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Automatic Detection of 'ROIs' for Plastic Bottle Classification

Suzaimah Ramli, Mohd Marzuki Mustafa, Aini Hussain & Dzuraidah Abdul Wahab

***Abstract*-- Recycling is widely assumed to be environmentally beneficial, although the collection, sorting and processing of materials gives rise to some environmental impacts and energy use. Previously, plastic recycling are based on the material used. In this work, we propose a new approach to classify plastic bottle by implementing the viability of imaging technology for automated sorting. According to the original image of plastic bottle, there are obvious features that can discriminate between 2 classes of plastic bottles which are PET and Non-PET. The methodology involves an automatic detection of 'ROIs' from region segmented technique and proposed the histogram of pixel intensity algorithm in order to differentiate between 2 class of bottle; i.e PET and Non-PET according to the property of transparency and opacity. The proposed technique shows ability to perform plastic bottle classification with more than 80% accuracy was obtained from this research.**

***Index Terms*—Histogram of pixel intensity value, Region of interest(ROIs), Linear discriminant analysis(LDA)**

I. INTRODUCTION

Sorting and classification is a major activity in the plastic recycling process. In Malaysia, manual sorting is still carried out by laborers. These bottles are sorted according to the resin categories, which is crucial in the recycling industry because in order for plastic to be recycled into reusable resins, a pure stream of resin must be obtained [1]. Plastic packaging can be made from different types of resins and the most common are PETE, HDPE, LDPE, PVC, PP and PS as listed in TABLE 1 [2]. With plastics recycling, however, there is usually only a single re-use. Most bottles and jugs don't become food and beverage containers again. For example, pop bottles might become carpet or stuffing for sleeping bags. Milk jugs are often made into plastic lumber, recycling bins, and toys.. When working with plastics there is often a need to identify which particular plastic material has been used for a given product. Most consumers recognize the types of plastics by the numerical coding system created by the Society of the Plastics Industry in the late 1980s. There are six different types of plastic resins that are commonly used to package household products. The identification codes listed in TABLE 1 [2], can be found on the bottom of most plastic packaging.

TABLE I.
CODE SYSTEM & MATERIAL FOR PLASTIC BOTTLE RECYCLING

Symbols of Plastic Bottle Code System

1-PETE Polyethylene Terephthalate 2-HDPE High Density Polyethylene
3-V or PVC Vinyl/Polyvinyl Chloride 4-LDPE Low Density Polyethylene
5-PP Polypropylene 6-PS Polystyrene 7-Others

In this study, a new approach for classifying plastic bottle using automatic detection of "regions of interests (ROIs)" is proposed. In the original image of plastic bottles, there are obvious features that can be used to discriminate between two classes of plastic bottles which are PET and Non-PET. Visually, the obvious features are the texture colors which are clear and opaque for PET and non-PET bottle, respectively. In optics, transparency (glare/shiny) is the property of allowing light to pass. The opposite property of transparency is opacity. In so doing, we proposed an algorithm for an automatic detection of ROIs in order to differentiate between two classes of bottles, i.e PET and Non-PET according to the property of transparency and opacity. Using the ROIs obtained from the image, the histogram of the pixel intensity value was plotted and its mean and standard deviation from pixel 1 to 100 possible intensities were computed. The mean and standard deviation will be used as the two input features for the classification stage. The results obtained showed that the proposed feature extraction method can be applied to discriminate plastic bottles according to types as either PET or Non-PET bottles respectively. The next section briefly reports related previous work done by others followed by the methodology section. Subsequently, the results and discussion section is presented and followed by the conclusion.

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S. Ramli is with the Department of Electric, Electronics and System Engineering, Faculty of Engineering, Universiti Kebangsaan Malaysia, bangi 43600 Malaysia (e-mail: suzaimah@vlsi.eng.ukm.my).

M. M. Mustafa is with the Department of Electric, Electronics and System Engineering, Faculty of Engineering, Universiti Kebangsaan Malaysia, bangi 43600 Malaysia (e-mail: marzuki@vlsi.eng.ukm.my).

A. Hussain is with the Department of Electric, Electronics and System Engineering, Faculty of Engineering, Universiti Kebangsaan Malaysia, bangi 43600 Malaysia (e-mail: aini@vlsi.eng.ukm.my).

D. A. Wahab is with the Department of of Mechanical & Materials Engineering, Faculty of Engineering, Universiti Kebangsaan Malaysia, bangi 43600 Malaysia (e-mail: dzuraida@vlsi.eng.ukm.my).

