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Resources, Conservation and Recycling 52 (2007) 266–285
Resources Conservation & Recycling
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Automatic multistage classification system for plastic bottles recycling

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Received 14 July 2006; received in revised form 24 March 2007; accepted 27 March 2007
Available online 16 May 2007

Abstract

In this work, an artificial intelligent plastic bottles classification system is proposed, developed and tested. Classifying bottles based on their chemical composition and color is attempted. Near infrared (NIR) reflectance measurements are used to identify bottle composition class. Charged coupled device (CCD) camera with the fusion of quadratic discriminant analysis (QDA) and tree classifiers are used to detect the bottle color.

Results have shown that the dip wavelength and average values of the reflective NIR spectrum could be used as features to distinguish between chemical compositions. This resulted in 94.14% classification accuracy. In addition to various preprocessing techniques, the use of principal component analysis algorithm for bottle orientation facilitates the detection of the bottle color avoiding mixing it with the bottle's label or cap. Ninety-two percent color classification accuracy is achieved for clear bottles while 96% is achieved for opaque one, with proposed method. The aggregate classification accuracy of the combined system (i.e. accurate classification of color as well as chemical composition) is 83.48%.

Keywords: Plastic recycling; Near infrared; Image processing; Classification; Artificial intelligent

1. Introduction

Everyday, tonnes of waste is generated; thus, causing a major problem to various cities and their municipal authorities due to the shortage of landfill to dump such waste. In

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doi:10.1016/j.resconrec.2007.03.008

addition, toxic hazard materials among the waste cause some health problems and damage to the environment. Hereby, recycling is becoming an important issue with the shortage of the landfill and environmental pollutions as well as its economical impact. An increasing demand to build automated material recycling facilities appears in different countries (Hall and Dunsmore, 2005; Hendrix et al., 1996; Shutov, 1999).

The efficiency and quality of the recycling process depends highly on the purity and accuracy of the sorted raw materials. Many studies have been conducted for detecting and sorting different materials such as metal, glass, paper and plastics in order to sort them out and prepare them to be recycled (Hall et al., 2005; Huth-Fehre et al., 1998; Biddle et al., 1999; Kowol et al., 1998; Stchur et al., 2002).

Plastic bottles are a major part of the municipal waste. They have special importance due to their low density to volume ratio. Moreover, they are chemically stable since they are non-biodegradable materials (i.e. the biodegradation process is very slow). This means that plastic waste will be visible for months or years, and waste will sit in landfill sites for years without degrading. Therefore, plastic bottles can cause a serious environmental problem (Hall et al., 2005; Huth-Fehre et al., 1998; Biddle et al., 1999; Resource Recycling, 2005).

Sorting whole plastic bottles or containers (macrosorting) is a challenging problem. Bottles with different sizes come to the classification area in different orientations and shapes, and may be crashed and deformed. Bottles are being compressed and crashed in the collection stage to save volume where the collection cost is based on the volume (container) while the cost of the sorted material is based on the weight. On the other hand, this practice will complicate the automatic sorting and classification problem.

In addition to the above, labels with different sizes and colors as well as having different handles and caps design make the classification more challenging. Therefore, it is required to have a complex and intelligent algorithm that can address these difficulties and be able to classify the bottles regardless of their orientation, shape and existence of label.

Many studies have been conducted to find the cost effective separation categories for plastic bottles. Plastic bottles can be sorted into different categories based on their chemical resin, transparency and/or color. There are seven plastic types based on chemical composition (Hammaad, 2005): (1) Polyethylene Terephthalate (PET), (2) High Density Polyethylene (HDPE), (3) Polyvinyl Chloride (PVC), (4) Low Density Polyethylene (LDPE), (5) Polypropylene (PP), (6) Polystyrene (PS) and (7) other plastics.

Plenty of techniques are available to identify the chemical resin of plastic such as chemical methods (Hall et al., 2005), mechanical methods based on their density such as air and water classification (Biddle et al., 1999; Hammaad, 2005; Hurd, 1997; Bruno, 2000), or electromagnetic methods based on measuring the electromagnetic spectrum absorption ratio. Electromagnetic technology is the only *plastic-from-plastic* identification technology that was found in wide use in the plastic recycling industry. In this work, we use the near infrared technology to identify the plastic type. Probably the most significant advantage of using NIR spectroscopy is the speed of identification (Great Lakes Institute for Recycling Markets, 1998). Another advantage is that color does not interfere with proper resin identification except for black colored bottles (Kowol et al., 1998). However, sorting the plastic bottles into the seven different chemical composition types will add a tremendous cost on the identification hardware compared to the value added to the plastic bottles by this finer sorting (Hurd, 1997). Other recycling industries require plastic waste sorted by transparency. It has been shown that the degree of light transmission through a sample provides information regarding polymer type (Dubanowitz, 2000). Moreover, this classification also distinguishes between pigmented HDPE (colored) and natural HDPE. Color sorting is also required to avoid recycling plastics from different colors so that it is possible to produce a one color recycled plastic (Stevens, 2003). Also, there is a trend to introduce a new set of colors into plastic bottles (Child, 2002). While the wider color choice is good for plastic bottle marketers, it poses new challenges and increases costs to plastic bottle recycling.

To identify the plastic transparency, light transmission and reflection techniques using different types of photodiodes and LEDs are used (Crank et al., 2000).

Recycling plastic bottles based on plastic type and color transparency is more useful and beneficial (Fisher, 2004). Color identification is performed using different technologies, mainly by using machine vision utilizing charged coupled device (CCD) cameras (Child, 2002) or array of LEDs (Paschos, 2001).

