RRRobot! Proposal

Team

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Motivation

Why should someone care about this project?
A major challenge in today's waste management and recycling process is separating the single stream of recyclable materials received at waste management facilities into multiple streams (glass, plastic, cardboard, etc.) that can be sold for re-use in industry. Our project aims to simulate the scenario at a recycling facility where a conveyor belt of items needs to be separated into trash and recycling. This involves classification and manipulation of items that may be in different orientations, shapes, or stacked on top of each other.

What makes it unique?
Most industrial implementations of trash/recycling sorting use end effectors similar to suction cups that do a good job of picking up items that have been flattened. We are aiming to use a robotic arm, similar to a human hand, that is able to sort items without requiring them to be pre-flattened. Glass, for example, cannot be flattened since it would shatter first. Thus, a hand-like end effector would do a better job of picking up a glass bottle and putting it in a recycling bin than a suction cup that requires a relatively flat surface.

Will it address specific challenges that have not been solved previously?
As mentioned before, a specific challenge that we believe has not been solved by current industrial implementations is the case of items without a flat surface. Suction cups would have trouble picking up and manipulating glass bottles or other items with curved surfaces. Current industrial implementations flatten the items before reaching the robotic sorting stage. For items that cannot be flattened, like glass bottles, a hand-like manipulator would be able to pick up and drop the glass bottle in the appropriate bin.

Requirements

Generally speaking, our system should identify, classify, and manipulate several household items to separate trash and recycling. Our system will be successful if it can safely (without breaking or dropping) pick up various items (glass bottles, empty soda cans, cardboard, etc.), identify if they are recyclable or not, and place it in the corresponding bin.

Evaluation

To evaluate our object detection we will present our system with a number of objects and measure how many times it is able to correctly identify the object. We will define success as 75% (or more) accuracy in identification and trash/recycling classification. To evaluate our arm's performance we will have it grasp and move a number of objects and measure the number of times it succeeds. We will define success as 0 instances of dropped or broken items. We will also judge the speed of our system by calculating the average time it takes to move an object to one of the bins. We will define success as 10 seconds from when the object is seen to when it is placed in a bin. Our end goal is to be able to grab items up to 3 inches in diameter off a conveyor belt moving at least 2 inches/second.

Implementation

General goal:

Our system will need to be able to move objects placed on a conveyor belt towards the arm. Then the arm will pick up the object and place it into the correct bin. The end effector of our arm should be able to grasp objects of various shapes and carry them to the correct bin without causing harm to observers (e.g. broken glass shards). Our object detection will need to classify objects as either metal plastic or cardboard with the goal of separating trash from recycling.

Object classification:

We plan on pursuing two approaches for classifying objects as trash or recyclables. One approach is to use existing neural network architectures and datasets for classifying objects in images (such as ImageNet). We could repurpose one of these neural networks to classify objects as recyclable or not using hand labeled correspondences between item classes and trash/recycling. One potential concern with this approach is that since the dataset wasn't intended for recycling applications, a large portion of the object classifications might not be helpful for our use case.

The second approach planned for object classification is gathering a custom dataset, and training a model to classify the images. Since we will be gathering the dataset, we can choose specific objects that are trash or recyclables, and label them appropriately. We can start with a small set of objects (maybe 3 or 4) to get a model working, then build up from there.

Manipulation:

There are two main aspects to manipulating objects: figuring out how to grab the object and moving the arm. The robot needs to have 3D information about the environment so that it can choose optimal locations to grab objects. We are planning on using the depth information from an XBox Kinect camera (or Intel RealSense) to get point cloud data. The Kinect cameras have depth information that is accurate to 4cm[1], although it is more accurate for objects that are closer to the camera. We can place the camera in such a way that we get the highest accuracy possible while still capturing the relevant areas in the frame. Finally, the arm needs to grab the object, and place it in the correct bin. We will use inverse kinematics to drive the arm to the desired positions.

