Automatic Segmentation of the Ribs, the Vertebral Column, and the Spinal Canal in Pediatric Computed Tomographic Images

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We propose methods to perform automatic identification of the rib structure, the vertebral column, and the spinal canal in computed tomographic (CT) images of pediatric patients. The segmentation processes for the rib structure and the vertebral column are initiated using multilevel thresholding and the results are refined using morphological image processing techniques with features based on radiological and anatomical prior knowledge. The Hough transform for the detection of circles is applied to a cropped edge map that includes the thoracic vertebral structure. The centers of the detected circles are used to derive the information required for the opening-by-reconstruction algorithm used to segment the spinal canal. The methods were tested on 39 CT exams of 13 patients; the results of segmentation of the vertebral column and the spinal canal were assessed quantitatively and qualitatively by comparing with segmentation performed independently by a radiologist. Using 13 CT exams of six patients, including a total of 458 slices with the vertebra from different sections of the vertebral column, the average Hausdorff distance was determined to be 3.2 mm with a standard deviation (SD) of 2.4 mm; the average mean distance to the closest point (MDCP) was 0.7 mm with SD = 0.6 mm. Quantitative analysis was also performed for the segmented spinal canal with three CT exams of three patients, including 21 slices with the spinal canal from different sections of the vertebral column; the average Hausdorff distance was 1.6 mm with SD = 0.5 mm, and the average MDCP was 0.6 mm with SD = 0.1 mm.

KEY WORDS: Computed tomographic (CT) images, vertebral column, rib structure, spinal canal, morphological image processing, opening-by-reconstruction, image segmentation, Hough transform, convex hull

INTRODUCTION

The development of automatic or semiautomatic algorithms for the detection and delineation of the anatomical or structural components in biomedical images offers a unique challenge, because the objects of interest are commonly irregular with no clear boundaries and are often

overlapped by other structures. Artifacts during imaging caused by the dynamic nature of physiological systems, the variability of human size and shape, and poor spatial resolution also increase the difficulty of the segmentation problem. In addition, the desired delineation could encompass pathological abnormalities, such as tumors, which could cause the structure of interest to deviate from the average or expected characteristics.

The vertebral column plays an important role in the human biomechanical system^{1,2}. The vertebral column extends from the skull to its anchoring point in the pelvis, through which it transfers the weight of the head and trunk to the legs. It also houses and protects the spinal cord. Cartilage pads with jelly-like filling called intervertebral disks separate the vertebrae³. The posterior body surfaces and arches of the stacked vertebrae form the spinal canal. Herniated discs, degenerative diseases like osteoporosis, vertebral neoplasms, accidental injuries, and scoliosis can derange, deviate, or restrict this vulnerable system^{1,2}. Three-dimensional (3D) re-

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construction of the spine from two-dimensional (2D) biplanar radiographic images has been used for the detection of vertebral fractures or deformity and idiopathic scoliosis⁴⁻⁶. 3D models of the spine have been used to predict the outcome of orthopedic treatment⁵. In clinical diagnosis, therapy, and surgical intervention, the identification and segmentation of the vertebral column in computed tomographic (CT) images are crucial and important steps. Due to the complexity of the vertebral surface, small distances between the articulated vertebrae and, above all, the presence of pathological regions such as tumors and calcification, the segmentation of the vertebral column in CT images is a challenging task.

Radiation therapy is an important procedure used to treat patients with malignant neoplasms. Precise image-guided treatment planning of radiation therapy requires the definition of treatment volumes and a clear delimitation of normal tissue of which exposure should be prevented or minimized⁷⁻⁹. An accurate segmentation procedure that delineates target volumes and neighboring organs of interest could greatly reduce the time and effort in planning of radiation therapy and surgery. The spinal canal is a radiosensitive organ, and therefore, it should be precisely identified to prevent complications arising from radiation-induced damage. The automatic detection of the spinal canal in CT images is a difficult problem, and while there has been much work done on registration and segmentation of images of the spine^{1,2,7,8}, the development of easily applicable, robust, and automatic registration and segmentation algorithms remains difficult¹⁰.

Digital atlases are widely used for registration, identification, and segmentation of organs and structures in medical images, as well as for assistance in the planning of surgery¹¹⁻¹⁴. However, clinical cases with pathological situations are often complicated and vary to a larger extent than normal cases. In the case of pediatric subjects, several organs and tissues may not be fully developed in size, shape, and tissue characteristics; there could also be large variations with age and level of maturity in the structure, proportion, location, and composition of most organs in children. These factors create difficulties in the segmentation of different organs in CT exams of children. The presence of abnormalities or pathological regions such as tumors restricts the use of standard atlases in practical cases. As a conse-

quence, pediatric CT images may possess few reliable reference structures to aid in the identification, registration, or segmentation of organs or tumors, or to facilitate the use of atlases. The identification and segmentation of the rib structure, the vertebral column, and the spinal canal can be helpful in this regard. These structures can also be used to separate the thoracic and abdominal cavities, to assist in planning radiotherapy, and to aid in image-guided surgery.

Various algorithms have been developed to identify the spine or the vertebral column^{1,2}, the spinal canal^{7,8,15}, and the ribs^{16,17}. The locations of the spine and the thoracic cage have been used for the purpose of landmarking in the segmentation of various abdominal and thoracic organs^{16,18}. All of the works cited above are applicable to CT exams of adults and are not appropriate for application to pediatric CT images. Rangayyan et al.¹⁰ proposed methods for the detection of the spinal canal in pediatric CT images using the Hough transform and fuzzy connectivity. Although the results showed promise, the dataset used was small, the procedure assumed the presence of the spinal canal within a particular portion of the CT images, and the parameters were not automatically selected. Rangayyan et al.¹⁹ also proposed methods for the delineation of the diaphragm, and Banik et al.²⁰ developed techniques for segmentation of the pelvic girdle in pediatric CT images; these methods have been applied to reduce false-positive regions in the segmentation of tumors due to neuroblastoma in CT images of pediatric patients²¹⁻²³.

