Rotation invariant bin detection and solid waste level classification

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A B S T R A C T

In this paper, a solid waste bin detection and waste level classification system that is rotation invariant is presented. First, possible locations and orientations of the bin are detected using Hough line detection. Then cross correlation is calculated to differentiate the true bin position and orientation from those of other similar objects. Next, features are extracted from the inside of the bin area and together with detected bin corners they are used to determine the bin’s waste level. A few features are also obtained from the outside of the bin area to check whether there is rubbish littered outside the bin. The proposed system was tested on shifted, rotated and unrotated bin images containing different level of waste. In the experiment, bin detection was treated separately from waste level classification. For bin detection, if 95% of the opening area is captured then the bin is considered detected correctly. The waste level classification is only considered for the correctly detected bins where the waste level is classified as empty, partially full or full. The system also checks the presence of rubbish outside the bin. In training, only images containing unrotated bin were used while in testing images containing both unrotated and rotated bin were used in equal number. The system achieves an average bin detection rate of 97.5% and waste level classification rate of 99.4% despite variations in the bin’s location, rotation and content. It is also robust against occlusion of the bin opening by large objects and confusion from square objects littered outside the bin. Its low average execution time suggests that the proposed method is suitable for real-time implementation.

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1. Introduction

Human activities generate waste that must be managed and disposed of properly. In areas of high human density, waste is a big concern and solid waste management (SWM) attempts to manage, re-use and reduce the amount of waste materials to be disposed of. Increasing population, growing economy, rapid urbanization and the rise in community living standard have greatly accelerated the daily rate of municipal waste production [1]. A survey on solid waste management system of different cities in developed countries shows that efficient SWM systems require skilled personnel, appropriate equipment, rich infrastructure, proper maintenance and the support of the central and local government as well as the consumers [2]. Sustained development in SWM systems can only be attained with financial support of the government, interest in solid waste management and increased awareness of the potential impacts of untended waste that pollutes the environment especially in overly populated areas [3–5].

A notable number of research works on SWM have been published but most of them are related to bin truck and land fill planning and management [6]. To increase the
accuracy and efficiency of SWM, the use of modern tools like radio frequency identification (RFID), general packet radio systems (GPRS), global positioning systems (GPS) and geographical information systems (GIS) are recommended [6]. Common issues that are prevalent in high density residential areas like apartments and slums are improper disposal of waste, overflowing waste bins and smelly bin area due to spill. These problems could be minimized with an online monitoring system where the garbage level in the bins is detected automatically so that the garbage could be collected before the bins overflow and the rubbish spills.

Static garbage collection is a common practice where waste is collected from bins at fixed interval, normally once or twice a week. Johansson [7] studied the effectiveness of different scheduling and routing policies based on real-time bin data from several recycling stations in Malmö, Sweden. The study indicates that dynamic garbage collection can be implemented with the use of bins equipped with level sensors to improve the collection process, and reduce operating costs and collection time as compared to static collection with fixed routes.

In this paper, rotation invariant bin detection and waste level classification is introduced. It consists of bin detection, feature extraction and level classification methods that are accurate and fast in execution. For bin detection, the proposed approach utilizes Hough line detection and cross matching. Its performance in detecting rotated and unrotated bins is compared to that of the DTW scheme. For feature extraction, eight features were extracted using rotated Sobel or Gabor filters from the bin area and outside of the bin area. These features are used to detect the bin’s waste level and the presence of rubbish outside the bin. Two types of classifiers are tested in conjunction with the features for this purpose and they are MLP and SVMs.

