# The triple histogram method for waste classification

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**Abstract.** Garbage management is a challenge for the whole world. The plastic waste might be automatically selected on the sorting lines businesses for waste disposal by using methods of Computer Vision. Manual sorting of garbage is a tedious and expensive process, which is why scientists create and study automated sorting techniques to improve the overall efficiency of the recycling process. The main problem considered in this article is the creation of an automatic waste segregation method. A gradient based features vector will be used to classify images into four distinguishable categories: PS, PP, PE-HD and PET., and should be applicable on a sorting plant.

## Keywords

Image processing, waste management, computer vision.

## 1. INTRODUCTION

All countries are struggling with the problem of recycling of municipal solid waste (MSW). Some European countries have already introduced waste segregation at the beginning of the recycling path, i.e. at home. People divide waste into groups such as plastic, metal, glass and organic / bio. The use of selectively automated techniques for these groups is easier than for municipal solid waste (MSW). Therefore, it is important to isolate individual types of materials from the Ministry of the Interior. Waste segregation techniques and procedures are applied to major groups of materials such as paper, glass, metal, wood, and plastic. However, the biggest challenge is separating different types of materials in a given group, e.g. sorting different colors of glass or different types of plastics. The problem of plastic garbage is interesting and important at the same time due to the possibility of recycling only certain types of plastics (e.g. PET -> polyester material). Thus, there is a problem with the separation of different types of plastics, some of which can be reused. One of the possibilities is the use of computer vision techniques, in particular image recognition. In household waste, the most are plastic components, and the dominant four dominant types: PET - polyethylene terephthalate, HDPE - high-density polyethylene, PP-polypropylene, PS-polystyrene.

The article presents a method for classifying plastic garbage to one of the above groups based on a digital image. The method uses Computer Vision techniques, in particular determining the properties based on the image gradient.

## 2. REVIEW OF PLASTIC WASTE SEPARATING METHODS

The process of automatic sorting of MSW and separation of materials suitable for recycling is complicated. First, the dry waste is separated from the wet one, and then the dry waste fraction is subjected to the milling process. In order to sort iron-containing materials, magnetic drum techniques are used. Subsequently, non-ferrous metals are sorted using various indirect sorting techniques, such as eddy current or X-ray radiation. However, one of the following bird methods may be used to separate plastic waste [1].

Commonly used techniques often used physical features, but ignored visual properties such as color, shapes, texture, and size for sorting waste. In optical sorting, sensors based on cameras are used to identify waste fractions. The sorting technique based on such features as shape and color was proposed by Huang et al. [2]. This method combines a three-dimensional color camera and a laser beam over a conveyor belt. This technique creates triangles on a camera image based on a laser beam, it is so-called triangulation scanning. The technique achieves 99% accuracy for plastic fractions.

Another method is spectral imaging, which is a combination of spectral measurement of light reflectance and image processing techniques. We can find several spectral imaging methods using NIR (Near Infrared), MIR (Mid Infrared), VIS (Vision Image Spectroscopy) and HSI (Hyper Spectral Imaging) [3, 4].

The hyperspectral sensor produces images in a continuous range of narrow spectral bands, and then analyzes the spectroscopic data. The conveyor system moves the waste pieces under the spectral camera, obtaining images. In the second stage, the data is processed, reduced and analyzed by a special algorithm [5, 6, 7].

In the case of techniques based on spectroscopy, wastes are illuminated by a wide range of light. Each type of plastic reflects the unique wave range, therefore NIR, MIR and laser sensors are used to read the wavelengths reflected from the material being tested. Then, the computer classifies the object based on a unique spectrum of material. Safavi et al. developed a technique that

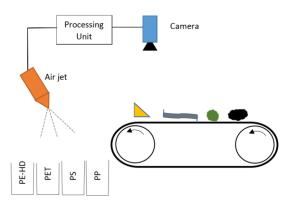
uses reflectometric spectroscopy to identify PP plastic in mixed wastes. The computer, based on the data from the spectrometer, analyzes the reflected light from the sample and determines the type of material, and the compressed air nozzle ejects the elements into suitable containers [8].

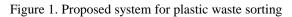
The HSI approach is applied to the classification of high purity PP and PE plastics from mixed waste using NIR near infrared light [9, 10]. A typical spectroscopic system is equipped with a movable conveyor belt and a sensor system including a backlight and a NIR spectral camera. The image of materials in the control zone is acquired by the NIR camera and then processed by the classification algorithm.

To improve the efficiency of the classification algorithm, the analysis of the main components (PCA) serves to reduce the classification dimensions of data obtained from spectral images [11]. Kassouf et al. [12] developed a quick way to classify plastics using a combination of MIR spectroscopy and independent component analysis (ICA).

# 3. PROPOSE METHOD

PET plastic waste dominates among domestic waste. Monthly observation of domestic garbage has confirmed this. For this reason, we decided to first develop methods for the selection of this type of plastic. An additional argument for this is the fact that it is possible to reprocess PET, e.g. obtaining a textile, fleece / polyester. While developing the algorithm, a simple and quick method was used so that it could be used in the garbage sorting department of the transport belt in real time, perhaps it was an important plant (Figure 1).





In the first step, we load the image and convert it to the gray scale. Edge detection is then performed to allow the object to be located. The standard operating mode using the Canny filter has been used for edge detection. After locating, the area of the RGB color image containing the object is extracted. Then we calculate the histogram for each component R, G and B of this part of the image. Histogram analysis based on summation of ranges is the next step. The first hundred and one hundred last elements of the histogram are added together. Considering that PET is a transparent material, and the background of images is black (similarly to the transmission belt in the sorting room), we compare the received previous sum values. In the case of PET, the value of the first sum will be higher, while in the case of other non-transparent materials, the second sum will be larger (Figures 2 and 3). In the last phase, the decision is made to classify the object to the PET class.

