



Spinal Curve Guide Network (SCG-Net) for Accurate Automated Spinal Curvature Estimation

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Abstract. Cobb angle plays an important role in the diagnosis of scoliosis, which can effectively quantify the degree of scoliosis. Manual measurement of Cobb angles is time-consuming, and the results are also heavily affected by the expert's choice. In this paper, we propose a spine curve guide framework to directly regress the cobb angle from single AP view X-rays images. We firstly design a segmentation network to accurately segment two spine boundary, and then aggregate the obtained boundary scoremap with the original spinal X-rays images to input another angle estimation network to make high-precision regression prediction for cobb angle. We evaluate our method in the AASCE19 challenge, and our result achieves 22.1775 SMAPE that shows strong competitiveness compared to other excellent methods.

1 Introduction

Scoliosis is a disease caused by abnormal curvature of the spine, the curve of the scoliosis usually appears as an “S” or “C” shape in a posteroanterior (back to front) X-ray. In the diagnosis and treatment decisions of scoliosis, cobb angle is widely used to evaluate the degree of curvature of the spine [4], which is shown in Fig. 1(a).

Traditional methods of measuring Cobb angles employed hand-crafted landmarks of spine to measure the cobb angle which is time-consuming. And these manual landmarks are affected by many factors such as the selection of vertebrae, the bias of observer, as well as image quality [1]. To improve the accuracy of cobb angle and eliminate manual impact, recent works are more focus on the end-to-end automated estimation methods based on deep convolutional neural networks. Wu *et al.* [6] integrate the robust ConvNet features with statistical information to adapt to the variability in X-ray images. After that, Wu *et al.* [5, 7] aggregate multi-view information from both AP and LAT x-rays, aiming at utilizing the structural dependencies of the two views. However, these works are directly regress the cobb angle from the raw X-rays, which don't make good use of clinical priori knowledge. More recently, Chen *et al.* [1] design a landmark-net

to learn the spinal boundary features from landmarks for comprehensive scoliosis assessment.

However, Chen *et al.* [1] only use landmarks for indirect Cobb angle calculation, which makes few contributions to the learning process of regression network. In this paper, we propose a spine curve guide framework (SCG-Net) to more accurately predict the cobb angle by utilizing the spine curve segmentation result as correction information to help network focus on more useful features during later regression task. Consider that the spine curve is capable of reflecting the degree of scoliosis intuitively, we firstly design a segmentation network to learn boundary of spine. Unlike latest work [1] that obtains auxiliary information from sporadic spinal landmarks (see Fig. 1(b)), we found that continuous spine boundary curve (see Fig. 1(c)) carries more complete analysis for the spine. In later regression task, the network directly predicts the cobb angles based on original input images and the spine curve map generated by segmentation model and the spine curve map could help the regression network focus on more useful features. To verify the effectiveness of the presented SCG-Net, we evaluate it on the test set of AASCE2019, and the leaderboard demonstrates our method achieves excellent performance.

2 Method

Figure 2 illustrates the pipeline of our method. Firstly, we learn the spine boundary curve from given X-rays images by a boundary segmentation network. Then the angle regression network takes X-ray images and obtained spine curve maps as inputs to produce the final prediction for cobb angle.

2.1 Boundary Segmentation Network

Based on clinical knowledge, we know that cobb angle reflects the crook extent of spine, therefore we design a segmentation network to obtain the spinal boundary. The segmentation network is designed as Unet [3] structure that consists of an encoder and a decoder and we add two skip-layer connections at 1X and 4X levels to refine the segmentation results by aggregating the low-level features and high-level semantic features. In order to learn more complete spine edge, we apply the Pyramid Pooling Block (PP block) [8] at the bottom of network to generate global information at different scales.

2.2 Angle Regression Network

Unlike classical classification and segmentation tasks, directly regress an impalpable cobb angle value from the raw X-ray image is lack of interpretability, even for experts. In fact, the cobb angle is usually calculated from spine curve, (see Fig. 1(a)(c)), therefore, we utilize the spinal boundary segmentation to build a relation between raw X-ray images and the feature learning of cobb angle to boost the network’s capability of understanding cobb angle.

