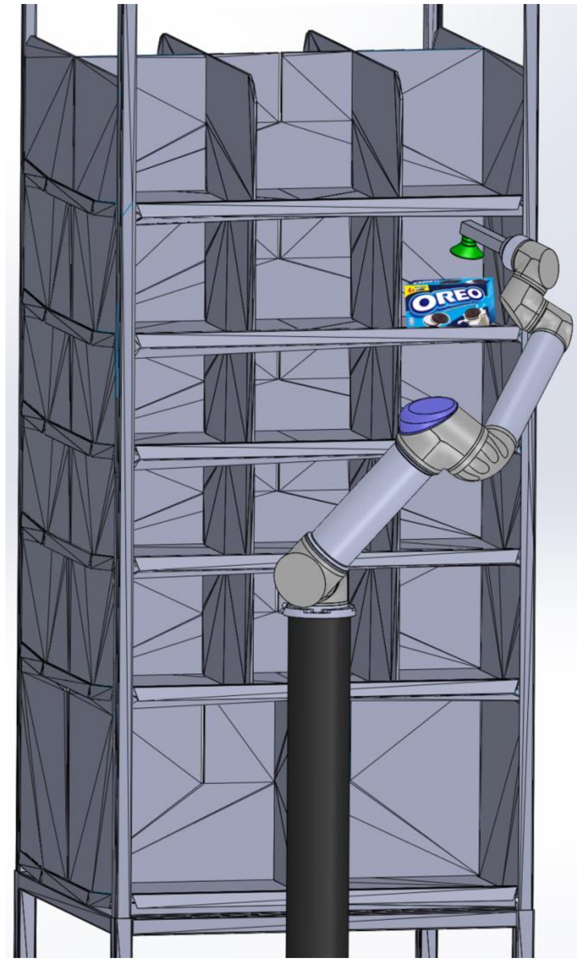


Figure 1: Use Case Graphic Representation

3. System-level requirements

The functional requirements are driven by our objective of creating a pick-and-place robot. The performance requirements were produced by analyzing the operation of the top three teams during the competition last year. Nonfunctional requirements are driven by both the MRSD course and requirements set forth to compete in the Amazon Picking Challenge.

3.1. Functional Requirements and Performance

FR1	Accept order list from user
PR1	Interpret work order with 100% accuracy
Description	The JSON format order list is processed.

FR2	Autonomously determine positions and orientations of target items
PR2	Autonomously identify object with 90% accuracy
Description	The position and orientation are calculated by the perception module using state-of-the art algorithms. The pose must be determined in order to acquire the objects.

FR3	Accurately determine item grasp position
PR3	Autonomously determine item grasp positions within 2 cm from the item on 75% of attempts
Description	The perception module outputs position of end-effector for optimal grasping.

FR4	Autonomously picks item from shelf bin
PR4	Autonomously picks item of known pose from shelf bin on 50% of attempts
Description	The kinematics planning is done to pick up the items from the shelf.

FR5	Autonomously places item in order bin
PR5	Autonomously places 90% of picked item in order bin from a height of no more than .3 meters
Description	Once the item is picked, the robot drops it off it in order bin.

FR6	Must follow the dimensional constraints set by Amazon Picking Challenge
PR6	Acquire items from bins located at a max height of 1.86m and minimum height of .78m Acquire items from a .27m x .27m shelf bin Be able to lift items up to .5kg mass
Description	The items and shelf units specified by the Amazon Picking Challenge rules add constraints to our design.

FR7	Does not drop items
FR8	Does not damage items
Description	During robot operation, the robot should not allow items to fall down. The robot should not deform the items in any way. This ensures we are only adding value.

PR7	Acquire at least 3 items of 10 total attempts in under 20 minutes
Description	Maximize the number of items successfully picked and placed in the given time.

3.2. Non-functional Requirements

NF1	Cost no more than $4000
NF2	Be completed by May 1st, 2016
Description	MRSD project requirements.

NF3	Transportable or available at ICRA 2016
Description	The robot should be capable of being disassembled and reassembled easily. Alternatively, the robot platform must be available for use at the ICRA competition in Sweden, Stockholm in May 2016.

NF4	Robust to environmental variations including lighting and physical geometry
Description	The robot's perception system should operate reliably under different lighting conditions and changes in physical geometry. This is because the competition lighting conditions cannot be reproduced accurately in our test setup.

NF5	Be available for testing at least 1 day per week
Description	We need to test the algorithms on the real platform every week to ensure consistency with simulation model.

NF6	Start and stay within a 2m by 2m boundary (except the end effector)
Description	The competition rules state that the robot should stay within the 2m x 2m workcell and only the end effector can reach into the shelf. The shelf is atleast 10cm away from the workcell area.

NF7	Have an emergency stop
Description	We require a stop button to halt the manipulator platform in case of accident.

