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Design of A Diamond Adsorption Detection System Based on Machine Learning Techniques

Zhun Fan, Youxiang Zuo, Fang Li, and Shuangxi Wang

***Abstract*—A diamond adsorption detecting system based on machine learning is presented in this paper. The paper describes the system from the perspective of hardware and software design, and presents the image processing and machine learning algorithms applied in the system. The hardware includes three major parts—the camera, light source and support platform. The software includes modules of image acquisition, image preprocessing, feature extraction, and machine learning. This paper utilizes three supervised machine learning algorithms, namely Support Vector Machine (SVM), Classification and Regression Tree (CART) and C4.5 decisions. Through the comparison study of the three algorithms, SVM is found to have the best performance for this system. It is demonstrated in experimental tests that the algorithm can obtain an accuracy of 97.84%, which improves the detection efficacy of the system significantly.**

Keywords—machine learning; SVM; Decision tree;

I. INTRODUCTION

WITH the rapid development of computer science and technology, intelligent equipment based on machine learning and machine vision have been more widely used and achieved good social and economical benefits. Machine intelligence can not only help the enterprise or the company save a lot of manpower and material resources, but also can save cost of time, etc.

In general, machine learning can be categorized into three types in terms of learning styles: supervised, Semi-Supervised and unsupervised learning methods. Supervised machine learning [1], [2] involves training a model from labelled data, and then the model is used to make a prediction for an unseen instance. This group include SVM, CART, C4.5 decisions and so on. In contrast, unsupervised methods [4] learn a model to describe hidden structure from unlabeled data. Semi-supervised learning is between supervised and unsupervised learning. It exploits both labeled and unlabeled data to learn a classification model [3].

The remainder of the paper is organized as follows. The section II describes the diamond absorption detection system and gives the overall architecture of the system. Then the design of the hardware system is shown in the Section III. The design of the software system based on VS2010, Halcon10.0 and the R platform is presented in the Section IV, with the image processing and machine learning algorithms used in the system explained. The Section V gives the experimental results and the Section VI concludes the paper.

II. THE SYSTEM DESIGN

The architecture of the diamond adsorption detection system is shown in Figure 1.

The system is divided into the module of hardware acquisition and module of the software processing. The hardware acquisition system includes the camera, illumination source and support platform. Software part is based on the VS2010, Halcon, as well as the R platform.

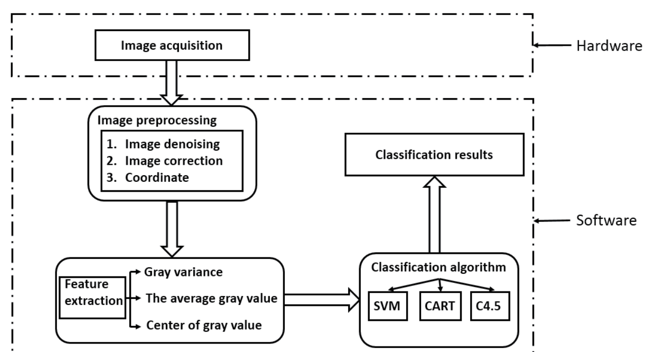

Fig.1.The overall structure of the diamond adsorption detection system.

The main purpose of the paper is on designing a system that can detect diamond adsorption and calculate the efficacy of adsorption. The diamonds to be detected is shown in Figure 2.

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Zhun Fan, is with the Guangdong Provincial Key Laboratory of Digital Signal and Image Processing and the Department of Electronic Engineering, Shantou University, Shantou, 515063 CHN (e-mail: zfan@stu.edu.cn).

Youxiang Zuo, is with the Department of Electronic Engineering, Shantou University, Shantou, 515063 CHN (e-mail: 13yxzuo@stu.edu.cn).

Fang Li, is with the Department of Electronic Engineering, Shantou University, Shantou, 515063 CHN (e-mail: 13fli@stu.edu.cn).

Shuangxi Wang, is with the Department of Mechanical Engineering, Shantou University, Shantou, 515063 CHN (e-mail: sxwang@stu.edu.cn)

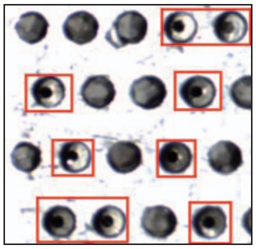


Fig.2. Dark gray diamond

As shown above, the red boxes represent no successful capture of diamond. A diamond suction nozzle template has a size of 39 mm × 12mm, with 339 suction nozzles deployed over it. Each suction nozzle can absorb a diamond, which has a diameter of 1.5 mm. The requirement of this program is that the error rate of the detecting is no more than 3%.

