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A FAST METHOD FOR SPINE LOCALIZATION IN X-RAY IMAGES

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ABSTRACT

Detection of spines in medical images are important tasks in medical applications. These tasks are relatively easy for CT/MR images because the bones are easily distinguishable from other tissues. However, they are difficult for x-ray images due to bone and soft tissue overlapping. This paper illustrates a method for detecting the medial axis of spine in x-ray images. Given an initial point on the spine in the x-ray image manually or automatically, the method iteratively searches for good feature points on the spine to locate the medial axis. As a result, the effort of determining the relevant medical information, such as *Cobb's angle*, can be minimized.

The proposed method is fast and efficient. In average it took less than 1 second for localizing the spine on a 3000×1000 gray scale x-ray image.

Index Terms— Imedical image, spine, torso, and x-ray.

1. Introduction

Automatically or semi-automatically segmenting spines in x-ray images with reasonable accuracy to be useful in classifying the spines into categories of interest to researchers in the related bone diseases, such as osteoarthritis and scoliosis.

The shape and curvature of the spine are important features for classifying the various types of scoliosis [1]. A computer system for scoliosis classification needs to compute the shape and curvature, which can be recovered from the medial axis of the spine. Detection of spinal medial axis in a CT/MR image is simple because the spine is very distinctive compared to other tissues in CT/MR image. On the other hand, detection of spinal medial axis in an x-ray image is difficult because the spine overlaps with other bones and soft tissues.

Many researchers have focused on the segmentation of some particular vertebrae in x-ray images [2, 3, 4]. On the other hand, segmentation or detection of the whole spine in x-ray images has not received much research attention, other than [5, 6]. Panjabi *et al.* demonstrated the importance of studying the 3-D shape of spine [6]. Benjelloun *et al.* suggested spine localization using regions of interests (roi) [7]. Consequently, in the last decade, many researchers have focused on the 3-D measurement, imaging, and modeling of the spine in CT/MR images [8, 9, 10, 11].

In clinical practice, x-ray imaging is still the most cost-effective method for the diagnosis and treatment of scoliosis. This paper illustrates a method for detecting the medial axes of spines in x-ray images. Test results show that the method is accurate and robust.

2. Method

Antero-posterior (frontal) x-ray images of spine have an interesting characteristic. The medial axis of the spine typically goes through intensity maximal along perpendicular cross section of the spine. This characteristic is used to guide our algorithm for detecting the medial axis of the spine.

2.1. detection of Spine

The algorithm for detecting the medial axis of the spine in an x-ray image takes a single user-specified point on the spine and a unit direction vector as the inputs. The user-specified point is regarded as the initial point $\mathbf{p}_0$ on the medial axis, and the unit direction vector $\mathbf{D}_0$ indicates the local direction of the spine at $\mathbf{p}_0$. For example, $\mathbf{p}_0$ can be located on the vertebra at the pelvic bone. For the x-ray image of a standing patient, $\mathbf{D}_0$ would be along the vertical direction.

The algorithm consists of 2 main steps that are repeated until the end of the image is reached:

1. Sample a sequence of pixels in the image.

2. Compute the next medial axis point $\mathbf{p}_{i+1}$ and the spinal direction $\mathbf{D}_{i+1}$ at $\mathbf{p}_{i+1}$.

When the algorithm terminates, the sequence of points $\mathbf{p}_i$ form the medial axis of the spine. An example is shown in Fig. 1, where straight bars are following the spinal structure, and the yellow semi-circles indicate the positions where the proposed algorithm are detecting. Finally, when the sequence of points $\mathbf{p}_i$ have been obtained, the location of the spine can be reconstructed by Support Vector Regression [12].

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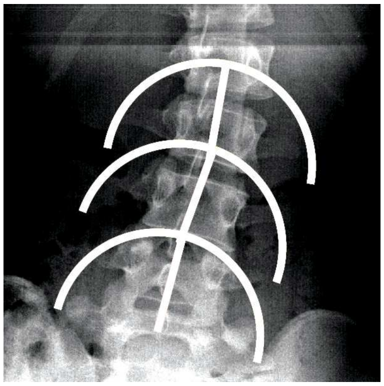

Fig. 1: An example of proposed algorithm.

