ARtPUT: Autonomous Rover to Pick Up Trash

Mentorship Proposal

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Abstract

Litter in public parks and shared spaces is a very serious issue in cities and urban areas. It is not just about looking messy: there are environmental, economic, and social costs. This project's solution is ARtPUT (Autonomous Rover to Pick Up Trash), an autonomous mobile robot built to spot, approach, and pick up everyday litter in outdoor public areas. ARtPUT brings together computer vision for object detection, depth-assisted grasp planning, and autonomous navigation, all mounted on a tracked platform tough enough for uneven ground. Two main approaches are tested for how the robot grabs trash: one uses only vision, while the other combines vision with depth sensing. To see how well each method works, controlled field trials are conducted and metrics such as how much trash the robot collects, how often its grasps succeed, its detection precision and recall, the rate of false pickups, and how much energy it needs per item are tracked. Statistical analysis is planned to compare both strategies, looking for clear differences in efficiency and reliability. Adding depth sensing is expected to boost the robot's grasp success and cut down on energy use compared to vision-only methods. The findings should help answer whether autonomous trash-collecting robots make sense for city parks, and they will add to the broader conversation about robotic perception, manipulation, and energy-efficient operations in unpredictable outdoor settings.

ARtPUT: Autonomous Rover to Pick Up Trash

It is not only ugly, but litter in city parks and public spaces injures wildlife, increases maintenance costs, and makes places people want to use uglier. And this is a widespread problem, especially here in the U.S. In 2020, cities and organizations spent $11.5 billion to combat over 51 billion pieces of debris [ranging from cigarette butts to food wrappers] that Americans left on roads and in waterways (Keep America Beautiful, 2021). In line with the current trend in cities becoming more crowded while residents increasingly gather in communal areas, cleaning these spaces by hand is an increasingly difficult and expensive job.

This is where modern technology comes in. Advances in robotics and autonomous systems have opened the door for robots to help tackle the tedious problem of litter. In places like warehouses and airports, autonomous cleaning robots are already making a difference. Companies like DHL and Ryder use Avidbots' robots in their warehouses to "reduce up to 80% of labor hours spent cleaning" (Avidbots, 2025). However, outdoor public spaces have more variability, with things like rough ground, changing light, bad weather, and people or animals suddenly in the way (Memmesheimer et al., 2025). Autonomous robots in public spaces need to have good perception, reliable navigation, and the ability to handle irregular environments.

Research on autonomous service robots shows that reliable perception and smart energy management are key. Vision-based object detection, using convolutional neural networks, does a good job spotting regular objects, but it struggles when things are hidden or when depth is hard to judge (Li et al., 2021). Adding the depth sensing aspect helps robots understand their surroundings and grab objects more accurately. Energy use matters too, as if a robot burns through its battery too fast, it cannot get much done (Boukoberine et al., 2019). Safety is another big concern. Robots working in public spaces have to dodge unpredictable things like people and obstacles in real time. Studies on cloud-based collision avoidance and cooperative autonomy show why strong monitoring and risk management matter when dealing with robots moving around in urban spaces (Primatesta et al., 2020).

Recent research gives strong support to vision-based autonomous trash-collection systems working outdoors. Kulshreshtha et al. (2021) built the OATCR, which was a robot designed to collect trash in tough terrain. They built the robot with a Rocker-Bogie system so it could handle rough terrain, then added a flap-bucket so it grabbed more trash at once. To figure out how the robot could best spot garbage, the team tested Mask-RCNN, YOLOv4, and YOLOv4-tiny. Out of these, YOLOv4-tiny was superior. It had a 95.2% mean average precision and picked out objects in just 5.21 milliseconds (Kulshreshtha et al., 2021). That is fast enough for real-time use on devices like the Raspberry Pi. Their results line up with what others have found, which is that robots need to be both fast and sharp if they're going to handle the complexity of the real world.

While OATCR showed strong mechanical design and reliable detection, it skipped over any real comparison of depth-enhanced perception strategies and didn't dig into energy efficiency. ARtPUT picks up where OATCR left off. By combining vision and depth sensing, ARtPUT aims to boost grasp accuracy and make operations more energy aware. It attempts to solve the practical deployment challenges that earlier designs have not really solved, and tests how different ways of seeing and grabbing litter actually shape the performance of an autonomous trash-collecting rover in a public park. By comparing vision-only grasping to approaches that combine vision and depth, the project goes into the trade-offs between processing power, energy use, and how well the robot gets the job done. This project aims to help cities bring autonomous robots into public spaces safely and efficiently, saving money on upkeep and cutting down on the environmental damage from litter.

