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# Stored-grain Pests Detection Based on SVM

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***Abstract*—Stored grain pests detection is essential for grain management. In this paper, we have proposed a machine learning method for stored-grain pest detection. We focus on crustacean pests detection using SVM. The 20 pixels width and 20 pixels height pests and background images are directly utilized for SVM training and classification. According to the experiment results, accuracy of SVM classifier is 99.40%, which outperforms LSSVM and PLS. We then conducted an interesting experiment using synthetic pest images. We employ these synthesized data as pest samples for training SVM classifier. According to the results, the SVM classifier trained via synthetic pest images is able to detect pests in images in some cases because synthetic pest images are quite different from real pest images.**

***Keywords—stored-grain pests; SVM; classification***

## I. INTRODUCTION

In recent years, China has increasingly attached importance to food security[1-4], and it's grain storage scale has gradually increased[5-7]. Pests of stored grain become one of the most important factors to food safety. Stored grain pests refer to those living or inhabiting in stored grain of grain depot. Crustacean pests mainly include Araecerus fasciculatus, Corn Weevil, Flat Grain Beetle, Lasioderma Serricorne BruchusPisorum[1] and Silvanidae[1] , as shown in Fig 1.

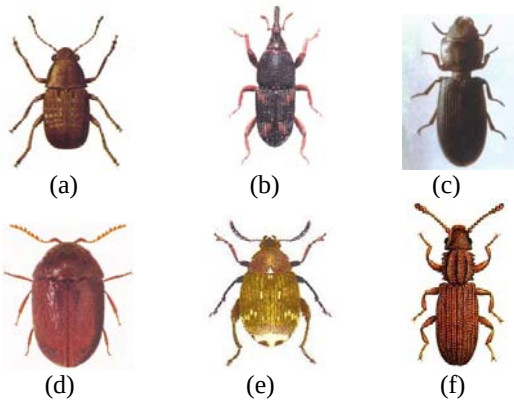


FIGURE I. STORED-GRAIN PESTS. (A) ARAECERUS FASCICULATUS, (B) CORN WEEVIL(C) FLAT GRAIN BEETLE (D) LASIODERMA SERRICORNE(E) BRUCHUSPISORUM (F) SILVANIDAE

Therefore, the use of modern information technology to achieve rapid and accurate identification of stored-grain pests is of great significance for the extension of food storage time. Nowadays, with the widely use of machine learning technologies, Especially SVM has the open source of supervised learning model, the detection of stored-grain pests has also entered a new developing stage. After the images are processed by machine learning and computer, the characteristics of stored-grain pests are extracted and a classifier is generated to identify the insects. Compared with the traditional artificial recognition, it greatly improves the processing speed and paves the way for the full automation of food processing in the future.

This paper proposes a new method to identify stored-grain pests of crustaceans by a SVM classifier. The contributions of our paper can be summarized as: (1)In training phase, we directly employ image to train SVM classifier. Because crustacean pests are black they are very obvious contrast with background.(2)For crustacean pests detection, synthetic pests images are employed to training detector, the detector is capable of detecting the pest in images, and obtain comparable results.

## II. BRIEF INTRODUCTION OF SVM

For the binary classification problem, the squares represent the negative sample, the circles represent the positive one. For linear classification problem there exists a hyperplane $H: wx+b=0$, which can classify these samples unmistakably. SVM can be written as:

$$\min\|w\|^2/2 \quad s.t.\ y_i(wx_i+b)-1\geq 0 \tag{1}$$

This model can be solved via Lagrange duality.

## III. EXPERIMENTS AND RESULTS

### A. Data Set

The samples are fixed on a data-collection platform, and the distance between the camera and the samples is set to be 50cm. The obtained original images are cropped as 256×256. As shown in Fig.2 and 3.

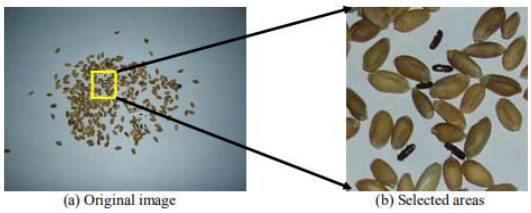


FIGURE II. SAMPLE PREPARATION

FIGURE III. IMAGES IN DATA SETS

### B. Positive and Negative Samples

The pests in the original images are cropped to form the positive sample set, as show in Fig 4.

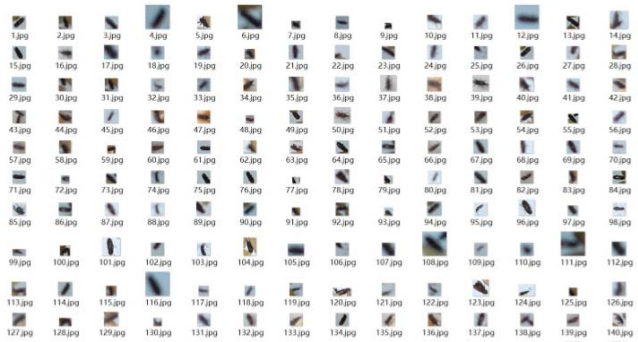

FIGURE IV. POSITIVE SAMPLE

For each 256×256 image, 200 images with a size of 20×20 are randomly selected as the negative samples of the training set, and the images containing pests are deleted. A total of 7,539 images are obtained to form the negative sample set. Some of negative samples are shown in Fig.5.

