

Glass Bottle Inspector Based on Machine Vision

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Abstract—This text studies glass bottle intelligent inspector based machine vision instead of manual inspection. The system structure is illustrated in detail in this paper. The text presents the method based on watershed transform methods to segment the possible defective regions and extract features of bottle wall by rules. Then wavelet transform are used to exact features of bottle finish from images. After extracting features, the fuzzy support vector machine ensemble is putted forward as classifier. For ensuring that the fuzzy support vector machines have good classification ability, the GA based ensemble method is used to combining the several fuzzy support vector machines. The experiments demonstrate that using this inspector to inspect glass bottles, the accuracy rate may reach above 97.5%.

Keywords—Intelligent Inspection, Support Vector Machines, Ensemble Methods, watershed transform, Wavelet Transform

I. INTRODUCTION

VARIOUS kinds of bottle products are used in large amount in food and drink production. Take the beer production for example, in 2006 the total beer output has surpassed 35 million tons in China, and the majority of beer is canned with glass bottles. Because bottles probably have some defects that may cause negative even dangerous consequences for production, glass bottles need to be checked before the products are canned in production. In many cases, this kind of work is performed manually. But manual inspection not only increases labor cost but is very difficult to guarantee inspection quality.

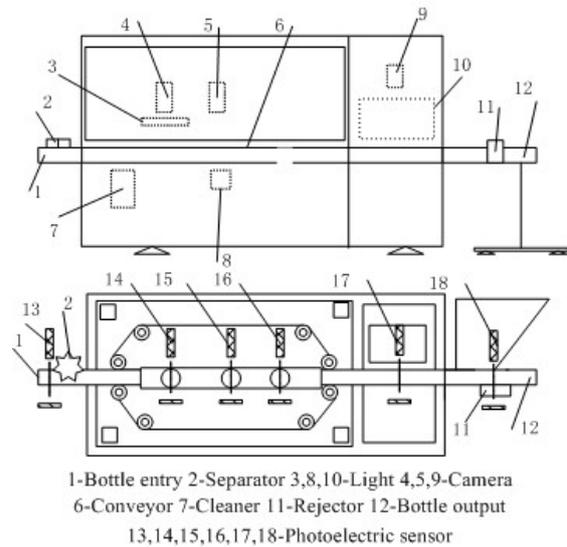
Machine vision inspection system has been successfully applied in many industries, for example, the integrated circuit production, the fruit and food quality inspection etc[1-5]. Some useful solutions for bottle inspection were also developed. The methods which were presented in the article [6] give their much attention to cracks in upper portion of glass bottle. The captured image is corrected by adaptive gray correction and then translated to binary image. The binary image is judged according to conditions. The reflection illumination is adopted to capture images. Hence it can get the clear images of crack on surface but hard to get the clear image of adhesive substance. The paper [7] putted forward a defect inspection method for empty water bottle. The defect is detected base on the intensity variations of the image within image segment. This method decides defect only according to one character, pixel intensity. So it is affected easily by noise. This paper studies the machine vision system and proposes a new glass bottle inspector. It can inspect roundly the bottle wall and finish.

II. INSPECTOR

A. Structures

The basic structure of the glass bottle intelligent inspector is shown in figure1.

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1-Bottle entry 2-Separator 3,8,10-Light 4,5,9-Camera
6-Conveyor 7-Cleaner 11-Rejector 12-Bottle output
13,14,15,16,17,18-Photoelectric sensor

Fig. 1 The structure of glass bottle intelligent inspector

Being simple in mechanical structure and convenient to maintain, line structure is chosen in our system. A separator at the entrance of glass bottle intelligent inspector is used to separate the bottles from each other in a certain distance. In this way, subsequent inspection can be performed reliably. A flexible rejector driven by a pneumatic power is equipped at exit of inspector besides the production line. A specific valve controls the rejector and enables it to reject the defective bottles off the production line at a required speed. The rejector adopts the method which hits goods with a ladder-type stroke. Thus, the rejected object is not easy to turn over even if it is on the high-speed movement. The figure 2 shows the structure of this rejector.

