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Automated measurement of bone-mineral-density (BMD) values of vertebral bones based on X-ray torso CT images

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Abstract—**Bone is one of the most important anatomical structures in humans and osteoporosis is one of the major public health concerns in the world. Osteoporosis is a main target disease of bone, which can be detected by medical image techniques. The purpose of this study is to develop a fully automated computer scheme to measure bone-mineral-density (BMD) values for vertebral trabecular bones. This scheme will aid osteoporosis diagnosis performed using computer tomography (CT) images. This scheme includes the following processing steps: segmentation of the bone region, recognition of the skeletal structures and measurement of the BMD value in vertebral trabecular bone of each vertebral body. The proposed scheme was applied to 20 X-ray torso CT cases to measure the BMD values for vertebral trabecular bones. The experimental results show that the mean and standard deviation of the difference between the BMD values measured by using the proposed method and those measured using a manual segmentation method were 6.93 mg/cm^3 and 6.82 mg/cm^3 respectively. The accuracy of the proposed scheme satisfied the requirement for a computer-aided system used in osteoporosis diagnosis.**

I. Introduction

As a result of the remarkable progress in volumetric X-ray CT tomography techniques, a whole body or torso can be scanned within 10-20 s. The volumetric torso CT image contains details of all anatomical structures (including all the different organs and tissues) and enables the detection of multiple lesions on multiple organs. However, interpretation of a torso CT case (constructed with 800-1000 CT slices) on screen without missing possible lesion locations needs a lot of time and experience; therefore, computer-aided diagnosis (CAD) systems are expected to reduce the number of overlooked lesions during radiologist interpretations, and provide some valuable information for lesion predictions at an early stage.

Osteoporosis is a major bone disease that leads to an increased risk of fracture [1]. Although it can affect anyone, the risk of developing osteoporosis increases with age [2]. Early diagnosis is important because the efficacy of treatment diminishes as osteoporosis progresses. Recently, in Japan, the X-ray torso CT images have been widely used in close examinations of internal organs. These CT images also enable osteoporosis diagnosis. Bone-mineral-density (BMD) is the most important criteria for diagnosis of osteoporosis. Automated measurement of the BMD values of different vertebral bodies is a fundamental requirement of computer-aided osteoporosis diagnosis. Although, some studies have been focused on the measurement of trabecular BMD in the thoracic spine by the use of CT images [3], automated measurement of trabecular BMD values in all vertebral bones is still a challenging task.

In this study, we propose a fully automated scheme that is designed to measure the BMD value for each vertebral trabecular bone in X-ray torso CT images. This scheme includes three processing modules: bone region segmentation, skeletal structure recognition, and BMD value measurement. In Section 2, we show the outline of the scheme and then describe the details of each processing module. Experimental results and a discussion on the accuracy evaluation of the BMD measurements are presented in Section 3. The conclusion is given in Section 4.

II. Methods

The proposed scheme includes three processing modules as shown in Fig.1. The basic steps in the scheme can be described as (1) segmenting the bone regions and recognizing each vertebral body in 3-D CT images; (2) normalizing the locations of 3-D vertebral regions on the bases of the location of the spinal canal and generating a 2-D median plane that shows the real median section of the vertebral bodies in CT images; (3) indicating a region of interest (ROI) for BMD measurement using a corner-point detector for each vertebral body; (4) measuring the CT numbers within the ROI and converting them to BMD values using a linear relation function between the CT number and BMD. An example of the result image obtained in each processing step is shown in Fig.2. In the following sections, we present the details of each step.

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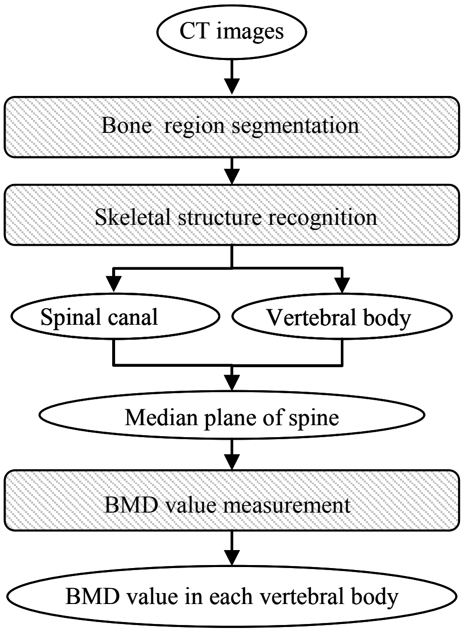


Fig. 1. Flowchart of the proposed scheme for BMD value measurement.

