Automated Spinal Curvature Assessment from X-Ray Images Using Landmarks Estimation Network via Rotation Proposals

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Abstract. Adolescent idiopathic scoliosis (AIS) is one of the most common type of scoliosis. In current clinical settings, the severity of scoliosis is assessed by evaluating the contralateral blending angle of the spinal cord. Cobb angle is one of the most widely accepted standards for angle measurement. However, the manual measurement of Cobb angle is time consuming and unreliable. In this article, we propose a novel two-stage method that can automatically estimate Cobb angle from vertebrate landmarks. The proposed method uses rotation vertebrate region proposals to increase the accuracy of vertebrate localization in curved spinal region. Our model uses a backbone of ResNet50 combined with FPN for multi-scale region proposal extraction. The rotation proposals are co-registered and fed into stage-two fully convoluted network (FCN) for vertebrate landmarks detection. The performance of proposed method is more robust than traditional landmarks segmentation networks for datasets with large variance, with a SMAPE score of 25.4784.

Keywords: Adolescent idiopathic scoliosis (AIS) · Cobb angle · Vertebrates detection · Landmarks detection

1 Introduction

Adolescent idiopathic scoliosis (AIS) refers to abnormal spinal curvature starts from later childhood or adolescence and continues to adulthood. AIS is one of the most common type of scoliosis, with about 4% occurrence in adolescents [1]. It causes skeletal muscle dysfunction, leading to lower back pain, ventilatory restrictions, or even pulmonary cardiac failure [2]. AIS is preventable, and early diagnosis and proper intervention in adolescents are critical for controlling abnormal spinal curve progression.

Patients with AIS may experience mild or no pain in the early stage. Clinically, the diagnosis of AIS are relying on curvature assessment on lateral spinal X-ray images, and one of the widely used standard is Cobb angle. However, the manual measurement of Cobb angles is time consuming and labor intensive. It can be challenge for experienced clinicians due to anatomical variations and low contrast of X-ray images.

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Recent advances in deep learning show the advantages of automatic spinal curvature assessment. Wu *et al.* [3, 4], Sun *et al.* [5] and Galbusera *et al.* [6] proposed one-stage bottom-up approaches to extract vertebrate landmarks or Cobb angle directly from spine images. One-stage approaches can incorporate structural information of whole spinal region but are easily affected by intra domain variance. One the other side, Horng *et al.* [7] used two-stage approach to first locate the rectangular vertebrate regions and then estimate vertebrate landmarks in each region. Two-stage approaches split the task of landmarks detection on the whole image into two easier sub-tasks: vertebrate region localization and landmarks detection on each region proposal. On problem with existing two-stage methods is that rectangular vertebrate proposals are not suitable for curved spinal cords. Since vertebrates are not horizontal when scoliosis occurs, and accuracy of both two sub-tasks can be affected due to region misalignment.

To address this problem, we propose a two-stage automated spinal landmarks detection network based on rotational regional proposals of vertebrates. In stage one, the proposed network detects location of vertebrates using rotated rectangular regions. In stage two, each vertebrate region undergoes rotation co-registration using rotation angle from previous stage. Landmarks detection are then performed on aligned proposals. Finally, we estimate Cobb angle using detected vertebrate landmarks.

2 Proposed Method

2.1 Vertebrates Detection via Rotational Proposals

We adopt feature pyramid network (FPN) as network's backbone (see Fig. 1), which performs multiscale feature extraction and gives regional proposals on each scale. In the training stage, the input ground truth of each rectangular vertebrate bounding box contains 5 parameters (x, y, w, h, θ). Among them, (x, y) and (w, h) describe bounding box center location and dimension, respectively. Rotation angle θ, ranging from $-\frac{\pi}{2}$ to $\frac{\pi}{2}$, is about the angle of tilted bounding box with respect to x-axis with rotation center fixed at (x, y). In addition, we design rotational anchors at 5 scales, 3 ratios and 3 rotational angles. We use minimum mean square loss for rotation angle regression. The rest parameters of bounding box are estimated as in [8]

2.2 Rotational ROI Align and Landmarks Detection

We propose to use rotational region of interest (ROI) align on vertebrate proposals (see Fig. 1). Rotated vertebrate proposals are adjusted using rotation angles regressed from previous stage. These proposals then undergo ROI align into fixed size feature maps as stated in [8]. Finally, they are sent to fully convolutional network (FCN) for landmarks detection.

