Machine vision recognition system for aerospace machined parts based on edge detection

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Abstract. Aerospace T-shaped machined parts are varied and have small structural differences. Manual identification has the problems of low efficiency and low accuracy. In order to realize efficient and accurate classification of aerospace machining parts, we built an image acquisition platform. To improve the edge detail extraction capability, we improved the edge detection algorithm based on deep learning. Furthermore, we employed the VisionTrain software to train recognition classification models for both large classes and subclasses. We then established a cross-granularity image classification process using VisionMaster software. Experimental results show that the improved edge detection algorithm in this paper is better than the existing common algorithm. The system achieves the goal of quickly and accurately recognizing all 60 machined parts.

1 Introduction

The aviation machined parts exhibit an inverted T-shaped structure, comprising a horizontal base plate and a vertical plate, as depicted in figure 1. These machined parts are categorized into ten distinct classes based on their unique characteristics, encompassing numerous subcategories that collectively amount to a total of 60 models. The subclasses exhibit similar attributes such as the number of holes and the shape of the base. Following the molding process, various machined parts undergo a uniform painting procedure. However, the post-painting classification identification has traditionally relied on manual methods[1]. Manual visual inspection has some problems, including strong subjectivity, susceptibility to fatigue, limited detection accuracy and a high rate of misjudgment.

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Therefore, it is imperative to investigate a system capable of swiftly and accurately discerning various types of machined parts.

The image features primarily encompass color, grayscale, shape, texture, and spatial geometric relationship attributes[2]. The category can only be determined based on the contour shape since the machined parts will undergo painting prior to recognition. Therefore, the recognition and classification of machined parts in this paper mainly rely on edge features. Scholars both domestically and internationally have extensively conducted research on the issue of workpiece classification. Traditional techniques for image recognition encompass algorithms such as differential operator edge detection, canny edge detection, corner detection, and others. Peilin L.[3] et al. designed a workpiece edge feature detection method. However, this method detects a limited variety of workpiece types and has relatively few workpiece features. Mittal, M.[4] et al. proposed a method that can detect thin edges with better edge continuity at a smaller noise ratio, but it cannot deal with fuzzy images efficiently and has a long computation time. Xia K.[5] et al. used the Canny algorithm to obtain the edge information of the workpiece, combined with the Hough transform and the Freeman chain code for shape recognition, but can only recognize a single workpiece. Krause, J.[6] et al. proposed a fine-grained recognition method which handles both feature learning and part recognition, but the part detection is too time-consuming and the results depend on the training dataset. Merino Bermejo, I.[7] et al. proposed a descriptor subset selection technique that automatically selects the most appropriate descriptor combination, and that outperforms approach involving single descriptors. To recognize the industrial parts a supervised classification is used with the global descriptors as predictors. Given the application, the best results are obtained with the Support Vector Machine with a combination of descriptors. But the classification effect is not good for a large number of high similarity industrial parts. In summary, these methods are primarily utilized for recognizing workpieces with simple geometries and a limited range of types.

In order to achieve more refined edge profiles, we propose a novel model for the detection of edges in machined part images. To ensure both efficiency and accuracy in our detection process, we initially perform rapid coarse-grained recognition and classification based on the frontal image of the machined part. Subsequently, final fine-grained recognition and classification are conducted using the edge detection image.

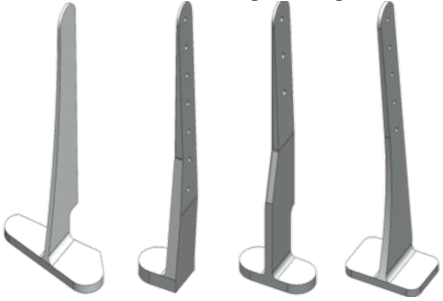


Fig. 1. Parts for machining in the field of aeronautics.

2 Imaging platform for T-shaped machined parts

The overall configuration of the imaging platform is illustrated in figure 2, comprising primarily three sets of face-parallel light sources, front and side cameras, a rotating platform, and an adjustable bracket.