II. PREVIOUS WORK

A variety of techniques and algorithms have been developed recently which use the automatic detected ROIs for image intensity, spatial arrangements of patterns and textural features to distinguish among features or to separate from their background. Some of the most popular techniques include the use of the 2-D wavelet transform as reported in [3] & [4] which are especially useful in the suppression of noise and detection of fine structures. In [5], neural networks were trained on ideal shapes that take into account the possible intensity changes at the edges of the structures and edge detection algorithms. It was also applied to detect oceanographic structures, using traditional gradient operators, grey level co-occurrence matrixes and derived texture measurements [6]. Danijela et al. in [7] proposed facial feature point detection method that uses individual feature patch templates to detect points in the relevant region of interest. Additionally, in [8] Tiffany presented an algorithm that selects regions of interest (ROIs) containing tumor based on combined texture and histogram analysis. The first analysis compares texture features extracted from different regions in an image to the same features extracted from known tumorous regions. The second analysis detects the ROIs with two thresholds computed from the histograms of known tumorous masks. As in [9], Seung et al, proposed a new region of interest (ROIs) extraction algorithm using scale salient information and multiple features such as a intensity, edge, R+G-, and B+Y- color to reflect more exact salient regions.

III. METHODOLOGY

In view of that, a study has been proposed to determine the viability of using computer vision for automated classification of plastic bottles. From the previous research, sorting and classification will be based on the material used for the plastic bottles [1]. There are several types as listed in TABLE 1 but we will only classify between PET and Non-PET bottles. This will lead us to focus on the 2-categorical pattern recognition task. For that reason, this work will only focus on categorizing the bottles as general as possible by classifying them in two different classes namely the PET and Non-PET bottle classes. In describing the image classification system, this work distinguished between three different operations of preprocessing, feature extraction and classification. The proposed automated detected ROIs algorithm for plastic bottle classification system is given as below:

- Feature extraction part:

Automatic detected ROIs algorithm**

START

- Preprocessing
  - for 1: total image
    - resizing 256 by 356 pixels
    - RGB to Binary image conversion
    - getting image's silhouette
    - getting bounding box and centroidal image's properties - **i**
- Region segmented
  - adjust the image intensity values - **k**
  - crop image according to the centroid of bounding box's image - **I2**
  - segmented to 5 types of region of the bounding box's image
  - find centroid of the fifth region image
  - crop 10 x 60 pixels from the centroid of the fifth region – **the ROIs**
  - plot the histogram of the pixel intensity value from the ROIs
- Feature extraction (from the histogram)
  - compute mean from 1 to 100 pixel value
  - compute standard deviation from 1 to 100 pixel value
  - save data

/*repeat loop for all image*/

-end (generate 2 feature vectors for every image)

STOP

A. Pre-processing

To obtain the HIPV set of feature vectors, an image has to go through the pre-processing stage. The image pre-processor module performs the following operations: image resizing, filtering, thresholding, getting silhouette image and region properties measurement for the bottle's image [10]. Image filtering will filter all the noise due to lighting and also perform background subtraction. Thresholding is a non-linear operation that converts a gray-scale image into a binary image where the two levels are assigned to pixels that are below or above the specified threshold value. The output of the binary image we call is called silhouette. Then, we use the regionprops Matlab command [11] to measure object or region properties in an image and returns them in a structure array. When applied to the plastic bottle image with basic components, it creates one structure element for each component. Here, only the bounding box and centroid property is used.

B. Feature Extraction

A **Region of Interests**, often abbreviated **ROIs**, is a selected subset of samples within a dataset identified for a particular purpose, for example on an image, the boundaries of an object is the ROIs. A ROIs is an area of an image defined for further analysis or processing [10]. It is sometimes of interest to process a single sub-region of an image, leaving other regions unchanged. In this paper, the ROIs according to PET and Non-PET plastic bottle appearance is selected. For PET bottle, the appearances are transparent with high gloss; clear or colored; no seams; injection molding nub on bottom or opaque with dull finish. While for the Non-PET bottle, the appearance are translucent matte finish [not shiny), Opaque matte finish (not shiny) [2]. After obtaining the ROIs of the two classes, from the intensity theory, the highest intensity is equal to white colour and the lowest intensity value is equal to black colour. Figure 1 shows all five segmented regions and the generated ROIs for this work. The ROIs is an automatic crop of a region from the center of the fifth region. Only this region is taken to avoid the region that is covered by the label and the region that have discriminant value between PET and Non-PET bottles.

