ISSN 2007-9737

Intelligent Waste Separator

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Abstract. Nowadays, trash has become a problem in the society and the ecosystem due to the way people get rid of it. Most of garbage is buried or burnt or even kept in places to which it does not belong. Big volumes of garbage thrown away and the methods used to store it cause air, water, and soil pollution. Fortunately, people can count on other methods to reduce the quantity of produced litter. An answer is recycling by re-using the materials. Currently, the traditional way to separate waste is to use different containers for each kind of waste separating trash manually, which does not always work. The aim of this paper is to present an Intelligent Waste Separator (IWS) which can replace the traditional way of dealing with waste; the proposed device receives the incoming waste and places it automatically in different containers by using a multimedia embedded processor, image processing, and machine learning in order to select and separate waste.

Keywords. Multimedia embedded processor, human machine interface, machine learning, trash can, ecosystem preservation.

1 Introduction

Garbage is a global problem that affects all living beings. A study from Grow NYC shows that 80% of the world's solid waste is produced in the United States of America [1]. Also, 70% of its trash is used once [2] and 45% is buried or burnt, such waste is paper, plastic, etc.

A lot of places like universities, downtowns, subways, and malls have different containers for specific kinds of waste. Unfortunately, there are people who do not place waste in the correct containers. For this reason, it is more difficult to recycle waste which has to go through a separation process of a high economic cost. Hence, this method does not work at all if there is no cooperation.

With the aid of technology this problem can be solved. A group of students from the University of South Florida designed an autonomous recycling robot [3] which can separate objects made of plastic, glass, or aluminum. It classifies waste using a metal detector and a switch that triggers by weight.

Another way of separating waste is reported in [4]. This method works with an indirect sorting process using an optical sensor, which detects the particles' sizes and positions, colors and shapes, and a mechanical separating system consisting of compressed air controlled by a computer in contrast to the traditional magnetic sorting technology which separates only ferrous and non-ferrous metals.

In fact, some companies like Reverse Vending® [5] sell waste separating machines. Reverse Vending® is a British company which produces reverse vending machines (RVM) focusing on separating aluminum cans, empty glass bottles, and plastic drink containers. After separation, it crushes them to a third of their original size. A reward system is used to offer smart cards or vouchers as options to compensate users who deposit waste. Another company that offers a similar solution is Beijing Incom Resources Recovery Recycling Co., Ltd. [6]. As the previous company, they separate the same kind of waste with an automatic recycling glass machine for bottles, cans, and PET plus paper recycles. In addition, it features the same compactor and the reward system.

An RVM is a device that accepts used (empty) beverage containers or any kind of waste, as in this work, and returns money or a ticket in interchange. The advantages of the RVM over the traditional way to separate waste are many. These are the most important ones: firstly, separation does not depend fully on humans; therefore, there will be less mix of waste. Secondly, it works like a common trash can, the user deposits the waste in one container, not in multiple containers and due to this people know where to deposit waste. Thirdly, the system can reward the user by tickets or radio frequency identification (RFID) cards that can keep track of the points generated for each deposited waste to later exchange them for products. Fourthly, the system is able to automatically communicate when the RVM is full of waste and needs to be emptied. And finally, the waste deposited in the system is secured and protected against theft.

This paper proposes a prototype of the Intelligent Waste Separator (IWS) that consists of a common trash can, with more containers inside it, using multimedia technology. People can throw their waste, no matter what kind, into the system. The latter is able to decide what kind of waste it belongs to and to deposit it in the correct container. Likewise, our system has another kind of benefit for the user: it employs an RFID which gives points each time the user deposits waste in the IWS. These points can be exchanged for items (gifts) from sponsors.

The paper is organized as follows. A description of the IWS system is given in Section 2. Section 3 explains the process of waste identification. The experimental results of the recognition process are presented in Section 4. Section 5 provides the analysis of the results. Finally, in Section 6, some conclusions and future work are given.

2 IWS System Description

Figure 1 shows the system diagram. It gives a general idea of how the IWS works and of the connections between the different blocks. First, the system starts when the button in the graphic user interface (GUI) represented by the touch screen is pressed. It triggers the system and the process in the multimedia processor (MMP) begins. Second, the webcam that is connected to the USB port takes an RGB image of the waste shape and sends it to the MMP. The latter processes the image in order to get the features of the waste.