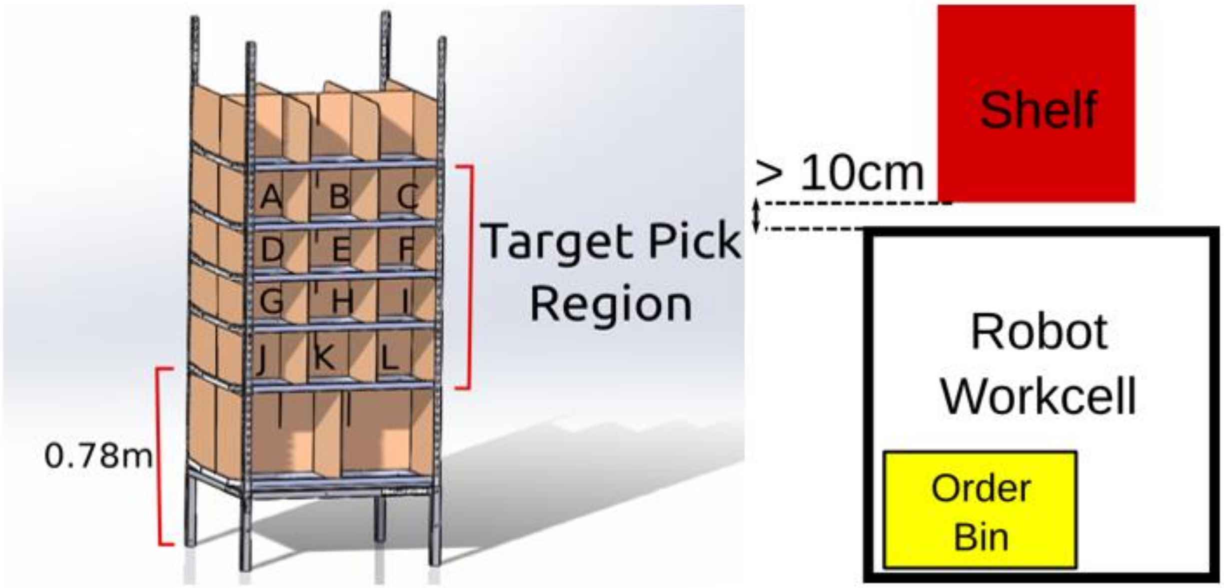


Figure 2: 2015 APC Competition Configuration

4. Functional architecture

The functional architecture of this project, shown in Figure 3, can be broadly categorized into four functional areas - input handling, perception, platform and grasping.

Input Handling: The robot autonomously parses the items in the list to generate an item plan. The input handling function uses an algorithm to select small and easy to grasp items and places them in the beginning of the list followed by larger and objects with no definite shape.

Perception: The perception function is responsible of scanning the shelf, scanning individual bins, determining item pose and providing the system with sufficient data to plan the manipulator trajectory to grasp the item from the shelf bin and place it in order bin.

Platform: Platform function takes the item pose data as input, focuses on kinematics of the path plan to determine the best trajectory (shortest distance and collision free), and moves the manipulator to best grasp position. Further, platform function also determines the reverse path based on inverse-kinematic calculations to move the manipulator towards the order bin.

Grasping: Grasping function decides on the best grasp strategy and moves the end-effector towards the object. Once the suction arm touches the object, grasping function switches on the suction mechanism and grasps the object.

The following process highlights the interaction between the four main functional areas. The user passes a Javascript Object Notation file which includes the item contents of all bins on the shelf and the desired order items. The robot generates an item plan to grasp the maximum number of objects in the desired timeframe. To do so, we plan to have an algorithm in place that assigns different weights such as ease of grasping, points associated etc. to each object and finally generates a work order that attempts to maximize the overall score.

Next, the robot localizes itself with respect to the shelf and develops a dimension matrix for each item in the world coordinates. Once ready, the robot begins with grasping and dropping operation on a per object basis. The details of the object to be picked is passed to perception, where the vision sensors scan the shelf to determine item pose and passes the information further to platform function. The platform plans the trajectory and moves the manipulator to the item location.

Once the manipulator is outside the shelf bin, the grasping system obtains the object using a suction gripper. Pressure sensor feedback provides the grasp status to the platform. If the grasping was successful, the platform plans the reverse trajectory based on inverse kinematic calculations for the manipulator and places the object into the order bin. If the grasp was unsuccessful, the system will abort further attempts to grasp the current item and start on the next item in the list. The rationale being if the first attempt to grasp an item was unsuccessful, any subsequent attempts to grasp the same item with either disturbed pose or other infeasibilities will be more time consuming. Therefore, to meet the performance requirement of picking 3 items in 20 minutes the time would be better spent attempting a new object from the list. The system re-iterates this loop of grasping and dropping until it has either picked up all items in the dictionary or the time limit has been reached. Once out of loop, robot moves back to the resting area.