With all sorting categories available for plastic bottle recycling, the infrastructure and operational cost will arise as a serious challenge for the success of an automatic plastic bottle system. Sorting by chemical composition requires more expensive identification hardware (such as spectrometers, lasers, X-rays) but provides a higher value plastic bottle output. On the other hand, plastic bottle transparency sorting can be achieved by much cheaper hardware (such simple LEDs or photodiodes), however, the output is at a lower value compared to the chemically sorted plastic bottles. The degradation in the output value is due to the sorting accuracy due to the effect of contamination that can lead into mixing between different transparencies.

In order to build a system that can achieve valuable sorting categories with a cheap infrastructure. A more intelligent sorting algorithm is required for plastic or color classification.

Early studies have presented the application of classical classification techniques based on linear discriminant analysis (LDA) and partial least squares (PLS) to classify the plastic based on its chemical composition (Stchur et al., 2002). Other studies had examined artificial neural networks to accommodate the nonlinear behavior of the spectral data in the near infrared region (Broek et al., 1998). Neural networks were also used to analyze the signals received from sensor fusion to perform material classifications through the information crossover between the magnetic and infrared signals (Sabatto and Bodruzzaman, 1993). However, the performance of these classifiers was affected by environmental conditions. This problem was addressed by improving the extraction techniques feature to enhance the noise immunity of the system and increase the robustness of the classification. Wavelets transformation and utilizing quaternion numbers were powerful enough to extract separable features so that an Euclidean distance classifier was able to produce a good classification result (Barcala, 2004). However, using highly complicated transformation techniques such as wavelet transform will add cost into the processing time as well as the processing hardware. Moreover, all the studies mentioned earlier are based on costly setup (Broek et al., 1998) or expensive identification hardware (Stchur et al., 2002; Barcala, 2004).

On the other hand, color identification using machine vision contains many problems that were addressed in the literature, such as optimal color space selection (Paschos, 2001; Wan and Kuo, 1998), foreground–background extraction and non-uniform illuminated image digitization (Gao et al., 2001; Zöller and Buhmann, 2002; Boskovitz and Guterman, 2002; Neumann, 2003; Huang et al., 1995; Li et al., 2004), and color segmentation (Chan et al., 1998; Papamarkos et al., 2000; Tsai and Lee, 2002). These problems exist in the application of plastic bottle color sorting; therefore, it is required to investigate similar algorithms and to verify the efficiency of adapting them in our application.

It is found that one of the proper methods for real time application is to record the background image (conveyor belt), then subtract them from the acquired image at the exact position of the conveyor belt. However, to guarantee the stability of this method in case of external noise such as light or background color variations, an adaptive background image update was proposed (Balthasar et al., 2001).

Although there are commercially available recycling systems (Hurd, 1997), conducting a research using artificial intelligence technique based on relatively cheap identification hardware will improve the efficiency and performance to existing plastic recycling system. It will overcome various limitations such as the number of the detectors, cost and the number of classification categories used in the classification unit (Broek et al., 1998). Intelligence can provide generality to the classification process so that it can be robust against new plastic bottle patterns as well as the variation of the operation environment.

In this work, an artificial intelligent multistage plastic bottle classification system is presented. This system is capable of classifying the chemical composition and transparency of the plastic bottle in the first stage while the color classification is performed in the second stage. Hence, the system is capable of achieving a competitive output value with a much lower cost compared with the commercially available systems. This will improve the operational and infrastructural cost of the proposed sorting system.

A new utilization of a classification technique is proposed to classify the chemical composition and transparency of the plastic bottle using a low cost near infrared spectrometer. Classical transparency classification utilizes the signals of the light or infrared light detectors, while the chemical composition is classified using the near infrared spectrum. The proposed technique merges these classifications into one classifier using near infrared measurements. It can be noticed that the most common plastic bottles are labeled with a #1 (Polyethylene Terephthalate) and #2 (High-Density Polyethylene) (Resource Recycling, 2005). Therefore, we focus on these two chemical types that can be divided into three different transparency categories. Moreover, while the recycling industry has experienced significant market challenges due to price fluctuations, the recovery of Polyethylene Terephthalate and High-Density Polyethylene is still being carried out in numerous large scale operations throughout the world (Resource Recycling, 2005).

More specifically, at this stage, the objective of the classifier is to group bottles into the following classes:

- *Clear Plastic* that includes Polyethylene Terephthalate. PET is clear, tough and has good gas and moisture barrier properties. Commonly used in soft drink bottles, mineral water and many injections molded consumer product containers.
- *Natural Plastic*: High Density Polyethylene containers that are not rigid, and are produced in single color. This type of plastic is used to make bottles for milk, juice and laundry products.
- *Opaque Plastic*: High Density Polyethylene containers are rigid and are produced in mixed colors. Virtually no light passes through, whereas in translucent plastic, light is diffused and the material cannot be seen through as in transparent.

Furthermore, color classification has been implemented using quadratic discriminant classifier and decision tree classifier fusion to compromise between the generality and overfitting. It also appears in these classifiers. The study shows different accuracies for different classifiers which necessitate the implementation of classifier fusion to boost the accuracy which is a further contribution in this work.

2. Classification methodology

Fig. 1 shows the classification methodology adopted. NIR is used as the first stage to classify bottles based on their chemical composition while image processing is the second stage that classify material based on color.

2.1. NIR spectroscopy

The NIR spectrum originates from radiation energy transferred to mechanical energy associated with the motion of atoms held together by chemical bonds in a molecule (Pasquini, 2003).