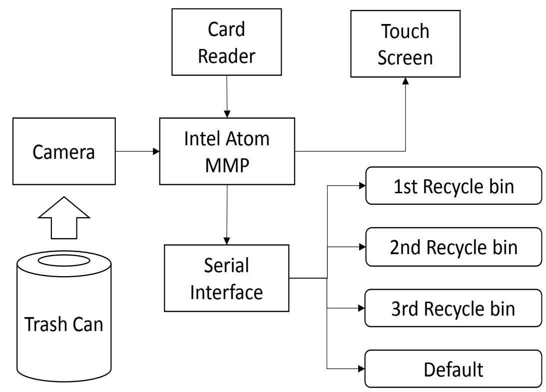

Fig. 1. Block diagram of the system

The system classifies the target based on the first two Hu's Invariant Moments (HIM) [7] in conjunction with the k-Nearest Neighbor (k-NN) [8] algorithm by using the Euclidean distance. Third, when the object is classified, the MMP sends a signal through the serial interface indicating which gate is to be opened. If the waste was not recognized, it is deposited in the default container. In order to deposit waste in the corresponding container, the previous steps are needed.

Finally, the MMP sends an invitation to the user through the touch screen to pass the RFID card through the RFID reader to get points from the waste just deposited. To accomplish that, the user has to register his/her RFID card previously in the system and deposit one of the three accepted waste items to obtain the corresponding points. A button in the GUI named "Register Eco-ID" is provided to register a new user.

2.1 Hardware Implementation

2.1.1 Multimedia Embedded Architecture

Intel Atom architecture is a technology in which the IWS is implemented. This architecture was chosen for some reasons: it is small, has low power average consumption (3.6W), and was designed for multimedia embedded applications [9]. In addition, the system can work with different operating systems like Windows or Linux. Table 1 shows the system specifications of the evaluation board and software platform used in the IWS.

2.1.2 Printed Circuit Boards

Figure 2 shows the layout of the circuit that performs communication between the MMP and the motors. It uses a microcontroller that interprets the data sent by the MMP using the RS232 serial protocol. The dimensions of this layer board are 3.5 inches width and 2.75 inches height.

The layout of the power stage is shown in Figure 3. It was designed using four NPN silicon power Darlington transistors to supply power to each motor. The board uses two standard voltages (5v and 3.3v) and has two LEDs (green and red) which indicate if the interface board is working. The board has one layer and its dimensions are 4 inches width and 3.125 inches height.

If the system recognizes the waste, it sends a signal to the serial interface board, which controls the corresponding motors by means of the control motor board which opens the correct gate.

2.1.3 Mechanical Design

The main requirements of the mechanical prototype are low cost, strong material, and a simple design to be placed almost anywhere, for example, in public areas where RVMs or ATMs could be located. The design involves the following features: a stable structure, not bulky, can be armed, disarmed, and stored with facility, high quality materials, low cost but efficient mechanisms, and an easy manufacture design (as it can be seen in Figure 4).

The IWS dimensions are 1.60 meters length, 0.40 meters width, and 1.50 meters height. This brings comfort for the user to see a smaller machine which does not take up too much space of its surroundings. The containers of the prototype are intentioned to be larger and wider, this will take more advantage of the inside container space.

The waste chamber consists of a box which has a web camera, LED illumination on the inside, an entrance, where the object is deposited, and a base which has motion and links to other parts of the machinery. The waste compartment is located on the top of a double slide. The evaluation board, the printed circuit boards, and the RFID card reader are placed on top of the chamber.

Attached to the entrance of the system, a door is used to close the entrance and to prevent the

Table 1. System specifications and software platform

Feature	Details
Processor	Intel(R) Atom(TM) CPU E640 @ 1.00 GHz
Operating System	Windows Embedded 7 Standard, 32 bit OS
RAM	1.00 GB
Library used	EmguCV 2.4.2
Library used	.NET 4.5
Language used	C# 4.5