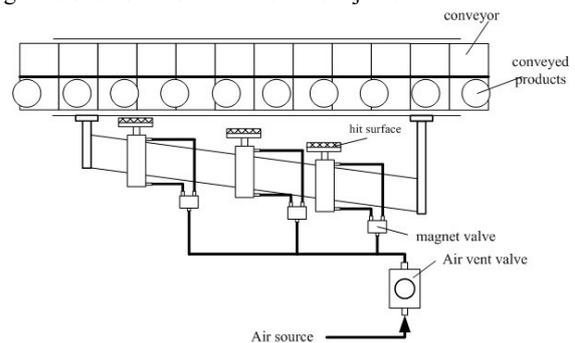


Fig. 2 The rejector

B. Illumination and Image Capturing

Good light source is very critical for a vision-based inspection system^[8]. An appropriate design of illumination is beneficial to simplify the image processing. The LED light source, being efficient and easily controllable, has been adopted in various machine vision applications. Considering the excellent performances of LED light^[9], this inspection system uses specific LED lights.

A plate LED light source is used when the system photos the bottle wall. The transmission-illumination is employed, like figure 3A. In this situation, Crackles and stains on the bottle can be displayed in the image very clearly, so it will be advantageous to next processing. For scanning whole wall, the two images are captured from different angles, like figure 3B.

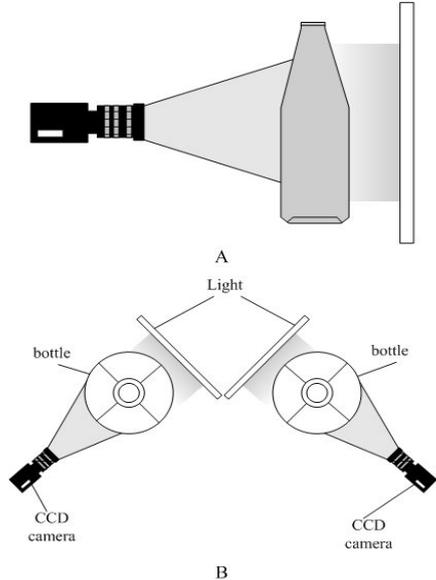


Fig. 3 The illumination of bottle wall

In order to gain the clear image of the bottle finish, an umbrella shape LED is adopted as the light source. The camera photos the bottle mouth from the hole of the light source, like Figure 4. In the photo of the bottle mouth like this, the normal region for the bright area appears; if there are some damages or stains, some regions for the dark area can also appear.



Fig. 4 The illumination of bottle finish

This inspection system uses a high-speed progressive scan CCD camera, which is able to obtain a whole frame image at one shuttle in 1/60 second. Progressive scan offers excellent resolution of the image and consequently improves the accuracy of inspection. The frame grabber is responsible for digitizing the image and provided several digital I/O connector, through which the industry PC are able to receive signal of sensors and send control signal to other components.

III. FEATURES

A. Features of Bottle Wall

The wall defect in captured image is a dark region. These dark regions need be segmented from the background before exacting features. To segmenting these regions, an algorithm based on watershed transform is presented.

The watershed transform is a popular segmentation method coming from the field of mathematical morphology^[10]. The intuitive description of this transform is quite simple: if the image is considered as a topographic relief, where the height of each point is directly related to its gray level and rain is considered gradually falling on the terrain, and then the watersheds are the lines that separate the “lakes” (actually called catchment basins) that form. Generally, the watershed transform is computed on the gradient of the original image, so that the catchment basin boundaries are located at high gradient points. But the traditional watershed transform generally leads to over-segmentation due to noise and other local irregularities of the gradient. For avoiding this problem, this paper introduces some prior information to improve watershed transform.

The gradient of image is calculated by morphology. The morphologic gradient can depend less on edge directionality^[10]. The gray-scale dilation of f by b , denoted $f \oplus b$, is defined as^[10]

$$(f \oplus b)(s, t) = \max \{ f(s-x, t-y) + b(x, y) \mid (s-x), (t-y) \in D_f, (x, y) \in D_b \} \quad (1)$$

Where D_f and D_b are the domains of f and b , respectively.

And the expression of erosion is^[11]:

$$(f ! b)(s, t) = \min \{ f(s+x, t+y) - b(x, y) \mid (s+x), (t+y) \in D_f; (x, y) \in D_b \} \quad (2)$$

The morphologic gradient of image is computed by dilation and erosion^[11].

$$g = (f \oplus b) - (f ! b) \quad (3)$$

The edge is a set of points lie on the boundary between two regions. Though the edge can not describe fully the boundary, it can show the information of defect region and background. So the edge is used to modified the gradient of image. According to the characteristics of defect region, the Sobel edge detection is selected. The formula of modified gradient is like as

$$gd(x, y) = \begin{cases} g(x, y) + C & \text{if there are edge point in } N(x, y) \\ g(x, y) & \text{else} \end{cases} \quad (4)$$

Where $N(x, y)$ is the 3*3 neighborhood of the point (x, y) , and C is the constant.

