Automated Intervertebral Disc Detection from Low Resolution, Sparse MRI Images for the Planning of Scan Geometries

X. Dong, H. Lu, G. Zheng, M. Reyes

Institute for Surgical Technology and Biomechanics, University of Bern,
Stauffacherstrasse 78, CH-3014 Bern, Switzerland;
Email: guoyan.zheng@ieee.org

Abstract. Robust and accurate identification of intervertebral discs from low resolution, sparse MRI scans is essential for the automated scan planning of the MRI spine scan. This paper presents a graphical model based solution for the detection of both the positions and orientations of intervertebral discs from low resolution, sparse MRI scans. Compared with the existing graphical model based methods, the proposed method does not need a training process using training data and it also has the capability to automatically determine the number of vertebrae visible in the image. Experiments on 25 low resolution, sparse spine MRI data sets verified its performance.

1 Introduction

Spine examinations represent one of the most important clinical applications of MRI. But the quality of the MRI scan diagnose depends on the accuracy and consistency of the scan planning, which is usually carried out on a low resolution, sparse survey data (usually only a few slices in the sagittal and coronal planes). The core of the scan planning is to determine the positions and orientations of intervertebral discs so that scan geometries of the follow-up diagnostic scans such as off-center, angulation and field-of-view can be computed. Compared with the operator dependent manual planning, automated scan planning (ASP) is preferable in the aspect of consistency and speed of the planning. On the other hand ASP is difficult due to the low image quality and the sparsity of the survey data and the high structural complexity of the spine.

Several research groups have proposed different automated spine detection and labeling methods, which is the core part of the ASP for the MRI spine scan. Pekar et al. [1] develop an approach for labelling the vertebral column as part of their scan geometry planning system. They search for possible disc locations by filtering the sagittal slices to find horizontal line structures and finding the centers of mass of the 3D connected components in the filtered images. Then 3D connected components are selected to find disc centers by applying an iterative procedure to remove candidates that form point triplets with unrealistically high curvature. Weiss et al. [2] propose a semi-automatic technique for labelling discs where disc centers are detected using threshold values, filters and noise suppression operators. The user manually marks one disc and the algorithm proceeds by an iterative intensity analysis based method to find the connected disc chain. In these approaches, the detection of candidate disc centers is highly dependent on imaging quality and data dependent threshold values. Also the disc chain detection procedure employs little contextual information of the spinal structure except for the constraints on the curvature of the detected disc chain.

There exist heuristic methods for detecting vertebral bodies and interverbral discs from dense CT or MR volume data [3][4][5]. For example, Peng et al. [3] detect the intervertebral discs from MRI images for the segmentation of a dense spine volume. In their method on each sagittal slice the disc clues are detected by convoluting a disc model followed by a polynomial curve fitting to the detected candidate points. The intensity pattern along the fitted curve helps to determine the best sagittal slice, on which refined disc detection is carried out by an intensity based local search along the fitted curve. Klinder et al. [4] developed a method for automatic detection, identification and segmentation of the vertebrae from a CT volume by exploiting statistical models of multi-cue informaiton including shape, gradient and appearance of the spinal structures. A more recent work by Štern et al. [5] introduced a completely automated algorithm for the detection of the spinal centreline and the centres of vertebral bodies and intervertebral discs in CT and MR volme images.

Probabilistic graphical models for automatically locating the vertebral column and labelling the intervertebral discs were recently proposed by Schmidt et al. [6] focusing on whole spine and Corso et al. [7] dealing with lumbar spine MR images. In each case, appearance information of the discs as well as spatial relationships between discs were incorporated in the model. In [6][7] they focus on either the lumbar or the whole spine so that the number of intervertebral disks is taken as fixed and they can thus build graphical models with a fixed number of nodes. But in a general case to detect an unknown number of discs, the graphical model approach faces a difficult model selection problem to determine the disc number. Another problem of this approach is that due to the complexity of the spine structure, most of the existing work ask for the involvement of prior knowledge which is usually obtained by an off-line training. In [6][7], both the low level image observation models and the high level disk context potentials are learned using training data. Besides the fact that the model training is a complex problem itself, the dependency on training data makes these approaches valid only on the data with similar characteristics to the training data.