In this context, methods based on multilevel thresholding and morphological image processing are proposed in the present work to perform automatic segmentation of the rib structure, the vertebral column, and the spinal canal in pediatric CT exams^{20,23,24}. The seed voxels for the spinal canal are automatically detected using the Hough transform^{10,25}. In “Methods” section, the methods of fuzzy connectivity, morphological reconstruction, and the Hough transform are briefly described. The experimental setup, the datasets used, and the methods of quantitative assessment of the results are described in “Experimental Setup and Assessment of the Results” section. The segmentation procedures for the ribs, the vertebral column, and the spinal canal are described in “Identification of the Rib Structure”, “Segmentation of the Vertebral Column”, and

“Identification of the Spinal Canal” sections, respectively. The results of qualitative and quantitative assessment of the results of segmentation are presented in “Results” section.

METHODS

Image Processing Techniques for Segmentation and Detection

Fuzzy Segmentation

Fuzzy sets originate from the generalization of conventional set theory and serve to quantify the imprecision in information to varying degrees^{26–28}. In the context of image segmentation, the notion of fuzzy sets combined with the concept of fuzzy connectivity, as proposed by Rosenfeld²⁹, is a powerful tool to quantify not only the degree to which the elements of an image satisfy the properties of the object of interest individually but also to quantify the way in which they are related. This forms the basis for fuzzy segmentation²⁸.

Theoretically, a fuzzy set A in a reference set X can be characterized by a membership function, m_A , that maps all elements in X into the interval $[0, 1]$. The fuzzy set may be represented as a set of fuzzy pairings, written as

$$A = \{(x, m_A(x)) | x \in X\}, \quad (1)$$

where m_A is the membership or characteristic function, defined as

$$m_A(x) = x \rightarrow [0, 1], \text{ for } x \in X. \quad (2)$$

The membership value $m_A(x)$ is called the *grade of membership* of x in A : This function indicates the degree to which x satisfies the membership criteria defining A . Values close to unity represent high degrees of membership, whereas values near zero represent the lack of similarity with the characteristics of the set. In defining $m_A(x)$, three properties should be satisfied: normality, monotonicity, and symmetry²⁷.

The unnormalized Gaussian function, defined as

$$m_A(x) = \exp\left\{-\frac{(x - \mu)^2}{2\sigma^2}\right\}, \quad (3)$$

is an example of a fuzzy membership function satisfying the properties listed above; μ and σ

correspond to the mean and standard deviation (SD) of a property [intensity or Hounsfield unit (HU) values in the present work] of the region or organ of interest.

Morphological Reconstruction

Morphological *opening by reconstruction* is a powerful tool to evaluate the connectivity of objects in images³⁰. Opening by reconstruction (hereafter referred to simply as “reconstruction”) is an iterative procedure that can extract regions of interest (ROIs) from an image identified or selected by a set of *markers*^{31,32}. Markers, commonly known as *seed pixels*, are the initial points to start the process and must be contained within the mask of the objects of interest. In the case of binary images, reconstruction is the process to perform extraction or segmentation of the objects connected to the markers in the image.

To explain reconstruction, let I and J be defined in the image domain D such that $J \subseteq I$. The reconstruction of the image I (called the mask) by the image J (called the marker or seed) can be performed by iterating the elementary geodesic dilation operation on J until further iterations result in no net change. An elementary geodesic dilation, $\delta^{(1)}$, of the marker, J , is simply a standard dilation, $\oplus$, with a unit-sized structuring element, B , followed by an intersection with the mask, I :

$$\delta_I^{(1)}(J) = (J \oplus B) \cap I. \quad (4)$$

Therefore, regardless of the extent of the dilations, the reconstruction remains constrained by the mask, I . Typical unit-sized structuring elements are either a four- or eight-connected neighborhood for a 2D image and a six- or 26-connected neighborhood for a 3D volume.

Formally, the reconstruction ρ_I of I from $J \subseteq I$ can be written as

$$\rho_I(J) = \bigcup_{n \geq 1} \delta_I^{(n)}(J), \quad (5)$$

where $\delta_I^{(n)}(J)$ represents n iterations of the elementary geodesic dilation operation, represented as

$$\delta_I^{(n)}(J) = \underbrace{\delta_I^{(1)} \diamond \delta_I^{(1)} \diamond \dots \diamond \delta_I^{(1)}(J)}_{n \text{ times}}. \quad (6)$$

In this context, $\diamond$ denotes the use of the result from the previous step in subsequent iterations.

For example, $\delta_I^{(1)} \diamond \delta_I^{(1)}(J)$ means that the initial geodesic dilation is performed, and the result of this step is then used in the next iteration to perform another iteration of the geodesic dilation operation.

For gray-scale images, the application of reconstruction is similar to the procedure for binary images. If I and J are two images in the same discrete domain D , where each element (pixel or voxel) of the images is a value in the discrete set $\{0, 1, \dots, L-1\}$, such that $J(p) \leq I(p)$ for every pixel in the image, $p \in D$, the result of reconstruction is obtained by iterating the elementary geodesic dilation operation (in gray scale) until the stopping criterion is reached.

According to Bloch³³, there exists an equivalence between the concept of connectedness as described in “Fuzzy Segmentation” section and that of the degree of connectedness as defined by Udupa and Samarasekera²⁸. As a result, the properties, transformations, and applications related to and derived from these two notions are similar³³. Morphological reconstruction operates on the notion of a connection cost, or the minimum distance between specific points in a defined set. As a result, because of the similarity, reconstruction was deployed to achieve segmentation using fuzzy connectivity²² and used to perform extraction of organs of interest in CT images as a part of the present work.

The Hough Transform

The Hough transform^{25,34,35} is a useful tool to detect any shape that can be represented by a parametric function (for example, a straight line, a circle, a sphere, an ellipse, an ellipsoid, or a more complex shape), using the information related to edges in the form of a binary image. The major strength of the Hough transform is the ability to recognize shapes and object boundaries, even with a sparse edge map.

The Hough transform can be used for the detection of complex parametric curves³⁵. For example, all points along the circumference of a circle of radius c centered at $(x, y) = (a, b)$ of an image $h(x, y)$ satisfy the relationship

$$(x - a)^2 + (y - b)^2 = c^2. \quad (7)$$

A circle is represented by a single point in the 3D parameter space (a, b, c) . Each point along

the circumference or the edge of a circle in the (x, y) plane describes a right circular cone in the Hough parameter space, which is limited by the image size. Prior knowledge of the possible radius values could assist in fast and accurate detection by overcoming the effects of artifacts. The use of the Hough transform to detect seed voxels in the spinal canal is described in “Detection of Seed Voxels Using the Hough Transform” section.

