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Organ Bounding Box Annotation based on Adaptive Selection of Bone References

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Abstract Accurate segmentation of abdominal organs is a key step in computer-aided diagnosis (CAD) system. To accurately segment a tissue, a volume of interest (VOI), in which the organ was located, was defined by a user. However, user interaction usually makes the task laborious and time-consuming. Hence, we propose a method that finds the VOI bounding box of the organ automatically based on the bone reference, which can be easily extracted from CT volumes. The basic idea of our proposed method is to achieve anatomical localization according to the statistical geometric location of organs within the bone reference. How to choose the bone as the reference was a difficult task, because the available abdominal volume have large variation during imaging procedure. With taking these into consideration, we prepared four different bone references. Using the adaptive selection of appropriate reference bone, the extracted bone from the input image is registered to the reference. After registration of all tissues of the training images, we find the VOI of the ensemble of tissues and use it as the organ bounding box. For the test images, according to the adaptive selection of bone reference, the candidate organ region is extracted based on this organ bounding box. We demonstrated the effectiveness of our method by finding the bounding box of kidney, liver and spleen.

Key words Bone reference, Organ bounding box, Bone segmentation, Adaptive selection

1. Introduction

Organ segmentation is to separate the organ of interest from its surroundings for clinical medical images. Manual segmentation of organ structures by a expert make the task laborious and time-consuming. Therefore, automatic or semiautomatic organ segmentation methods have been developed to provide reproducible, accurate and robust alternative. In order to segment the CT images into different organs, various approaches have been proposed in the literature[1-4].

Recently, the development of bounding box-based method is a new trend for organ segmentation, which can be easily extracted from CT volumes. Rich literatures have been published on bounding box at the estimation region of organs [5-12]. For the efficient, automatic detection the localization of organs within 3D CT scans, the methods can be attributed to: regression-based [5-7], classification-based [8-9], registration-based [10-12]. The first two methods usually need to deal with large amounts of data and spend the longest time in a computation for training.

However, the registration-based approaches are more efficient and achieve the organ localization in only a few seconds. For registration-based approaches, atlas-based methods [11-12] have enjoyed much popularity for their conceptual simplicity. Thus, the bounding box of atlas can be regarded as the organ bounding box. To build an bounding box of an organ, training images have to be registered to compensate for scale and pose differences. In conventional method, the diaphragm [10] or the xiphoid [11] is used as the landmarks to transform. However, the errors of landmark extraction may cause incorrect estimation of the transformation.

Our algorithm incorporates atlas concept within a bounding box construction by warping the bone. Since the bone of the body is considered as a rigid part, we perform registration using the bones. Due to variations in bone shape/size, only depending on one style bone is not enough. With taking these into consideration, we prepared four different bone references for constructing the bounding box.

For the training data, firstly, we extracted the bone of the input image. Then, using the adaptive selection of appropriate reference bone, the extracted bone from the input image was registered to the reference by an affine transform. The transform matrix of the registration is used to transform the segmented organ of the input data. Finally, after registration for all training images, we find the volume of interest (VOI) of the ensemble of this organs and use it as the organ bounding box. For the test data, according to the adaptive selection of bone reference, the candidate organ region was extracted based on this organ bounding box.

The paper is organized as follows: In section 2, we describe our proposed method including the bone segmentation, bone registration and the organ bounding box construction. Section 3 shows experimental results and section 4 concludes the paper.

2. Method

The flowchart of our proposed method is shown in Figure 1.

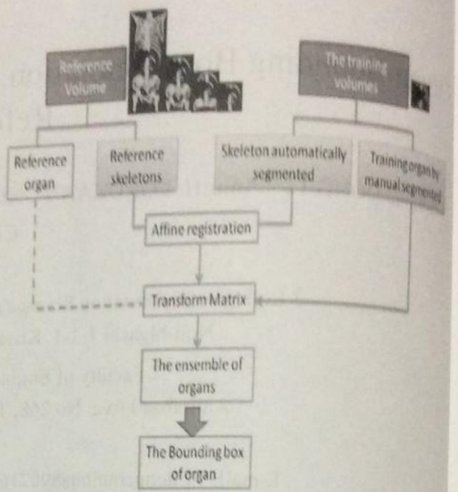


Figure 1 The flowchart of organ bounding box construction

The proposed method constructed the bounding box based on the reference and training data. Firstly, we need to manual segmented the organs of the training/reference volume by experts and used automated bone segmentation method to extract the bones. Then, the bone registration was used to transform the bone of training volume onto the reference bone by affine transformation. We can transform the segmented organ of the training volume onto the reference volume by that transform matrix. Finally, the ensemble of the transformed organs can regarded as the bounding box of this organ.