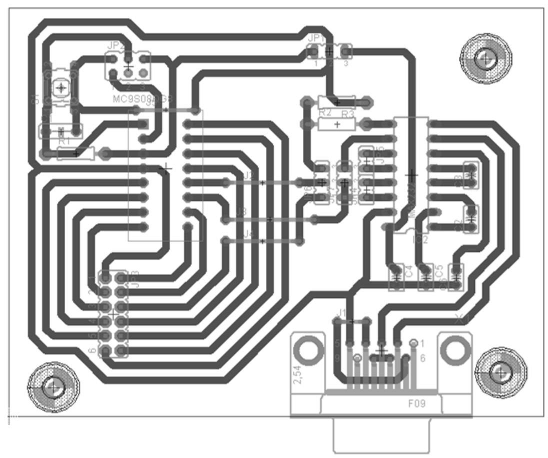

Fig. 2. Serial interface layout

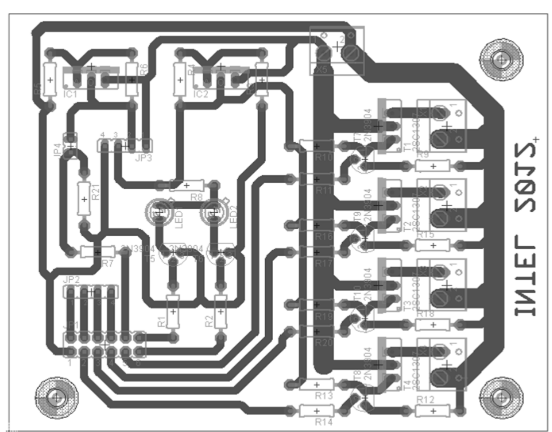

Fig. 3. Motor control layout

Fig. 4. 3D design

Fig. 5. Ramp and chamber connection

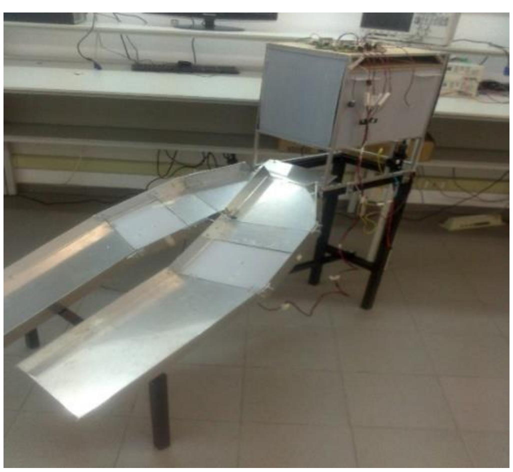

Fig. 6. Chamber and ramp

light input at the identification stage. The base of the receiver, as shown in Figure 5, is also a slide where the object will slip and connect to the ramp. The ramp is made of a smooth-hard aluminum with caliper 12 and 3105-H22 alloy. It contains a separator, two passage exits, and two motorized door exit, as shown in Figure 6, which are activated with the usage of car automatic locks as seen in Figure 7.

When the automatic entrance does not open, it leads the item to the end of the slope, where a recipient that collects a specific type of waste is placed. Otherwise, if the gate is unlocked, it leads the waste into the corresponding compartment that is underneath the slide. A spatula is a mechanism that designates which ramp of the double slide to choose (Figure 8). It is activated with the same type of motors that open the door exits as seen in Figure 9.

2.2 Human Machine Interface

A GUI is implemented in an LCD touch screen, and it is used for communication between the system and the user; it can trigger the system and show useful information about the waste that has been deposited. The interface is developed on Windows Forms using C# language. It shows a button named “Separate” which is used to trigger the system to start waste recognition; another button named “Register Eco-ID” is used to register an RFID card. Figure 10 shows the GUI of the IWS.

2.3 Reward System

The reward system provides an incentive for people to use the IWS and get rewards from it. As it can be seen in Figure 11, this system consists of an RFID reader module installed in the prototype which can identify RFID cards (Figure 12), for instance, Student ID or any kind of card with an RFID chip. Such ID uniquely identifies a user in the IWS.

When waste is deposited into the system, it adds the corresponding points according to the waste deposited. For instance, if the user deposits an aluminum can, s/he gets 50 points, if the user deposits plastic cutlery, s/he gets 10 points, but if the system does not recognize such types of waste, the user does not get any point. Also, to get

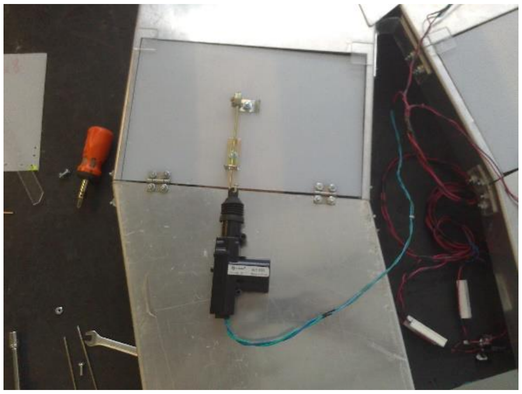

Fig. 7. Door motor

Fig. 8. Ramp separator

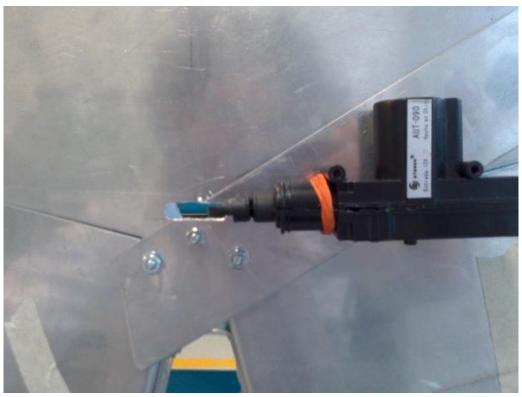

Fig. 9. Separator motor

Fig. 10. GUI of the IWS

the points, the user has to possess an RFID card; otherwise s/he will not be able to get any point.