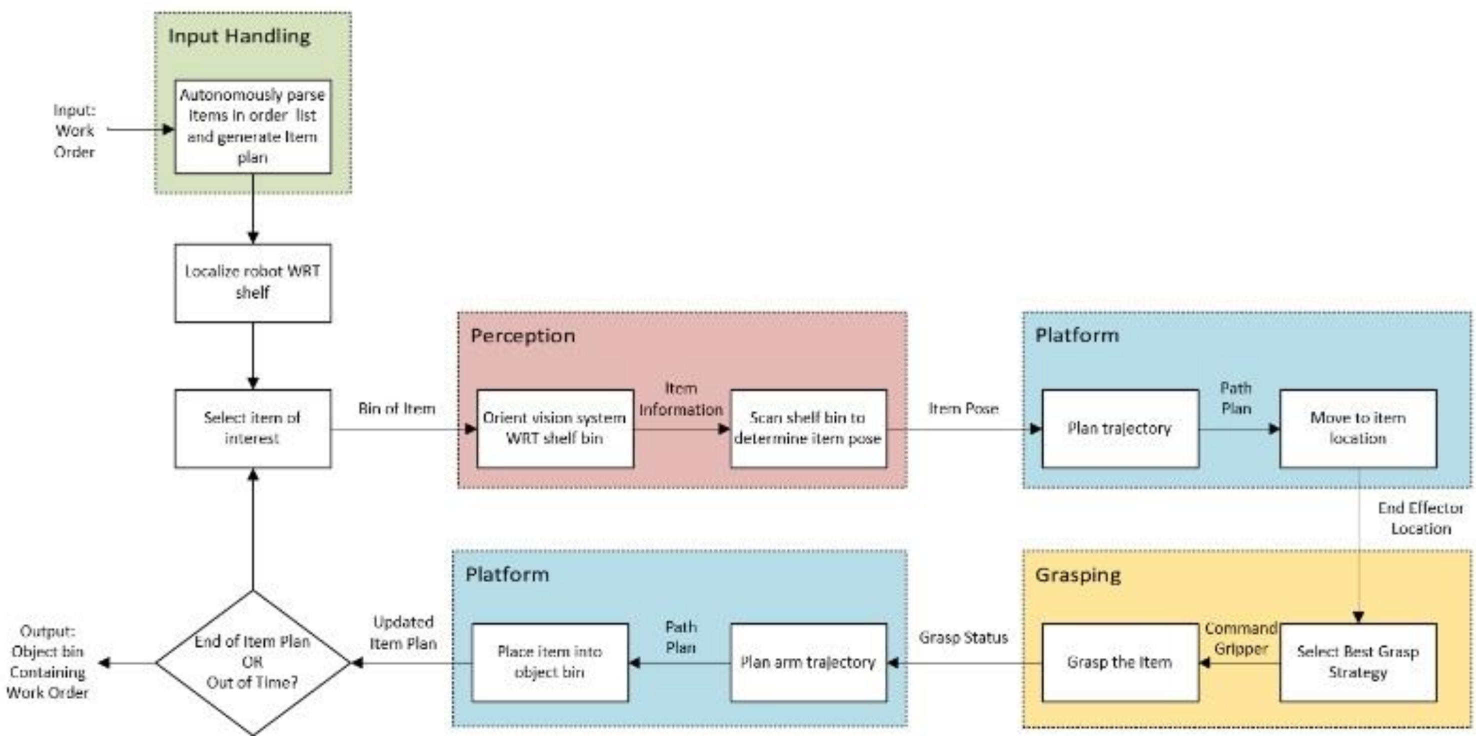


Figure 3: Functional Architecture

5. System-level trade studies

Three major trade studies were performed in order to determine system architecture. These three trades were based on the three major functions highlighted in the functional architecture. In this section, the decision criteria used in order to make design choices are explained.

5.1. Platform Trade Study

The platform is defined as the combination of arm and mobility system. The top three options considered in the trade study were an industrial arm (on a 1D track), a mobile manipulator, and a gantry system. The two most significant decision criteria were ease of integration and dexterity. Ease of integration refers to a system's available support. Since commercial mobile manipulators often offer ROS support, this scored highest in this category. Since a gantry would require all custom hardware, the team would have to build up software support. Dexterity refers to the ability to have precise control inside the tight shelf spaces. Most off-the-shelf manipulators are large and bulky. The gantry system would be designed to maneuver in tight spaces.

Table 1: Platform Trade Study

		Platform Trade Study		
Decision Criteria	**Weight**	**Vertical Track Industrial Arm**	**Mobile Manipulator**	**Gantry System**
Mechanical Development	3	2.2	4.2	1
Transportability	3	2.4	3.8	1.4
Ease of Integration	5	2.8	5	2.2
Accuracy	4	5	3	4.6
Speed	1	5	2.6	4.2
PayLoad Capacity	1	5	3	3.4
Dexterity	5	3.8	3	3.8
Weighted Overall Score		**76.8**	**81.6**	**63.2**

The mobile manipulator (such as the PR2 or Baxter on a DataSpeed mobile base) is the preferred option due to mechanical simplicity and ease of integration with ROS. However, the team must find a sponsor to pursue this option. The industrial arm would also require less mechanical overhead and a few small robotic arms are available around campus. Finally, a 3D gantry system, similar to last year's Pantry Robot was considered. This option would allow for precise shelf alignment but would require a significant development of the mechanical hardware.

5.2. Perception Trade Study

The team already identified the need for both camera and depth sensors to determine object pose on the shelf. Depth data might come from a LIDAR or a depth map sensor, depending on the final platform configuration. The final trade study compared two different perception strategies. The first strategy would be to use only these stationary sensors to determine object position. The second option would be to include a camera in the gripper which could provide closed loop feedback to position the suction relative to the item. The first method would allow for simpler algorithm implementation and would require less processing power. However, an

Eye-in-Hand strategy would allow for a more flexible solution that could correct for errors in initial pose estimation.

Table 2: Perception Trade Study

		Perception Trade Study	
Decision Criteria	**Weight**	**Stationary Perception**	**Stationary + Eye-in-Hand**
Reliability	5	3	5
Flexability/Controllability	5	3	5
Processing Power	1	5	1
Cost	3	3	1
Algorithm Implementation	5	5	3
Weighted Overall Score		**69**	**69**

5.3. Grasping Trade Study

Finally, several different grippers were compared. The major weighting criteria were derived from the size and shape of the items defined by the Amazon Picking Committee. An additional criteria included not damaging the items. The clear winner was the suction gripper. Suction can grip a variety of object geometries. It will only struggle with very odd and complex shapes. In addition, gripping algorithms will be simplified as suction can grab a variety of surfaces.

Table 3: Grasping Trade Study

		Grasping Trade Study		
Decision Criteria	**Weight**	**n-Finger Gripper**	**Suction**	**Push or Scrape**
Lifting capacity	1	5	5	5
Can grasp small items (4 / 23)	3	3	5	1
Can grasp boxed items (10 / 23)	5	3	5	3
Can grasp plastic covered items (6 / 23)	3	3	5	3
Can grasp 'loose' items (5 / 23)	1	3	3	3
Will not damage item and shelf	3	3	5	1
Difficult to implement	5	1	5	1
Weighted Overall Score		**55**	**103**	**43**

6. Cyberphysical architecture

The cyberphysical diagram below explains the control and feedback mechanisms necessary in order to achieve the functional architecture. The user input, in the form of a text file, is given to the master ROS controller, which begins the state machine. In the 'perception' state, the master ROS controller passes in an item of interest, which also includes the specific bin number. The robot then aligns the perception sensor (combined depth plus camera) and captures data. This raw data is passed back (over USB) to the main computer. The item recognition algorithms then determine the item's position and orientation on the shelf. Specifically, using image segmentation techniques, bag of words classifiers, and known shelf geometry, the approximate item location is determined. Using this data, the point cloud depth data is downsampled to the region of interest. Using ground truth 3D object data, the known geometry is fit to the depth data acquired by the LIDAR. Algorithms available in OpenCV will be used to simplify the vision task. This results in a position and orientation of the item of interest relative to the robot.