I. THE HARDWARE DESIGN

The hardware contains three parts, i.e. the CMOS color camera with 5 million pixels, quadrilateral strip light source and support platform. In addition, the camera and illumination modules are installed and integrated in the support platform. The design of the support platform is shown in Figure 4.

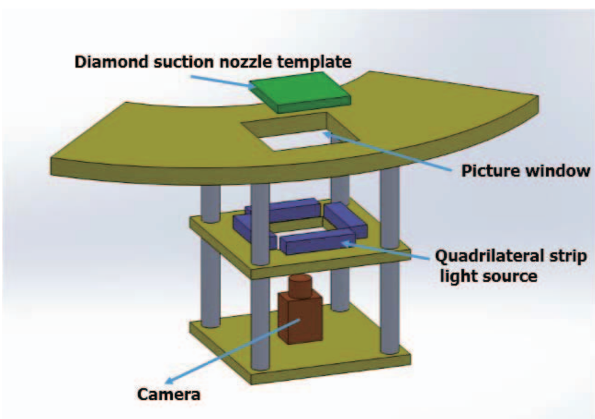


Fig.4.The diagram of the support platform design

After the platform is built up, images can be acquired via the platform. The working process of the image acquisition is divided into three steps. First, the adsorption process of diamond is completed. Then, the whole fixture of suction nozzles moves to the picture window of the camera. Finally, the camera receives a trigger signal and takes a picture.

II. THE SOFTWARE DESIGN

Software design includes the design of user interface and algorithms. Interface design is based on VS2010. In terms of algorithms, this paper studies the algorithms of image preprocessing, image feature extraction and supervised machine learning. Halcon 10.0 is used to complete the image preprocessing and feature extraction. The algorithm of machine learning is mainly implemented in the R platform.

A. User interface design

Interface is designed to facilitate the user's operation. Three main modules are designed, including image processing, parameter setting and results display. The main interface is shown in Figure 5.

The processing module includes those buttons of image acquisition, stop acquisition, save image, processing image, and read image. In the parameter setting module, the exposure time of camera and two corner point coordinates of the reference image are set. The corner coordinates of the reference image are used to do image correction operation, which can be completed by the button of the 'Coordinate Matching'. The interface of coordinate matching is shown in Fig. 6. Finally, interface display on three results: the number of suction nozzle, the quantity of diamond suction and the success rate of diamond suction.

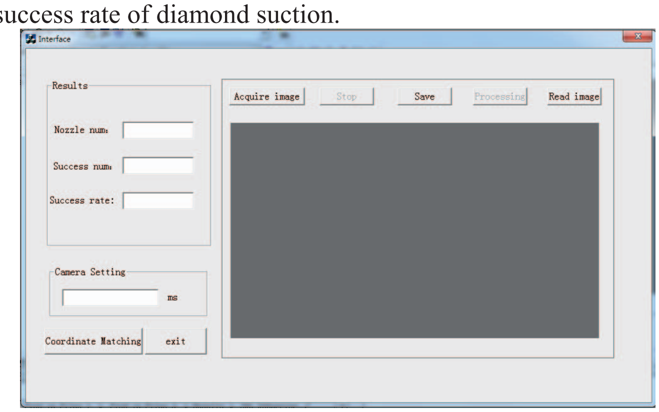


Fig.5.The design of the main interface

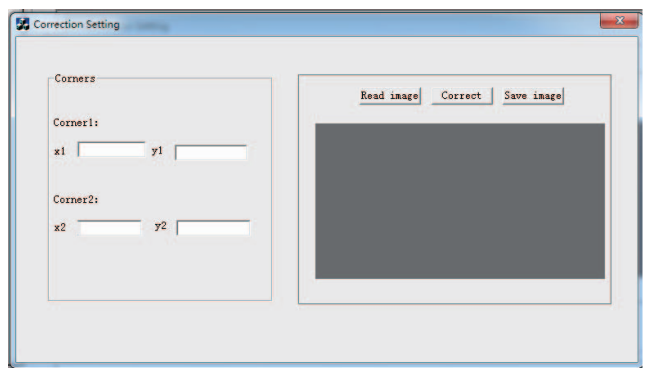


Fig.6.The design of the coordinate setting interface

B. Image processing based on Halcon 10.0

There is a variety of machine vision software in the market. The system uses the German MVTec Halcon 10.0. It provides a comprehensive library of visual processing functions, which include all standard image processing methods and the tools typically required in applications such as Blob Analysis, Morphology, Pattern Recognition, Measurement, Data Analysis and other arithmetic operations. It has the features of open architecture and facilitating rapid prototyping [5]. In this paper, the image processing includes image denoising, image geometric correction, suction nozzle coordinates matching, feature extraction

