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Spine Curve Modeling for Quantitative Analysis of Spinal Curvature

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***Abstract*—Spine curvature and posture are important to sustain healthy back. Incorrect spine configuration can add strain to muscles and put stress on the spine, leading to low back pain (LBP). We propose new method for analyzing spine curvature in 3D, using CT imaging. The proposed method is based on two novel concepts: the spine curvature is derived from spinal canal centerline, and evaluation of the curve is carried out against a model based on healthy individuals. We show results of curvature analysis of healthy population, pathological (scoliosis) patients, and patients having non-specific chronic LBP.**

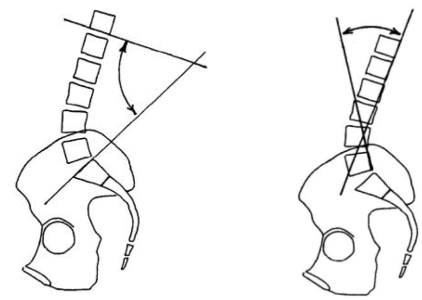

Fig. 1: The Cobb (left) and Tangent (right) methods for measuring lumbar angle in the sagittal plane. Cobb technique use vertebral endplate lines to construct angles. The tangent method is an angle between two lines, drawn tangentially to the posterior vertebral body wall of the end vertebrae.

I. Introduction

Correct posture and adequate back support are important since malposture can add strain to muscles and put stress on the spine. Over time, the stress of poor posture can change the anatomical characteristics of the spine, leading to pressure on blood vessels and nerves, as well as rapid degeneration of muscles, discs and joints. All of these can be major contributors to back and neck pain, as well as headaches, fatigue, and possibly major organs dysfunction and breathing problem 0[1].

The aim of this study is to investigate a new method for spine curvature evaluation. The method is uses CT imaging of the spine to give 3D curvature description of the spine, which in turn is compared against a model curve of the spine. The curves are based on the spinal canal, avoiding pitfalls of using bone features for curve estimation. The analysis is done against a model so both local and global descriptors are examined in a single framework.

A. *Previous work*

Quantitative analysis of spine curvature is important for understanding the nature of normal and pathological spine anatomy. Several techniques are available. The Cobb technique [2] (Figure 1) is the most established method for quantifying spinal curvature in the coronal plane in the case of scoliosis deformities as well as in the sagittal plane to measure lordosis and kyphosis. Other methods for measuring the degree of spinal deformity exist, e.g. [4], [5] (see [3] for review of spinal curvature evaluation methods). Most of the proposed methods (e.g. Harrison Method [5], Figure 1) are too complex for routine use, and provided only 2D geometric descriptors of spinal deformity. Studies emphasized that 3D descriptors might yield a more complete assessment of 3D spinal curvatures [6].

Several methods have been published aiming at an segmentation of the spinal canal and spine curvature assessment. Automatic extraction and partitioning of the spinal cord in CT images was presented by Yao [9]. The spinal cord was detected by watershed algorithm followed by graph search. Vrtovec [9] presented a method for spine curve detection in CT by polynomial model to provide a curved planar reformation (CPR) of the spine column, based on vertebral bodies. Vrtovec [11] also present a method for quantitative analysis of spinal curvature in 3D from vertebral body lines, using geometric curvature and curvature angle.

Since spine curvature has both local and global characteristics (e.g. scoliosis or lordosis, in contrast with spondylolisthesis), most methods prove insufficient. Another drawback of previous methods is that measurements are based on features along the vertebrae bodies. Thus small deformation of the vertebra body (e.g. osteophytes) may result in miscalculation of the curvature.

In this paper we present a new method for spine curve extraction, based on spinal canal centerline, with a novel method for curvature analysis using spine curve model.

II. Methodology

The spine assessment framework components are outlined as follows: (1) Segmentation of spine canal based on two step segmentation the spinal canal is extracted. (2) Curve extraction using the spinal canal segmentation the spine curve is found using minimal path algorithm. (3) Curve Modeling based on curves extracted from healthy individuals. (4) Curvature analysis through curve evaluation against the model and assessment of the deviations. The implementation was carried in C++ out using ITK library.

A. *Spinal Canal Segmentation*

The spinal canal is a tubular object that has sharp edges (with the spine), weak edges (with intervertebral disk) and no edges (with nerve roots). This makes segmentation of the

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canal a difficult problem. Several techniques to extract the canal have been suggested [7], [8]. We are using a two step method for canal segmentation: initial segmentation is carried out using morphological region growing technique, followed by fine 3D active surface segmentation. This method allows very fast (within 2-3 seconds for 400 images) initial segmentation followed by fine and accurate adaptation of the segmentation to canal shape.

