Lumbar and Thoracic Spine Segmentation Using a Statistical Multi-object Shape+Pose Model

A. Seitel, A. Rasoulian, R. Rohling and P. Abolmaesumi

Abstract The vertebral column is of particular importance for many clinical procedures such as anesthesia or anaelgesia. One of the main challenges for diagnostic and interventional tasks at the spine is its robust and accurate segmentation. There exist a number of segmentation approaches that mostly perform segmentation on the individual vertebrae. We present a novel segmentation approach that uses statistical multi-object shape+pose models and evaluate it on a standardized data set. We could achieve a mean dice coefficient of 0.83 for the segmentation. The flexibility of our approach let it become valuable for the specific segmentation challenges in clinical routine.

1 Introduction

Segmentation of the spinal column is an important task for many computer-aided diagnosis and intervention procedures. Despite the high contrast of bony structures in CT volumes, it remains challenging due to the presence of unclear boundaries, the complex structure of vertebrae, and substantial inter-subject variability of the

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anatomy. Most of the proposed methods for automatic or semi-automatic spine segmentation rely on an initialization step of one or multiple vertebrae followed by a separate segmentation of each vertebra [1–7]. Considering each vertebra separately, however, may result in overlapping segmentations in areas where a clear boundary is missing in the volume data. Although there exist approaches as the one of Klinder et al. [2] that e.g. penalize overlapping areas, to our knowledge there is no method that incorporates common shape variations among the vertebrae of one subject which can be of great benefit for the segmenation quality. We thus propose an approach for segmentation of the spine in CT data which is based on a statistical multi-object model which incorporates both shape and pose information of the vertebral column.

2 Methods

Our segmentation technique is based on a statistical multi-vertebrae shape+pose model which is registered to the bony edges of the spinal column as extracted from the CT volume. The basic principles of this method have previously been presented in [8, 9] and will be summarized in the following paragraphs.

2.1 Model Construction

For construction of the model the idea is to analyze the pose and shape statistics separately as they are not necessarily correlated and are not formulated in the same parameter space. The model training then results in the modes of variations for both shape and pose, represented by v^s and v^p, respectively. Hence, a new instance of the model can be calculated as follows

$$S = \Phi\Big(\sum_{k=1}^{N_s} w_k^s v_k^s, \sum_{l=1}^{N_p} w_l^p v_l^p\Big). \tag{1}$$

where Φ is a similarity transform, N_s and N_p are the number of modes of variations for shape and pose, and w_k^s and w_l^p are the corresponding weights.

Building a single model for the entire vertebral column would require all vertebrae to be present in the training images and the images to be segmented. This limits the choice of volumes for the training data set and restricts the applicability of the segmentation method to such "complete" volumes. To be able to cope with arbitrary number of vertebrae present in the CT images and for segmentation of the whole spinal column, we propose to construct and align small sub-models with limited number of vertebrae. For this purpose, training data is collected for every vertebrae (in this case T1 to L5) and is used to build individual sub-models each containing 3 vertebrae and the ensemble of all models covering the whole spinal column (Fig. 1). The training step then results in many models and their associated modes of variation.

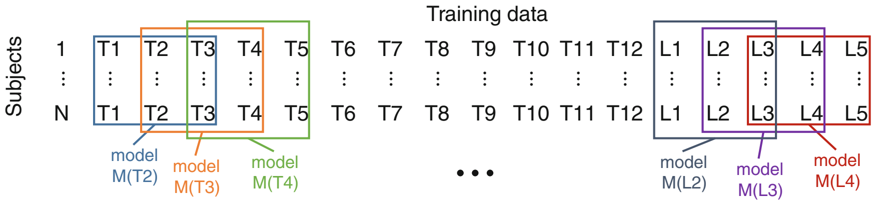

Fig. 1 Construction of the 3-vertebrae statistical shape+pose sub-models. Training data is available for all vertebrae. The individual models are build as detailed in [9]