Algorithm:

- load the photo
- convert to grayscale
- edge detection
- location of the object
- select the object from the original RGB photo
- calculate the histogram for each RGB component separately
- Analyze the histograms of RGB components
- decision: PET / notPET

## 4. **EXPERIMENT**

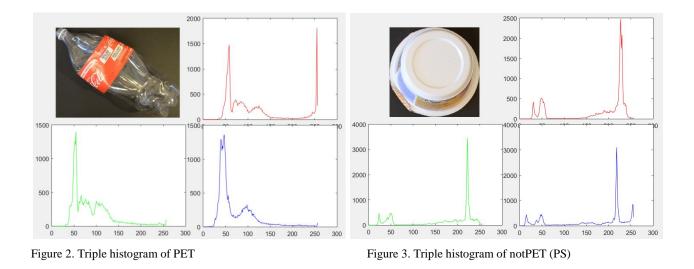
#### 4.1 Database

The experiment was based on the *WaDaBa* plastic waste database [14]. Pictures in the database were obtained using a digital camera placed above the object. The facilities were plastic household waste. The tests were obtained under different lighting conditions. Two types of light sources were used: fluorescent lamp and LED lamp. Waste objects used in the base were obtained from households. The waste was collected and photographed for four months in order to obtain typical MSW waste. The object was placed on the research position and then photographed with the first and second type of light. A series of 10 photos was taken with different rotation angle for each object (in the vertical axis). Then the object was damaged to a different degree: small, medium and large. 10 photographs were taken for each type of destruction. Taking into account all variants for each object, 40 photographs were taken, multiplying them by the number of objects, 4,000 images were created in the database.

Photo parameters:

- size 1920x1277 pixels
- resolution 300 dpi
- color palette RBG 24 bits
- file format JPG

Regarding to image parameters, individual image is approximately 1 MB in size, and the entire database 4 GB. The obtained image was saved on the disk under a normalized name defining the parameters of image acquisition and the type of waste.



## 4.2 Results

The experiment was carried out on the WaDaBa database. We used ten sets of data with 200 images, which means we used two thousand images. Table 1 shows the results of the experiment performed on 20 random data sets. The proposed method achieved an average efficiency of 82%, with FRR = 5% and FAR = 13%. These results are preliminary to the development of advanced waste selection techniques based on computer vision techniques. Analyzing the current state of knowledge in this field, we did not find solutions of this type. The review of waste sorting methods presented at exhibitions shows that the existing methods of computer vision are not used in the automatic selection of whole waste, but only after the fragmentation of waste. Therefore, it is difficult to compare our results with other existing methods. Table 2 presents a comparison to other methods (particle of shredded waste) and the first attempt to classify using a single histogram. The proposed method using a triple histogram is 7% better.

| No. | Name of<br>images set | FRR [%] | FAR [%] | RR [%] |
|-----|-----------------------|---------|---------|--------|
| 1   | 01-05                 | 10,5    | 0       | 89,5   |
| 2   | 06-10                 | 1,0     | 16,5    | 82,5   |
| 3   | 11-15                 | 11,5    | 23,5    | 65,0   |
| 4   | 16-20                 | 2,0     | 8,0     | 90,0   |
| 5   | 21-25                 | 0,5     | 30,0    | 69,0   |
| 6   | 26-30                 | 0,5     | 9,0     | 90,5   |
| 7   | 31-35                 | 0       | 11,5    | 88,5   |
| 8   | 36-40                 | 1,5     | 42,5    | 61,0   |
| 9   | 41-45                 | 17,5    | 4,5     | 78,0   |
| 10  | 46-50                 | 4,0     | 8,0     | 88,0   |
| 11  | 51-55                 | 4,0     | 0,5     | 95,5   |
| 12  | 56-60                 | 7,0     | 4,5     | 88,5   |
| 13  | 61-65                 | 2,0     | 20,0    | 78,0   |
| 14  | 66-70                 | 4,5     | 0-      | 95,5   |
| 15  | 71-75                 | 3,5     | 13,0    | 83,5   |
| 16  | 76-80                 | 4,0     | 26,0    | 70,0   |
| 17  | 81-85                 | 1,5     | 2,5     | 96,0   |
| 18  | 86-90                 | 8,0     | 4,5     | 87,5   |
| 19  | 91-95                 | 12,0    | 19,5    | 68,5   |
| 20  | 96-100                | 1,0     | 30,0    | 69,0   |
|     |                       |         | Average | 81,7   |

Table 1. Results of experiment.

FRR - False Rejection Rate

FAR - False Acceptance Rate

RR - Recognition Rate

Table 2. Comparison to other methods.

| Method                        | <b>Recognition rate</b> |
|-------------------------------|-------------------------|
| PCA-particles [11]            | 95%                     |
| ICA-particles [12]            | 99%                     |
| Histogram - in one piece [13] | 75%                     |
| 3Histogram - our              | 82%                     |

# 5. CONCLUSIONS

The presented method is faster compared to others, because it is simpler computationally. Other methods require a complex spectrum analysis process. In addition, this method does not require expensive and advanced optical sensors.

The research results presented seem promising. Therefore, further research is planned on the development of more advanced methods using computer vision techniques like deep learning. We analyse the types of errors we have found to improve the selection results by more accurate object extraction techniques. Improvement of the recognition level of objects can be sought by improving the feature extraction technique and operation on complex sets of features.

Further work will mainly consist of extending the database of segregated waste images with photos of waste in more realistic conditions. Hence, efforts to obtain recordings of waste on a conveyor belt from enterprises dealing with waste segregation. We also want to determine the accuracy for real images of waste taken from the conveyor belt during the segregation process.

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