The reward system is created with the purpose to motivate people to use the IWS. For example, if potential users see a plastic bottle on the street they will immediately pick it up because they will get points.

Finally, the user can interchange these points for rewards from sponsored stores like souvenir stores, as it can be seen in Figure 13.

3 Waste Identification

The prototype has to distinguish between three different kinds of inorganic waste. Our proposal is to train the program to identify aluminum cans, plastic bottles, and plastic cutlery. Figure 14 shows sample images of each kind of waste: plastic cutlery (a), plastic bottle (b), and aluminum can (c).

Figure 15 shows the process to identify waste. It is split into three steps: image processing, characteristic extraction, and machine learning. The output of each step is the input to the next step.

3.1 Image Processing

Image processing consists in converting an RGB image to grayscale and then binarizing it. This stage removes the unnecessary features from the image.

The image is acquired by a Microsoft Webcam VX-6000 and converted to grayscale [10]. The grayscale conversion consists in calculating the average value of the three components of the

ISSN 2007-9737

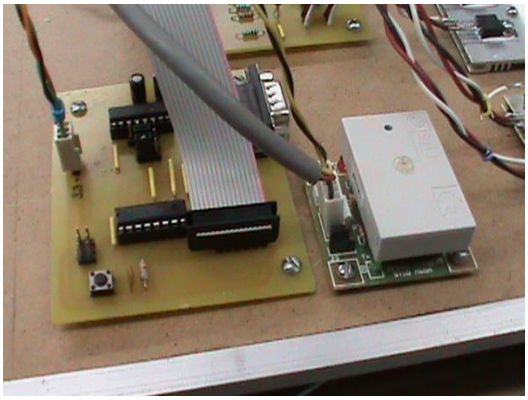

Fig. 11. RFID reader module

Fig. 12. Student ID

Fig. 13. University souvenir store

image: red, green, and blue. To accomplish that, a function from OpenCV library is used. Its prototype is described in Table 2 and the flow diagram of the algorithm is shown in Figure 16.

After the grayscale image is obtained, it is binarized. To make the gray scale image with only two colors (0 and 255, respectively), the binarization process [11] is applied. A fixed threshold, 127 in this case, is used to specify which intensity of color values are converted to 0 and which, to 255. Figure 17 shows the algorithm used to binarize the image.

Table 2. OpenCV, grayscale function conversion

cvtColor(source, destination, code, dstCn)	
Parameter	**Description**
source	The source of the image
destination	The destination of the image
code	The color space conversion code; in this case CV_RGB2GRAY
dstCn	Default parameter to 0, no need to set it

3.2 Image Invariant Moments

The mathematical concept of statistical moments has been in existence for many years and has been used in many diverse fields ranging from mechanics and statistics to pattern recognition and digital image processing. Describing images with moments instead of other more commonly used image features, for instance, width and height, means that global properties of the image are used rather than local properties.

Historically, Hu [7] published the first significant paper on the utilization of moment invariants for image analysis and object representation. Hu's approach was based on the work of the nineteenth century mathematicians Boole, Cayley, and Sylvester on the theory of algebraic forms.

This method is useful for selection of a set of numerical attributes to be extracted from the waste of interest for the purpose of classification. It is independent of the fact if the same waste is turned, if it is not centered, or its size is different, i.e., it works well in spite of geometric distortions [12]. The values remain more or less similar for the purpose of classification. However, the moment invariants may vary with image geometric transformation but, as it will be stated, it represents a minor problem in the classification stage.

a) Plastic cutlery

b) Plastic bottle

c) Aluminum can

Fig. 14. Sample images

Invariant moments are used in the system because waste will be deposited with the conditions previously mentioned.

The (p,q) moment of a 2-dimensional continuous function $f(x,y)$ is defined as follows:

$$m_{pq} = \int_{-\infty}^{\infty}\int_{-\infty}^{\infty} x^p y^q f(x,y)\,dx\,dy. \tag{1}$$

Due to the discrete nature of an image, we cannot apply Equation 1 straightforwardly, so a discrete version of Equation 1 can be obtained as [13]:

$$m_{pq} = \sum_x \sum_y (x)^p (y)^q f(x,y), \tag{2}$$

where $f(x,y)$ represents the discrete representation of the image, and x,y represent the width and height coordinates of the image, respectively. The sum of p and q represents the order of the calculated moment.

After that, we have to get the invariance of the moments. In order to do that, the coordinates of each point are subtracted from the centroid of the segmented binarized target. The central moments are the result of

$$\mu_{pq} = \sum_x \sum_y (x-\bar{x})^p (y-\bar{y})^q f(x,y), \tag{3}$$

where $\bar{x}$ and $\bar{y}$ are defined as

$$\bar{x} = \frac{m_{10}}{m_{00}}; \quad \bar{y} = \frac{m_{01}}{m_{00}}, \tag{4}$$

and represent the centroid of the object in the ordinate and abscissa axes, respectively, m_{10} is the ordinary moment of the first order, m_{01} is the ordinary moment of the first order, m_{00} is the moment of zero order representing the total area of the segmented object.