In the following sections, we describe how to segment the bone in the abdominal region.

2.1 Bone segmentation

Several methods have been proposed for bone extraction [13-14]. The main approach of these methods has been to estimate the intensity range of the bone and apply the region-growing technique to find the bones. We follow the same approach and find the intensity range of bones, employ region-growing algorithm to segment bone, and use morphological operators to refine the results. The flowchart of our bone extraction method is shown in Figure 2 which mainly consists of the estimation of bones' intensity range and segmentation of the bone by region growing algorithm.

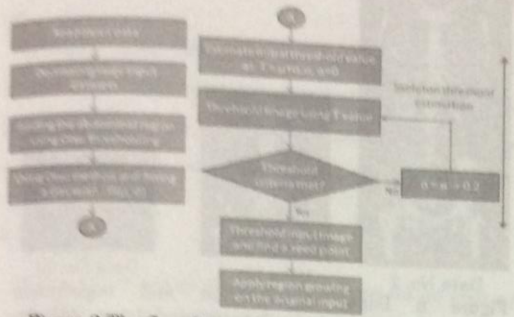
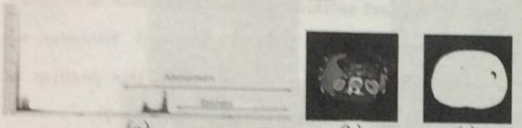


Figure 2 The flowchart of bone segmentation method.

As shown in Figure 1, the intensity range corresponding to abdominal region (Figure 3-a) is found using Otsu thresholding method. Finally, we used an iterative search approach to find the bones threshold.

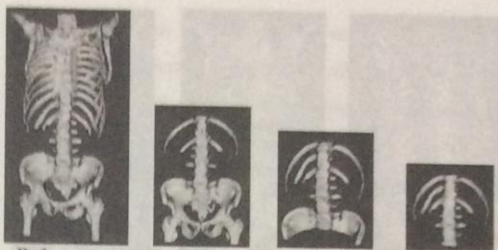


(a) (b) (c)

Figure 3 (a) Intensity distribution of a typical CT image. (b) One slice of a CT image. (c) The corresponding segmented abdominal region.

2.2 Bone registration

Registration was an important step in the whole process since it primarily influenced the overall accuracy of the bounding box. We used an affine transform for the registration. The affine transform considers translation, rotation and scaling. To register an image, we need a reference data. The reference data have to approximately resemble the whole set of input images. Due to the variation of abdominal region which was scanned during imaging procedure, the bone shape/size was difference. Hence, only using one style bone to register is not enough. With taking these into consideration, we prepared four different bone references for the registration. We selected one training data as the reference and extracted different regions of this data. Four different bone references were shown in Figure 4.



Reference 1 Reference 2 Reference 3 Reference 4

Figure 4 The four bone references.

The problem was how to adaptively select the appropriate bone reference when we wanted to register a new data. We used the root mean squares (RMS) metric to select the appropriate reference to register a new image.

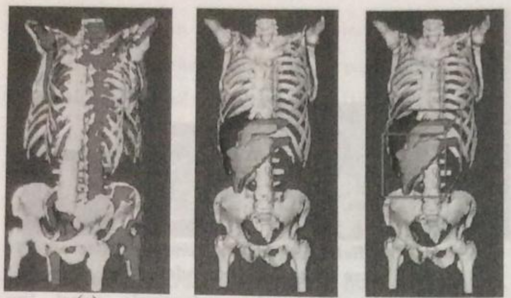
Firstly, we registered an input bone to all four bone references. Then, we calculated the RMS metric, defined in Eq. (1), as a measurement for the accuracy of the registration result.

$$RMS(R,M)=\sqrt{\frac{1}{N}\sum_{i=1}^{N}(R_i-M_i)} \quad (1)$$

where R_i and M_i are the i-th voxel of the reference and moving image, respectively. In Eq. (1), N is the total number of image voxels. When the RMS value is the lowest, the input bone was registered to the proper reference bone.