2. Literature review

Garbage bin level detection has been proposed and studied as a means to improve the collection and disposal of wastes in the last five years. In one pilot study, infrared LED level sensors equipped with wireless communication system were installed in 3300 garbage bins in Sweden [7]. In each bin, four sensors were installed at different height. The garbage level is detected by the highest sensor obstructed by waste in the bin. Enevo one is a commercial smart bin which sense the waste level using robust ultrasonic sonar technology [8]. Other types of sensors proposed by researchers are capacitive moisture sensor [9], point-level capacitive sensor [10] and optical sensor [11]. However, the cost of installation and regular cleaning of the sensors lead many to believe that using sensors for bin level detection is impractical. Skilled personnel are needed to clean and troubleshoot defective sensors and mountings regularly if maintenance and the process are tedious and time consuming. Moreover, some sensors are only suitable to be used in certain conditions. For example, capacitive sensors are sensitive to humidity so these type of sensors work well for volume measurements during rainy season.

An automated bin collection system based on a combination of image processing and digital distance sensors was developed by a team of researchers from Politecnico di Milano and the Shanghai Jiao Tong University [12]. A low cost image acquisition system and distance sensors were used to detect changes in waste level in the bins. The difference between two consecutive frames of acquired images and the height of the bin level measured by the distance sensors were monitored in real time. In another work, Vicentini et al. employed a similar image difference technique to detect both change and height of the waste level in a bin by subtracting the previous frame from the current frame [13]. An intelligent real time image processing method using a motion sensor and camera was introduced by Zhu et al. [14]. The closing and opening of bin was detected by motion sensor and images of the bin were captured by a camera mounted over it. The level of waste in the bin was determined by comparing two consecutive images. The drawback of methods that rely on image difference is the need to always capture exactly the same area or objects in consecutive image frames. Thus, it is important to ensure the camera position is fixed relative to the bin opening area at all time. A little jitter, shift or rotation to the mounting or the camera itself results in erroneous classification. This stringent requirement is impractical in real time applications. To neutralize this deficiency, advanced statistical learning theories and image processing techniques were used in subsequent works that adopted image difference technique [10].

A method using gray level aura (GLAM) matrix as a feature extractor and K-nearest neighbor (KNN) as a classifier was developed by Hanna et al. [15]. The method provided a robust solution for automated solid waste bin level detection, collection and management. GLAM of an image measures the amount of each gray level occur in the presence of other grey levels in the neighborhood. Feature vectors were constructed by the aura measures of captured image frames. Samples of features were extracted from training images and stored as references in the form of vectors. In the classification process, a feature vector is extracted from the captured frame and then compared to the stored reference vectors. K reference vectors that are nearest to the input feature vector are selected and the class of the input vector is determined by a majority vote of the classes of its nearest neighbors [16]. The system showed good classification rate but its accuracy dropped when the bin was shifted or rotated.

Islam et al. [17], came up with a solution for shifted bin using template matching and Dynamic Time Warping (DTW). DTW is a pattern matching algorithm which finds the warping path of two patterns from their distance metric [18]. First, the captured image was scanned section by section to find the location of the bin using a template of the bin as a reference. The similarity between the section and the template was measured using DTW. The section that registered the minimum score was considered as the location of the bin. Then a few features were extracted from the bin area using a single Gabor filter (GF) and vertical projections. The features were used as inputs to a Multi-Layer Perception (MLP) that classified the waste level into several classes. However, the system is not
designed to locate the bin position accurately. It is not robust against bin rotation and its performance is affected by the presence of square objects with size similar to the bin opening in the images. Consequently, the accuracy of the method drops when the bin is rotated or overflown with rubbish and when square objects are present in the image.

Hannan et al. [19], utilized Hough transform to extract line information from the entire image and used the line coordinates as a feature for bin level classification. In their work, gradient information is used with Hough transform to find lines in each frame. Then using the voting procedure of Hough Transform the coordinates of edge lines with high intensity are extracted and used to detect the presence of waste inside and outside of the bin. They claim that a good classification is achieved in detecting the presence of waste outside the bin. However, the accuracy of the waste level in the bin is only 82.93%. This is because the edge information is obtained from the entire image rather than just from the inside the bin area since no attempt is made to locate the bin opening. Thus it is assumed that the level of rubbish in the bin corresponds to the number of lines detected in the whole image, which is not always accurate since there is no guarantee that the rubbish will always display strong linear edge gradient.