The template of the suction nozzle contains 339 effective suction nozzles in our experiments. The relative position between the suction nozzles is fixed. Considering that deviation may exist from frame to frame, we need to choose one image as the reference template. The new images need to be corrected according to the reference template. Then we can use Blob and ROI (Region of Interest) analysis to locate the position of each suction nozzle, and extract its coordinates afterwards. Based on the types of diamond and suction nozzle, three main features are extracted from each suction nozzle, which are the variance, average, and center of its pixels' grey values. The experimental data set is composed of suction nozzle label (suction or non-suction) and above-mentioned feature information.

Next, we can use machine learning algorithms to classify the suction nozzles (with or without suction of a diamond).

C. Machine learning algorithm

Three types of supervised machine learning methods are investigated in this paper: SVM, CART and C4.5 decision tree. The three algorithms have their own advantages and disadvantages. The following is a simple introduction of the three algorithms.

(1) SVM

SVM (Support Vector Machines) was proposed by Vapnik in the 1990s [6]. SVM has attracted attention thanks to its high generalization ability and good performance for a wide range of applications. SVM has rigorous theoretical foundation and is based on the idea of finding an optimal classification hyper-plane that divides the classes. When the data points are not linearly separable, the SVM maps data points to a high dimensional feature space where a separating hyper-plane can be found. This mapping implicitly transforms the input space into another high dimensional feature space by the kernel trick [7].

In the SVM, the choice of an appropriate kernel is very important [8]. In this paper we use the linear kernel because it has better performance than other kinds of kernels in this work through empirical study, which is defined as [9]

$$K(x_1, x_2) = \langle x_1, x_2 \rangle \tag{1}$$

Where: x_1 and x_2 are referred to as the feature vectors. $K(x_1, x_2)$ is the inner product of x_1 and x_2.

(2) CART

CART (Classification and Regression Trees) is a basic classification method, which is known as regression trees and proposed by Breiman in 1984. It has been widely applied in statistics and data mining [10].

A complicated tree structure is generated by the CART algorithm at first, and then pruned according to cross validation and test set validation. CART algorithm employs the economics-Gini Index as the criteria for choosing the best characteristic variables [11]. Gini Index is defined as follows [12]:

$$Gini = 1 - \sum_{i}^{I} p^2(i/k) \tag{2}$$

$$p(i/k) = \frac{n_i(k)}{n(k)} \tag{3}$$

$$\sum_{i}^{I} p(i/k) = 1 \tag{4}$$

Where $p(i/k)$ is the probability of a characteristic variable k belongs to I when being a random sample from the training sample set; $n_i(k)$ is the number of the characteristic variable k belongs to I; $n(h)$ is the number of the feature variable k in the training sample; I is the number of classes.

(3) C4.5 decision tree

Decision tree is roughly divided into two steps. Firstly, the training dataset is used for learning, and then a classification model is built. Secondly, we use the model to classify sample datasets.

The C4.5 decision tree is based on the improvement of ID3 [13]. ID3 is also a decision tree method, which choose the characteristic variables as the decision tree node according to the information gain as the criteria and can only process the discrete attributes. C4.5 extends ID3 with capability of processing continuous value of attributes. In addition, the criteria of choosing the node is information gain ratio in C4.5 algorithm, instead of information gain in ID3. The definition of information gain ratio is as follows [14]

$$Gain\text{-}Ratio(\mathrm{A}) = \frac{Gain(\mathrm{A})}{SplitI(\mathrm{A})} \tag{6}$$

$$SplitI(A) = -\sum_{j=1}^{v} p_i log_2(p_i) \tag{7}$$

Where A refers to the property. $Gain(A)$ is the information gain of A, and $SplitI(A)$ is the concept of entropy.