The defective region of bottle wall is dark region, so the gray level of these regions is relative low. Hence the regional minima of image should be in object region. Regional minima are connected components of pixels with the same intensity value, t , whose external boundary pixels all have a value greater than t . This paper uses the regional minima as the markers.

The images of bottle wall are segmented by the modified watershed transform, and the results are like as figure 5.

The fig.5 (a) are the images of bottle wall, the (b) are the

results of modified watershed transform, the (c) are the results of classic watershed transform.

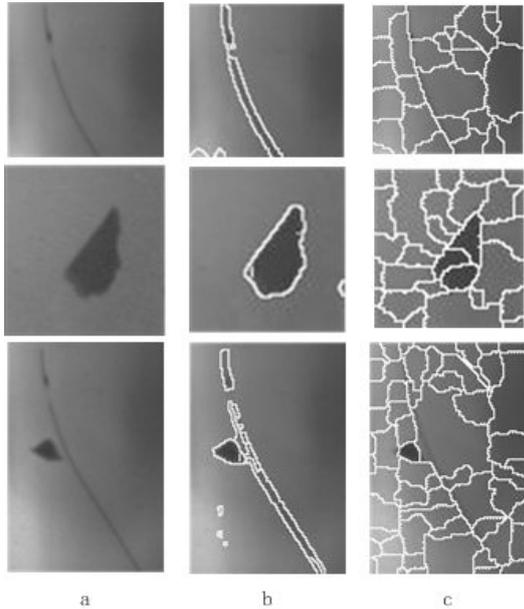


Fig. 5 The results of watershed transform

The modified watershed transform can segment the defective regions, and reduce over-segmentation. But the segmented regions are not all defective regions, some are the noise.

Some features are exacted in these regions for identifying if they are defect.

$$F_b(1) = N_d \quad (6)$$

Where N_d is number of possible defective regions.

$$F_b(2) = \sum_{n=1}^{N_b} n \cdot A_n \quad (7)$$

Where A_n is area of possible defective region n .

$$F_b(3) = A_m \quad (8)$$

Where A_m is the maximum area in all possible defective regions.

$$F_b(4) = \bar{G}_m \quad (9)$$

Where \bar{G}_m is the mean of gray level in the region whose area is the maximum in all possible defective regions.

$$F_b(5) = \sum_{j=\bar{G}_m-1}^{\bar{G}_m+1} P_j(j) \quad (10)$$

Where $P_r(r)$ is probability density function of gray level r in the region whose area is the maximum.

$$F_b(6) = A_g \quad (11)$$

Where A_g is the area of the region which the mean of gray level in this region is maximum in all possible defective regions.

$$F_b(7) = \bar{G}_g \quad (12)$$

Where \bar{G}_g is the mean of gray level in the region

which the mean of gray level in the region is the maximum.

$$F_b(8) = \sum_{j=\bar{G}_g-1}^{\bar{G}_g+1} P_j(j) \quad (13)$$

Where $P_r(r)$ is probability density function of gray level r in the region which the mean of gray level is the maximum.

B. Features of Bottle Finish

In procedure of extracting the features of the bottle finish, in view of the bottle finish shape, the circular law is used to carry on the scanning. In scanning, the center of the bottle finish is taken as the center of a circle; each point is scanned through changing the radius and central angle. Because the round size of the real glass bottle finish ring has differences in practice, the round width of the ring in obtained bottle finish image can also be varied. So the scope of the ring's radius is given in advance. The ring's radius of the normal bottle finish lies in this range. The scanning point is obtained by formula (14).

$$\begin{cases} x = x_C + r * \cos \theta \\ y = y_C - r * \sin \theta \end{cases} \quad (14)$$

Where (x_C, y_C) is the center of the bottle finish, the scope of the r is (r_1, r_2) , and θ ranges from 0 to 359.

In scanning, the average gray level of different central angle is calculated by formula (15).

$$L_\theta = \frac{\sum_{r_1}^{r_2} f(x, y)}{r_2 - r_1} \quad (15)$$

Where $f(x, y)$ is the gray level of (x, y) , (x, y) is decided by formula (14).

