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Fully Convolutional Network with Intermediate Reservation for Insulator Segmentation

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Abstract. Insulator state detection is a challenging problem for facilitating the process of inspecting in power transmission system. Nowadays, intense interest in applying convolution neural networks in image analysis is wide spread, its success is impeded by the limitation of the depth of the network and is also dependent on how to improve the information propagation and how to make full use of all the hierarchical features. To address these problems, this paper proposed a novel framework, called as the Fully Convolutional Network with Intermediate Reservation (FIR-Net), for insulator segmentation. In this framework, Intermediate Reservation has been adopted to solve the problem of gradients disappearance. The Intermediate Reservation reserves and fuses the intermediate loss of different layers, so as to improve the propagation of the network. Overall, this framework effectively propagates features both on the shallow layers and the deep layers, and increase the information diversity for insulator segmentation. By evaluating the proposed framework, it has achieved the good performance on the dataset provided by STATE GRID Corporation of China. This work is one of the early attempts of employing the idea of Intermediate Reservation on insulator segmentation.

Keywords: Insulator Segmentation, Deep Learning, FCN, Intermediate Reservation.

1. Introduction

Insulator is one of the most primary section of power transmission system. In traditional transmission lines inspection, how to precisely detect a flaw in the insulator is a key point for further troubleshooting and fault. Traditional way for transmission lines patrol is carried out with manual labor. However, this process is time-intensive and error prone, thus resulting in high maintenance cost. Manual-style inspection can't fully meet the requirement of the power industry development, and it brings great difficulties to the security, management and maintenance of power network. Consequently, an automatic detection method is needed to facilitate the process of troubleshooting and fault.

The traditional identification methods of electrical equipment are mainly dependent on the color and geometric features of the target. These methods are often influenced by the factors such as brightness change and complex background, therefore, they have poor generalization ability. The machine learning techniques used for intrusion detection, including neural network and support vector machine, are sensitive to noise of training samples, and lead to the poor generalization ability and classification accuracy. In the document [2], the ASIFT algorithm is used to match the transmission line video with the insulators in the standard library, and then to identify and locate the insulators in the video.

In order to improve the accuracy of location and recognition, a lot of researches have been investigated and developed to locate and identify insulators in recent years. In literature [3], the gray feature matrix of the image is converted into a differential representation matrix and its mean, normalization and sparsity are used. Then the DBN network is used to train the difference characteristics to identify the fault of insulators.

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Machine learning methods have been applied to recognition by adopting the traditional machine learning algorithm, document [4] utilizes SVM (Support Vector Machine) to train insulator images and combines Hough transform to locate insulators in images. Nevertheless, due to the limitation of traditional machine learning in image processing, the performance is not gratified. While in deep learning method, literature [1] proposes a six-layer convolution neural network (CNN) to train the detection model on the insulator image, and successfully uses the training model to locate the insulator. In document [5], a new method of description of difference feature is proposed, which can represent different features such as gray difference and shape change of the image. It is used for target recognition and insulators recognition of actual aerial images.

The advanced neural network based on CNN can extract more abstract features and can reach the tasks of classification, target detection and semantic segmentation.

The proposals mentioned above are focus on the location, in our proposal framework, we regard the detection task as a semantic segmentation rather than a location task. Semantic segmentation aims to understand an image at pixel level. Apart from recognizing the object in the image, semantic segmentation also has to delineate the boundaries of each object. Therefore, unlike classification, it need dense pixel-wise predictions from the research models. Before deep learning arrogate computer vision, traditional approaches like TextonForest and Random Forest based classifiers are used for semantic segmentation. As with image classification, convolutional neural networks (CNN) have had enormous success on segmentation problems. In order to solve the problem of insulator segmentation under complex background, this paper propose an end to end pixel-level classification framework based on the Fully Convolutional Network (FCN) [6] to complete the segmentation task of the insulator image.

2. Algorithm Description

2.1. CNN

Convolutional Neural Network (CNN) use a special architecture which is particularly well-adapted to image classification and semantic segmentation. The prior neural network with fully-connected layers does not take into account the spatial structure of the images, which treats input pixels which are far apart and close together on exactly the same footing. Using CNN makes networks fast to train and helps us train deep, many-layer networks, which has good performance on classification and semantic segmentation. CNN make connections in small, localized regions of the input image, in other words, each hidden neuron has a sharing bias and sharing weights connected to its local receptive field. This means that all the neurons in the same hidden layer detect exactly the same feature, just at different locations in the input image. One big advantage of sharing weights and biases is that it greatly reduces the number of parameters involved in a convolutional network. In this paper, we utilize the convolution layer with 3×3 or 1×1 convolution kernel, and insert a max-pooling layer after each convolution layer, which combines the features using 2×2 pooling windows.