3. Methodology

An automatic waste level detection system should be robust against bin shift, rotation, occlusion of the bin opening by large objects and confusion from objects littered outside the bin. To achieve this objective we propose a system that accurately detects the bin opening area and extracts features from inside and outside of the bin. Then features are used as inputs to a classifier that determines the waste level in the bin. Fig. 1 shows the flow of steps in the proposed algorithm. Details of each step are given in the following subsections.

3.1. Image

The images are 800 × 600 pixels in size and they are captured in a real setup with a Logitech HD Pro Webcam C910 camera that is approximately positioned 2 m away from the bins and 3 m above the ground. The bins used are real garbage bins with 120 L capacity and rectangular in shape. In the images, the size of its opening is approximately 300 × 300 pixels. Samples of some bin images with different waste levels are shown in Fig. 2. For training, 100 images of unrotated bin with different waste levels were used. Features were extracted from these images and used to train the classifier to recognize the four waste levels. For testing, 60 images of unrotated bin and 60 images of rotated bin were used. It should be noted that the test images are different from the training images.

3.2. Bin opening detection

Assuming that the bin is upright, the bin opening is the area that contains the waste. To detect this area, we must first locate the four corners and the edge of the bin opening. So, the first step is to obtain the edge information of the image using Canny Edge Operator before employing Hough transform to detect straight lines in the edge image. The Hough transform only provides two parameters for each line detected in the image. They are the magnitude of the vector from the reference point to the nearest point on the line, and the angle formed by the vector and the horizontal axis at the reference point. In the line equation these parameters are normally represented by \( \rho \) and \( \theta \). The line equation can be written as:

\[
ax + by = \rho \tag{1}
\]

where \( a = \cos \theta \) and \( b = \sin \theta \). A table consisting of all possible combinations of \( \rho \) and \( \theta \) is rendered and for each pair of \( \rho \) and \( \theta \), the total number of edge pixels that fall on the line represented by the two parameters is recorded. Thirty lines with the most number of edge pixels are analyzed and the length of each line is checked to see whether it belongs to the bin contour. But more importantly, the intersection points of two orthogonal lines are sought because they are candidates for bin corners. When two lines intersect at point \((x, y)\), Eq. (1) can be written for each line at \((x, y)\) as follows:

\[
a_1x + b_1y = \rho_1 \tag{2}
\]

\[
a_2x + b_2y = \rho_2 \tag{3}
\]

The orthogonality of the intersecting lines can be tested by multiplying \( a_1 \) by \( a_2 \) and \( b_1 \) by \( b_2 \) and summing their products. If the two lines mentioned in Eqs. (2) and (3) are orthogonal then the following equation is true.

\[
a_1a_2 + b_1b_2 = 0 \tag{4}
\]
If the sum is zero or nearly zero (±0.2) then the two lines are considered orthogonal. The point of intersection \((x, y)\) for the orthogonally intersecting lines are obtained from:

\[
x = \frac{\rho_1 b_2 - \rho_2 b_1}{a_1 b_2 - a_2 b_1} \tag{5}
\]

\[
y = \frac{\rho_1 a_2 - \rho_2 a_1}{a_2 b_1 - a_1 b_2} \tag{6}
\]

If the bin is rotated, all of its corners will also be rotated by the same angle. For each corner candidate, the angle of rotation can be obtained from the \(\theta\) parameter of one of the two lines that form the corner. Then a template of an empty bin is rotated according to the detected angle of rotation before it is superimposed on the corner candidate for similarity matching. The locations of the remaining three bin corners of the template are checked to see if they coincide with other corner candidates. If other candidates

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**Fig. 2.** Samples of bin images at different waste levels.