Experimental Setup and Assessment of the Results

The CT exams used in this work, containing varying numbers of slices, are anonymous cases from the Alberta Children’s Hospital, Calgary. The proposed procedure for segmentation of the rib structure, vertebral column, and spine was tested on 39 CT exams of 13 subjects with age varying from 2 weeks to 20 years. One of the CT exams in the dataset was not processed (exam 8.1), because it contains a scan of the pelvic region only. The CT exams in the dataset were acquired using a GE Medical System Lightspeed Plus or VCT helical CT scanner. The CT exams have varying interslice resolution of 2.5 or 5 mm, and the intraslice resolution varies from 0.35 to 0.70 mm. The computer used to process the exams is a Dell Precision PWS490 with an Intel® Xeon™ 3.00 GHz processor and 4 GB of random-access memory.

Approval was obtained from the Conjoint Health Research Ethics Board, Office of Medical Bioethics, University of Calgary and the Calgary Health Region. The results of segmentation of the vertebral column and the spinal canal were assessed quantitatively in comparison with manual segmentation performed by an expert radiologist (G. S. B.) using the Hausdorff distance³⁶ and the mean distance to the closest point (MDCP)³⁷.

The Hausdorff Distance

The Hausdorff distance is a popular measure to compare the results of segmentation of ROIs in medical images^{36,38}. The Hausdorff distance between two sets is the maximum of the distances of the points in one set to the corresponding nearest points in the other set³⁶. Formally, the directed

Hausdorff distance from set A to set B is a max–min function, defined as

$$h(A, B) = \max_{a \in A} \left[\min_{b \in B} \{d(a, b)\} \right], \quad (8)$$

where a and b are points in the sets A and B , respectively, and $d(a, b)$ is a distance measure between the points; for simplicity, $d(a, b)$ can be regarded as the Euclidean distance (ED) between a and b . It should be noted that the Hausdorff distance is oriented (or asymmetric), which means that, in general, $h(A, B)$ is not equal to $h(B, A)$.

A more general definition of the Hausdorff distance is

$$H(A, B) = \max\{h(A, B), h(B, A)\}, \quad (9)$$

which defines the Hausdorff distance between A and B . In comparison, Eq. 8 gives the directed Hausdorff distance from A to B . The two distances $h(A, B)$ and $h(B, A)$ are, sometimes, termed as the forward and the backward Hausdorff distances of A to B .

Mean Distance to the Closest Point

The Hausdorff distance measures the mismatch between two sets that are at fixed positions with respect to one another and represents the worst case in matching the two sets. Another measure of comparison called the MDCP³⁷ has been proposed to provide a more general measure of distance between two sets than the Hausdorff distance. MDCP evaluates quantitatively the degree of affinity between two sets by computing the average distance to the closest point (DCP) between the two sets (see Saha et al.³⁹ for a related measure).

Given two sets, $A = \{a_1, a_2, \dots, a_M\}$ and $B = \{b_1, b_2, \dots, b_N\}$, DCP is defined as

$$DCP(a_i, B) = \min \|a_i - b_j\|, \quad j = 1, 2, \dots, N, \quad (10)$$

where $\|\cdot\|$ is a norm (e.g., the Euclidean norm) computed for the points a_i and b_j . MDCP is then defined as

$$MDCP(A, B) = \frac{1}{M} \sum_{i=1}^M DCP(a_i, B). \quad (11)$$

The smaller the value of the MDCP is, the more similar the two sets are to each other.

Preprocessing of CT Volumes

Each CT volume was processed to identify and remove peripheral artifacts, the skin, and the peripheral fat using the procedures described by Vu et al.²² and is summarized in the following paragraphs.

Air, by definition, has a CT number of $-1,000$ HU. Using thresholding, binary reconstruction, and morphological dilation, the external air region and the peripheral artifacts were removed.

The first expected layer from the outside of the body is the skin, which usually has a thickness of $1\text{--}3$ mm¹⁰. Using the parameter of the expected skin thickness, the air region was dilated in 2D using a disk-shaped structuring element of radius 2 pixels to separate the skin layer from the body. The next layer after the skin is the peripheral fat. Fat has a mean CT value of $\mu = -90$ HU with $\sigma = 18$ HU^{40,41}. Peripheral fat around the abdomen varies in thickness from 3 to 8 mm in children. After removal of the skin, voxels within a distance of 8 mm from the inner skin boundary were examined; if these voxels fell within the range of $-90 \pm 2 \times 18$ HU, they were classified as peripheral fat.

Identification of the Rib Structure

The segmentation procedure to detect and delineate the rib structure in pediatric CT images is initialized by removing the external air, peripheral artifacts, and the skin layer^{10,22} and thresholding each CT volume at 200 HU. Then, the binarized volume is morphologically opened using a disk of radius 3 pixels to disconnect the rib structure from the spine. The ribs in the upper thoracic region are smaller and closer to one another than in the middle of the thorax. Based on this observation, the compactness factor (defined as $cf = 1 - 4\pi a/P^2$, where a is the area and P is the perimeter of the corresponding region or contour) of the inner contour of the peripheral fat region on each slice is used to differentiate between the upper portion of the thoracic region and the rest of the thorax as well as the abdomen. Because cf is a measure of the complexity of the shape of a region, starting from the top-most slice of a CT scan, the first slice with $cf < 0.4$ is considered to be the end of the upper portion of the thoracic region present in the CT volume.

For each slice, a central line along the medial sagittal plane is defined based on the inner contour of the peripheral fat region. The use of the information related to the peripheral fat boundary aids in defining the central line close to the midsagittal plane regardless of the position of the body in the image. An example of the defined central line is shown in Figure 1a. Note that the defined central line passes through the spine, as expected.

