Object Rearrangement for Robotic Waste Sorting

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***Abstract*— The challenge of waste management demands innovative solutions, particularly in automating waste sorting processes. This project addresses this critical issue by exploring the efficacy of robotic object rearrangement on conveyor belts, a key step in automated waste sorting systems. The primary objective is to augment the discovery and segregation of waste items, facilitating more efficient sorting. To achieve this we introduce and evaluate three distinct methods: KMeans clustering, Principal Component Analysis (PCA), and Density Estimation. These techniques are employed to determine strategic start and end points for creating trajectories along which a robotic arm moves to rearrange objects on the conveyor belt.**

The crux of our research lies in the development and application of two novel metrics designed to measure the effectiveness of object discoverability and spatial distribution post-rearrangement. These metrics allow for quantifiable assessment of each method's performance in spreading objects apart, thus enhancing the potential for precise waste identification and categorization. By implementing these methodologies, the project aims to increase the accuracy and efficiency of waste sorting, minimizing manual intervention and fostering a more sustainable approach to waste management.

The expected outcome is a robust framework that not only optimizes waste sorting but also serves as a scalable model adaptable to various contexts within the realm of automated material handling and sorting. This research not only contributes to the field of waste management but also advances the capabilities of robotic automation in complex sorting tasks.

I. INTRODUCTION

One of the significant challenge in robotic waste sorting lies in enabling the robot to recognize and handle objects that are partially obscured by other objects. To address this, we have developed an end-to-end pipeline using ROS (Robot Operating System) (Fig 1), specifically designed to enhance the uncovering and identification of objects on conveyor belts. This system represents a significant step forward in overcoming the obstacles associated with automated waste sorting. By focusing on improving the visibility and accessibility of objects, our solution aims to streamline the sorting process, paving the way for more efficient and accurate waste management.

Key metrics have been identified for evaluating the performance of the sweeping actions performed by the robotic system. These metrics are designed to quantitatively assess the effectiveness of the robot in redistributing objects on the conveyor belt, thereby improving object segregation and identification. This evaluation framework is crucial for optimizing the sorting process and ensuring the reliability and efficiency of the robotic system.

To establish a comprehensive understanding of the system's capabilities, we have instituted several baseline methods for sweeping the objects. These include KMeans clustering, Principal Component Analysis (PCA), and Density Estimation. Each method offers a unique approach to determining the most strategic start and end points for the robot's sweeping trajectory. By implementing these methods, we aim to explore various strategies for rearranging objects, ultimately identifying the most effective technique for uncovering and segregating waste items.

The objective of this project is to refine and enhance the process of object rearrangement. By improving the robot's ability to uncover and separate waste items on the conveyor belt, we expect to significantly boost the efficiency and accuracy of waste sorting. This not only contributes to more effective recycling processes but also aligns with broader environmental sustainability goals. The outcomes of this project are anticipated to have a substantial impact on the field of waste management, potentially leading to innovative solutions that can be adopted in various industrial applications.

II. Related Work

Effective waste management is crucial environment sustainability. One key aspect of this is sorting garbage, which significantly reduces the volume of waste that ends up in landfills [1]. Automating the segregation process of garbage is of paramount importance. The primary reason for this is the enhancement of safety and efficiency. Manual sorting of waste can be hazardous, exposing workers to potentially dangerous materials and unsanitary conditions. By automating this process, we not only safeguard the health and well-being of workers but also improve the efficiency of waste sorting [2].

Many waste identification and sorting methods heavily relies on vision-based systems. [3] studies Convolutional Neural Networks(CNNs) applied on datasets such as WASTE and TrashNet. The authors have identified the data limitations and hardware requirements of using a deep neural network like CNNs. In paper [4], the authors critically examined current computer vision based solid waste sorting methods. However these vision systems are not integrated with practical robotic applications. We present an innovative simulation of a robotic manipulator,specifically designed to rearrange objects that mimic waste items. our focus is on implementing baseline methods for object rearrangement in the context of robotic waste sorting. These methods provide efficiency and data economy. This efficiency is crucial in real-world waste sorting environments where the ability to rapidly and reliably process large volumes of waste is paramount.