The central moments allow detecting figures inside an image independently of their position. The central moments of the first order are by definition 0, the second order creates the rotation matrix to calculate the rotation angle and the object eccentricity, and the central moments of the third order are used to calculate the invariant moments. Hence, the central moments up to the third order remain as shown in Eq. 5.

The next step is to obtain the invariant moments of rotation and scale. To do that, the normalized central moments are defined first as shown in Eq. 6.

$$
\begin{aligned}
\mu_{10} &= \sum_x \sum_y (x-\bar{x})^1 (y-\bar{y})^0 f(x,y) \\
&= m_{10} - \frac{m_{10}}{m_{00}}(m_{00}) \\
&= 0, \\
\mu_{11} &= \sum_x \sum_y (x-\bar{x})^1 (y-\bar{y})^1 f(x,y) \\
&= m_{11} - \frac{m_{10} m_{01}}{m_{00}}, \\
\mu_{20} &= \sum_x \sum_y (x-\bar{x})^2 (y-\bar{y})^0 f(x,y) \\
&= m_{20} - \frac{2m_{10}^2}{m_{00}} + \frac{m_{10}^2}{m_{00}} = m_{20} - \frac{m_{10}^2}{m_{00}}, \\
\mu_{02} &= \sum_x \sum_y (x-\bar{x})^0 (y-\bar{y})^2 f(x,y) \\
&= m_{02} - \frac{2m_{01}^2}{m_{00}}, \\
\mu_{30} &= \sum_x \sum_y (x-\bar{x})^3 (y-\bar{y})^0 f(x,y) \\
&= m_{30} - 3\bar{x}m_{20} + 2\bar{x}^2 m_{10}, \\
\mu_{12} &= \sum_x \sum_y (x-\bar{x})^1 (y-\bar{y})^2 f(x,y) \\
&= m_{12} - 2\bar{y}m_{11} - \bar{x}m_{02} + 2\bar{y}^2 m_{10}, \\
\mu_{21} &= \sum_x \sum_y (x-\bar{x})^2 (y-\bar{y})^1 f(x,y) \\
&= m_{21} - 2\bar{x}m_{11} - \bar{y}m_{20} + 2\bar{x}^2 m_{01}, \\
\mu_{03} &= \sum_x \sum_y (x-\bar{x})^0 (y-\bar{y})^3 f(x,y) \\
&= m_{03} - 3\bar{y}m_{02} + 2\bar{y}^2 m_{01}.
\end{aligned} \tag{5}
$$

$$\eta_{pq} = \frac{\mu_{pq}}{(\mu_{00})^{\gamma}}, \tag{6}$$

with

$$\gamma = \frac{p+q}{2} + 1, \tag{7}$$

for $(p+q) = 2,3,\ldots,n$.

Scale independent values are obtained in dividing each moment for the area (moment of zero order). From the second and third moments, a set of seven invariant moments are derived:

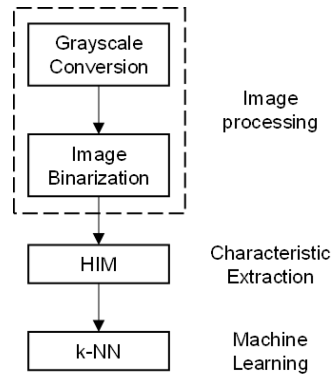

Fig. 15. Waste identification process

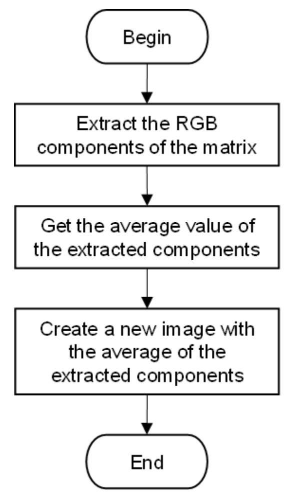

Fig. 16. Grayscale conversion

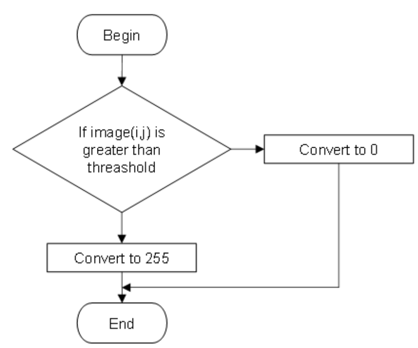

Fig. 17. Binarization process

Fig. 18. Plastic bottle RGB image

Fig. 19. Plastic bottle grayscale image

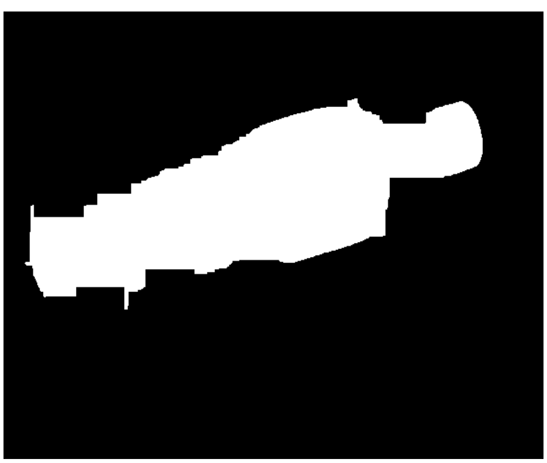

Fig. 20. Plastic bottle binarized image

$$
\begin{aligned}
\varphi_1 &= \eta_{20} + \eta_{02}, \\
\varphi_2 &= \left(\eta_{20} + \eta_{02}\right)^2 + 4\eta_{11}^2, \\
\varphi_3 &= \left(\eta_{30} + 3\eta_{12}\right)^2 + \left(3\eta_{21} + \eta_{03}\right)^2, \\
\varphi_4 &= \left(\eta_{30} + 3\eta_{02}\right)^2 + \left(\eta_{21} + \eta_{03}\right)^2, \\
\varphi_5 &= \left(\eta_{30} + 3\eta_{12}\right)\left(\eta_{30} + \eta_{12}\right) \\
&\quad \left\{\left(\eta_{30} + \eta_{12}\right)^2 - 3\left(\eta_{21} + \eta_{03}\right)^2\right\} \\
&\quad + \left(3\eta_{21} + \eta_{03}\right)\left(\eta_{21} + \eta_{03}\right) \\
&\quad \left\{3\left(\eta_{03} + \eta_{12}\right)^2 - 3\left(\eta_{21} + \eta_{03}\right)^2\right\}, \\
\varphi_6 &= \left(\eta_{20} + \eta_{02}\right) \\
&\quad \left\{\left(\eta_{30} + \eta_{12}\right)^2 - 3\left(\eta_{21} + \eta_{03}\right)^2\right\} \\
&\quad + 4\eta_{11}\left(2\eta_{30} + \eta_{12}\right)\left(\eta_{21} + \eta_{03}\right), \\
\varphi_7 &= \left(3\eta_{21} + \eta_{03}\right)\left(\eta_{30} + \eta_{12}\right) \\
&\quad \left\{\left(\eta_{30} + \eta_{12}\right)^2 - 3\left(\eta_{21} + \eta_{03}\right)^2\right\} \\
&\quad - \left(3\eta_{21} + \eta_{03}\right)\left(\eta_{21} + \eta_{03}\right) \\
&\quad \left\{3\left(\eta_{30} + \eta_{12}\right)^2 - 3\left(\eta_{21} + \eta_{03}\right)^2\right\}.
\end{aligned}
\tag{8}
$$

Our proposal uses only the first two HIMs. The reason for this decision is explained in the section devoted to the analysis of the results.

3.3 System Training and Waste Classification

Training is defined as guidance of a system to begin the classification stage. The k-NN classifier [14] is an effective lazy classifier. It classifies a new item by searching for its k nearest training items (neighbors) according to a distance metric. In this case the Euclidean distance is used.

Then, the new item is classified as belonging to the most common class defined by the majority vote of its k nearest neighbors; in this implementation k = 3. In a case of ties, two or more classes collecting the same number of votes can be resolved by choosing one of the common classes randomly or the class of the nearest neighbor.

The k-NN classifier is a widely used classification algorithm because (a) it is simple, (b) it is easy to implement, and (c) it can be exploited in various application domains. On the other hand, since the distances between a new item and all items in the Training Set (TS) must be computed, the main drawback of the algorithm is its high computational cost that can render its execution prohibitive for large datasets. In other words, the computational cost depends on the size of the TS. The IWS employs a TS of 60 samples (20 for each class) for training, which are few samples that do not require a high computational cost.

The first two HIMs extracted from each binary image are used to compute the distance metric. The rest of the HIMs are not used because these two are enough to classify aluminum cans, plastic bottles, and plastic cutlery as we prove later.

The algorithm for training the system is very simple, it only consists in calculating the first two HIMs for each binary image obtained as described in the previous section. With the purpose to generate samples of the TS, the algorithm used is explained below; it gets and saves the first two HIMs for every binary image of each kind of waste. In total, 60 samples * 2 = 120 of numerical data are used.

