Research on defect pattern recognition of Light Guide Plate based on Deep Learning semantic Segmentation

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Abstract. Because the defects of the light guide plate are still extremely small under the image taken by the high-resolution industrial camera, and the characteristics of different defects are different, as well as the texture characteristics of the whole light guide plate, such as dense and uneven distribution of light guide points, the traditional image processing and detection methods require experienced visual engineers to do a lot of feature extraction algorithm programming and expensive code maintenance. The accuracy is low and the stability is poor. However, the surface defects of the light guide plate are still mainly detected by artificial visual observation, and only a few manufacturers use traditional image processing methods to detect them. For this reason, a defect detection method based on deep learning semantic segmentation is proposed. In this method, the defect features of the light guide plate are extracted by self-learning by training the neural network, so as to avoid the complicated programming work of feature extraction algorithm. First of all, the defects of the collected light guide plate are marked to make a sample set; secondly, the pre-trained pyramid scene parsing network (PSPNet) is used to retrain the labeled samples; furthermore, the defect detection of the light guide plate is realized by using the trained model. The single deep learning semantic segmentation defect detection method usually can not meet the needs of industrial applications, finally, it is necessary to combine the simple machine vision method to judge and screen all the suspected defect regions detected by the deep learning semantic segmentation method. The experimental results show that the detection rate of bright spots, dark spots and scratches is as high as 96%, which can basically meet the requirements of industrial inspection.

Keywords: Machine vision Guide plate, Defect detection, Pyramid Scene Analysis Network (PSPNet), Semantic segmentation.

1. Introduction
Light Guide plate is an acrylic plate with optical grade, and then a high-tech material with extremely high reflectivity and no light absorption is used to print light points on the bottom of the acrylic plate with laser engraving, UV screen plate and other printing technologies [1]. One-sided side entry type
light guide plate USES acrylic sheet to absorb the light from one-sided line light source to stay on the surface of acrylic sheet. When the light shoots to each light point, the reflected light will diffuse to all angles, and then destroy the reflection condition and shoot from the front of the light guide plate. Through a variety of density and different size of light guide points, the light guide plate can be uniformly luminous [2]. High-precision side in light guides are widely used in liquid crystal display (LCD). In the manufacturing process of light guide plate, due to the influence of factors such as raw material composition, equipment use, processing technology and workers' operation, processing defects such as bright spot, leak point, line scratch and shadow will inevitably appear on the surface [3]. The defect detection of the light guide plate can effectively prevent the improper light guide plate from assembling into the LIQUID crystal display, thus avoiding the greater waste of resources. Therefore, the defect detection must be carried out before the light guide plate leaves the factory.

At present, most domestic light guide plate manufacturers employ a large number of young employees with good eyesight to detect the defects of light guide plate from multiple angles under harsh lighting, as shown in Figure 1. Manual detection of defects causes a large amount of waste of human resources; Long-term visual bowing will cause great damage to the eyes and cervical vertebrae of employees, and affect the detection accuracy and efficiency of light guide plate defects. Only a few manufacturers and researchers use the traditional image processing and machine vision methods to detect the defect of light guide plate. Li Junfeng et al. [4] proposed a detection method based on multi-direction Gabor filtering and sub-pixel analysis for a specific type of light guide plate slight line scratch defect. This method has a good extraction of minor line scratch, but it is not applicable to other defect types. Huang et al. Someone proposed an automatic detection method based on computer vision. This method firstly USES image segmentation method to segment the guide spot area, and then USES Fourier transform to eliminate the texture formed by the circular pattern of the guide spot with approximately periodic distribution on the guide plate. Then, Otsu threshold method and morphology technique were used to extract the defect areas. Finally, pattern recognition classification method was used to classify the defects, but this method had poor robustness and low defect detection rate. Mr. Li, etc. Some research team proposed a guide plate defect detection based on machine vision method, according to the density of the accurate automatic partition, in different partitions using different defect detection algorithm, although this method can realize the bright spot, crushed, the extraction of line 3 kinds of defects such as scratches, but different types of defects need different feature extraction algorithm, algorithm programming is difficult and complicated. It can be seen that the traditional image processing method is difficult to deal with the difficult problems such as the diversity of the shape characteristics of the guide plate defects and the inconsistency of the density distribution of the guide spot.

![Fig. 1 Manual detection of light guide plate defects real picture](image-url)
In this paper, taking the unilateral side-in light guide plate as the experimental object, according to its image imaging taken by a black-and-white linear array camera with a resolution of 16 K, a defect detection method of light guide plate based on deep learning semantic segmentation is proposed. This method independently learns to extract the advanced features of the defects of the light guide plate by training the neural network so as to avoid complicated feature extraction algorithm programming. Secondly, the pre-trained PSPNet semantic segmentation neural network model is used to retrain the labeled samples by using the transfer learning technology. Furthermore, the defect detection of the light guide plate is realized by using the trained segmentation model. Finally, because the separate deep learning semantic segmentation defect detection method usually can not meet the needs of industrial practical applications, the experimental results show that the detection rate of bright spots, dark spots and scratches is as high as 96%. It can basically meet the requirements of industrial inspection.

2. Guide plate

2.1. Image acquisition system of light guide plate
The light guide plate is perpendicular to the light axis of the line-light source and the line-array camera. In the multi-angle line light source, the light is concentrated on the same line through mirrors of different angles, and the area of the light guide plate under the line is exposed to the light axis of the camera. Part of the light penetrates the light guide plate, and part of the light reflects back to the camera. The gray intensity of the image corresponds to the intensity of the reflected light. During the detection, the light guide plate moves along the conveyor belt and the line-array camera captures the image line by line.