Questions and Hypotheses

Questions:

1. How effectively can an autonomous rover detect and collect common types of litter (paper, cigarette butts, plastic bottles, cans) in a small public park setting?
2. Which perception and manipulation strategy maximizes items collected per energy consumed while minimizing false pickups and human disruption?

Hypotheses:

- H1 (performance): The rover will successfully detect and collect ≥ 70% of visible litter items in a controlled park zone under daylight conditions.
- H0 (null): The rover's detection-and-collection rate is ≤ 50%.
- H2 (efficiency): A combined vision + depth-based grasping method will yield a higher items-per-energy ratio than a vision-only grasp heuristic.

Materials

Mobile Platform and Structural Components

- For this project, the DFRobot Devastator Tank Mobile Robot Platform serves as the mobile base. Its tracked design lets it handle rough outdoor surfaces, like pavement, grass, gravel, without struggling for traction or stability. Unlike platforms that rely on individual wheels, the tracks keep the robot steady and reliable during field tests, even in busy public spaces. The Devastator platform also makes life easier when adding new hardware. It works with most processing units, including the ones used here, and comes with two DC gear motors, sturdy metal tracks, and a set of mounting points ready for extra sensors or manipulators.

Processing and Control Electronics

- Two controllers actuate this autonomous rover. The first of these, the Raspberry Pi 4 Model B, will serve as the brains of the robot. It is a USB camera-driven computer vision system and can see trash, figure out where to go to get it, and how to pick things up. All the complexities of the robot's dozens of functions begin here. The Raspberry Pi does store its currently-logged operating system, project code, and all of the data logs in a 32 GB microSD card.
- At the same time, Arduino UNO takes care of more elementary things. It spins the motors, steers the servos, and reads the sensors. Dividing up the work in this way ensures that both controllers are running normally and allows the team to easily track down problems if something goes wrong.

Sensing and Perception Components

- This robot keeps an eye on its surroundings with a mix of cameras and distance sensors. Up front, there is a USB webcam streaming live video straight to the computer vision algorithms, which pick out trash on the spot. Around the base, you will find four HC-SR04 ultrasonic sensors. Each one scans for obstacles, making sure the robot does not bump into anything as it moves.
- A NEO-6M GPS module tracks every spot where the robot picks up trash. That way, it can map out its cleaning routes and plan smarter paths next time. An infrared sensor watches the bin's fill level, giving the system a heads-up before anything spills over. And to keep from getting lost, the robot uses a digital compass (magnetometer) to stay on course and make quick corrections whenever it wanders off track.

Trash Manipulation and Collection System

- A tiny robotic gripper with two fingers and a suction-assisted collection bin with a 500–1000 mL capacity are used to collect trash. While suction helps with light objects like paper or plastic wrappers, the gripper enables the robot to grasp larger or irregularly shaped debris. A servo motor allows the gripper to be very precise on how much to open and close.
- A 12V DC suction pump pulls any stray debris into the bin. By combining both the gripper and suction pump, the robot handles different kinds of waste more efficiently and reliably.

Motor Control and Power Systems

- The Devastator's DC drive motors run through L298N motor drivers, allowing the robot to control both direction and speed. The suction pump is controlled by a separate driver or relay module. Two 11.1V Li-Po batteries power everything from the motors, suction, and the electronics on board. Buck converters keep the voltage steady and safe for the Raspberry Pi, Arduino, and all the sensors.

Testing Equipment

- Field tests use the same set of measurement and safety tools every time, so results stay consistent. Measuring tape and ground markers are used to make the 10-by-10-meter test plots. Cones and temporary signs keep people out of the restricted areas. For timing, a stopwatch is used to track how long each trial takes and to mark key moments. On top of the automated sensor logs, manual observations are written in a field notebook, including missed items, weather, and pedestrians interacting with the setup. These notes help to add context and detail for later analysis.