The L_θ of bottle finish is like figure 8.

If the quality of bottle finish is eligible, its image should be a ring which has a consistent width, and the gray level is smooth. So the L_θ would have little changes in different central angle. Otherwise the L_θ would have big changes.

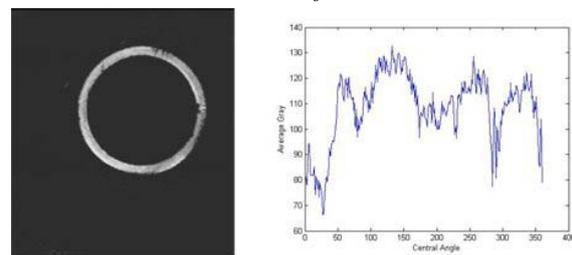


Fig. 8 The L_θ of the bottle finish

For finding these changes, the 1D wavelet transform^[11] is used. There are many jagged noise and other information in the curve of L_θ . The multilevel approximation coefficients of wavelet transform is used for reducing the noise and unimportant information. The multilevel approximations of L_θ are shown in figure 9.

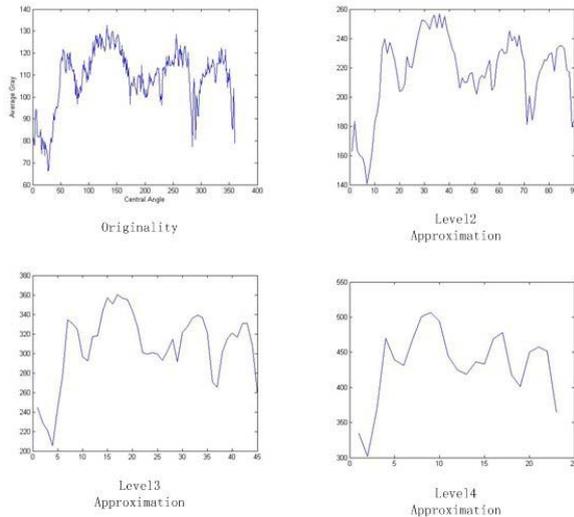


Fig.9 The multilevel approximations

The level 3 approximation coefficients not only keep the main information but also reduce the noise, so the level 3 approximation coefficients are chosen as the base of features. The features are as follow:

$$F_f(i) = \begin{cases} cA(i) & \text{if } cA(i) \text{ is a extreme} \\ 0 & \text{others} \end{cases} \quad (16)$$

Where $cA(i)$ are the level 3 approximation coefficients.

IV. FUZZY SUPPORT VECTOR MACHINE ENSEMBLE

After getting the features, the classifier is used to classify the bottles, which is based on fuzzy support vector machine ensemble.

A. Fuzzy Support Vector Machine

The support vector machines (SVMs) were proposed originally in the context of machine learning, for classification problems on (typically large) sets of data which have an unknown dependence on (possibly many) variables. The SVMs are based on structural risk minimization methods, and produce a decision surface as the optimal hyperplane that separates that two classes with maximal margin^[12, 13]. The support vector machines have been used as one of the high performance classifying systems because of their ability to generalize well.

The fuzzy theory uses fuzzy set instead of normal set, and can process the fuzzy information. The fuzzy theory simulates the thinking method of human, and the fault tolerance is good.

A fuzzy support vector machine is proposed in this paper as basic classifier. It synthesizes the fuzzy theory and support vector machines, and uses a genetic algorithm based optimization method to choose the parameters.

The fuzzy support vector machine consists of the fuzzy layer and the SVMs. The function of the fuzzy layer is fuzzification. The features are input into the fuzzy layer, and then they are translated into fuzzy outputs. This layer uses Gaussian function as the membership function. The function is:

$$\mu(x) = \exp\left[-\left(\frac{x-a}{b}\right)^2\right] \quad (17)$$

Then, the support vector machines are used as classifier for

fuzzy outputs.

In the SVMs when input data can not be lineally separated, they should be mapped into high-dimensional feature spaces, where a linear decision surface discriminating two classes can be designed. So the kernel functions are important to the SVMs, they would influence on the performance of the SVMs. The best parameters of kernel functions need to be chosen before training the SVMs. On the other hand, there are two parameters of the Gaussian function in fuzzy layer, these parameters also need to be optimized.