The energy that can be transferred from a photon of a given wavelength (λ), for which the energy (E_p) can be given by

$$E_p = h\nu = \frac{hc}{\lambda} \quad (1)$$

where h is the Planck's constant and c is the velocity of light.

The excitation of a molecule occurs when the radiation of a given frequency is capable to provide the exact energy between two vibrational levels or of their overtones bands or combinations of two vibrations. The match of radiation energy with the energy difference between two vibrational levels causes different absorption percentage. Some frequencies will be absorbed; others (that do not match any of the energy differences possible for that molecule) will not be absorbed while some will be partially absorbed. This complex figure of the intensity of absorption versus wavelength forms the absorption spectrum of the tested sample.

The plastic spectrum has absorption bands in the range of 600–2500 nm due to the stretching vibration of the C–H bond that is commonly found in all plastics (Broek et al.,

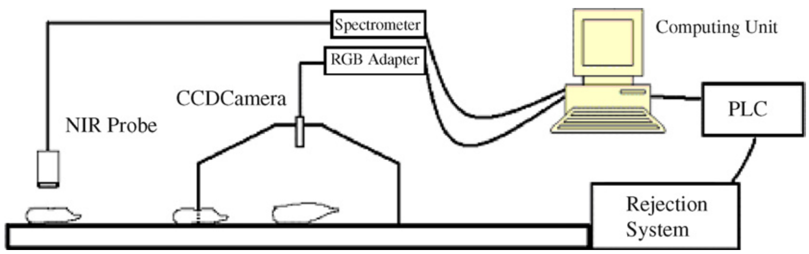

Fig. 1. Overall classification method with consecutive classification stages.

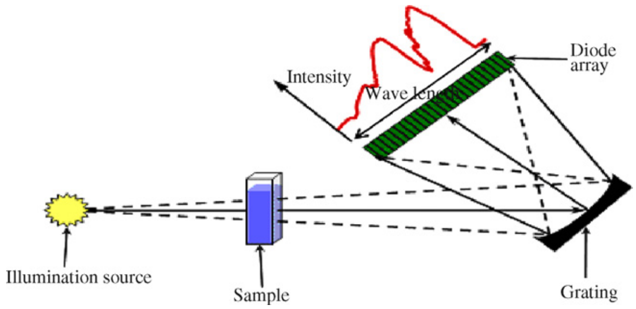

Fig. 2. Diode Array Spectroscopy (JETI Technische Instrumente GmbH, 2005).

1998; Inada et al., 2001). However, in our system, we utilized the range between 900 and 1700 nm for the following two reasons:

- The cost of manufacturing the sensitive components that operate at these ranges is low.
- This wavelength range is sufficient to achieve the classification objectives with the support of artificial intelligent classifiers.

To obtain the NIR spectrum of the different plastic to be classified in this work, a dispersive instruments based on diffraction gratings is employed due to its relatively low cost and acceptable resolution and accuracy.

Fig. 2 depicts the operation principle of the diode array spectrometer. Having the parallel sensor array with fixed position of the meter allow to have scanning time of milliseconds to get the spectra signal. This will allow for higher classified throughput of the system.

The general hardware setup for spectroscopic measurement is illustrated in Fig. 3. The probe or the measurement head in the setup direct the light to the spectrometer where it is analyzed using array of detectors; the resulting spectrum is then fed to the digital computer for further analysis.

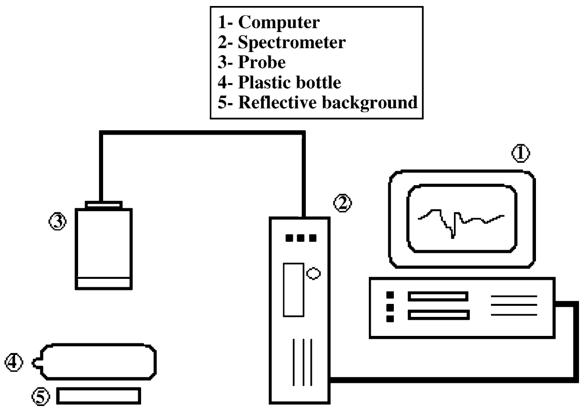

Fig. 3. The general hardware setup for spectroscopic measurement.

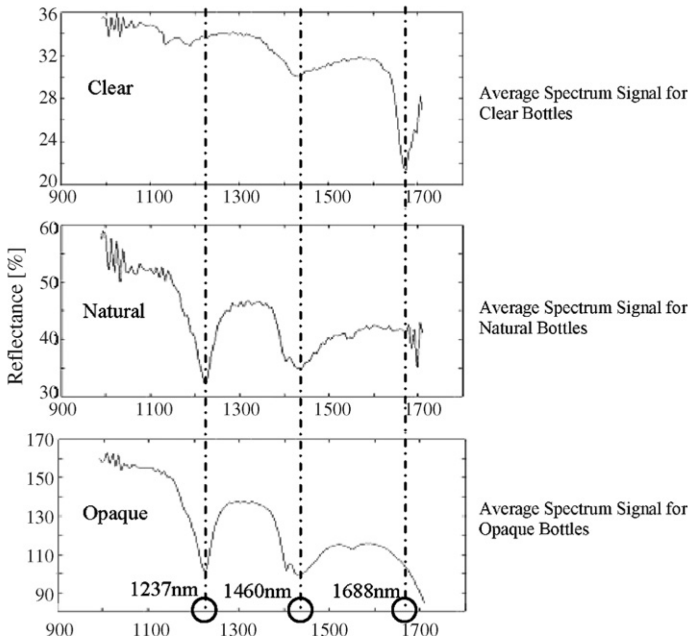

Fig. 4. Typical NIR spectrum signals of clear, natural and opaque plastic bottles.