Procedure

1. Dataset & training: To train an object-detection model (YOLO/SSD-style), gather and label a significant number of photos of the target litter types in the target park. Use artificial occlusions to enhance.
2. Software stack: Put in place a perception pipeline (object detection on RGB-D + depth clustering), SLAM-based localization (Lidar + odometry), and a manipulation controller that translates detected object pose to a grasp technique. This project will test two modes of perception manipulation: Vision-only bounding-box grasping (A); vision plus depth-point-cloud grasp planning (B).
3. Three 10 m × 10 m test plots in a public park with low pedestrian traffic are chosen for the test. A fixed number (N = 20) of different litter items are placed in each plot at random locations (pre-approved with park authority). Mark the start and goal points.
4. Trials: For each mode (A, B) run 10 trials per plot (total 60 runs), each trial starting from the same location, time-limited to 15 minutes or until bin full. Rotate item arrangements between trials. Record video, sensor logs, and manual observer notes.
5. Baseline: Include 10 human-assisted pickup runs (human uses same route, picks items by hand) for performance comparison.

Data Analysis

The purpose of the data analysis is to quantitatively evaluate the performance, efficiency, and reliability of the ARtPUT autonomous rover and compare two perception–manipulation strategies under controlled outdoor conditions. All analyses are designed to directly test the stated hypotheses while accounting for environmental variability and operational constraints.

Performance Metrics

Several primary and secondary metrics are computed for each trial:

- Collection Rate tracks how many pieces of litter the system picks up every hour. This is the main metric that will be used to judge how well the task gets done.
- Grasp Success Rate shows what percentage of grasp attempts actually succeed. Every time the system tries to pick up something, someone will count the wins and misses, then report the success as a percentage.
- Detection accuracy tells how well the system actually finds and recognizes different kinds of litter. To measure this, this project will use precision, recall, and the F1-score for every category.
- Energy efficiency tracks the battery power the system spends on each piece of trash it collects. This will be measured in watt-hours per item, and it is the key metric for efficiency.
- False Pickup Rate shows how often the system grabs the wrong thing (non-trash objects). This rate reflects how reliably the system can tell trash from everything else, which matters for both safety and performance.
- Operational Interruption Rate tracks how often the system must stop or change course because of people or obstacles in its way.

These metrics are calculated separately for each perception mode: Mode A, which uses vision-only grasping, and Mode B, which adds depth-based grasp planning.

Data Processing and Organization

Raw sensor logs are time-synchronized and preprocessed to remove incomplete or corrupted entries. Distance traveled, battery usage, and grasp attempts are normalized by trial duration to enable fair comparisons. Manual observation notes are coded into categorical variables and integrated with automated logs for comprehensive analysis. All processed data are organized into structured datasets using Python-based data analysis libraries.

Statistical Analysis

To evaluate differences between perception–manipulation modes, descriptive statistics including the mean, standard deviation, and confidence intervals are computed for each performance metric. Paired statistical tests are used to compare Mode A and Mode B across identical plots and trial conditions. If the data appears normal, then a paired t-test will be used. If not, a Wilcoxon signed-rank test will be used instead. The statistical significance is $\alpha = 0.05$, and effect sizes are calculated to see not just whether the changes are statistically significant, but how big the real differences are. Effect sizes are calculated to quantify the magnitude of observed differences beyond statistical significance.

Classification Performance Analysis

Detection performance is assessed using confusion matrices for each litter class. Precision, recall, and F1-score are computed to identify systematic misclassifications. These results are used to evaluate whether detection errors contribute significantly to failed grasp attempts or false pickups.

Energy and Navigation Analysis

Regression analysis is performed to examine relationships between energy consumption, distance traveled, obstacle density, and collection success. This analysis helps isolate whether efficiency differences arise from perception quality, navigation behavior, or environmental factors.

Data Visualization

Results are visualized using clearly labeled figures and tables, including:

- Bar graphs comparing mean collection rates and energy per item between perception modes
- Line plots illustrating battery consumption over time
- Confusion matrix heat-maps for object detection performance

All figures include descriptive captions and are referenced in the text to support interpretation.

Software and Tools

All of the analyses are to be done in Python, either in Google Colab or in an environment that works with Robot Operating System. For processing data, this project uses NumPy and Pandas. SciPy and scikit-learn handle the stats, and Matplotlib takes care of the visualizations.

Reproducibility and Validity

To keep everything reproducible, all the scripts, datasets, and parameter configs are saved. Consistently following the same testing procedures and keeping the plot layouts controlled will limit confounding factors. Running repeated trials helps make the statistics more reliable.

ARtPUT

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