2.2. Pixel Sampling

Given a medial axis point $\mathbf{p}_i$ and spinal direction $\mathbf{D}_i$, a semi-circle C is drawn for pixel sampling. The center of C is $\mathbf{p}_i$ and the radius R of C is a constant proportion of the width W of the spine. In our current implementation, R is set to a value in the range of $2W$ to $3W$ depending on the quality of the image. The semi-circle covers a range of angles from $-90°$ to $+90°$, with $0°$ aligned at the direction of $\mathbf{D}_i$ (Fig. 2). Let us denote the range of directions by $\mathbf{D}_{i,\gamma}$ in polar-coordinate form (ρ,θ):

$$\mathbf{D}_{i,\gamma} = (\rho, \theta_i + \gamma),\ \ \gamma \in \left[-\frac{\pi}{2}, \frac{\pi}{2}\right]. \tag{1}$$

For unit diector vectors $\mathbf{D}_{i,\gamma}$, $\rho = 1$. The parameter θ_i is the angle of $\mathbf{D}_i$, i.e., $\mathbf{D}_i = (1, \theta_i)$. Then, the sequence of pixels is sampled along the semi-circle C at a sampling interval T.

The above sequence of pixels is sufficient for detecting the medial axis when the spine is sufficiently distinct in the image. In practice, however, x-ray images can be very noisy. To make the spine detection algorithm more robust, multiple sequences of pixels can be sampled at various ranges of radius $R + k\varepsilon$, where k is an integer and ε is a small constant for varying the range of radius.

Now, the intensities of the pixels that are sampled can be represented by the equation:

$$Z_{i,k}[j] = I[\mathbf{p}_i + (R + k\varepsilon)\mathbf{D}_{i,\gamma}]\,\delta(\gamma - jT), \forall j. \tag{2}$$

where $I[\cdot]$ is the intensity of an image pixel, $\delta(\cdot)$ is the *Dirac Delta Function*. $Z_{i,k}[j]$ needs to be normalized to $[-1,1]$ for all m. The sequence S_i of normalized pixel intensities can be obtained by

$$S_i[j] = \sum_{k=-m/2}^{m/2} T Z_{i,k}[j], \tag{3}$$

where m denotes the number of samples.

To remove the noise in the sequence S_i, a low-pass filter is applied on it. Since the length of the sequence is quite small,

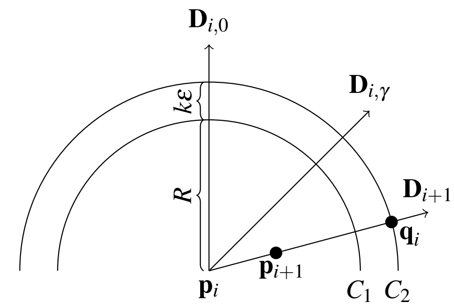

Fig. 2: A figure of the proposed algorithm.

a biquad filter is chosen in order to achieve narrow-band filtering. Biquad filtering provides precise frequency manipulation. As a result, the desired information can be detected conveniently. The transfer function of the biquad filtering in the z-domain is given by [13]

$$H(z) = \frac{b_0 + b_1 z^{-1} + b_2 z^{-2}}{a_0 + a_1 z^{-1} + a_2 z^{-2}}. \tag{4}$$

The most straightforward implementation for S_i would be

$$\begin{aligned} S_i'[j] &= (b_0/a_0)S_i[j] + (b_1/a_0)S_i[j-1] + \\ &\quad (b_2/a_0)S_i[j-2] - (a_1/a_0)S_i'[j-1] - \\ &\quad (a_2/a_0)S_i'[j-2], \end{aligned} \tag{5}$$

where S_i' is the result of noise filtering. The parameters b_0, b_1, b_2, a_0, a_1 and a_2 are given by [13]

$$\begin{aligned} a_0 &= 1 + \alpha, b_0 = \frac{1 - \cos(\omega_0)}{2}, \\ a_1 &= -2\cos(\omega_0), b_1 = 1 - \cos(\omega_0), \\ a_2 &= 1 - \alpha, b_2 = \frac{1 - \cos(\omega_0)}{2}. \end{aligned} \tag{6}$$

In Eq. 6, the parameters ω_0 and α are defined as

$$\begin{aligned} \omega_0 &= 2\pi f_0/F, \\ \alpha &= \sin\omega_0 \sinh\left(B\frac{\log 2}{2}\frac{\omega_0}{\sin\omega_0}\right), \end{aligned} \tag{7}$$

where F is the sampling frequency, f_0 is the central frequency, and B is the bandwidth in octaves.

Here the relevant parameters are highly related to the quality of the given images. In our experiments, the following parameter values are found to be appropriate: $F = 600$, $f_0 = 9$ and $B = 0.5$.