As mentioned before, three types of plastic bottles are to be classified; namely: clear, natural and opaque. Typical NIR spectrum signals for the three categories are shown in Fig. 4.

It can be realized from the figures that the clear plastic bottle spectrum has a significant absorption frequency (dip) at around 1688 nm while the natural and opaque bottles have two main frequency dips at 1237 and 1460 nm. Actually these dips present the chemical type of the plastic. As mentioned before, most of the clear plastic bottles are made of PET, while the natural and opaque are made of HDPE. This explains the similarity between the natural and opaque spectrums. Furthermore, since transparent (clear) plastic bottles will allow more light to pass through compared to natural and opaque ones the reflectance spectrum of clear bottles has lower level compared to natural and opaque bottles as shown in Fig. 4. Therefore, the average level of the reflectance spectrum could be utilized to distinguish clear bottles. Fig. 5 shows the average of the NIR spectrum level for various clear, natural and opaque bottles. As shown in Fig. 5, the spectrum average level for clear and natural bottles could overlap and the average alone will not be a sufficient feature to classify clear plastic. Consequently, spectrum frequency dips as well as average spectrum level are to be used as features to support plastic classification.

One problem to be addressed is to determine the dip frequencies. Although the dip frequencies for each plastic type are repeatable but still could vary by several nanometers. Furthermore, the spectrum signal could show two valleys in the same vicinity but they represent same chemical response to the frequency bandwidth. To automate the feature

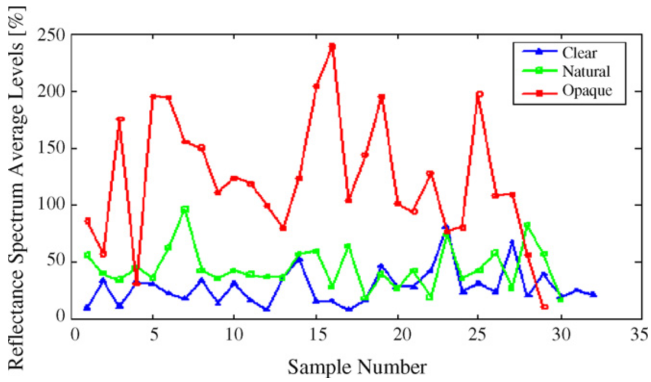

Fig. 5. NIR spectrum average level for various clear, natural and opaque bottles.

extraction process, it is found that dividing the spectrum range into six equally spaced regions and the minimum valley frequency from each region is used for further analysis.

In this work, the two global minimum dip frequencies are extracted as features for classification. One should test in the conjunction of the sub-regions and test that it is not dip frequency while the region has a slope without dips as depicted in Fig. 6 between regions 3 and 4.

We examined the performance of quadratic discriminant function based classifier (DFBC) (Webb, 2002; Statistics Toolbox User's Guide, 2003). The DFBC is a Bayes rule based classifier where the class-conditional densities are not known and they should be learned from the available training patterns. The form of the class-conditional densities in these classifiers are assumed to be a multivariate Gaussian, but some of the parameters of the densities (e.g., mean vectors and covariance matrices) are unknown, and can be estimated from the training data. Using Bayes' rule and the normal assumption for the conditional densities above, we can obtain the discriminant rule out of the posterior (Webb, 2002). More details about DFBC can be reviewed in (Statistics Toolbox User's Guide, 2003).

Four different shapes of quadratic classifiers have been used, namely: linear, Quadratic, DiagQuadratic and Mahalanobis (Webb, 2002).

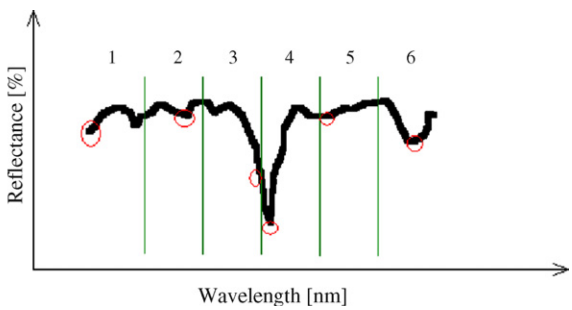

Fig. 6. Dividing the spectrum into six equally spaced regions to investigate the positions of valleys.

2.2. Color classification using machine vision

To be able to develop an intelligent machine vision capable of distinguishing various colors of the plastic bottles, color representation is a critical issue. Humans perceive colors by a combination of three primary colors (red, green and blue (RGB)), but as this perception may differ between humans (Davies, 2005), it is required to convert the usual RGB channels that are generated by traditional CCD cameras into HSI (hue, saturation, intensity) domain. The hue parameter (H) is adopted for color classification as opposed of using the since the latter is particularly sensitive to lighting variation that could be present in our application. A rigorous check on the color can be achieved by constructing the hue distribution of the H parameter and comparing it with the hue distribution of a suitable training set. The most straightforward way to carry out the comparison is to compute the mean and the standard deviation of the two distributions to be compared and to perform the classification using a choice of classifiers such as quadratic discriminant analysis.

In this work, the image vision system is made of a CCD camera with RGB adapter, frame grabber, illumination unit and a computing and display unit. The CCD camera provides analog signals which are the responses of the CCD pixels to the three different wavelength ranges (red, green and blue). These signals are received by the RGB adapter and transformed to an analog standard NTSC TV signal. The TV signal is acquired by the frame grabber that will sample, digitize and quantize the image multi-spectral signal to get a digital colored image. The image is analyzed by the computing unit which executes the algorithms for color classification. Fig. 7 shows the basic components of a machine vision system.