Then, an initial estimation procedure is applied as follows²⁴:

1. Consider each slice starting from the top of the binarized CT volume and mark each of the thresholded regions on each slice
2. Define the central line
3. Measure the shortest ED from the edge and the centroid of each of the regions to the defined central line and also to the inner edge of the peripheral fat region
4. If the corresponding slice is not from the upper portion of the thoracic region (as defined previously using the measure of cf), consider a marked region initially to be a part of the rib structure if the region satisfies all of the following criteria:
 - (a) Shortest ED from the centroid of the region to the inner edge of the peripheral fat region ≤ 3.5 cm
 - (b) Shortest ED from the edge of the region to the inner edge of the peripheral fat region ≤ 1.8 cm
 - (c) Shortest ED from the centroid of the region to the defined central line ≥ 1.5 cm
 - (d) Shortest ED from the edge of the region to the defined central line ≥ 1.5 cm
5. If the corresponding slice is from the upper portion of the thoracic region, consider a marked region initially to be a part of the rib structure if the corresponding region satisfies all of the following criteria:
 - (a) Shortest ED from the centroid of the region to the inner edge of the peripheral fat region ≤ 4.5 cm
 - (b) Shortest ED from the edge of the region to the inner edge of the peripheral fat region ≤ 3 cm
 - (c) Shortest ED from the centroid of the region to the defined central line ≥ 1 cm
 - (d) Shortest ED from the edge of the region to the defined central line ≥ 1 cm
6. Calculate the area, the minor axis length (a measure of thickness of the corresponding region on a slice) and cf of each of the selected regions in the corresponding slice. If, for a given region, $cf \leq 0.85$, area of the region $\leq 5,000$ pixels, and the minor axis length ≤ 2 cm, accept the region to be a part of the rib structure
7. Continue the process until the lowest slice that contains possible parts of the rib structure is processed

The aforementioned spatial distance limits were empirically selected through experimentation with ten arbitrarily selected CT scans in the dataset as described in “Experimental Setup and Assessment

Fig 1. a A 512×512-pixel CT slice after thresholding at 200 HU. The defined central line is shown as a dash-dot line. The inner edge of the peripheral fat region is shown for reference. b After the application of the reconstruction procedure, the boundary of the defined elliptical region to remove unwanted structures inside the body is shown in dash-dotted contour. Calcified parts of a tumor are visible in both figures and are removed from the result of segmentation of the rib structure by this procedure.

of the Results” section. The spatial distance limits and parameters obtained were used in all the CT exams. The structure obtained with the aforementioned procedure can be considered to be a preliminary estimate of the rib structure; the results could include other bony or calcified structures that do not belong to the rib structure.

The initially detected rib structure is skeletonized by the morphological thinning operation and the skeleton of the rib structure is used as a region marker to perform opening by reconstruction in 3D using the 26-connected neighborhood; the result is thresholded at a high fuzzy membership value of 0.8. The result of reconstruction may still include other calcified structures in the abdomen or in the thorax.

To eliminate unwanted structures in the result of reconstruction, a 2D elliptical region is defined on each slice inside the thoracic and abdominal regions based on the outer boundary of the initially detected rib structure and the inner contour of the peripheral fat region for the corresponding slice. The center, the major axis, and the minor axis are chosen in such a manner that the elliptical region fits inside the initially segmented rib structure for each slice. To obtain the center of the defined elliptical region, the center point of the inner contour of the peripheral fat region is shifted toward the anterior of the body by 10% of the maximum distance along the sagittal plane between the anterior and posterior side of the inner contour of the peripheral fat region on each slice and is considered to be the center of the defined elliptical region for the corresponding slice. The shift is required to ensure that parts of the rib structure close to the spine are not removed. The major axis length is defined to be 90% of the maximum distance between the ribs on the left and the right side (along the coronal plane); the minor axis length is defined to be 80% of the maximum distance along the sagittal plane between the anterior and posterior side of the inner contour of the peripheral fat region. All pixels inside the defined elliptical region are removed. An example of the defined elliptical region is shown in Figure 1b. This procedure also helps in finding the lower limit of the rib structure in the CT exam, by eliminating the calcified regions in the abdomen which could create ambiguity in the process of detection of the rib structure.

After removing the unwanted structures within the thoracic and abdominal regions, the features used in the initial estimation step are applied again to differentiate between the ribs and other regions. Finally, after removing the voxels corresponding to other regions and filling in holes, the resulting volume is dilated in 2D using a disk-type structuring element of radius 2 pixels, to obtain a refined result of segmentation of the rib structure.

Segmentation of the Vertebral Column

For segmentation of the vertebral column, the CT volume is thresholded at 180 HU and the result is morphologically opened using a tubular structuring element of radius 2 pixels and height 3 pixels. The segmented rib structure obtained using the procedures described in “Identification of the Rib Structure” section is eliminated from the binarized volume. Then, the remaining volume is morphologically eroded in 2D by a disk of radius 3 pixels to disconnect the connected components.

For each slice, a central line up to the midpoint of the body along the midsagittal plane is defined based on the inner contour of the peripheral fat region; the defined central line is expected to pass through the vertebral column, as shown in Figure 2b. The relative position and the orientation of the body are taken into account by this step. For each slice, if any pixel in any region is within the Euclidean distance of 8 mm from the central line, the region is initially considered to be a part of the vertebral column. Then, the resulting image is evaluated in 3D and the longest bony structure along the interslice direction is considered to be the vertebral column.

Following the procedure as described above, the gradient of the detected binary volume is computed, binarized for all nonzero gradient magnitude values, and then added to the detected binary volume to create a combined mask of the vertebral column to reduce the possibilities of missing parts with low HU values²⁴. The gradient helps to include the low-HU voxels in the vertebral column (see Fig. 2d).

The image within the combined mask is then thresholded at 150 HU. To minimize the errors due to the partial-volume effect, the pixels within the combined mask are evaluated using a 5×5 window; the maximum and minimum are calculated, and if their difference is above 50 HU, then the center pixel is examined to determine if it is within the range

Fig 2. a A 512×512-pixel CT slice from exam 4.1, with the display range [−400, 500] HU. b The CT slice shown in a after thresholding at 180 HU and removing the rib structure. The defined central line is shown as a *dotted line*. The inner edge of the peripheral fat region is shown for reference. c Initial result of segmentation. d The binarized gradient magnitude of the result of segmentation considering only the longest bony structure in the initial result. e The region separated after applying the combined mask. f Final result of segmentation of the vertebra. See Figure 10b for a related 3D illustration.

related to the vertebral column. If the constraints mentioned above are satisfied, the center pixel is included in the result of segmentation. Finally, the segmented vertebral column is morphologically

closed using a disk of radius 2 pixels to remove isolated pixels and perform smoothing. Figure 2f shows the final result of segmentation for the CT slice shown in Figure 2a of the same figure.