**Fig. 3.** The Gabor filters obtained by setting \(K = 1, \gamma = 0.5, \lambda = 8, \varphi = 0\) and (a) \(\theta = 0^\circ\), (b) \(\theta = 45^\circ\), (c) \(\theta = 90^\circ\) and (d) \(\theta = 135^\circ\).
are present, the similarity matching is based on all of the candidates. Otherwise, it is calculated for a single candidate only.

The similarity between the corners in the image and the template is calculated using edge pixels along the intersecting lines which are 10 pixel wide. In our work, correlation coefficient is chosen as the measure of similarity and it is calculated by the following equation.

$$
\text{Corr}(I, T) = \frac{\sum_m \sum_n (I_{mn} - \mu_I)(T_{mn} - \mu_T)}{\sqrt{\left(\sum_m \sum_n (I_{mn} - \mu_I)^2\right)\left(\sum_m \sum_n (T_{mn} - \mu_T)^2\right)}}
$$

(7)

where $I$ is the candidate bin area in the image, $T$ is the bin template, $m$ and $n$ are indices to each pixel in $I$, and $\mu_I$ and $\mu_T$ are means of pixel values of $I$ and $T$ respectively. The location of the template superimposed on the corner candidate with the highest correlation value is considered as the correct bin area.

### 3.3. Feature extraction

Gabor filter is a Gaussian envelope modulated by a sinusoidal function. A 2-D Gabor filter can be written as [20]

$$
G_{\sigma, \gamma, \varphi, \theta}(x, y) = K \exp \left( -\frac{x'^2 + \gamma^2 y'^2}{2\sigma^2} \right) \cos \left( 2\pi \frac{x'}{\lambda} + \varphi \right)
$$

(8)

where $x' = x \cos \theta + y \sin \theta$, $y' = -x \sin \theta + y \cos \theta$, $K$ is scale of magnitude, $\gamma$ is spatial aspect ratio, $\lambda$ is wavelength of the
sinusoidal function, $\phi$ is phase offset and $\theta$ is orientation angle of the Gaussian envelope. Features used in the classification of the waste level are obtained by convolving the bin area in the image with a set of Gabor filters. At each pixel $(x, y)$ in the bin area, the absolute value of the convolution of a Gabor filter and the pixels in the neighbourhood centered at $(x, y)$ is calculated. Then the absolute values of the convolution at all pixels in the bin area are summed to produce one feature. By changing the angle of rotation $\theta$, a different Gabor filter is obtained and with this new filter another feature can be generated by repeating the same convolution process. In our experiment, the value of $\theta$ was fixed at $0^\circ$, $45^\circ$, $90^\circ$ and $135^\circ$ so that four different Gabor filters were obtained as shown in Fig 3. Using these Gabor filters, 4 features can be obtained from the bin area and another 4 can be extracted from the area outside of the bin.

Sobel operator is a $3 \times 3$ mask used for edge detection. To capture edge information in all directions the mask is rotated to four positions as shown below.

$$G_1 = \begin{bmatrix} -1 & -2 & -1 \\ 0 & 0 & 0 \\ 1 & 2 & 1 \end{bmatrix}$$

$$G_2 = \begin{bmatrix} -2 & -1 & 0 \\ -1 & 0 & 1 \\ 0 & 1 & 2 \end{bmatrix}$$

$$G_3 = \begin{bmatrix} -1 & 0 & 1 \\ -2 & 0 & 2 \\ -1 & 0 & 1 \end{bmatrix}$$

$$G_4 = \begin{bmatrix} 0 & 1 & 2 \\ -1 & 0 & 1 \\ -2 & -1 & 0 \end{bmatrix}$$

where $G_1$ is the original sobel operator and $G_2$, $G_3$ and $G_4$ are obtained by rotating $G_1$ by $45^\circ$, $90^\circ$ and $135^\circ$ in counterclockwise direction.