In this paper we propose a graphical model based intervertebral disc detection method from sparse MRI data for the automated MRI scan planning based on our work on automated vertebra identification from X-ray images [8]. Different from the general approaches to directly locate the discs, we detect the positions and orientations of discs in a two-step approach. We first designed a graphical model to detect vertebra bodies from a user selected sagittal slice, which can automatically determine the number of visible vertebrae during the inference procedure. In our graphical model, both the low level image observation model and the high level vertebra context potentials need not to be learned from training data. Instead they are capable of self-learning from the image data during the inference procedure. Taking the vertebral body detection results as the initialization, the positions and orientations of intervertebral discs can then be detected by a particle filtering based procedure. The reliability of the proposed method is demonstrated by an experiment on 25 low resolution fast echo MRI spine data.

2 Method

2.1 A two step approach for the intervertebral disc detection

The work flow of the proposed intervertebral disc detection method is described as follows

Initialization Users select a sagittal slice in which all the intervertebral discs are visible. On the selected slice, users pick two landmarks to indicate the center of the first and the last visible vertebral bodies.

Vertebral body detection A graphical model based approach is implemented to detect the number, positions, orientations and sizes of all the vertebral bodies on the user selected sagittal slice.

Intervertebral disc detection On the user selected sagittal slice intervertebral discs are detected using the vertebral body detection results as an initialization. For each detected disc on this sagittal slice, a coronal slice is automatically selected and a second round of disc detection on this coronal slice is carried out. Combining the disc detection results on both the sagittal and coronal slices, the 3D geometrical information of intervertebral discs can then be reconstructed.

2.2 Graphical model based vertebral body detection

Similar to [6], we build a graphical model $G = \{V, E\}$ with N nodes for the spine structure as shown in Figure. 1. Each node $V_i, i = 0, 1, ..., N-1$ represents a vertebral body in the spine, which is modelled as a rectangular. We assign $\mathbf{X}_i = \{x_i, y_i, r_i, h_i, \theta_i\}$ to V_i to describe the center, radius, height and orientation of V_i on a 2D slice as shown in Figure. 2. $E = \{e_{i,j}\}, i, j = 0, 1, 2, ..., N-1$ defines a connection matrix of the graph G. On G, we define the component observation model $p(\mathbf{I}|X_i), i = 0, 1, ..., N-1$ of a single component and potentials $p(X_i, X_j), i, j = 0, 1, ...N-1, e_{i,j} = 1$ among neighboring components. $p(\mathbf{I}|\mathbf{X}_i)$ represents the probabilities that the configuration $\mathbf{X}_i$ of the nodes V_i matches the observed images I and $p(\mathbf{X}_i, \mathbf{X}_j)$ encodes the geometrical constraints between components V_i and V_j. The identification of the spinal structure is then to find the configurations of $\{V_i\}$,$\mathbf{X} = \{\mathbf{X}_0, \mathbf{X}_i, ..., \mathbf{X}_{N-1}\}$, that maximizes

$$P(X|I) \propto \prod_i p(I|\mathbf{X}_i) \prod_{e_{i,j}=1} p(\mathbf{X}_i, \mathbf{X}_j) \tag{1}$$

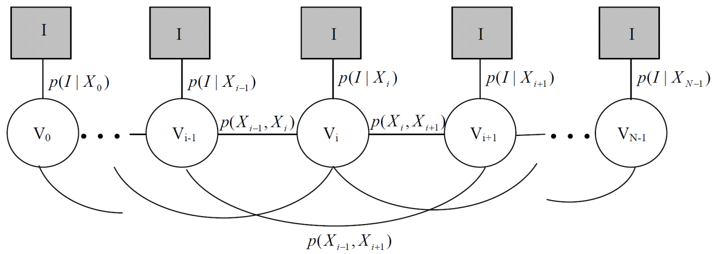


Fig. 1. Graphical model of the spine

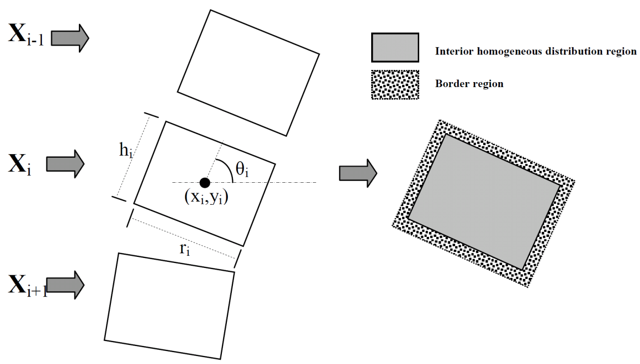


Fig. 2. Vertebra body template for the component observation model

Component observation model The component observation model $p(\mathbf{I}|\mathbf{X}_i)$ is to match a template determined by $\mathbf{X}_i$, a rectangular shown in Fig. 2, with the observed image $\mathbf{I}$ defined as

