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A new classification scheme of plastic wastes based upon recycling labels

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ABSTRACT

Since recycling of materials is widely assumed to be environmentally and economically beneficial, reliable sorting and processing of waste packaging materials such as plastics is very important for recycling with high efficiency. An automated system that can quickly categorize these materials is certainly needed for obtaining maximum classification while maintaining high throughput.

In this paper, first of all, the photographs of the plastic bottles have been taken and several preprocessing steps were carried out. The first preprocessing step is to extract the plastic area of a bottle from the background. Then, the morphological image operations are implemented. These operations are edge detection, noise removal, hole removing, image enhancement, and image segmentation. These morphological operations can be generally defined in terms of the combinations of erosion and dilation. The effect of bottle color as well as label are eliminated using these operations. Secondly, the pixel-wise intensity values of the plastic bottle images have been used together with the most popular subspace and statistical feature extraction methods to construct the feature vectors in this study. Only three types of plastics are considered due to higher existence ratio of them than the other plastic types in the world. The decision mechanism consists of five different feature extraction methods including as Principal Component Analysis (PCA), Kernel PCA (KPCA), Fisher's Linear Discriminant Analysis (FLDA), Singular Value Decomposition (SVD) and Laplacian Eigenmaps (LEMAP) and uses a simple experimental setup with a camera and homogenous backlighting. Due to the giving global solution for a classification problem, Support Vector Machine (SVM) is selected to achieve the classification task and majority voting technique is used as the decision mechanism. This technique equally weights each classification result and assigns the given plastic object to the class that the most classification results agree on. The proposed classification scheme provides high accuracy rate, and also it is able to run in real-time applications. It can automatically classify the plastic bottle types with approximately 90% recognition accuracy. Besides this, the proposed methodology yields approximately 96% classification rate for the separation of PET or non-PET plastic types. It also gives 92% accuracy for the categorization of non-PET plastic types into HPDE or PP.

1. Introduction

Plastic products have become an inseparable part in our lives as many objects of daily use are made of some kind of plastic. They have special importance since they costs less, resists corrosion, have low density to volume ratio and being highly flexible and strong, (Bruno, 2000). However, biodegradation process of plastics is very slow because, plastics used today are synthesized using non-renewable fossil resources. Therefore, the plastic wastes should be recycled to decrease these effects.

Since there are about 50 various types of plastics with hundreds of different varieties, the American Society of Plastics Industry developed a standard marking code in order to help consumers identify and sort the main types of plastic; so the classification during classification can be easy. The plastic products are labeled and separated into seven groups as Polyethylene Terephthalate (PET), High Density Polyethylene (HDPE), Low Density Polyethylene (LDPE), Vinyl/Polyvinyl Chloride (PVC), Polypropylene (PP), Polystyrene (PS), and OTHER (Other kinds of plastic products). The fractions of these plastic bottles used in the United States plastic bottle market are over 96% (96.4%) for PET and HDPE bottles. Moreover,

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the fractions for PP and LDPE are 1.9% and 0.84%, respectively. PET and HDPE bottles also continued to dominate the bottles collected for recycling, collectively being 98.3% and PP being 1.7% (American Chemistry Council, 2012). If a novel classification system is widely preferred, it can be a comprehensive solution to separate the PET, HPDE, and PP type plastic bottles since they dominate the bottles collected for recycling.

Sorting of plastic wastes at Materials Recovery Facilities (MRFs) can be done either manually or automatically. In manual systems, workers visually identify and physically sort plastic bottles moving on a conveyor belt system. Automatic systems analyze one or more properties of plastic wastes using some detection method, so they sort these bottles into several categories. Several important factors such as cost affect the implementation of an automatic sorting system for a particular facility. Serranti et al. examined hyperspectral imaging and Raman spectroscopy for separation of polypropylene and polyethylene from contaminants (Serranti et al., 2011). The authors state that applying PCA on HSI average spectral signatures gives 77.98% accuracy. The design of sorting system crucially depends on the incoming plastic quality. Besides, the mixtures of multiple plastic types require more detailed sorting methods (Al-Salem et al., 2009; Scott, 1995; Lotfi and Hull, 2003; Hendrix et al., 1996; Van Den Broek et al., 1998; Park et al., 2007; Tsuchida et al., 2009; Ramli et al., 2008). Serranti et al. classified plastic flakes according to their typologies using hyperspectral with sensitivity and specificity ranging from 0.90 to 0.99 (Serranti et al., 2012). PCA and partial least square discriminant analysis are used for dimension reduction and classification, respectively in the study. Furthermore, plastics with different sizes come to a classification area in the different orientations and shapes complicate the automatic sorting problem. In addition to different shape of plastics, the labels with different sizes and colors make the sorting process more challenging. Therefore, it is required to have a complex and intelligent algorithm that can overcome these difficulties and be able to classify the plastics regardless of their orientation, shape and label color (Shahbudin et al., 2010; Tachwali et al., 2007; Viola and Jones, 2001). Most common sorting methods for plastic wastes are triboelectric separation, density sorting methods, hydrocyclones, hyperspectral imaging, speed accelerator technique (Hu et al., 2013; Dalal and Triggs, 2005).

