

AUTOMATED DETECTION AND EVALUATION OF LUMBAR DISCS IN CT IMAGES

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Abstract—Lumbar spondylolisthesis is one of the most common spinal diseases. It is caused by the anterior shift of lumbar vertebrae relative to its subjacent vertebrae. In current clinical practices, staging of spondylolisthesis is often conducted in an empirical and qualitative way. Although Meyerding grading system opens the door to diagnose and stage spondylolisthesis in a more quantitative way, it relies on the manual measurement of the relative shift between neighboring lumbar vertebrae, which is time consuming and irreproducible. Thus, an automatic algorithm to measure lumbar vertebrae shift becomes desirable for spondylolisthesis diagnosis and staging. However, there are two challenges: (1) Accurate detection of the most anterior and posterior points on the superior and inferior surfaces of each lumbar vertebrae. Due to the small size of the vertebrae, slight errors of detection may lead to significant measurement errors, hence, wrong disease stages. (2) Automatic localize and label each lumbar vertebrae is required to provide the semantic meaning of the measurement. It is difficult since different lumbar vertebrae have high similarity of

both shape and image appearance. To resolve these challenges, a new auto measurement framework is proposed and the main contributions lie in the following aspects:

First, a learning based spine labelling method that integrates both the image appearance and spine geometric information is used for detection of each lumbar vertebrae. Second, a hierarchical method which uses both the population information from atlases and domain-specific information in the target image is proposed for most anterior and posterior points positioning. Our method has been extensively evaluated on 258 CT spondylolisthesis patients, and experimental results show that our method achieves very similar results to manual measurements by radiologists and significantly increase the measurement efficiency.

1. INTRODUCTION

Lumbar spondylolisthesis is one of the most common spinal diseases. Previous studies demonstrated that about 4% to 6% of population has spondylolisthesis and spondylolysis. Lumbar spondylolisthesis is

mainly caused by the anterior shift of one lumbar vertebrae relative to its subjacent one. Patients with spondylolisthesis may not have symptoms in the early stage. In addition, different treatment plans shall be selected for different disease stages. Therefore, early detection and proper staging of spondylolisthesis become important clinical tasks. In today's musculoskeletal (MSK) clinical workflow, the stage of spondylolisthesis is determined by the amount of anterior shift of the lumbar vertebrae (i.e., namely the Meyerding grading system). More precisely, the percentage of the anterior shift relative to the subjacent vertebrae's upper surface length is calculated, and it falls in one of the five stages: 0-25 percent - Grade 1, 26-50 percent - Grade 2, 51-75 percent - Grade 3, 76-99 percent - Grade 4, 99 percent or more - Spondyloptosis. For different stages of spondylolisthesis, different treatment methods will be used in the MSK clinical workflow. For instance, for Grade 1 spondylolisthesis, normally physical therapy and exercise will be the first option for treatment. For more severe spondylolisthesis grades, patients may need to receive surgical treatments such as spinal fusion.

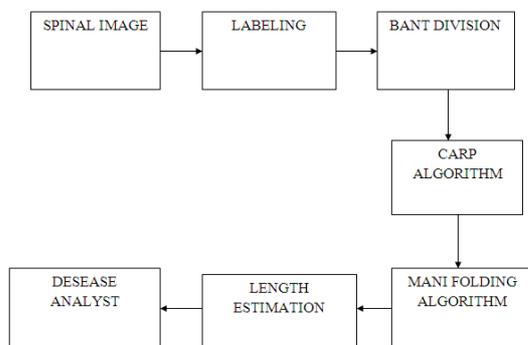


Fig. 1 System structure

II PROPOSED METHOD

New framework for automatic spondylolisthesis measurement which can resolve the above two challenges. In this paper, we mainly focus on the measurement on CT images, which is one of the most commonly used image modalities for spondylolisthesis diagnosis. First, a learning based spine labeling method that integrates both the image appearance and spine geometric information is used for detection of each lumbar vertebrae. Second, a hierarchical method which uses both the population information from atlases and domain-specific information in the target image is proposed for most anterior and posterior points positioning.

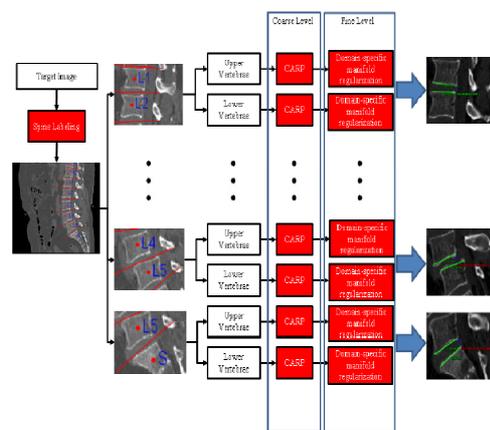


Fig.2 Flowchart of proposed method

III. AUTOMATIC SPINE LABELING WITH HIERARCHICAL LEARNING

In the first step of our framework, it is necessary to automatically detect and label vertebrae centers and intervertebral discs. The output of the spine labeling algorithm provide useful information to spondylolisthesis measurement in two-fold: 1) the locations of the vertebrae will

be used to initialize the atlases, and 2) the labels of the vertebrae will provide semantic information to report the spondylolisthesis measurements. We design a robust algorithm using a hierarchical learning approach.