In order to effectively sort objects, it is crucial to have clear visibility of the object. [5] explain the challenges inherent in robotic manipulation for sorting, particularly in scenarios involving densely cluttered scenes, objects with similar visual features, and irregular shapes. To address these challenges, they propose a deep Q-learning method for interactive segmentation, tailored to enhance instance segmentation in complex environments. This method, pioneering in the field, employs a deep reinforcement learning framework. It optimizes a Q-value function to determine the most effective non-prehensile manipulation actions, like pushing, to improve object singulation and visibility. The approach is distinctively innovative, as it leverages depth images and trains a Mask-RCNN model to generate reward signals, thereby facilitating the autonomous segregation of objects in cluttered settings. Our research centers on the exploration of non-learning-based approaches for determining the trajectory of robotic manipulators.

As highlighted in [5], managing texture-less objects poses a significant challenge in robotic manipulation, a scenario that is particularly common in the field of robotic waste sorting, as noted by [6]. Our method is immune to this challenge as we rely on point cloud data and is not dealing with image segmentation problem. Our method effectively circumvents this challenge by utilizing point cloud data, steering clear of the complexities associated with image segmentation.

Interactive segmentation has received extensive attention in the field of robotics, as evidenced by a wealth of literature [7], [8], [9]. The predominant approach in these studies involves over-segmenting the image into super-pixels. These super-pixels are then tracked across consecutive frames, clustered, and ultimately assigned to their respective objects. This methodology is fundamental in understanding and improving the interaction between robotic systems and their operational environments. We present an interactive method designed to sort and search objects in cluttered workspace, a solution with significant potential for robotic waste sorting and various other robotics applications.

III. Methodology

Our proposed method leverages the advanced simulation capabilities of the Unity3D environment. This setup allows for a realistic and controlled replication of the waste sorting scenario, providing a robust platform for testing and refining our algorithms. Key to our approach is the extraction and processing of point cloud data. Utilizing ROS (Robot Operating System) packages, we efficiently gather information from the workspace. This data forms the basis of our simulation, enabling the robotic arm to interact with the objects in its environment. Our pipeline, as illustrated in Fig. 1, involves several stages of preprocessing and filtering of the collected point cloud data. These stages include **Plane Segmentation, Extraction of Non-Planar Points, Voxel Grid Downsampling, and Outlier Removal**. Once preprocessed, the point cloud data is utilized by the scene_understanding_node, which runs the sweeping algorithm and evaluate its performance.

The workspace depicted in Fig. 2 depicts the experimental setup. A robotic arm is tasked with sweeping piles of waste, which are conveniently modeled as cubes for ease of representation and analysis. To rigorously evaluate our method, we have developed 27 unique pile configurations, each specifically designed to test different aspects of our system. These configurations are categorized and named for ease of reference: 'lp' (longitudinal pile), 'tp' (transverse pile), 'cp' (cross pile), followed by 'mp1' to 'mp4', and 'p1' to 'p20'. This diverse array of configurations ensures a comprehensive assessment, covering a wide range of scenarios that a robotic system may encounter in real-world applications. This setup serves as a critical testing ground for evaluating various baseline methods, including K-means clustering, Principal Component Analysis (PCA), and density estimation techniques. The performance of these algorithms to find a effective sweeping path is evaluated using the metrics mentioned in IV and are integrated to the scene_understanfding_node.

