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Characterization parameters in urban areas to detect solid waste through the use of artificial vision

Parámetros de caracterización en zonas urbanas para detectar residuos sólidos mediante visión artificial

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Abstract

Objective: To determine the conditions under which images can be acquired in urban areas to detect solid waste using artificial vision techniques.
Methodology: Two urban areas were selected; characterization parameters were defined; color segmentation techniques and cascade detectors were applied; and, finally, the effectiveness of the applied waste detection techniques was determined.
Results: In the characterization parameters for the heights of 1.5 m and 0.5 m, inclination angles of 60° and 20°, and brightness levels ranging from 300 to 1800 lux, the accuracy of the color segmentation technique ranged from 71% to 96%. The accuracy of the cascade detector technique, on the other hand, ranged from 70% to 96%.
Conclusions: In both color segmentation and cascade detector techniques, it has been determined that the angle of inclination is the most significant characterization parameter that affects efficiency. This provides an average accuracy of 92.25% and 94% for a 20° angle, while 73% and 76.75% were the accuracy averages for a 60° angle.

Keywords: Cascade detector, characterization parameters, waste, color segmentation, urban areas.

Abstract

Objetivo: Determinar las condiciones de adquisición de imágenes en zonas urbanas para detectar residuos sólidos mediante técnicas de visión artificial.
Metodología: Se seleccionaron dos zonas urbanas, se definieron los parámetros de caracterización y se aplicaron las técnicas de segmentación por color y detectores en cascada, por último, se evaluó la eficiencia de las técnicas de detección de residuos aplicadas.
Resultados: En los parámetros de caracterización para alturas de 1.5 m y 0.5 m, ángulos de inclinación de 60°y 20°, niveles de luminosidad entre 300 a 1800 Lux, se obtuvo la exactitud de la técnica de segmentación por color con valores del 71 % al 96 %, a su vez, la exactitud de la técnica de detector en cascada tuvo valores del 70 % al 96 %.
Conclusiones: Se determinó que, tanto para el rendimiento de la técnica de segmentación por color como para la técnica de detector en cascada, el parámetro de caracterización que más afectó la eficiencia, es el ángulo de inclinación, obteniendo una exactitud promedio de 92.25 % y 94 % para un ángulo de 20°, mientras que, en un ángulo de 60° la exactitud promedio fue de 73 % y 76.75%.

Palabras clave: Detector en cascada, parámetros de caracterización, residuos, segmentación por color, zonas urbanas.

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Introduction

Artificial vision is a field that focuses on image and video processing using computational intelligence techniques. Its goal is to extract relevant information from visual files to facilitate decision-making. Artificial vision encompasses various processes, such as image acquisition, processing, edge detection, segmentation, feature extraction, recognition and localization, and interpretation [1]. Artificial vision is regularly employed in industry and research sectors because of the visual elements present in their technological applications [2].

Improper waste management is a major global issue, compounded by continuous population growth and the corresponding increase in single-use item production, which accelerates waste generation [3]. Artificial vision tools are used for addressing the issue of waste-related problems; within this approach, object detection is among the most active fields of research and development. Waste detection involves image processing techniques, machine learning, and deep learning, utilizing high-capacity computing equipment to handle data volumes that facilitate the training of classifiers and object detectors [4].

The performance of artificial vision systems is directly related to image quality; therefore, lighting, camera location height, and viewing angle are key factors in image acquisition [5]. As a result, when applying this technology in uncontrolled environments where conditions vary, the perspective and resolution of images, as well as their quality, are affected. This makes failures in the performance of artificial vision systems likely [6].

This article identifies the image acquisition conditions in urban areas to detect solid waste through artificial vision. Techniques such as color segmentation and cascade detectors trained with custom image sets are employed. The efficiency of both techniques is compared in terms of accuracy, number of detections, false positives, and false negatives. The programming was done in the Python programming language, and open-source computer vision libraries and the Cascade Trainer GUI tool were used. The tests were conducted in the city of Cúcuta, Colombia.

Methodology

The methodology consists of four stages: the selection of urban areas, characterization parameters that assess image acquisition conditions, application of techniques for waste detection, and evaluation of waste detection techniques.

Selection of urban areas

Two urban areas around the Bogotá Canal in the city of Cúcuta were selected to learn about waste generation in the urban area of Cúcuta [7]. The selection process involved a visual review of the areas to verify the presence of waste and analyze the specific characteristics of these zones. Additionally, a consultation was conducted using city maps to recognize areas with high population density, as well as residential, domiciliary, and industrial zones. These sectors significantly influence the origin of solid waste, providing a representative sample of waste in the urban area [8]. The description of the selected zones, including their geographical location and relevant characteristics, is presented below.