2.2. FCN

Fully Convolutional Network (FCN) is the representation of the underlying model to solve semantic segmentation. It generates segmentation maps from images of any size by omitting the use of fully connected layers which has the fixed-size constraint. With the purpose of capturing the global context of the image, the last fully connected layer is replaced by a convolution layer with 1x1 kernel size in FCN. The up-sampling layer is down by transposed convolutions, thus a fine granularity increase in the image quality from low-resolution to high-resolution can be obtained. In a word, FCNs dramatically improve accuracy of semantic segmentation tasks by transferring pre-trained classifier (Alex-net, VGG-net and Google-net) weight, fusing different layer representations, and learning end-to-end on whole image. In this article, our approach which based on FCN architecture, includes an estimation block, not only to learn and reserve the feature of shallow layer, but also to obtain the spatial structure of the image.

3. Framework

Based on the FCN architecture, we proposed a novel framework called fully convolution network with Intermediate Reservation (FIR-Net) for insulator segmentation. The network structure consists of FCNs

Block and Intermediate Reservation Block. The detailed information for each part will be presented in the following section. The proposed framework is illustrated in Fig.1.

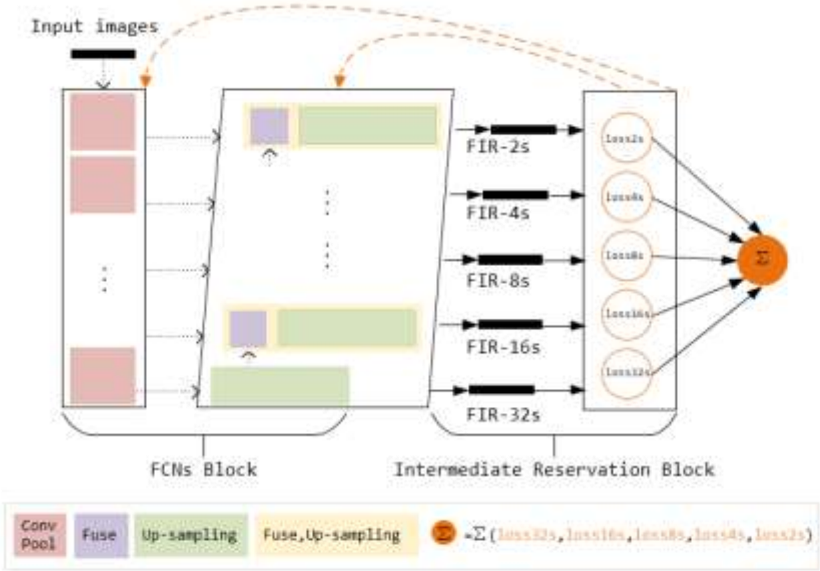

Fig. 1: The Illustration of the proposed architecture.

3.1. FCNs block

FCNs Block utilize the VGG-Net [8] layer pattern: [Conv -> Relu] × N -> Pool] × M. This means that each convolution layer uses kernel of dimension 3 × 3, followed by a rectified linear unit(Relu). After each convolution operation, we insert a max-pooling layer, which combines the features using 2 by 2 pooling windows. In this paper, we set M = 5, which means there are five groups, the first two group with N=2 and the remaining three group with N = 3. The five groups are immediately followed by the up-sampling layer. The convolution layers and max-pooling layers learn about local spatial structure in the input training image, while the up-sampling layers maintain the spatial capability by deconvolutions. In addition, the naming of different levels network is at the discretion of the multiple that resize the output by up-sampling. For example, the result size of fifth pooling layer is 1/32 of the original image size, therefore, we need to magnify the result 32 times. That's the derivation of FCN-32s. The FCNs Block is shown specifically in Fig 2.