A variety of identification methods have been proposed and commercialized recently for the automatic plastic sorting systems (Lowe, 2004). Lotfi and Hull developed an algorithm to identify the plastic types using fuzzy-rule-based system as classifier, (Lotfi and Hull, 2003). They claimed that the high frequency components of an ultrasound wave applied to a material identify the type of material. Park et al. used charge polarity and charge-to-mass ratio to classify the plastic types (Park et al., 2007). Tsuchida et al. used Raman spectroscopy for the identification of shredded plastics (Tsuchida et al., 2009). In Raman spectroscopy, a molecular vibration is observed at each peak that gives information about the molecule structure, and plastic types are identified accordingly. Since the preprocessed dataset gives many peaks, this method is more efficient when used on preprocessed data. Ramli et al. classified plastic bottles as PET and non-PET using two different algorithms for feature extraction and Linear Discriminant Analysis (LDA) for classification (Ramli et al., 2008). In the first algorithm of feature extraction, bounding box image algorithm, where the average of white pixel values in the intensity histogram of the image is calculated was implemented. In the second algorithm, the segmented region of interest (ROI) algorithm, in which they segmented the images into five regions, was carried out. In both of the algorithms, they succeeded more than 80% accuracy while the segmented ROI had slightly higher identification rate than bounding box image algorithm. Like this study, Shahbudin et al. categorized the plastic bottles as PET and non-PET plastics using Support Vector Machine (SVM) with 97.3% accuracy (Shahbudin et al., 2010). Luciani et al. identified PVC, polyethylene, and rubber using near infrared – hyperspectral imaging (Luciani et al., 2013). Ulrici et al. classified PET and poly lactic acid with efficiency higher than 98% (Ulrici et al., 2013). Tachwali et al. proposed a two-stage classification scheme for sorting plastic bottles (Tachwali et al., 2007). In the first stage, Near Infrared Imaging (NIR) was used for feature extraction while Linear, Quadratic, and DiagQuadratic classifiers were utilized for classification; and plastic bottles were sorted with 94.1% accuracy with respect to their types. In the second stage, they classified the bottles according to their colors using a CCD camera, and the classification was resulted in 92% and 96% accuracies for the clear and opaque bottles, respectively. They succeeded 83.5% recognition rate for the overall system.

Despite of many methodologies developed, the majority of these technologies are relatively slow, and most of them involve expensive or complicated apparatus. When one may consider selecting waste plastic bottle separation systems, the issues of cost and speed should be certainly taken into account. The Near Infrared Imaging system (Tachwali et al., 2007) is expensive and slow. As another type of plastic waste separation systems, triboelectrostatic separation is not cost effective. Due to not only cost but also speed aspects, our decision mechanism uses a setup with a simple web camera and homogenous backlighting and performs five different feature extraction methods such as Principal Component Analysis (PCA), Kernel PCA (KPCA), Fisher's Linear Discriminant Analysis (FLDA), Singular Value Decomposition (SVD) and Laplacian Eigenmaps (LEMAP). While the conventional classification methods generally apply minimization of the empirical risk, SVM based classifier is built to minimize the structural misclassification risk. Therefore, SVM is selected to achieve the classification task. Ultimately, a majority voting scheme is performed for combining the recognition results of five different feature extraction methods. In this scheme, the outputs obtained from five feature extraction methods are combined and then the most voted plastic bottle type is accepted.

