CSSAM: U-net Network for Application and Segmentation of Welding Engineering Drawings

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Abstract

Heavy equipment manufacturing splits specific contours in drawings and cuts sheet metal to scale for welding. Currently, most of the segmentation and extraction of weld map contours is achieved manually. Its efficiency is greatly reduced. Therefore, we propose a U-net-based contour segmentation and extraction method for welding engineering drawings. The contours of the parts required for engineering drawings can be automatically divided and blanked, which significantly improves manufacturing efficiency. U-net includes an encoder-decoder, which implements end-to-end mapping through semantic differences and spatial location feature information between the encoder and decoder. While U-net excels at segmenting medical images, our extensive experiments on the Welding Structural Diagram dataset show that the classic U-Net architecture falls short in segmenting welding engineering drawings. Therefore, we design a novel Channel Spatial Sequence Attention Module (CSSAM) and improve on the classic U-net. At the same time, vertical max pooling and average horizontal pooling are proposed. Pass the pooling operation through two equal convolutions into the CSSAM module. The output and the features before pooling are fused by semantic clustering, which replaces the traditional jump structure and effectively narrows the semantic gap between the encoder and the decoder, thereby improving the segmentation performance of welding engineering drawings. We use vgg16 as the backbone network. Compared with the classic U-net, our network has good performance in engineering drawing dataset segmentation.

\textit{Keywords:} U-net, Welding Engineering, Attention Module, Double Pooling

1. Introduction

Manufacturing automation processes continue to evolve. However, a customized method is still adopted for the massive field of heavy industrial equipment manufacturing. Heavy industry equipment is formed by stacking and welding sheet metal parts. The kit can cut the unit according to the extracted shape, but the industrial manufacturing efficiency is low. At present, the method of human-computer interaction is still used to remove the contour of welding drawings.

Deep learning has recently played a pivotal role in image segmentation, especially in the U-net [1] network. U-net is composed of an encoder and decoder, which is different from other types of segmentation networks. In the semantic segmentation process, the encoder encodes the low-dimensional features of the input image, and the decoder captures the encoded semantic features. By adopting the skip structure, the features between the encoder and the decoder can be better integrated, and the feature loss in the partial encoding and decoding process can be eliminated to achieve better global segmentation. When we first trained the complex welding engineering drawing dataset with the classic U-net, it did not perform well. The traditional U-Net model has low accuracy in segmenting complex callout lines and section outlines in engineering drawings. However, The first experiment was to verify the feasibility of using U-Net to segment the method of engineering drawings. In the following, we further study and analyze the U-Net structure and principle and get inspiration from[2][3][4]. Finally, we propose to replace the classic U-net skip structure with CSSAM. Our proposed method can infer attention features along channels and spatial order, and at the same time, we also design lower-layer encoder features to integrate with upper-layer encoder feature clusters.

In this way, the network can achieve better global information fusion of encoder and decoder features, which can be used to attain
higher-precision segmentation of welding engineering drawing contours.

Our contributions to this paper are as follows:
1. U-net applies to weld engineering drawing contour segmentation.
2. Propose the CSSAM attention module to extract global information better.
3. Double pooling convolution compact semantics reduces dimensional differences.
4. Longitudinal encoding semantic fusion to extract more global context information.
5. The excellent segmentation performance of our network for complex weld maps is verified.

2. Related Work

Inspired by the automatic segmentation of graphics and images in the medical field, we propose a contour segmentation method based on U-net for welding engineering drawings. As we all know, many excellent segmentation networks in deep learning image segmentation have existed. The preferred segmentation network, Fully Convolution Networks (FCNs)[5], was proposed by Jonathan Long. FCN discards traditional fully connected layers and achieves pixel-level dense prediction between end-to-end. The convolution operation is added at the end of the network structure, which is applied to more complex full-convolution semantic segmentation tasks. The transposed convolution is used to restore the original image size, and the jump connection structure is used to fuse the features of the deep layer (including the classification information) and the middle layer (including the position information) to improve the feature accuracy of the output. U-net[1] can be considered a variation of FCN, which still uses the encoder-decoder and skip structure. Compared with the former, the unique skip connection architecture of the U-net enables the decoder to obtain more spatial information lost during the pooling operation and restore a complete spatial resolution. The semantic difference between encoder and decoder is reduced to achieve better segmentation performance. U-Net mainly has two cores: (1) The problem of semantic information fusion of the encoder feature layer and the decoder feature layer. How to effectively fuse the encoder image features with the decoder image features? (2) The problem of image spatial position information, how can the encoder and decoder realize the learning of image spatial position information? Researchers have introduced many methods to solve the above problems to reduce the incompatible feature differences between these two groups.

Whether learning low-resolution Deeplab-v1, Deeplab-v2, Deeplab-v3, PSPNet [6][7][8][9] or recovering high-resolution SegNet, DeconvNet [10][11] and parallel high and low resolution HRNet [12]. Even deep neural networks ENet and UpperNet can achieve real-time prediction[13][14]. The segmentation networks focus on acquiring global image semantic features and spatial location information. Therefore, the model mainly integrates the global upper and lower semantic features in image segmentation and learns spatial location feature information. In recent years, there have been many improved models based on U-net.