These coordinates are passed back into the ROS master controller. A desired end effector position is determined based on the item location. This desired position is passed into the manipulator planner. The manipulator planner creates a series of actuator commands, using inverse kinematics, that are required to position the robot relative to the item. Error collision checks that we will not intersect with the shelf. These commands are executed by low level microcontrollers. Position feedback, supplied by encoders and other sensors, verifies that the trajectories are executed properly. Once this occurs, the final position of the arm is sent to the ROS master controller.

Finally, manipulator and item positions are send to the grasping mechanism. Using trained methods of item acquisition, unique to each item, a grasping plan is generated. Again, a microcontroller is responsible for low level commands. Tactile feedback (in the case of a vacuum, a pressure sensor), indicate successful grasp. In addition, an eye-in-hand camera provides closed loop control during item acquisition. Once the item is acquired, the ROS controller receives a grasp success signal from the grasp controller. The manipulator planner repeats, moving the item from the shelf to the box. This cycle repeats until all items from the original text file have been acquired.

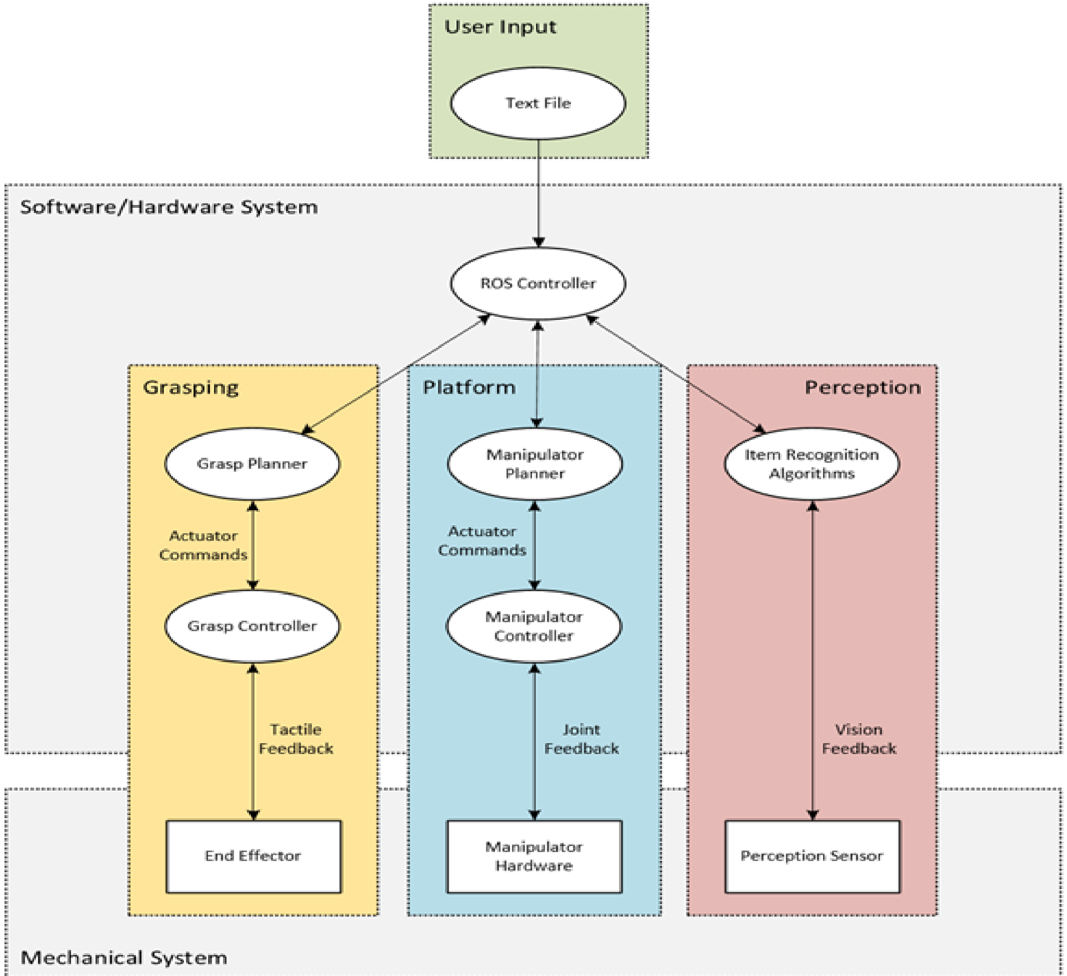


Figure 4: Cyberphysical Architecture

7. Subsystem descriptions

7.1. Perception Subsystem

Vision guided robot system encompasses cameras/depth sensors that allow robot to give an estimate of the real-world location coordinates of the objects it has to grasp. We are considering stationary camera system and eye-in-hand vision system for our project.

A stationary vision system is mounted on the head of the robot that scans the target environment within its field of vision. The complexity of computation is low when compared to the dynamic vision system. Stationary vision system is also less prone to errors. When an industrial arm is unable to meet the performance requirement with the gripper, we could consider eye-in-hand coordination system where camera is attached to the arm of the robot. Visual servoing gets feedback from this system to control the movement of the robot arm. It is robust to calibration error and the accuracy is very high, but greater computational speed is a requirement here to constantly update the robot arm parameters, which increases the complexity of the computation [3].

We are considering Kinect and LIDAR systems for our project. Using Kinect sensors, the robot will be able to estimate the depth of an object and transform its position from image coordinates to the world coordinates. Kinect is a RGB-D camera whose range is up to 3.5 meters. The response time of Kinect is much faster than LIDAR system.

LIDAR uses a beam of a laser scanner to estimate the depth of the target object. It measures the distance or depth by analyzing reflected light beam. LIDAR is capable of working in the dark and is computationally faster to process. It doesn't require camera calibration, which implies our risk for computational error is less. LIDAR suffers certain limitations as well. It can read only grayscale images from a spectrum of InfraRed and the system as a whole is costly.

Table 4: Perception System Comparison

System	Hokuyo Lidar	Microsoft Kinect
Field of View	240 Deg	43x57 Deg
Min Range	20 mm	800 mm
Max Range	5600 mm	4000 mm
Resolution	0.2 mm	<4 cm

The vision subsystem involves identifying the object, transforming its coordinates with respect to the bin, plan the path and grasp the object according to the algorithm process below.

