

A Deep Detection Model based on Multi-task Learning for Appearance Defect of Solid Propellants

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Abstract. Solid propellants (SPs), as a high-energy material, are commonly used in military and industrial power systems, such as solid rocket and missiles. The SPs, however, confronts severe difficulties of inevitable defects while being made, thus bringing about the significance of inspection. However, the literatures before typically tackled this problem separately, which subsequently combines different models for the variety of defect patterns. Despite of the effectiveness, this act of matters usually brings excessive complexity and additionally computational burden. In this article, we managed to solve this problem in an integrated framework, which unite both the size detection task and shape detection task at the same time, but with different training strategies. To be specific, our framework is mostly consisted of two stage. Firstly, the SPs region is output using a semantic segmentation network, and size measurements are completed with traditional image processing to determine the size defects of the SPs. Then, the depth features of the segmentation network are combined with the semantic segmentation map to make a spatial attention mechanism, which is input to the deep classifier to complete the shape defect detection. The focus of model is gradually shifted from the segmentation task to the classification task as the number of training sessions increases by introducing dynamic balancing factors. The experimental results show that the multi-task learning approach can greatly improve the generalization and robustness of the model, and the accuracy and speed are improved for appearance defect detection of SPs.

Keywords: Solid Propellants (SPs); Integrated Framework; Deep Detection Model.

1. Introduction

As a high-energy material, SPs are commonly used in the power system of solid rocket or missiles to provide powerful power for the operation of this type of power system, which plays on significant role in the fields of aviation [1], aerospace [2], mining [3], etc. The working performance of this power system is closely related to the quality of SPs. In the production process of SPs, the product has different types of defects caused by the backwardness of production equipment and process technology, mainly in the form of size and shape defects, so the quality detection of SPs is essential part [4].

At present, detecting the appearance defects of SPs by manual naked eye is the main method, the detect method not only has low accuracy rate and high labor cost, but also the production environment of SPs is full of volatile gases such as ether, acetone and alcohol, which seriously affects the health of workers [5]. In recent years, with the rapid development of artificial intelligence and intelligent manufacturing, machine vision technology has been extensively used in the manufacturing industry [6-11]. The detection technology based on machine vision has gradually become the mainstream detection method because of its advantages of high detection accuracy and efficiency. In the paper, we will take the appearance defects detection of SPs as an example, and carry out research on the quality detection method of appearance defects based on machine vision to provide new solution ideas for defect detection of similar industrial products [12].

Traditional detection methods based on machine vision is divided into three steps: region segmentation, feature extraction, and statistical data. The Traditional detection methods are easily affected by environmental noise, and the parameter thresholds of the algorithm need to be adjusted

according to the environment, and the generalization ability of the detection algorithm is weak, which is difficult to meet the detection requirement of actual production [13]. Detection methods based on deep learning have attracted more and more attention in the field of intelligent manufacturing because it does not require manual feature extraction and has strong generalization ability [14]. Based on this, the work done in this paper is as follows:

(1) A multi-task integration framework based on deep learning is designed, which improves detection accuracy and speed by sharing feature layers and spatial attention mechanisms.

(2) Semantic segmentation-based method for SPs size defects detection is proposed. The semantic segmentation network is used as the image pre-processing technique, then the traditional edge detection method is used to extract the edge information of SPs. Finally, the actual size is determined by the statistical method to achieve the size defects detection

(3) A multi-task joint training loss function calculation is designed to solve the problem of model gradient explosion and difficult convergence by introducing a dynamic balance factor.

2. Hardware System for Defect Detection

The device for machine vision-based detection of appearance defects of SPs, as shown in Figure 1, uses three cameras in concert to acquire image information of the appearance of SPs from different orientations. The images are sent to the controlling system, and the SPs are detected using the designed detection algorithm for appearance defects. After obtaining the detection results, the controlling system drives the pneumatic devices to place the defect-free and defective products in the qualified and waste boxes respectively. The image data used in the training and testing of the algorithm in this paper are from this device. Noted that the proposed method can lead to the production efficiency of a single equipment reaching 315kg per shift in actual production. In addition, the intelligent application for appearance defect detection of solid propellants can replace repetitive human work, and achieve a reduction rate of personnel of 60%.