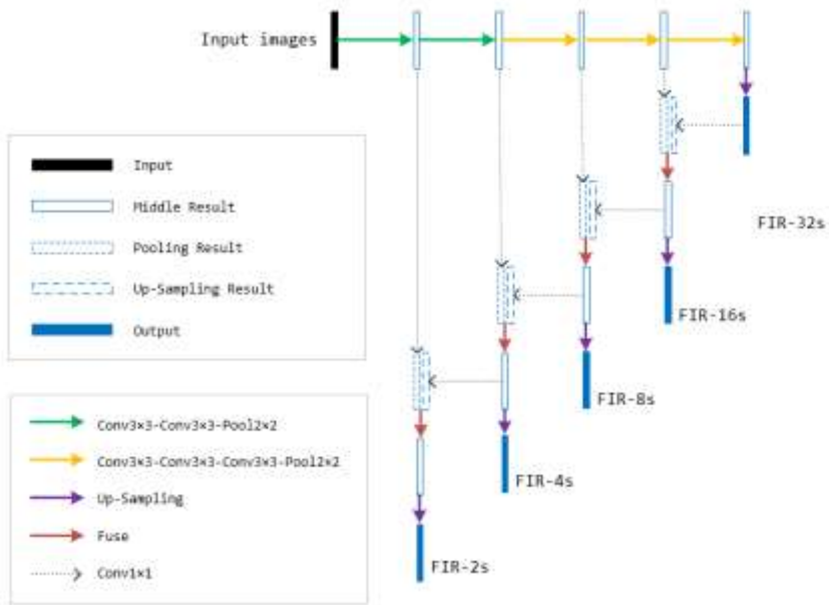

Fig. 2: The detail of FCNs Block. The route is from the input images to the up-sampling layers.

3.2. Intermediate reservation block

The low-level information diversity will be lost with the continuous convolution operations, as shown in the left part of Fig 1. Each FCNs (include FCN-32s, FCN-16s, FCN8s, FCN-4s, FCN-2s) produces the middle results and the losses can be calculated on after each up-sampling layer. Therefore, we designed Intermediate Reservation Block to reserve the middle results and different feature levels' losses for the propagation from the intermediate layer to the outputs. The middle losses of FCNs with different depth are calculated and reserved in the Intermediate Reservation Block. In other words, it creates short paths from bottom layers to top layers. The Intermediate Reservation Block are shown in the right part Fig 1. Instead of propagating the loss layer by layer in the original back-propagation algorithm. The back-propagation is able to approximate the local minimum value of the loss function in fewer iterations. It combines the losses of different levels, so as to updates parameters for each layer, the loss can be directly propagated to the layer ahead (represented as the dashed line in Fig 1).

4. Experiments

4.1. Dataset

Our dataset is a set of images without labels that provided by STATE GRID Corporation of China. These images are surveillance insulator images captured from the electrified wire netting Supervising System. We took half of them as training data, and the rest as test data.

4.2. Image processing

This step is done for the purpose of training the network faster. All original images are manual annotated by a tool named Labelme. There are two classes on each sample image label, the insulator label and the background label. Both the original images and the one-hot labels are fed into the network as the inputs. These samples are resized to the same size and restored in numpy binary type.

4.3. Training detail

In this article, the pre-trained model VGG-Net is loaded for the parameters initialization. It could speed up the learning process. We choose the RMSPropOptimizer with the learning rate 3e-4 for gradient descent optimization. Besides, the proposed framework runs on Nvidia GTX-1080Ti, and it is executed in Python with Tensorflow package.

After 500 iterations of training, our network has reached good performance while predicting the pixel's class is insulator or not on the dataset. As the depth increasing, the prediction of different layer has shown in Fig 3. The performance in each scales generally improves through increasing the depth while training.

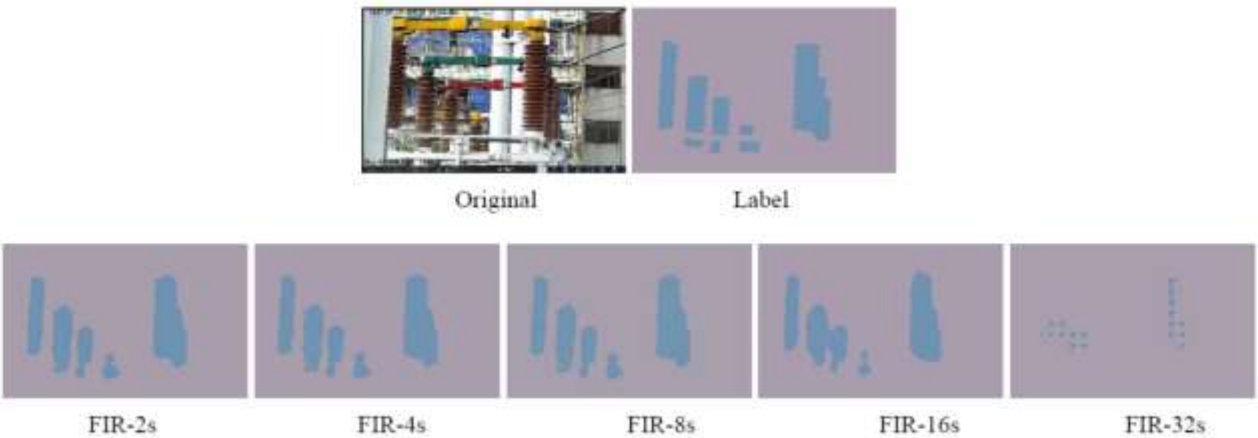

Fig. 3: The prediction of different layer.