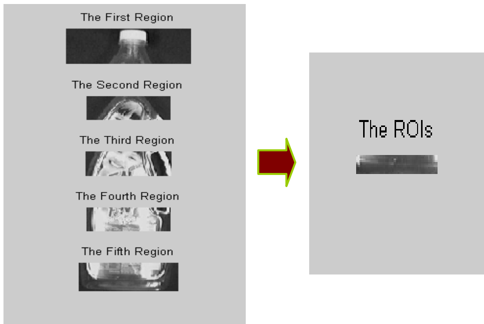

Figure 1: All Five Segmented Regions and Generated ROIs

The intensity image is the equivalent to a "gray scale image" and this is the image focused in this study. It represents an image as a matrix in which every element has a value corresponding to how bright or dark the pixel at the corresponding position should be colored. Once the suitable region obtained, the histogram of the pixel intensity value is plotted. In an image processing context, the histogram of an image normally refers to a histogram of the pixel intensity values [10]. This histogram is a graph showing the number of pixels in an image at each different intensity value found in that image. For an 8-bit grayscale image there are 256 different possible intensities, and so the histogram will graphically display 256 numbers showing the distribution of pixels amongst those grayscale values. The probability of occurrence of gray level r_k in an image is approximated by;

$$p_r(r_k) = n_k / n, \; k = 0, 1, 2, \ldots, L-1 \qquad (1)$$

where, n is the total number of pixels in the image, n_k is the number of pixels that have gray level r_k, and L is the total number of possible gray levels in the image or equal to 256. From the histogram, we extract the mean and standard deviation from pixel 1 to 100 out of 256 different possible intensities. The mean and standard deviation value are the two feature values which will be used as input to the Linear Discriminant Analysis(LDA) classifier.

C. *Linear Discriminant Analysis*

Linear Discriminant Analysis (LDA) is a powerful tool for dimensionality reduction and classification [12],[13]. It is also a method to discriminate between two or more groups of samples. The groups to be discriminated can be defined either naturally by the problem under investigation, or by some preceding analysis, such as a cluster analysis. In this work , the groups to be discriminated are based on the ROIs of PET and Non-PET plastic bottle appearance. In principle, any mathematical function may be used as a discriminating function. In case of the LDA, a linear function of the form :

$$y(x) = w^t x + \omega_0 \qquad (2)$$

is used, where w is the weight vector and ω_0 the bias or threshold weight. For a discriminant function of the form of equation (2), a two-category classifier implements the following decision rule: Decide ω_1 if $y(x) > 0$ and ω_2 if $y(x) < 0$. Thus, x is assigned to ω_1 if the inner product $w^t x$ exceed the threshold $-\omega_0$ and to ω_2 otherwise. The parameters $w^t x$ have to be determined in such a way that the discrimination between the groups is the best. Given that a discriminating function can be found which provides satisfactory separation, this function can be used to classify unknown objects. All the extracted HIPV from the processed images are used as input to the LDA for the classification purposes.

IV. RESULTS AND DISCUSSION

A total collection of 100 images of plastic bottle constitutes the database to generate the input images. All these images are divided into two groups, PET and Non-PET. In this work, the extracted HIPV feature vectors which were derived from the generated intensity pixel based on the following function, the mean value $m_{s_{xy}}$ of the pixels in S_{xy} c an be computed using the expression;

$$m_{s_{xy}} = \sum_{(s,t)\in S_{xy}} r_{s,t}\, p(r_{s,t}) \qquad (3)$$

Where $r_{s,t}$ is the gray level at coordinates (s,t) in the neighborhood, and $p(r_{s,t})$ is the neighborhood normalized histogram component corresponding to that value of gray level. The gray level standard deviation of the pixels in the region S_{xy} is given by;

$$\sigma^2_{S_{xy}} = \sum_{(s,t)\in S_{xy}} [\, r_{s,t} - m_{s_{xy}} \,]^2 \; p(r_{s,t}). \qquad (4)$$

The local mean is a measure of average gray level between 1 and 100 pixel value, in neighborhood S_{xy}, and the standard deviation is a measure of contrast in that neighborhood. Figure 2 and 3 displays the step-by-step results obtained from the pre-processing and automated detected ROIs implementations for the two categories of plastic bottles.