The clear and opaque plastic bottles can be sorted into different colors, while the natural plastic bottles do not require color classification since they appear in white color only. Preprocessing operations are used to prepare the acquired image by performing the required measurements and data analysis to extract the features and feed them to the classifiers. The preprocessing aims to reduce the noise and redundant data since acquiring an optimum-quality image is sometimes impractical due to imperfect detectors, inadequate illumination, illumination on irregular surface or other sources of noise.

The potential difficulties and challenges in identifying the color of the plastic bottle include extracting the bottle image from the conveyor belt image and removing the blurring of a moving plastic bottle. The color of the bottle cannot be identified from an arbitrary area of the bottle image, since the existence of the label and the color of the cap should be eliminated in the process of detection. The classification algorithm should be geometrically independent, which means that it can deal with the bottles coming in different orientations.

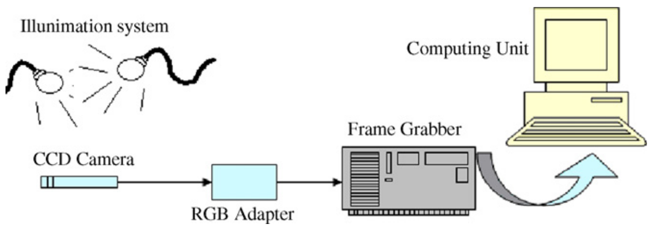

Fig. 7. Basic components of a machine vision system.

It is very important to isolate the detected bottle image from the background conveyor belt at the beginning of the acquired image processing. This operation will minimize the amount of pixels data to be processed. The accuracy of this operation is very critical for the results of the following processing operations.

Background subtraction technique is widely used to extract the image of a stationary object on a moving background. Since the colored object landing on the conveyor is random, various color noises could occur such as conveyer gets dirty with time. To minimize this effect, various reference marks were located on the conveyor and the background image is continuously updated by the image processing.

The bottle label and cap do not represent the bottle color and usually the bottom and upper part represent that. Hence, finding the orientation of the plastic bottle is a critical step to determine its color. The principal component analysis (PCA) is used in this work to find bottle orientation. Although PCA is widely used for dimensionality reduction and data compression, it is also used for principal axis detection of a set of data (Luo, 1998).

In PCA, a set S of N points or feature vectors in a two dimensional space represented by the *XY* coordinates of the white pixels (foreground pixels) in the binary image can be projected into an equivalent dimensional space, where the components of the transformed vectors are aimed to be uncorrelated (i.e. the scatter matrix of the vectors is diagonalized). The first of these components provide the greatest variance from the d components (which will be interpreted later as the orientation of the data in the feature space).

As a result, principal component transformation can be considered as a translation and a pure rotation. In two dimensional space, let X be a set of points of an object in coordinate system x. If the origin of x is translated to the center of mass of the object and the coordinate system x is rotated by angle θ to a new coordinate system y, then the transform matrix C is given by

$$C = \begin{bmatrix} \cos\theta & \sin\theta \\ -\sin\theta & \cos\theta \end{bmatrix} = \begin{bmatrix} C_1 \\ C_2 \end{bmatrix} \tag{2}$$

Then, the new set Y of the points in coordinate system y is expressed by

$$Y = C(X - \bar{X}) = \begin{bmatrix} C_1 \\ C_2 \end{bmatrix} [X - \bar{X}] = \begin{bmatrix} Y^1 \\ Y^2 \end{bmatrix} \tag{3}$$

where

$$Y^{\mathrm{i}} = C_{\mathrm{i}} \begin{bmatrix} X_1 - \bar{X} & X_2 - \bar{X} & \cdots & X_{\mathrm{N}} - \bar{X} \end{bmatrix}$$

If the transformation matrix C is given as

$$C = \begin{bmatrix} c_{11} & c_{12} \\ c_{21} & c_{22} \end{bmatrix} = \begin{bmatrix} C_1 \\ C_2 \end{bmatrix} \tag{4}$$

Then

$$\begin{bmatrix} \cos\theta & \sin\theta \\ -\sin\theta & \cos\theta \end{bmatrix} = \begin{bmatrix} c_{11} & c_{12} \\ c_{21} & c_{22} \end{bmatrix} \tag{5}$$

Thus, the angle θ of the principal axis is

$$\theta = \mathrm{Arctan}\left(\frac{c_{12}}{c_{11}}\right) \tag{6}$$

Because the length of the principal axis reflects the longest diagonal of the object, the direction θ of the principal axis is taken as the orientation of the object.

In order to optimize the time required for computing the angle using this method, it is sufficient to take the points of the boundary of the object rather than taking the points of all foreground pixels in the binary image. This will reduce drastically the execution time required for this method.

Fig. 8 shows some binary images of plastic bottles as captured by the camera and after applying the PCA based orientation algorithm.

After orientation, the image is enclosed by a minimum enclosing rectangle. The PCA orientation does not guarantee to bring the top part of the bottle upwards. Hence, the second stage is to distinguish between the top and bottom of the bottle. Distinguishing the bottom from top parts is required since more weight is given to the features obtained from it for color classification. This is mainly significant if the bottle cap is of different color.

Color measurements are performed in HIS space. Each of the top and bottom parts is divided into five equal parts of the same width of the original image as shown in Fig. 9.

