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Glass Product Defects Detection Method Based on Machine Vision

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Abstract: This paper develops the machine vision based detection method to detect glass products defects. The novel segmentation method based on unsupervised learning is proposed to segment the defect regions and background. The fuzzy support vector machine was adopted as classifiers for the extracted features. The experimental results indicated the accuracy rate can reach up to 96.7 % by using the methods developed to detect glass bottles defects. *Copyright © 2013 IFSA.*

Keywords: Machine vision, Intelligent detection, Unsupervised learning, Fuzzy support vector machines.

1. Introduction

Large numbers of glass products are used in life and production. For example in China over 35 millions tons of beers were produced in 2012 with the majority of beer products packed in glass bottles. To ensure the quality of the final products, it is necessary to detect the glass products for defects. In many cases, this kind of work is performed manually. However, manual detection is not only expensive time-consuming, but also very difficult to guarantee the quality.

The machine vision detection system has been successfully applied in the field of the integrated circuit, intelligent vehicle, image analysis, fruit and food quality detection etc. [1-6]. It also offers certain solutions for glass products detection. The method described in the article [5] gives much attention to cracks in the upper portion of glass bottles. But the crack problem is one of the defects. The detection precision of other defects is not desirable using this method.

In this paper, a new machine vision method has been developed, which can be used to detect the glass products. The system took image photos of glass products by a digital camera, and then extracted and analyzed the features of the images to determine the defects of the glass products

2. Illumination System

A plate LED light was used when the camera took a picture of the glass products. The glass products were placed between the light and the camera, constituting the transmission-illumination relationship, shown in Fig. 1. In this case, breakages and stains on the glass products can be clearly displayed, which is beneficial to the next step of glass product detection.

3. Detection Methods

3.1. Possible Defective Region Segmentation

The glass products defects in captured image were dark in region. To segment these regions, the image segmentation need be used. The gray level of motion regions is different from the background in differenced image. So in this method the region segmentation is key thing for detect regions. Many algorithms for converting a gray image into a binary image are presents. However the image of glass has different characters. The gray of background in image is varied, so the segmentation result using tradition algorithms is not ideal. To segment these image, a novel algorithm based unsupervised learning is presented. Clustering can be used to divide a digital image into distinct regions for border detection or object recognition [6, 7]. This paper puts forward to a novel methods based on unsupervised pattern classification. This method firstly uses Fuzzy C-means methods to classify the image, and then chooses the samples which is high-confidence by fuzzy voting. These samples are used to train the fuzzy support vector machines. Finally the image is classified by trained fuzzy SVM.

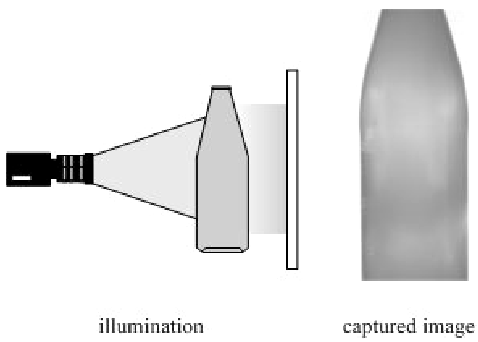

Fig. 1. The illumination of the glass product.

The fuzzy c-means objective function $\{x_K\}_{k=1}^{N}$ for partitioning into clusters is given by:

$$J=\sum_{i=1}^{c}\sum_{k=1}^{N}u_{ik}^{p}\left\|x_k-v_i\right\| \quad (1)$$

where $\{v_i\}_{i=1}^{c}$ are the prototypes of the clusters and the array $[v_{ik}]=U$ represents a partition matrix, $U\in u$, namely

$$u\{u_{ik}\in[0,1]\left|\sum_{i=1}^{c}u_{ik}=1\ \forall k\ \ 0<\sum_{k=1}^{N}u_{ik}<N\ \forall i\right.\} \quad (2)$$

The parameter is a weighting exponent on each fuzzy membership and determines the amount of fuzziness of the resulting classification. The FCM objective function is minimized when high membership values are assigned to voxels whose intensities are close to the centroid of its particular class, and low membership values are assigned when the voxel data is far from the centroid.

Because the pixels in image are not isolated points, the features which can represent the characters of region are chose. The three features are used for FCM, which are as follow.