Classification: A ground truth dataset, generated from images of the 2016 Amazon Picking Challenge items, is used to train image classifiers based on filter responses. A dictionary is created for each item in the 2016 competition.

Filtering and Segmentation: Next, our sensors capture a camera image of the shelf bin. Given the picking order, we know the object of interest exists in the bin. Segmentation and filtering techniques, using K-means clustering and edge detection, are used to detect the features and contours of the image. This allows for us to determine foreground and background on the shelf.

Recognition: A histogram of each segment in the image is generated and compared to the item classification. Object recognition is based on feature learning and matching, edge detection, and gradient matching, a bounding box is created approximating the items location on the shelf. Risks include object not getting detected and ghost objects or objects are detected even if they are not there.

Point Cloud Filtering: Data collected from depth sensors is down sampled to a manageable size based on the item recognition results.

Pose Estimation: The depth data is compared to the ground truth 3D model of the item of interest. Specifically, the ground truth data is aligned with the sensor data to minimize the sum of squares error between the two datasets. This is accomplished through bounded optimization techniques. The exact item location is then sent back to the master state machine to determine manipulation and grasping strategies.

Transformation: Transformation involves transforming/mapping the location from vision coordinate frame to real world coordinate frame. Reconstructing the object and applying inverse kinematics will help robot retrieve the object at the specified location.

Eye in Hand Feedback: If the gripper is initially unable to acquire the object, closed loop feedback using a camera in the end of the arm allows for precise positioning. Visual servoing and feature recognition algorithms from this system control the movement of the robot arm.

7.2. Platform Subsystem

The primary function of the platform subsystem is to move both the perception system to analyze the item and orient the grasping system in space in order to pick and place items. The design of this subsystem is not finalized due to the high uncertainty of the availability of platforms at the venue in Stockholm Sweden. The design of the platform subsystem reflects this difficulty as there are three options we are currently pursuing.

The most preferred option for platform subsystem would be a mobile manipulator like the PR2 from Willow Garage. The PR2 offers a rich feature set in the ROS environment, onboard computing, and a high degree of dexterity. These capabilities will reduce time to build, test, and debug the system integration and allow more focus on the perception and grasping tasks. The most significant drawback to this option is the availability. To date, we have been unable to gain support on campus to use a mobile manipulator and estimate the chances of gaining access is low.

The next preferred option is to use a commercially available industrial arm in tandem with a vertical track system. Currently, our preferred option is the Sawyer robot from Rethink Robotics coupled with a custom stationary base with a prismatic joint in the vertical direction. Other attractive arms include the WAM arm from Barett Industries or traditional industrial arms from companies like ABB, KUKA, Fanuc, and Universal Robots. An arm would provide precise, repeatable motion and would likely have ROS support.

Figure 5: Sawyer by Rethink Robotics

While the benefits are high for the robotic arm and track option, there are several downsides in availability and transportability, and ease of integration. Currently, we only have access to one ABB arm but are reaching out to many companies for support. However, we estimate a high likelihood of finding a sponsor that can provide a robotic arm.

We anticipate the need for additional degrees of freedom to move the base of the arm to ensure the arm can reach into each of the bins with sufficient dexterity. The introduction of an off-the-shelf mobile base, such as Dataspeed Inc's Mobile Baxter Platform or Clearpath Robotic's Ridgeback or custom designed base would increase development time and effort and may not yield precision localization of the end effector. The preferred solution is a custom designed prismatic sliding joint to support the robotic arm and increase manipulation dexterity. This custom base will be repeatable and precise but will require additional electronics and software integration and may prove difficult to transport. Despite the risks of availability and challenges of integration, we feel this option offers the highest likelihood of success.

Finally, the last option being considered for the platform subsystem is a gantry system. The gantry system consists of a Cartesian robot with 3 degrees of freedom in the XYZ directions. The gripper and perception subsystems would translate on the gantry. The gripper end effector would likely have an additional rotational degree of freedom normal to the plane on the face of the shelf. This option excels at ensuring each shelf bin is accessed in a consistent way, in contrast with the other options which may have limited dexterity reaching into the bins furthest from the base. Also, this system should be fast and does not depend on 3rd party sponsorship. The downsides are the design will require a significant amount of our development time and resources to design, build, test, and integrate into ROS and drive high transportation cost. For these reasons, the gantry system option will only be pursued if sponsorships cannot be obtained.

7.3. Grasping Subsystem

Based on the trade study discussed above for various grippers, suction based gripper won by a large margin, basically for its ease of development and utility with respect to item dictionary. For developing the suction gripper, we intend to use a suction cup, pressure sensor, vacuum pump, pneumatic tube and a microcontroller. There are multiple options for a suction cup such as flat, flat concave, bellows, multibellow's etc. The most desirable option among these seems to be the bellows suction cup (image shown below) as it is suitable for objects with height differences and slightly uneven or curved surfaces, which will account for maximum items from the dictionary.

Figure 6: Bellow Suction Cup [4]

The suction mechanism is switched on once the manipulator reaches the desired object in the shelf bin. A vacuum pump produces negative pressure of 5.7 PSI, allowing a suction cup of 0.8 inches to produce a force necessary to lift the heaviest object with a safety factor of 2. See Appendix C for more details. A pressure sensor detects a spike in pressure once object has been grasped, providing feedback to the robot controller. After acquiring the object, it is lifted and placed into the object bin.

