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Application of automated image analysis to the identification and extraction of recyclable plastic bottles*

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Abstract: An experimental machine vision apparatus was used to identify and extract recyclable plastic bottles out of a conveyor belt. Color images were taken with a commercially available Webcam, and the recognition was performed by our homemade software, based on the shape and dimensions of object images. The software was able to manage multiple bottles in a single image and was additionally extended to cases involving touching bottles. The identification was fulfilled by comparing the set of measured features with an existing database and meanwhile integrating various recognition techniques such as minimum distance in the feature space, self-organized maps, and neural networks. The recognition system was tested on a set of 50 different bottles and provided so far an accuracy of about 97% on bottle identification. The extraction of the bottles was performed by means of a pneumatic arm, which was activated according to the plastic type; polyethylene-terephthalate (PET) bottles were left on the conveyor belt, while non-PET bottles were extracted. The software was designed to provide the best compromise between reliability and speed for real-time applications in view of the commercialization of the system at existing recycling plants.

Key words: Computer vision, Pattern recognition, Automated sorting, Recycling
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INTRODUCTION

Recycling of waste plastic has become a standard industrial procedure for economic and environmental reasons (Schut, 2007; Siddique *et al*., 2008; Stewart, 2008). Used plastic packaging, which forms the largest part in the stream of recyclable plastic, is made of different types (i.e., generally being classified into seven categories) of resin (Agante *et al*., 2006; Coltro *et al*., 2008). In recycling plants, plastic needs to be sorted according to the resin category (Coltro *et al*., 2008). This is an important step due to the fact that in order to recycle plastic materials, pure streams of resin must be obtained for further manufacturing processes (Guha, 2006). Inefficient sorting could also lead to exposing Chlorine-based resins to thermal treatments that would engender the release of hydrochloric gases (Scott, 1995).

In modern recycling plants plastic containers are sorted according to the resin type, whose recognition is usually performed by means of infrared, ultraviolet, X-ray detectors (Tachwali *et al*., 2007), or manually (Kopardekar *et al*., 1993; Mital *et al*., 1998). Automated sorting systems can treat large volumes of plastic efficiently with minimal human intervention but will require high investments in specific technologies (Hearn and Ballard, 2005; Taylor, 2006). Manual sorting that generally relies on plant personnel for visual identification and manual extraction of the plastic containers, however, may not be a suitable solution for plants with a large throughput, thus reducing the efficiency of the process. Nevertheless, in many developing countries human labour is still cost effective when compared to the investment for automated systems, and manual sorting in recycling plants is still the preferred procedure (Wahab *et al*., 2007).

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A novel application was developed to identify plastic bottles using a computer vision system (Wahab *et al*., 2006). The development of this automatic sorting system uses available image processing techniques, in which images of the bottles on a conveyor belt are digitized, pre-processed with standard filtering algorithms, and then analyzed to extract meaningful features of the objects in the image. The classifying process requires the comparison of the extracted features with those present in a database. While requiring a database where the features of a large number of bottles are stored, this technique is automated, fast, and inexpensive.

A prototype was built to determine the capabilities of this technique. Besides the electromechanical system, a set of customized algorithms were developed for all stages of the computer vision system, namely pre-processing, feature extraction, and object classification.

A test database containing a set of features of 50 different types of plastic bottles was developed and the whole system commissioned and tested. The plastic bottles were taken out of public recycling containers, as well as from stacks of plastic waste in local recycling centers. Some specimens, being deformed or crushed, were used to test the robustness of the recognition system.

This paper focuses on the machine vision system for the identification and recognition of plastic bottles moving on a conveyor belt. The description of the prototype is given, followed by a review of the image processing and bottle recognition techniques that have been customized for this study. The experimental results, in particular the speed and accuracy of the prototype system, are presented.

MATERIALS AND METHODS

The intelligent sorting prototype comprises the material handling system and the detection system (Wahab *et al.*, 2006). Among the main components of the handling system are the conveyor belt, the ejector, and the collecting bins for different kinds of plastic, as shown in Fig.1.