The rest of this paper is organized that the constructed experimental setup is introduced in the second section while all the feature extraction and classification methods are briefly explained in the third section. The fourth section presents the detailed results of this study whereas the last section includes all of the conclusions.

2. Experimental setup and preprocessing

An experimental platform with a camera and homogenous backlighting was constructed to take colored photos of plastic bottles. The photographic image for the constructed platform is given in Fig. 1. In this platform, the sorting capacity is 750 kg/h, the sorting belt speed is 0.25 m/s and the bottom limit size of plastic parts is not important since our study has a segmentation process prior to feature extraction step. Despite everywhere around conveyor belt has been shot brightly; in reality, the interior part of the conveyor belt is expected to be dark. It is also assumed that plastic bottle images will appear clearly. Once the images are captured, the sorting procedure has been automatically activated. The web camera, whose brand is A4Tech, was placed on the one side of the conveyor belt in order to take photos.

After the photographs of the plastic bottles have been taken, several preprocessing steps were carried out. All of the steps are illustrated by some photos and images in Fig. 2. The first step is to extract the plastic area of a bottle from the background (segmentation). There are various object detection algorithms proposed to extract objects in 2-D intensity images using boasted cascade (Viola and Jones, 2001), histogram of gradient (Dalal and

Fig. 1. A photographic image of the prototype automatic sorting system.

Triggs, 2005), shift invariant feature transform (Lowe, 2004), etc. However, we have operated a simple but effective method to extract the plastic area of a bottle from its background. Initially, the location of a plastic image was determined by the Otsu's thresholding method which chooses a threshold minimizing the within-class variance (Otsu, 1975). It can be turned out as same as maximizing the between-class variance for threshold selection criteria. In Fig. 2(d), the location of an image was identified by the Otsu's thresholding method. The image was subtracted from its background and the opening and closing morphological image operators were performed to the acquired grayscale image in order to wholly isolate image from background. The morphological image operators are particularly useful for the analysis of binary images and their common usages include edge detection, noise removal, hole removing in foreground/background, image enhancement, and image segmentation. These mathematical morphology operators can be generally defined in terms of the combinations of erosion and dilation. The dilation is used for enlarging foreground and shrinking background. The erosion operator is applied as a reverse case of dilation. In this study, details and redundancies (see right side of Fig. 2(d)) were filtered by morphological opening (erosion followed by dilation) (Fig. 2(e)). Then, a closing operation (dilation followed by erosion) was performed on the image given in Fig. 2(e) in order to obtain the area of plastic image. Therefore, the area of plastic (Fig. 2(f)) is extracted by using the mentioned morphological operators.

3. Methods and procedure

3.1. Feature extraction

Feature extraction is an important preprocessing step in many pattern recognition problems. The purpose of a favorable feature extraction is to represent data in a lower-dimensional space with the most discriminative features. In this study, PCA, KPCA, FLDA, SVD, and LEMAP were used for the feature extraction. These techniques are explicitly explained below.

3.1.1. Principal component analysis

PCA is a linear technique, used for dimension reduction of data or classification purposes and developed by Pearson (1901) and Hotelling (1933). This technique relies on the fact that the eigenvectors corresponding to the largest eigenvalues are the principal components of data. These principal components are utilized as the feature vectors of data. Thus, data is represented without much loss of information in a low-dimensional space by projecting data onto these principal components.

The steps of PCA are given below:

(i) Calculate the mean of all data vectors in the database.
(ii) Standardize the database by subtracting the mean.
(iii) Calculate the covariance matrix of the standardized database.
(iv) Compute eigenvalues and eigenvectors of the covariance matrix.
(v) Choose m eigenvectors (principal components) corresponding to the m largest eigenvalues.
(vi) Project all mean-removed data vectors onto the feature vectors using principal components to represent the data vectors in m-dimensional space.

3.1.2. Kernel PCA

Kernel PCA is a nonlinear form of PCA for feature extraction developed by Schölkopf et al. The nonlinearity here is introduced by mapping original data set into a distinct space via a nonlinear transformation named as the kernel function. The commonly preferred kernel functions are polynomial and Gaussian kernel functions (Schölkopf et al., 1997). Then, KPCA has the same procedure with PCA. It is again quite important that the mapped data vectors satisfy the zero-mean condition, as in PCA. Furthermore, the eigenvalues and eigenvectors of covariance matrix are computed. Followed by the projection step, the data is represented in m-dimensional space like PCA. KPCA improves the data representation capability of PCA due to its consideration of non-linear relationships (Ma and Zabaras, 2011).