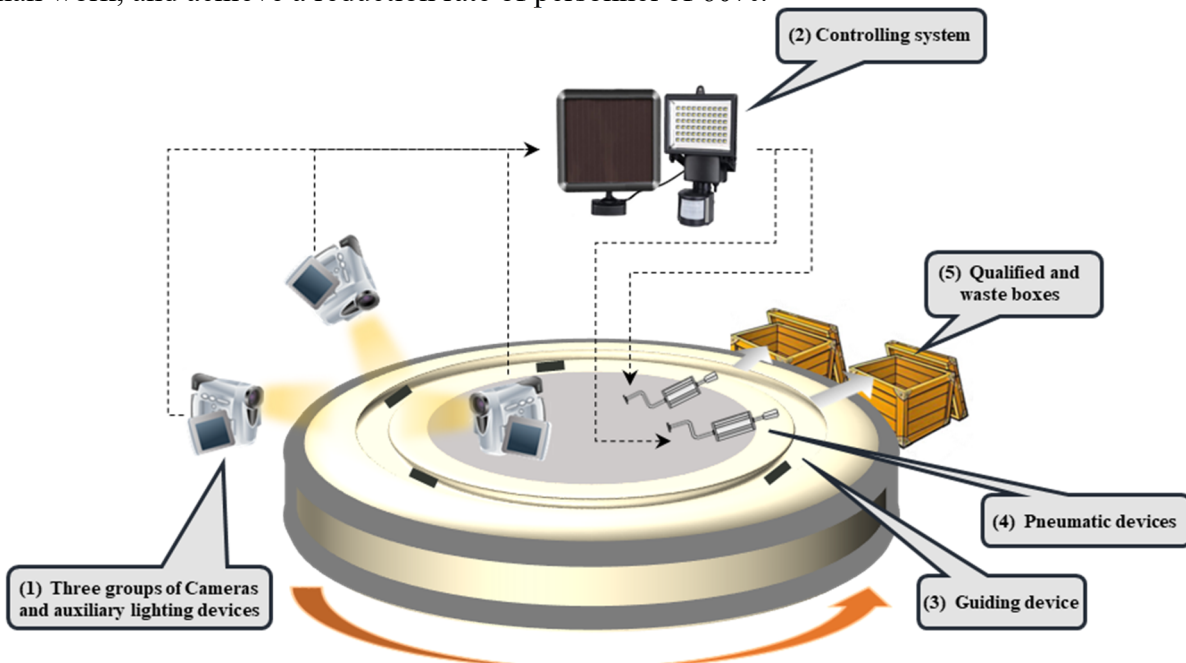


Figure 1. Visual detection device

3. Appearance Defect Detection

In the actual production line of SPs, inadequate cutting technology can lead to size defects of overlong, long or short, as shown in Figure 2, and strict control of solid propellant size is essential to guarantee the performance of its back-end products in use. In addition, there are deformed shape

defects such as bevel, and due to the sticky nature of the cladding material itself, multiple cladding products may stick together.

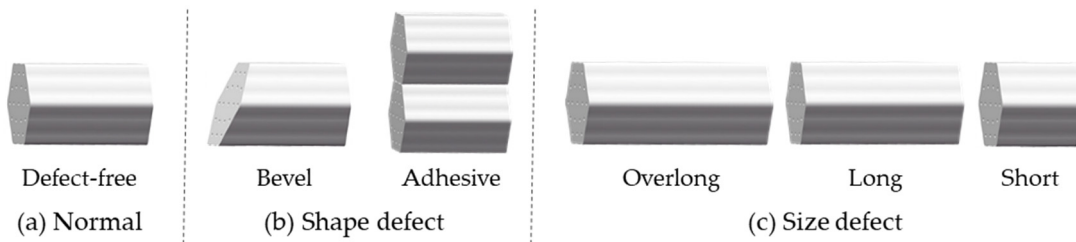


Figure 2. Types of appearance defects of SPs

As shown in Figure 3, it is the overall structure of the detection algorithm for appearance defects, the detection of both shape and size defects relies on contour features. Therefore, multi-task learning techniques are used to integrate deep classifier and deep semantic segmentation networks.