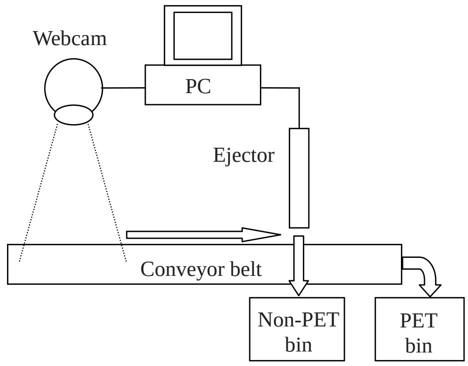


Fig.1 Diagrammatic illustration of the automated sorting system

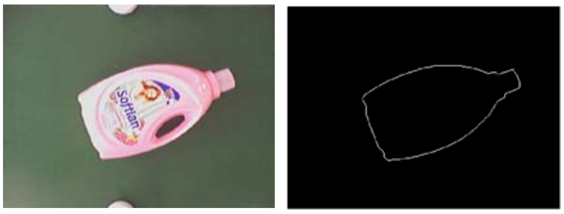
The conveyor belt, 150 cm long and 50 cm wide, runs at a speed that can be varied to a maximum of 15 cm/s. Considering the purpose of the prototype, we should drop bottles on the conveyor belt in their horizontal position. While several bottles in parallel can be treated by the vision system, it is important that possible clusters contain two bottles at most (Scavino *et al.*, 2007) for the identification stage. The prototype is capable of handling, detecting, and sorting bottles of any size, as small as a Vitagen® bottle (150 ml) to a recyclable as large as a domestic cooking oil bottle (3000 ml).

For image acquisition, the most cost-effective choice was a commercially available Logitech® Webcam. The camera was placed vertically over a stretch of the conveyor belt at a height of 90 cm, in order to encompass its whole width. In laboratory conditions, the amount of light on the object plane made it possible to capture one color image every 1/20 s, while shorter exposure time would lead to excessively dark images.

Bottle extraction was performed in a single stage by means of a computer activated pneumatic arm, capable of swiping the whole width of the conveyor belt. The category of plastic materials that can be separated is limited to polyethylene-terephthalate (PET) and non-PET only. Nevertheless, the recognition algorithm has been designed to match the correct plastic type to any bottle. A more refined sorting system will in consequence simply depend on the availability of multiple extraction devices.

Image processing and feature extraction

A commercially available Webcam was used to acquire the RGB image of the bottle on the conveyor belt, with a resolution of 320×240 pixels, as shown in Fig.2a. The resulting matrix was already layered in three planes carrying the intensities for each color.



(a) (b)

Fig.2 (a) An example of a digitized image as it is taken by the Webcam; (b) The binarized edge of the object after pre-processing

The edge detection was performed on each color (‘layer’) of R, G and B to get independent of the color and intensity of the background. An edge was in general a sharp change of either color or intensity or of both; internal edges were detected in the first part of this procedure, but subsequently removed. At the beginning, each layer was filtered with an averaging mask to avoid the edge detection of single spikes in the brightness. The edges in the filtered layer were detected by means of a modified Sobel mask of size 5×5, which proved to be more reliable than the standard 3×3 mask in case of blurred edges. The partial edges obtained for each of the three layers were combined to generate the complete edge binary image.

An object in the binary image was identified by a completely closed edge made of a sufficient number of pixels. For the sake of simplicity and speed, the minimum number was taken as a fraction of the minimum perimeter among the bottles in the database.

The binary image was checked against missing points in the edges. Bridging points were added and the closed edges were filled with a standard flooding routine. In order to avoid the connection of near distinct objects, the bridging points were subsequently removed and the perimeters of the remaining binary silhouettes were taken. A result of this image processing is shown in Fig.2b. The edges of an object, if touching the boundary of the image, were discarded as the correct feature extraction would be prevented as a result of lacking a part of the object in the binary image.

After the image pre-processing phase, a set of features were extracted for the identification stage. Multiple objects in the same image were treated separately in distinct binarized images.