3.1.3. Fisher's linear discriminant analysis

FLDA is a well-known feature extraction technique developed by Fisher (1936). FLDA transforms data into a low-dimensional space which maximizes between-class separability while minimizing within-class variability of data. The function is to be maximized by FLDA is given in Eq. (1).

$$J(\boldsymbol{w}) = \frac{\boldsymbol{w}^T S_B \boldsymbol{w}}{\boldsymbol{w}^T S_w \boldsymbol{w}} \tag{1}$$

where $\boldsymbol{w}$ indicates the linearly independent vectors that maximizes the cost function $J(\boldsymbol{w})$ and S_B and S_w are between-class and within-class scatter matrices, respectively. $\boldsymbol{w}^T$ is the transpose of $\boldsymbol{w}$ For a two-class data, the between and within-class scatter matrices are computed as follows if S_i is the covariance matrix of ith class c_i.

$$S = \sum (x - \mu_i)(x - \mu_i)^T \tag{2}$$

$$S_w = S_1 + S_2 \tag{3}$$

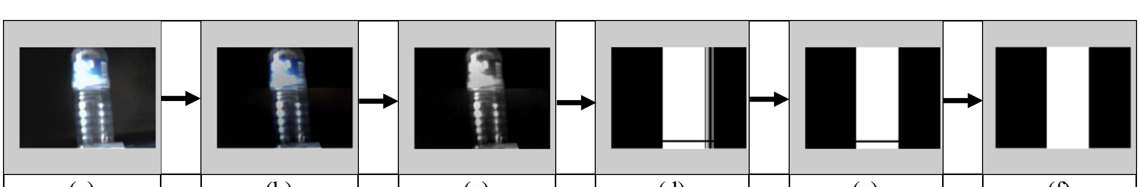

Fig. 2. The preprocessing steps for structure identification of a plastic bottle photograph.

$$S_B = (\mu_1 - \mu_2)(\mu_1 - \mu_2)^T \tag{4}$$

where μ_i is the mean of the ith class. To maximize the cost function, $J(\boldsymbol{w})$, the eigenvalues and eigenvectors of $(S_w^{-1} S_B)$ are calculated for the generalized eigenvector problem:

$$(S_w^{-1} S_B)\boldsymbol{w} = \lambda \boldsymbol{w} \tag{5}$$

Then, m eigenvectors corresponding to the m largest eigenvalues are selected. If the sum of m largest eigenvalues corresponds to 90% of the total sum of all eigenvalues, the most representative $\boldsymbol{w}$ vectors can be found. The number m can be identified by this relation. Finally, all data vectors can be represented in the m-dimensional space by projecting data vectors onto the m eigenvectors corresponding to the m largest eigenvalues.

3.1.4. Singular value decomposition

SVD of a data matrix X is a factorization of X into $X = U \times D \times V^T$, where U and V are orthonormal left and right singular matrices, respectively, and D is the diagonal matrix of singular values (Lee et al., 2010). Each singular value in D corresponds to a two-dimensional image obtained from a column in U, and a row in V. Using SVD in feature extraction, the representation of an image with fewer singular values is intended. In order not to cause much information loss in the data set, m singular vectors corresponding to the largest singular values are selected. Thus, by projecting the data onto these singular vectors, the data is represented in m-dimensional space instead of the large space determined by the vector dimension of raw data.

3.1.5. Laplacian eigenmaps

Laplacian Eigenmap (LEMAP) is a nonlinear, graph based dimension reduction technique proposed by Belkin and Niyogi (Belkin and Niyogi, 2001). It first constructs an adjacency graph of the image data by connecting any two pixels i and j if the Euclidean distance between vectors, x_i and x_j, is close. The term *close* can be determined in three different ways:

i. *ϵ-neighborhoods:* Pixels i and j are assumed to be close if the square of their Euclidean distance differences is smaller than a predefined real number $\boldsymbol{\epsilon}$. This can be formulated as in Eq. (6).

$$\|x_i - x_j\|^2 < \in \tag{6}$$

ii. *n nearest neighbors:* Pixels i and j are assumed to be close if i is one of n nearest neighbors of j, and vice versa.

iii. *ϵ-neighborhoods with n nearest neighbors:* Pixels i and j are assumed to be close if the square of their Euclidean distance differences is smaller than a predefined real number $\boldsymbol{\epsilon}$ and i is one of n nearest neighbors of j, or vice versa.