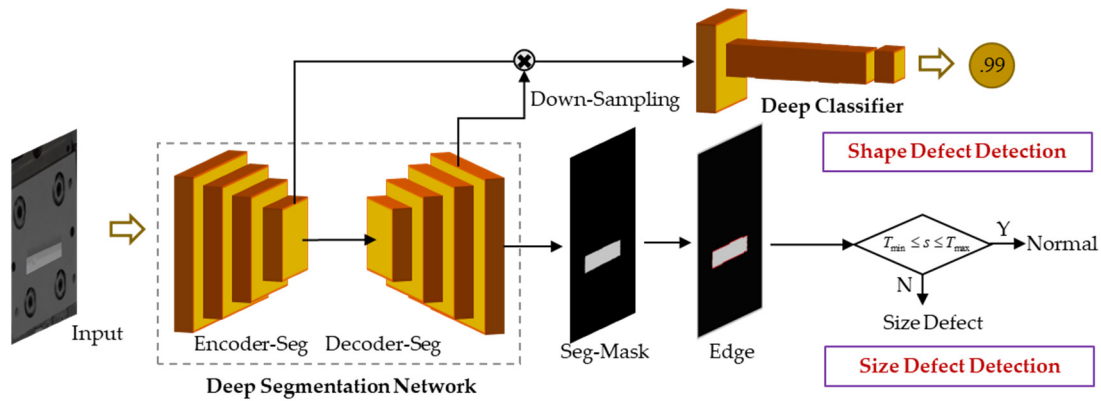


Figure 3. Overall structure of detection algorithm for appearance defects

3.1 Size Defects Detection

According to the problem that SPs have size defects of overlong, long or short, a detection algorithm for size defects detection based on semantic segmentation network is proposed. As shown in Figure 4, the principle is: first, the binary segmentation map of the SPs is obtained by using semantic segmentation network. Then the edge features of SPs are extracted by the traditional edge detection methods. Finally, the statistics of the feature information are completed to obtain the actual size, which is compared with the set threshold. If the measured size is within the valid range, it is considered as a normal product, otherwise it is a product with abnormal size.

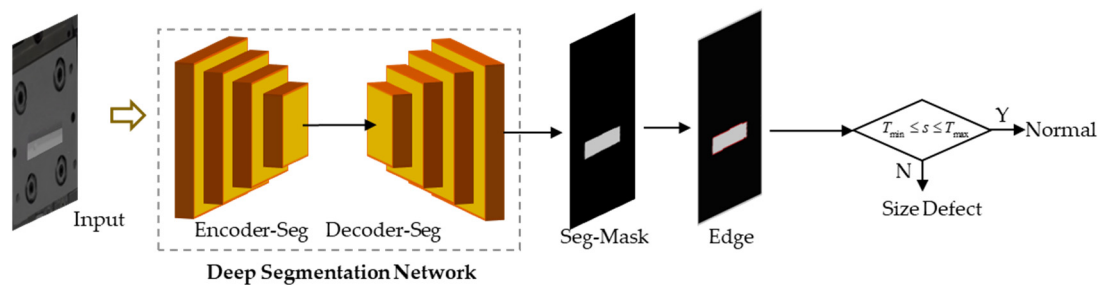


Figure 4. Size defects detection of SPs

The semantic segmentation network is used as a pre-processing technique for detection, i.e., the segmentation mask is obtained using the semantic segmentation network (the mask value is one in the SPs region and zero in the background region). Then, the contours and external rectangles are

extracted from the semantic graph by the Canny edge method. Finally, the actual size is obtained by counting the number of pixels in the size direction and thus the actual size. If the actual size calculated is within the set bilateral threshold, it means that the size meets the production requirements, otherwise it is recognized as a size defects.