$$p(\mathbf{I}|\mathbf{X}_i) = p_I(\mathbf{I}|\mathbf{X}_i)p_G(\mathbf{I}|\mathbf{X}_i)p_V(\mathbf{I}|\mathbf{X}_i) \tag{2}$$

The three items in (2) come from the intensity, gradient and local intensity variance distribution on the template.

Intensity observation model $p_I(\mathbf{I}|\mathbf{X}_i)$: Given $\mathbf{X}_i$, it determines a disk-vertebra-disk template on the 2D image plane as shown in Fig. 2. We assume that the interior area of the vertebra body has a homogeneous intensity distribution, a Gaussian model $\mathcal{N}(\mu_i, \sigma_i)$, which is different from the intensity distribution of the border region, which is defined as a small neighbourhood outside the vertebra body. For each pixel s that falls in the interior and border region of the template as shown in Fig. 2, the image appearance value of s is defined as

$$p(s|\mathbf{X}_i) = e^{-\frac{(I(s)-\mu_i)^2}{2\sigma_i^2}} \tag{3}$$

We define $p_I(\mathbf{I}|\mathbf{X}_i) = e^{\omega_I c_I^i}$, where c_I^i is the cross-correlation between the image appearance values $p(s|\mathbf{X}_i)$ and a binary template which sets value 1 to the interior area of the template and 0 to the border region. $\omega_I > 0$ is a weighting factor. Intuitively this means that we assume that the interior region of the template should obey the Gaussian distribution and the border area should have a different intensity distribution. The Gaussian model $\mathcal{N}(\mu_i, \sigma_i)$ can be learned from the observed image once $\mathbf{X}_i$ is given.

Gradient observation model $p_G(\mathbf{I}|\mathbf{X}_i)$: Similar to $p_I(\mathbf{I}|\mathbf{X}_i)$, we can define $p_G(\mathbf{I}|\mathbf{X}_i) = e^{\omega_G c_G^i}$, where c_G^i is the cross-correlation between the gradient image values of the observed image in the template area and a binary gradient template, which sets 0 in the interior area and 1 in the border region. This means strong gradient values should only happen on the border of the vertebra template.

Local variance observation model $p_V(\mathbf{I}|\mathbf{X}_i)$: We compute the local variance image I_V of the image I, which is defined as the intensity variance in a small window centered at each pixel. We define $p_V(\mathbf{I}|\mathbf{X}_i) = e^{\omega_V c_V^i}$, where c_V^i is the cross-correlation between the local variance values and a binary template identical to the gradient template.

It can also be observed that the three items in the component observation model do not depend on prior information learned from training data.

Potentials between components Inter-node potentials set constraints on the geometries of the nodes $\{\mathbf{V}_i\}$ so that all the nodes will be assembled to a meaningful spine structure. We define

$$p(\mathbf{X}_i, \mathbf{X}_j) = p_S(\mathbf{X}_i, \mathbf{X}_j) p_O(\mathbf{X}_i, \mathbf{X}_j) p_D(\mathbf{X}_i, \mathbf{X}_j) \tag{4}$$

Size constraints $p_S(\mathbf{X}_i, \mathbf{X}_j)$ is used to set constraints on the sizes of the neighboring components defined as

$$p_S(\mathbf{X}_i, \mathbf{X}_j) = e^{-(\omega_r \frac{|r_i - r_j|}{|r_i + r_j|} + \omega_h \frac{|h_i - h_j|}{|h_i + h_j|})/|i-j|} \tag{5}$$

Orientation constraints We define

$$p_O(\mathbf{X}_i, \mathbf{X}_j) = e^{-\omega_o \mathbf{a}_i \bullet \mathbf{a}_i / |i-j|} \tag{6}$$

to ensure that neighboring vertebra bodies should have similar orientations.

