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Classification for plastic bottles recycling based on image recognition

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ABSTRACT

Recycling of used plastic bottles is an important measure to protect the environment and save energy. Usually, bottles in different colors have different value for recycling. Classification of plastic bottles recycling based on image recognition during recycling is an effective way, where the position and color recognition are the key technologies. To classify the plastic bottles on the conveyor belt, their position relationships are firstly defined as three categories, i.e. disjoint, adjacent and overlapping. The disjoint ones can be easily identified by the ratio of concave and convex area based on their image. For the adjacent and overlapping bottles, a combination method called distance transformation and threshold segmentation is proposed to distinguish their position relationships. Once the adjacent bottles are identified, the method of concave point search based on convex hull will be used to separate the adjacent recycled bottles further. Then, the color of both the disjoint and adjacent bottles is identified because it is too complex and difficult to recognize color of and separate the overlapping bottles. In the aspect of color recognition, the colors of recycled bottles are divided into seven categories in the sorting process. Color features of the bottom section are used to represent the one of the recycled bottle because there may be a bottle cap and a label on the top and in the middle of the bottle, respectively, resulting in the wrong recognition. ReliefF algorithm is applied to select color features of recycled bottles and the color is identified by support vector machine (SVM) algorithm. The influence of training sample size on classification model is studied and the experimental results show that the accuracy of color recognition of recycled bottles reach 94.7%.

1. Introduction

The rapid growth of the consumption of beverage bottles has led to the emergence of various issues, such as the resource depletion and environmental pollution. It is worth noting that significant amount of oil is used for producing plastic bottles. At present, 4% of the world's oil is used for plastics production (Cagnetta et al., 2018; Singh et al., 2017). As we all know, oil is a type of the non-renewable resource and becomes less and less. On the other hand, plastic wastes can cause great damage to the environment, as shown in Fig. 1.

An important strategy for dealing with these problems is recycling (Al-Salem et al., 2009; Ramli et al., 2008). Recycled plastics can be used as raw materials for new products, such as concrete, automotive products and textiles (Vélez and Vélez, 2017; Arafat et al., 2015). Recently, the recycling of plastic bottles has become an important branch in the plastic bottle industries, which not only has the potential to save fossil fuels, but also reduces greenhouse gas emissions (Zhang and Wen, 2014; Dahlbo et al., 2017).

The recycling technology of beverage bottles can be categorized into physical and chemical recovery method. In terms of environmental benefits, the physical method has great value and become the most widely used (Goto et al., 2006; Chen et al., 2011; Ragaert et al., 2017; Wang et al., 2015), which process usually involves collection, sorting, washing, crushing, flotation and drying of bottles. There are two key points for sorting: material classification (Zheng et al., 2017; Yoshioka and Grause, 2015), and color classification. The material sorting is to identify and remove non-Polyethylene Terephthalate (non-PET) plastic bottles (Shahbudin et al., 2010; Scavino et al., 2009; Zulkifley et al., 2013; Ramli et al., 2007) and other impurities (Karaca et al., 2013; Rozenstein et al., 2017). The color classification is to classify plastic bottles based on their color because bottles in different colors present different values for recycling. Therefore, the color classification for recycled bottles is crucial as well but fewer studies are reported in the color classification of recycled plastic bottles than those on material classification.

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0956-053X/

(a) Plastic bottles washed up on the beach (b) Plastic bottles in rivers

Fig. 1. Environmental pollution caused by plastic bottles.

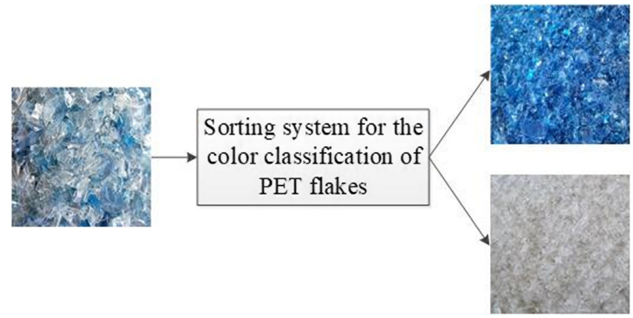


Fig. 3. The color classification of PET flakes.

Usually, the color classification can be conducted into two ways: manual classification and automatic classification based on machine vision. In many areas, manual classification is still the main method, as shown in Fig. 2. The efficiency and quality of the final product are largely determined by the process of color classification (Pfeisinger, 2016), and automatic classification based on machine vision can achieve a higher efficiency than the manual classification. That is why some scholars have done related research on color classification based on machine vision. However, most of them focused on the color classification of PET flakes by identifying color after crushing (Jiao and Sun, 2016; Zeiger, 2003), as shown in Fig. 3. In fact, the color classification can also be carried out before crushing to classify the color of bottles. The color classification of bottles can reach a higher efficiency compared with the color classification of PET flakes such that it has broad prospects and a high value of research. Nevertheless, the color classification of bottles has been paid less attention.

The whole bottle sorting system can be described as the following process. After plastic bottles are flattened and delivered to the conveyor belt of sorting equipment, the image of these bottles on the conveyor belt is captured. The color recognition can be carried out based on the image and the position of the plastic bottles can also be identified through the images and the velocity of the conveyor belt. Then, the bottles of a certain color can be blown to be sorted out at the end of the conveyor belt with high pressure air, as shown in Fig. 4. According to the application requirements, the sorting equipment only needs to pick plastic bottles of a single color in a round of sorting process. So the positioning and color recognition of the bottles are very crucial in the sorting system based on machine vision, which are two main contents in this paper.

Regarding the position recognition, most research focused on the extraction algorithm of the location information, including the process of preprocessing, image segmentation, and so on. After strengthening the image of plastic bottles, Özkan et al. used Otsu algorithm to realize threshold segmentation. Then morphological treatment was carried out, and a relatively complete region of interest was segmented from its background (Özkan et al., 2015). Zulkifley et al. modeled the background and used the background subtraction method to realize image segmentation, and then realize positioning of plastic bottles (Zulkifley et al., 2014). He Xiangyu proposed the extraction method of the region of interest in the image of plastic bottles based on double threshold segmentation, in which three channels of the background image were fitted by Gauss function to determine the high and low thresholds for segmentation. Then, the centroid of each plastic bottle was obtained by centroid equation after obtaining the region of interest (He, 2017). House et al. introduced the support vector machine algorithm into the process of segmentation. Firstly, each original image captured by camera was divided into image blocks with the size of 10×10 pixels. Then the histogram of each image block was calculated. Every histogram was used as the input of SVM algorithm to determine whether corresponding image block was a background image block, which will be discarded. Otherwise, it will be further processed at regional growth stage (House et al., 2011). Tachwali et al. used principal component analysis algorithm to obtain inclination angle of plastic bottles, and then corrected the image of each bottle, and finally realized the positioning of plastic bottles with their respective minimum enclosing rectangle (Tachwali et al., 2007). To summary, all the aforementioned methods assumed that recycled bottles on the conveyor belt are disjoint. However, this assumption is not valid in the real-world situations because the adjacency or overlapping of bottles also happens. Without the proper identification of such positional relation, the algorithm would bring obvious sorting error. He et al. identified disjoint plastic bottles with shape features and computed location information (He et al., 2017) but not for adjacent and overlapping ones. In addition, they did nothing to adjacent plastic bottles, leading to the omission of some plastic bottles that could be removed.