Identification of the Spinal Canal

The procedure to detect the spinal canal proposed by Rangayyan et al.¹⁰ is modified extensively in the present work to make the process of automatic extraction of the spinal canal adaptive. The method operates on the observations that the spinal canal is homogeneous in CT characteristics, contrasts strongly with the surrounding bony structure of the vertebral column, is almost triangular in the lumbar and cervical regions, and is nearly circular in the thoracic region⁴². Instead of the fuzzy connectivity algorithm used by Rangayyan et al.¹⁰, in the present work, reconstruction is deployed to grow the region within the vertebral foramen to perform 3D segmentation of the spinal canal. In order to achieve automatic segmentation, the segmented vertebral column and the rib structure are taken as reference, and the Hough transform is used to detect seed voxels in the spinal canal. The process is described in the following sections.

Delimitation of the Search Range for Seed Detection

An adaptive approach is followed for the purpose of detection of the seed voxels for the spinal canal. The segmented vertebral column is used to delimit the search range for seed voxels. Because the spinal canal is contained within the vertebral column, a rectangular window is defined on each slice in such a manner that the segmented vertebra in the corresponding slice completely fits within the rectangular window. Because the spinal canal is nearly circular in the thoracic region^{10,42}, to limit the scope of application of the Hough transform, only the thoracic region bounded by the highest and the lowest portions of the rib structure is considered for seed selection.

Detection of Seed Voxels Using the Hough Transform

The Hough transform for the detection of circles, as given in Eq. 7, is applied to the edge map of the cropped region containing the binarized vertebral column to detect the center of the best-fitting circle for each slice, with the radius limited to the range of 6 to 10 mm¹⁰. The edge map is obtained by applying Canny's procedure for edge detection⁴³. Because of the sparseness of the edge map, the global maximum in the Hough space may

relate to the external curve of the anterior parts of the vertebra (i.e., the vertebral body) instead of the desired circular boundary of the spinal canal inside the vertebra. To obtain the center and radius of the desired circle, the intensity values of bone marrow ($\mu=+142$ HU and $\sigma=48$ HU)¹⁰ and the spinal canal ($\mu=+23$ HU and $\sigma=15$ HU) are used. The values of μ and σ for the spinal canal were manually estimated from ten CT images. If the HU value of the voxel at the center of the best-fitting circle for a given slice is not within the range of $\mu \pm 2\sigma$ of the spinal canal (that is, within the range $[-7, 53]$ HU), the corresponding circle is rejected, and the next maximum in the Hough space is evaluated. This process is continued until a suitable center is determined. The process of seed detection is illustrated in Figures 3, 4, 5, and 6.

Figure 3d shows the best-fitting circle drawn on a CT slice, shown in Figure 3a. The related Hough space is shown in Figure 4 for circles with radius $c=\{15, 16, 17, 18, 19, 21\}$ pixels. When the bone structure is clearly delineated, the best-fitting circle approximates the spinal canal boundary well without ambiguity, and the center of the circle is close to the center of the spinal canal in the corresponding slice, as can be seen in Figure 3d. The center of the circle with radius 17 pixels is detected as a seed voxel for the spinal canal in this example because the detected center voxel corresponds to the maximum value in the Hough space, as marked by a diamond ($\diamond$) in Figure 4c, and satisfies all the imposed constraints.

Figure 5d shows the six circles related to the top six values in the Hough space for the CT slice shown in Figure 5a. Figure 6a–d shows slices of the Hough space related to the circles with radius $c=\{13, 14, 20, 21\}$ pixels for the edge map of the vertebral column in Figure 5c; these slices include all of the top six values in the Hough space. Because of the disjoint structure of the vertebral column, the pixels corresponding to the top three values in the Hough space (marked in solid, dashed, and dash-dotted line, respectively, in Fig. 6) do not satisfy the selection criteria. As a result, they are rejected and the pixel corresponding to the center of the circle related to the fourth maximum value (marked with a thick black line in Fig. 6) is selected to be one of the seeds. The circles related to the fifth (marked in dotted line) and the sixth (marked in thin black line) maximum values are shown only for illustrative purposes.

Fig 3. a A 512×512-pixel CT slice from exam 1.1, with the display range [−300, 400] HU. b Detected vertebral column (binarized) cropped from the slice shown in a and enlarged. c Edge map of the detected and cropped vertebral column. d The best-fitting circle (shown in *dashed line*) as determined by the Hough-space analysis. The circle has a radius of 17 pixels or 6.97 mm; the detected center is shown by a *diamond*. See Figure 4 for illustrations of the Hough space for this example.

Extraction of the Spinal Canal

The centers of the circles detected by the procedure described in the preceding section are used as the seed voxels for the reconstruction process using the 26-connected neighborhood. The mean and the standard deviation for the reconstruction process are calculated within the neighborhood of 21×21 pixels (approximately 1×1 cm) of each of the seed voxels for the corresponding CT exam. Voxels in the defined neighborhood having HU values not within the range of $23 \pm 3 \times 15$ HU (i.e., within three times the standard deviation from the prior estimate of the mean HU value for the spinal canal) are rejected from the parameter calculation process. Subsequently, the reconstructed fuzzy region is thresholded at 0.80 and the region is closed in 2D using the convex hull.

Then, the result is morphologically closed in 3D using a 3D tubular structuring element of radius 2 mm and height 10 mm. Due to the expected tubular structure of the spinal cord and the spinal column, a tubular structuring element is appropriate¹⁰. The method described above is summarized in the flowchart in Figure 7.

RESULTS

The results of segmentation of the vertebral column and the spinal canal were assessed qualitatively and quantitatively; the results of segmentation of the rib structure were qualitatively evaluated. The following sections describe the important results.