A seed point for the spinal canal segmentation is found using pattern recognition. The detection is carried out on a 2D image created by fusion of several axial slices that account for 10mm (the amount of slices depends on the scan parameters) at the superior part of the scan. On this image a hole detection algorithm is performed using circle detection Hough transform. Of the resulting circles, the most appropriate circle is chosen by its morphological characteristics and its relation to bone segments on that image – a hole at the mid posterior part of the image surrounded by bone. The center of the hole is the seed point. To extract the initial region on the axial slice (where the seed is located), region growing segmentation, based on JSEG texture, is performed. If the initial 2D segmentation differs significantly from the hole (circle) detected above for seed point, then the hole is taken as the initial 2D segmentation, although in most cases it is much smaller. Next, the spinal canal is segmented by stepwise morphological region growing. At each step all neighborhood pixels within adaptive thresholds are considered. The candidates are then divided into connected components, and the most appropriate component (i.e. component with similar size and mean HU values) is added to the segmentation. At the end of the process leak detection is carried out by checking the size of the components at each step, and checking if there is a large change of size indicating leakage.

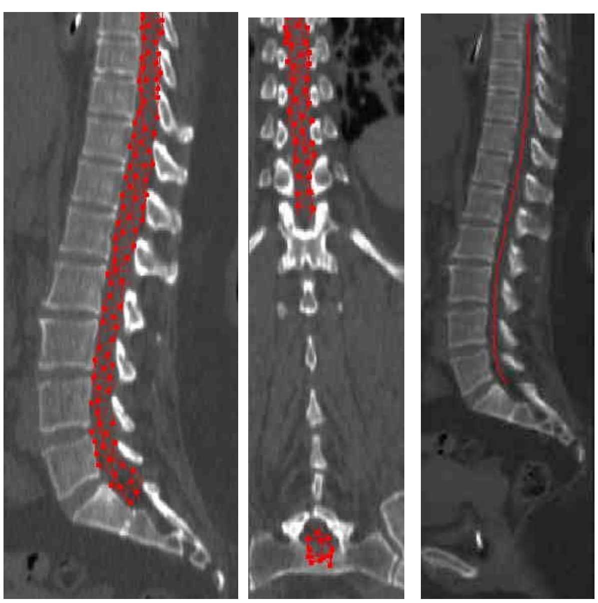
(a) (b) (c)

Fig. 2: Spinal Canal final mesh segmentation (a), (b), and centerline extraction (c).

The next step is a fine segmentation process based on a 3D discrete deformable model. An initial boundary (a simplex mesh) is deformed under internal (shape-based) and external (image-based) constraints until an equilibrium is reached (see [12] , [13] for reviews). To overcome weak edges we adopted a coarse-to-fine approach: first a low-resolution mesh is deformed until convergence, and then the mesh is refined and deformed again but allowing only small deformation.

Mesh deformation is governed by a second order evolution equation, which can be rewritten for discrete meshes as follows:

$$m\frac{\partial^2 P_i}{\partial t^2} = \alpha \cdot \mathbf{Fint} + \beta \cdot \mathbf{Fext}$$

where α and β are global weights for the internal and the external forces respectively. This equation can be discretized in time t, using an explicit discretization scheme as follows:

$$P_i^{t+1} = P_i^t + \alpha \cdot \mathbf{Fint} + \beta \cdot \mathbf{Fext}$$

The internal force imposes smoothness constraints on the polygonal mesh. External forces were computed along the normal of each vertex '*on the fly'* to allow fast computation. We combined both texture edge information and intensity information for the computation of the external forces:

$$\mathbf{Fext} = \beta_1 F_{Texture} + \beta_2 F_{Intensity}$$

The texture edge image was based on JSEG (J measure based SEGmentation) algorithm [14]. The basic idea of the JSEG method was to separate the segmentation process into two stages: color quantization and spatial segmentation. In the first stage, quantization algorithm based on peer group filtering (PGF) and vector quantization reduces image gray to produce a class map. Based on the class map, spatial segmentation was performed based on pixel *J val* [15]. The measure J is defined as

$$J = \frac{S_B}{S_W} = \frac{S_T - S_w}{S_W}$$

Where S_T is the within class variance and S_W is the total variance. For each pixel, its corresponding J value was calculated over the local (5x5x5) window centered on this pixel. Thus, a J-image was formed. To allow fast computation J values were computed only along the normal line for each vertex, the edge along the normal was found, and the texture force value was the product of the distance of the vertex to the edge, and the edge strength.