Considering the cost of the system and other factors, it mainly relies on classical machine learning rather than deep learning represented by CNN at present although deep learning has a good performance in many fields (Yuan et al., 2018; Zuo et al., 2018; Altenberger and Lenz, 2018; Rachmadi and Purnama, 2015; Nanni et al., 2017). In order to identify the colors of plastic bottles, Tachwali et al. extracted H component as the color features of plastic bottles. The decision tree and dynamic naive Bayes algorithm were fused to identify the colors of plastic bottles, and the aggregate accuracy was 96%. But the plastic bottles were only divided into three categories: colorless bottles, blue bottles and green bottles (Tachwali et al., 2007). Zhou Ming selected the color histogram of H-S as color features of plastic bottles. Similarly, plastic bottles were divided into three categories: green bottles, blue bottles and colorless bottles (Zhou, 2014). He Xiangyu used the K means clustering algorithm to divide plastic bottles into four categories: blue bottles, green bottles, white bottles and colorless bottles (He, 2017). In fact, Plastic bottles can be classified into seven categories based on their color: light blue bottles, lilac bottles, brown bottles, blue bottles, light green bottles, dark green bottles, and colorless bottles. Of course, a further precise classification of colors for the plastic bottles will result in an increased difficulty of recognition.

(a) Offline manual sorting (b) Online manual sorting station

Fig. 2. Manual classification of the whole bottles.

Considering the actual positional state of plastic bottles on the conveyor belt, in this paper a rule is presented to define their relationship as disjoint, adjacent and overlapping. At the same time, the corresponding algorithm is also given to judge these relationships and how to deal with them. In order to obtain a more precise color classification and improve the utilization value of plastic bottles, this paper discusses the possibility of dividing the color of plastic bottles into seven kinds, instead of the usual three or four, and how to identify them. Of course, the number of samples will also affect the correct rate of color recognition, this problem is also carried out in this paper.

This paper first explains the method for distinguishing the three kinds of relative positions (i.e. disjoint, adjacent and overlapping). Then, the method based on the concave points for the separation of adjacent plastic bottles is presented. In addition, a method based on support vector machine algorithm is proposed to classify the colors of recycled bottles into seven categories, mainly including color features extraction and selection, model training and testing. Finally, the experimental verification of the proposed methods is carried out and the conclusions are drawn.

2. Identification and treatment of the positional relationships between the recycled plastic bottles

2.1. The positioning process of recycled bottles

The recycled plastic bottles are sorted by a pneumatic jet separator with many pneumatic nozzles on it, as shown in Fig. 4. Therefore, in order to determine the identifiers of pneumatic valves that should be triggered and when these pneumatic valves should be triggered, it is necessary to obtain the centroid of every bottle by means of image processing.

Before conducting the theoretical research of this topic, we conducted a simple experimental study. Experiments have shown that there are three cases of disjoint, adjacent and overlapping (as shown in Fig. 4) when the plastic bottle is placed randomly on the conveyor belt. Disjoint bottles refer to the bottles that have no contact with each other. Adjacent bottles refer to the bottles that contact with each other but no bottle is covered. And if the bottles are overlapping, it means that one bottle is covered by the other. Based on these actual conditions, we have developed a general sorting scheme shown in Fig. 4.

The entire sorting plan is like this. Before each recognition, one must first determine a color that needs to be sorted. After the position of the plastic bottles of this color on the conveyor belt are recognized, the bottles are blown onto a farther conveyor belt through the pneumatic nozzles, as shown in Fig. 4. This achieves the automatic separation of the color bottles. Plastic bottles of other colors are transported to other locations and waiting for the next sorting. After the bottles of this color are selected, then switch to another color for sorting. Loop this way until all colors have been executed. At last, the entire sorting process is finished. It can be seen from the principle of this sorting scheme that if the bottles in the overlapping state are also blown out by the high-pressure air, the bottles of other colors may be blown out at the same time. Therefore, the position of the bottle in the overlapping state may not be performed. Instead, only the disjoint and adjacent bottles need to be sorted.

The whole positioning process is shown in Fig. 5. First, the image of the plastic bottles is grayed, and then the threshold value was used to get the binary image. The mask is not complete enough to get the complete contour of each bottle, so it is necessary to perform operations of morphological processing and hole filling on the image. Then the contours of the plastic bottles can be obtained. After obtaining the contour of the target, the position relationship of plastic bottles is judged first. If it is a disjoint target, the centroid is directly calculated by using the contour moments. The equation of calculating centroid can be written as the following

$$x_c = \frac{M_{10}}{M_{00}}, \quad y_c = \frac{M_{01}}{M_{00}} \tag{1}$$

where the point (x_c, y_c) is the centroid coordinate of the plastic bottle, and $M_{00}$is the zero moment of the plastic bottle contour. M_{10} and M_{01} are the first moments of the plastic bottle contour.

As shown in Fig. 5, if the plastic bottles are not disjoint, it need to be further determined whether the targets are adjacent. If so, the concave point search is carried out. After concave points are connected, the adjacent targets are divided into two ones and their centroids are obtained respectively. If not, the whole process ends.

2.2. Identification of the positional relationship of plastic bottles

Identification of the positional relationships of plastic bottles is to distinguish the three situations shown in Fig. 4. To identify disjoint plastic bottles, their contours and their convex hulls of targets on the conveyer belt are firstly obtained. The convex hull *H* of arbitrary set *S* is the minimal convex set contained *S*, and the difference *H-S* is called convex defect. In this paper, Jarvis stepping convex hull algorithm is used to get the convex hull of the contour of every plastic bottle, and the results are shown in Fig. 6. In addition, the

