Journal of Physics: Conference Series

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To cite this article: Yongcheng Tu *et al* 2019 *J. Phys.: Conf. Ser.* **1187** 042100

IOP Conf. Series: Journal of Physics: Conf. Series **1187** (2019) 042100 doi:10.1088/1742-6596/1187/4/042100

Automatic measurement algorithm of scoliosis Cobb angle based on deep learning

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Abstract. Aiming at the subjective experience of the physician, the high measurement error in the Cobb angle measurement of scoliosis X-ray images and the X-ray image of spine is difficult to segment. A deep learning based scoliosis Cobb angle measurement algorithm which can automatically calculate Cobb angle without the physician's manual definition is proposed. A DU-Net detection and segmentation network is proposed in this paper to remove the unrelated regions and to segment the spine contour in the spine X-ray image. The aggregated channel features in pedestrian detection algorithm is introduced to scoliosis image to realize the spine region detection. And the DU-Net network is training to segment spine contour. Therefore, the spine curve can be fitted by the spine contour and the Cobb angle can be automatically measured by the tangent line of spine curve. As a result, the Cobb angle measure methods yields an average error of 2.9° to reference Cobb angle which are measured manually by special orthopaedist. The detection algorithm in this paper yields an average precision of 98.5% and a recall of 99.5%. Moreover, the DU-Net reach an average Dice coefficient to reference segmentation of 90.28%, an IOU of 82.29% and a precision of 86.30%.

1. Introduction

The spine is the backbone of the body, located in the middle of the back, composed of the vertebrae and the intervertebral disc**.** Scoliosis is a three-dimensional spinal disorder, generally characterized by the lateral deviation of spine, which is accompanied by an angle of spine curvature in coronal plane larger than 10°. The Cobb angle which can be seen in Figure 1 have become a quantitative standard for doctors to diagnose or observe the symptoms of scoliosis patients[2].

The radiologists always measure Cobb angle by using protractor after the end-vertebrae was selected manually. Therefore, the accuracy of Cobb angle measurement was mainly depended on the subjective experience of radiologists[2]. Some researchers had investigated the deviations of manually measured Cobb angle under different end-vertebrae selection or operation methods, and they reported that the maximum measurement error could be up to 11.8°[3]. The error was so high that it would affect the diagnosis and treatment of scoliosis patients. In addition, tedious and time-consuming operations for scoliosis increase the possibility of operation mistakes. Therefore, computer-aided methods to measure Cobb angle are in urgent need due to the less rely on prior-knowledge and personal operation.

Zhang et al. [4] proposed a computer-aided method to measure Cobb angle on the basis of Hough-transform, which can calculate Cobb angle automatically after manually selected the end-vertebrae region of interest (ROI) and adjusted the brightness and contrast of the images. Samuvel et al. [5] proposed a segmentation algorithm to measure Cobb angle by putting mask on images. However, the

IOP Conf. Series: Journal of Physics: Conf. Series **1187** (2019) 042100 doi:10.1088/1742-6596/1187/4/042100

accuracy of Cobb angle measurement mainly depended on the place of mask. Zhang [6] proposed a Cobb-angle computer-aided measurement algorithm based on deep neural network, which can automatically estimate the slope of the spine after manually selecting the block of interest in the upper and lower vertebrae, and automatically measure the Cobb angle. Moreover, some computer-aided and mobile-aided soft-wares were designed to measure Cobb angle for the purpose of improving the efficiency of radiologists[7][8]. They indeed improved the efficiency of measuring Cobb angle, however, upper and lower end-vertebrae had to be manually selected, which was time-consuming and subjective. With the continuous development of computer vision, image processing algorithms such as machine learning target detection algorithms[1] and medical image automatic segmentation algorithms [9] are constantly improved. The computer-aided diagnosis methods for medical images are gradually proposed and improved.

In this study, we propose an automatic Cobb angle measurement algorithm based on deep learning. A DU-Net detection and segmentation network is proposed to segment spine contour. The aggregated channel features is used to construct the spine detection model while the U-Net is used as the spine image segmentation model. In the end, the spine curve can be fitted by the spine contour and the Cobb angle can be automatically measured by the tangent line of spine curve. The 6th polynomial can better characterize the curvature of the spine [10][11], so the Cobb angle can be automatically measured.