The intensity force is based on given range of intensity values. Assuming the vertex is within the object, the closest point along the normal to be outside the range is considered as the edge, and the force magnitude is defined as the distance to this edge.

The Mesh adaptation is carried out until no further deformation is observed (i.e. deformation step size is smaller than threshold) or 20 iteration have passed, to give final spinal canal segmentation (figure 2).

B. Spine Curve Extraction

The spine canal centerline defines the spine curve in our method. We examined few centerline extraction techniques: morphological skeletonization, flux driven medial curve, and fast marching minimal path extraction. The last method proved to be most accurate for our purpose. The method requires a speed function to generate an arrival function, start and end points, and an optimizer which steps along the resultant arrival function perpendicular to the Fast Marching front. The speed function used is based on distance transform using the spine canal segmentation. The start (end) point is defined as the center of the segmentation of its topmost (bottom) axial slice. The optimizer used is a Gradient Descent Optimizer (Figure 3).

After spinal canal curve is found, the curve is scaled to obtain independent measure curve (e.g. curve that is independent of the patient height), and rotated so that the anterior-posterior line is oriented on a common axis (the Y axis). The scaling and rotating are used to establish patient independent coordinate system for the spine curvature.

As a final step for each curve the curvature and torsion are calculates. Intuitively, curvature is the amount by which a geometric object deviates from being flat. For curve defined as a function r(t) the curvature at a given value of t is:

$$\kappa = \frac{|\dot{r} \times \ddot{r}|}{|\dot{r}|^3}$$

where $\dot{r}$ and $\ddot{r}$ are first and second derivatives of $r(t)$.

The torsion of a curve measures how sharply it is twisting. And is defines as:

$$\tau = \frac{\det(\dot{r}, \ddot{r}, \dddot{r})}{|\dot{r} \times \ddot{r}|^2} = \frac{|\dot{r} \times \ddot{r}| \cdot \dddot{r}}{|\dot{r} \times \ddot{r}|^2}$$

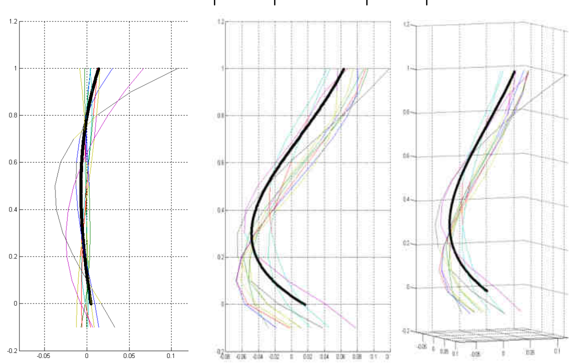

Fig. 3. Spine Model Curve (black line) composed from various curves (color lines) of healthy individuals

C. Spine Curve Modeling

The spine curve model is created from a set of samples of spine curve in 3D of healthy individuals. The modeling created from sample of curves of the normal population, preprocessed as mentioned above (scaled, and oriented). All curves for the model are dimensionless curves, and oriented along a common line. All curves have common superior point (at the level of T12 inferior endplate), and inferior point (at the level of L5 inferior endplate), and oriented to the same axis, thus no registration between the curves is required. Model curve is created as the median of location of all sample curves on cross sections along the curves. The model curve's standard deviation is the calculated standard deviation of location of all sample curves from the model curve. The model curve's spine curvature and torsion are calculates as the median curvature and torsion of all sample curves at each axial cut as well (black and blue lines in figure 3).

D. Spine Curve Analysis

Individual's spine curvature as extracted from spine imaging is assessed against the model. The curve is extracted as describe before. Given a spinal curve after being scaled and oriented, the curve is compared to the model. The comparison is simple distance measurement of the curves, distance measurement of the curvature and torsion (figure 4). These values are evaluated compared to the model standard deviation. If the curve deviates from the model by more than determined factor of standard deviations the curve is said to be abnormal.