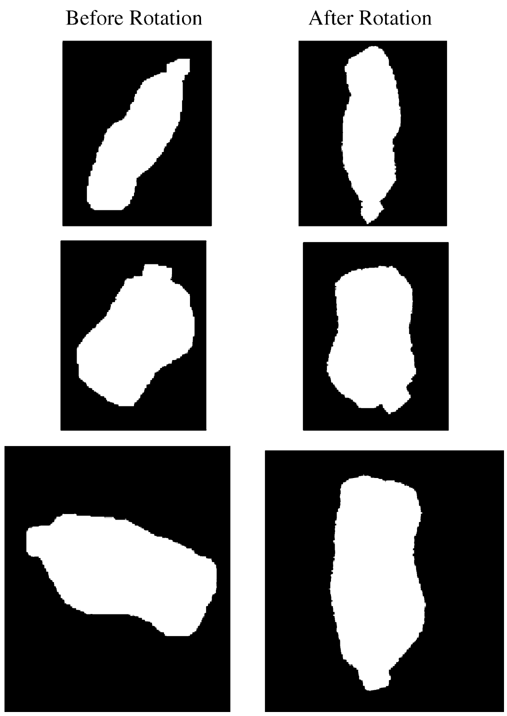

Fig. 8. Examples of bottle binary image rotation.

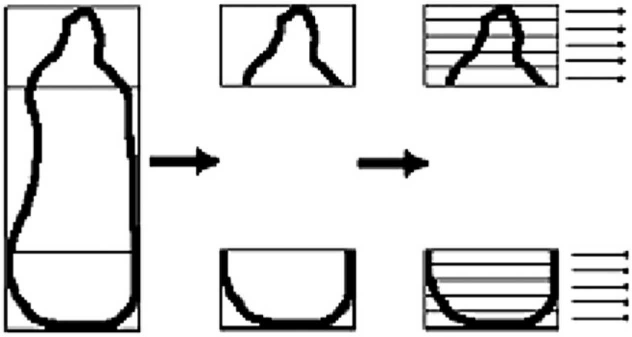

Fig. 9. Color feature extraction for a plastic bottle image.

For each line, the mean and standard deviation of its hue and saturation (*H* and *S*) values is obtained. The hue measurement is essential for color classification, while the saturation measurement facilitate the reparability between very close plastic colors such as transparent and light blue plastics. Based on the four feature values, the color of each line is classified individually and the resulting aggregate color is the color class voted more by the quadratic discriminant classifier from the lines.

It is found in our work that the fusion between DFBC and tree classifiers improved the color classification. Decision tree classifier is one of the fast classifiers so that it is possible to interpret the decision rule in terms of individual features. Decision trees do not require any assumptions about the distribution of the measurements in each class (Statistics Toolbox User's Guide, 2003). These rules are found during the construction of the decision tree (training session). The rules are chosen so that there is the largest decrease in diversity of the classification label within each partition (i.e. increase in homogeneity). More in depth details can be found in (Statistics Toolbox User's Guide, 2003).

Fig. 10 depicts the procedure of bottle color classification based on combining the outcome of both the DFBC and tree classifiers.

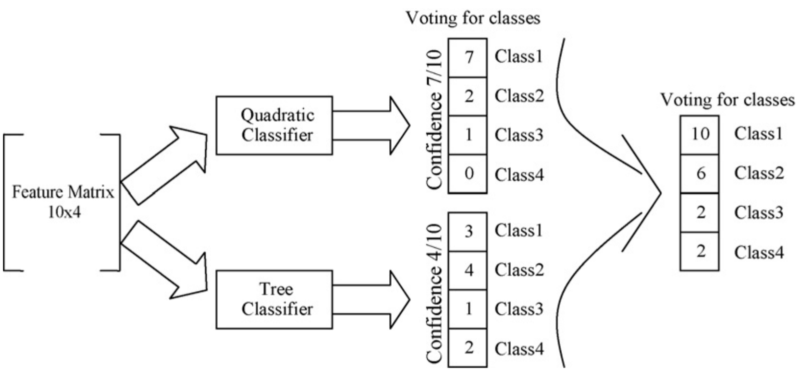

Fig. 10. Color classification voting procedure.

The accuracy of this classification can be affected by the misleading measurements due to some faulty colors obtained from some divisions where part of the bottle label may appear on them or due to different cap color in the top image part.

3. Experimental setup and results

3.1. The mechanical system

In the practical plant situation, plastic bottles from domestic wastes are carried away by conveyor belt drives and the inspection system operates on the plastic bottle images grabbed in motion. The mechanical system is represented by the conveyor system which is basically a rubber belt driven by an AC motor with a gearbox. The motor speed is controlled by a frequency inverter; this system transmits the inspected bottle through the NIR probe to acquire the NIR reflectance spectrum and then to the inspection chamber installed at the middle of the system. An enclosing box is built to isolate the inspected bottle from external lighting and provide a fixed lighting for the testing area by lamps mounted at the top of the box. The lamps surround the CCD camera which is mounted at the middle of the box roof. The system prototype is designed to identify the bottle color on the fly without stopping the motor for inspection. Fig. 11 is a photographic image of the prototype mechanical system.

3.2. NIR measurements and features extraction

The essential configuration parameter that identifies the acquisition speed is the NIR sampling integration time. NIR spectrometer integration time and conveyor belt speed were optimized to get the maximum throughput. Empirical tests showed that the setting of 40 ms is

Fig. 11. A photographic image of the automatic color sorting system.

an optimum setting for the integration time in terms of the spectrum measurement accuracy and acquisition speed.