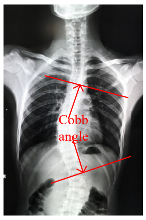

Figure 1. Cobb angle measurement

2. Spine detection

2.1. Aggregated channel features

The Aggregated channel features(ACF) proposed by Pitor Dollar[1] for the pedestrian detection algorithm, which combines features such as LUV, gradient magnitude and gradient histogram. The feature is introduced in our study to realize the spine region detection. The characteristics of each channel of the spine image are shown in Figure 2.

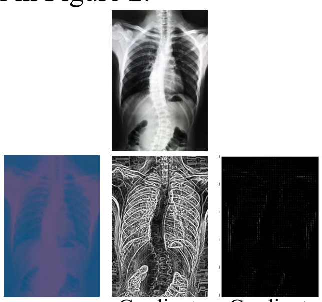

Figure 2. Aggregated channel features

The spine ACF are trained and cascaded by the weak classifier. The classification algorithm used in this paper is Adaptive Boost (Adaboost)[15].

2.2. Spine detection algorithm

Due to the strong expression ability of the ACF, it can effectively describe the contours of the target. Therefore, this paper introduced the ACF to detect the spine, extracts the features of the multi-scale features from the spine image, and use the Adaboost algorithm to train the cascade classifier. The detection steps and detection flow chart are shown in Figure 3.

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Step1:Label the area where the foreground spine is located, extract the features of the front and background ACF in input image, form the feature vector and send the corresponding background label to the weak classifier for classification training, iteratively obtain the current optimal weak classifier;

Step2:constructing a spine image feature pyramid, sliding window detection on different scale feature images, and using the above-mentioned trained classifier to determine the front result image;

Step3: Use the non-maximum suppression algorithm to obtain the final detection result.

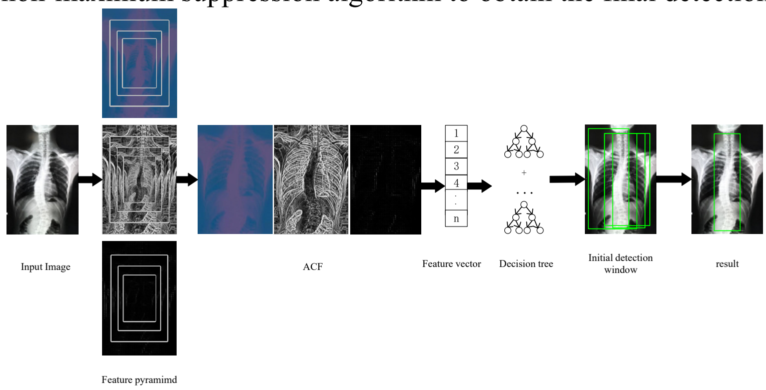

Figure 3. Detection algorithm flow chart

3. Cobb angle automatic measurement algorithm

In this paper, the DU-Net detection segmentation network is proposed. The spine image detection algorithm is used to detect the spine region, and the region where the spine is located is obtained. The DU-Net segmentation network can automatic segment the spine to obtain the spine contour. The spine contour central point can be extracted after segmentation, and the curve fitting is performed using a 6^{th} order polynomial curve fitting algorithm. The scoliosis Cobb angle can be automatically calculated by calculating the slope of the curve.

3.1. DU-Net segmentation algorithm

The algorithm flow of the DU-Net detection segmentation network proposed in this paper is shown in Figure 4. The ACF of the X-ray spine image is extracted, and the Adaboost algorithm is used to train the cascade detection classifier. The labelme is used to label the spine contours and use the spine detection area to train the DU-Net segmentation network.