Distance constraints For direct neighboring nodes $\mathbf{V}_i, \mathbf{V}_j$, $|i - j| = 1$, we define constraints on the distance between the vertebra body centers as

$$p_D(\mathbf{X}_i, \mathbf{X}_j) = \begin{cases} e^{-\omega_D \frac{d_{C,ij} - (d_{h,ij})/2}{d_{h,ij}}} & , \frac{5}{4} d_{h,ij} > d_{C,ij} > d_{h,ij} \\ 0 & , \text{elsewhere} \end{cases} \tag{7}$$

This asks the distance between neighboring vertebral centers is roughly the same as their mean height so that $\mathbf{V}_i, \mathbf{V}_j$ are closely connected.

Inference The graphical model based inference aims to find both the number of vertebrae N and their geometrical parameters. Instead of carrying out the inference on $\{\mathbf{X}_i\}$ and N simultaneously, we implement a sequential inference procedure on a simplified graphical model, a Markov chain where each node is only connected with its previous node so that

$$P(\mathbf{X}_0, \mathbf{X}_1, .., \mathbf{X}_i | I) \propto p(I|\mathbf{X}_0) \prod_{k=1}^{i} p(I|\mathbf{X}_k) p(\mathbf{X}_k, \mathbf{X}_{k-1}) \tag{8}$$

Given the configuration of $\mathbf{X}_0, ..., \mathbf{X}_{i-1}$, the distribution of node V_i depends only on its image observation model $p(I|\mathbf{X}_i)$ and the potential $p(\mathbf{X}_i, \mathbf{X}_{i-1})$. The inference can then be achieved by a *trunked* particle filtering on this Markov chain as follows

---

Given the configuration X_{i-1} of node V_{i-1},
(a). Draw K random configurations (*particles*) of V_i, $\mathbf{X}_i^k, k = 0, 1, ..., K-1$ and compute the *believes* of each particle as $b_i^k \propto p(I|\mathbf{X}_i^k) p(\mathbf{X}_i^k, \mathbf{X}_{i-1})$.
(b). Re-sample the particles according to $\{b_i^k\}$ and update their configurations by a Gaussian random walking.
(c). Repeat a,b till converge and select the particle with the highest believe as the configuration of V_i.

Given the user initialization to indicate the first vertebra, this sequential inferencing procedure can be carried out on the user selected sagittal slice to detect all the vertebra bodies until the user indicated last vertebral body is reached. Obviously the inference result includes both the number and configurations of the vertebral bodies.

3 Intervertebral disc detection

The detected vertebra bodies provide a descent initialization for the disc detection. Similar to the rectangular template for vertebra bodies, intervertebral discs can also be modelled by a rectangular with a parameter set Y_i. Accordingly an image observation model $p(I|\mathbf{Y}_i)$ and the potential between a disc and its neighboring vertebral bodies $p(\mathbf{Y}_i, \mathbf{X}_i), p(\mathbf{Y}_i, \mathbf{X}_{i+1})$ can be defined for discs.

3.1 Intervertebral disc detection on sagittal slices

On the user defined sagittal slice, between each pair of neighboring vertebra bodies a disc can be detected by a particle filtering similar to the vertebra body detection, where the believe of a disc is computed as $p(I|\mathbf{Y_i}) p(\mathbf{Y}_i, \mathbf{X}_i) p(\mathbf{Y}_i, \mathbf{X}_{i+1})$.

3.2 Intervertebral disc detection on coronal slices

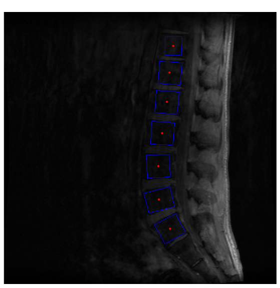
The detected 2D geometrical configuration of a disc can guide us to automatically select a coronal slice which is nearest to the detected disc center. Accordingly the same disc can also be detected on this coronal slice.

3.3 3D intervertebral disc configuration from 2D detection results

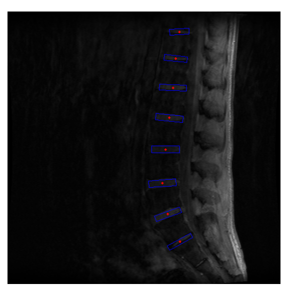
The 3D geometrical information of a disc, for example its center, orientation, radius and height, can be easily reconstructed from the 2D detection results on both the sagittal and coronal slices.