A. Bone region segmentation and skeletal structure recognition

The CT numbers of bone regions are higher than those of other tissue regions of the human body in non-contrast CT images. Therefore, density (CT number) based methods such as gray-level thresholding or region growing are effective for extracting the bone regions in CT images [4]. We select the simplest method (a gray-level thresholding) to keep the high generality and capacity of the segmentation process and keep accuracy high by specifically optimizing the parameter (a threshold value) for each patient during the segmentation of the bone regions in CT images [4]. Although most bone regions have higher CT numbers that can be easily distinguished from those of the other tissues, the CT number distributions of the cartilage, muscle and liver regions overlap each other in the histogram. It is difficult to find an optimum threshold value that can separate the cartilage from other tissues properly. In order to solve this problem, we propose a method to determine a specific optimum threshold value for each patient case by dynamic histogram analysis. In this analysis, it is assumed that the distributions for the bone region and liver region are Gaussian distributions and a search is performed for the best separation point (threshold value) of those two distributions automatically by observing its variations. Gray-level thresholding with a dynamic threshold value selection is effective and can provide a stable and satisfactory result during the bone segmentation as shown in Fig.2 (b).

B. Generation of a median plane of the vertebral body using CT images

The BMD value is estimated from the CT numbers inside the vertebral body regions. In order to obtain highly accurate BMD estimates, careful selection of an ROI in each vertebral body is necessary. The basic method of BMD measurement is to select a median plane (the sagittal section) for each vertebral body and select an ROI region around the center point of the vertebral body on a median plane as the target region for BMD measurement.

The 2-D median plane generation can be considered a normalization of human body location and orientation. We consider the center axis of the spinal canal to be the body axis. The median plane of the human body is a curved surface that passes through the body axis. We deform the body axis to ensure that all the pixels in the body axis are located in the same sagittal section (median plane) of the volumetric CT image. The deformation is only performed in left-right body direction to avoid further distortion of the vertebral body in the CT images. Finally, only the median plane in the volumetric CT image is used for BMD measurements. An example of the median plane before and after normalization is shown in Fig. 3.

C. ROI decision in each vertebral body

The CT number distribution in each vertebral body is measured based on the basis of the median plane generated in Section B. Although, the range of the vertebral body in CT images has been determined in Section A, the cortical bone and trabecular bone of vertebral body could not distinguished in the results (refer to Fig.2(e)). In a CAD system for osteoporosis diagnosis, BMD in the trabecular bone of each vertebral body must be known. Therefore, an ROI decision (inside the trabecular bone) is necessary before the BMD measurements can be performed.

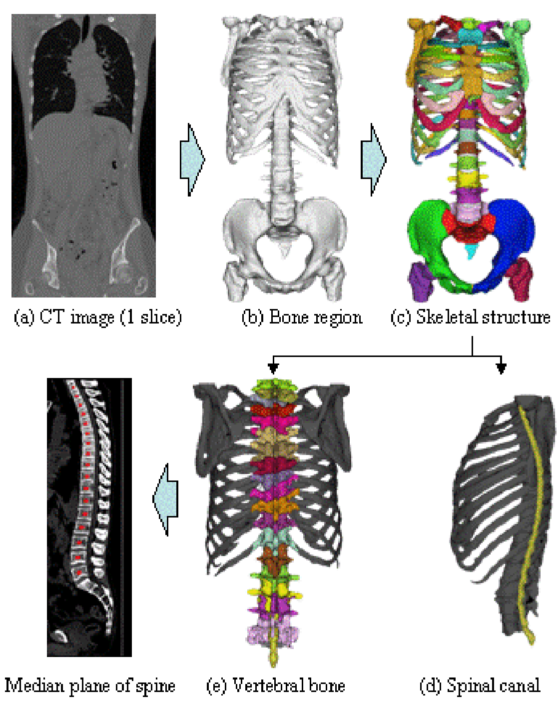


Fig. 2. An example of the resulting image in each processing step of the proposed scheme.

(a) Before normalization (b) After normalization

Fig.3. An example of the median plane before and after normalization based on spinal canal. The distortion in upper vertebrae has been fixed.