The first step consisted in the reorientation of each object along its principal axes of inertia. This technique, most reliable in the case of nearly symmetrical shapes, provided a rotation of a bottle shaped object to a standard position with the cap pointing horizontally to the right. Then a set of features, namely the object length L, width W, area A, aspect ratio $R=L/W$, and filling fraction $F=A*W/L$ of the boundary box, were measured in pixel units. Moreover, the perimeter was mapped with a Cartesian profile and a polar profile. The former consisted of the width of 90 equally spaced slices covering the bottle length from 5% to 95% of the total length, while the latter consisted in the set of centroid-edge distances measured on 90 equally spaced angles. The length of the perimeter was not considered, as the number of pixels was found to be very sensitive to the initial orientation of the bottle.

The accuracy of the feature acquisition was tested by repeating the image acquisition and analysis procedure many times in different lighting conditions and bottle orientations. The variance in the value distribution for each of the above features was found to be approximately 0.5% of the respective average value.

Bottle recognition and sorting

Once the image features were calculated, six methods were tested for pattern recognition. In three of them, the Euclidean distance was taken between the measured features and the values stored in the database. One method used a pre-constructed Kohonen map (Gonzalez and Woods, 2002) and two deployed neural networks. Each method provided a unique target bottle out of the 50 specimens contained in the database. However, all methods would also assign to each target bottle a factor-of-merit that can be summed in case of lacking unanimous recognition. The target bottle with the highest sum was considered to be the final choice.

1. Euclidean distance in the n-dimensional space

For each target bottle i in the database, the relative error of a selected subset of measured values and the same stored values was calculated as

$$e_i = \left(\frac{L-L_i}{L_i}\right)^2 + \left(\frac{W-W_i}{W_i}\right)^2 + \left(\frac{A-A_i}{A_i}\right)^2 + \left(\frac{R-R_i}{R_i}\right)^2, \tag{1}$$

where L_i, W_i, A_i, and R_i are the length, width, area, and aspect ratio of the target bottle i, respectively. The aspect ratio R could also be neglected as it has been found to have no effect in increasing the sensitivity of the method. The item with the smallest error was considered to be the correct target bottle. The factor-of-merit for pattern matching with the other methods was calculated as

$$f_i = \frac{\exp(-20e_i)}{\sum_i \exp(-20e_i)}. \tag{2}$$

The values were subsequently normalized to a sum of 1000 for ease of reading.

2. Profile comparisons

The error in the Cartesian profile was taken as the sum of the squared differences in the thicknesses of the measured and stored profiles:

$$e_i = \sum_n (w_n - w_{in})^2, \tag{3}$$

where w_{in} is the width of the nth slice in the stored bottle i. The error in the polar profile was calculated in a similar way:

$$e_i = \sum_n (r_n - r_{in})^2, \tag{4}$$

in which the error is calculated on the differences of the centroid-to-perimeter distances measured on 90 equally spaced angles. The factor-of-merit in the profile comparisons is calculated as for the Euclidean distance method.

3. Kohonen mapping

This method was based on a 500×500-pixel self-organized map (SOM), which was pre-constructed using a four-dimensional input containing the length, width, area, and filling fraction of each bottle of the database. At the end of the learning stage, each bottle was associated to one pixel of the map, while similar inexact geometrical features were associated to nearby pixels. This method proved to be useful to overcome a possible inexactness of the measured values, and to provide a correct recognition all the same. The factor-of-merit was calculated as above, taking into consideration the Euclidean distances between the pixels in the SOM.

4. Neural networks

The last method used for bottle recognition was based on a 1-hidden-layer neural network. The input was made by the 90 measured values of the polar profile; the hidden layer was a vector of 20 elements. The network output consisted in a binary string in which each bit corresponded to one bottle, as per the ordered sequence in the database. The network was trained to provide, for each bottle, the corresponding bit in ‘high’ values above a given threshold while keeping all other bits in ‘low’ values. This technique would allow the maintenance of the same two-bit distance in the output space between any bottle and all others in the database, regardless of the database size. By analogy with the SOM technique, the neural network would be capable of somehow correcting inexact measurements of the geometrical features of the bottles.