The proposed method combines the respective advantages of deep learning and traditional image processing, extracts image semantic information autonomously with the help of deep learning, and completes pixel extraction by traditional image processing methods. At the same time, it avoids the disadvantages of both, i.e., the disadvantages of deep learning due to translation invariance, which makes the deep model insensitive to size accuracy, and the disadvantages of traditional image processing, which requires manual selection of parameters according to different backgrounds. It provides new research ideas and reference implications for solving vision detection problems in similar industrial scenarios.

3.2 Shape Defects Detection

The task of shape defects detection can be considered as an image classification problem, which mainly includes three shape categories: adhesion, bevel and normal. As shown in Figure 5, the feature map extracted by the feature extractor is used as the input of the subsequent network to achieve the shape defects detection using the deep classifier.

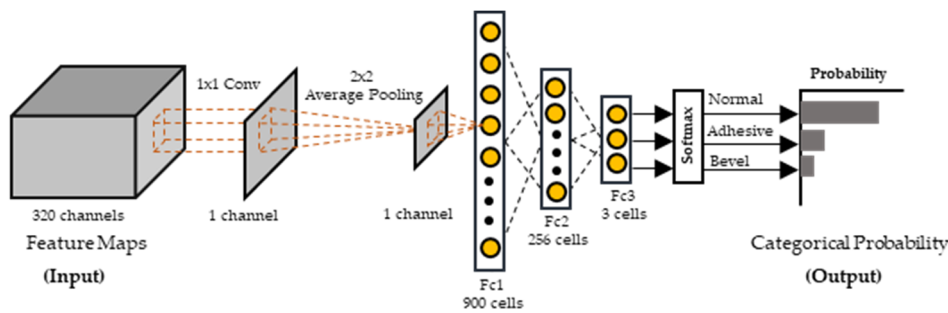


Figure 5. Deep classifier

3.3 Multitasking Learning

Multi-task learning [15-17] is a learning strategy that uses the same backbone network to implement different visual tasks, and commonly requires the optimization of parameters of this model jointly with multiple loss functions. The gradient information is passed from the last network layer backwards layer by layer according to the chain rule, which in turn continuously updates and optimizes the deep model. Where the update of parameters is subjected to the joint action of both size defects detection and shape defects detection tasks. The expression of the jointly trained loss function is given by:

$$L_{total} = \lambda \cdot L_{seg} + (1 - \lambda) \cdot L_{cls} \quad (1)$$

where L_{seg} and L_{cls} denote the loss function of the semantic segmentation network and the loss function of the classification network, respectively. The λ represents the hyper parameter for balancing the two tasks, which can be set to different values according to the learning tasks. In this paper, the λ is adaptively and dynamically adjusted by the number of iterations. The λ expression is.

$$\lambda = 1 - n / t \quad (2)$$

where n and t respectively denote the current number of iterations and the total number of training sessions. The design of dynamic balance factor can alleviate the problem of difficult convergence of the jointly trained deep model. Since the integrated deep model is affected by random noise at the early stage of training, the learning process of the two tasks interferes with each other, prompting the model to be extremely unstable and prone to gradient explosion. The dynamic balance factor is introduced to ensure that the integrated deep model can learn stable features and thus overcome the

problem of difficult model convergence and gradient explosion caused by the multi-task learning process. The improved expression of the joint training loss function is

$$L_{total} = \lambda \cdot L_{seg} + \delta \cdot (1 - \lambda) \cdot L_{cls} \quad (3)$$

where δ denotes the additional classification loss weight, a parameter that prevents the classification task from dominating the entire training process.