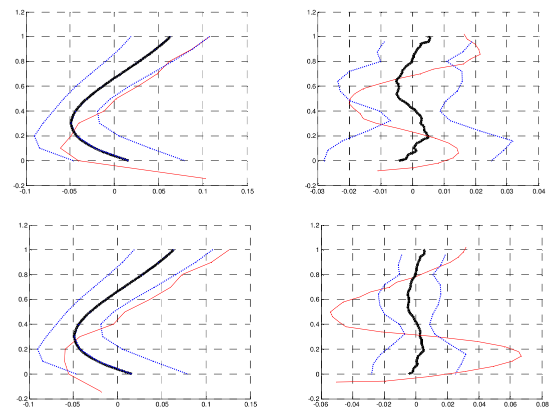

Fig.4: Curve Assessment as viewed on the *sagittal* plane (left) and *coronal* plane (right). These individuals show curve deviations from the model. The top left has very mild hyper lordosis, the bottom left has mild flat back. The top right has mild scoliosis, and bottom right has scoliosis. Graphs coordinates are normalized, negative values are continuation of the curve beyond L5 to the sacrum

III. Results

The model was create using 21 individuals that underwent CT scan of the abdomen, have no spinal disorders, and have no history of low back pain. The images obtained with a voxel size in-plane ranging from 0.5 mm to 1.2 mm and a slice thickness of 0.9 to 3mm. Each image plane had 512x 512 voxels with varying number of slices (250–500). The processing time was 57-370sec with mean time of 123sec.

A. Segmentation and Curve Validation

For the evaluation of our method, especially for the curve extraction segmentation, we used canal centerline curves, extracted manually by two experienced radiologists of 24 patients. To obtain inter observer error both radiologists extracted the curve of 5 patients extracted. Inter observer error average difference was 1.36 ± 1.61 mm. The manually extracted curves were then compared to the algorithm automatic extracted curves. The average difference was 1.70mm, a little higher than the inter observer difference, but still well within acceptable range.

B. Curvature Analysis

The curvature assessment method was tested on 24 individuals that underwent CT scan of the abdomen, and 4 patients with scoliosis. Our main goal was to establish correlation between curvature deformities and low back pain. Of the 24 individuals: 8 had no history of back pain, 10 had previous low back pain episode with no specific cause, and 6 had low back pain with no specific cause, as well as 4 other patients who have clear scoliosis. For each case the deviations of the curve from the model were calculated. Deviation was above 3 standard deviations are registered, and for each curve we count segments of the curve that differ from the model by more than 3 standard deviations (the results are summarize in table 1).

The spine curvature assessment method can clearly be used to detect and quantify the pathological (e.g. scoliotic) spinal curvatures. As can see from the results (Table 1) all patients with scoliosis have large deviation from the model as expected. It can also be seen that patients with low back pain have more deviations of the curve, curvature and torsion from the model. These patients were not identified as having posture deformations and the deviations are sub-acute curvature deformation (i.e. deformations are not defined as pathologies). This may suggest that there is a correlation of posture problems and low back pain.

TABLE I
RESULTS OF CURVE ASSESSMENT

Measurement Type		Patient Type			
		No LBP	LBP History	Current LBP	Scoliosis
Number of Patients		8	10	6	4
Curve	Segments	1	4	4	5
	Percentage of patients	12.5%	30%	33%	100%
Curvature	Segments	1	3	3	3
	Percentage of patients	12.5%	20%	33%	75%
Torsion	Segments	0	1	1	2
	Percentage of patients	0%	10%	16%	50%

Three types of deviations were examined: curve deviation from the model curve, deviation of the curvature along the curve, and deviation of the torsion along the curve. For each type of measurement, two values were recorded: total amount of deviation segments per patient types, and percentage of patients exhibiting deviations.

IV. DISCUSSION

The purpose of this study is to present a new method for 3D quantitative assessment analysis of spinal curvature. Spinal deformities may be of local nature, or global nature, and may occur in image plane (axial, sagittal and coronal). In order to study the properties of such complex structures, we use a modeling technique based not on the vertebral bodies, which induce inaccuracies, but on the spinal canal. The results clearly show that this method is suitable for detection and quantification of pathologies. It is also clear that there is a correlation between sub-acute curvature deformation (i.e. deformation that are not defined as pathologies) and low back pain. Further data is required for establishing strong correlation between low back pain and curvature deviation, and expansion of the model.

To conclude, the proposed model based spine curve assessment method may improve understanding of spine anatomy and aid in clinical quantitative evaluation of spinal deformities. Since changes of posture are minor and rare, this method may also improve diagnosis of low back pain.

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