IV. AUTOMATIC SPONDYLOLISTHESIS MEASUREMENT

In this section, a hierarchical framework to automatically measure the anterior shift of each pair of lumbar vertebrae based on the spine labeling results obtained in Section III is introduced. In the flow chart of the proposed method, the coarse level, the population information is used to give a robust yet rough estimation for the superior and inferior surfaces of vertebrae with a critical anatomy region propagation (CARP) method. In the fine level, the domain-specific information in the target image is used to refine the critical regions estimation and the most anterior and posterior points are extracted.

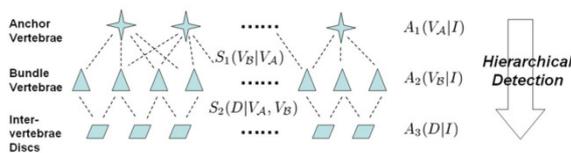


Fig. 3 Proposed spine detection framework

V. EXPERIMENTAL RESULTS

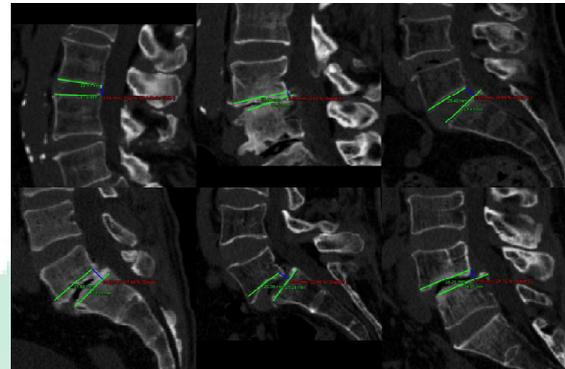


Fig. 4 Typical spondylolisthesis measurement results obtained by our method

The proposed method has been extensively evaluated on a CT lumbar spondylolisthesis dataset. The dataset consists of 258 patients. Each image has an in-plane resolution of 512×512 , with a voxel size of $0.98 \times 0.98 \text{ mm}^2$ and an inter-slice voxel size around 0.7 mm . Each image is obtained from a Siemens Somatom Definition CT scanner with various scanning parameters. For instance, the peak kilovoltage (KVP) is ranged from 80 to 120, and the CT reconstruction kernel is ranged from B30s to B60s. Therefore, there are large image appearance and noise level variations in the database. The most anterior and posterior points of the upper and lower surfaces of each vertebrae are also manually annotated by three clinical experts independently. One of the clinical experts has also annotated the dataset twice independently to study the intra-rater differences. From the annotation results, the anterior shift percent and the stage of the disease for each pair of adjacent lumbar vertebrae can be determined.

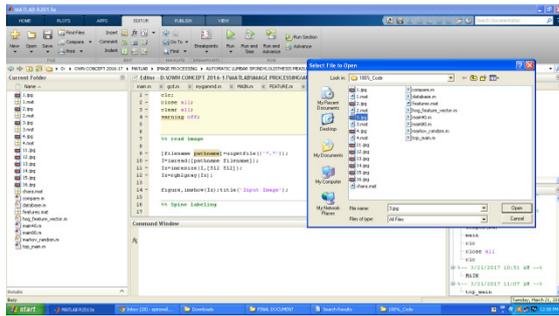


Fig.4 Input image

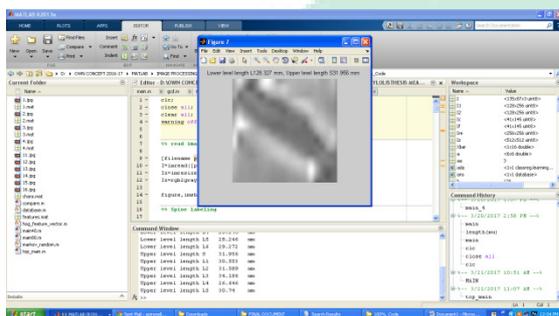


Fig. 5 Output image

VI.CONCLUSION

In this paper, we propose an automatic lumbar spondylolisthesis grade estimation method. It mainly consists of two main stages: automatic spine labeling, and critical region determination. In the spine labeling stage, anchor landmark detectors are first trained to locate vertebrae with salient anatomical context, and it is integrated with an articulated spine model to detect and label the remaining vertebrae with bundle landmark detectors trained on less salient vertebrae. After spine labeling, a hierarchical learning method is used to determine the critical regions in each vertebrae to estimate the spondylolisthesis grade. In the coarse level, the critical region is roughly yet robustly located by a multi-atlases kernel sparse representation method using the population information. In the fine level, the patient-specific information is

used to further refine the critical region with a semi-supervised manifold regularization method. Our method has been extensively evaluated on a CT lumbar spondylolisthesis dataset consists of patients and possible alternatives are compared. Experimental results show that our method achieves inter-rater level measurement accuracy. Our method is also efficient as it only takes several seconds in average to estimate the spondylolisthesis grade of each lumbar vertebrae pair for one CT spine image. Future research includes to train the vertebrae detectors using deep learning or random forests to improve the robustness of the detection.

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