2.3. Compute Medial Axis Point and Spinal Direction

As discussed in Section 2, the medial axis of the spine typically goes through intensity maximal along perpendicular cross section of the spine. This intensity maximal corresponds to the maximum of the sequence $S_i'[j]$ of noramlized samples. Let $\mathbf{q}_i$ denote the pixel position of the intensity maximal in the sequence $S_i'[j]$, and J denote the index of the intensity maximal in $S_i'[j]$. The angle Θ_i of $\mathbf{q}_i$ with respect to $\mathbf{p}_i$ can be computed as follows:

$$\Theta_i = \frac{J\pi}{m} + \frac{\pi}{2}. \tag{8}$$

The unit direction vector $\mathbf{D}_{i+1}$ at angle θ_i from $\mathbf{p}_i$ is then

$$\mathbf{D}_{i+1} = (1, \theta_i + \Theta_i), \tag{9}$$

This vector $\mathbf{D}_{i+1}$ is regarded as the spinal direction of the next medial point $\mathbf{p}_{i+1}$, which is computed as

$$\mathbf{p}_{i+1} = \mathbf{p}_i + \eta \mathbf{D}_{i+1} \tag{10}$$

where η is a constant step size smaller than 1.

After computing $\mathbf{p}_{i+1}$ and $\mathbf{D}_{i+1}$, the algorithm is repeated until the end of the x-ray image is reached. When the algorithm terminates, a sequence of points $\mathbf{p}_i$, $i = 0, 1, \ldots$, reconstruct the medial axis of the spine is obtained.

2.4. Reconstruct the Medial Axis of the Spine

Following the previous section, the sequence $\mathbf{p}$ can be used to form a mathemtical model of the medical axis of the spine based on Support Vector Regression (SVR)[12]. SVR operates in high-dimensional feature sapce to approximate unknown functions in the output space, thereby using non-linear functions to linearity estimate an unknown function. In this step, a B-spline is used as the kernel function of the SVR. SVR results a flexible and piecewise continual curve. Based on the proposed procedure the curve indicates the position and the shape of the spine in torso x-ray images.

The sequence of points $\mathbf{p}_i$, $i = 0, 1, \ldots, N$ can be noted as

$$\Omega_r = \{(\mathbf{p}_1, y_1), (\mathbf{p}_2, y_2), \ldots, (\mathbf{p}_N, y_N)\}, \tag{11}$$

where $y_i \in \mathbb{R}, \forall i \in [1, N]$. The target function is taking the form

$$f(\mathbf{p}) = \langle \mathbf{w}, \mathbf{p} \rangle + b, \text{ with } \mathbf{w} \in \mathbb{R}^d, b \in \mathbb{R}.5 \tag{12}$$

$\langle \cdot, \cdot \rangle$ denotes the dot product in $\mathbb{R}^d$. A small $\mathbf{w}$ is desired in order to obtain the flatness of the Eq. 12, the minimized norm, $||\mathbf{w}||^2$ is required. A convex optimization problem can be established as,

$$\min(\frac{1}{2}||\mathbf{w}||^2 + C\sum_{i=1}^{N}(\xi_i^+ + \xi_i^-))$$

subject to

$$-\xi_i^- \le |y_i - (\mathbf{w}^T \phi(\mathbf{p}_i) + b)| - \varepsilon \le \xi_i^+, \tag{13}$$

where $\xi_i^-, \xi_i^+ \le 0, \forall i \in [1, N]$. $\phi(\cdot)$ is the kernel function. Here the B-Spline is selected as the kernel function of the SVR.

SVR results a flexible and piecewise continual curve. Based on the proposed procedure the curve indicates the position and the shape of the spine in torso x-ray images.

3. Experiments and Discussions

The proposed algorithm was tested on more than 30 x-ray images. Some results are shown in Fig.Fig. 3. The results show that the algorithm is accurate in detecting the medial axes of the spines in the images. The detected medial axes always lie in the middle of the spines regardless of the seriousness of the scoliosis (Fig. 3(a)–(d)) and the lateral bending of the patinet's torso (Fig. 3(e, f)) during medical examination.

The algorithm is not significantly affected by the location of the initial point. This feature is presented in Fig. 4.

The proposed algorithm is fast. For a 3000×1000 (which is a typical size of a x-ray image for the diagnosis of scoliosis), it took less than 1 second in a recent model of laptops.