The weighted adjacency matrix W is formed by weighted edges that may have either simple-minded or Heat Kernel weights. The simple-minded and Heat Kernel weights of the edge between i and j (W_{ij}) are formulated as in Eqs. (7) and (8), respectively.

$$W_{ij} = \begin{cases} 1 & \textit{if } i \text{ and } j \text{ are connected} \\ 0 & \textit{otherwise} \end{cases} \tag{7}$$

$$W_{ij} = e^{\frac{\|x_i - x_j\|^2}{2\sigma^2}} \tag{8}$$

Finally, eigenvalues and eigenvectors are computed for the generalized eigenvector problem:

$$Ly = \lambda Dy \tag{9}$$

where D, diagonal degree matrix of W, consists of column (or row) sums of W, and L is the Laplacian matrix.

$$D_{ii} = \sum_j W_{ji} \tag{10}$$

$$L = D - W \tag{11}$$

Finally, the eigenvector corresponding to the smallest eigenvalue is left out and the following m eigenvectors corresponding to the smallest nonzero eigenvalues are selected. In this study, the weighted adjacency matrix is constructed according to $\boldsymbol{\epsilon}$-neighborhood adjacency with Heat Kernel weights. The terms ϵ^2, σ^2, and m are chosen as 250, 5, and 17, respectively.

3.2. Classifier: Support Vector Machine (SVM)

In brief, SVM is originally proposed as a binary classifier and determines the optimal hyperplane which maximizes the distance between the optimal hyperplane and the nearest sample to this hyperplane (Vapnik, 2000). For this reason, it is also known as the maximum margin classifier (Burges, 1998). Support vectors correspond to the data samples which are nearest to the optimal hyperplane (Bredin et al., 2006; Hotta, 2004; Cevikalp et al., 2011). If a two-class problem is investigated, the training set is denoted as $\text{TS} = \{(\mathbf{x}_1, L_1), (\mathbf{x}_2, L_2), \ldots (\mathbf{x_M}, L_M)\}$ .In this set, $\mathbf{x_i}$ (i = 1, 2, ..., M) is the data sample and L_i ($L_i \in \{-1, 1\}$) is the class label (either negative or positive class.). Any vectorial test data ($\mathbf{x_{test}}$) can be classified using the following decision function:

$$f(x_{test}) = \sum \{\alpha_i L_i (x_i^T x_{test}) + b\} \tag{12}$$

where α_i (i = 1, 2, ..., M) are the nonzero coefficients that are the solution of the quadratic programming problem, $(|b|/\|\mathbf{w}\|)$ is the perpendicular distance from the optimal hyperplane to the origin and $\mathbf{w}$ is the normal vector of the hyperplane. The sign of this decision function gives the label of the class to which the test data ($\mathbf{x_{test}}$) is assigned and this decision function assumes the linearly separable case. The SVM classifier explained above is a two-class classifier. For dealing with multi-class problems (with S classes), it is possible to construct "$S(S-1)/2$" classifiers (Ruiz-Pinales et al., 2006).

4. Experimental study

In this study, a data set consisting of randomly selected 90 plastic bottle images from our country was used since there is no commonly accessible data set in the literature. The plastic bottle images were manually taken from the real objects. Each image has a size of (240 × 320). The data set includes three different plastic bottle types of images (PET, HDPE, and PP) and it has 30 images for each bottle type. Since the background information is not much important for each image, this information was firstly eliminated using several preprocessing steps mentioned in Section 2. Then, each image was converted from its pixel-wise matrix form into a row vector so that the image vectors with a dimension of (1 × 1000) were obtained. Finally, the dimension of images was reduced by applying widely used feature extraction methods in order to obtain a lower-dimensioned feature-space before the classification scheme. Except for the method of LEMAP, PCA, KPCA, FLDA, and SVD were applied on the mentioned database; therefore, each image in the database was represented by the vectors whose dimension is (1 × 100). Thus, the classification procedures were implemented in a 100-dimensional space. All of the experimental steps are illustrated in Fig. 3. All experiments were implemented using Matlab 9.0 (MATLAB, 2013) running on 2.33 GHz Intel Dual Core PC operating the Windows XP. When the plastic bottle image is taken from the camera, the classification scenario is automatically triggered. A two stage classification is performed. PET or non-PET categorization was firstly achieved, and then non-PET plastic bottles were classified as HPDE or PP.