For example, R2UNet, R2U++Net, CAggNet, MultiResUNet, NonlocalUNets and UCTransNet [15][16][17][18][19][20], etc. These networks are all improvements to the U-net skip structure to achieve a better fusion of global contextual feature information in the encoder and decoder and achieve excellent segmentation performance. The U-net skip structure can better realize the fusion of global semantic information. However, as mentioned in UNet++ [21], the skip-structure front-end encoder semantic features have lower dimensionality than the back-end decoder semantic features. Therefore, there is a large difference in feature dimension in the skip structure, which makes the segmentation performance not good enough.

On the other hand, Fei Wang [2] proposed a residual attention network using an encoder-decoder approach. Based on this, Sanghyun Woo [3] proposed the CBAM (Convolutional Block Attention Module) module to realize the entire convolution channel semantic and spatial information calculation. UCTransNet [20] is a recently proposed attention module inspired by the Self Attention Mechanism and Multi-Head Attention mechanisms in Transformer[22], and its purpose is to enable the encoder-decoder to obtain more global information fusion. Our proposed CSSAM module considers the information fusion of channel and spatial dimensions and the dimensional difference between encoder and decoder features. Besides, we make global information linkage between U-net encoders, which includes feature cluster integration between vertical encoders and vertical and horizontal double-pooling convolutions. The output features are fused with the original features through the attention module, and the whole jump to the high-dimensional feature layer of the decoder to achieve secondary fusion.
Semantic differences are mitigated through these implementations. Our method dramatically affects the engineering problem of segmenting complex welded structure assembly drawings through verification. In this way, it enables the network model to achieve a better fusion of semantic information and spatial location information.

Where \( \odot \) means element-wise multiplication. In the operation process, CSSAM will mark the corresponding attention weight and constrain the channel weight and spatial position information through the attention mechanism to transmit the channel information along the spatial dimension. After the CSSAM module outputs \( X^* \), at this time, \( X^* \) it has more significant dimensional global details than the original U-net. At the same time, 2x2 upsampling is performed on \( X^* \) and fused with the low-dimensional feature clusters of the horizontal encoder to output the final feature \( F \). The image feature \( F \) is combined with the decoder upsampled graph feature clusters to reduce the global context semantic difference, as shown in Fig 2. The CSSAM module is described in detail below.

\[
X' = Tc(X) \odot X \quad (1.1)
\]
\[
X^* = Ts(X') \odot X' \quad (1.2)
\]
4. Attention Module

Residual attention network[2] adopts pre-activated residual units ResNeXt [23] and Inception[24] as a two-branch parallel network structure stacked with residual attention modules. Bolei Zhou and Jie Hu et al.[25][26] used average pooling to aggregate and count spatial information, respectively. The convolutional attention module [3] uses inter-channel feature relationships to compress the spatial dimension of the input feature map to compute channel attention. Moreover, it is verified that the average pooling and max pooling simultaneously can improve the feature network’s representation ability. The detailed structure of the attention module is shown in Fig 4 we feed the Upper-encoder and Lower-encoder feature information \(X\) into a shared multi-layer perceptron (MLP). At the same time, the perceptual layer integrates the input image feature clusters, and the ReLU operation generates the channel attention feature map \(Tc \in \mathbb{R}\). \(Tc\) It contains the attention feature relationship between each channel axis of the input feature \(X\). Then, \(Tc\) is integrated with the input feature \(X\) (note: \(X\) is the image feature of the original image Image after the upper and lower encoder pooling and convolution) to generate the feature map \(X'\). According to the semantic difference between Upper-encoder and Lower-encoder features, convolution and linear rectification unit (ReLU) are adopted. Continue to perform spatial information relationship calculations on the feature \(X'\) to generate attention spatial feature map \(Ta \ (X')\). The channel attention feature \(X'\) is merged with the spatial location attention feature \(Ta \ (X')\) to generate a globally informative feature \(X''\) with channel-spatial dual Attention. The detailed calculation process of the attention module is as follows.

\[
Tc(X) = S(M(\text{Upper} \ (X))) + M(\text{Lower} \ (X))
\]

\[
= S(W2 (W1(\text{Upper} \ (X)))) + W2 (W1(\text{Lower} \ (X))) \quad (1, 3)
\]

\[
Ta (X') = S(W_{3x3x3} \ (Tc (\text{Upper} \ (X), \text{Lower} \ (X)))) \quad (1, 4)
\]

Among them \(Tc \ (X)\) is the 1-dimensional channel attention image feature, \(S\) the sigmoid function, \(M\) is the multi-layer perceptron (MLP) shared layer, and Upper and Lower are the inputs of the two longitudinal encoders, respectively (Upper represents high-dimensional encoding, encoder features, Lower represents low-dimensional encoder features). \(W1\) and \(W2\) are denoted as shared weights to the input multi-layer perceptron (MLP). And the output of the ReLU activation layer is \(W1\). \(Ta \ (X')\) It is a 2-dimensional spatial position information feature \(f_{3x3x3}\) representing three 3x3 convolution operations.