For each bottle, NIR spectrum measurements are performed on three segments of the bottle: at the top (neck), at the bottom and next to the label if exist. In order to remove unreliable and misleading noise in acquired the signal (bottle image), a low pass filter was applied to the spectrum taking into consideration mirroring the signal on both sides to avoid the boundaries effect during the convolution procedure. The low pass filtering is implemented by passing an averaging window over the whole signal. The width of the averaging window is determined empirically to be around 5% of the signal length.

Then, four different sets of feature vectors are extracted to examine the best features combination to be used in the classification stage:

- The average value of the three readings and the most frequent valley wavelength position from the three readings (one average reading and dip reading: (1A1D).
- The average value of the three readings and three dip wavelength positions from the three readings (1A3D).
- The three average values and the most frequent dip wavelength position from the three readings (3A1D).
- The three average values and three dip wavelength positions from the three readings (3A3D).

Bottles are collected from local household and evenly distributed among the three categories (clear, natural and opaque). Half of the bottles were used to train the classifier while the rest were used for testing. Round-robin cross validation technique is used to enhance the statistical accuracy of classification results (Webb, 2002). Classification accuracy is defined as the ratio of the number of correctly classified bottles to the total number of tested bottles.

Table 1 shows the aggregate classification accuracy results using various combinations of NIR spectrum features as defined above with different classifier modulates for each plastic category. The results show that the DiagQuadratic classifier had the best classification accuracy using the three averages obtained from the three NIR reading separately and the average wavelength position of the main dip in the three spectrum readings.

The performance of the Quadratic classifiers in general was very good in terms of output accuracy and especially for DiagQuadratic classifiers. This is due to possible redundancy between feature values by using the global position of minima, which are ideally the same. Therefore, there is a correlation between components in the feature vectors and this correlation may harm the classification process. DiagQuadratic ignores this effect by just taking into consideration the autocorrelation determined in the diagonal of the covariance matrix only.

Also it can be realized that increasing the dimension of feature vector will not enhance the classification accuracy, which indicates that some of the features are not independent or they are overlapped in a way that disturb the process of finding the classification boundaries.

3.3. Color classification

To test for color classification, the bottles were divided equally into training and testing samples. As mentioned above, the top and bottom parts are detected and features obtained

Table 1
Classifiers accuracy using the dip position and average value features in the range 900–1700 nm for each plastic category

Classifier	Feature dimension			
	A1D1 (%)	A1D3 (%)	A3D1 (%)	A3D3 (%)
Linear				
Clear	100	100	100	100
Natural	91.67	83.34	90.28	80.56
Opaque	66.67	70.83	63.89	63.89
Total	86.49	85.13	85.14	81.98
Quadratic				
Clear	97.44	87.18	97.44	87.18
Natural	87.5	76.39	83.33	77.78
Opaque	87.5	87.50	88.89	81.94
Total	90.99	83.78	90.09	82.43
Mahalanobis				
Clear	91.03	74.36	71.8	61.54
Natural	81.95	75	68.06	69.45
Opaque	95.83	91.67	95.84	87.50
Total	89.64	80.18	78.38	72.52
DiagQuadratic				
Clear	97.44	88.46	97.44	88.46
Natural	86.11	83.34	94.45	84.72
Opaque	87.5	87.5	90.28	87.5
Total	90.54	86.49	94.14	86.94

from these parts are used as input to the classifier. Table 2 shows the classification accuracy of clear plastic bottles.

The results reflect the benefit of fusing the quadratic classifier and decision tree classifier to enhance the accuracy of system as in the case of the clear (no color) or at least scores the maximum accuracy obtained from one of the two fused classifiers. The low performance in the blue bottles using the decision tree can be related to the overtraining.

However, the fusion was successful in bringing the classification decision of the most confident classifier where the confidence is measured by the ratio of number of votes from the winning class over the total number of votes.

Table 3 shows the results of the color classification of opaque plastic bottles.

We had better performance in the opaque bottles because the standard deviation features are less noisy since the opaque bottles are less shiny and the appearance of white luminance

Table 2
The color classifier accuracy for clear bottles

	Clear (no color) (%)	Clear blue (%)	Clear green (%)	Total (%)
Quadratic	83.33	86.67	93.33	87.78
Tree	86.67	63.33	100	83.33
Fusion	90.00	86.67	100	92

Table 3
The color classifier accuracy for opaque bottles

	Blue (%)	Grey (%)	White (%)	Yellow (%)	Total (%)
Quadratic	90.00	100	66.67	80.00	84.17
Tree	86.67	100	96.67	93.33	94.17
Fusion	93.33	100	96.67	93.99	96

dots is less than their appearance in the clear bottles. Hence, the performance of the feature vector in providing better separability is increased.

3.4. Type and color classification

The overall accuracy of the system is measured by the ability of the classification method in correctly classifying the type of the plastic (clear, natural and opaque) as well as classifying the color. Hence, the overall system is tested in grouping the bottles overall all classification to the following groups:

- Clear bottles (no color).
- Clear bottles (light blue).
- Clear bottles (light green).
- Natural bottles (white).
- Opaque (different colors).

Table 4 contains the summary of the integration accuracy results.

As the color classifier parameters are adjusted (foreground extraction threshold values) according to the result of plastic type classifier, therefore, the accuracy of the color classifier is affected heavily. This cascaded classification scheme as shown in Fig. 1 can be improved by making the classifiers working in parallel individually. This requires adding more intelligence in the color classifier to adapt the thresholding parameter automatically for each bottle type (clear, natural or opaque) without receiving any feedback from the first classifier. The results represent the accuracy of the integrated system while each of the classifiers works independently.