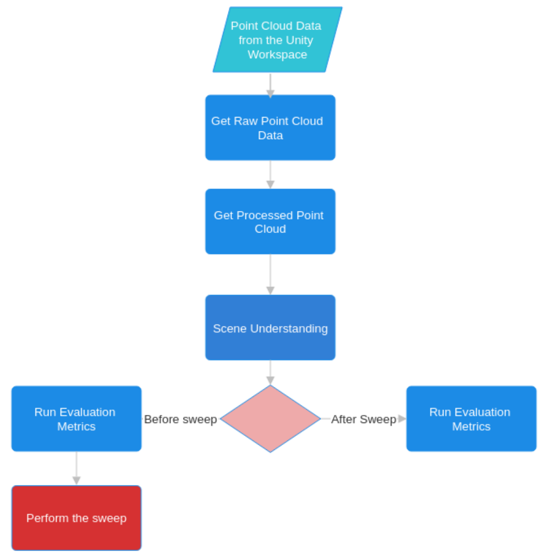


Fig. 1: Flowchart of the Pipeline for simulation

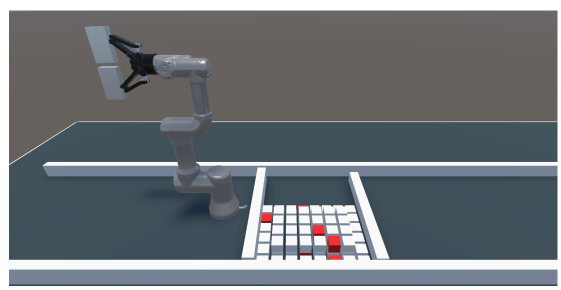


Fig. 2: Workspace in simulation

IV. Formulation of Evaluation Metrics

We developed two unique evaluation metrics that take into account the vertical dimension as well as the spatial distribution of the objects in the workspace in order to thoroughly evaluate the effectiveness of our sweeping methods.

A. Standard deviation of point combined with height variance

The standard deviation of the point cloud combined with height variance can be expressed as follows: Let P be the point cloud with n points, where each point p_i is represented as a three-dimensional vector $p_i = (x_i, y_i, z_i)$.

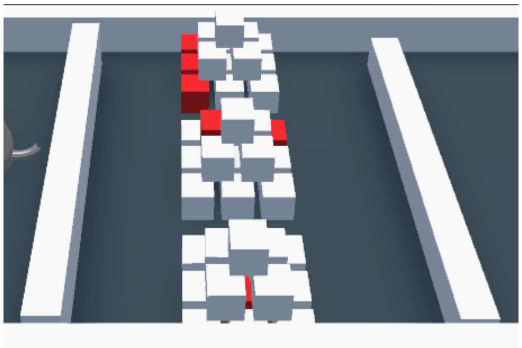
1) Height Variance: The variance in height, assuming height is in y-direction, is calculated as:

$$\sigma_y^2 = \frac{1}{n}\sum_{i=1}^{n}(y_i - \bar{y})^2 \tag{1}$$

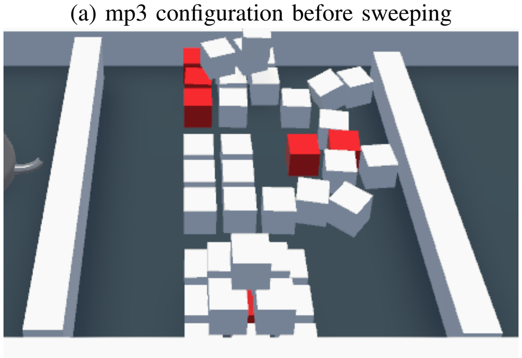
where $\bar{y}$ is the mean of y-values of all points in P.

2) Standard Deviation: The standard deviation for each dimension is calculated as:

$$\sigma_x = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(x_i - \bar{x})^2} \tag{2}$$



(a) mp3 configuration before sweeping



(b) mp3 configuration after the sweep

Fig. 3: Demonstrating how the sweep operation spreads mp3 configuration on the workspace

$$\sigma_y = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \bar{y})^2} \tag{3}$$

$$\sigma_z = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(z_i - \bar{z})^2} \tag{4}$$

Where $\bar{x}, \bar{y}, \bar{z}$ are the mean values of the x,y, and z coordinate of points in P respectively. The overall spread S is the mean values of the x,y,z coordinates of all points in P respectively.

$$S = \frac{\sigma_x + \sigma_y + \sigma_z}{3} \tag{5}$$

3) Combined Metric: The final metric M that combines the standard deviation with the height variance is given by:

$$M = S + C \cdot \sigma_y^2 \tag{6}$$

Where C is a constant factor used to scale the contribution of height variance. We chose C is set to 10.

B. Geometric Spread combined with height variance

For the geometric spread calculation, we define the metric as follows:

1) Area Calculation: For each 'pile' of points at a particular height level *h*, we define the area A_h as:

$$A_h = (\max(\{x_i\}) - \min(\{x_i\})) \cdot (\max(\{z_i\}) - \min(\{z_i\})) \tag{7}$$

where x_i and z_i are the x and z coordinates of the points in the pile at height *h*.