The most crucial point in classification is the feature extraction procedure. A well-defined feature extraction algorithm makes a classification process more effective and efficient. Although a large number of feature extraction methods existed in the literature, the new studies are arisen with the following question: Which feature extraction method is the best for a given application? This question led us to evaluate the available feature extraction methods in terms of plastic object classification; therefore the most promising methods can be used. For this purpose, the most popular feature extraction methods such as PCA, KPCA, FLDA, SVD, and LEMAP were used to obtain recognition results. The final step is sorting the plastic objects with a robust classification method. In literature, many authors have realized image classification algorithms based on SVM (Xu et al., 2006; Chapelle et al., 1999; Song and Civco, 2004). SVM has been successfully applied to many image analysis areas such as image denoising and image classification. It was developed to classify linear separable data sets. While conventional classification methods generally apply the minimization of the empirical risk, an SVM based classifier is built to minimize the structural misclassification risk. In this study, SVM was selected to achieve the classification task. The majority voting algorithm was also carried out as the decision-making rule in classification (Fisher et al., 1990; Artaechevarria et al., 2009). This algorithm is also called as decision fusion or label voting and it equally weights each classification result and assigns the given plastic object to the class that the most classification results agree on. In this study, the classification decisions obtained from five feature extraction methods are taken into account and the most voted class was accepted.

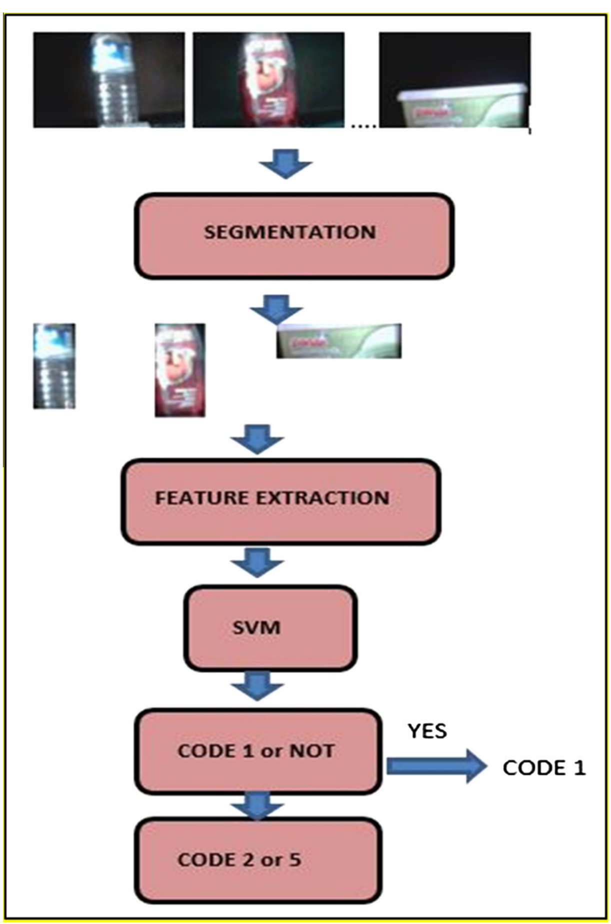

Fig. 3. The experimental stages of the recognition scenario.

The classification framework in this study consists of two stages. In the first stage, plastic bottle images were classified as PET and non-PET with a recognition accuracy of 96% using the SVM classifier. In the second stage, the non-PET plastic bottle images were categorized into HPDE or PP. The classification accuracy for the second stage is 92%. Thus, all plastic images were classified into three categories (PET or HPDE or PP). When one might wonder the overall recognition accuracy for our two-stage classification framework, it can be easily seen from Table 2 that the average recognition accuracy is 88%. The detailed experimental results are reported in the following figures and tables. The confusion matrix in Table 1 exhibits the classification performance of our system. Confusion matrix is generally utilized to explicitly visualize the classification performance and the values in the confusion matrix display the number of correctly/incorrectly classified data. Each column of the matrix indicates the predicted class, while each row refers to an actual class. All correct results are located in the diagonal of the matrix. It is constructed by applying sixfold cross validation for each plastic bottle class. So, the 1/6 of dataset was used as testing whereas 5/6 was utilized as training in order to test all plastic bottle photos in the database. It can be easily observed that 4 PET images are misclassified among the 30 samples when the first row of Table 1 is examined. Moreover, it is obviously seen that the HPDE and PP were mixed more with each other due to the high similarity between the shapes of them.