The feature $fs_1(x,y)$ of point (x, y) is:

$$fs_1(x,y)=gray(x,y), \quad (3)$$

where gray(x, y) is the gray level of point (x, y).

The feature $fs_2(x,y)$ is:

$$fs_2(x,y)=\frac{\sum_{i=-1}^{1}\sum_{j=-1}^{1}gray(x+i,y+j)}{9}, \quad (4)$$

where gray(x, y) is gray level of point (x, y). $fs_2(x,y)$ is average gray level of the 9 point in neighborhood of point (x, y).

The feature $fs_3(x,y)$ is:

$$fs_3(x,y)=Var(X)=\frac{\sum_{i=-1}^{1}\sum_{j=-1}^{1}(gray(x+i,y+j)-\mu)^2}{9} \quad (5)$$

where gray(x, y) is gray level of point (x, y),

$$\mu=\frac{\sum_{i=-1}^{1}\sum_{j=-1}^{1}gray(x+i,y+j)}{9}$$

After classifying the image by FCM according to the features, the high-confidence samples are chose by following condition. First the membership value of the sample is larger than a threshold:

$$fm(x,y)>T_m, \quad (6)$$

where $fm(x,y)$ is a membership value of point (x, y) which is assigned by FCM, and the T_m is a threshold which is 0.8 in this paper.

Second condition is that there are 2 points in neighborhood of the sample which also meets the first condition.

After choosing the samples, these samples are used to train the fuzzy support vectors. The support vector machines (SVMs) are proposed initially in the field of machine learning, to classify problems on (typically large) sets of data having an unknown dependency on (possibly many) variables. The SVMs are based on structural risk minimization methods, and produce a decision surface as the optimal hyperplane that separates the two classes with maximal margin [8, 9].

The fuzzy theory uses fuzzy sets instead of normal sets. It can process the fuzzy information. The fuzzy theory simulates the way of human thinking. Its fault tolerance is good. A fuzzy support vector machine neural network was used in this study as the classifier. It combined the fuzzy theory with the support vector machines. We used an optimization method adopted from a genetic crossbred algorithm to select the optimized parameters.

The fuzzy support vector machine consists of the fuzzy layer and the SVMs. The structure is shown in Fig. 2.

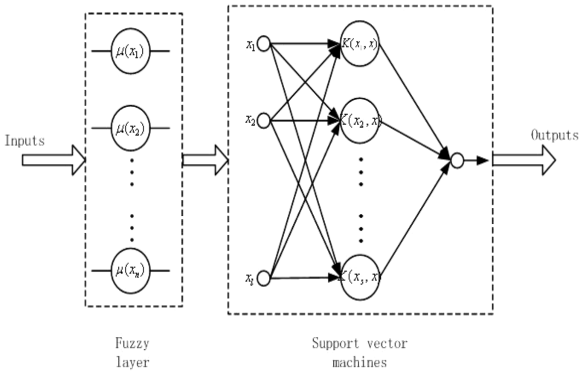

Fig. 2. The structure of the FSVM.

Fuzzification is the function of the fuzzy layer. The features are inputted into the fuzzy layer, and translated into fuzzy outputs. This layer uses Gaussian function as the membership function. The function is as follows:

$$\mu_i\left(x_i\right) = \mathrm{e}^{-\left(\frac{x_i - a_i}{b_i}\right)^2} \tag{7}$$

Then, SVMs are used as the classifier for fuzzy outputs.

Research shows that the use of the hybrid kernel yields a better performance than those with a single common kernel [10]. Hence, the hybrid kernel is applied in this study. The kernel function adopted in this paper is as follows:

$$K\left(x, x_i^*\right) = k_1\left(x \cdot x_i^*\right)^d + k_2\,\mathrm{e}^{-r\left|x - x_i^*\right|^2} \tag{8}$$

Genetic algorithms (GA) constitute the global optimization techniques known to be successful in many domains. Thus, a GA based selection of components for fuzzy support vector machine was proposed in this study. This method was employed to firstly optimize fuzzy support vector machines. The accuracy of classification and the risk of classifier are often used to evaluate the performance of classification. But the traditional GA only performs optimization process according to one goal. This paper adopted a crossbred genetic algorithm，which simulates crossbreeding in biology. There are two different fitness functions, with which the individuals are selected for breeding. So this algorithm suits the optimization of fuzzy support vector machines.

