Automatic Generation and Validation of Patient-Specific, Anatomically Inclusive Spine Models for Biomechanics-Informed Surgical Planning

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Introduction

Adolescent idiopathic scoliosis (AIS) is a condition that affects 3% of the population aged 10 to 18. Severe AIS deformities, defined by Cobb angles greater than 45 degrees, require treatment with invasive procedures such as posterior spinal fusion (PSF) surgery [4, 11]. Currently, routine computed tomography (CT) images provide limited preoperative data as to how the spine will respond to pedicle screw implantation, rod rotation in situ, direct vertebral rotation, multiple ligamentous releases, and Ponte osteotomies performed by surgeons working toward these outcomes. Thus, extra steps to mobilize the spine are often performed intra-operatively, increasing patient morbidity, operating room time, and blood loss [10]. By predicting how the spine responds to surgery through finite element (FE) biomechanical simulations, corrective procedures could become safer and more efficient. Accurate FE studies must appropriately consider all anatomical elements of the spine, including realistic soft tissue volumes rather than the traditional representation of crude springs, one-dimensional rods, or simplified elastic shell elements set with hand-designated anchor points [6, 8]. Some studies have succeeded in automatically segmenting vertebrae and intervertebral discs (IVDs) with convolutional neural networks (CNN) [9, 12 - 14], few studies have labeled or segmented these conspicuous tissues from scoliotic case images [7 ,16], and only one study has used deformable vertebral models to produce segmentations on relevant image space [9], but no studies have automatically produced anatomically inclusive, ligamentous spine models or validated the soft-tissue positions contained in these models [1, 15]. Thus, a methodological groundwork for the generation of a deformable surface model that estimates ligaments and other soft tissue positions in the spinal column using clinically relevant imaging, namely CT scans, is necessary for advancements in ligamentoskeletal surgery. Therefore, this research proposes a methodology to generate patient-specific, anatomically inclusive meshes, based on segmented triangulated surface boundaries, which provide a true and realistic foundation for FE biomechanical simulations that will enhance orthopedic pre-surgical planning.

Methods

Models are generated through the fitting of an anatomist-drawn Computer-Aided Design (CAD) templates onto vertebral segmentations of routine, preoperative CT images. Due to the inconspicuous presentation of spinal ligaments in CT and other modalities, an anatomist-drawn, CAD torso model, is a necessary starting point [17]. The CAD torso represents bone, ligament, cartilage, soft tissue, and other anatomy as accurate and realistic meshes, permitting a top-down, model-based segmentation approach. Before CAD mesh deformation, vertebral segmentations from CT images are obtained using a 3-part, coarse-to-fine CNN. The first part predicts a heatmap of the x and y coordinates of the spine, the second part localizes the center of the vertebral bodies through heatmap regression, and the third part segments the localized vertebrae using a U-Net variant. ShapeWorks then characterizes the segmentations surfaces with landmark points that are used for an initial affine transformation [3]. Next, CT segmentation intensities are normalized, and the CAD mesh is deformed with a framework of physically based triangular meshes. All mesh vertices are lumped as mass particles and are attracted toward the vertebral segmentations using Newtonian based forces. Weighting factors applied to the conspicuous portions of the CT image result in aggressive deformation of the CAD, pulling it toward the vertebral segmentations of the CT image. Simultaneously, the other anatomy surrounding the vertebral CAD mesh is locally deformed based on the mass particle grouping to surmise accurate positions of the soft tissues. Using synthetic image data, novel validation substantiates the soft tissue deformation reliability. The synthetic data, which includes all tissue structures present in the CAD mesh, is produced by randomized shape space projections of previously subsampled CAD meshes to provide a somewhat similar, but notably different ground truth image [2]. While this method is robust if CT segmentations for vertebrae are obtained, CNNs and other deep NNs still struggle with automatic segmentation of highly symptomatic cases due to limited training datasets, which contain minimal scoliotic images. However, molded spines validate the applied method for highly symptomatic cases CNNs cannot segment. With a VTK framework, individual vertebra are manipulated along 4 degrees of freedom (1T3R), to match a given Lenke classification [18]. Finally, surface meshes are converted into volumetric models using periodic mesh generation methods from CGAL. Mesh edges and boundaries are preserved in the models, which are later used FE studies.

Results

CNN training used the CT dataset from the VerSe 2020 challenge [19]. Training used a mini-batch size of 1 for all networks and 10,000 iterations for the spine localization network, 50,000 iterations for the vertebrae localization network, and 50,000 iterations for the segmentation network. The spine localization and vertebrae segmentation use an Adam optimizer with a learning rate of 10^{-4}. The vertebrae localization use the Nesterov optimizer with a learning rate of 10^{-8}. A series of asymptomatic and symptomatic CT scans from SpineWeb and the VerSe were used for the overall method testing [20]. Symptomatic cases included 5 individuals with mild to moderate scoliotic curvatures. Soft-tissue inclusive testing was performed with 15 synthetic images. Molded spines, including 8 different types of Lenke classifications (3A, 1B, 1C, 2C, 3C, 4C, 5 and 6), were fit with the CNN-absent method. In total, 249 vertebra, spanning cervical, thoracic and lumbar regions were generated and validated based on their respective ground truth segmentations. All fits were evaluated with Dice similarity coefficient (DSC) and average Hausdorff distance using the segmentation comparison tools of 3D Slicer [21]. The table below summarizes the results.

Tested on	Vertebrae Total	Scoliotic	Soft Tissues	DSC (%)	Hausdorff (mm)
CT Scan	83	Yes	No	77	1.41
Synthetic Image	30	No	Yes	94	0.81
Molded Spine	136	Yes	No	81	1.17
All	249	Yes	Yes	84	1.13

Illustrated Methodologies and Qualitative Results

Conclusion

This study applied a methodology for the automatic generation of anatomically inclusive, patient-specific, deformable multi-surface models that contain soft tissue anatomy, such as ligaments and cartilage, by warping CAD meshes to CT segmentations. The method first uses a CNN that outputs CT segmentations of vertebrae, which are characterized with homologous point pairs. Next CAD meshes are affinely aligned and made patient-specific through deformable surface algorithms that elastically fit the meshes onto the vertebrae segmentations. During the deformation process, soft tissues of the CAD are locally warped to reconstruct contextually appropriate positions. Finally, the models are converted into volumetric representations for the subsequent use in FE biomechanical simulations that seek to provide advancements for the orthopedic presurgical planning community. This technique is broadly applicable to a myriad of surgical scenarios, such as the shoulder and knee, where accurately modeling ligaments in patients is essential to meaningful surgical planning and simulation. However, the focus of this study was centered on methodological testing for spines, particularly AIS symptomatic spinal columns. Further experimentation with synthetically generated image data and vertebrae molded into a Lenke classified deformity supplemented the validity of the methodology for instances of inconspicuous soft tissue presence and CNN segmentation limitations, respectively. Quantitative results were validated using DSC and Hausdorff distance. Qualitative results showed current progress on the formation of a soft-tissue inclusive, deformed spinal column model. Future work will explore the accuracy of models produced with pre-operative images compared to intra-operative images.

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