8. Project Management

8.1. Critical Subsystem Tasks

The team has identified critical subsystem tasks as such:

Perception
- Finalize depth sensing device
- Choose algorithms for segmentation and item identification
- Train model with dataset of catalog items
- Estimate grasping position for item
- Verify and validate perception system meets performance requirements

Kinematics
- Decide motion planning package
- Determine the coordinate transformations
- Simulate path planning
- Integrate with perception subsystem
- Verify and validate kinematics system meets performance requirements

Software & Computing Hardware
- Acquire high performance computer with CUDA supported graphics card to accelerate perception algorithms
- Setup drivers for robot platform - end-effector, manipulator and robot base
- Setup ROS, MoveIt and gazebo simulation environment

Robot Platform - End-effector, manipulator and base
- Choose robot manipulator and base
- Finalize design of vacuum end effector - electrical and pneumatic circuits
- Mount end-effector on manipulator platform

Documentation
- Submit reports and update website
- Use version control for software development
- Develop readable, extensible ROS package

Testing setup
- Acquire and assemble shelf setup
- Prepare workcell with adjustable lighting setup and correct order bin position

8.2. Project Milestones

The major milestones that the team will achieve in order to develop a system capable of meeting the performance requirements listed in Section 2.1 can be found in Table 5. A full Gantt chart, which details the project timeline in more detail, can be seen in Appendix A.

For progress review 1, the team will prepare several deliverables. First, we will present a CAD model of the suction gripping mechanism, including suction cup, mechanical structure, and vacuum system. In addition, the team will implement item recognition algorithms using Berkeley training dataset. Our algorithms will work with a recognition accuracy of 70% by this time. PR2 requires that the system must eventually autonomously identify object with 90% accuracy.

For progress review 2, the team will finalize sponsorships and thus be able to make a more informed decision on build vs. buy system platform. By this time, the 2015 Amazon Picking Challenge rules should be released. We will review these and modify our requirements and design decisions accordingly. Finally, the team will acquire all 2016 APC items and create a ground truth image dataset.

Table 5: Project Milestones

Date	Milestone	Tasks to be Completed
10/02/2015	Concept Design Review	- Finalize system requirement - Develop functional architecture - Perform trade studies to generate cyberphysical architecture
10/22/2015	Progress Review 1	- Present overall gripper CAD model - Implement item recognition algorithm on 2015 APC dataset
10/29/2015	Progress Review 2	- Review 2016 APC rules and modify design/requirements accordingly - Acquire all 2016 APC items and create ground truth image dataset
11/03/2015	Preliminary Design Review	- Explain how design meets all system requirements - Show all risks are identified and mitigated
11/12/2015	Progress Review 3	- Apply to 2016 Amazon Picking Challenge - Integrate item recognition on 2016 APC dataset and show ability to recognize item with 90% accuracy
11/24/2015	Progress Review 4	- Finalize sponsorships and determine design direction - Build suction gripper and demonstrate ability to acquire X% of objects - Develop software state machine architecture - Create ground truth image depth dataset of 2016 Amazon Picking Challenge items
12/03/2015	Progress Review 5	- Pose determination of objects using image depth data - Present system CAD model
12/10/2015	Progress Review 6	- Import mechanical system design into gazebo - Perform all fall validation experiments successfully

12/14/2015	Critical Design Review	- Demonstrate design is ready for full-scale construction and testing - Ensure project will meet time and cost constraints
January 2015	Mechanical Integration and System Simulation	- Compilation of mechanisms (perception, platform, and gripping) - Implement simulated pick-and-place mechanisms
February 2015	Software-Hardware Integration	- Transfer manipulation actions from simulation to hardware - Demonstrate single item pick-and-place
March 2015	Game Strategy and Debug	- Demonstrate multi-object pick and place - Optimize system performance to maximize score - Margin and Debug month
April 2015	System Validation	- Perform all fall validation experiments successfully (refer to section X.X)
May 2015	Wrap Up and Competition	- Final MRSD demonstration - Transport robot to Stockholm - Compete in the Amazon Picking Challenge

8.3. Fall Validation Experiment

The fall validation experiments shall demonstrate the capabilities of the perception and gripping subsystems. The first experiment will demonstrate correct input file handling, recognize 90% of items from the 2016 Amazon Item Dictionary and determine item pose of 75% the items once identified. The second experiment will showcase a gripper prototype will grip at least 50% of items in the Amazon Item Dictionary. Given the high uncertainty, the platform subsystem is not planned for demonstration for the Fall Validation Experiment but a detailed design review will be prepared for Progress Review Six.

8.3.1. Perception Experiment

Test Conditions
- The shelf environment will be constructed according to Amazon’s instructions and items taken from Amazon’s item dictionary
- Lighting will vary in brightness between 320-500 lux simulating typical indoor lighting conditions [5]
- The testing shall take place in the MRSD lab and take approximately 2m x 2m of floor space

Procedure
- Shelf will be populated with 1, 2, or 3 items from the item dictionary
- The system will be given an input file reflecting the correct item configuration
    - The perception system will automatically attempt to recognize items in the bin and report the results to GUI on computer
    - The perception system will automatically attempt to determine item pose to find a valid suction vector

- This procedure will be demonstrated at least 3 times with different items from the item dictionary to show robustness

Performance Metrics

- The system can recognize the items on 75% of attempts when light is between 320–500
- Once Identified, the system can determine pose of item on 50% of attempts and specify valid suction vector within 2 cm of surface of item

8.3.2. Gripper Experiment

Test Conditions

- The shelf environment will be constructed according to Amazon's instructions and items taken from Amazon's item dictionary
- The testing shall take place in the MRSD lab and take approximately 2m x 2m of floor space
- The suction end effector will be fixed to a hand-held wand

Procedure

- Shelf will be populated with 1, 2, or 3 items from the item dictionary
- System will be manually triggered to begin suction system
- Suction end effector will be manually placed to acquire various object
- The system will recognize when an item has been grasped
- A manual signal will be sent to the system to release item into order bin

Performance Metrics

- The system can grasp 25% of attempts
- Once item is grasped, 90% of items do not fall while being held
- When commanded to release, the system releases item 100% of time

8.4. Spring Validation Experiment

The spring validation experiments shall acquire at least 3 items of 10 total attempts in under 20 minutes.