2.3 Organ bounding box construction

To build an bounding box of an organ, training images have to be registered to compensate for scale and pose differences. We selected one data as the reference and register all training data to it. Then, the bones of one training data were extracted and registered to the reference data by an affine transform. The transform matrix of the registration was used to transform the segmented organ of the input data. After registration of all organs of the training images, we found the VOI of the ensemble of organs and use it as the bounding box of the organ. And Figure 5 gave an example of the liver bounding box based on six samples.



(a) (b) (c)

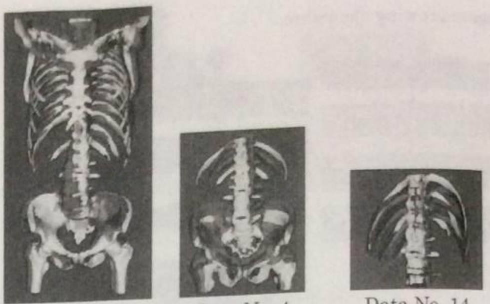
Figure 5 (a) Registration of bone (gray--reference bone, blue--moving bone, green--the registered moving bone); (b) the ensemble of six registered organ; (c) the bounding box of the organ;

3. Experiments

The proposed algorithm was implemented in MATLAB and C++ environments. Our dataset comprised 60 CT volumes, including 55 data with a resolution of $0.683\times 0.683\times 1mm^3$ and a size of $512\times512\times(185\text{-}263)$ and the other 5 data with a resolution of $0.663\times0.663\times1.2mm^3$ a size of $512\times512\times(309\text{-}607)$. The organ (Liver, Spleen, Left-kidney and Right-kidney) was manually segmented for all 60 data by the experienced experts, and 37 data were randomly chosen as the training data for constructing the organ bounding box and the remaining 23 were used for testing the performance.

(1). Bone segmentation and registration

In Figure 6, several cases of the extracted bones were shown. Using the affine transformation, we registered these bones with the adaptive selection of bone references. As shown in Figure 6, for these extracted bones, this registration process was a very effective method to compensate for scale and pose differences with the reference bone.



Data No. 1 Data No. 4 Data No. 14

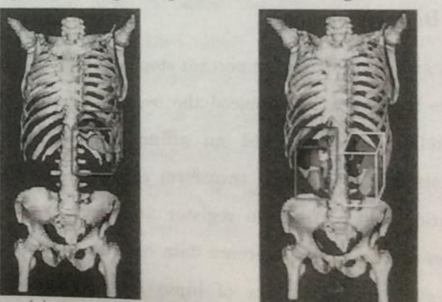
Figure 6 Bone segmentation and registration (gray--reference bone, yellow--moving bone, red--the registered moving bone);

(2). The organ bounding box

After the organ of all training data were registered, we build the bounding box of the organ that the ensemble of organs. In the last sections, we described how to estimate the bounding box of the liver (Figure 4-c). However, we also extended our method to estimate the position of Spleen, Left-kidney and Right-kidney (Figure 7).

(3). Finding the organ bounding box in the test data

Now, we used these organ bounding box for finding the correspondence organ region on the test image.



(a) Spleen (b) Left- and Right-kidney

Figure 7 The bounding box of different organ

For the test image, using the adaptive selection of appropriate reference bone, the transformation between the extracted bone of the test image and the reference can be estimated by using affine registration techniques. Then the organ bounding box can be transformed onto the test volume. Thus, we can achieve the estimated bounding box.

We prepared two examples to prove our method: (1) Detecting on the reference; (2) Detecting on the new test image. These two volumes are used for the objective