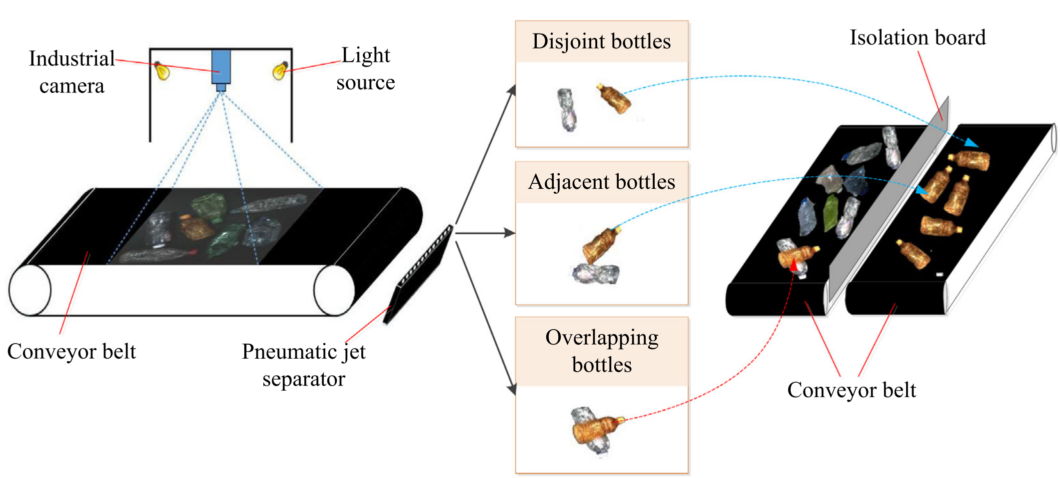


Fig. 4. The whole bottle sorting system.

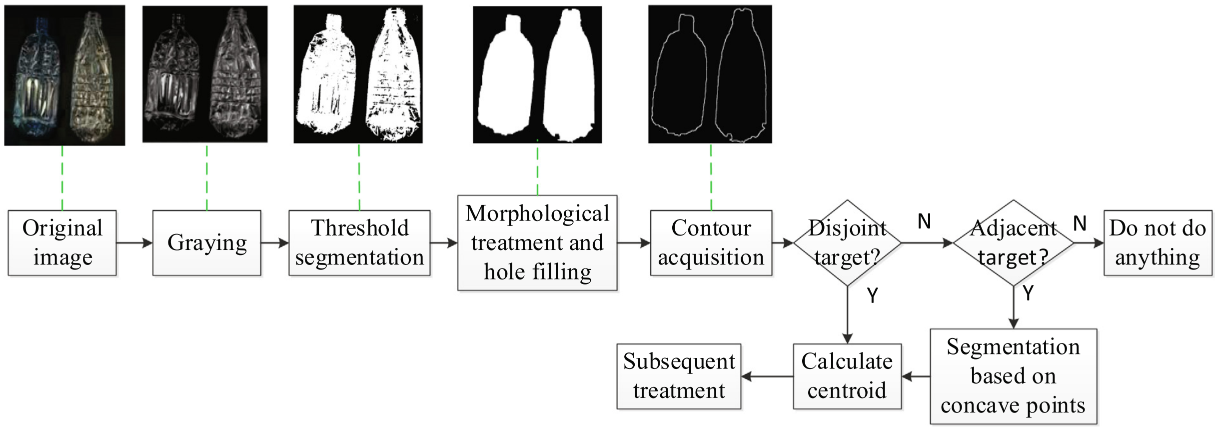
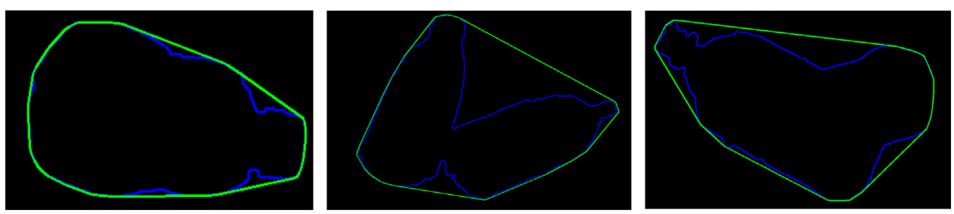


Fig. 5. The positioning process of recycled plastic bottles.



(a) The convex hull of the disjoint target (b) The convex hull of the adjacent target (b) The convex hull of the overlapping target

Fig. 6. The convex hull.

area of the contour and convex hull denote as a (the area surrounded by the blue curve in Fig. 6) and b (the area surrounded by the green curve in Fig. 6) respectively, and the ratio of them refers to c($c = a/b$). As shown in Fig. 6, because of the difference in the area of convex defects, the value c in the three cases may be significantly different. Therefore, a number of images with three kinds of positional relationships were collected for the statistics of the value c, as shown in Fig. 7. It can be seen that the value c of disjoint bottles clearly differentiate from that of the other two conditions. Therefore, a threshold 0.915 can be used to separate disjoint plastic bottles, which, however, cannot distinguish adjacent targets and other method will be adopted.

In this paper, the combination method called distance transformation and threshold segmentation is used to distinguish adjacent bottles from overlapping ones. The Euclidean distance transformation is applied to the binary image first. Then the threshold segmentation is carried out for the transformed image. A fast distance transformation algorithm in two scans was used by Shih and Wu (2004) and the general process for the binary image of plastic bottle is as follows:

(1) The first scan starts from the top left corner all the way to the right and then jumps to the left side to continue until covers the whole image. The template for distance transformation is L as shown in Fig. 8(a). The following equation is used for calculation.

$$f(p) = min[f(p), D(p, q) + f(q)], \quad q \epsilon L \tag{2}$$

where D refers to the Euclidean distance, $f(p)$ is the pixel value of the current pixel.

(2) The second scan starts from the lower right corner all the way to the left and then jumps to the right side until it covers the whole image. The template for distance transform is R, as shown in Fig. 8(b).
(3) The final image after distance transformation is obtained based on the scanned result of template L and template R.

The treatment of the binary image for the overlapped and the adjacent plastic bottles is shown in Fig. 9 and Fig. 10. The results of Euclidean distance transformation of the binary image for the overlapped (Fig. 9(a)) and the adjacent plastic bottles (Fig. 10(a)) are shown respectively in Fig. 9(b) and Fig. 10(b). It can be seen that there is only one connected domain for the binary image of overlapping plastic bottles after applying the proposed method of distance transformation and threshold segmentation and two for the adjacent bottles, as shown respectively in Fig. 9(c) and Fig. 10(c). The conclusion is that the adjacent targets can be distinguished from overlapping targets.

