3D Biplanar Statistical Reconstruction of Scoliotic Vertebrae

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Abstract. A new 3D reconstruction method of scoliotic vertebrae of a spine, using two calibrated conventional radiographic images (postero-anterior and lateral), and a global prior knowledge on the geometrical structure of each vertebra is presented. This geometrical knowledge is efficiently captured by a statistical deformable template integrating a set of admissible deformations, expressed by the first modes of variation in the Karhunen-Loeve expansion of the pathological deformations observed on a representative scoliotic vertebra population. The proposed reconstruction method consists in fitting the projections of this deformable template with the preliminary segmented contours of the corresponding vertebra on the two radiographic views. The 3D reconstruction problem is stated as the minimization of a cost function for each vertebra and solved with a gradient descent technique. The reconstruction of the spine is then made vertebra by vertebra. The proposed method allows also to efficiently obtain an accurate 3D reconstruction of each scoliotic vertebra and, consequently, it allows also to get an accurate knowledge of the 3D structure of the whole scoliotic spine. This reconstruction method is in final phase of validation.

1. Introduction

The scoliosis is a three-dimensional deformation of the natural curve of the spinal column, including rotations and vertebral deformations. In order to analyze 3D characteristics of these deformations, which can be useful for the design, the evaluation and the improvement of orthopedic or surgical correction, several 3D reconstruction methods have been developed. The methods using a limited number of projections and some simple \textit{a priori} knowledge on the geometry of the object to be reconstructed are interesting but are widely supervised; for example it may require to manually identify (by an operator) a set of 19 different landmarks on the two different radiographic images (postero-anterior ($I_{PA}$) and lateral ($I_{LAT}$)) of 17 lumbar and thoracic vertebrae [7][8]. In addition to being highly operator dependent, these methods do not exploit all the information contained in the two radiographic images (e.g., the contours of each vertebra)[4][7].

In this way, we propose a new statistical 3D reconstruction model for the scoliotic vertebrae from biplanar radiographic images. Our approach relies on the description of each vertebra by a deformable template which incorporates statistical knowledge about its geometrical structure and its pathological variability. The deformations of this template are expressed by the first modes of variation in the Karhunen-Loeve (KL) expansion of the pathological deformations observed on a representative scoliotic vertebra population. This prototype
template, along with the set of admissible deformations, constitute our global prior model that will be used in order to rightly constrain the ill-posed nature of our 3D reconstruction problem. In our application, the proposed method consists in fitting this template with the segmented contours of the corresponding vertebra on the two calibrated radiographic views. This matching problem leads to an optimization problem of a cost function, efficiently solved in our application by a gradient descent algorithm initialized by a rough and rigid 3D reconstruction method estimated in the least square sense.

This paper is organized as follows. Section 2 and 3 present the statistical deformable model and the proposed 3D reconstruction method. The experimental results of our 3D reconstruction method are presented in Section 4. Finally, we conclude the paper in Section 5 with a conclusion.

2. Statistical Deformable Model

The statistical deformable model under concern has been introduced by the authors in [1]. The shape $s$ of each vertebra is defined by a set of $n$ control points “landmarks”, which approximate the geometrical shape of each vertebra in $IR^3$ [3]. In the following, we will assume that $s$ is a realization of a random vector that follows a normal law of mean vector $\bar{s}$ and covariance matrix $C$ as suggested in [3].

After aligning of the training shapes, we calculate the mean shape and the covariance matrix. A Principal Component Analysis (PCA) on the displacement vectors $\tilde{s} = s - \bar{s}$ computed from the set of vertebra base allows to deduce the deformation modes relative to the mean shape. The eigenvectors of the covariance matrix $C$ of this random vector describe the information on the variability of the scoliotic deformations in the vertebra base and the associated eigenvalues are the amplitudes of these variation modes.

An accurate description of the main variation modes may be obtained by retaining only the $m$ eigenvectors associated to the $m$ largest eigenvalue [3]. The model allows the generation of new instance of the shape by adding linear combinations of the $m$ most significant variation vectors to the mean shape,

$$s = \bar{s} + \phi b,$$  \hspace{1cm} (1)

with $\phi$ represents the matrix of the first $m$ variation modes of the models of the vertebra base, and $b$ is the global deformation parameter vector setting the amplitudes of each deformation mode $b_i$. By ensuring,

$$b_i \in [-3\sqrt{\lambda_i}, +3\sqrt{\lambda_i}],$$

only the important deformations are extracted, discarding training data noise [3]. This low parametric representation of a vertebra constitutes our global prior model that will be used in our 3D reconstruction method.