5. Experiments

Dataset

The dataset we use for training is the engineering atlas of complex welded structures used in the heavy industry equipment manufacturing of the Riveting Heavy Company. We know that the dataset size directly affects the training results. When the training samples are few, the network may overfit. To avoid the problem of biased training results due to fewer datasets, we perform dataset enhancement processing on the graph. We augmented the dataset by cropping, mirroring, deflecting, adding noise, etc., and finally obtained a dataset of 4094 labeled engineering drawings. Then, these datasets were modified into training atlases in VOC format, and 8:2 random sampling was performed according to the number of atlases as training and testing.
Implementation Details

We use GPU and Vgg16 [27] as the backbone network and the Adam optimizer with internal parameters of 0.9 to train the network model. The initial learning rate is set to 0.0001, and the learning rate decline method is cos decline. We also use a combination of dynamically scaled cross-entropy loss, FL loss, and dice loss, mainly to reduce the weight of easy-to-distinguish samples and focus on indistinguishable ones. When training to the 50th epoch, the network starts to load and evaluate the validation set, and the network model will fluctuate slightly during this process. To directly demonstrate the segmentation effect of our proposed U-net network on welding engineering drawings, we compare the experimental results with the classical U-net. Its visualization effect is shown in Fig 5. For evaluation, we evaluate the segmentation method using the Intersection Over Union (IoU), Accuracy (Accu), and Mean Predicted Precision (mAP) metrics. Through the comparison experiments of different methods, the average pooling verification of the classic U-net and the horizontal encoder, and the integration experiments of the horizontal encoder and the CSSAM module. As shown in Table 1 in the following experiments, the corresponding exponent of our method applied to weld engineering drawing segmentation is higher than that of the classical U-net.

Avoid problems such as increased estimated value variance and mean shift when extracting features. In the U-net network, we propose letting the horizontal encoder perform average pooling, and the vertical encoder performs maximum pooling to better capture global feature information. After the encoder performs a double pooling operation, two convolutional layers are used to extract higher-dimensional spatial information. The input image resolution is 512x512, and the encoder uses a 3x3 (same-padding) repeated convolution followed by a linear rectification unit (ReLU). The vertical encoder uses a max-pooling operation with a stride of 2 of size 2x2, and the horizontal
encoder uses an equal-sized average pooling operation. After two convolution operations, it is input to the CSSAM module to achieve global context information fusion. The feature information output by the CSSAM module adopts 2x upsampling and 1x1 convolution operation and then combines with the low-dimensional encoder feature information. Then, the integrated features are again passed through 1x1 convolution to generate a 512x512 feature map with channel 64. At the same time, the up-sampled feature clusters are integrated with the decoder through a skip structure. Perform 3x3 convolution and 1x1 convolution on the integrated feature map to realize the mapping of each component feature vector class.

| Method                  | IoU   | mAP  | Accu |
|-------------------------|-------|------|------|
| Base (U-net)[1]         | 0.6262| 0.6775| 0.9937 |
| Base +Ave               | 0.6324| 0.6947| 0.9605 |
| Base+CSSAM             | 0.7299| 0.7549| 0.9745 |
| Base+Ave+CSSAM         | 0.8472| 0.8684| 0.9942 |

Table 1. Comparison of welding engineering map segmentation by different methods, Ave is denoted as average pooling and convolution operations, and CSSAM is denoted as attention module. Same benchmark, bold font means excellent.

\[
IoU = \frac{\text{Area}(P_p \cap P_{gt})}{\text{Area}(P_p \cup P_{gt})}
\]  

\[
Accuracy = \frac{(TP + TN)}{(TP + FP + FN + TN)}
\]

\[
AP = \sum \frac{\text{Precision}}{N}
\]  

\[
mAP = \sum \frac{AP}{N_{\text{class}}}
\]

Precision is the sample precision, and \(N\) is the total number of samples.

Image segmentation can achieve excellent performance in many fields. In this work, we propose using a U-net network to realize the segmentation of welding structure engineering drawings in heavy industrial equipment manufacturing. Based on the research and analysis of existing state-of-the-art methods, we propose the CSSAM module and the double-pooling skip structure of the upper and lower encoders. The encoder and decoder work end-to-end to achieve a multi-scale fusion of image feature channels and spatial location information. Not only that, we take inspiration from U-net++[21]; the convolution operation is performed after double pooling to reduce the dimension mismatch problem in the skip structure process of the encoder and decoder. Our proposed method is trained and validated on a dataset of complex welded structural engineering drawings. Compared with the classic U-net, the results show that our proposed method can offer better results in segmenting welded structural engineering drawings. In terms of intelligent manufacturing practice, the semantic segmentation method is used to complete the outline extraction of engineering drawings. The machine can automatically cut the sheet metal according to the extracted contour, which significantly improves the manufacturing efficiency of heavy industry equipment.
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