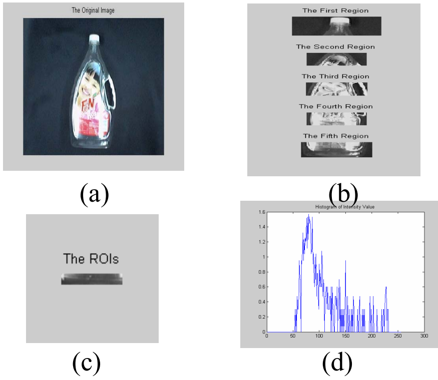

Figure 2: PET bottle image (a) original (b) segmented (c) generated ROI and (d) ROI's Histogram

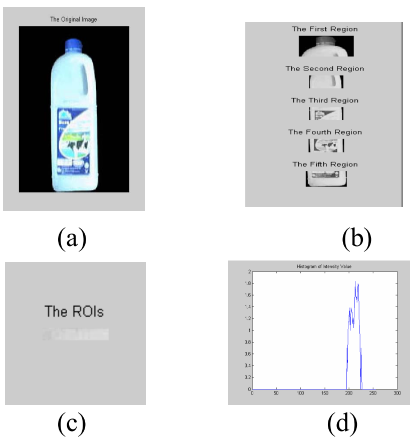

Figure 3: Non-PET bottle image (a) original (b) segmented (c) generated ROI and (d) ROI's Histogram

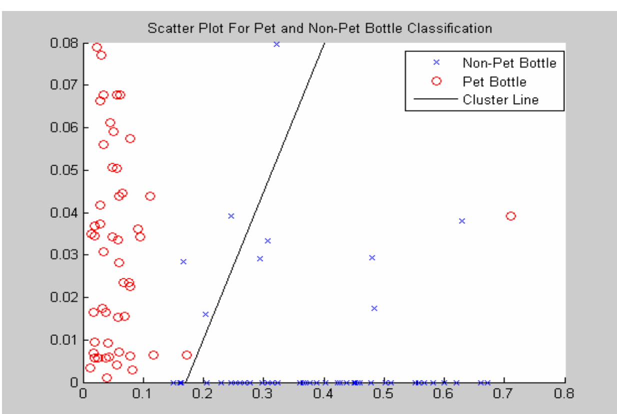

Figure 4: Scatter plot of PET and Non-PET Bottle Classification Result

Next, Figure (4) shows the scatter plot between PET and Non-PET bottle classification. Here, the linear line that separated the class is the discriminating function that yields the best separation results.

Based on testing for the discriminating function **-0.001724x_1 + 0.000660x_2 + 0.000002 = 0,** we get the following result;

TABLE II
CLASSIFICATION RESULT

Bottle Type	Correct Classification
PET Bottle	100 %
Non-PET Bottle	82.5 %

V. CONCLUSION

This paper has presented a novel feature extraction (FE) of image processing method to represent images of plastic bottles for classification according to their plastic type. The automated ROIs detection method has been based on region segmented technique and histogram of the pixel intensity values (HPIV). Initial results suggest that the extracted feature vectors obtained via HPIV have unique characteristics and can be used as signatures to represent plastic bottles category PET and Non-PET. The HIPV based feature vectors though considered simple descriptors are able to correctly classify the two-classes of plastic bottles with more than 80% accuracy. This work is still in its infancy and further work involving more recent and advance algorithms are required to enhance the results.

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VIII. BIOGRAPHIES

Suzaimah Ramli obtained her bachelor degree in information technology from University Utara Malaysia. She is a lecturer with the Department of Computer Science University Technology Malaysia. Currently, she is a Phd student with the Vision & Robotics Research Group (VIROB), Department of Electrical, Electronics & System Engineering, Universiti Kebangsaan Malaysia. Her current research interests are machine vision system, image processing and computational intelligence.

Mohd. Marzuki Mustafa is a professor of instrumentation and control system at Universiti Kebangsaan Malaysia. He obtained his B.Sc. in Electrical Engineering degree from the University of Tasmania, Australia, M.Sc in Control System Engineering from the University of Manchester Institute of Science & Technology, England and his PhD in Automatic Control System Engineering from the University of Salford, England. His research interests are instrumentation, computer-controlled system and image processing.

Aini Hussain (M'97) received the BSEE, M. Sc. and Ph.D in Electrical Engineering from Louisiana State University, UMIST and Universiti Kebangsaan Malaysia, respectively. She is a professor at the Department of Electrical, Electronic & Systems Engineering, Universiti Kebangsaan Malaysia. Her research interests include intelligent signal processing, pattern recognition and computational intelligence.

Dzuraidah Abd. Wahab is a senior lecturer at the Department of Mechanical and Materials Engineering, Universiti Kebangsaan Malaysia. Prior to joining UKM in October 2003, she was attached to the National CAD/CAM Centre of SIRIM Berhad. She received her Bachelor Degree in Chemical and Process Engineering from Universiti Kebangsaan Malaysia and her M. Sc. in Design and Manufacturing and PhD in Concurrent Engineering (Concept Design) from Manchester Metropolitan University, United Kingdom in 1995 and 1999 respectively. Her research interests include mechanical engineering design, tools for Concurrent Engineering and product engineering life cycle.