Fig 4. Illustration of the Hough space for the image in Figure 3c. Hough parameter space: a for $c = 6.15$ mm (15 pixels), b for $c = 6.56$ mm (16 pixels), c for $c = 6.97$ mm (17 pixels), d for $c = 7.38$ mm (18 pixels), e for $c = 7.79$ mm (19 pixels), and f for $c = 8.61$ mm (21 pixels). The display intensity is $\log_{10}(1 + \text{accumulator cell value})$ of the Hough space. The detected center is marked by a diamond in c. The circular paths trace the edges of the vertebral column shown in Figure 3c.

Segmentation of the Rib Structure

The proposed procedure for the detection of the rib structure was tested with 39 CT exams of 13 patients. The segmented rib structure obtained by the pro-

posed procedure was observed to be a satisfactory representation of the actual rib structure. Two examples of the segmented ribs from exams 4.4 and 1.3, in 2D, are shown in Figure 8; the 3D representations of the segmented rib structure for two

Fig 5. a A 512×512-pixel CT image with the display range [−300, 400] HU. b Detected vertebral column (binarized) cropped from the slice shown in a and enlarged. c Edge map of the detected and cropped vertebral column. d The circles relating to top six values in the Hough space. The radius values are 7.15 mm (13 pixels) for the *dash-dotted circle*, 7.70 mm (14 pixels) for the *thick black circle*, 11.00 mm (20 pixels) for the *thin black circle*, and 11.55 mm (21 pixels) for the *solid, dashed, and dotted circles*. After satisfying the imposed constraints in the proposed procedure, the center of the *thick black circle*, marked by a *diamond*, is detected as the seed pixel for the spinal canal. See Figure 6 for illustrations of the Hough space sections for this example.

CT exams (exams 4.4 and 14.2) are shown in Figure 9.

The proposed procedure produced good results irrespective of the position of the patient in the image and did not include any part of the spine in any of the 39 CT exams processed. The process did not include any calcified tumor region or any other ambiguous region close to the rib structure, except in two CT exams, in which calcified portions of the tumor were spatially connected to the ribs.

Because the regions within the adaptively defined elliptical boundaries were removed from consideration (see Fig. 1b), the proposed methods detected precisely the lower limit of the rib structure by eliminating the possibilities of including other regions in the result of segmentation in all of the 39 CT exams processed. A limitation of the present work on segmentation of the rib structure is that the results include the scapula, clavicles, and the humerus at the top of thoracic

Fig 6. Illustration of the Hough space for the image in Figure 5c. The top six values in the Hough space are marked with *diamonds* for the corresponding *circles* shown in Figure 5d. a Hough parameter space for $c = 7.15$ mm (13 pixels). b Hough parameter space for $c = 7.70$ mm (14 pixels). c Hough parameter space for $c = 11.00$ mm (20 pixels). d Hough parameter space for $c = 11.55$ mm (21 pixels). The display intensity is $\log_{10}(1 + \text{accumulator cell value})$ of the Hough space. The circular paths trace the edges of the vertebral column and also the artifacts in Figure 5c.

region in all cases, if they are present in the corresponding CT exams. However, these bones are part of the pectoral or shoulder girdle and not of the rib cage. Further work is required to separate these bones from the result, if desired. The proposed procedure does not include steps to eliminate these structures from the result of segmentation because their removal is not relevant

in the present work. In some cases, where parts of the ribs were totally fused with the spine, they were not included in the results of segmentation (see Fig. 9). In two CT exams, exams 3.1 and 3.2, the patient being of age 2 weeks and 3 months, respectively, a few parts of the rib structure were not detected because of the small size of the patient and the low spatial resolution of the image data.

Fig 7. Flowchart describing the procedure for segmentation of the spinal canal.

Other methods for segmentation of the rib structure reported in the literature^{8,16,17} have been able to produce good results for CT exams of adults. However, most of the published procedures are

meant to be applicable to CT scans of adults, where the ribs are well developed and may not lead to good results when applied to pediatric CT exams. In pediatric cases, the ribs may not be well developed, the bones are not fused together, and bony structures possess lower HU values than those of adults. In addition, the datasets used in the present work contain tumors and calcification in thoracic and upper abdominal regions that make the segmentation process more difficult. Although some of the spatial distance limits used in the proposed procedures were obtained through experimentation, the proposed procedures produced good results with a wide variety of CT scans of patients of age varying from 2 weeks to 20 years.

Segmentation of the Vertebral Column

Qualitative Evaluation of the Results

In general, the results of segmentation were observed to be good representations of the vertebral column, excluding the pelvic girdle and the rib structure. Three examples of the 3D representation of the detected vertebral column are presented in Figure 10, along with the segmented spinal canal. The methods performed well by minimizing errors due to the partial-volume effect and including the parts of the vertebrae with low HU values. The proposed procedure included most of the parts of the vertebral column, some of which are barely identifiable in the corresponding CT slices because of low HU values due to poor interslice resolution and the partial-volume effect. The results did not include any tumoral or other tissues in thoracic and abdominal regions in any of the 39 CT exams processed.

Segmentation of the lower end of the vertebral column poses a great challenge. In six CT exams, the proposed method failed to include precisely the small parts of the vertebrae in the lower spinal region, such as some portions of the sacrum or the coccyx; this was mainly due to the use of morphological erosion to eliminate the connected parts of the bowels with higher HU values than expected because of the use of a contrast agent and the fusion of the pelvic girdle with the lower end of the spine. In five CT exams, the results included some parts of the bowels or the intestine, because of their inseparable appearance with the lower end of the spine in the corresponding CT images.

The proposed method did not perform well in segmenting the vertebral column in two CT exams

Fig 8. a A 512×512 -pixel CT slice from exam 4.4, with the display range $[-200, 400]$ HU. b Detected ribs in the slice shown in a. See Figure 9a for related 3D illustration. c A 512×512 -pixel CT slice from exam 1.3, with display range $[-200, 400]$ HU. d Detected ribs in the slice shown in c. Note that the proposed procedure has detected the rib structure satisfactorily, regardless of the patient's position, and with the presence of a calcified tumor close to the ribs (see the lower left-hand side of the image in c).