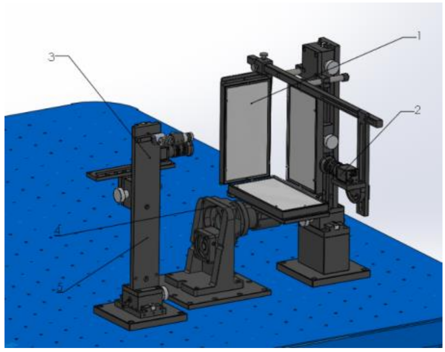


Fig. 2. General structure of the workpiece imaging platform.

The utilization of uniform transmitted light illumination on the backside of the object results in a pronounced contrast, thereby accentuating the contour features of the object[8]. Since cross-granularity recognition classification using artifact images mainly utilizes their edge information without focusing on the surface features, we adopt a back-to-light source methodology.

In order to ensure a clear and complete image, two industrial cameras are placed perpendicular to the light source. On the premise of satisfying the accuracy of cross-granularity recognition, the cost of this method is much lower than that of 3D scanning reconstruction[9]. After the image acquisition, the image preprocessing[10,11] is carried out, including the interception of ROI, mean filtering, image binarization and scaling operations. The resulting front and side images are then stitched together into 1000 × 1000 pixel images. The image acquisition method is shown in figure 3. Subsequent experiments confirm that the acquired images meet the requirements for edge detection and recognition.

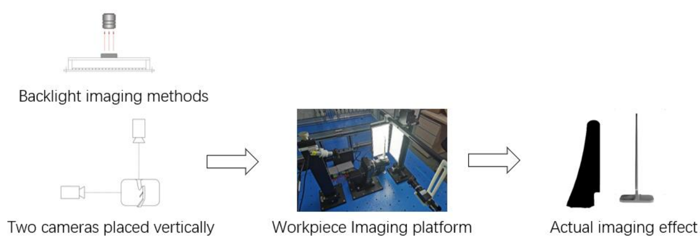


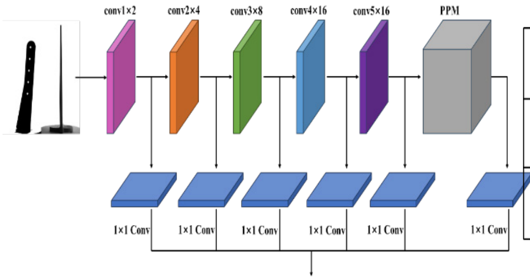
Fig. 3. Method of image acquisition.

3 Introduction to edge detection algorithms

At present, the edge detection method filters image edge points based on extreme image points[12]. However, its performance is suboptimal, particularly when dealing with images of machined parts in complex industrial scenes. Although general deep learning edge detection algorithms have achieved significant results in certain domains, they are limited in their adaptability to meet the needs of efficiently detecting machined parts.

Building upon the findings presented in reference[13], we propose a new edge detection model for edge detection of machined parts images. This model comprises three distinct segments, each of which will be thoroughly examined and analyzed.

The Resnet-50 model is employed as a feature extractor, as illustrated in figure 4. Initially, conv1, conv2 _ 3, conv3 _ 4, conv4 _ 6, and conv5 _ 3 are applied to the input image to obtain S1~S5. Subsequently, a pyramid pooling module (PPM)[14] is incorporated on top of ResNet-50 to capture more comprehensive global information. To dynamically and independently integrate the features extracted from the backbone ({Si}, where $1 \le i \le M$ and $M = 6$), a series of dynamic feature integration modules with varying output downsampling rates are designed, as depicted in figure 5.



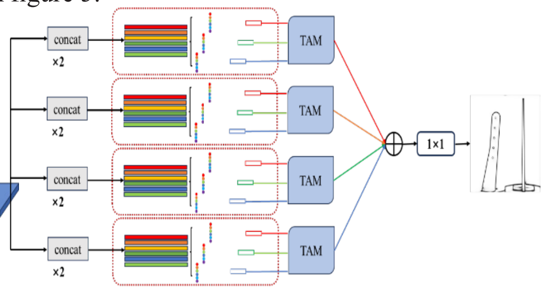


Fig. 4. Edge detection model.