Genetic algorithms constitute a global optimization technique that has been shown to be successful in many domains^[14]. Thus, a GA-based selection of components for the fuzzy SVM is proposed in this text. The flow is shown in figure 10.

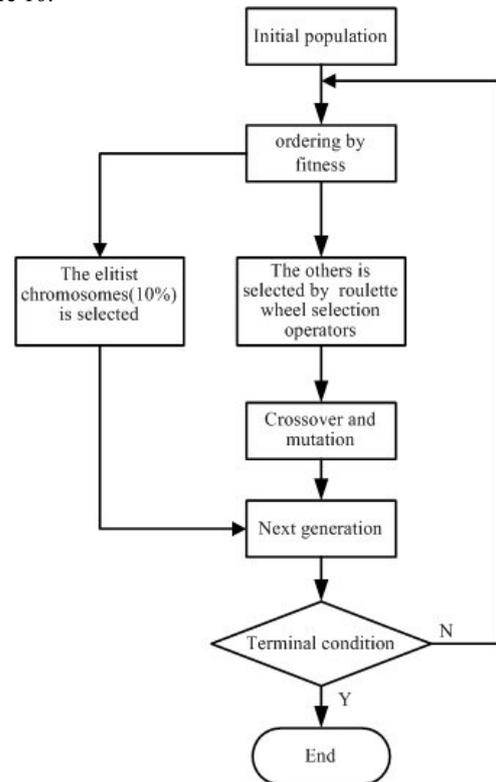


Fig. 10 The flow chart of optimization algorithm

In this method chromosomes are encoded as real number. The structure of the chromosomes is as follows:

$$(F_{a1}, F_{b1}, \dots, F_{am}, F_{bm}, P_1, P_2, \dots, P_n)$$

Where parameter P_k is a parameter of kernel function. The

F_{ak} and F_{bk} are the parameters of Gaussian functions in fuzzy layer. The initial population is random crafted in different regions. This method can make the initial population distribute more uniformly. The elitist selection (10%) and roulette wheel selection operators are employed for reproduction. The fitness function, in accordance with which the individuals are selected for breeding, is given by:

$$F_k = \frac{1}{1 - A_k} \quad (18)$$

Where the A_k is the accuracy of classification. The cross-validation is used for getting the accuracy of classification. In u-fold cross-validation, the training sets are

firstly divided into u subsets of equal size. Sequentially one subset is tested using the classifier trained on the remaining $u-1$ subsets.

The crossover operator is as follows:

For two chromosomes $A_i = (a_1, a_2, \dots, a_n)$ and $B_i = (b_1, b_2, \dots, b_n)$, the chromosomes are $A'_i = (a'_1, a'_2, \dots, a'_n)$ and $B'_i = (b'_1, b'_2, \dots, b'_n)$ after crossover. Where

$$a'_i = \beta_i a_i + (1 - \beta_i) b_i \quad (19)$$

$$b'_i = \beta_i b_i + (1 - \beta_i) a_i \quad (20)$$

The β_i is a random number in $[0, 1]$.

The mutation operator is given by:

$$a'_i = \begin{cases} a_i + f(t, a_{i_{\max}} - a_i) & rad = 0 \\ a_i - f(t, a_i - a_{i_{\min}}) & rad = 1 \end{cases} \quad (21)$$

Where rad is a random

number, $f(t, y) = y(1 - r^{(1-\frac{t}{T})^2})$, t is the number of generation now, T is maximum of generation, r is a random number in $[0, 1]$.

The probabilities of crossover and mutation are adaptively decided; namely these probabilities relate to the situation of evolution. The probability of crossover is decided by:

$$P_c = \begin{cases} (f_{\max} - f') / (f_{\max} - \bar{f}), f' > \bar{f} \\ 0.8, f' \leq \bar{f} \end{cases} \quad (22)$$

Where f' is the bigger fitness in the two chromosomes.

The probability of mutation is:

$$P_m = \begin{cases} 0.5 * (f_{\max} - f') / (f_{\max} - \bar{f}), f' > \bar{f} \\ 0.5, f' \leq \bar{f} \end{cases} \quad (23)$$

Where f' is the fitness of the chromosomes.

B. Ensemble Method

Because the fuzzy support vectors obtained from the learning is not sufficient to classify all unknown bottle samples completely, a single FSVM can not be guaranteed that it always provides the global optimal classification performance over all bottle. To overcome this limitation, this paper proposes to use an ensemble of fuzzy support vector machines. On the other hand the best kernel function in fuzzy support vector machines is difficultly chosen, but in ensemble, the different fuzzy support vector machines can choose different kernel functions. So the best kernel must not be chosen.