AP X-ray Image

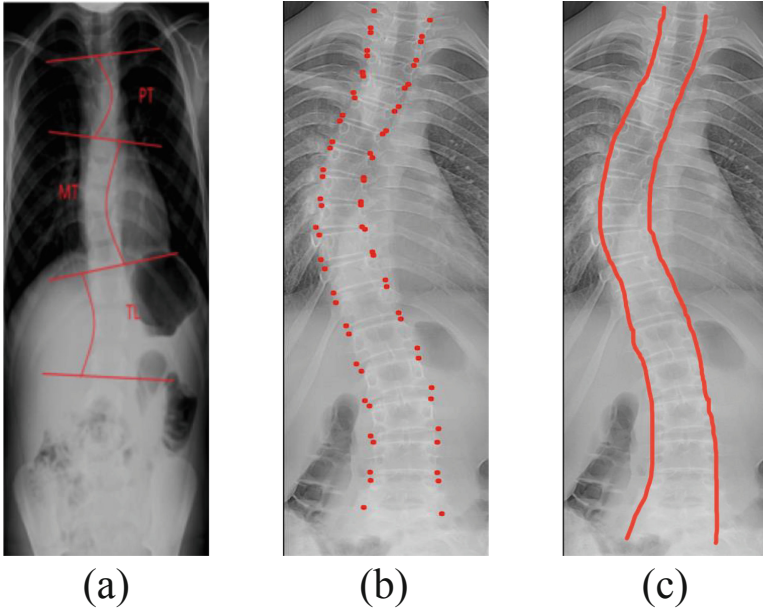


Fig. 1. (a) cobb angles in the posteroanterior (back to front) X-ray (b) given landmarks of spine, (c) boundary curve of spine

Our angle regression network takes the raw X-ray images and their corresponding segmentation results as inputs and directly produces three predictions for cobb angles. The main body of our regression network is DenseNet [2], which connects each layer to every other layer in a feed-forward fashion and shows excellent performance in a lot of tasks.

3 Experiments

3.1 Dataset and Data Augmentation

The AASCE2019 challenge supplies 609 spinal anterior-posterior X-ray images as train set and each image contains three cobb angle tags (PT, MT, TL). In addition, organizers provide corresponding landmark information for each image in train phase (see Fig. 1(b)). In test phase, all participants need evaluate their method on 98 images without landmark information.

For the train dataset, we make little data augmentation except for random crop and resize, because we are concerned that excessive transformations may affect the accuracy of the angle tag. For segmentation task, we firstly connect given landmark points together to generate two continuous spine boundaries and then we make dilation operation on the curve to generate final segmentation mask.

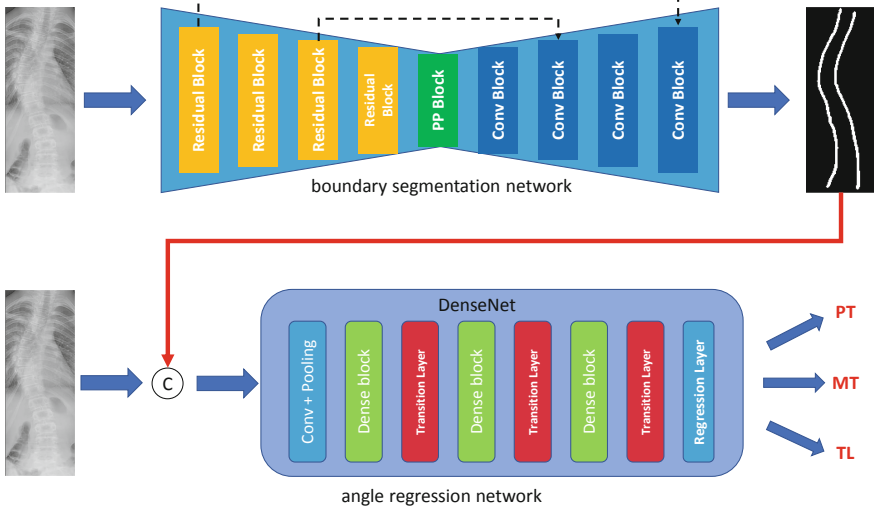


Fig. 2. The workflow of our method, which consists of two networks. The above network generates segmentation maps for spine boundary curves and the one below takes the original inputs as well as obtained spine curves mathe crook extent of spineps as input to make the final prediction for cobb angles.

3.2 Evaluation Metrics

In this challenge, the symmetric mean absolute percentage error (SMAPE) is used to evaluate the effectiveness of each method, which is defined as following:

$$SMAPE = \frac{1}{N} \sum_N \frac{SUM(|A - B|)}{SUM(|A + B|)} \times 100\% \tag{1}$$

where A is ground truth, B is predicted result, N is the number of test data.

3.3 Challenge Result

The evaluation result of the on-site challenge of AASCE 2019 is listed in Table 1, and our method demonstrates good performance and strong robustness. Our results finally rank 5th place on the public leaderboard and there is only a slight gap between our results and the first place.

Table 1. There are 257 teams participated in this challenge and 78 teams submitted their results. Our method ranks the 5th place.

Team	SMAPE	Rank
mr.waste(TencentX)	21.7135	1
Walker(iFLYTEK)	22.1658	2
AIchallenge2019	22.1729	3
Haru1994	22.1746	4
Our method	22.1775	5
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soeci92	50.6884	78

4 Conclusion

In this paper, we present a novel cobb angle estimation framework (SCG-Net) that introduces the spine curve map as a guidance to help angle estimation network understand this task better. Finally, our method ranks 5th in the AASCE2019 challenge and there is only a slight gap between our results and the first place.

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