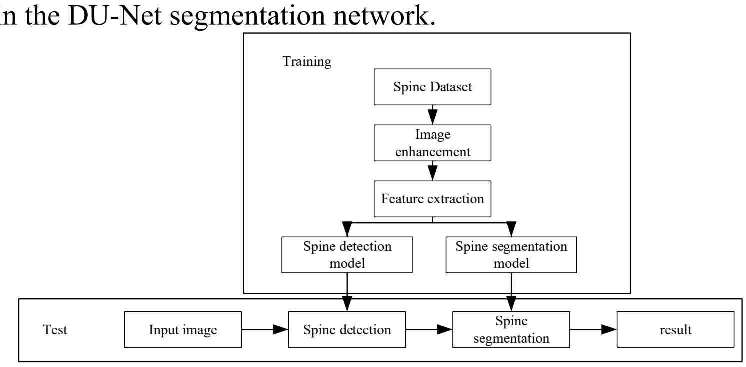

Figure 4. Segmentation algorithm flow chart

*3.1.1. U-Net.*U-Net [9] is a semantic segmentation network model based on FCN[14] structure proposed by Olaf Ronneberger et al. in 2015. It was originally applied to medical cell image segmentation and is suitable for medical image segmentation. Therefore, U-Net is introduced to implement the spine segmentation module in DU-Net.

*3.1.2. Training.*Using a deep convolutional neural network based on the PyTorch framework, implemented in Python and accelerated with the GPU. PyTorch is a deep learning neural network framework that Facebook has open source, which is flexible and efficient to use. The Loss function in our paper can be seen in below:

$$\text{Loss(x)} = \text{SoftmaxLoss}(x)+1\text{-Dice(x)} \tag{1}$$

As shown in the above formula, Loss function combines SoftmaxLoss and Dice coefficients. The Dice coefficient is used to measure the difference between the prediction results and the labels during training. The network uses the RMSprop optimizer to update the parameters. The model training time is about 8 hours, and the convergence speed is faster. Part of the feature map during training are shown below.

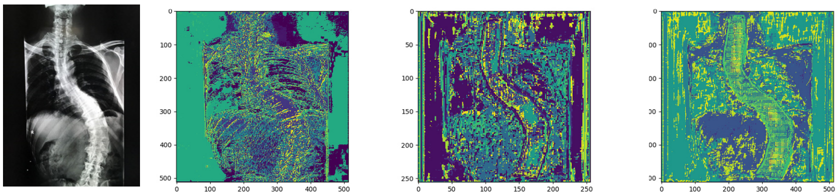

Figure 5. Feature map

3.2. Spine curve fitting
The spine contour has been obtained in above. And the central point can easily extracted by the spine contour. Therefore, the spine curve can be fitted by a set of points in the center of the spine contour, reflecting the shape and orientation of the central set of points in the spine and obtaining the curve equation of the spine.

3.3. Automatic Cobb Angle Calculate
Cobb angle is defined as the angle between the lines drawn along the most tilted vertebrae on the spine image, which is actually the angle between the tangent vector to the curve at the corresponding central point [13]. The definition of Cobb angle in this work is illustrated in Figure 6.

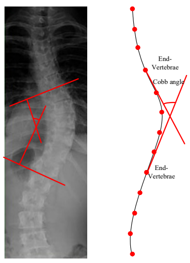

Figure 6. Cobb angle

4. Experimental results and analysis

4.1. Dataset
The self-built dataset of spinal image training, verification and testing was obtained from the Department of Radiology of the First Affiliated Hospital of Anhui Medical University and the NIH [12] public chest X-ray dataset. The dataset have a total of 800 X-ray images of the spine, including 600 training sets and 200 test sets. A total of 100 X-ray images of the scoliosis were concentrated in the training, and a total of 10 X-ray images of the scoliosis were measured. In order to carry out network training, testing and algorithm verification, labelme is used to segment the mask of the image to obtain the corresponding segmentation label. The results obtained by the Cobb angle automatic measurement algorithm in this paper are verified by the orthopedic experts of the Affiliated Hospital of Anhui Medical University. The image and label in the dataset are shown in Figure 7.