Zone 1:

a) *Location*: Encompassing the stretch of the Bogotá Canal from the SENA (National Learning Service) to Diagonal Santander Avenue.

b) *Characteristics*: Located between the Merced and Lleras neighborhoods, this zone experiences high traffic. It has been a site where previous waste issues have occurred, reflecting public dissatisfaction with such situations [9].

Zone 2:

a) *Location*: Encompassing the stretch of the Bogotá Canal from the Unicentro shopping center to the La Ceiba urbanization.

b) *Characteristics*: Located in the southern part of the city, this zone features residential and commercial areas. The area has previously faced issues related to improper waste management and pollution. Because of the high presence of solid waste, it is considered a relevant site [10].

Characterization parameters

The characterization parameters used to determine image acquisition conditions in urban areas are the camera height, inclination angle, and brightness level in the image-taking area [11].

a) Camera height: Images were captured at the heights of 0.5 m and 1.5 m above the canal's surface in the selected zones. These positions were defined by analyzing factors such as perspective. This ensured less variability in the size of the observed waste and retained relevant details in the waste detection process [12]. Two capture devices with 12 MP f/1.6, OIS and 64 MP OIS f/1.9 were used for image acquisition.

b) Inclination angle: The inclination angles of the image capture device were set at 20° and 60°. These angles were established considering the specific characteristics of the urban area and understanding how it affects the perspective of images. The angles were adjusted to obtain an appropriate view of waste, considering the camera lens constraints that determine the field of view in image capture [13].

c) Brightness: To assess the brightness level during image acquisition, a digital light meter was employed. Adequate illumination facilitates the extraction of the most relevant features in an image, influencing the execution of algorithms in artificial vision systems [14].

Techniques for waste detection

This section outlines the technical foundations required for waste detection using color segmentation and cascade detector techniques.

- Color Segmentation: This method uses color information to reduce the influence of shadows and brightness in an image through representations in the hue, saturation, and value (HSV) color space; thresholding; and morphological operations [15].

a) HSV Color Space: To segment the image, it was initially converted from red, green, and blue (RGB) to the HSV color space. This space consists of the following channels: hue, saturation, and brightness. Specific color ranges for waste detection were defined in this section. The conversions from RGB color components to the HSV color space are presented by Equations 1, 2, and 3.

$$= \begin{Bmatrix} 60 \cdot \frac{G-B}{\max(R,G,B)-\min(R,G,B)} + 0, \quad donde \max(R,G,B) = R \\ 60 \cdot \frac{B-R}{\max(R,G,B)-\min(R,G,B)} + 120, donde \max(R,G,B) = G \\ 60 \cdot \frac{R-G}{\max(R,G,B)-\min(R,G,B)} + 240, donde \max(R,G,B) = B \end{Bmatrix} \quad (1)$$

$$S = \frac{\max(R,G,B) - \min(R,G,B)}{\max(R,G,B)} \quad (2)$$

$$V = \max(R,G,B) \quad (3)$$

The H value represents hue, ranging from 0 to 360°, while S indicates color purity and ranges from 0 to 100%. Finally, the V value refers to the brightness of the color, varying between 0% and 100% (black and white) [16]. Table 1 shows the configured parameters for colors in the HSV color space.

Table 1. Configuration of HSV Parameters.

Color space	Component (H,S,V)
Lower white	0, 0, 200
Upper white	255, 45, 255
Lower blue	100, 50, 50
Upper blue	270, 255, 255
Lower red	0, 146, 110
Upper red	30, 217, 243

Source: Author's elaboration.

b) Thresholding: Thresholding was applied to the segmented HSV color space to separate pixels corresponding to waste from the image background, allowing the binarization of the image based on a specified threshold [17]. The threshold value set is 35, assigning a pixel value of 0 to the image segment if it is less than the threshold and a pixel value of 1 otherwise.

c) Morphological operations: Morphological operations were employed to eliminate imperfections and enhance the quality of binarized images [18]. The morphological operations used are dilation, erosion, and closing, defined by Equations 4, 5, and 6, respectively. A morphological unit element of 5×5 was created.

$$X \oplus Y = \left\{f \middle| (\hat{Y})_f \cap X \neq \varphi \right\} \quad (4)$$

$$X \pm Y = \left\{f \middle| (Y)_f \cap X \neq \varphi \right\} \quad (5)$$

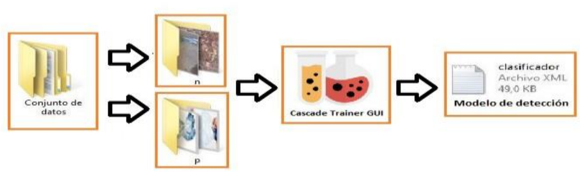
$$X \cdot Y = (X(+)Y)(-)Y \quad (6)$$

Cascade Detector: This involves combining multiple weak classifiers, where each is trained to detect a specific waste feature that needs to be identified [19].