4.4. Evaluation and results

The employed evaluation strategy is DSC (Dice Similarity Coefficient). The DSC is a measure of precision and recall. It is defined as:

$$DSC = 2TP/(FP + 2TP + FN) \quad (1)$$

In the formula (1), TP, FP and FN are the numbers of true positives, false positives and false negatives, respectively.

As presented in Fig 4, the loss, accuracy and DSC of train process perform well with the increase of iterations. The losses decreased and have ranged down to near zero. The accuracy reaches 0.99. What's more, the Dice Similarity Coefficient is 0.85. While the test results keep in a stable state because of the reloaded model has been well trained.

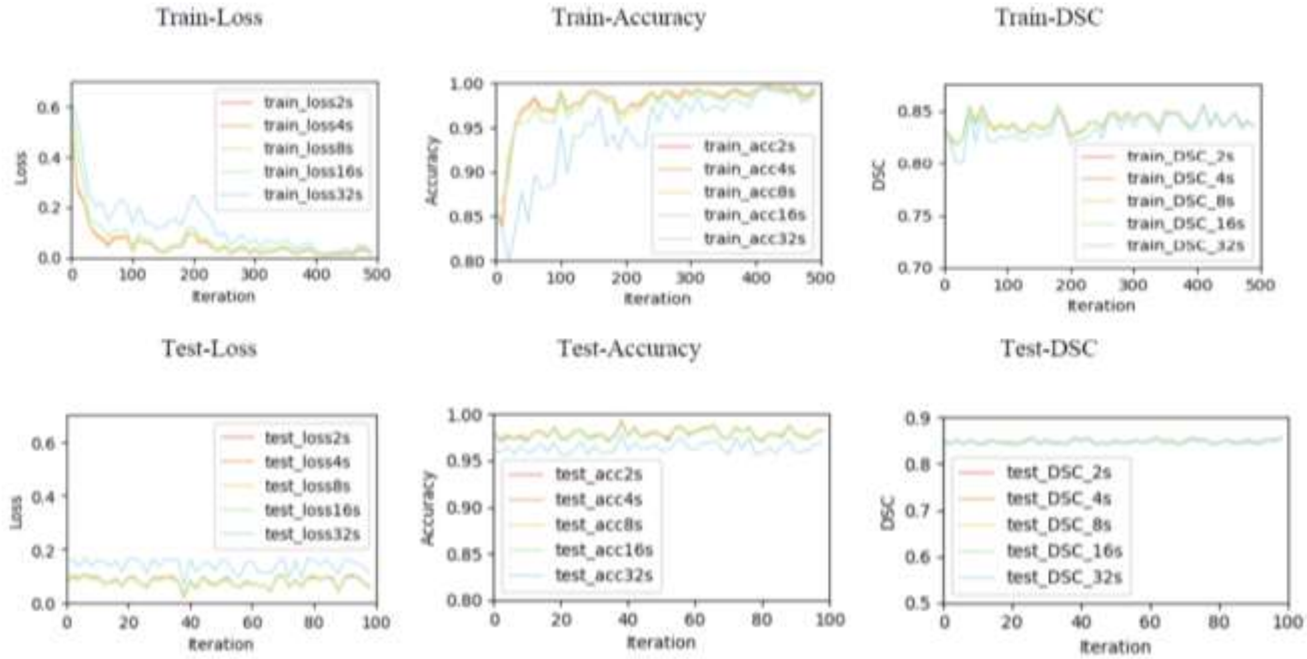

Fig. 4: The loss, accuracy and dice similarity coefficient are shown in the first row. The second row are the result on test data.

As displayed in Table 1. The mean accuracy of hierarchical network has reached 0.98 as the best result. The Dice Similarity Coefficient of FIR-8s performs best.

Table. 1: The performance on the Test Data.

	Mean-Acc	Mean-DSC
FIR-2s	0.97884	0.84955
FIR-4s	0.97971	0.84977
FIR-8s	**0.98007**	**0.84994**
FIR-16s	0.97872	0.84966
FIR-32s	0.96466	0.84645

5. Conclusion

This paper proposes a method of insulator segmentation based on FCN called Fully Convolution Network with Intermediate Reservation (FIR-Net). Experiments show that the model obtained in this task has achieved good performance, which enhance information propagation by adopting the Intermediate Reservation Block. In the future, a better model for sematic segmentation will be investigated and developed to improve our proposal.

6. Acknowledgments

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