The procedure of obtaining features from the bin area and outside of the bin area using the Sobel masks is the same as the one for Gabor filters. First a mask is convolved with the area. At each pixel $(x, y)$ in the bin area, the absolute value of the convolution of a sobel operator and the pixels in the neighbourhood centered at $(x, y)$ is calculated. Then the absolute values of the convolution at all pixels in area are summed to produce one feature. From the four masks, 8 features can be extracted from the image where four features are extracted from the bin area and the other four from the outside of the bin.

3.4. Classification

The number of bin corners detected can be used as one of the features for waste level classification. From the detected bin area, a total of 4 features can be extracted using four different Sobel operators or Gabor filters. Then, from the area outside of the bin, another 4 more features are obtained using the same Sobel operators or Gabor filters. The four features from the bin area plus the number of bin corners detected are used to determine the waste level in the bin which can be empty, partially full or full. The other 4 features from the outside of the bin area are solely used to check the presence of rubbish outside the bin.
An SVM is a supervised binary classifier that uses a decision function to split the data into two classes. Graphically, the decision function can be visualized as a hyperplane separating the classes [21]. In our experiments, three SVM classifiers with radial basis kernel are used for the waste classification as shown in Fig. 4 (a). Using the number of bin corners detected and the first four Gabor features from the bin area, the first SVM decides whether the bin is empty or filled. For the filled class, the second SVM takes the same set of input features and divides it into partially full and full classes. The third SVM operates independently of the first two. It takes the four Gabor or Sobel features from the outside of the bin area to check whether waste is littered outside the bin. Just like an MLP or any

**Fig. 7.** Bin detection by DTW and proposed method (a) input images, (b) the results of bin detection by DTW and (c) the results obtained by the proposed method.
other supervised classifier, the SVM requires training. In training, only unrotated images were used while in testing unrotated and rotated images were used in equal number. The performance of the SVM classifiers is compared with that of MLPs with a similar architecture as shown in Fig. 4(b).

4. Experiments

The database consists of images of rotated and unrotated bin with different waste levels classified as empty, partially full and full. In some images, there is rubbish littered outside the 120 L bin as well. Each image is 800 x 600 pixels in size and the bin area is approximately 300 x 300 pixels. In our experiments, only unrotated images were used for training while testing involved unrotated and rotated images in equal number. Altogether there are 220 bin images of which 60 are rotated. 100 unrotated bin images with different waste levels are used for training the classifiers and the remaining 120 images of rotated and unrotated bin are used for testing. For each image, greyscale conversion is performed to transform it into a grayscale image followed by edge detection using canny edge detector. The output is a binary edge image as shown in Fig. 5.

Then line detection is performed on the binary image using Hough transform as shown in Fig. 6. The aim is to detect the four sides of the bin opening and its corners. Each corner is represented by the intersection of two orthogonal lines. The position and orientation of the corner are obtained from the two intersecting lines that form it. Since rubbish with sharp corners and edge may be present in the image, a total of up to 20 corner candidates are considered in each image. Then each corner candidate is superimposed on one corner of an empty bin template after the template is rotated to match the candidate’s orientation. Correlation coefficient between the candidate and template corner is calculated using the edge pixels of the image and the template around the corner position.

In calculating the correlation coefficient of a candidate, if other candidates exist at the other corners of the template area, they are considered collectively. Otherwise only the edge pixels of one corner are used in the calculation since the rest of the bin area is assumed covered by rubbish.

Once the bin area is determined, 4 features can be extracted from the bin area and another 4 from the outside of the bin area using the Sobel masks or Gabor filters. The number of bin corners detected plus the eight Sobel or Gabor features are used as inputs to an MLP or SVM for waste level classification.