The ROI decision involves three processing steps: (1) extracting the four corner points of a vertebral body; (2) estimating the center position of the vertebral body on basis of the locations of the corner points; (3) Determining the size of the ROI (ROI decision). The ROI decision is performed for each vertebral body independently. The details of each processing step are described in the following sections.

The approximate location of each vertebral body region can be obtained from the skeletal structures (Fig.2(e)) that are shown in Section A. In order to accurately determine the size and position of the ROI region in each vertebral body, a pattern matching method is proposed to precisely detect the four corner points of each vertebral body from the median plane as shown in Fig.4. This method transforms the median plane of a vertebral body from Cartesian coordinates (Fig.4(a)) to polar coordinates (Fig.4(b)). Then, the edges in the median plane are enhanced using a combination of Gaussian and Laplacian filters, as shown in Fig.4(c). A series of pattern images (Fig.4(d)) is developed in advance using sine functions with different periods, phase shifts and amplitudes to assist corner detection. Each pattern image is a binary image with a density of 1 at the locations of the sine function outputs (expand the band to five pixels) and 0 on background. The locations of four corner points are pre-calculated and marked in each pattern image. In the last step, each pattern image is compared with the edge-enhanced median plane and a pattern image is selected by maximizing the matching degree that is defined as the integration of edge amplitudes in edge-enhanced median planes within non-zero regions in a pattern image. The locations of four corner points in the selected pattern image (Fig.4(e)) are converted from polar coordinates to Cartesian coordinates to accurately show the location and range of each vertebral body in the median plane [7].

After corner point detection, the center position of each vertebral body is identified by averaging the coordinates of four corner points. The size (height and width) of each

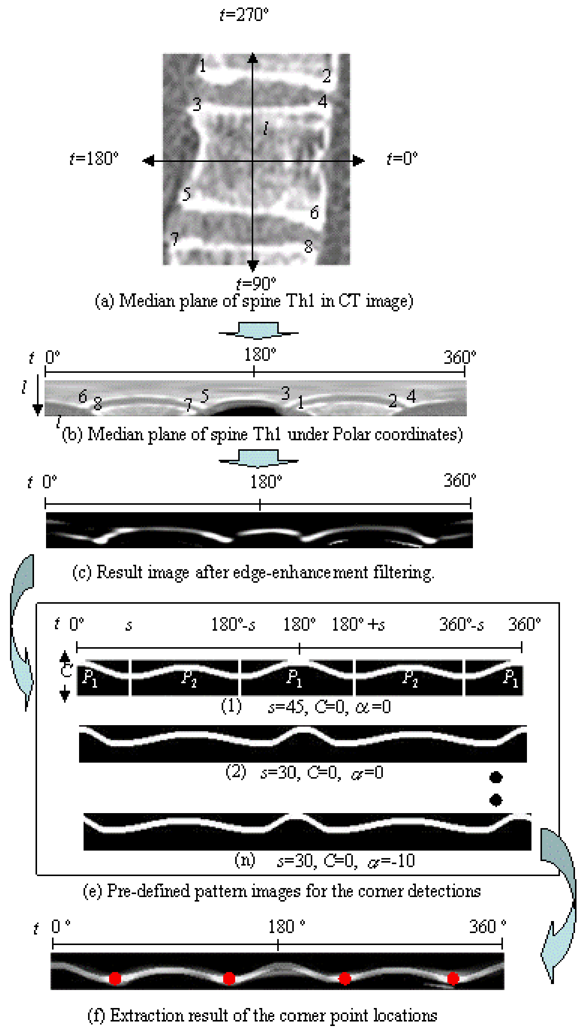
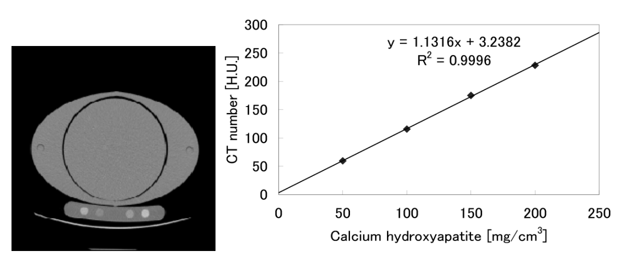


Fig.4. The detection of four corner positions of a vertebral body region from median plane based on a pattern matching method.

vertebral body is also calculated on the basis of the coordinates of the four corner points. An ROI is defined as a 2-D rectangle with the same center position, orientation and a reduced size (1/3 height and 1/3 width) of the corresponding vertebral body in median plane as shown in Fig.2(f).