4. Experiment

4.1 Experiment Setup

1) *Datasets*: The image dataset of SPs in this paper was acquired from the appearance defects detection device described in Section II, and a total of 982 grayscale images with a size of 480×480 pixels were acquired. There are five types of appearance defects in SPs, of which overlong, long and short are size defects, and adhesion and bevel are shape defects, the dataset contains 155 images of overlong defect, 185 images of long defect, 160 images of short defect, 97 images of adhesion defect, and 156 images of bevel defect. Both size and shape defect detection tasks are randomly divided into training, test and validation datasets in the ratio of 6:2:2.

2) *Experimental environment*: In this experimental environment, the processor is Inter Core i7-9700K and the GPU is NVIDIA RTX Titan, and the appearance defects detection model of SPs is built based on Opencv3.4 and pytorch1.3.

3) *Evaluation Metrics*: We use the following to evaluate our performance metrics:

$$Pre = \frac{TP}{TP + FP}$$

$$Rec = \frac{TP}{TP + FN}$$

$$Acc = \frac{TP + TN}{TP + TN + FN + FP}$$

$$IOU = \frac{DR \cap GT}{DR \cup GT}$$

where the various indicators and parameters are described in detail as shown in Table 1.

Table 1. Evaluation indicator of experiment

Indicator	Full name	Description
<i>TP</i>	True Positive	Defective SPs was correctly predicted
<i>FP</i>	False Positive	Defect-free SPs was incorrectly predicted
<i>FN</i>	False Negative	Defective SPs was incorrectly predicted
<i>TN</i>	True Negative	Defect-free SPs was correctly predicted
<i>DR</i>	Detect Region	Segmented region of SPs
<i>TR</i>	True Region	Correct results of SPs detected as defective
<i>Pre</i>	Precision	Detected as defective SPs, the actual is also defective SPs
<i>Rec</i>	Recall	Defective SPs correctly detected
<i>Acc</i>	Accuracy	type of SPs correctly judged
<i>IOU</i>	Intersection of Union	Intersection of union detect region and true region
<i>FPS</i>	Frame per second	Number of image frames processed per second

4.2 Experimental Results

In this paper, the semantic segmentation network is used as the pre-processing method of the detection algorithm for size defects, so the segmentation accuracy of the semantic segmentation network directly affects the accuracy of size defects detection. As shown in Table 2, comparing FCN [18], U-Net [19], DeepLabv3 [20] and DeepLabv3+ [21], the experimental results show that DeepLabv3 slightly outperforms DeepLabv3+ in terms of the number of parameters and operation speed metrics, but the remaining metrics of DeepLabv3+ outperform the other three semantic

segmentation networks. Taken together, DeepLabv3+ is considered as the pre-processing network for the detection algorithm for size defects.

Table 2. Comparison of the results of different semantic segmentation networks

Method	Precision (%)	Recall (%)	Accuracy (%)	IOU (%)	Param (K)	Speed (FPS)
FCN [18]	97.05	96.91	97.89	95.95	9210	16.99
U-Net [19]	93.66	97.64	97.76	93.95	17267	14.77
DeepLabv3[20]	97.59	97.75	98.86	96.36	5109	24.64
DeepLabv3+[21]	99.14	98.39	99.90	98.08	5221	24.01

The detection results of shape defects are represented by a confusion matrix. Where the values on the diagonal in the table represent the accuracy rate for each category. As shown in Figure 6, the detection rates of both adhesion and bevel defects exceed 99%, indicating that the designed deep classifier has a good classification performance for alien shapes. In addition, it is also verified that the deep classifier performs in treating overlong, long and short defects as shape defects. As shown in Figure 7, the detection accuracy of overlong, long and short size defects is only 90.02%, 76.92% and 83.12%, which is far below the 99% detection rate required for production.