5. Results and discussion

The performance of the proposed and the DTW methods in bin area detection. The database consists of images of rotated and unrotated bin with different waste levels classified as empty, partially full and full. In some images, there is rubbish littered outside the 120 L bin as well. Each image is 800 x 600 pixels in size and the bin area is approximately 300 x 300 pixels. In our experiments, only unrotated images were used for training while testing involved unrotated and rotated images in equal number. Altogether there are 220 bin images of which 60 are rotated. 100 unrotated bin images with different waste levels are used for training the classifiers and the remaining 120 images of rotated and unrotated bin are used for testing. For each image, greyscale conversion is performed to transform it into a grayscale image followed by edge detection using canny edge detector. The output is a binary edge image as shown in Fig. 5.

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The accuracy of the proposed method in locating the bin area and classifying the waste level is evaluated separately. First, the bin area is detected since garbage level classification is only meaningful if the bin is located correctly. The performance of the proposed method in locating the bin is compared against that of the DTW approach used by Islam et al. [17]. Both methods use an empty bin template, but in the DTW method the template is simply moved in 20 pixels step across the image to find an area that best matches the template. Therefore, it is not designed to find the exact location of the bin. At each location, row and column intensity projection is performed on a 300 x 300 area to produce a series of values. Then the sequence of the projection values is compared with the one obtained from the template, using DTW. The location that gives the minimum distance between the two sequences is considered as the true location of the bin.

The percentage of the correctly detected bin opening area is calculated manually by inspecting the result and calculating the number of pixels in the captured bin opening area. For bin detection, if 95% of the opening area is captured then the bin is considered detected correctly. For empty and partially full unrotated bins, the detection accuracy of the DTW method is 100% but it drops to 85% for full bin. This is because in some erroneous images the edge and corners of the bin are occluded by rubbish. To achieve good bin detection, the DTW method requires the bin opening area to be as similar to the template as possible. Thus, the presence of objects that are absent in the templates confuses the DTW algorithm and affects its accuracy. The bin detection rate of the proposed method is 100% for empty and partially full bins. For full bins the accuracy drops a bit to 95%. The only error occurs when the bin opening is almost completely occluded by waste.

For empty and partially full rotated bins, the detection accuracy of the DTW method is 85% and 35% respectively. For full bins, none of them was detected correctly. This is

<table>
<thead>
<tr>
<th>Image type</th>
<th>Classes</th>
<th>DTW TP</th>
<th>DTW FN</th>
<th>Sensitivity</th>
<th>Proposed method TP</th>
<th>Proposed method FN</th>
<th>Sensitivity</th>
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</thead>
<tbody>
<tr>
<td>Unrotated Bin</td>
<td>Empty</td>
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<td>0</td>
<td>100.00%</td>
<td>20</td>
<td>0</td>
<td>100.00%</td>
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<tr>
<td></td>
<td>Partial</td>
<td>20</td>
<td>0</td>
<td>100.00%</td>
<td>20</td>
<td>0</td>
<td>100.00%</td>
</tr>
<tr>
<td></td>
<td>Full</td>
<td>17</td>
<td>3</td>
<td>85.00%</td>
<td>19</td>
<td>1</td>
<td>95.00%</td>
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<tr>
<td>Rotated Bin</td>
<td>Empty</td>
<td>16</td>
<td>4</td>
<td>80.00%</td>
<td>20</td>
<td>0</td>
<td>100.00%</td>
</tr>
<tr>
<td></td>
<td>Partial</td>
<td>7</td>
<td>13</td>
<td>35.00%</td>
<td>20</td>
<td>0</td>
<td>100.00%</td>
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<tr>
<td></td>
<td>Full</td>
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<td>0.00%</td>
<td>18</td>
<td>2</td>
<td>90.00%</td>
</tr>
<tr>
<td>Average accuracy</td>
<td></td>
<td></td>
<td></td>
<td>80.00%</td>
<td></td>
<td></td>
<td>97.5%</td>
</tr>
</tbody>
</table>
| Average execution time |      |        |        | 1.49 s      |                    |                    | 0.51 s
because the method is not designed to detect rotated bins. The proposed method obtained 100% detection rate for empty and partially full rotated bins. For full bins, the accuracy drops to 90%. However in the two wrongly detected cases, the bins are not completely missed altogether but partially misdetected only. Samples of detected bin area by DTW and the proposed method are shown in Fig. 7 while the results are summarized in Table 1. True positive (TP) and false negative (FN) are defined as the number of correctly and wrongly classified cases respectively. Sensitivity is the ratio of TP to (TP + FN).