8.4.1. Full System Experiment

Test Conditions

- The shelf environment will be constructed according to Amazon's instructions and items taken from Amazon's item dictionary
- A picking order will be input in compliance with competition rules
- The testing shall take place in MRSD lab(external test platforms if any) and take approximately 2m x 2m of the work space

Procedure

- Shelf will be populated with multiple items from the dictionary complying with the APC 2016 rules
- The system will be given an input file reflecting the correct item configuration

    - The perception system will automatically recognize items in the bin and report the results to GUI on computer
    - The perception system will localize itself with respect to the bin, automatically detect object and recognize its pose to find a valid suction surface and the results will be shown in a GUI on computer for subject performance evaluation
    - Next, the grasping system will actuate to attempt to grasp the item
    - Finally the end effector will withdraw out of the shelf bin without damaging or dropping the item
    - The end effect will localize itself with the order bin, drop the items inside the bin
- The system will deliver repeat for 20 minutes and attempt to deliver as many items in the order bin as possible

Performance Metrics

- The system can recognize 100% of attempts
- Once Identified, the system can determine pose of item on 75% of attempts
- Once grasp vector is determined, the system can grasp on 50% of attempts
- Once item is grasped, the system can withdraw out of the shelf and drop items in the order bin on 90% of attempts
- The system can recognize the items on 75% of attempts regardless of lighting conditions
- Once Identified, the system can determine pose of item on 50% of attempts and specify valid suction vector within 2 cm of surface of item

8.5. Team Responsibilities

Alex Brinkman will be responsible for Kinematic Path planning which consists of searching for collision free motion paths, executing the inverse kinematics of the path plan, and visual-servoing the end effector during the grasp. Additionally, he will contribute to the software architecture and ROS node development. Alex will also be leading efforts to seek academic and industrial sponsorship.

Abhishek Bhatia will be the electrical lead for this project. His responsibilities include detailed design, verification and bring up of the electrical subsystem - embedded programming, PCB design, sensor integration and microcontroller interfacing, etc. Besides this, he will support Rick with mechanical subsystem design. Abhishek will also maintain project documentation; system/sub-system architecture and test plan.

Feroze Naina will lead the software development. He will be responsible for deploying the computer hardware, software platform and the simulation environment. Additionally, he will work on integrating perception and kinematic path-planning. He will also assist Abhishek Bhatia in implementing the electrical subsystem.

Lekha Mohan will be the perception engineer in this project. Her responsibility will comprise of developing a vision system that will recognize, detect and retrieve items from the shelves. Additionally she will also be reaching out to various industrial sponsors/ faculty in and out of RI, people who have expertise in computer vision.

Rick Shanor will lead the hardware design. This will include computer aided design, subsystem fabrication, and system integration. In addition, Rick will support development of perception algorithms. Finally, Rick will be managing schedule and budget to ensure the team is prepared to be competitive in the 2016 Amazon Picking Challenge.

8.6. Budget

Table 6: Preliminary Budget

Part	Supplier	Price	Notes
Perception Subsystem			
Kinect 2.0	Microsoft	$140	May replace w/ LIDAR
Wide Angle Camera	Amazon	$52	Eye-in-hand
High Performance Computer	Newegg	$1,200	High Performance
USB Power Hub	Amazon	$12	
Platform Subsystem			
Universal Robotics UR5	Sponsor	$0	Subject to Change
High Torque DC Gear Motor w/ Encoder	TBD	$200	Lift Motor
USB Motor Controller	Phidgets	$120	
DC Power Supply	Amazon	$24	12V 30 Amp
Belt and Pulley	SDP/SI	$200	Est.
Aluminum Structure	McMaster	$400	Est.
Grasping Subsystem			
Suction Cup	Piab	$75	No listed price
Pneumatic Tubing	McMaster	$50	Est.
Arduino Micro	Amazon	$20	Read pressure sensor
Automotive Pressure Sensor	Amazon	$25	
Vacuum Pump	Robot Shop	$40	
Aluminum Structure	McMaster	$40	Est.
Misc			
Testing Items	Amazon	$100	Est.
Kiva Shelf	APC	$0	
	Total Spending	$2,698	

8.7. Risk Factors

The team has identified three major risks factors for this project: platform availability, competitive advantage, and significant changes to the 2016 APC rules. First, we are concerned about platform availability. As explained in the subsystem description, our goal is to use an off-the-shelf manipulation system so that we can focus on perception, software development, and gripping mechanisms. While we have been actively reaching out to RI faculty, nobody has had hardware available that we could borrow for the duration needed in the MRSD project course and for the Amazon Picking Challenge. Currently, we are having ongoing discussions with Rethink Robotics, SAKE Robotics, Universal Robotic, DataSpeed Inc, and FoxConn about potential sponsorships.

The next risk we have identified focuses on competitive advantage. Other teams have one year experience developing hardware and software for this competition. In addition, manipulation is a very hard challenge. These risks have been mitigated through solid systems design principles. In addition, we are taking advantage of all resources in the Robotics Institute in order to achieve the highest likelihood of success.

Finally, Amazon Competition rules for 2016 have not yet been released. The rules committee hinted at including stowage task. So far, we have designed to the 2015 rules. However, there is margin in the schedule to modify system requirements and development plans based on rule changes. The MRSD project still remains the team's primary focus. If rules overhauls are deemed too demanding within our timeframe and the scope of the class, we may not be able to compete.

9. References

[1] Administration for Community Living, http://www.aoa.acl.gov/Aging_Statistics/index.aspx

[2] The Verge, http://www.theverge.com/2013/12/26/5245008/amazon-sees-prime-spike-in-2013-holiday-season

[3] Allen, Peter, Bil Yoshimi, and Alex Timcenko, "Real-time visual servoing,' 'ProceedingsDARPA Image Understanding Workshop, Pittsburgh, PA, September 1 1-13, 1990.