Meanwhile, a figure is also presented to demonstrate some misclassified plastic bottle samples of different types (Fig. 4). This figure can help us to determine which shape of plastic bottles confuses with the others and degrades our recognition accuracy, so that the classification rates can be increased.

Furthermore, the classification accuracy obtained from each feature extraction method is given in Table 2. As it can be seen in Table 2, this study classifies three types of plastic bottles as PET or HPDE or PP. It is precisely observed that LEMAP gives the worst recognition performance whereas KPCA is the best among five feature extraction methods.

If the first stage of our classification framework is taken into consideration, Fig. 5 depicts the experimental results obtained by only classifying the PET and non-PET plastic bottle images. In the illustration of Fig. 5, the recognition rates were computed for each feature extraction method by means of SVM. The legend 'ALL' refers to the accuracy evaluated by realizing the majority vote classifier combination method. The LDA-based feature extraction method outperforms the other feature extraction methods with respect to the accuracy values. As mentioned above, the one-third of the database is the PET samples (1–30) and the rest of the database consists of the non-PET samples (31–90).

Another two-class classification study was performed in the second stage to categorize the non-PET samples as HPDE or PP-type plastic bottles. The recognition outcomes of this study are illustrated graphically in Fig. 6. Like in Fig. 5, the legend 'ALL' refers to the rate found by implementing the majority vote classifier combination method. The KPCA method exhibits the greatest performance in this stage. The leave-five-out strategy was carried out and the plastic bottle images between the interval (31–60) represent the HPDE type and the others (61–90) are the PP type of plastic bottles.

Table 1
Confusion matrix for all classes.

	PET	HPDE	PP
PET	26	3	1
HPDE	1	27	2
PP	1	5	24

Table 2
Classification rates (%) of plastic types.

	PCA	KPCA	LDA	LEMAP	SVD	Majority voting classifier combination
PET	70	77	**80**	57	**80**	87
HPDE	77	80	**87**	63	83	90
PP	60	**83**	70	73	67	80
Average	69	80	79	64	77	88

The classification rates written in boldface implies the highest rates on each plastic type.