III. Experimental Results

A. Performance evaluation of the algorithms

The performance of algorithms can be evaluated by obtained results measured in terms of accuracy (ACC), sensitivity (SE) and specificity (SP). ACC, SE, SP are given by the following equations.

$$ACC = \frac{TP+TN}{TP+TN+FP+FN} \tag{8}$$

$$SE = \frac{TP}{TP+FN} \tag{9}$$

$$SP = \frac{TN}{TN+FP} \tag{10}$$

Where *TP, FP, TN*, and *FN* are defined as true positive, false positive, true negative and false negative events detected respectively.

B. Experimental results

The classification process contains two phases, the training phase and the testing phase. In order to get reliable estimates for classification accuracy, every experiment has been performed using 10-fold cross-validation.

The results of AC, SE and SP in the training set are shown in Table 1. The comparison results of testing set are shown in Table 2. The data in the table represents the average validation value after 10-fold cross –validation.

Table1.The comparison on training set

Training set			
Algorithm / Precision	SVM	CART	C4.5
ACC	98.44%	97.16%	**98.62%**
SE	96.44%	94.00%	**96.85%**
SP	99.39%	98.65%	**99.46%**

Table2.The comparison on testing set

Testing set			
Algorithm / Precision	SVM	CART	C4.5
ACC	**97.84%**	96.43%	96.82%
SE	**95.33%**	93.66%	93.66%
SP	**99.29%**	97.45%	98.36%

It can be observed from the results that the C4.5 method is better than SVM and CART algorithm in the training phase (as shown in Table 1). In the validation phase, the results of SVM are better than the others, as shown in Table 2.

From Table 1 we can see that the difference between SVM and C4.5 is not significant. In addition, the performance of C4.5 in training stage is good, but it is inferior to the SVM in the testing phase. Considering that the decision tree algorithm is prone to over-fitting, SVM is chosen as the final classification algorithm for the system.

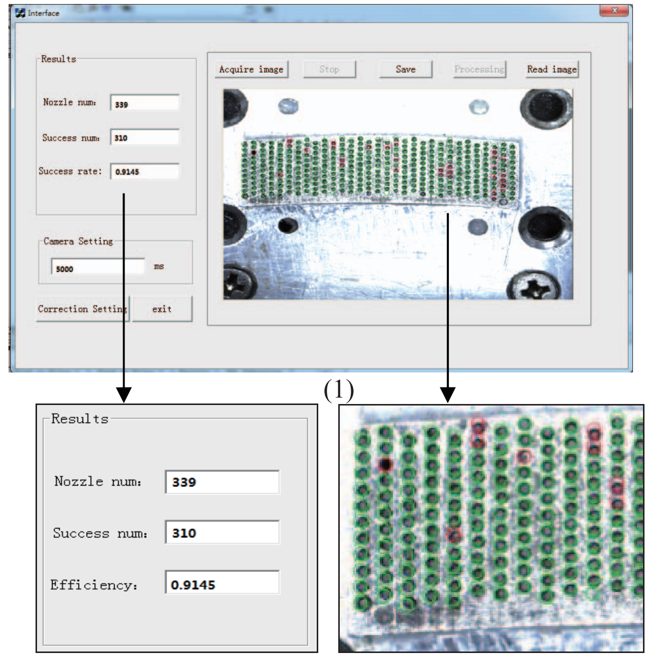
C. Experimental results of the system

An example of diamond suction testing result is shown in Fig.6. 'Nozzle Num' presents effective number of suction nozzle. 'Success Num' is equal to the amount of the suction nozzle that absorbs the diamond successfully. The success rate of suction is as follows：

$$Efficiency = \frac{Success \quad Num}{Nozzle \quad Num} \qquad (12)$$

IV. Conclusion And Future Work

In this paper, we built a system of diamond suction detecting system based on machine learning algorithms. The SVM, CART and C4.5 decision tree three supervised machine learning algorithms tested. Through comparison study of the algorithms via the 10-fold cross-validation experiment, the SVM is chosen as the classification algorithm of the system eventually. It is demonstrated that the system of diamond suction detection achieved the design requirements.



(2) (3)

Fig.7. An example of the system detecting results (1) The overall user interface of the system; (2) The enlarged part of the parameter setting; (3) The enlarged part of the image of diamond suction detection

Considering a full-fledge application of the system to industrial production in the future, a lot more work needs to be done. At present, only one equipment is built and used to do experiments. However, according to our survey, at least 5 sets of equipment need to work at the same time in the factory. The design of the user interface is still relatively simple. In addition, the robustness of the algorithm also needs to be confirmed through a large number of experiments in practice.

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