2.2. Typical defects
The side with light guide point printed on the light guide plate is called net surface, and the surface is relatively rough; there is no printing light guide point on the back, which is called mirror surface, and the surface is relatively smooth. There may be defects on both sides of the light guide plate. The common defects of light guide plate are mirror spot, net surface scratch, net surface leakage light guide spot, residual glue, mirror scratch, net scratch and so on. Due to the high light transmittance of the light guide plate, the defects of the mirror and network can be clearly photographed by a 16K black-and-white linear array camera. And because the image features of the same type of defects (such as scratches) under the camera are very similar, it is impossible to judge whether the defects are on the mirror or the net, so this paper classifies the defects on the basis of the imaging features of the camera. it is divided into bright spots, dark spots and scratches. The imaging of these defects in a 16 K black-and-white linear camera is shown in figure 2.

![Fig. 2 Typical defect types of light guide plates](image)

3. A defect detection method based on PSPNet semantic Segmentation network model

3.1. Semantic segmentation
Semantic segmentation refers to the understanding of the image at the pixel level, that is, we want to assign an object class to each pixel in the image. Color labeling for all constituent pixels of targets of different categories is essentially to classify targets of different categories in the image. In this paper,
the light guide plate image is marked into background and defect. In the label image in Figure 3, white and black respectively represent background and defect. The black outer border is of no practical significance and only plays a role in determining the position of the image.

![Image](image.jpg)

**Fig. 3** Light guide plate defect original drawing and label drawing

3.2. **Pyramid scene analysis network**

(1) For the obtained feature map, the 4-layer pyramid-pooling module was used for average pooling of partitions at different levels. Level 1: The entire feature map is globally averaged to generate the roughest level of a single bin output. Layer 2: Divide the feature map into 2×2 subregions, and then pool each subregion on average. Layer 3: Divide the feature map into 4×4 subregions, and then pool each sub-region on average. Layer 4: the characteristics of the map is divided into 8×8 is the area of the finest level, then the average pool for each child areas. (2) through a 1×1 convolution layer would reduce the dimension of the feature map to the original 1/N, N as the pyramid layers, this article N = 4) and (3) after using bilinear interpolation of each pool of low dimensional feature map on sampling, make its have the same size as the original feature map. (4) after all different levels of sampling feature map is as the original feature map together. These feature maps are fused into the global scene prior information and serve as the final feature map of the deep neural network.

![Diagram](diagram.png)

**Fig. 4** Tower Scene Analysis Network (PSPNet)

Finally, a deconvolution layer is used to restore the final prediction graph of the same size as the input image. Because the defects of some bright spots in the light guide plate are very similar to the characteristics of the light guide spot, there may be only different spatial positions, which is easy to cause confusion and misjudgment. The dark spot defect may be caused by missing the guide spot, but there is no obvious defect feature. And some small defects in only a few pixels, too subtle, but find out these small defects is crucial. Advantages of PSPNet network segmentation is one of the pyramid pooling module to different scales, different regions of the global features and local features is together, can not only ensure the details of the local features is not neglected, extract the inconspicuous defects at pixel level, also can ensure the global characteristics of deep space location information (such as defects) will not be lost, together to make the final prediction is more reliable.
3.3. Model to evaluate
Intersection over Union (IoU) and pixel accuracy are two typical indicators used to evaluate the performance of the trained semantic segmentation model. IoU is the ratio of the Intersection and Union of "predicted region" and "true region" of the segmentation model, as shown in Figure 5. Pixel accuracy is the proportion of correct pixels in the total pixels predicted by the segmentation model, which are respectively calculated according to Equation (1).

\[
\text{IoU} = \frac{\text{Area of Overlap}}{\text{Area of Union}} = \frac{A_{\text{prediction} \cap A}}{A_{\text{prediction} \cup A}}
\]

\[ \text{(1)} \]

Fig. 5 Diagram of index calculation

IoU is calculated based on specific semantic categories. In this paper, it is divided into the IoU values of the background class and the IoU values of the defect class. Mean IoU is the average value of these two types of IoU. The IoU value of the defect class can determine the degree of defect capture (the coincidence degree between the defect prediction area and the real area of the defect marker), and the pixel accuracy can measure the accuracy of the model. As can be seen from Table 3, the parameter values of pixel accuracy index are all very high and of little significance. And defect class IoU low values of only 0.348, because the segmentation model to predict the defect area is larger than the real defect area actual tag, but predict the defects of the region to complete a mark defect area, still had the defects of good positioning effect, so the defect class IoU low value does not affect the overall testing requirements.

3.4. Model to evaluate
The ratio of the Intersection and Union of Figure 5 compares the defect segmentation results tested on the validation set by the PSPNet segmentation model generated by training and the real value of the label graph. Careful observation revealed that the trained model could successfully predict the location of the defect area, but it was slightly wider than the actual defect area in the label diagram.

Fig. 6 The defect segmentation results of PSPNet on the validation set (purple and red represent the background and defect, respectively)
4. Conclusion
In order to solve the problem of surface defect detection of light guide plate, a defect detection method based on deep learning semantic segmentation is proposed in this paper. Compared with the traditional defect detection methods in image processing, this method does not need to extract defect features artificially, and deep learning can automatically extract appropriate feature vectors in the training process by means of supervised learning, greatly reduce the workload of defect feature extraction algorithm programming and code maintenance costs, and improve the stability and accuracy of defect detection. We are sure that the defect detection method of light guide plate based on deep learning semantic segmentation will soon be applied to the actual production detection of light guide plate.

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