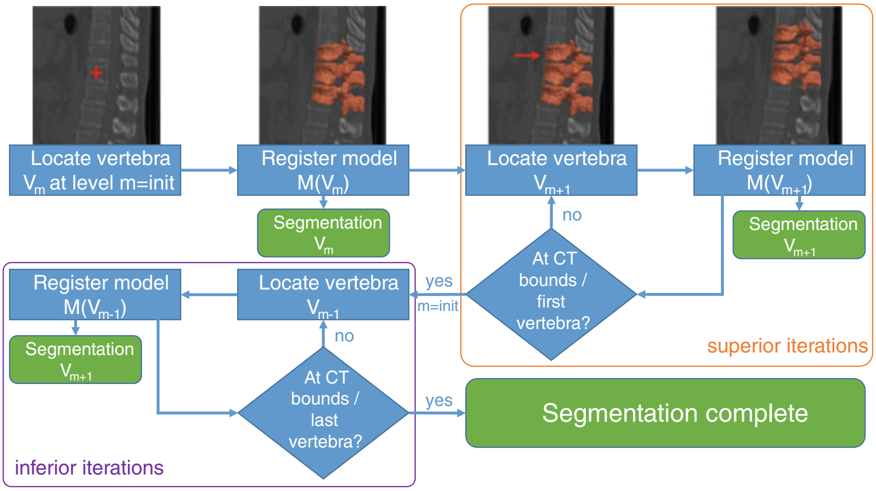

Fig. 2 Workflow of the segmentation approach. Initially, the center of gravity of one vertebral body is selected in the CT volume (*cross*). Next, the corresponding 3-vertebrae model is registered and the *middle* vertebra is segmented. The *last* vertebra (superior iterations) or the *first* vertebra (inferior iterations) of the registered model (*arrow*) is then used to initialize the next model. This process continues until it reaches the extents of the CT volume or the first/last vertebra

2.2 Segmentation

Segmentation using a single statistical multi-object shape+pose model can be formulated as a registration problem where the model is registered to the bone edge point cloud extracted from the CT volume using a canny edge detection preceded by a median filter (kernel radius 1). The transformation parameters as well as the described weights are then optimized using the Expectation Maximization (EM) algorithm such that the resulting model maximizes its likelihood of observing the CT edge point data [9].

The workflow for segmentation of the whole spinal column is depicted in Fig. 2. For initialization, the user has to specify the center of gravity of one specific vertebral body. After registration of the model starting at this initial position, the resulting registered instance is used to initialize the neighboring model either one level superior or one level inferior. This iterative registration is repeated until the new models reach

Table 1 Mean (μ) and standard deviation (σ) of dice coefficient for segmentation of individual vertebrae averaged over $n = 10$ cases

	L5	L4	L3	L2	L1	T12	T11	T10	T9	T8	T7	T6	T5	T4	T3	T2	T1
μ	0.82	0.85	0.85	0.87	0.83	0.82	0.75	0.75	0.76	0.76	0.76	0.75	0.75	0.84	0.83	0.82	0.75
σ	0.10	0.05	0.05	0.02	0.06	0.06	0.06	0.07	0.07	0.05	0.05	0.05	0.06	0.06	0.06	0.06	0.05

the extent of the CT volume or the first/last vertebra covered. The segmentation is then obtained from the registered models.

3 Results

Data from 87 CT volumes containing parts of the lumbar or thoracic spine were used for model construction. Evaluation and parameter optimization was performed on the provided training data. The segmentation results for the training data of the MICCAI challenge (leave-one-out approach) yielded a mean dice coefficient of 0.83 ± 0.04 (averaged over the ten cases) for the complete spine segmentation. The results for the individual vertebrae are shown in Table 1.

4 Discussion

Statistical multi-object models that incorporate both pose and shape statistics are evaluated with respect to their applicability for segmentation of the whole spinal column. We could achieve a mean dice coefficient of the segmentations of 0.83 ± 0.04 which is comparable with other approaches for spine segmentation. The usage of 3-vertebrae sub-models for the segmentation task let our method become flexible in terms of vertebrae covered by the input CT volume. This flexibility comes to price of a possible segmentation overlap at the boundaries of the sub-models especially for the closely spaced thoracic vertebrae. We are currently working on a generic n-vertebrae model that is able to cope with this issue and also allows for automatic model initialization. Further improvement is to be expected by consideration of the CT intensity information e.g. by means of an appearance modeling approach. We thus believe that the segmentation approach can be of great benefit for various interventional and diagnostic applications.

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