The flow chart of this algorithm is shown in Fig. 3.

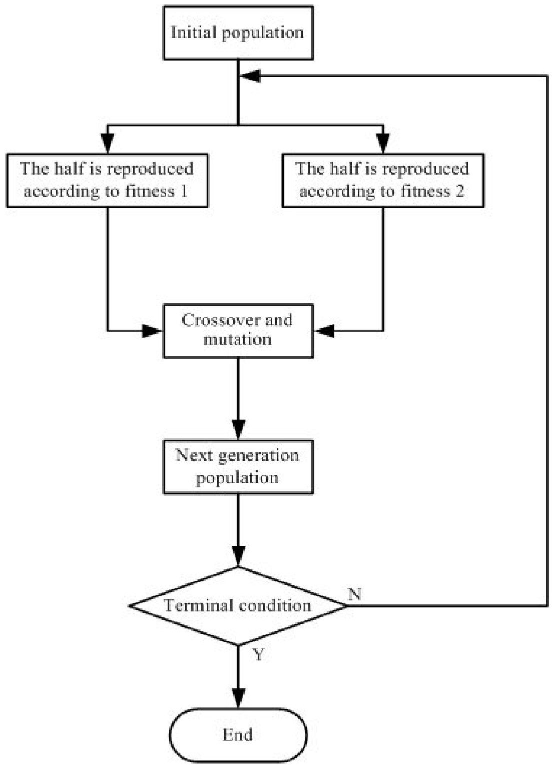

Fig. 3. The flow chart.

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

$$(GF_{a1}, GF_{b1}, \cdots, GF_{am}, GF_{bm}, KP_1, KP_2, \cdots, KP_n) \tag{9}$$

where KP_k is a parameter of the kernel function. The GF_{ak} and GF_{bk} are the parameters of Gaussian functions in fuzzy layer.

The initial population is randomly crafted in different regions. There are two fitness functions, with which the individuals are selected for breeding. The two fitness functions are produced according to the accuracy of classification and the risk of the classifier. One is given by:

$$Fit_{k1} = \frac{1}{1 - C_k} \tag{10}$$

where the C_k is the accuracy of classification, $k = 1, \cdots n$. This accuracy is obtained by u-fold cross-validation. 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 risk can be estimated by VC dimension，which is hard to calculate directly. So the *RT* is employed [12]. *RT* is:

$$RT = \frac{N_{sv}}{l}, \tag{11}$$

where l is the number of train data set, and N_{sv} denotes the number of support vectors.

And another fitness function is given by:

$$Fit_{k2} = 5 / RT_k \tag{12}$$

In reproduction, one half is selected according to fitness function Fit_{k1}, and the other half is selected according to fitness function Fit_{k2}. The elitist selection (10 %) and roulette wheel selection operators are employed for reproduction.

The crossover operator is as follows:

For two Chromosomes $A_i = (a_1, a_2, \cdots, a_n)$ and $B_i = (b_1, b_2, \cdots b_n)$, the Chromosomes are $A_i^{'} = (a_1^{'}, a_2^{'}, \cdots, a_n^{'})$ and $B_i^{'} = (b_1^{'}, b_2^{'}, \cdots b_n^{'})$ after crossover, where

$$a_i^{'} = \beta_i a_i + (1 - \beta_i) b_i \tag{13}$$

$$b_i^{'} = \beta_i b_i + (1 - \beta_i) a_i \tag{14}$$

where β_i is the random number in [0, 1].

The mutation operator is given by:

$$a_i^{'} = \begin{cases} a_i + f(t, a_{i\max} - a_i) & rad = 0 \\ a_i - f(t, a_i - a_{i\min}) & rad = 1 \end{cases} \tag{15}$$

where *rad* is the random number, and

$$f(t, y) = y(1 - r^{(1-\frac{t}{T})^2}) \tag{16}$$

t is the number of generation now, T the maximum generation, r a random number in [0,1].

The probabilities of crossover and mutation are decided adaptively; that is to say, these probabilities relate to the situation of evolution.

The probability of crossover is calculated by:

$$P_c = \begin{cases} (f_{\max} - f_b) / (f_{\max} - \bar{f}), f_b > \bar{f}, \\ 0.8, \qquad f_b \le \bar{f} \end{cases} \tag{17}$$

where f is the hybrid fitness, which is given by:

$$f = 0.6 Fit_{k1} + 0.4 Fit_{k2} \tag{18}$$

And f_b is the bigger f of the two chromosomes, $f_{\max}$ is the maximal f in population, $\bar{f}$ is the mean f of population.