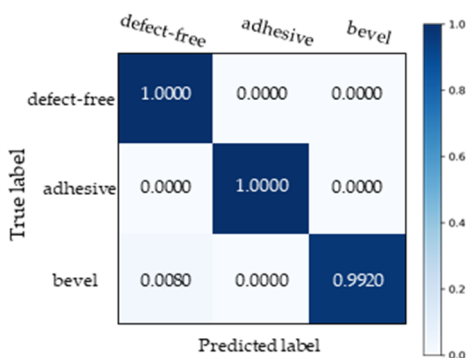


Figure 6. Shape defects detection results

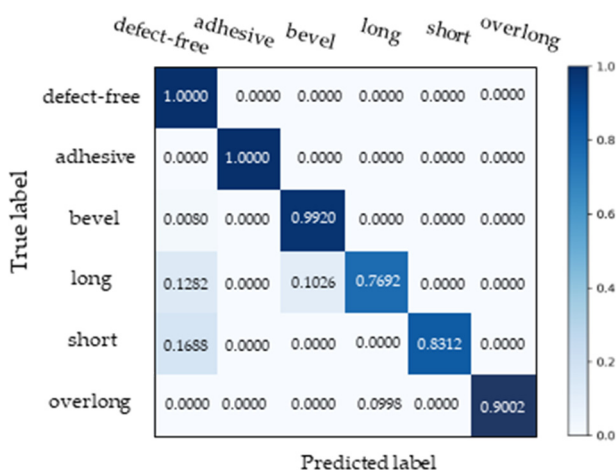


Figure 7. Regarding overlong, long and short SPs as shape defects.

4.3 Experimental Results on Joint Versus Individual Training

In this paper, a multi-task integrated model based on semantic segmentation network is designed, and both combined and individual training are used for the classification and segmentation tasks of this model, and the results are shown in Table 3. The performance of combined training is better than individual training in terms of accuracy, recall, precision, and IOU. We deem it is because joint

training enables the model to learn the semantic information of both classification and segmentation, and the integrated model outperforms the Separate model in all metrics. Although the detection speed of the Separate model is faster than that of the integrated model, the detection algorithm is deployed on the same hardware platform. So the Separate model needs to be executed serially and its actual detection speed is 13.09 fps, which is much lower than the detection speed of the integrated model. In addition, the results for the appearance defect detection of solid propellants are shown in Table 4, and it reveals the proposed method can obtain excellent performance for appearance defect detection of solid propellants in actual manufacturing.

Table 3. Combined training versus individual training results

Training mode		Precision (%)	Recall (%)	Accuracy (%)	IOU (%)	Param (K)	Speed (FPS)
Separate model	Classifier	99.90	94.39	98.30	—	464	28.78
	Seg model	99.14	98.39	99.00	98.08	5221	24.01
	Total	—	—	—	—	5685	13.09
Integrated model	Classifier	99.00	98.13	99.43	—	5453	23.28
	Seg model	99.16	99.05	99.91	98.19		

Table 4. The results for the appearance defect detection of solid propellants.

Defect type	Accuracy
Bevel	99.2%
Adhesive	100.0%
Overlong	100.0%
Long	99.7%
Short	99.5%

5. Conclusion

In this paper, we propose an integrated model based on multi-task learning, which integrates a deep classifier and a semantic segmentation network in same model through a multi-task learning strategy. While sharing the feature layer, a dynamic balance factor is introduced to achieve learning the segmentation task in the first stage and learning the classification task in the later stage, which makes full use of the features and detection results of the segmentation task. Compared with the multi-task detection model in stages, the number of model parameters is reduced, and the results can be obtained by performing one forward calculation, which greatly improves the detection speed. In particular, the two tasks constitute a spatial attention mechanism between them, which makes the deep classifier focus only on the region of solid propellant and suppress the effect of background noise. The experimental results show that the integrated detection method based on multi-task learning can yield better detection results and faster detection speed. In further research, we expect that the method can be applied to other industrial scenarios.

Acknowledgments

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