What follows is the k-NN algorithm [8] used to classify waste:

a. Beforehand, determine the parameter k = the number of the nearest neighbors.
b. Calculate the distance between the query instance and all the training samples.
c. Sort the distances for all training samples and determine the nearest neighbor based on the k-th minimum distance.
d. Since this is supervised learning, get all the categories of your training data for the sorted value which fall under k.
e. Use the majority of nearest neighbors as the prediction value. Ties are resolved using the class of the nearest neighbor as the winner class.

Object classification can start if a TS has been successfully obtained. Then, a base point is computed using the first two HIMs from the binary image just taken and processed. The distances from the base point towards each of the training points are calculated. The algorithm keeps track of the nearest training points to the base point in each calculation. The class that has the majority of the nearest training points to the base point is the class that belongs to the base point.

This algorithm, in order to find the nearest object to a centroid, relies on getting the shorter distance; to do so the Euclidean distance is used. It is a classic distance, being the length of a straight line that joins n points in the Euclidian space.

The Euclid distance between the points $X = (x_1, x_2, x_3, \ldots, x_n)$ and $Y = (y_1, y_2, y_3, \ldots, y_n)$ is defined as

$$d(X,Y) = \sqrt{\begin{matrix}(x_1 - y_1)^2 + (x_2 - y_2)^2 \\ +(x_3 - y_3)^2 + \cdots + (x_n - y_n)^2\end{matrix}}. \qquad (9)$$

And the k-NN algorithm uses the following equation:

$$d(X,Y) = \sqrt{\sum_{i=1}^{n} (x_i - y_i)^2}. \qquad (10)$$

3.4 Object Classification Algorithm Complexity

As it was established in Section 3.3, the algorithm complexity or computational cost for the k-NN algorithm is proportional in the size of the TS [15]. So, if the TS is not big, the algorithm works faster, otherwise the performance will be slower. This is true for the space requirement of the size of the TS and for the classification time.

For instance, if the TS is twice as big, calculating the Euclidean distance for each point in the TS takes twice as long. The same is true for the space requirement.

The complexity order is given by $O(n)$ or $T = n$, where T is the time needed for the classification process and n is the number of samples in the TS.

4 Experimental Results

In order to illustrate in more detail the process of waste identification and classification, several experiments were carried out using the proposed scheme. As it was mentioned before, the proposed algorithm considers only three types of inorganic waste: plastic bottles, plastic cutleries, and aluminum cans. It is assumed that only these types of waste will be introduced to the system.

The experimental results were obtained performing the classification of 20 plastic bottles, 20 pieces of plastic cutlery, and 20 aluminum cans. It is worth noting that some limitations were considered for the test waste: it must be of a common standard size (maximum 2 liters for plastic bottles, 355 ml for aluminum cans, and a regular size for plastic cutlery) and it must be visually identifiable (not extremely crushed or mutilated).

In what follows, image acquisition is described. In the first stage, the image of the waste, in this case a plastic bottle, was taken directly in the prototype using a Microsoft Webcam VX-6000 in the RGB format. Figure 18 shows this picture. The second phase is grayscale conversion. It is necessary to convert the image from the RGB format into a monochromatic image in order to apply it in the subsequent algorithms. The OpenCV function cvtColor is used to accomplish that and the result of the grayscale conversion is shown in Figure 19.

After grayscale conversion is applied to the RGB image, the third step is binarization of the image. As a result of this process, the image of the waste is represented by means of the area of the object. The result is shown in Figure 20. Following image binarization, the fourth stage corresponds to feature extraction. During this process, the HIMs are applied to get the features of the waste. Table 3 presents the seven HIMs of this particular image.

Finally, the last stage corresponds to the object classification where the inputs for this module are the first two HIMs previously computed. For object classification, the k-NN algorithm was executed with a value of k = 3. The result of the classification process was positive, detecting properly the plastic bottle in the image. After such detection, the process of object classification is almost finished. At the end of this process, the IWS sends a control command through the interface to open the right container and put the waste into storage.

5 Analysis of Results

As it was previously stated in Section 3.3, 20 samples of each class were taken to train the system. Figure 21 shows that with only two of the seven HIMs it is possible to have a position-independent object classification algorithm that allows differentiating and classifying aluminum cans, plastic cutlery, and plastic bottles. The cutlery points are somewhat dispersed but the results are not critical. On the other hand, the points of the bottles and cans are not as dispersed as the cutlery points, but they are close to each other. This is a possible issue because some bottles could be taken as cans and vice versa.

Table 3. The seven HIMs of the image

Moment	Numerical Value
1	1.432223
2	1.106231
3	1.000317
4	1.000163
5	1.0
6	1.000051

With respect to the classification efficiency, Table 4 summarizes the results of the tests using 20 samples of each class. As it can be seen, the experiment achieved an efficiency of 98.33% using the k-NN algorithm with k = 3.