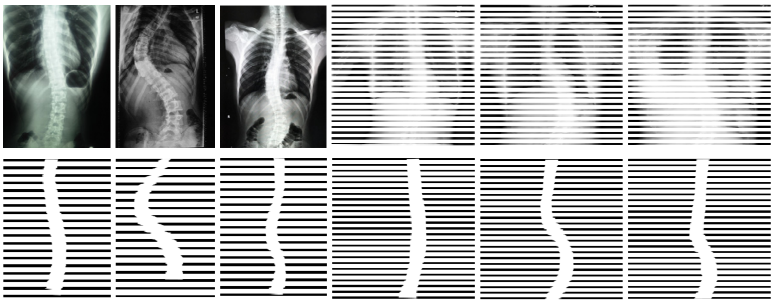

Figure 7. Training data

4.2. Result and analysis

In this section, the DU-Net and U-Net segmentation results are compared. Figure 8 shows the comparison between the DU-Net and the U-Net segmentation result.

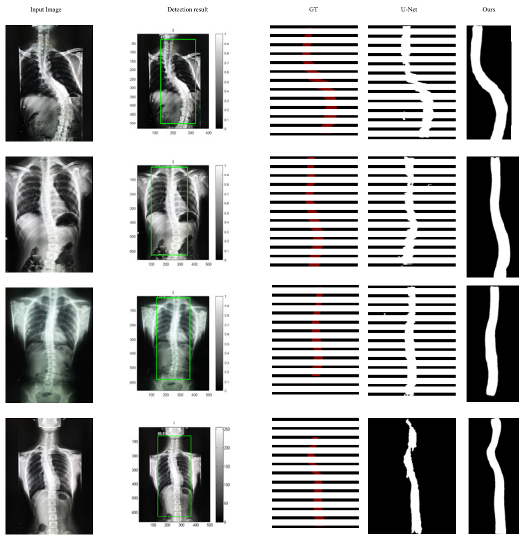

Figure 8. Segmentation result

In order to quantify segmentation results among DU-Net and U-Net, four measures of Dice coefficient, IOU, Precision and Recall[16] are selected. Moreover, the higher values of the segmentation results, the better the segmentation result will be. Our method is superior to U-Net algorithm in the segmentation of spine for X-ray images. ours yields a higher Dice coefficient of 90.28% and an IOU of 82.29%. The more accurate the spine segmentation is, the more accurate the Cobb angle measurement would be.

Table1 Segmentation indicator

Method	**Dice**	**IOU**	**Precision**	**Recall**
U-Net	0.7127	0.5700	0.7036	0.7457
DU-Net	**0.9028**	**0.8229**	**0.8630**	**0.9493**

The Cobb angle can be automatically calculated by the fitted curve with the tangents and the comparison result of ours and the reference Cobb angle which are measured manually by special orthopaedist are as follows:

Table2 Cobb angle measure result

Test	**ours**	**reference**	**bias**
1	49.2°	47.8°	1.4°
2	39.1°	40.1°	-1.0°
3	43.8°	49.2°	-5.4°
4	23.5°	25.2°	-1.7°
5	24.2°	29.3°	-5.1°

6	12.2°	15.5°	-3.3°
7	54.8°	51.5°	3.3°
8	31.5°	33.8°	-2.3°
9	32.1°	28.1°	4.0°
10	16.9°	15.2°	1.7°

5. Conclusion

Aiming at the subjective experience of the physician, the high measurement error in the Cobb angle measurement of scoliosis X-ray images and the X-ray image of spine is difficult to segment. A deep learning based scoliosis Cobb angle measurement algorithm which can automatically calculate Cobb angle without the physician's manual definition is proposed. A combination of target detection algorithm and image segmentation algorithm is introduced to form a DU-Net network structure and apply it to the spine image segmentation task. The results of this work have showed a good consistency between the automatic and reference measurements of Cobb angle. Our work can not only improve the accuracy of spine X-ray image segmentation but also simplifies the Cobb angle measurement step. The future work will optimize the segmentation network and to further improve the accuracy of spine X-ray image segmentation.

Acknowledgements

This work is supported by the Natural Science Foundation of China under Grant 61672032, and the Key Projects of Outstanding Youth Talent Support Program of Anhui Provincial Universities under Grant gxyqZD2016012.

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