FIGURE V. NEGATIVE SAMPLE

Firstly, a certain number of images of pests are cut out of all images for the positive samples by manual recognition, and then cut out randomly another certain number of images from the original pictures then remove the stored-grain pests in these pictures artificially and take them as the negative samples. Secondly, select 123 pictures from the positive samples and 3770 pictures from the other respectively as the training set, and take the rest of the positive samples and negative samples as the test set, label the positive samples of the training set and the test set as 2, and the negative ones will as 1 to get the images'labels in the training set and test set, after normalizing the two sets, take the training set and it's label as the parameter to obtain the two parameters of the gaussian kernel function for the model, and input both the training set and the two parameters to train the classifier for the classifier model. select the test sample again, after the samples grizzled processing, randomly cut the 33*33 images and compress them into 20×20 for a matric manipulation, the processed imagines become a matrix with one row and 400 columns, the images and the training set and testing set images as well as the cutted testing image matrixes with normalized processing will return the new training set normalized samples and a classifier model that can be used as parameters to forecast, then identify and display the predicted results (i,e.the pests' imagines ) with a rectangular box in the test samples.

### C. Results and Analysis

We randomly select a part of negative and positive samples for training SVM[8,9, 8, 10–18],PLS[19–23] and LSSVM[24–28] classifiers and the rest for testing.

Background and pest images are labeled as 1 and 2 respectively. In PLS regression, we using a threshold to classify the regression results. The ratio and accuracies are reported in Table.1. As shown in this table, SVM outperforms LSSVM and PLS.

TABLE I. SVM CLASSIFICATION ACCURACY

| accuracy \ ratio / method | 10% | 20% | 30% | 40% | 50% | 60% |
|---|---|---|---|---|---|---|
| SVM(training) | 0.9822 | 0.9888 | 0.9913 | 0.9924 | 0.9930 | 0.9936 |
| SVM(testing) | 0.9833 | 0.9902 | 0.9924 | 0.9927 | 0.9937 | **0.9940** |
| PLS(training) | 0.9986 | 0.9954 | 0.9934 | 0.9937 | 0.9933 | 0.9924 |
| PLS(testing) | 0.9735 | 0.9791 | 0.9833 | 0.9852 | 0.9869 | 0.9877 |
| LSSVM(training) | 0.9691 | 0.9685 | 0.9683 | 0.9685 | 0.9684 | 0.9684 |
| LSSVM(testing) | 0.9682 | 0.9682 | 0.9683 | 0.9681 | 0.9685 | 0.9685 |

Pest detection results are shown in Fig.6, the results demonstrate that the proposed method for stored-grain pest detection method is efficient and effective.

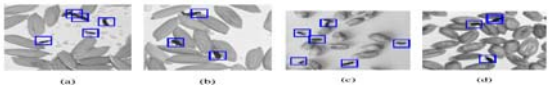

FIGURE VI. DISPLAY RESULTS USING BOUNDING BOX

We then conduct an experiment using synthetic data as shown in Fig.7. We employ these synthesized data as pest samples for training SVM. The detection results are shown in Fig.8. As shown in this figure, we have detect the pests. This idea are similar with small object detection.

FIGURE VII. SYNTHETIC SAMPLE

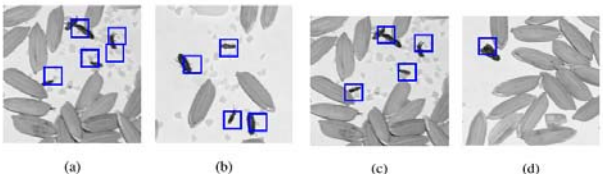


FIGURE VIII. DISPLAY RESULTS USING SYNTHETIC SAMPLE

## IV. CONCLUSION

In this paper, we have proposed a machine learning method for stored-grain pest detection. We focus on crustacean pests detection using SVM. In our experiments, the 20x20 pests and background images are directly utilize for SVM, PLS and LSSVM training and testing. In PLS testing phase, we set 1.3 as a threshold for pests classification. According to the experiment results, SVM achieves the highest accuracy. We then conducted an interesting experiment using synthetic pest images. We employ these synthesized data as pest samples for training SVM classifier. According to the results, the SVM classifier trained via pest images are able to detect pests in an image. This idea are similar with small object detection. After all, synthetic pest images are quite different to real pest images, in some cases, this pest detector can't detect a pest at all. Our future work will focus on deep learning based pest detection and recognition. Deep learning is a powerful tool. It's a useful feature leaning framework in computer in computer vision. In stored-grain pests detection area, it may have higher performance than traditional methods.

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