3 Experiments and Results

3.1 Implementing Details

Dataset. The proposed study is based on AASCE2019 whole spine X-ray dataset, including 481 train images, 128 validation images, and 98 test images. Images in train

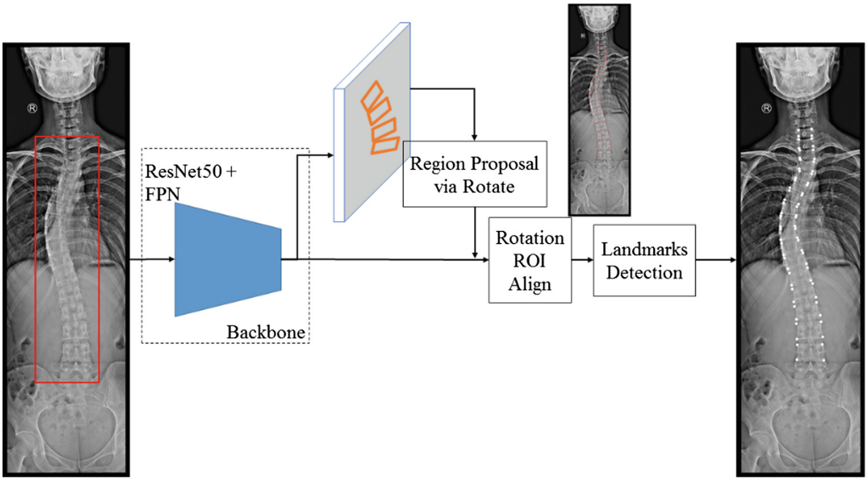

Fig. 1. Pipeline of proposed method. We use ResNet50 combined with FPN as backbone for multiscale feature extraction. Rotational region proposals are extracted from stage one and fed into FCN for landmarks detection.

and validation set consist of 68 manually annotated landmarks (4 landmarks for each of the 17 thoracic vertebrates). Trainset and validation set are manually cropped to remove head and pelvis floor, whereas test set images have increased field of view from upper femur to head. In addition, image contrast and texture of test set are visually different from train and validation set. The intra domain variance among three datasets, particularly the presence of head and pelvis floor in test set, has a significant impact on model performance (see Fig. 2(a) and (b)). To solve this, we propose a standardized image preprocessing routine to reduce the influence of dataset variance.

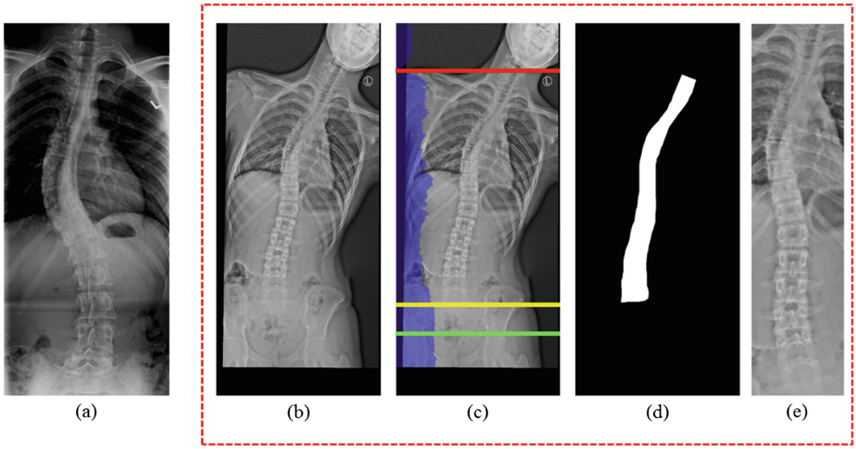

Fig. 2 Illustration of preprocessing steps for spine region isolation and refinement.

Spine Region Isolation. We first isolate the area of spine region using horizontal intensity projection to remove head and pelvis floor (see Fig. 2(c)). The intensity thresholds for different body parts are determined by statitcal evaluation of whole dataset.