The probability of mutation is:

$$P_m = \begin{cases} 0.5 * (f_{\max} - f) / (f_{\max} - \bar{f}), f > \bar{f}, \\ 0.5, \qquad f \le \bar{f} \end{cases} \tag{19}$$

where f is the hybrid fitness of the chromosomes to be mutated, and is calculated by formula 25. $f_{\max}$ and $\bar{f}$ are the same as formula 17.

The procedure would not be terminated until both the changes of average fitness 1 and average fitness 2 between two neighboring populations are less than the thresholds.

The results of segmentation are shown in the Fig. 4.

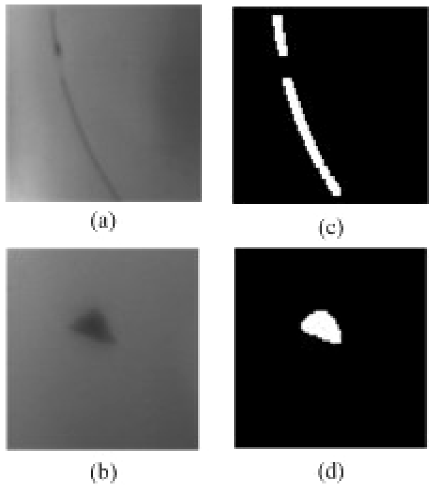

Fig. 4. The segmentation result.

3.2. Classification

The defective region is in dark. So the average gray level of the whole glass products and the segmented regions are calculated. If the mean gray level in some regions is below the whole glass product's, these regions may be defective. Some features are extracted in these regions.

$$F_b(1) = Num_d, \tag{20}$$

where Num_d is the number of possible defective regions.

If there are more possible defective regions with low mean gray level, the glass products can be not good.

$$F_b(2) = \sum_{n=1}^{N_d} Area_n, \tag{21}$$

where A_n is the area of the possible defective region.

This feature indicates the area of all possible defective regions. If this feature is big, the glass products may be defective.

$$F_b(3) = Area_m, \tag{22}$$

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

The feature 4 and the 2 following features show the characters of possible defective regions, of which the area is the largest. This region is one of the most possible defective regions. The size of the defective region is not too small; so if this feature is large, this region may be a defective one.

$$F_b(4) = \bar{G}_m, \tag{23}$$

where $\bar{G}_m$ is the mean gray level in the region, of which the area is the maximum in all possible defective regions.

The gray level of the defective region is low. If the mean gray level is low, this region may be a defective one.

$$F_b(5) = \sum_{j=\bar{G}_m-1}^{\bar{G}_m+1} P_j(j), \tag{24}$$

where $P_j(j)$ is the probability density function of the gray level j in the region， of which the area is the maximum.

The gray level of pixel in defective region is not different. So if this feature is bigger, this region may be the defective one.

$$F_b(6) = Area_g, \tag{25}$$

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

When the mean gray level of the region is the maximum, it is another most possible defective region. This feature and the 2 following features show the characters of this region. And they have the same meaning as features 3-5.

$$F_b(7) = \bar{G}_g, \tag{26}$$

where $\bar{G}_g$ is the mean gray level in the region, in which the mean gray level is the maximum.

$$F_b(8) = \sum_{j=\bar{G}_g-1}^{\bar{G}_g+1} P_j(j), \tag{27}$$

where $P_j(j)$ is the probability density function of gray level j in the region ,where the mean gray level is the maximum.

Then a classifier need be used to classify whether the region is the defect. The defects are diversified, so the glass products detection is a small- size sample problem. And the defects in image are hardly described. The fuzzy support vector machine proposed in this paper is used to classify these regions.

4. Experiments

Experiments were conducted to examine this method. A prototype equipped with an annular conveyor was developed according to section 2. The glass bottles were used as detection objects. The 500 images of glass bottle have been captured separately using this prototype.