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[1] https://www.ncbi.nlm.nih.gov/pmc/articles/PMC3304120/

Segmentation (Stretch Goal):
As a potential stretch goal, we want the robot to be able to pick through cluttered piles of objects, identifying each object individually. To do this, the robot needs to be able to reliably break the image down into individual objects. When there is a cluttered pile, image segmentation methods aren't completely accurate. To deal with this, the robot would interact with the objects in the pile to verify the image segmentation. If an object is segmented before the interaction, and stays intact after being moved, it must be a single object, so the robot can classify and sort that object. This process would repeat until all objects in the pile are removed from the conveyor belt.

Prototype

For our prototype test setup, we plan to have an RGBD camera (Microsoft Kinect sensor for example) that will provide image and depth information. This will allow us to both classify items we are attempting to sort and provide a 3D point cloud for determining the motion of the robot arm. On the table, we will have a motor actuated conveyor belt that moves the items to be sorted towards the robot arm. Once the item is classified, the robot arm will pick it up and put it in the trash or recycle bin positioned next to the robot arm. Figure 1 below shows a representative CAD model of the proposed prototype test setup. The size and design of components are not final or to scale.

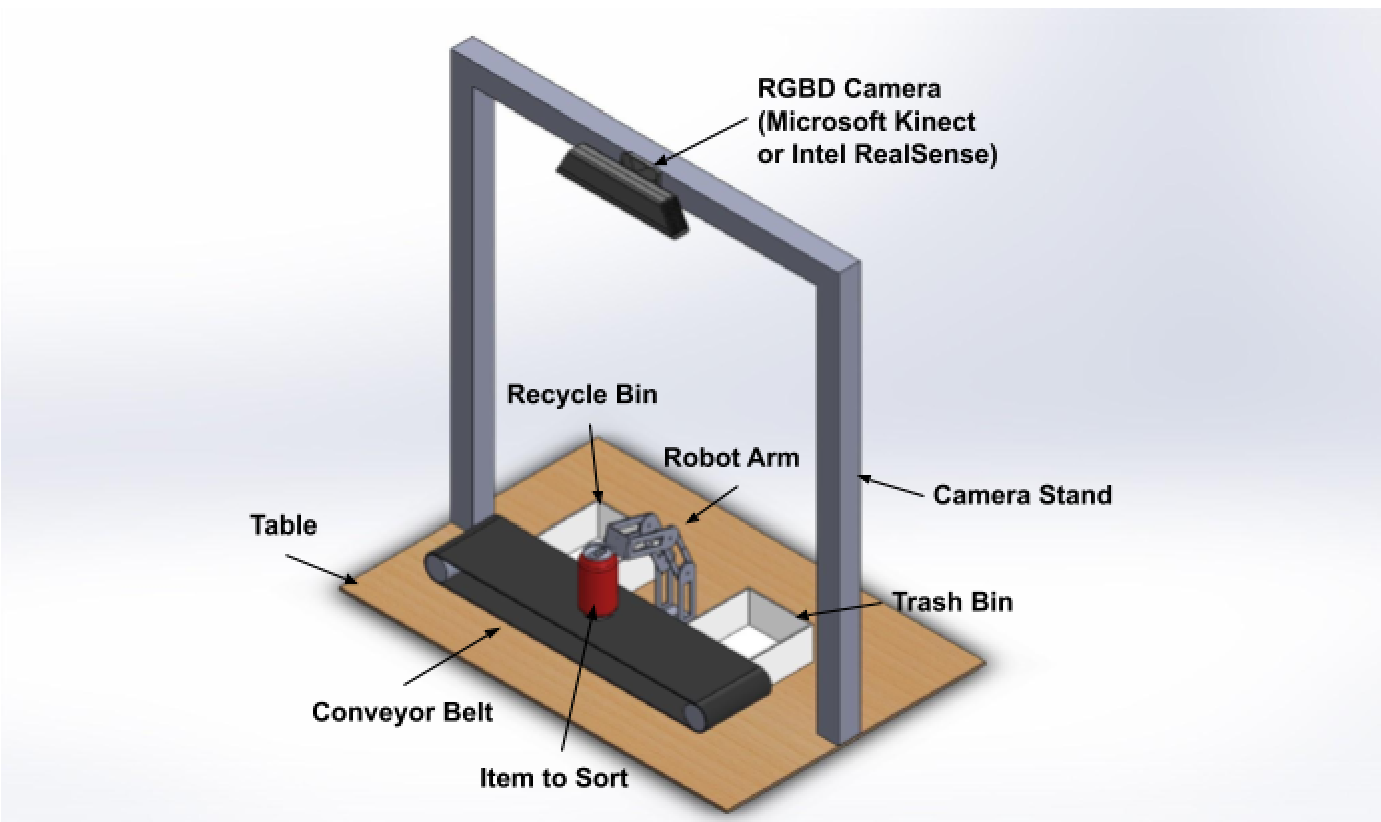

Figure 1: Representative CAD model of test setup (not final or to scale).

