Experimental Design: Autonomous Waste Collection: A Robotic Approach to Urban Park Maintenance

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October 27, 2025

Rationale

Litter buildup in urban parks and public areas damages wildlife, raises maintenance expenses, and lowers user satisfaction. More than $11.5 billion was spent on cleanup in 2020 after nearly 51 billion pieces of litter [anything from cigarette butts to food wrappers and fast-food packaging] were found on American roads and waterways (Keep America Beautiful, 2021). By performing routine, low-risk pickup duties, working during off-peak hours, and offering constant monitoring, autonomous rovers can assist human crews. In terms of science, this project investigates perception and navigation in cluttered, unstructured outdoor settings and assesses the performance of vision-based object classification and lightweight manipulation under realistic circumstances. Successful rovers can benefit society by lowering municipal expenses, enhancing public cleanliness, and influencing legislation for the safe deployment of robots in public areas. (Memmesheimer et al., 2024)

Question

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

Hypothesis

H1 (performance): The rover will successfully detect and collect $\geq 70\%$ of visible litter items in a controlled park zone under daylight conditions.

H0 (null): The rover's detection-and-collection rate is $\leq 50\%$.

H2 (efficiency): A combined vision + depth-based grasping method will yield a higher items-per-energy ratio than a vision-only grasp heuristic.

These hypotheses follow the rationale, as perception and integrated manipulation are the limiting factors in outdoor trash-collecting autonomous rover.

Materials/Research Methods

Materials:

- Mobile base with differential drive, speed controller, and battery pack (specific model TBD)
- Onboard computer (like a NVIDIA Jetson or equivalent) running an application like Google Colab or Robot Operating System
- RGB camera with depth sensor (RGB-D)
- Lidar (2D) for localization and obstacle avoidance
- Small two-finger gripper and a suction-assisted collection bin with a 50 to 1000 mL capacity
- Wireless telemetry and logging storage
- Test zone marking cones, measured tape, stopwatch, and notebook for manual annotations

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. We'll 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 Collection Methods:

- Automated logs: timestamps of detections, attempted grasps, success/failure flags, battery consumption, distance travelled.
- Manual annotations: items missed, misclassifications, pedestrian interactions, environmental notes (wetness, wind).
- Post-run bin content check to count unique items collected.

Data Analysis

Primary metrics:

- Collection rate = items collected / trial time (items/hour)
- Success rate = successful grasps / attempted grasps (%)
- Detection precision & recall for object detector
- Energy per item = battery energy consumed (Wh) / items collected
- False pickup rate (non-target objects picked)

Analysis plan:

- Compute mean ± standard deviation for each metric per mode.
- Use paired t-tests (or Wilcoxon if non-normal) to compare Mode A vs Mode B for collection rate and energy per item.
- Confusion matrix for detection classes and compute precision/recall/F1.
- Regression analysis to see influence of distance travelled and obstacle density on success rate.
- Tools: Google Colab/Robot Operating System, Python (NumPy/Pandas), scikit-learn for stats, and Matplotlib for plots.

Risk and Safety

Working on an electronic rover during the engineering design phase carries a number of possible risks, such as the possibility of burns, impact injuries, and electrocution. All team members will always wear the proper PPE, such as safety glasses and insulated gloves, to reduce these risks. Before performing any repairs or modifications, the rover will always be turned off, and all work will be done carefully and in accordance with safety protocols. In order to guarantee that safe procedures are followed, an authorized mentor will also be present during all testing and construction activities.

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