2) Total Spread: The total spread *TS* is the sum of the areas of all piles:

$$TS = \sum_h A_h \tag{8}$$

3) Volume Calculation: The total volume V considering the height variance is calculates as:

$$V = TS \cdot (\max(\{y_i\}) - \min(\{y_i\})) \tag{9}$$

4) Combined Metric for Geometric Spread: The final geometric spread metric GS combined with the height score is:

$$GS = V + C \cdot \sigma_y^2 \tag{10}$$

where *C* is the same constant factor as used in the standard deviation metric.

V. Baseline Sweeping methods

For the purpose of this study, we established three baseline methods to systematically sweep objects in the workspace. These methods were chosen for their distinct approaches to handling spatial data, allowing for a comprehensive analysis of their effectiveness in different scenarios.

A. KMeans Clustering

This method involves segmenting the workspace into clusters based on the proximity of points in the point cloud data. KMeans clustering [10] identifies central points (centroids) and groups nearby objects, guiding the sweep path towards these dense clusters. This method is particularly effective in scenarios where objects are unevenly distributed across the workspace.

B. Principal Component Analysis(PCA)

PCA [11] is employed to identify the principal directions of variance in the point cloud data. By determining these directions, the sweeping path can be oriented to align with the second major axes of object distribution, thus ensuring a comprehensive coverage of the area. PCA is useful in understanding the underlying structure of the object distribution in the workspace.

C. Density Estimation

We have introduced a novel technique to estimate the density of objects in different areas of the workspace. By calculating the concentration of points in each grid cell of the workspace, the sweep path is directed from the highest to the lowest density area. Density estimation is beneficial in scenarios where object distribution varies significantly. We formulated a direct method for the purpose of our project. The method(Fig. 4) is initialized by dividing the workspace into a grid of cells. We calculate the density of each cell based on the number of points in each cell. The manipulator must plan a trajectory from the highest to lowest dense cell. The method introduced is notably straightforward, yet it demonstrates the capability to yield results that are comparable to more complex approaches. This balance of simplicity and effectiveness clearly shows its potential applicability in various practical scenarios.

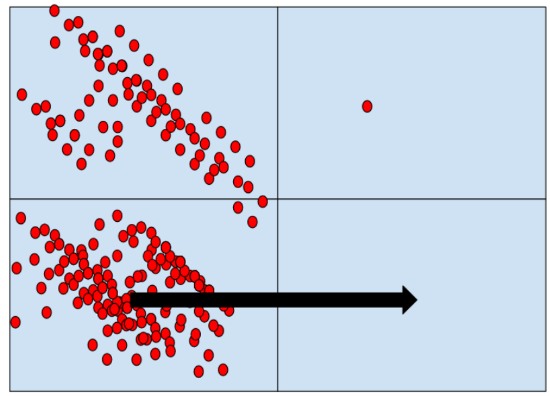


Fig. 4: Demonstration of density estimation method

VI. Results and Discussions

Our study's findings, as outlined in Table. I-III, demonstrate the sweeping method's performance across various scenarios. Notably, the KMeans-based approach achieved successful sweeps in 26 out of 27 configurations. This high success rate underscores the method's effectiveness in rearranging objects for better sorting and identification. In Fig. 3, we showcase a successful sweep operation executed within a simulated environment, utilizing the K-means algorithm. As illustrated in Fig 5, all observed difference values are either positive or zero, with a zero difference suggesting no change in the pile post-sweep. Conversely, both Fig 6 and Fig 7 show instances of negative difference values. These negative values signal ineffective sweeps, where the process results in additional clutter or fails to adequately disperse the cubes. This distinction is critical in evaluating and refining the sweeping methods for optimal performance. In contrast, PCA resulted in successful sweeps in 23 of the 27 configurations, as detailed in Table. II. Although slightly less effective than the KMeans method, PCA still shows considerable promise in enhancing the waste sorting process by effectively rearranging the objects.

For the Density Estimation method, our results (see Table. III) indicate successful sweeps in 22 of the 27 configurations tested. This method, which focuses on the object density within the workspace, demonstrates its potential in effectively organizing objects, particularly in environments with unevenly distributed waste items.