2.3. Separation of adjacent plastic bottles

It is not easy to obtain the centroid of each bottle of the overlapping ones but adjacent plastic bottles, one can still acquire the centroid of each bottle by the way of image processing. As shown in Fig. 11(a), the binary image of adjacent plastic bottles is presented. It is easy to see that after connecting the two red dots shown in Fig. 11(a), the adjacent target can be separated as two disjoint targets. Then, their centroids can be obtained separately. In this paper, the convex hull and the convex defects of the contour have been used to find the two concave points. For the image of adjacent plastic bottles, the treatment process is as follows:

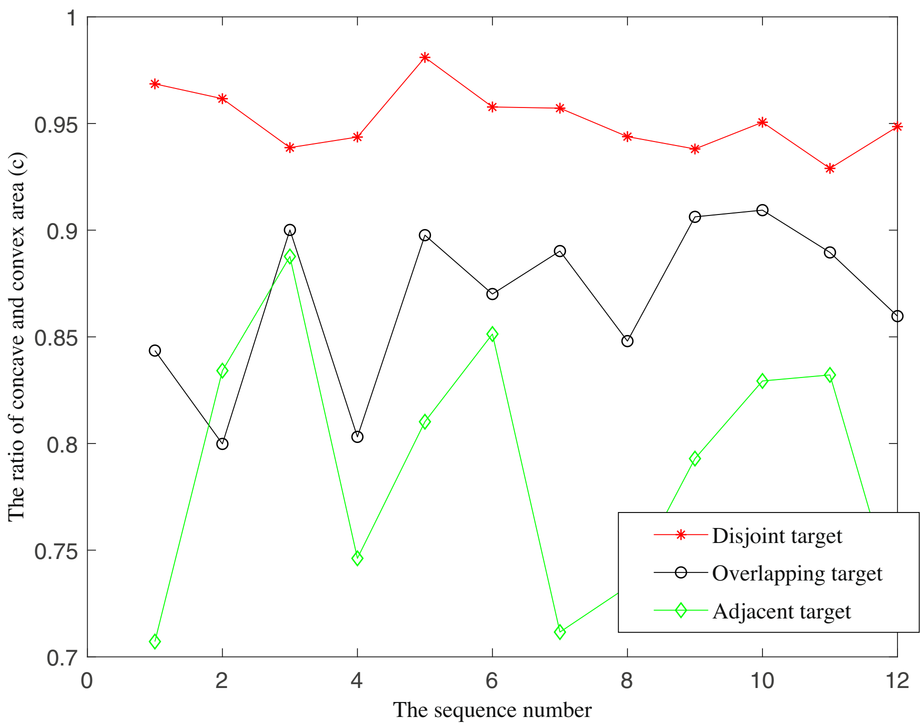


Fig. 7. Statistical results.

q_2	q_3	q_4
q_1	p	

(a) Template *L*

	p	q_5
q_8	q_7	q_6

(b) Template *R*

Fig. 8. Templates for distance transform.

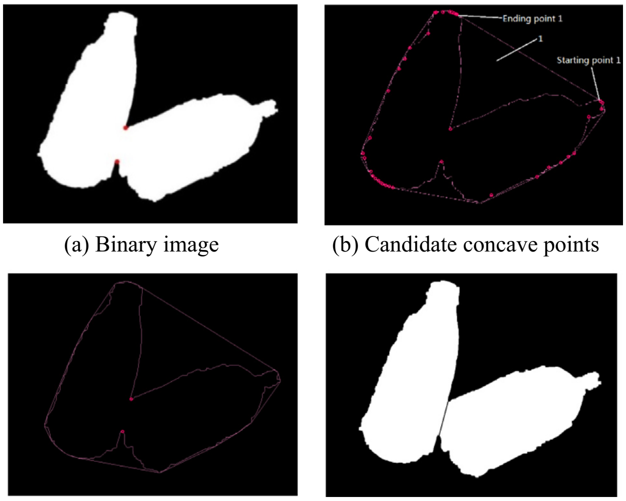
(1) The convex hull and convex defects of adjacent plastic bottles are calculated. The definition of the starting point and the ending point of a convex defect is as follows: Traverse convex hull vertices in counter clockwise direction, and observe convex defects in counterclockwise direction. Each convex defect contains two vertices of the convex hull. The first vertex in the counterclockwise direction is defined as the starting point of the convex defect, and the other vertex

(a) The binary image (b) Distance transform (c) Threshold segmentation

Fig. 9. Processing of the binary image of overlapping targets.

(a) The binary image (b) Distance transform (c) Threshold segmentation

Fig. 10. Processing of the binary image of adjacent targets.



(a) Binary image (b) Candidate concave points

(c) Concave points for separation (d) Separation result

Fig. 11. Separation of adjacent plastic bottles.

is defined as the ending point. The starting point of each convex defect is the ending point of the last convex defect. Similarly, the ending point of each convex defect is the starting point of the next convex defect. Taking convex defect labeled 1 (as shown in Fig. 11(b)) as an example, the starting point labeled 1 shown in Fig. 11(b) is the starting point of this convex defect, and the ending point labeled 1 is the ending point of this convex defect.

(2) Find the farthest point away from the convex hull line on the contour as a candidate concave point for separation. Suppose the vertices of the convex hull Q are set B, so

$$B = \{(x_i, y_i)\}, \quad i = 1, 2, \ldots, m$$

where the point (x_i, y_i) is the *mth* vertex. The search procedure was as follows:

a. First, find the convex defect with the point (x_1, y_1) as the starting point and the point (x_2, y_2) as the ending point. Start from the point (x_1, y_1) to traverse the contour of plastic bottles until the end point (x_2, y_2). Assuming that a point on the contour is point (x_{cur}, y_{cur}), the distance from that point to the convex hull line is calculated by the following equation:

$$d = \frac{|-(y_2 - y_1) \times ((x_{cur} - x_1)) + (x_2 - x_1) \times (y_{cur} - y_1)|}{\sqrt{(y_2 - y_1)^2 + (x_2 - x_1)^2}} \tag{4}$$

Note that all the distances obtained under this convex defect is set D, the maximum distance *dist_i* can be obtained by sorting all the elements in D.

b. Repeat the previous step, and find a convex defect with the point (x_2, y_2) as the starting point and the point (x_3, y_3) as the end point until a convex defect is found with the point (x_m, y_m) as the starting point and the point (x_1, y_1) as the end point.

c. The maximum distance *Dist* between the points on the contour and the convex hull line in each convex defect is obtained.

$$Dist = \{dist\_i\}, \quad i = 1, 2, \ldots, n \tag{5}$$

where *dist_i* represents the maximum distance obtained under the *ith* convex defect, and the corresponding point on the contour is a candidate concave point, which has a total of n convex defects.

The candidate concave points were labeled as red circles shown in Fig. 11(b).

(3) The elements in the set *Dist* in the previous step were sorted out. Then two concave points with the largest distance away from the convex hull line were selected and labeled as the red circles shown in Fig. 11(c), which would be the concave points for separating adjacent targets.

(4) After concave points for separation are confirmed and they are connected, the secant line is obtained. The separation of adjacent plastic bottles is completed, as shown in Fig. 11(d). Then, the centroids of two plastic bottles would be calculated separately.

3. Color recognition of recycled plastic bottles

3.1. Overall scheme of color recognition for plastic bottles

The color of plastic bottles on the market can be divided into seven categories, as shown in Fig. 12. The plastic bottle sorting system based on machine vision picked the plastic bottles of a single color in a round of sorting process, as shown in Fig. 4. So the sorting system must be able to identify the plastic bottles in any of the seven colors.