Milestones

Project Update 1: March 16

- Evaluation of dataset (is publicly available dataset sufficient or do we need to collect our own images?)
- Purchase / receive hardware components
- Full CAD model of setup
- Pseudocode outline of all software components

Mid-Project Milestone Presentation: March 30

- Camera calibration
- Distinguish cans of different colors (75% accuracy)
- Able to pick up static items and place in a bin (50% success)
- Full hardware setup built (conveyor belt operational)
- Classification and sorting process takes < 1 minute

Project Update 2: April 13

- Arm able to pick up all slow moving objects and place in bin (90% success)
- Classification of various items (metal cans, plastic bottles, cardboard box, etc. with 75% accuracy)
- Classification and sorting process takes < 30 seconds

Final Deliverables: April 24

- Final Report
- Video
- Repository w/ Comments

Barriers

Are there any barriers to achieving these milestones that have significant risk?

Finding and/or collecting and training our own dataset should not be too difficult because we have found some datasets and three model architectures (proposed in three papers) that seem promising. If the online dataset(s) does not work well for our purpose, we need to collect data ourselves. This could be time-consuming, so we may severely restrict the objects we hope to classify (e.g. 3 - 4 very dissimilar objects).

Building the full hardware setup may be difficult depending on when parts arrive, availability of facilities/tools for building hardware, complications, etc. The main difficulty will be in the construction of the conveyor belt.

Tuning PID might be difficult for manipulating arm to safely pick up and deliver objects to bin. If a pre-defined motion path for grasping objects is not possible, we may need to rely on the creation of a bounding box, mapping of point clouds to robot frame, etc. This will be difficult and error-prone. The biggest challenge will be the interaction of the arm with moving objects on conveyor belt as we have a limited time frame to grab the object and less room for error.

Final Demonstration

For the final demonstration we will let observers choose objects to place onto the conveyor belt for our system to sort. Our project video will show our system sorting a variety of objects from our chosen categories. We want people to see the accuracy of both our object detection and our object manipulation, as well as the speed of our system.

Budget/Parts

Part name	Cost Per	Quantity	Total	Comments
Camera	$43.95	1	$43.95	Potentially use kinect camera or Intel realsense provided by Prof. Jenkins
Conveyor belt material	$21.00	1	$21.00	
Conveyor belt rollers	$0.00	2	$0.00	3D printed cylinders
Conveyor belt motor	$15.99	1	$15.99	
Loctite Epoxy	$4.99	1	$4.99	
Shaft (cylinder)	$32.69	1	$32.69	
Timing Belt	$6.99	1	$6.99	This is for driving the conveyor belt.
Timing Belt Pulleys	$6.89	1	$6.89	
Mounting wood (for robotic arm + conveyor)	$22.44	1	$22.44	
Custom end effector	$0.00	1	$0.00	We will 3D print a custom end effector if we need to
H-bridge	$6.99	1	$6.99	
Raspberry pi	$35.00	1	$35.00	
micro SD card	$11.99	1	$11.99	
Power supply	$0.00	1	$0.00	Potentially use one of the lab power supplies (if not locked), backup: mbot battery
Wood (2x4s)	$3.70	2	$7.40	Use to build mount for camera and mount for conveyor belt
Wood screws	$6.25	1	$6.25	
Mounting solution for kinect camera			$0.00	This will likely be an angled bracket made from the wood we are already accounting for in the budget.
Items to be Sorted			$10	Budget for purchasing cans, boxes, etc. for sorting

Estimated Total Cost (if all items above need to be purchased): $232.57. If we are provided with a camera, arm, and raspberry pi, the estimated cost drops to $141.63.