First, the images of glass bottle were compared to the real bottles so as to identify the glass bottles. Then the features from the 300 images were extracted according to the rules described in section 3, which would be used as a base for learning the fuzzy support vector machine After the fuzzy support vector machine were trained, they started to judge the features extracted from the other images. In crossbred genetic algorithm, the initial population is randomly crafted in 10 regions. The number of population is 20. The terminated threshold is 0.5. In comparison with the fuzzy support vector machine, the SVM and neural networks were also applied. The RBF kernel function was selected for the SVM. The function is as follows:

$$K_{RBF}(x) = \exp(-r\left|x - x_i^*\right|^2) \tag{37}$$

According to experience, the r is set as 0.5. The number of neurons in hidden layer of neural networks is the number of neurons in input layer adding one. The BP method is applied to train neural networks, and the learning rate is 0.4. The means were calculated based on the experiments repeated 10 times and shown in Table 1.

Table 1. Comparison of accuracy of detecting glass bottle body by using three methods.

	Support vector machine	Neural network	Fuzzy support vector machine
Good(90)	95.6	95.6	96.7
Bad(110)	95.5	93.6	96.4

The experiment results indicated that the fuzzy support vector machine neural networks were superior to the support vector machine and the neural network respectively.

5. Conclusion

This study offers an intelligent detection method to examine the glass products defects. The possible defective regions of glass products were segmented by the novel segmentation methods based on unsupervised learning, and the features were summarized after comparing to the real glass product defects. Then these features were classified by fuzzy support vector machine. As a result, the classifier possesses not only good generalization ability but also strong anti-noise ability. Experiments have been performed on the prototype to prove whether the methods can work effectively. The results showed the method developed in this study was able to detect defective glass bottles with an accuracy rate up to 96.7 %.

References

[1]. Bulnes, F. G., Periodic Defects in Steel Strips: Detection Through a Vision-Based Technique, *IEEE Industry Applications Magazine,* Vol. 19, Issue 2, 2012, pp. 39 – 46.

[2]. Resendiz, E., Automated Visual Inspection of Railroad Tracks, *IEEE Transactions on Intelligent Transportation Systems,* Vol. 99, 2013, pp. 1-10.

[3]. Tsai, Du-Ming, A Shift-Tolerant Dissimilarity Measure for Surface Defect Detection, *IEEE Transactions on Industrial Informatics,* Vol. 8, Issue 1, 2012, pp. 128-137.

[4]. Chen, Shengyong Yong, The Specular Exponent as a Criterion for Appearance Quality Assessment of Pearllike Objects by Artificial Vision, *IEEE Transactions on Industrial Electronics,* Vol. 59, Issue 8, 2012, pp. 3264-3272.

[5]. Irfan Ullah, Furqan Ullah, Qurban Ullah, and Seoyong Shin, Sensor-Based Robotic Model for Vehicle Accident Avoidance, *Journal of Computational Intelligence and Electronic Systems,* Vol. 1, 2012, pp. 57-62.

[6]. S. Rahul Sharma, A. Anand Jain, Khushal Jain and B. Persis Urbana Ivy, Real Time Application of Superimposing Two 2-D Images and Their Projection on Screen, *Journal of Computational Intelligence and Electronic Systems,* Vol. 1, 2012, pp. 54-56.

[7]. Huimin Ma, Guangda Su, Junyan Wang, Zheng Ni, A Glass Bottle Defect Detection System without Touching. in *Proceedings of the First International Conference on Machine Learning and Cybernetics,* Beijing, Vol. 2, 2002, pp. 628-632.

[8]. Zhang Y, Fu-Lai Chung, Wang S T., Robust fuzzy clustering based image segmentation, *Applied Soft Computing,* Vol. 9, Issue 1, 2009, pp. 80-84.

[9]. Yang M-S, Tsai H-S., A Ganssian kernel-based fuzzy c-means algorithm with a spatial bias correction, *Pattern Recognition Letters*, Vol. 29, 2008, pp. 1713-1725.

[10]. Vapnik V. N., Statistical learning theory, *John Wiley & Sons Inc,* 1998.

[11]. Vapnik V. N., Levin E., Le Cun Y., Measuring the VC-dimension of a learning machine, *Neural Computation,* Vol. 6, 1994, pp. 851−876.

[12]. Ying Tan, Jun Wang, A Support Vector Machine with a Hybrid Kernel and Minimal Vapnik-Chervonenkis Dimension, *IEEE Transactions on knowledge and data engineering,* Vol. 16, Issue 4, 2004, pp. 385-295.