In this paper, a color recognition method of recycled plastic bottles based on SVM is presented as shown in Fig. 13. The color recognition process is divided into two parts: training and testing. The purpose of the training process is to obtain the SVM model used for color classification of plastic bottles, and the test process is to test its classification ability. First, the images of plastic bottles collected for training are pre-processed and their centroids are obtained according to Section 2.1. Then color features of plastic bottles are extracted and test images are processed in the same way. The color features of the training set are used as input of SVM algorithm. After setting and optimizing parameters, training is carried out and SVM model is obtained.

The learning strategy of SVM is to maximize the interval and the optimization problem is formalized as the following (Flores-Fuentes et al., 2014):

$$min\frac{1}{2}\,||\boldsymbol{\omega}||^2 + C\sum_{i=1}^{n}\xi_i \tag{6}$$

The constraints are $y_i(\boldsymbol{\omega}^T\boldsymbol{x}_i + b) \geq 1 - \xi_i, \;\; \xi_i \geq 0, \;\; i = 1, 2, \cdots, n$.

3.2. Extraction of color features

Regarding the color classification of plastic bottles, it should be noted that the color of the whole bottle cannot be selected arbi-

(a) Light blue (b) Lilac (c) Brown (d) Blue (e) Light green (f) Dark green (g) Colorless

Fig. 12. Plastic bottles with different color. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

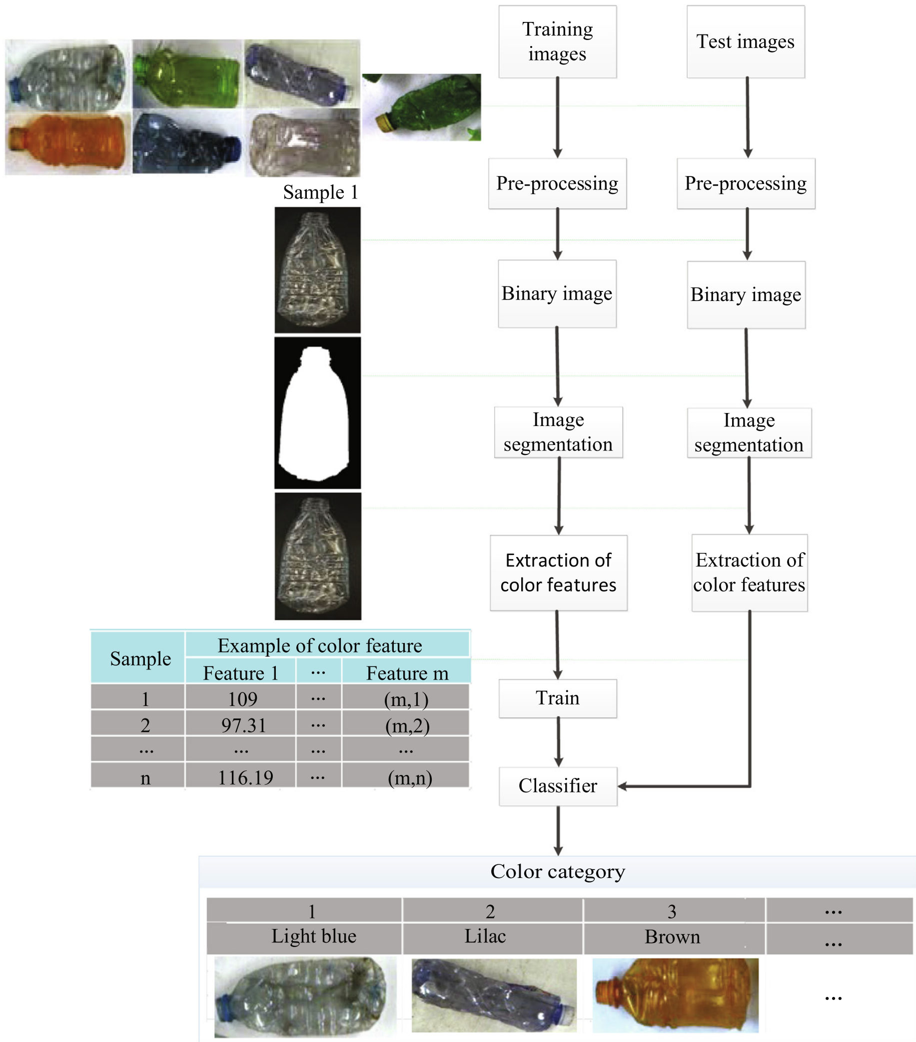


Fig. 13. The scheme for color recognition of plastic bottles. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

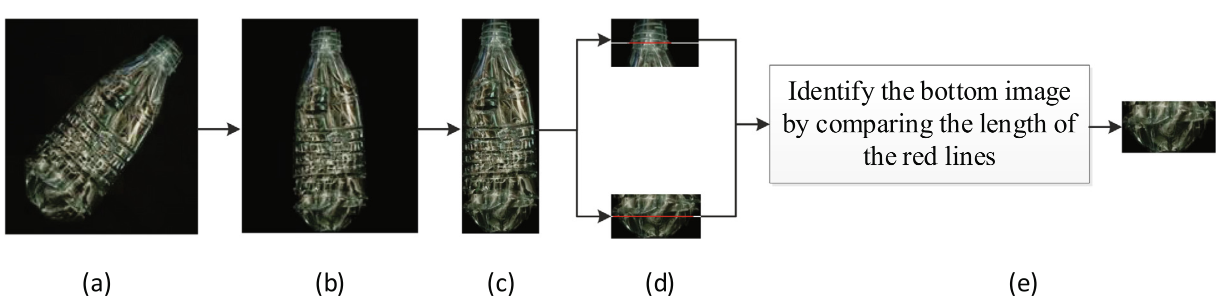


Fig. 14. Extraction of the bottle bottom image. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

trarily. Before plastic bottles are transported to the sorting equipment, their labels should be stripped off and usually the success rate of off-label treatment can reach 95%. Thus, the middle part of the bottle is not suitable for the extraction of color features in case the label is still on. In addition, the cap may be still left on the plastic bottle, bringing an adverse effect on color recognition. Therefore, the bottom of the bottle is the most suitable position for extraction of color features. Getting the image of the bottom of each bottle has become a key problem and the steps are shown in Fig. 14:

(1) Acquire the rotation angle according to the minimum circumscribed rectangle of the contour.
(2) Correct the orientation of the original image. According to the correction equation Eq. (7), the initial image is shown in Fig. 14(a) and the corrected one is presented in Fig. 14(b).

$$\begin{bmatrix} x_3 \\ y_3 \\ 1 \end{bmatrix}^T = \begin{bmatrix} x_0 \\ y_0 \\ 1 \end{bmatrix}^T \begin{bmatrix} 1 & 0 & 0 \\ 0 & -1 & 0 \\ -centerx & centery & 1 \end{bmatrix} \begin{bmatrix} cos\theta & -sin\theta & 0 \\ sin\theta & cos\theta & 0 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} 1 & 0 & 0 \\ 0 & -1 & 0 \\ left & top & 1 \end{bmatrix} \quad (7)$$

where point (x_0, y_0) is the coordinate of the pixel before correction, and the point (x_3, y_3) is the coordinate of the pixel after correction. The coordinate of the rotation center in the original image coordinate system is (*centerx*, *centery*). θ refers to the rotation angle. The value *top* is the ordinate of the highest point after rotation, and the value *left* is the abscissa of the most left point after rotation.