Variance of basic classifiers affects ensemble's performance^[17]. The bigger variance of basic classifiers is advantage to performance of ensemble methods. And for SVM, there are some kernel functions which need to be chosen. But because choosing the kernel functions relates to model of the object, it is a difficult problem. In fuzzy support vector machines ensemble, the kernel functions are choose at random. It not only can enlarge the variance and avoid the problem of choosing the best kernel function.

The article^[18] reveals that in the context of classification, when a number of neural networks are available, ensembling

many of them may be better than ensembling all of them, and the networks that should be excluded from the ensemble satisfy equation.(24)

$$\sum_{j=1}^m \text{Sgn}((\text{Sum}_j + N_{kj})d_j) \leq 0 \quad (24)$$

$j \in \{j | \text{Sum}_j \leq 1\}$

And the selective ensemble methods base on genetic algorithm is presented in the article^[18], which is proved that it can generated ensembles with better ability than Bagging and Boosting. So in this paper, this ensemble method is use to ensemble fuzzy support vector machines.

The procedure of constructing the fuzzy support vector machines ensemble is follows:

- 1) The N training sets is generated by bootstrap method;
- 2) The fuzzy support vector machine is optimized and trained according to one train set, and the kernel function is chosen randomly;
- 3) The step 2 is repeated N times, and then N fuzzy support vector machines are trained;
- 4) These fuzzy support vector machines are ensemble by the selective ensemble method based on GA;
- 5) The most voted methods is adopted to ensemble fuzzy support vector machines.

V. EXPERIMENTS

Based on the research of this paper, a prototype equipped is developed. The figure 11 shows the machine. Some experiments have been done on this prototype equipped in order to test this machine and these methods.



Fig. 11 The prototype of inspector

The 500 bottles are used in experiments. The 300 bottles are used for training. The 600 images include 300 images of bottle finish and wall have been photoed separately. First, these images of bottle finish and bottle wall are compared with the real glass bottles so as to identify the glass bottles. After that, decide whether the bottle is good. If bottles are good, they belong to class 1, otherwise they belong to class 2. The other bottles are used for test. Then, extract features from these images according to the rules in section 3, and the features can be used as training samples for the fuzzy support vector machines ensemble.

The features are firstly scaled down to $[0, 1]$. The kernel functions can be chosen from the RBF functions, polynomial functions and, 25 bootstrap replicates are used. The F_{ak} and F_{bk} are in $[0, 1]$. The parameters P_k of kernel functions are in $[0, 10]$. The number of chromosomes in population is 20; the initial population is crafted in 10 regions at random. In contrast with fuzzy support vector machine ensemble, a single FSVM is use as classifier. The experiments are

repeated 10 times, the means are taken as last results.
The table 1 shows the test results.

TABLE I THE TEST RESULTS(%)

	<i>Good bottle (single)</i>	<i>Defective bottle (single)</i>	<i>Good bottle (GA based ensemble)</i>	<i>Defective bottle (GA based ensemble)</i>
Bottle finish	97.5	97.8	98.1	98.4
Bottle wall	95.3	96	97.5	97.3

The wall defect which is larger than 1.5mm² can be detected by this method on the prototype. And the minimum size of the finish defect which can be detected is 0.5mm².

VI. CONCLUSION

In this study, the structure of a glass bottle intelligent inspector is developed and its feasibility is proved. The possible defective regions of bottle wall are labeled by morphologic methods, and features are summarized after comparing with the real glass bottle defects. The bottle finish features are extracted by methods based on 1D wavelet transform. These features extracted from the images are classified by the fuzzy support vector machines ensemble. The fuzzy support vector machines synthesize the fuzzy theory and SVMs, and the parameters are optimized by the GA. In fuzzy support vector machines, the features are performed fuzzification, and then classified by the SVMs. Because the fuzzy support vectors obtained from the learning is not sufficient to classify all unknown bottle samples completely, a single FSVM may be far from theoretically classification performance. To improve the limited classification performance of the real FSVM, this paper proposes to use the SVM ensemble with selective ensemble methods based on GA. And the ensemble methods are also helpful to the problem of choosing the kernel function in fuzzy support machines. The experimental results show that the inspector is effective.

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