Spine Region Refinement with Cord Segmentation. After obtaining spine region, we perform spinal cord segmentation and midline extraction (see Fig. 2(d)), which are used for spinal cord co-registration and false-positive key points suppression. Finally, spine region is further refined with locked aspect ratio 3.5 between image height and width (see Fig. 2(e)).

3.2 Results

Figure 3. shows experiment results of vertebrate localization and landmarks detection of test dataset. Our model predicts the location of each vertebrate using rotation bounding box (as in Fig. 3(b)). Despite significant difference among train, validation and test dataset, our model achieves a recall of >98% in vertebrate detection and a precision of >99% after post-processing using spinal cord mask. The proposed vertebral region and co-registered using rotation angle and used for landmarks detection. Each region proposal yields 4 landmarks, which are projected back into original image for Cobb angle estimation.

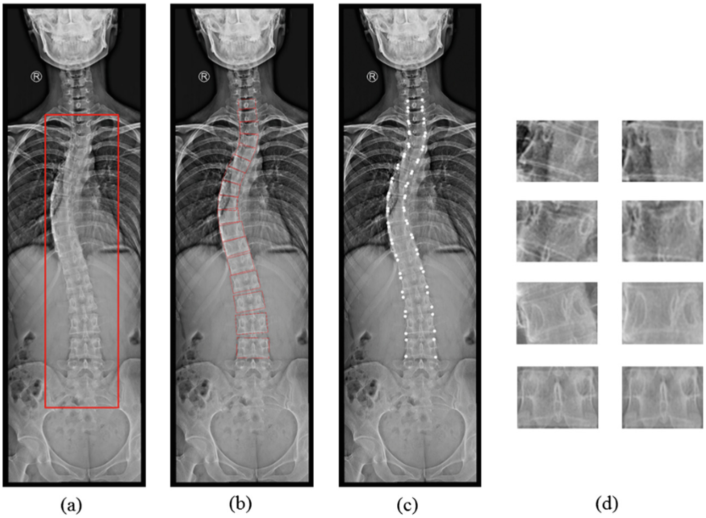

Fig. 3. Qualitative experiment results of test dataset. (a) shows the original image with refined spine region. (b) shows the rotational bounding box results from stage one region proposal network. (c) shows vertebrate landmarks segmentation results from stage two landmarks detection module. (d) illustrates vertebrate patches before and after rotation angle adjustment.

We compare our method with V-Net and Cascade Pyramid Network (CPN). V-Net is a robust architecture that succeed in many medical image applications. For V-Net, we divide the landmarks into four groups (upper left, lower left, upper right, and lower left), according to the location of landmarks to corresponding vertebrate. CPN is a powerful two-stage landmark detection network that demonstrate its ability in human landmarks detection. We use similar settings for CPN with our method. Experiments results shows that our method achieves better performance that the other two, with a score of 25.4784 for proposed method, 30.7135 for V-Net and 40.7873 for CPN ((as in Table 1). By visual inspection, we find that rotation region proposals fit vertebrate region better and non-rotate proposals, thus reduce noises from non-spinal regions and therefore increase the accuracy of landmark detection.

Table 1. Quantitative comparison of three different methods.

Model	V-Net	CPN	Our method
SMAPE	30.7135	40.7873	25.4784

4 Conclusion

In this paper, we introduce an end-to-end deep convolutional neural network for spinal landmarks detection and Cobb angle estimation. Our method is motivated by MaskR-cnn but customized for the task of rotated vertebrate detection using rotational region proposals. Compared to other methods, the proposed method is more robust to intra domain variance. Rotation region proposals provide a better fitting of vertebrates in curved spinal regions, which are of greater clinical importance than straight spinal area. Given the accurate detection of vertebral regions, our model has a lower false-positive rate of estimated landmarks.

The task of Cobb angle estimation intrinsically requires locating the first and last thoracic vertebrate. However, our model is more likely to detect all existing vertebrates on image. We have incorporated preprocessing steps such as head and neck removal, which can partly solve this problem. In practice, however, the last cervical vertebrate is often mis-recognized as the first thoracic vertebrate. One future direction is to introduce additional network for more accurate localization of the first and last thoracic vertebrate.

Overall, we have proposed a novel and robust framework for spinal landmarks detection. The proposed method demonstrates its ability in dataset with large variance and can potentially be used for other medical image applications.

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