3. 3D Reconstruction

Besides the above mentioned global deformation parameters, we also consider 3D global transformations from the similarity group which finally lead to the following model for global deformations,

$$s = M(k, \alpha)[\bar{s} + \phi b] + T,$$  \hspace{1cm} (2)

with $T$ is a global translation vector, and $M(k, \alpha)$ performs a rotation by $(\alpha_1, \alpha_2, \alpha_3)$ around the $x$, $y$, and $z$ axis respectively and a scaling by $k$. 

In order to ensure a first crude and rigid reconstruction of each vertebra, we use the technique proposed in [6] to estimate the position of six anatomical points (namely, the center of the superior and inferior end-plates, the upper and lower extremities of both pedicles) for each vertebra of the spine. The corresponding points on the shape of the mean vertebra being known, we can compute an initial estimate of the parameter vector \((k, \alpha T)\). This leads us to a crude and rigid reconstruction for each vertebra that will be then refined by our 3D reconstruction model.

Our reconstruction model from two radiographic views is stated as the minimization of the following cost function,

\[
E(s, \theta) = E_i(s, I_{PA}, I_{LAT}) + \beta * E_p(s),
\]

where \(E_i\) is the likelihood energy term and \(E_p\) is the prior energy term, used to constrain the ill-posed nature of this optimization problem. \(\beta\) is a factor that provides a relative weighting between the two penalty term and allows to control the rigidity of the statistical template [5], and \(\theta=(M(k, \alpha), T, b)\) is the deformation parameter vector of the model to be estimated. In our application, the likelihood energy term is expressed by a measure of similarity between the external contour of the lateral and the postero-anterior perspective projections of the deformed template and the spatial edges detected in the two radiographic views. It attains its minimum value when there is an exact correspondence between the projected contours (of the deformed template) and the preliminary segmented contours of the two radiographic views. The prior energy term penalizes the deviation of the deformed template from the mean shape. This term does not penalize affine transformations.

Finally, Equation (3) is minimized by a gradient descent technique initialized by the estimations given by the rigid reconstruction technique.

4. Experimental Results

In our application, we use the vertebra base constituted of 1020 thoracic and lumbar vertebrae (510 normal and 510 scoliotic). Details of this base have been presented in [9].

The mean vertebra shape of each vertebral level is computed on sample of 30 normal vertebrae. The deformation modes of each vertebral level is computed on a sample of 30 scoliotic vertebrae.

We have used the Canny edge detector to estimate the edge map on the two radiographic views [2]. In our application, we have chosen to take the number of deformation modes that allows to represent at least 90% of the admissible deformations for each type of vertebra.

Besides, experiments have shown that the crude and rigid reconstruction procedure is not always a good initialization for the gradient-based optimization technique. In order to overcome this problem, our solution consists in placing the template at evenly spaced positions and in deforming it according to a discretized set of translation orientation or scale (corresponding to the rigid parameters) within a range of value around the initial estimate obtained by the rigid reconstruction procedure. These deformed template configurations can then be used to initialize a deterministic gradient descent algorithm. However, the spacing between the template positions and the sampling of the transformations must be chosen judiciously: not too spaced out to cover all the significant local minima of the energy surface and not too small to avoid high computational requirements.

For the experiments, we have chosen \(\beta=1\) for the weighting factor penalizing the prior energy term with respect to the external energy. Figure 1 and Figure 2 present
projections of the shape of a L2 and T8 vertebra on postero-anterior and lateral radiographic images for a scoliotic patient.

![L2 reconstructed vertebra](image1)

Figure 1. Visualization of:
(a) the projections of the shape of a L2 vertebra on postero-anterior and lateral radiographic images.
(b) L2 reconstructed vertebra: coronal and axial view.

![T8 reconstructed vertebra](image2)

Figure 2. Visualization of:
(c) the projections of the shape of a T8 vertebra on postero-anterior and lateral radiographic images.
(d) T8 reconstructed vertebra: coronal and axial view.

5. Conclusion

We have presented an original statistical method of 3D reconstruction of scoliotic vertebrae using both the contours extracted from biplanar radiographic images and a prior knowledge on the geometrical structure of each vertebra. The proposed scheme thus constitutes an alternative to CT-scan 3D reconstruction with the advantage of low irradiation and will be of great interest for 3D clinical applications and for reliable geometric models for finite element studies. This reconstruction method is in final phase of validation.

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References