4. Conclusion

This paper demostrated a method for detecting the medial axes of spines in antero-posterior torso x-ray images. Test results show that the medial axes detected are accurately located in the spine. Moreover, the method can detect accurate medial axes even when the positions of the initial points are not accurately specified by the user. The method can be used in our continuing work to analyze the shape and curvature of the spine and to classify scoliosis.

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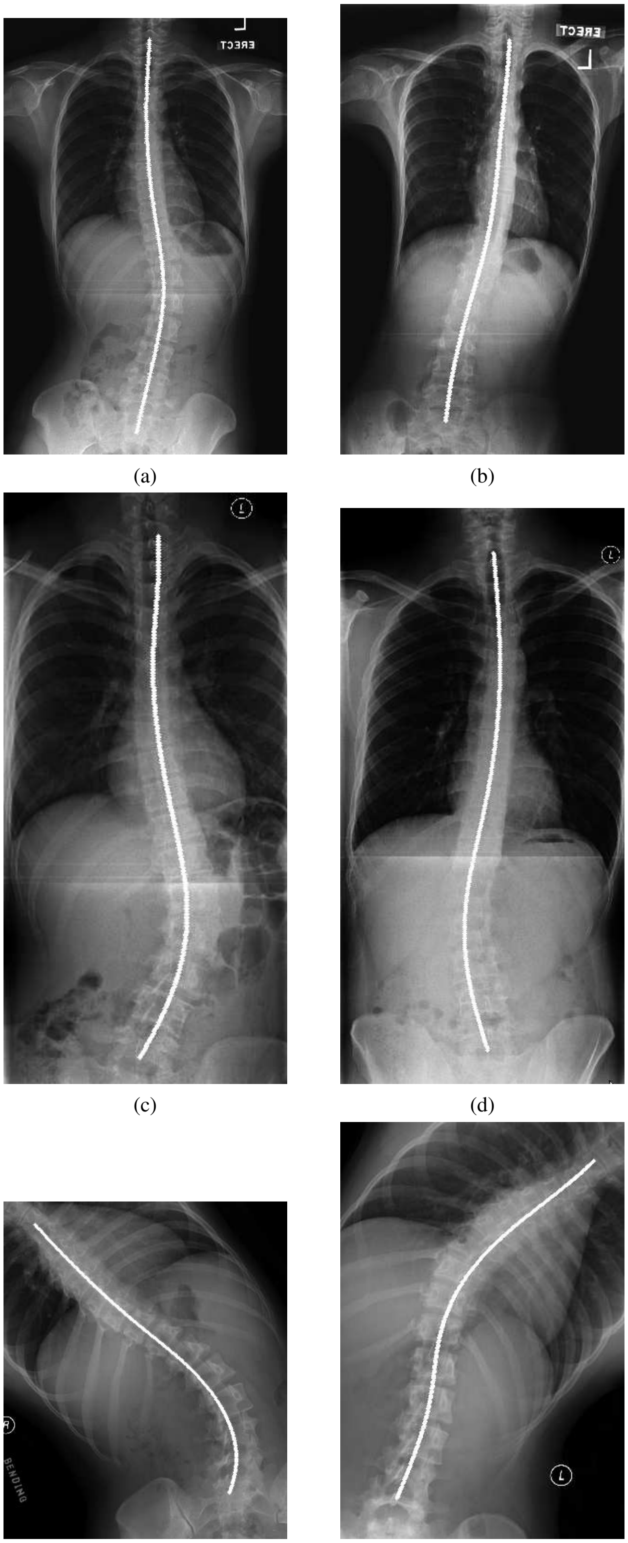
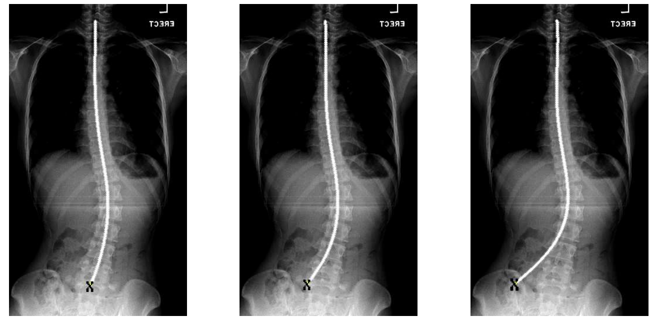


(a) (b) (c) (d) (e) (f)

Fig. 3: The results of the proposed method for the antero-posterior images.



(a) (b) (c)

Fig. 4: Robustness test results, (a) with a good inital point at X, (b) with a little bit distance from the vertebra, and (c) with a bigger distance from the vertebra.

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