D. *BMD value measurement of vertebral trabecular bone*

A standard BMD phantom (B-MAS200) is scanned by the same CT scanner with the same scan protocol that is used in this study to generate the CT images. The relation between CT number and BMD value can be approximated by a linear



(a) CT image of a BMD phantom. (b) Relation of BMD and CT number.

Fig. 5. Investigation of the relation between BMD value and CT number.

relation function (Fig.5(b)) using the phantom CT images (Fig.5 (a)). The mean value of the CT numbers within the ROI of each vertebral body is calculated and converted into BMD values using this linear relation function. BMD values are considered the final outputs of the proposed scheme.

III. Results and Discussion

The proposed scheme was applied to 20 cases of non-contrast X-ray CT images to measure the BMD value of vertebral trabecular bone in each vertebral body. Each CT image covered the whole torso region with an isotopic spatial resolution of 0.63 mm and a 12 -bits density resolution. No indications of osteoporosis were found in any of the CT cases used in the present study.

We carried out a subjective validation for the bone segmentation and skeletal structure recognition, and we confirmed that the bone structures in all CT cases were segmented and recognized successfully. Some false positive regions near the lumbar vertebrae were observed in two CT cases. An example of the segmentation results is shown in Fig.2.

Further quantitative evaluation was carried out for detection of the corner positions of the vertebral body. The locations of the four corner points of each vertebral body in 20 CT cases were also identified manually by a medical expert and used as a reference. The error in the corner point detections was measured by calculating the Euclidean distance between the corresponding points identified by the proposed scheme and the manual input in CT images. We confirmed that the mean and standard deviation of the error were 2.35 mm and 0.84, respectively, for 20 CT cases. The errors in the lumbar vertebrae were larger (1.35 mm) than those in the thoracic vertebrae. The reason for this was the influence of aortic calcifications near the vertebral body in two CT cases. The skeletal structure recognitions were not as good in two CT cases because aortic calcification had been misunderstood as a part of the vertebral body in those cases. This caused a big shift in the corner point's locations in the corner detection process.

The BMD values measured by the proposed scheme using 20 CT cases are shown in Fig.6. (Mean value of BMD and the standard deviation for each vertebral body). We also generated a reference for the BMD value by setting an ROI manually in each vertebral body and calculating the BMD values from the CT numbers. The mean and standard deviation of the differences between the BMD values in the results obtained using the proposed scheme and those obtained by manual input were 6.93 mg/cm^3 and 6.82, respectively. The differences of the BMD in thoracic vertebrae were slightly greater than the values in the lumbar vertebrae. The standard deviation of BMD in the thoracic vertebrae was also larger than the values in the lumbar vertebrae [7].

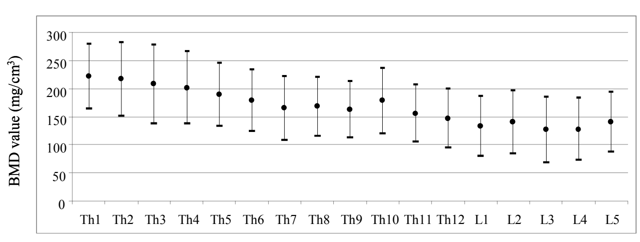


Fig. 6. Mean value and standard deviation of BMD values of vertebral trabecular bone in each vertebra using 20 CT cases.

Bone region segmentation and skeletal structure recognition were fundamental parts of this study. The accuracy of these processes was satisfactory for the CT cases that have common bone regions. However, the robustness and accuracy should be improved to adapt the processing for CT images with aortic calcification, fracture and other skeletal diseases.

IV. Conclusion

We proposed a fully automated scheme to measure the BMD values in each vertebral body by the use of non-contrast torso X-ray CT images. This method was utilized in 20 CT cases. The accuracy of the measurements was evaluated by comparison with manual segmentation performed by a medical expert and the usefulness of the proposed scheme has been shown. This scheme enables the investigation of the BMD distribution in different vertebral bodies at different ages by the use of a large CT image database (over 1000 cases). The result of the investigation is expected to be useful for predicting the risk factors for osteoporosis at the early stage.

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