Fig 9. Two examples of rib structures detected by the proposed procedure, displayed in 3D. a Detected rib structure for exam 4.4. See Figure 8a, b for related illustrations for a selected slice. b Detected rib structure for exam 14.2. Note that some parts of the ribs that are close to the vertebral column have not been included in the result. The scapula and the clavicle are included in the results of segmentation.

Fig 10. Three examples of the result of segmentation of the vertebral column and the spinal canal. The vertebral columns are shown in *light gray* and the spinal canals are shown in *dark gray*. a Exam 1.1. b Exam 4.1. c Exam 4.2.

(exams 9.1 and 9.2) and included a few parts of the pelvic girdle. The patient is of 20 years of age, an exception in the dataset of pediatric CT exams in the present study, and the pelvic girdle appeared to be merged with the spine.

Quantitative Evaluation of the Results

The Hausdorff distance and MDCP measures were used to compare the contours of the vertebrae obtained by the proposed method for each CT slice, with the corresponding contour drawn independently by the radiologist, for 13 CT exams of six patients. The results are listed in Table 1. The Hausdorff distance was computed for some of the selected CT

slices where a section of the vertebral column was present, for each CT exam listed in the Table 1. The min, the max, the average (mean), and the SD were computed for each CT exam, over the selected 2D slices containing a section of the vertebral column. The mean Hausdorff distance for the corresponding CT exam was determined by taking the average of the Hausdorff distance over the selected individual 2D slices.

The MDCP was calculated on the same selected slices of the dataset, where a section of the vertebral column was present; the min, the max, the average (mean), and the SD were calculated over all the selected slices for each CT exam. Over the 13 CT exams processed of the six patients

Table 1. Quantitative Evaluation of the Results of Segmentation of the Vertebral Column

Exam no.	Number of slices	Hausdorff distance (mm)				MDCP (mm)			
		Min	Max	Mean	SD	Min	Max	Mean	SD
5.2	25	0.96	4.87	2.04	0.95	0.29	0.91	0.46	0.15
5.3	26	1.38	15.16	3.97	3.69	0.32	3.03	0.75	0.67
5.4	30	0.99	17.69	3.09	3.34	0.31	2.74	0.60	0.48
5.5	27	1.10	9.01	3.62	2.20	0.32	7.63	1.10	1.76
6.1	24	1.08	13.27	3.86	2.83	0.32	8.64	1.05	1.68
6.2	28	1.09	5.85	3.06	1.51	0.33	1.03	0.60	0.21
6.3	30	0.99	12.07	2.73	2.33	0.31	2.16	0.61	0.48
7.2	32	0.95	4.86	2.02	0.90	0.29	0.71	0.50	0.10
7.3	32	0.97	17.83	3.03	2.98	0.35	3.23	0.61	0.49
7.4	36	0.96	12.22	2.92	2.49	0.29	3.51	0.73	0.66
12.2	60	1.03	7.63	2.63	1.58	0.29	2.56	0.63	0.39
13.1	49	1.19	25.18	5.24	4.89	0.36	4.76	1.09	1.01
14.2	59	1.05	8.03	3.03	1.55	0.35	0.73	0.73	0.30

All distances are in millimeters

mean average, SD standard deviation, min minimum, max maximum

listed in Table 1, a total of 458 CT slices were used to perform the quantitative evaluation.

The maximum Hausdorff distance and the maximum MDCP for each of the CT exams were calculated by considering the maximum of the corresponding measures over all of the selected 2D slices in the exam. The maximum values are significantly larger than the corresponding average measures in all CT exams because of isolated cases of slices in which there was an overestimation or an underestimation of the vertebrae. This is indicated by the large standard deviation in the results for a given exam, as shown in Table 1.

The 95% confidence interval, obtained by the one-sample two-tailed t test⁴⁴, is [8.18, 15.46] for the maximum Hausdorff distances listed in the fourth column of Table 1. For the mean MDCP, listed in the ninth column of the Table 1, the corresponding interval is [0.60, 0.86]. The average MDCP for the 13 exams processed, listed in Table 1, is 0.73 mm and is of the order of the intraslice resolution of the CT images. The average error (in terms of MDCP), in relation to the representative dimension of the vertebral column in the lumbar region (60 mm) for pediatric patients, is approximately 1.2%.

The errors in terms of the average Hausdorff distance and the average MDCP are small and indicate that the proposed procedure is able to produce good results. In general, the results were found to be in good agreement with the corresponding results of manual segmentation. The contours obtained by the proposed method and the

contours obtained by manual segmentation overlapped completely in almost all cases. However, the error was observed to be relatively high in the lower vertebral region because of the complex structure of the vertebral column in the pelvic region, poor spatial resolution, the partial-volume effect, the effect of the contrast agent, and the disjoint appearance of the vertebrae in the CT images.

The results of segmentation for four representative CT slices from different sections of the body are illustrated in Figure 11. The corresponding Hausdorff distance and MDCP are also given in the caption. Figure 11a–c illustrates CT slices where the proposed methods performed well; the contours obtained by the proposed method and the contours drawn by the radiologist overlap almost completely, producing small errors. In Figure 11d, an example in which the proposed method did not include parts of the vertebral column is displayed; the error is relatively high in this case.

Segmentation of the Spinal Canal

Qualitative Evaluation of the Results

The final results of the procedure for three CT exams are shown in 3D in Figure 10 as examples, with the corresponding segmented vertebral column shown for reference. An example of the result of segmentation of the vertebral column and the spinal canal is shown separately in Figure 12a, b.

Fig 11. Four 512×512-pixel CT slices, illustrating qualitative and quantitative analysis of the results of segmentation of the vertebral column. The *solid black line* denotes the contour of the vertebrae drawn independently by the radiologist, and the *dashed line* represents the contour of the vertebrae produced by the proposed method. a A slice from the abdominal region in exam 5.2. MDCP = 0.3 mm. Hausdorff distance = 1.4 mm. b A slice from the thoracic region in exam 5.3. MDCP = 0.4 mm. Hausdorff distance = 1.5 mm. c A slice from the pelvic region in exam 5.2. MDCP = 0.5 mm. Hausdorff distance = 2.4 mm. d A slice from the pelvic region in exam 5.4. MDCP = 2.7 mm. Hausdorff distance = 17.7 mm. In this case, the result does not include some parts of the vertebral column.