For waste level classification, only the waste level of the correctly detected bins was classified. The four features from the bin area plus the number of bin corners detected are used to classify the waste level in the bin which can be empty, partially full or full. The other 4 features from the outside of the bin area are used to determine the presence of rubbish outside the bin. Tables 2 and 3 summarize the outcome of the waste level classification and the performances of the Sobel and Gabor features respectively with MLP and SVM classifiers. It is observed that their performances are nearly identical. Both Sobel masks and Gabor filters are normally used to detect the change of gradient in the images like edge and line. If the bins are filled with rubbish that displays no prominent edge, the detected waste level would become inaccurate. Therefore, color information can be added to improve the classification accuracy for such cases. Furthermore, we conclude that any line or gradient detector can be used as replacement for Sobel masks or Gabor filters.

6. Conclusion

This paper introduces a rotation invariant bin detection and waste level classification algorithm. The exact position and orientation of the bin are detected using Hough line detection and cross correlation. Features are then extracted from the bin opening area and outside of the bin area using Sobel masks or Gabor filters. Together with an MLP or SVM classifiers, the features are used to determine the waste level of the bins which are empty, partially full or full. The system also checks the presence of rubbish outside the bin. In training, 100 unrotated images of a garbage bin with different waste levels were used. Then the system was tested on 120 bin images, where some of which are shifted, rotated and occluded by garbage of various levels. It achieved an excellent bin detection rate of 97.5% and waste level classification rate of 99.4%. The results prove that the system is robust against bin shift and rotation, occlusion by large objects and uncertainty introduced by

<table>
<thead>
<tr>
<th>Table 2</th>
<th>Performance of Sobel masks feature extractor with SVM and MLP classifier in waste level classification.</th>
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</thead>
<tbody>
<tr>
<td>Bin type</td>
<td>Classification area</td>
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<tr>
<td></td>
<td></td>
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<tr>
<td>Unrotated bin</td>
<td>Inside level</td>
</tr>
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<td></td>
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<td></td>
<td></td>
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<tr>
<td>Outside waste</td>
<td>Absent</td>
</tr>
<tr>
<td>Rotated bin</td>
<td>Inside level</td>
</tr>
<tr>
<td></td>
<td></td>
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<tr>
<td></td>
<td></td>
</tr>
<tr>
<td>Outside waste</td>
<td>Absent</td>
</tr>
<tr>
<td>Average accuracy</td>
<td></td>
</tr>
<tr>
<td>Average execution time</td>
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<table>
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<tr>
<th>Table 3</th>
<th>Performance of Gabor filters feature extractor with SVM and MLP classifier in waste level classification.</th>
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<tbody>
<tr>
<td>Bin type</td>
<td>Classification area</td>
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<tr>
<td></td>
<td></td>
</tr>
<tr>
<td>Unrotated bin</td>
<td>Waste level</td>
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<tr>
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<td></td>
<td></td>
</tr>
<tr>
<td>Outside waste</td>
<td>Absent</td>
</tr>
<tr>
<td></td>
<td>Present</td>
</tr>
<tr>
<td>Rotated bin</td>
<td>Waste level</td>
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<td></td>
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<tr>
<td>Outside waste</td>
<td>Absent</td>
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<td>Present</td>
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<tr>
<td>Average accuracy</td>
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<td>Average execution time</td>
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similar square objects littered outside the bin. Its low execution time makes it suitable for real time application.

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References