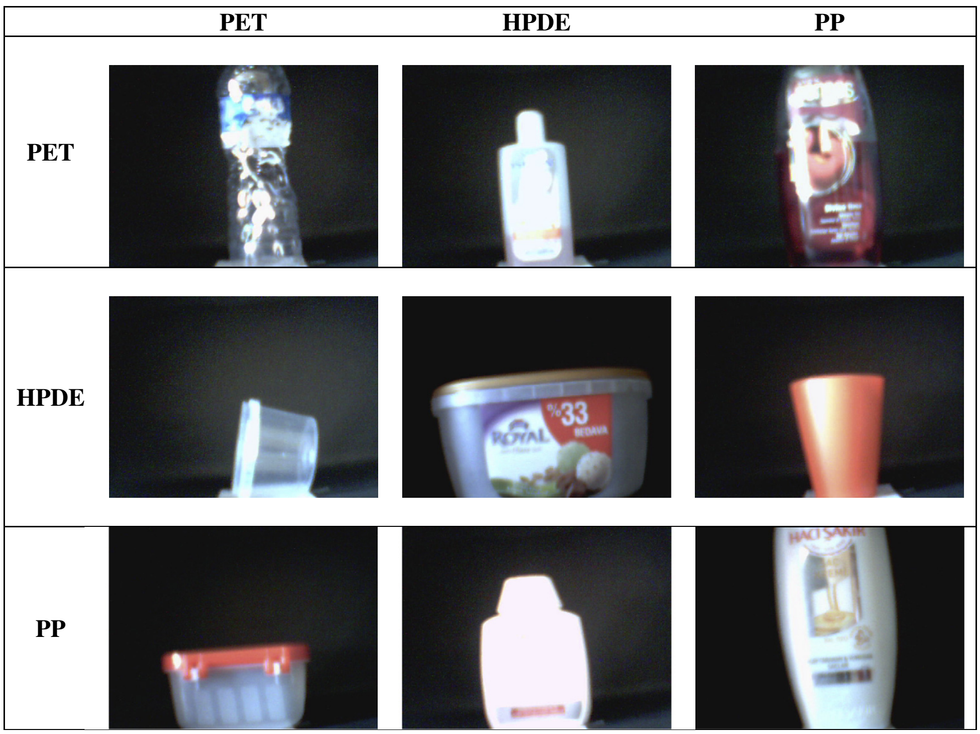

Fig. 4. A few samples of some correctly and incorrectly classified plastic objects.

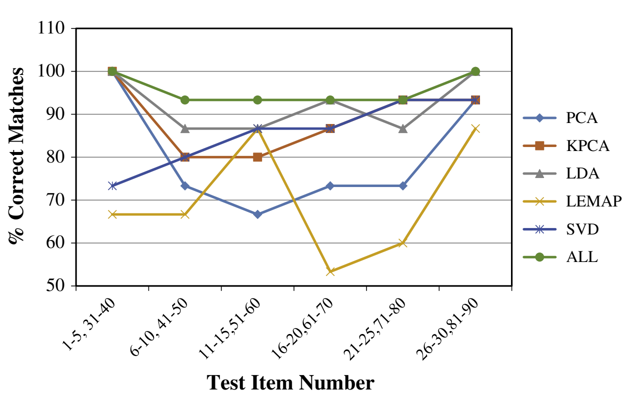

Fig. 5. Experimental results on the classification of the PET and non-PET plastic bottles.

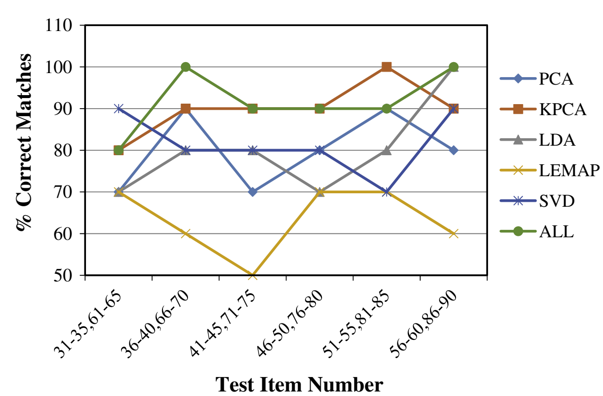

Fig. 6. Experimental results on the classification of the HDPE and PP plastic bottles.

As a summary, the experimental procedures performed in this manuscript can be composed of three main stages: The preprocessing operations of plastic bottles, the extraction of analytical features and the classification of plastic bottles as PET/HPDE/PP. In an online implementation of the procedures described in this paper, the main possible problem is that a plastic bottle may be wrinkled so that the morphological image operations cannot be correctly conducted on the conveyor belt. Another problem is that a plastic bottle may be cut or damaged so that PET or non-PET bottles are confused with each other in the classification stage. The possible solution for these problems is that plastic bottles can be smoothed before locating them on conveyor belt. Besides, fast computer systems should be operated in a real-time application of the procedures in this paper.

5. Conclusion

This paper explains the development of a novel approach for the plastic bottle classification in a two-stage process. The first stage is to classify a given plastic bottle image as PET or non-PET type. Once this stage is carried out, then the categorization of non-PET plastic bottle is performed. Five different and widely preferred feature extraction methods are implemented and SVM which is the one of the most popular classification method is applied on the obtained feature vectors. The most crucial part of this paper is to incorporate the recognition results of those five distinct features into a unique classification scheme using majority vote classifier combination mechanism. Approximately 90% accuracy clearly implies that our new classification scheme is more powerful than individual classifier results and also is capable to be applied in real-time applications. The second important outcome of this paper can be summarized that the abovementioned recognition accuracy is obtained only a simple and cheap experimental setup. Finally, this method allows the sorting of different wastes by training with different waste types. One can definitely suggest that the accuracy of our system may be increased if a modern industrial camera is installed into our system. As a future work, an enhanced database can be constructed and the recognition performances of other classifier combination techniques can be investigated.

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