However, it does not guarantee that the bottle bottom image is at the bottom of the image after correction such that step (3) and step (4) were necessary.

(3) Crop the image by the minimum envelope rectangle of the plastic bottle. The result is shown in Fig. 14(c). The uppermost 20% (Marked as A) and the lowest 20% (Marked as B) of the corrected image were selected as candidates of the bottom image.
(4) Draw a line of pixels in the middle of A and B, respectively. This line in bottom image has more non-zero pixels, which are marked as red points as shown in Fig. 14(d). The image with longer red line is identified as the bottom image of the bottle as shown in Fig. 14(e).

Table 1
The candidates of color features.

The color of plastic bottles	The candidates of color features
Light blue	{115.063, 125.125, 121.188, −10.0625, −6.125, 3.9375, 43.0625, 23.875, 124.5, 19.1875, −81.4375, −100.625, 130.313, 125.063, 132.063, 5.25, −1.75, −7}
Lilac	{109.625, 97.875, 98.625, 11.75, 11, −0.75, 107, 30.875, 110.688, 76.125, −3.6875, −79.8125, 105.563, 130.813, 121.875, −25.25, −16.3125, 8.9375}
Brown	{6.75, 104.5, 185, −97.75, −178.25, −80.5, 16.5, 247.625, 188.5, −231.125, −172, 59.125, 135.938, 154.375, 187.75, −18.4375, −51.8125, -33.375}
Blue	{117.063, 101.125, 82.0625, 15.9375, 35, 19.0625, 99.25, 78.9375, 117.5, 20.3125, −18.25, −38.5625, 105, 124.625, 117.125, −19.625, −12.125, 7.5}
Light green	{26.375, 127.125, 108.063, −100.75, −81.6875, 19.0625, 35.375, 209.25, 124.563, −173.875, −89.1875, 84.6875, 124.938, 107.688, 175.75, 17.25, −50.8125, −68.0625}
Dark green	{34.125, 107.125, 59.0625, −73, −24.9375, 48.0625, 49.9375, 178.188, 108.063, −128.25, −58.125, 70.125, 104.25, 97.8125, 162.563, 6.4375, −58.3125, −64.75}
Colorless	{148.688, 160.438, 169.875, −11.75, −21.1875, −9.4375, 42.8125, 38.75, 168.313, 4.0625, −125.5, −129.563, 166.313, 129.625, 135.25, 36.6875, 31.0625, −5.625}

After obtaining the bottle bottom image, color features are extracted. Frequently used color spaces include RGB color space, HSV color space, Lab color space, etc. In this paper, features in 18 dimensions of recycled plastic bottles are extracted as the candidates of color features that would be eventually used, including $\bar{R}, \bar{G}, \bar{B}, \bar{R}-\bar{G}, \bar{R}-\bar{B}, \bar{G}-\bar{B}, \bar{H}, \bar{S}, \bar{V}, \bar{H}-\bar{S}, \bar{H}-\bar{V}, \bar{S}-\bar{V}, \bar{L}, \bar{a}, \bar{b}, \bar{L}-\bar{a}, \bar{L}-\bar{b}$ and $\bar{a}-\bar{b}$. The results are shown in Table 1.

3.3. Selection of color features and development of classification model

A. Selection of color features

Not all the color features extracted in Section 3.2 are useful for color recognition. Using excessive features can only be a waste and increase the workload of the processor. Therefore, it is necessary to optimize the number of color features, that is, to select the most advantageous features for color recognition.

In this paper, ReliefF algorithm is used to select color features of plastic bottles, which calculates the feature weight and gives different weights to each feature according to the correlation between each feature and each category. The higher the weight of one feature is, the more advantageous feature is for the color recognition of recycled plastic bottles. When dealing with multiple classification problems, this algorithm randomly extracts one sample R from the training set, and then finds out k neighbor samples of sample R from the same sample set of R and k nearest neighbor samples from different sample sets respectively. Then, the weight of each feature is updated by Eq. (8).

$$W_a(A) = W_b(A) - D_1 + D_2 \tag{8}$$

$$D_1 = \sum_{j=1}^{k} diff(A, R, H_j)/(mk) \tag{9}$$

$$D_2 = \sum_{C \notin class(R)} \left[\frac{p(C)}{1 - p(class(R))} \sum_{j=1}^{k} diff(A, R, M_j(C)) \right] \Big/ (mk) \tag{10}$$

where label A represents one feature and label R denotes one sample in the training set. The value $W_b(A)$ is the weight of the feature A before being updated in one iteration and $W_a(A)$ is the weight of the feature A after being updated in one iteration. The value m is the number of iterations. Label $diff(A, R_1, R_2)$ represents the difference between the sample R_1 and R_2 on the feature A. Label H_j is k neighbor samples of sample R from the same sample set of R. Label C represents the category of samples. Label $M_j(C)$ represents the *jth*

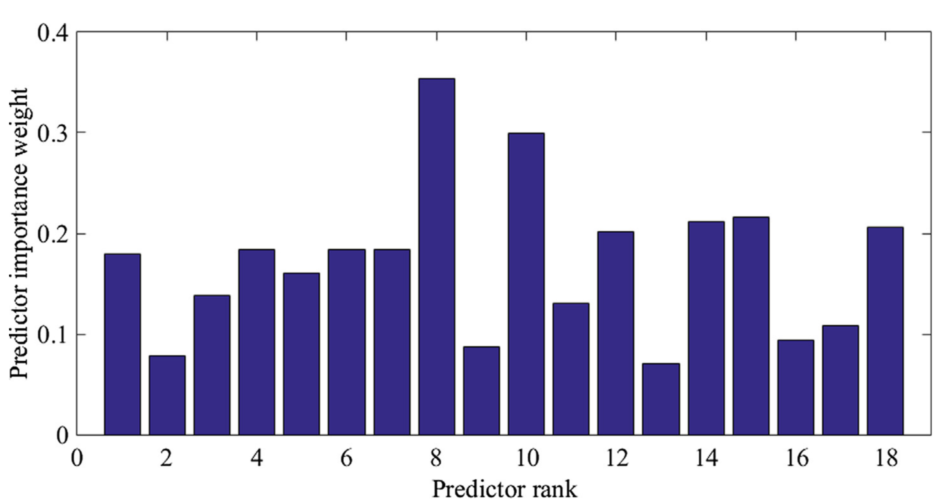


Fig. 15. Weight of each feature.

nearest neighbor samples in category$C \notin class(R)$. Label $p(C)$ is the proportion of the number of the samples in category$C \notin class(R)$ to the total number of samples.