A noteworthy observation from our results is that in certain instances, the metric values decreased post-sweeping. This trend suggests an increase in clutter or a less optimal distribution of objects after the sweep. Such outcomes highlight the complexity of the sweeping task and the fact that improved object visibility and accessibility are not guaranteed in every scenario. Our metrics serve as crucial tools in these cases, providing quantitative insights that help us understand and analyze the efficacy of different

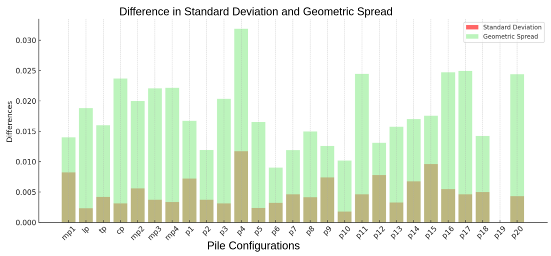


Fig. 5: Difference in metric values after sweeping using kmeans for each configurations

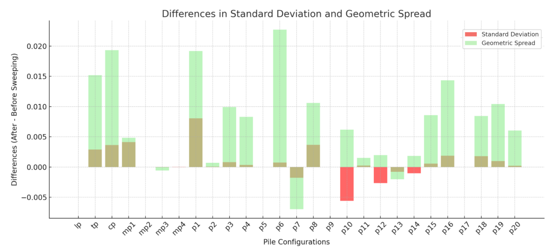


Fig. 6: Difference in metric values after sweeping using pca for each configurations

sweeping strategies under varying conditions.

To enhance our understanding of the evaluation results, we plotted (Fig. 5-7) the differences in metric values post-sweeping. This analytical approach aims to shed light on the relative effectiveness of each method. Notably, while comparing results within the same configurations, the trends in the differences for standard deviation and geometric spread may vary. This variation is expected, as these metrics do not necessarily measure the same aspects. Geometric spread tends to favor configurations with higher volume, whereas standard deviation is indicative of uniformly spread distributions.

As illustrated in Fig 5, all observed difference values are either positive or zero, with a zero difference suggesting no change in the pile post-sweep. Conversely, both Fig 6 and Fig 7 show instances of negative difference values. These negative values signal ineffective sweeps, where the process results in additional clutter or fails to adequately disperse the cubes. This distinction is critical in evaluating and refining the sweeping methods for optimal performance.

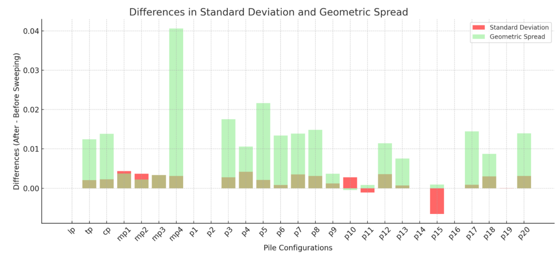


Fig. 7: Difference in metric values after sweeping using density estimation for each configurations

TABLE I: Evaluation on the performance of Kmeans

Pile Configurations	Before Sweeping Std+hv	Before Sweeping geo+hv	After Sweeping Std+hv	After Sweeping geo+hv
mp1	0.086332	0.017289	0.094553	0.031276
lp	0.087776	0.021416	0.090089	0.040224
tp	0.087762	0.021527	0.091966	0.037509
cp	0.087202	0.020378	0.090306	0.044054
mp1	0.086332	0.017289	0.094553	0.031276
mp2	0.086377	0.021567	0.091938	0.041520
mp3	0.087858	0.032249	0.091587	0.054315
mp4	0.092726	0.064012	0.096085	0.086173
p1	0.089860	0.026188	0.097042	0.042912
p2	0.085122	0.012423	0.088835	0.024319
p3	0.085278	0.021819	0.088364	0.042166
p4	0.091816	0.032881	0.103498	0.064776
p5	0.092358	0.059717	0.094747	0.076231
p6	0.092955	0.045098	0.096159	0.054119
p7	0.082787	0.012254	0.087373	0.024115
p8	0.083313	0.015363	0.087430	0.030321
p9	0.088554	0.025489	0.095917	0.038074
p10	0.089053	0.037870	0.090833	0.048034
p11	0.084804	0.028713	0.089385	0.053151
p12	0.087186	0.034015	0.094963	0.047128
p13	0.084253	0.020765	0.087509	0.036529
p14	0.084864	0.011510	0.091580	0.028487
p15	0.094213	0.032150	0.103819	0.049718
p16	0.082816	0.007278	0.088276	0.031999
p17	0.086634	0.016594	0.091220	0.041507
p18	0.082957	0.011922	0.087951	0.026140
p19	0.090420	0.040092	0.090420	0.040092
p20	0.084195	0.027178	0.088512	0.051562