Fig. 5. Dynamic feature integration.

After each integration of dynamic features, a task-adaptive attention module (TAM) is employed to intelligently distribute information, thereby preventing the network from being biased towards optimization. Subsequently, the corresponding feature maps generated by TAM for each task output are upsampled and accumulated. Finally, a ***1×1*** convolutional layer is applied for the ultimate prediction.

3.1 Acquisition and partitioning of the data set

In the previous part, we obtained the image of the front and side splicing of the machined parts after preprocessing. The processing method includes operations such as size standardization and grayscale to ensure the consistency and trainability of the input model. In order to ensure the authenticity of the label edge maps, this study uses a hand-drawn method to generate the edge images. The original image of one of the parts and the corresponding hand-drawn label edge image are shown in figure 6.

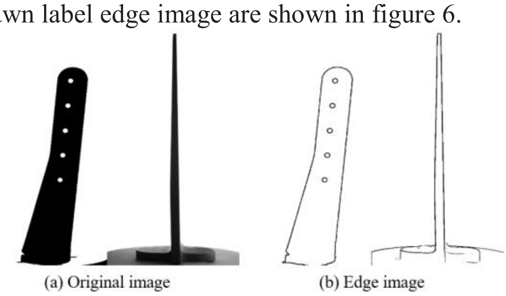


Fig. 6. Original and edge images of the machined parts.

To construct the dataset, a total of 1000 sets of front and side stitched images depicting various machined parts were collected. Subsequently, manual drawing techniques were employed to obtain precise edge maps for these machined parts. These original images along with their corresponding edge maps serve as the training data for our model. Furthermore, we partitioned this dataset into a training set comprising 70% of the data and a validation set consisting of the remaining 30%.

3.2 Results analysis

The model was trained using the aforementioned dataset. The results are obtained through a Python Jupyter notebook running on Google Colab (Intel1 Xeon1 CPU at 2.20 GHz, 13-GB RAM, Nvidia Tesla T4 GPU).Some of the training parameters are shown in table 1.

Table 1. Training parameters.

Parameters	Option
Initial learning rate	0.001
optimizer	Adam
Validation set ratio	0.3
gradient threshold	1
Batch Size	32
Maximum number of iterations	200

We compare the present model with several mainstream edge detection models, as shown in figure 7.

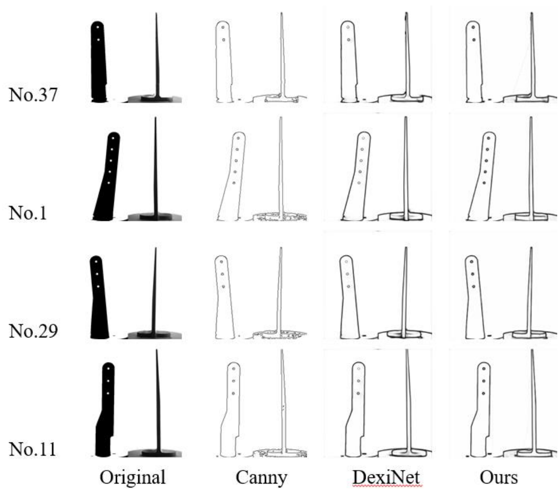


Fig. 7. The effect of three edge detection models.

4 Based on VisionMaster machine vision algorithm development platform

Aiming at the multi-species, high similarity, and high classification accuracy requirements of this problem, we adopt a cross-granularity recognition classification scheme[15]. The cross-granularity classification process is established and the workflow diagram is shown in figure 8. Initially, the frontal image is trained as a dataset to obtain a broad category differentiation model. It is then imported into the image classification module for recognition and outputs the broad class to which the part belongs. Based on the output a corresponding fine-grained classification process is activated by the branch feature module. There are ten fine-grained classification processes. Edge detection images are used as a dataset for training the subclass differentiation model. They are then imported into the image classification module of the fine-grained classification process for recognition and final output of the part number. The image preprocessing operations are the same as when acquiring the dataset.