The IWS has some limitations at the current prototyping stage. Here is the list of more significant constraints:

a. The IWS can only separate aluminum cans, plastic bottles, and plastic cutlery. But if it is desirable for the system to separate other kinds of waste, it can be easily trained to do so.
b. The IWS can only process one piece of waste at a time. Hence, the user has to deposit one piece at a time due to the segmentation limitation.
c. The IWS cannot identify deformed waste because the object identification relies on the shape of the waste.

Although the current implementation uses the techniques presented here to separate waste in a controlled environment, it needs improvement to be used in public areas. The following ideas could

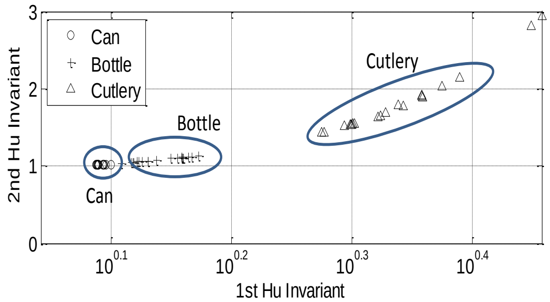

Fig. 21. Two first HIMs

Table 4. Results of the tests

Class	Pass	Efficiency
Plastic bottles	19	95%
Plastic cutlery	20	100%
Aluminum can	20	100%

be implemented in a commercial version of the IWS:

a. Increase the number of types of recognized waste for system customization. For instance, having a DB of TS in memory, the designer can decide which waste to separate.

b. Use other sensors, beside a web camera, to enhance the object classification algorithm. For example, a 3D camera sensor like Kinect can be used.

c. Test other feature extractors, apart from HIM, and other object classification algorithms, apart from the k-NN, to improve the IWS separation results on other kinds of waste.

d. Implement the framework with aluminum or stainless steel. Within the same structure two door entrances will be located. The first is the entrance of the waste chamber. The second one will be a door located at the bottom where the waste containers are placed.

e. Install a movable door between the chamber entrance and the framework's aperture to be opened and closed automatically by placing a proximity sensor.

f. Make a new and smaller chamber with better illumination and a new base that gets rid of water and food residues.

g. Install a screen to show information and the menu; the screen can be placed on one side or above the waste chamber entrance.

6 Conclusions and Future Work

In this work, the challenge was to create an Intelligent Waste Separator (IWS) which can separate inorganic waste like plastic bottles, aluminum cans, plastic cutlery, and other kinds of waste. It uses knowledge from different areas like computer sciences, optics, mechanics, and electronics. The specific topics that we have focused on are image processing, computer vision, machine learning, pattern recognition, embedded systems, and circuit design. Although this proposal does not really solve the trash problem, it solves part of it by simplifying waste separation, saving money, and reinforcing the environmental culture. With the aid of the current technology (Intel Atom processor with multimedia capabilities), the waste can be categorized correctly by the machine using HIM, as a principal core, avoiding undesired human errors. Therefore, the IWS enables the recycling process to be more efficient.

Regarding comparison of the IWS against some products on the market, it was found that the latter sort similar kinds of waste and have a reward system like the IWS. The main advantage of the prototype presented in this paper is a flexible way to separate different kinds of inorganic trash; it has a machine learning feature that helps to train the system depending of the waste that is going to be separated.

The IWS has several advantages over the traditional way to separate waste. Here are the most important ones:

a. The correct separation of waste does not depend on people due to the IWS full autonomy. Therefore, it avoids mixing of waste in recycle bins with fewer percentage of error.

b. The IWS can be easily trained to separate other kinds of waste which are not necessarily aluminum cans, plastic bottles, or plastic cutlery. This is useful for the needs of a specific place where other kinds of waste are generated. This feature is not used by the RVMs described in Section 1.

Our project has obtained many funds by participating in local, national, and international contests and at the same time winning many awards.

As future work, a comparison with other classification algorithms will be performed in order to validate the current scheme or improve it. In addition, we consider changing the microcontroller to another one with a higher computing capacity to be able to implement more complex computer vision algorithms.

In the nearest future, a proposal to the authorities of a university will be made to implement the functional prototype in a common area of the university. This will allow demonstrating the capacities of the waste separator system and obtaining information concerning the response of the people to the system, for instance, if an increment in the amount of people taking care of waste is observed. This can be easily done by means of the reward system which will provide solid statistics to prove the effectiveness of the overall system.

Acknowledgements

This work has been funded by ITESO-Jesuit University of Guadalajara and Intel. The authors thank CINVESTAV-Unidad Guadalajara, especially Heriberto Casarubias Vargas and Alberto Petrilli for their support in bringing light in the dark to start this project from scratch.

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ISSN 2007-9737

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Article received on 03/12/2014; accepted on 10/04/2015.
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doi: 10.13053/CyS-19-3-2254