The dataset used for training the cascade detector consisted of jpg format images, divided into two folders: one folder contained information about the waste to be detected (positive images) comprising 160 elements, while the other folder contained 500 elements corresponding to information not to be detected (negative images) [20].

The Cascade Trainer GUI software, which is exclusively available for the Windows operating system, was utilized to train the cascade detector. In this software, the dataset was loaded, and training parameters, such as the previously specified number of positive and negative samples, were configured. Additionally, the number of stages was set to 15, and image dimensions were defined as 48×70 pixels [21]. Figure 1 illustrates the structure for obtaining the waste detection model.

Figure 1. Structure for obtaining the waste detection model.



Source: Author's elaboration

Evaluation of waste detection techniques

The waste detection techniques were executed on a personal computer with an AMD Ryzen 5 processor clocked at 2400 MHz and 8 GB of RAM. The algorithms for waste detection techniques were coded using the Python programming language version 3.11 on the Windows 10 operating system. Additionally, the Visual Studio Code integrated development environment was employed. OpenCV libraries version 4.7 and NumPy version 1.24 were utilized.

The evaluation of characterization parameters (i.e., camera height, inclination angle, and brightness of the areas) was conducted by comparing the performance of color segmentation and cascade detector techniques. Aspects such as detections made, false positives, and false negatives were assessed with regard to image acquisition conditions. Accuracy was calculated based on these data, using it in this context to determine the effectiveness of each technique, representing the proportion of predictions successfully detected by the techniques. Equation 8 was used to calculate accuracy [22, 23].

$$Exactitud = \frac{Número\ \ de\ predicciones\ correctas}{Número\ total\ de\ predicciones} \quad (8)$$

Results

In the implementation of waste detection techniques, image capture was performed in the two selected zones. During this action, brightness measurements were taken using a digital light meter. It was observed that in images captured between 10:00 a.m. and 11:30 a.m., the brightness levels ranged from 610 lux to 1800 lux, whereas in images captured between 4:00 p.m. and 5:30 p.m., the brightness levels varied between 300 lux and 500 lux.

After executing the processes of representing the image in the HSV color space, thresholding, and employing morphological operations, the result of applying the color segmentation technique can be visualized in Figure 2 under lighting conditions of 300–500 lux and 610–1800 lux. Section (a) displays the result of the technique's application at a height of 1.5 m and an inclination angle of 60°, while in (b), it was applied at a height of 1.5 m and an inclination angle of 20°. Section (c) presents the result at a height of 0.5 m and an inclination angle of 60°. Likewise, section (d) shows the technique's result at a height of 0.5 m and an inclination angle of 20°.

Figure 2. Waste detection through color segmentation. (a) Height of 1.5 m and inclination angle of 60°. (b) Height of 1.5 m and inclination angle of 20°. (c) Height of 0.5 m and inclination angle of 60°. (d) Height of 0.5 m and inclination angle of 20°.

Source: Author's elaboration

Waste detection through the cascade detector obtained using the Cascade Trainer GUI tool was applied to images captured in urban areas under lighting conditions of 300–500 lux and 610–1800 lux. Figure 3 illustrates the performance of the cascade waste detector.

In section (a), the result of applying the technique is observed at a height of 1.5 m and an inclination angle of 60°, while in (b), it was applied at a height of 1.5 m and an inclination angle of 20°. Section (c) presents the result at a height of 0.5 m and an inclination angle of 60°. Similarly, section (d) shows the technique's result at a height of 0.5 m and an inclination angle of 20°.

Figure 3. Waste detection using the cascade detector. (a) Height of 1.5 m and inclination angle of 60°. (b) Height of 1.5 m and inclination angle of 20°. (c) Height of 0.5 m and inclination angle of 60°. (d) Height of 0.5 m and inclination angle of 20°.

Source: Author's elaboration

Table 2 presents a comparison of the outcomes derived from the color segmentation technique. This comparison through tables serves to assess the accuracy of the two employed waste detection techniques concerning the evaluated characterization parameters.