Table 4
Total classification accuracy

	Color classifier accuracy (%)	Plastic type classifier accuracy (%)	Overall accuracy (%)
Clear (no color)	86.67	96.67	83.33
Clear (light blue)	83.33	93.33	76.67
Clear (light green)	96.67	93.33	90
Natural	–	93.33	93.33
Opaque (different colors)	85.19	88.88	74.07
Total accuracy (%)			83.48

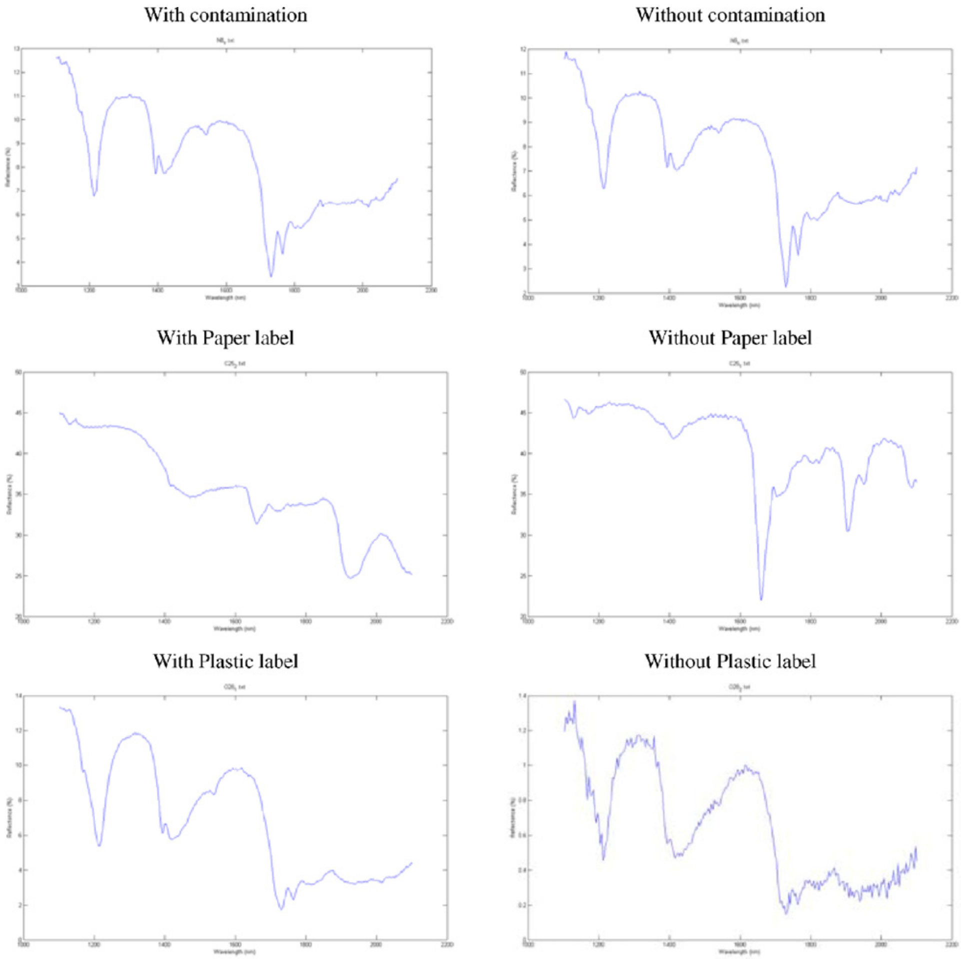

Fig. 12. The effect of the label and contamination on the signal spectrum.

The contamination effect was studied; and it was found that the dry contamination on the plastic bottle does not harm the quality of NIR signal. However, the existence of paper label deforms the signal while a very thin plastic label does not. This problem was solved by taking more than one reading to cancel out the deformation caused by a paper label. Experimental results as shown in Fig. 12 show the effect of the label and contamination on the signal spectrum.

4. Conclusion

This work reports the initial development, implementation and testing of a real time automatic plastic bottle sorting system. The system is composed of two classification stages;

each classification stage is composed of two main architectures: hardware and software architectures.

The first classification stage is the plastic type classification using Near infrared spectroscopy, while the second stage is color classification using machine vision based on a CCD camera.

For the plastic type classification system, different feature extraction methodologies were examined, some of them was based on a new technique of measuring the plastic bottle type based on the power of the NIR signal as well as examining the chemical characteristic of the signal through the detection of the wavelength positions of the peaks and dips in the plastic NIR spectrum.

Quadratic discriminant function based classifier and decision tree classifier were fused to achieve the task of color recognition of the plastic bottle. The combination of was accomplished in multiple stages, and the classifiers combiner used is a static voting based combiner. Some results showed enhancements in the overall color classification accuracy since it differs from one classifier to another for each color.

The classification accuracy of this cascading (serial) combination was measured at each classification stage and the overall accuracy was 83.48%.

This system can be developed later to support multiple bottle classification rather than a single bottle classification. Shape classification can be implemented also to separate heavily deformed plastic bottles as well as non-bottle shaped plastic materials.

Acknowledgments

The authors would like to acknowledge the support of Katrin Glatzer from Sentronic Company/Germany in the development of the NIR spectroscopy hardware. Acknowledgment is due to Mr. Abbas Taher from Aqua Engineering/Dubai and the Mechatronics Center at the American University of Sharjah for their financial support to the project. Special Thanks to Basil Tachwali for his efforts in collecting plastic bottle image database.

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