VII. Conclusion

The results provide a valuable insights into different non-learning based interactive sorting and searching methods in the context of robotic waste sorting. By quantitatively assessing their performance across a range of scenarios, we gain a deeper understanding of the underlying dynamics

TABLE II: Evaluation on the performance of PCA

Pile Configurations	Before Sweeping		After Sweeping	
	Std+hv	geo+hv	Std+hv	geo+hv
lp	0.087833	0.020494	0.087833	0.020494
tp	0.087868	0.021622	0.090754	0.036803
cp	0.087140	0.020306	0.090786	0.039607
mp1	0.086416	0.017515	0.090539	0.022362
mp2	0.086407	0.021442	0.086407	0.021442
mp3	0.087916	0.032687	0.087889	0.032112
mp4	0.092703	0.064623	0.092719	0.064625
p1	0.089539	0.025930	0.097601	0.045114
p2	0.085093	0.012405	0.085146	0.013092
p3	0.085268	0.021813	0.086077	0.031727
p4	0.091786	0.030762	0.092149	0.039045
p5	0.092635	0.055098	0.092635	0.055098
p6	0.092756	0.045304	0.093501	0.068019
p7	0.082786	0.012254	0.081014	0.005305
p8	0.083328	0.015336	0.086991	0.025935
p9	0.087734	0.025059	0.087737	0.025057
p10	0.089187	0.039116	0.083613	0.045285
p11	0.085258	0.025838	0.085500	0.027350
p12	0.087260	0.037581	0.084619	0.039566
p13	0.084253	0.020765	0.083462	0.018755
p14	0.084897	0.011522	0.083856	0.013350
p15	0.094191	0.033916	0.094767	0.042503
p16	0.082816	0.007278	0.084679	0.021597
p17	0.086634	0.016600	0.086634	0.016600
p18	0.083031	0.011973	0.084833	0.020415
p19	0.090067	0.040859	0.091036	0.051285
p20	0.084632	0.028795	0.084828	0.034817

TABLE III: Evaluation on the performance of Density Estimation

Pile Configurations	Before Sweeping		After Sweeping	
	Std+hv	geo+hv	Std+hv	geo+hv
lp	0.087760	0.020475	0.087760	0.020475
tp	0.087762	0.021527	0.089788	0.033945
cp	0.087202	0.020378	0.089479	0.034207
mp1	0.086425	0.017361	0.090771	0.021074
mp2	0.086273	0.021506	0.089957	0.023741
mp3	0.087927	0.032569	0.091256	0.035888
mp4	0.092875	0.066064	0.095982	0.106693
p1	0.089464	0.025929	0.089464	0.025929
p2	0.085092	0.012405	0.085092	0.012405
p3	0.085280	0.021822	0.088091	0.039378
p4	0.091593	0.029743	0.095778	0.040301
p5	0.092871	0.060582	0.095007	0.082197
p6	0.093464	0.046583	0.094283	0.059958
p7	0.082786	0.012254	0.086291	0.026126
p8	0.083301	0.015670	0.086433	0.030524
p9	0.088555	0.025491	0.089779	0.029158
p10	0.089053	0.038366	0.091857	0.037907
p11	0.085258	0.025838	0.084177	0.026640
p12	0.086771	0.033721	0.090352	0.045130
p13	0.084453	0.020810	0.085187	0.028380
p14	0.084897	0.011522	0.084897	0.011522
p15	0.094387	0.032091	0.087876	0.032998
p16	0.082816	0.007278	0.082816	0.007278
p17	0.086628	0.019226	0.087477	0.033660
p18	0.083031	0.011974	0.086027	0.020683
p19	0.090310	0.039908	0.090350	0.039912
p20	0.084622	0.029224	0.087769	0.043175

of the object rearrangement task. This knowledge is instrumental in refining our approaches and developing more sophisticated algorithms that can adapt to the intricate challenges of automated waste management. Looking ahead, we are poised to explore the integration of learning-based and computer vision techniques for interactive segmentation, aiming to further augment the efficiency and effectiveness of sorting processes.

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