Table 2. Comparison of results obtained from the color segmentation technique.

Comparison of the Color Segmentation Technique							
Brightness level	Height	Inclination angle	Real amount of waste	Correct detections	FP	FN	Accuracy
610–1800 lux	0.5 m	60°	50	42	10	0	81%
610–1800 lux	0.5 m	20°	50	48	3	1	92%
610–1800 lux	1.5 m	60°	50	46	6	4	82%
610–1800 lux	1.5 m	20°	50	49	3	2	91%
300–500 lux	0.5 m	60°	50	42	12	5	71%
300–500 lux	0.5 m	20°	50	49	1	1	96%
300–500 lux	1.5 m	60°	50	44	10	6	73%
300–500 lux	1.5 m	20°	50	46	1	4	90%

Source: Author's elaboration

Similarly, in Table 3, the results obtained from the cascade waste detector are compared based on the number of false positives (FP) and false negatives (FN).

Table 3. Comparison of results obtained from the cascade detector technique.

Comparison of the cascade detector technique							
Brightness level	Height	Inclinatio n angle	Real amount of waste	Correct detections	FP	FN	Accuracy
610–1800 lux	0.5 m	60°	50	36	1	14	71%
610–1800 lux	0.5 m	20°	50	47	0	2	96%
610–1800 lux	1.5 m	60°	50	38	0	10	79%
610–1800 lux	1.5 m	20°	50	49	1	3	92%
300–500 lux	0.5 m	60°	50	35	3	12	70%
300–500 lux	0.5 m	20°	50	50	2	1	94%
300–500 lux	1.5 m	60°	50	39	3	12	72%
300–500 lux	1.5 m	20°	50	48	1	2	94%

Source: Author's elaboration

The result with the highest accuracy for the color segmentation technique occurred under the characterization parameters corresponding to a brightness level ranging from 300 to 500 lux, with the camera positioned at a height of 0.5 m and an inclination angle of 20°. In these conditions, the highest performance was achieved with 96% accuracy, making 49 correct detections out of 50 possible, with 1 FP and 1 FN. On the other hand, under characterization conditions corresponding to a brightness level ranging from 300 to 500 lux, with the camera at a height of 0.5 m and an inclination angle of 60°, the results showed the lowest accuracy, achieving 71%, with 12 FPs and 5 FNs.

For the cascade detector technique, the highest degree of accuracy was achieved at a brightness level ranging from 610 to 1800 lux, with the camera at a height of 0.5 m and an inclination angle of 20°. Under these conditions, 96% accuracy was obtained with 2 FNs and no FPs.

Meanwhile, the lowest accuracy occurred under the brightness level ranging from 610 to 1800 lux, with a camera height of 0.5 m and an inclination angle of 60°. In this case, 71% accuracy was achieved with 14 FNs and 1 FP.

Overall, both waste detection techniques exhibited higher accuracy when the camera was inclined at a 20° angle for image acquisition, with an average accuracy of 92.25% for the color segmentation technique and an average accuracy of 94% for the cascade detector technique. Conversely, at an inclination angle of 60°, the lowest accuracy values were found, with an average accuracy of 76.75% for the color segmentation technique and an average accuracy of 73% for the cascade detector technique.

Conclusions

The characterization parameter that most influenced the performance of the waste detection techniques was the angle of inclination since, at an angle of 60°, the average accuracy of the techniques reached 73% and 76.75%, respectively. Using the color segmentation and cascade detector techniques, the average accuracy increased to 92.25% and 94% at an inclination angle of 20°.

The application of image processing stages (mathematical morphology) helped mitigate the effects generated by factors such as variability in the shape and size of solid waste and its differentiation from the background and other objects in the image frame. This process eliminates imperfections generated by noise and determines a region of interest, considering relevant information about edges, contours, and sizes. Additionally, partially visible objects can be considered after applying morphological stages.

The data obtained from applying the color segmentation technique compared to the cascade detector allowed determining the effectiveness of this technique for waste detection in urban areas and the importance of adjusting color spaces with regard to variations in brightness levels, influencing the number of FPs and FNs in detections.

By using the cascade detector system with the custom image set, factors such as computational efficiency were prioritized. Since it is a technique that does not focus on identifying solid waste but on eliminating from consideration all pixels that do not correspond to such waste, computational resources are significantly reduced, along with a shorter training time. This allows for quick iteration and adjustment of the cascade classifier model. Additionally, this approach presents a lower risk of overfitting and improves the model's generalization to detect new objects.

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