The segmented rib structure in 3D for this CT exam is presented in Figure 9a.

The relatively obvious appearance of the spinal canal within the region enclosed by the vertebral foramen in CT images enables easy visual verification of the results of segmentation. The spinal canal was successfully detected and segmented in all of the 39 CT exams processed. The proposed algorithm fully automates the detection and segmentation of the spinal canal; the method is effective and adaptive.

The detected spinal canal in two of slices from exam 1.3 is shown in Figure 13. The contours in solid black line correspond to the contours of the spinal canal drawn by the radiologist; the contours shown in dashed line represent the results obtained by the proposed method. Note that, in Figure 13a, the contour of the segmented spinal canal matches almost completely with the contour drawn by the radiologist. In Figure 13b, although the result is in good agreement with the contour drawn by the

radiologist, the proposed method did not include regions with low HU values.

Quantitative Evaluation of the Results

Quantitative comparative analysis of the contours of the spinal canal detected by the proposed method was performed with reference to the contours drawn independently by the radiologist, for 21 representative CT slices of three patients, by using the measures of Hausdorff distance and the MDCP. The CT slices for the comparative analysis were selected so as to include cervical, thoracic, and lumbar sections with varying shapes of the spinal canal. Several of the selected sections have distinct artifacts due to the partial-volume effect. In most of the slices, the contours obtained by the proposed method and those drawn by the radiologist overlapped almost completely. The quantitative analysis was performed in the same manner as described for the vertebral column in “Quantitative

Fig 12. An example of the result of segmentation of the vertebral column and the spinal canal (exam 4.4). a The vertebral column. b The spinal canal. c The vertebral column and the spinal canal. See Figure 9a for the result of segmentation of the rib structure for the same CT exam.

Evaluation of the Results” section. The results of quantitative evaluation are presented in Table 2.

The 95% confidence interval, obtained by the one-sample two-tailed t test, is [1.35, 3.61] for the maximum Hausdorff distances listed in the fourth column of Table 2. For the mean MDCP, listed in the ninth column of Table 2, the corresponding interval is [0.41, 0.83]. The average MDCP for the three exams processed, listed in Table 2, is 0.62 mm and is approximately equal to the size of 1 pixel in the CT images. Compared to the representative dimension of the spinal canal in the

thoracic region (25 mm) for pediatric patients, the average error (in terms of MDCP) is approximately 2.5%.

The small values of the maximum Hausdorff distance and the maximum MDCP indicate that there is no significant overestimation or underestimation over the 21 slices of three CT exams evaluated quantitatively. Given that the slices were selected from different sections of the body with varying shapes of the spinal canal, the proposed method is able to produce good results regardless of the position and shape of the spinal canal.

Fig 13. Two examples of the detected spinal canal from exam 1.3. The contours in *solid black line* were drawn manually by the radiologist. The contours in *dashed line* correspond to the boundary of the spinal canal detected by the proposed procedure. a Hausdorff distance = 1.05 mm and MDCP = 0.44 mm. b Hausdorff distance = 2.62 mm and MDCP = 0.79 mm.

DISCUSSION

The identification and segmentation of the rib structure, the vertebral column, and the spinal canal can facilitate the localization, identification, and segmentation of other organs. The rib structure, the vertebral column, and the spinal canal can be used as important landmarks to perform segmentation, registration, and evaluation of other normal as well as abnormal organs and tissues; they can also be used to assist in the localization and analysis of spinal pathology, such as scoliosis and osteoporosis. The rib structure and the vertebral column can be used to develop relative coordinate systems in the abdominal and thoracic regions to assist in the localization of the corresponding internal organs. The proposed methods should find use in procedures for image segmentation, the development of atlases, and in the planning of image-guided surgery and therapy. A limitation of the proposed methods lies in the

use of empirically selected parameters from a subset of the CT images analyzed. The small dataset used does not permit assessment of the robustness of the methods. In addition, the sensitivity of the results to variations in the spatial distance limits was not evaluated in the present work. Regardless, large deviation from the anticipated results is not expected with other CT images in the same pediatric age group.

In other works related to the present work, it has been observed that the abdominal parts of the vertebral column with low HU values interfere with the process of segmentation of the neuroblastic tumor^{21,22}. The spinal canal also creates ambiguity in automatic segmentation of the tumors by increasing the false-positive rates^{21,22}. The vertebral column and the spinal canal segmented by the proposed methods could be removed from consideration in the process of segmentation of the neuroblastic tumor to improve the result of segmentation²³. The 3D rib structure is used in the

Table 2. Quantitative Evaluation of the Results of Segmentation of the Spinal Canal

Exam no.	Number of slices	Hausdorff distance (mm)				MDCP (mm)			
		Min	Max	Mean	SD	Min	Max	Mean	SD
1.3	5	1.05	2.62	1.64	0.63	0.44	0.79	0.62	0.13
2.2	10	1.41	2.85	1.92	0.58	0.59	0.86	0.71	0.09
4.1	6	0.77	1.97	1.25	0.39	0.35	0.75	0.54	0.14

All distances are in millimeters

mean average, SD standard deviation, min minimum, max maximum

present work to assist in the procedure for seed selection within the spinal canal (see “[Identification of the Spinal Canal](#)” section) and could be used to delimit the lower boundary in procedures for the segmentation of the lungs²³. The vertebral column and the spinal canal can also be used to assist in the process of delineation of the pelvic surface²⁰.

CONCLUSION

In this paper, methods were proposed for automatic identification and segmentation of the rib structure, the vertebral column, and the spinal canal. The rib structure is identified using morphology-based image processing techniques. Then, the vertebral column is segmented; using the information related to the ribs and the vertebral column, the spinal canal is segmented. The procedure includes a few parameters and thresholds that were determined based on experiments with several pediatric CT images. The results of segmentation were evaluated qualitatively; the results of segmentation of the vertebral column and the spinal canal were also assessed quantitatively by comparing with the results of manual segmentation.

We have proposed a novel algorithm that fully automates the detection and segmentation of the spinal canal. The rib structure, the vertebral column, and the spinal canal can be used as important references for various applications; they can be used to aid the process of delineation of the diaphragm and the pelvic surface and also in the process of segmentation of other thoracic and abdominal organs.

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