The data obtained from the Section 3.2 is used as the input of this algorithm to select the most suitable color features for the color recognition of plastic bottles. The weight of each feature is shown in Fig. 15. The coordinates 1–18 represent respectively the color features $\bar{R},\bar{G},\bar{B},\bar{R}-\bar{G},\bar{R}-\bar{B},\bar{G}-\bar{B},\bar{H},\bar{S},\bar{V},\bar{H}-\bar{S},\bar{H}-\bar{V},\bar{S}-\bar{V},\bar{L},\bar{a},\bar{b},\bar{L}-\bar{a},\bar{L}-\bar{b}$ and $\bar{a}-\bar{b}$. According to the order of weight of features, the number of color features has been gradually increased. Using the previous method, the SVM model is trained for classification respectively and test the accuracy of test data.

The test results are shown in Fig. 16, which shows when the number of features reaches 8, the accuracy of classification tends to be stable. This suggests that some of these candidate features with lower weights do not play a significant role, so it is possible to limit the number of features. So 8 features with the highest weight are selected as the color features for color recognition of plastic bottles, which include $\bar{S}$, $\bar{H}-\bar{S}$, $\bar{b}$, $\bar{a}-\bar{b}$, $\bar{a}$, $\bar{R}-\bar{G}$, $\bar{H}$ and $\bar{S}-\bar{V}$, as shown in Fig. 15.

B. Selection of the size of training set

In this paper, based on the actual working environment of the system, using 8 selected color features, the influence of the size of training set on color recognition is studied combining SVM algorithm.

The classification models with different size of training set is trained and tested with the test set. The number of each color of plastic bottles is identical in both training and test sets. The results are shown in Fig. 17. The accuracy of test set increased significantly with the increasing number of training set samples as shown in Fig. 17. But when the size of training set reached 1400, the accuracy became stable.

For the color recognition of plastic bottles, there are many factors that can affect the size of training set, such as illumination conditions, color features, recognition algorithm, etc. There is no general scheme to solve the problem of color recognition. These factors only can be adjusted according to actual application conditions in order to achieve the best results.

C. Training and evaluation of the color classification model

In this paper, parameters of the classification model are varied iteratively through grid search process and k-fold cross validation is performed to obtain average classification performance in each iteration. The SVM model trained with the optimized parameters is preserved. 700 samples are used as test set, including 100 samples for each category.

The confusion matrix obtained by training set and test set is shown in Table 2 and Table 3, where light blue, lilac, brown, blue,

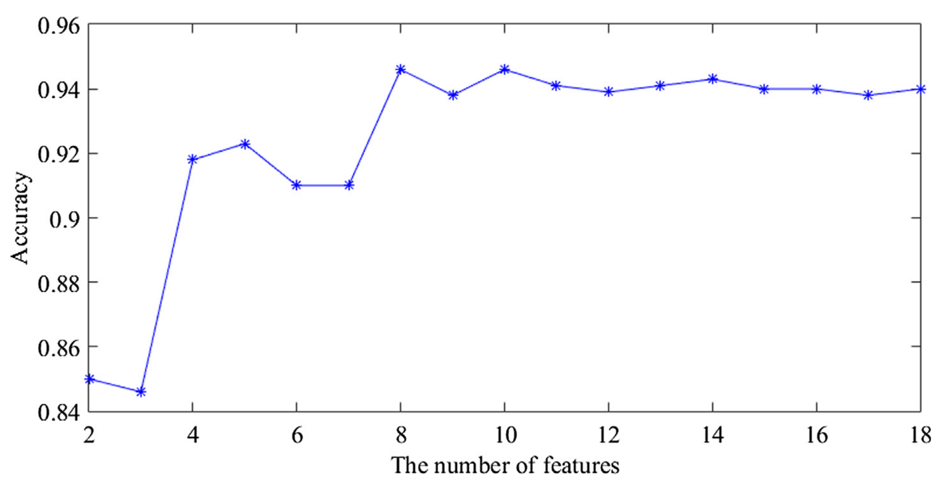


Fig. 16. Accuracy rate with different number of features.

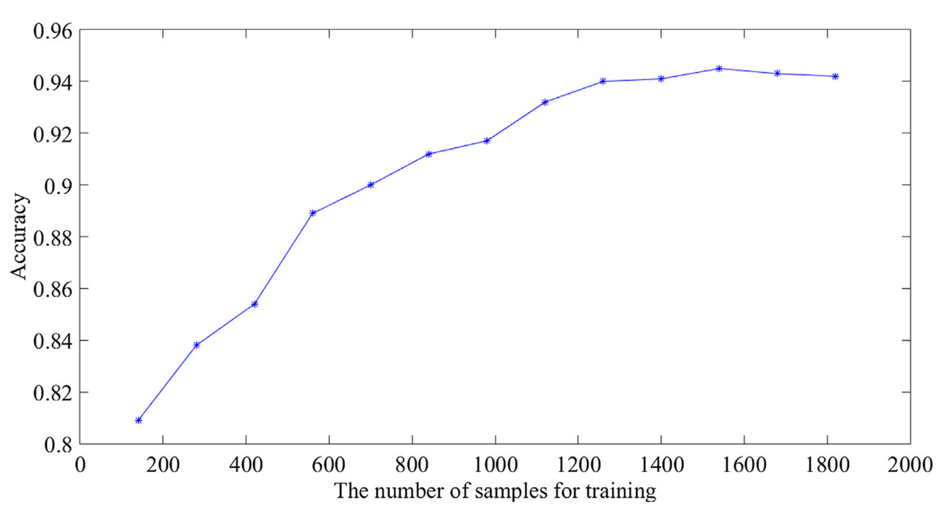


Fig. 17. The relationship between the number of samples for training and the accuracy of test set.

Table 2
Confusion matrix of training set.

	Predicted category							
Actual category		1	2	3	4	5	6	7
	1	176	16	0	2	0	0	6
	2	17	176	0	7	0	0	0
	3	0	0	200	0	0	0	0
	4	2	4	0	194	0	0	0
	5	0	0	0	0	193	7	0
	6	0	0	0	0	5	195	0
	7	8	0	0	0	0	0	192

Table 3
Confusion matrix of the test set.