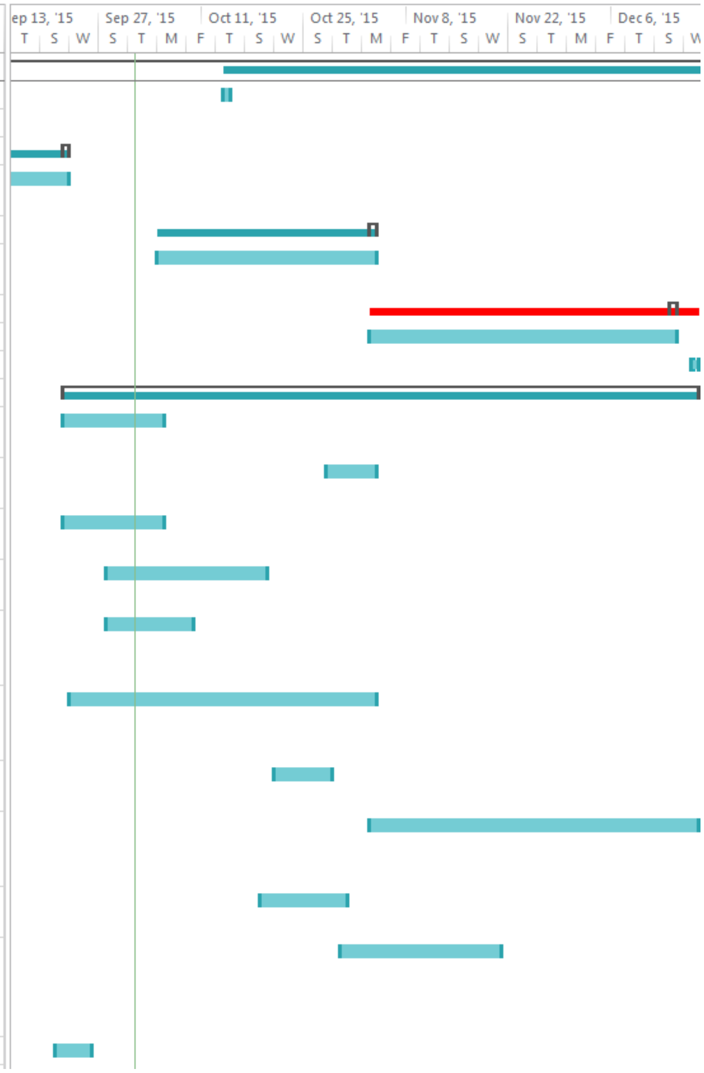
[4] Numatics vacuum products catalog, http://www.numatics.com/common/pdf/numatics-vacuum-products-catalog.pdf

[5] Wikipedia, Lux, https://en.wikipedia.org/wiki/Lux

[6] Amazon Picking Challenge. http://amazonpickingchallenge.org/

Appendix A) Gantt Chart

Task Name	Duration	Start	Finish
MRSD Project	**190 days**	**Mon 8/31/1!**	**Fri 5/20/16**
Submit Proposal to A	1 day	Wed 10/14/1	Wed 10/14/15
Win APC at ICRA	5 days	Mon 5/16/1€	Fri 5/20/16
CoDR Presentation	**1 day**	**Tue 9/22/15**	**Tue 9/22/15**
Prepare CoDR Materials	7 days	Mon 9/14/15	Tue 9/22/15
PDR Presentation	**1 day**	**Tue 11/3/15**	**Tue 11/3/15**
Prepare PDR Materials	22 days	Mon 10/5/15	Tue 11/3/15
CDR Presentation	**1 day**	**Mon 12/14/1**	**Mon 12/14/15**
Prep CDR Materials	30 days	Tue 11/3/15	Mon 12/14/15
CDR Report Due	1 day	Thu 12/17/1!	Thu 12/17/15
Tech Development	**63 days**	**Tue 9/22/15**	**Thu 12/17/15**
Finalize Robotic Arm Selection	10 days	Tue 9/22/15	Mon 10/5/15
Test Basic Arm Kinematics	5 days	Wed 10/28/15	Tue 11/3/15
Finalize Mobility Selection	10 days	Tue 9/22/15	Mon 10/5/15
Prototype Manipulators	16 days	Mon 9/28/15	Mon 10/19/15
Acquire Computational Platform	10 days	Mon 9/28/15	Fri 10/9/15
Prototype Vision Algorithms on Published Datasets	30 days	Wed 9/23/15	Tue 11/3/15
Acquire Perception Sensor(s)	6 days	Wed 10/21/15	Wed 10/28/15
Prototype Vision Algorithms w/ Real Hardware	33 days	Tue 11/3/15	Thu 12/17/15
Final Manipulator Design	10 days	Mon 10/19/15	Fri 10/30/15
Integrate Manipulator, Mobility Platform, and Arm	16 days	Fri 10/30/15	Fri 11/20/15
Acquire Test Objects	5 days	Mon 9/21/1!	Fri 9/25/15



Appendix B) Item Dictionary 2015 competition

Appendix C) Suction Design

The pressure rise once the object is sucked provides feedback about the gripping status. Below are the necessary gripper specifications required to meet the requirement of picking up objects of upto 1 pound.

- Suction Cup Dimension: 0.8 in diameter.
- Vacuum Pump Strength: 5.7 PSI.

These dimensions are derived from holding force equation:

$$F = \Delta p \text{ x } A \tag{1}$$

F = Holding force (without safety factor, purely static)
Δp = Difference between ambient pressure and pressure of the system
A = Effective suction area (the effective area of a suction cup under vacuum)

Equation 1 could be further simplified to [4]:

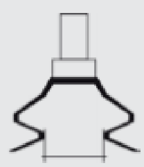
For horizontal pick-up:

$$d = 1.12 \text{ x } \sqrt{\frac{m \text{ x } S}{P_u \text{ x } n}}$$

For vertical pick-up:

$$d = 1.12 \text{ x } \sqrt{\frac{m \text{ x } S}{P_u \text{ x } n \text{ x } \mu}}$$

d = Suction cup diameter in cm
(with double lip ~ internal diameter, with bellows suction cup = inner diameter of sealing lip)



m = Weight of the workpiece in kg
P_u = Vacuum in bar
n = Number of suciton cups
μ = Friction coefficient
S = Safety factor