Images with inference prediction errors are uniformly saved into the training set and the model is retrained after relabeling using VisionTrain. This approach increases the sample capacity and effectively optimizes the model.

The probability of correctly recognizing all machine-added parts by the large class differentiation module is more than 95%, which indicates that the large class differentiation model has a high confidence level. After practical testing, the recognition rate of 60 machine-added parts is close to 100%. In addition, the system has certain robustness to the rotation of machined parts. The recognition effect of some machined parts is shown in figure 9.

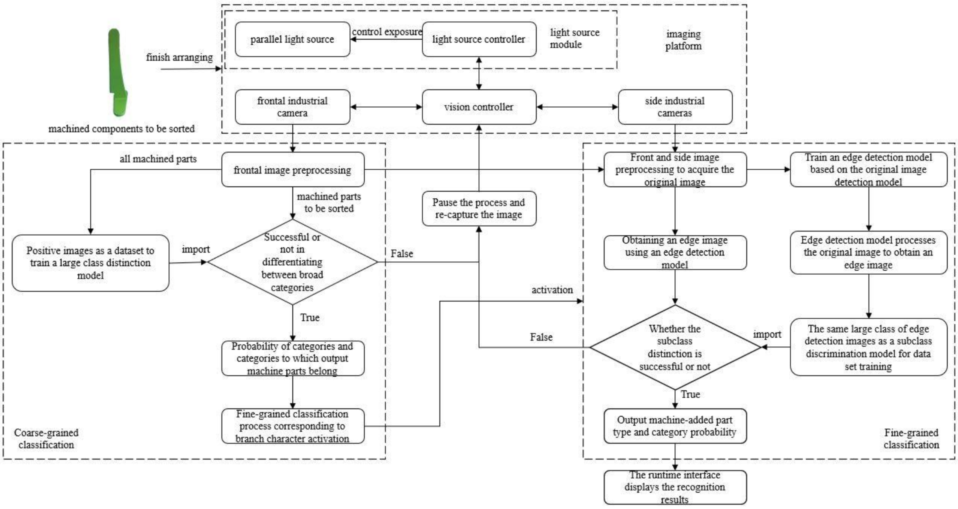
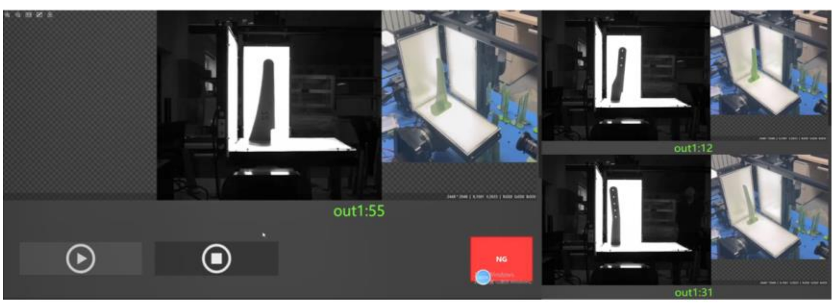


Fig. 8. VM workflow diagram.



(a) The interface of identification. (b)No.12 and No.31.

Fig. 9. Recognition effect of partially machined parts.

5 Conclusion

Addressing the challenges and issues encountered in the automated sorting of workpieces, this study presents a machine vision recognition system for aerospace T-type machined parts based on edge detection. We propose a novel deep learning-based edge detection model that utilizes Resnet-50 to extract features from both front and side spliced images, integrating and assigning these features. The model is trained using manually labeled edge images, and its applicability is verified through recognition experiments. By selecting and arranging hardware equipment, we ensure the acquisition of high-quality images of machined parts. Using VisionTrain software, we train datasets comprising frontal images as well as frontal-side spliced edge detection images, resulting in one broad category differentiation model and ten subclass differentiation models. These models are then imported into VisisonMaster's cross-granularity recognition and classification process, where they are optimized through parameter adjustment and dataset supplementation to achieve rapid and accurate recognition of 60 aerospace machined parts.

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