	Predicted category							
Actual category		1	2	3	4	5	6	7
	1	80	12	0	2	0	0	6
	2	10	90	0	0	0	0	0
	3	0	0	100	0	0	0	0
	4	0	2	0	98	0	0	0
	5	0	0	0	0	100	0	0
	6	0	0	0	0	2	98	0
	7	4	0	0	0	0	0	96

light green, dark green, and colorless bottles are labeled 1 to 7, respectively. In Table 3, it can be seen that 12 light blue bottles are mistaken as lilac bottles, while 10 of lilac bottles are mistaken as light blue bottles, and 4 of colorless plastic bottles are mistaken as light blue bottles. The plastic bottles in these three colors show the phenomenon of mutual misjudgment. The recognition accuracy of plastic bottles in other colors is pretty high. As shown in Table 3, brown and light green plastic bottles are all correctly identified. Only 2 of blue bottles are mistaken as lilac bottles and 2 of dark green bottles are mistaken as light green bottles. Through observation, the colors of light blue, lilac and colorless bottles are comparatively similar, which determines that it may relatively difficult to identify them accurately. On the contrary, the distinction of the other four colors is relatively obvious, which determines that it may easy to identify them accurately. So the test results are in line with expectations.

4. Experimental results and analysis

In this paper, the method of identifying position relationships of plastic bottles and the color recognition scheme described in this paper are verified experimentally. The experimental platform needs to be built first. The illumination conditions have been simulated and analyzed, in which the luminous flux is 24 lm and the value of CCT (correlated color temperature) is 3200 K (working current @IF = 60 mA). The light source is set up based on the simulation results. Two strip light sources are placed symmetrically and their distance in the horizontal direction is 1350 mm. Each strip light source contains 400 lamp beads (5 rows and 80 columns) with an interval of 10 mm. The distance of the light sources to the recycling line is 1000 mm. The angle between the light sources and the horizontal surface is 0°. The brightness of the light sources has been adjusted appropriately. The width of the conveyor belt is 800 mm. The sorting system does not require very high positioning accuracy for plastic bottles and the positioning accuracy of 2 mm is acceptable based on a study. So the longitudinal resolution of the camera must be greater than 400. In order to ensure the running efficiency of the system, the resolution of the camera selected is 672×512. The focal length of the camera lens is 4 mm. The distance of the camera to the recycling line can be calculated by the width of the conveyor belt and camera parameters, which is set to 1000 mm. The processing program has been designed in advance, in which the computational time of one frame is about 270 ms. The experimental scene is shown in Fig. 18.

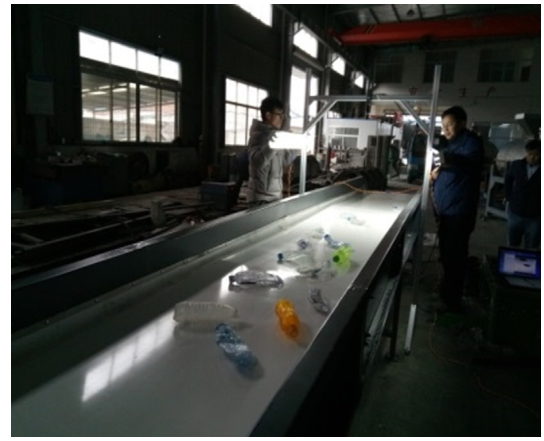


Fig. 18. Experimental scene.

Table 4
Experimental results of the discrimination of the position relationships between plastic bottles.

Position relationship	Disjoint targets	Adjacent targets	Overlapping targets
Quantity	30	30	30
Quantity with correct judgment	30	27	30
Accuracy	100%	90%	100%
Total accuracy	96.67%		

For the verification of the identification of position relationships, images of disjoint plastic bottles, adjacent plastic bottles and overlapping bottles are grabbed, respectively. The position relationships of plastic bottles are determined by the method described in Section 2.2.

For the color recognition, the model trained in Section 3.3 is used. Color recognition of 1446 plastic bottles is carried out in this experiment.

The result of the discrimination of the position relationships between plastic bottles is shown in Table 4, which shows the accuracy of disjoint plastic bottles and overlapping plastic bottles reached 100%, but the accuracy of adjacent bottles only reached 90%. After careful analysis, all the wrong targets are misjudged to be overlapping bottles. See the misjudged images shown in Fig. 19, the degree of contact between plastic bottles is large, resulting in errors that some adjacent bottles are misjudged as the overlapping ones. Therefore, the method for the identification of position relationships between plastic bottles is more accurate for disjoint bottles, mild adjacent bottles and overlapping bottles.

For the color recognition, the model trained in Section 3.3 is used. Color recognition of 1446 plastic bottles is carried out in this experiment and the result is shown in Table 5. It can be seen that by using the developed SVM algorithm, all seven kinds obtain the higher accuracy except for light blue, lilac, colorless plastic bottles.

Efficiency and accuracy of the system are two main performances that need to be improved continuously. There are many factors affecting them. In addition to hardware improvements, such as illumination conditions and the processor, the choice of algorithms is also very important.

Fig. 19. Plastic bottles with larger contact.

Table 5
Experimental results of color recognition of plastic bottles.

Colors of plastic bottles	Quantity	Quantity with correct judgment	Accuracy
Light blue	182	162	89%
Lilac	186	168	90.3%
Brown	194	194	100%
Blue	239	233	97.5%
Light green	217	209	96.3%
Dark green	205	198	96.6%
Colorless	223	205	91.9%
Total	1446	1369	94.7%

5. Conclusion

This study proposed a systematic method to sort the plastic bottles in different colors for the purpose of the recycling. The present work in this paper tried to solve some key problems, such as the identification of the positional relationship between the surrounding bottles, the treatment of the adjacent bottles, and the color classification of all the bottles.

The disjoint plastic bottles can be identified directly by the ratio of the area of the contour to the area of the convex hull based on their image. For the adjacent plastic bottles, the presented method called distance transform and threshold segmentation was useful for distinguishing them from overlapping plastic bottles. The results demonstrated that disjoint ones can be identified accurately. In most cases, the method that applied to identify the adjacent bottles was useful, but it was easy to misjudge the adjacent bottles with larger contact as overlapping plastic bottles. The number of samples could affect the accuracy of color recognition. But the stability and accuracy of the identification was almost saturated when the number of samples reached 1400.

Overall, the color recognition method proposed in this paper witnessed higher recognition accuracy. But light blue, lilac and colorless plastic bottles were easily misjudged because their difference on color is not obvious. In the future work, better color features and a better recognition algorithm should be selected to improve the accuracy of color recognition especially for light blue, lilac, and colorless plastic bottles. In addition, the improvement of SVM with data pre-processing of database will be very valuable. The hardware, such as light source and the color of the conveyor belt, will be another direction for the improvement of the system.

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