4 Experimental Results

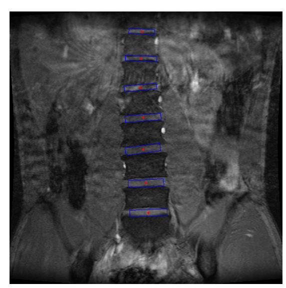
We verified out algorithm on 25 fast echo spine *locator* data set focusing on the thoracic and lumbar region. In each data set there are 5 to 11 slices in sagittal and coronal planes. The slice distance varies from 6.5mm to 10mm. The image resolution varies from 0.58mm to 1.95mm. The result of our algorithm on one data set is shown in Figure. 3. Our evaluation focuses on the disc center and the disc plane orientation which are the most important factors for scan planning geometries. On each data set the ground truth of these parameters is defined manually. Since our algorithm is a statistical solution, we carried out 4 trials on each data set. On all the 25 data sets the numbers of discs are correctly detected. The mean errors of the disc center and disc plane orientation are less than 5mm and 5 degrees respectively. It also need to be pointed out that the detection error of the disc center is mainly along the directions of disc planes but not in the normal directions so that the 5mm error of the disc center detection is acceptable for the scan geometry computation. the The execution time on a normal PC is around 1 second per disc.



(a) Vertebral body detection results on the user selected sagittal slice



(b) The detection of the intervertebral discs on the user selected sagittal slice



(c) The detection of the intervertebral discs on the coronal slices

Fig. 3. The result of the graphical model based vertebra body detection and particle filtering based intervertebral disc detection on a spine locator data

5 Discussion and Conclusion

In this paper we proposed a graphical model based method for automated detection of intervertebral discs from low resolution MRI images. The reason that we first detect the vertebral bodies to guide the disc detection instead of directly detecting the discs is that the vertebral bodies can be more reliably detected than the discs due to its relatively strong border. Another reason is that the geometrical information of vertebral bodies can help to design the potentials between nodes in our graphical model, i.e. the geometrical parameters of vertebral bodies can provide more context information to guide our graphical model based detection. Compared to existing graphical model based approach, our approach has the following advantages: (1) It need not to be trained using training data, (2) It does not ask for the prior information of the examined anatomical region and (3) It can automatically identify the number of vertebrae visible in the image. The experimental results on the low resolution spine locator data show that our method can achieve robust and accurate intervertebral disc detection, which can be feeded to the scan geometry planning of the spine MRI check.

References

1. V. Pekar, D. Bystrov, H.S. Heese, S. Dries, S. Schmidt, R. Grewer, C.J. den Harder, R.C. Bergmans, A.W. Simonetti, and A. van Muiswinkel, "Automated planning of scan geometries in spine mri scans.," in *MICCAI 2007*, pp. 601–608.
2. K.L. Weiss, J.M. Storrs, and R.B. Banto, "Automated spine survey iterative scan technique," *Radiology*, vol. 239, pp. 255–262, 2006.
3. Z. Peng, J. Zhong, W. Wee, and J. Lee, "Automated vertebra detection and segmentation from the whole spine mr images," in *IEEE EMBS 2005*, vol. 3, pp. 122–133.
4. T. Klinder, J. Ostermann, M. Ehm, A. Franz, R. Kneser, and C. Loternz, "Automated model-based vertebra detection, identification, and segmentation in ct images," *Medical Image Analysis*, vol. 13, pp. 471–482, 2009.
5. D. Štern, B. Likar, F. Pernuš, and T. Vrtovec, "Automated detection of spinal centrelines, vertebral bodies and intervertebral discs in ct and mr images of lumbar spine," *Physics in Medicine and Biology*, vol. 55, pp. 247–264, 2010.
6. S. Schmidt, J.H. Kappes, M. Bergtholdt, V. Pekar, S. Dries, D. Bystrov, and C. Schnörr, "Spine detection and labeling using a parts-based graphical model.," in *MICCAI 2007*, pp. 122–133.
7. J.J. Corso, R.S. Alomari, and V. Chaudhary, "Lumbar disc localization and labeling with a probabilistic model on both pixel and object features.," in *MICCAI 2008*, pp. 202–210.
8. X. Dong, and G. Zheng, "Automated vertebra identification from X-ray images.," in *ICIAR 2010*, pp. 1–9.