In a related attempt, the network was trained to provide the set [length, width, area] in pixels, but the results were fairly less accurate. In addition, the network training was found to take much more time, so this technique was dropped.

RESULTS AND DISCUSSION

The computer vision system was tested for speed and accuracy. The requirement for fast industrial processes has led to an optimum compromise between the set of image processing techniques and the computing time involved. For this study, a non-compiled version of the algorithm has been used on a standard PC. In this configuration it is possible to perform the whole procedure from image acquisition to classification in no more than 150 ms, regardless of the number of objects in the acquired image. Based on the computing time alone, it would be possible to process a minimum of 400 000 bottles per day in a 24-h operating scheme with minimal human intervention. The size of the database, i.e., the number of recorded specimens, does not appear to influence the speed of the whole procedure, as it consists in a sort of ‘table lookup’. Most of the computing time is in fact required for the image processing phase.

In the present prototype system, the pneumatic ejector is the slowest part, allowing one bottle expulsion every 600 ms. Despite being operated to extract non-PET bottles that statistically constitute a minority of the total number of bottles, this component might result in the bottleneck for the overall operational speed. The addition of several extraction systems in parallel in an industrial application will certainly overcome this problem.

The recognition accuracy was evaluated for each available technique, under normal laboratory lighting. The camera settings, such as exposure time, electronic gain, and contrast, were manually optimized as the autosettings could not always provide a neat image. Every bottle of the database was dropped on the conveyor belt dozens of times in random positions and orientations, separate from the preceding one.

The success rate for each recognition technique is shown in Table 1. The reported values refer to the rate of positive and correct identification of the kind of bottles. When dealing with the material type, the rate climbs to almost 100% as very few wrong material recognitions were observed over a span of thousands of tests. Lower values (around 80%) in the accuracy of the recognition technique were observed in very poor lighting conditions; in such cases, a failure in the procedure would generally be owing to a lack of edge identification rather than to problems in the identification phase.

Table 1 Plastic bottle classification success rate for various techniques used

Classification method	Features used	Accuracy
Euclidean distance	Geometrical features	~90%
	Cartesian perimeter	~85%
	Polar perimeter	~85%
Neural network	Polar profile	~95%
Self-organized mapping	4D input	~70%
All techniques combined		~97%

The results listed in Table 1 indicate that the neural network technique provides the best success rates, followed by the geometrical features of the binarized images. The success of the neural network is supported by its resiliency to measuring errors of the geometry of the bottles in the binarized image. In order to create a noisy test input, random errors were inserted in all 90 measured distances of the polar profile. Hundreds of tests consistently proved that the accuracy of the method was not affected for both random and systematic errors up to 10%, which would allow the correct identification of bottles with non-excessive deformations. Crushed bottles, whose widths were sensibly changed, led to confusing values of the factor-of-merit. In such cases, the neural network alone was used for classification due to its robustness and could often provide successful recognition.

Some mistakes in the identification were mostly due to the geometrical similarity of a number of half-liter water bottles, which were considered as different kinds in the database. As far as the plastic type was concerned, most of the identification mismatches observed for the kind of bottles were related to very similar PET specimens, namely the group of half-liter water bottles. For this reason, the final classification in terms of the material type would yield success rates just short of 100%.

CONCLUSION

A prototype system for the automatic sorting of plastic bottles based on computer vision was built and tested. The recognition algorithm was designed to overcome difficulties such as poor lighting, deformed bottles, as well as multiple and touching bottles in a single frame. Parameter selection issues in the feature extraction process were addressed, and standard artificial intelligence techniques were successfully applied to provide additional data for the classification.

When combining all techniques together, the success rate of positive recognition reached values of about 97% for the species of bottles and almost 100% for the plastic type. Extensive testing showed that a single frame requires just 150 ms for the whole procedure of image capture, filtering, segmentation, and recognition, regardless of the number of bottles in the frame. The overall computing time is comfortably short for the implementation in real-time industrial applications.

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