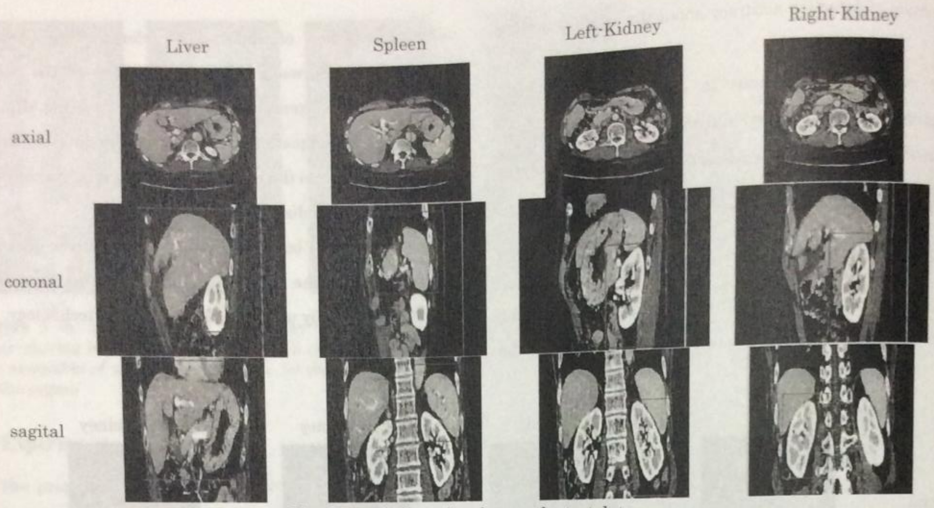


Figure 9 The bounding box on the test data

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References

[1] K. Kasiri, K. Kazemi1, M. J. Dehghani, M. S. Helfroush,"Atlas-based Segmentation of Brain MR Images Using Least Square Support Vector Machines," IEEE Conference on Image Processing Theory Tools and Applications, IPTA 2010, pp. 306-310, 2010.

[2] A. H. Foruzan, Y. W. Chen at. al., "Segmentation of Liver in Low-contrast Images Using K-Means Clustering and Geodesic Active Contour Algorithms," IEICE Trans., Vol.E96-D, pp.798-807, 2013.

[3] Y. Boykov, "Graph Cuts and Efficient N-D Image Segmentation," International Journal of Computer Vision, vol.70, no.2, pp.109-131, 2006.

[4] S. Andrews, G. Hamarneh, A. Saad, "Fast Random Walker with Priors Using Precomputation for Interactive Medical Image Segmentation," IEEE International Conference on International Conference for Medical Image Computing and Computer-Assisted Intervention, MICCAI 2010, pp. 9-16, 2010.

[5] A. Criminisi, J. Shotton, D. Robertson, E. Konukoglu, "Regression Forests for Efficient Anatomy Detection and Localization in CT Studies," MICCAI 2010 Workshop MCV, LNCS 6533, pp. 106-117, 2011.

[6] S. K. Zhou, J. Zhou, D. Comaniciu, " A boosting regression approach to medical anatomy detection," IEEE International Conference on Computer Vision and Pattern Recognition, CVPR 2007, pp. 1-8, 2007.

[7] S. Zhou, B. Georgescu, X. Zhou, D. Comaniciu, "Image-based regression using boosting method," IEEE International Conference on Computer Vision, ICCV 2005, vol. 1, pp. 17-21, 2005.

[8] J. Gall, V. Lempitsky, "Class-specific Hough forest for object detection," IEEE International Conference on Computer Vision and Pattern Recognition, CVPR 2009, pp. 1022-1029, 2009.

[9] A. Torralba, K. P. Murphy, W. T. Freeman, " Sharing visual features for multiclass and multiview object detection," IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 22, no. 5, pp. 859-869, 2007.

[10] X. Zhou, T. Kitagawa, T. Hara, H. Fujita, X. Zhang, R. Yokoyama, et al., "Constructing a Probabilistic Model for Automated Liver Region Segmentation Using Non-contrast X-Ray Torso CT images," IEEE International Conference on International Conference for Medical Image Computing and Computer-Assisted Intervention, MICCAI 2006, pp. 856-863, 2006.

[11] M. G. Linguraru, J. K. Sandberg, Z. Li, F. Shah, and R. M. Summers, " Automated segmentation and quantification of liver and spleen from CT images using normalized probabilistic atlases and enhancement estimation," Int. J. Medical Physics, vol.37, no.2, pp. 771-783, 2010-

[12] C. Y. Li, X. Y. Wang, S. Eberl, M. Fulham, Y. Yin, D. G. Feng, "Fully Automated Liver Segmentation For Low- and High-Contrast CT Volumes Based on Probabilistic Atlases," IEEE International Conference on Image Processing, ICIP 2010, pp. 1522-1736, 2010.

[13] J. Staal, B. van Ginneken, M. A. Viergever, "Automatic Rib Segmentation in CT Data," Computer Vision and Mathematical Methods in Medical and Biomedical Image Analysis, Lecture Notes in Computer Science, vol.3117, pp. 193-204, 2004.

[14] K. Zhao Kai, B. Kang, Y. Kang, H. Zhao, "Auto-Threshold Bone Segmentation Based on CT Image and Its Application on CTA Bone-Subtraction," IEEE International Conference on Symposium on Photonics and Optoelectronic, SOPO 2010, pp. 1-5, 2010 .