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Preliminary Study for Automated Recognition of Anatomical Structure from Torso CT images

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Abstract—The anatomical human structure recognition is very important and necessary during the development of computer-aided diagnosis (CAD) system. In this paper, we propose an image processing scheme that can recognize the general structure of human torso by identifying the human torso region from CT images automatically and separating it into 7 parts: skin, subcutaneous fat, muscle, bone, diaphragm, thoracic cavity and abdominal cavity based on CT number distribution and spatial relations between different organ and tissue regions. We applied this scheme to 313 patient cases of torso CT images and confirmed its usefulness from the preliminary experiment.

I. INTRODUCTION

MODERN CT scanners can generate a large number (500-1000) of slices to construct a volumetric CT image which covers a wide volume of human body within a short time (10-20 seconds). This enables the radiologists to use an isotropic voxel imaging for the whole human torso diagnosis. Although such a volumetric CT image can provide entire and detailed information of whole human internal organs, the interpretations (viewing 800-1200 slices of CT images manually before a monitor for each patient case) need a lot of time and energy. Therefore, the computer–aided diagnosis (CAD) systems which can support the multi-lesion interpretations for multi-organs in a CT image are strongly expected to increase the lesion detection accuracy of radiologist and decrease the interpretation burden. The anatomical human structure recognition from CT images is necessary during the CAD development.

Lesion detection and image visualization were required by the CAD system. Such functions require an automated segmentation of the different internal organ regions which is a very difficult task and cannot be solved till now. Recognizing the general anatomical structure and identifying the torso cavity of human body firstly can simplify the complex and difficulty of organ segmentation algorithms and

enhance the efficiency and accuracy of segmentation process. Although some research works have been reported for segmenting the special organ regions from the CT images [1], few of them tried to identify the torso cavity and recognize its structure.

The purpose of this research is to develop a fully-automatic image processing scheme to recognize the general structure of human torso by identifying the human torso region from CT images and separating it into 7 parts: skin, subcutaneous fat, muscle, bone, diaphragm, thoracic cavity and abdominal cavity using its density (CT number) distribution and spatial location. We describe the details of this scheme in section 2, and then show the experiential results in section 3. A conclusion for this research work is made in section 4.

II. METHODS

The basic idea of our method is, firstly, to separate a CT image into air, bone, fat and muscle and organ regions based on the difference of their density distributions, and then, separate subcutaneous fat from fat regions and identify the thoracic cavity using the spatial information of bone and subcutaneous fat regions. Finally, the diaphragm is extracted to divide the thoracic cavity into thoracic cavity and abdominal cavity [2]. We describe the details of our method in following 5 steps as shown in Fig.1.
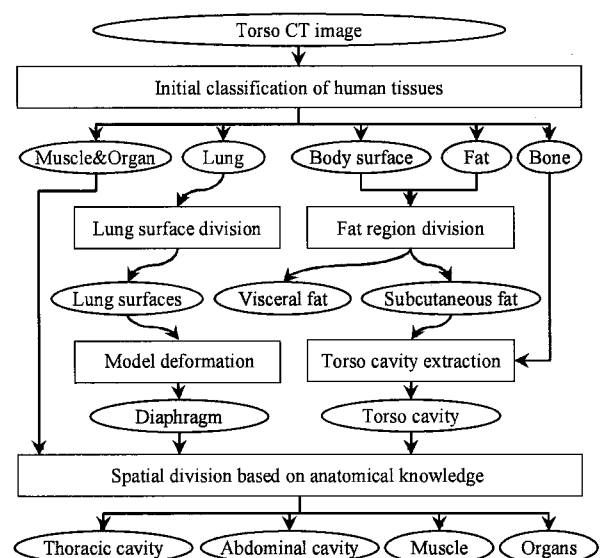

Fig. 1. The processing flow of the anatomical structure recognition from torso CT images.

Initial classification of human tissues

The whole region in none-contrast torso CT images can be divided into 4 parts (Air, Fat, Muscle, and Bone) which have the unique density distributions that can be distinguished from the density (CT number) histogram of CT images [3]. A gray-level thresholding process is used for the region division. The optimized threshold values for segmenting each target region are estimated dynamically from the inputted images. A connected component processing including a combination of small region deletion and a binary morphological operator is used to refine the extracted regions. The skin is extracted using the density and the distance to the body surface [3].

Fat region division

The fat regions identified in step 1 consist of visceral fat and subcutaneous fat that are connected together in 3-D. We developed a method to separate the subcutaneous fat from the visceral fat regions based on the minimum 3-D distances from the muscle (including organ regions) to the body surface. This process includes 3 steps as shown in Fig.2. (a): We extract the torso region [Fig.2(b)] and identify the body surface [Fig.2d)] using a 3-D surface tracing algorithm; (b): A 3-D distance map [Fig.2(e)] from the muscle and organ regions [Fig.2(c)] is generated using a Euclidean distance transformation algorithm [4] and the minimum Euclidean distance from the each voxel on body surface to the muscle and organ regions is calculated as shown in Fig.2(f); (c): the range the of subcutaneou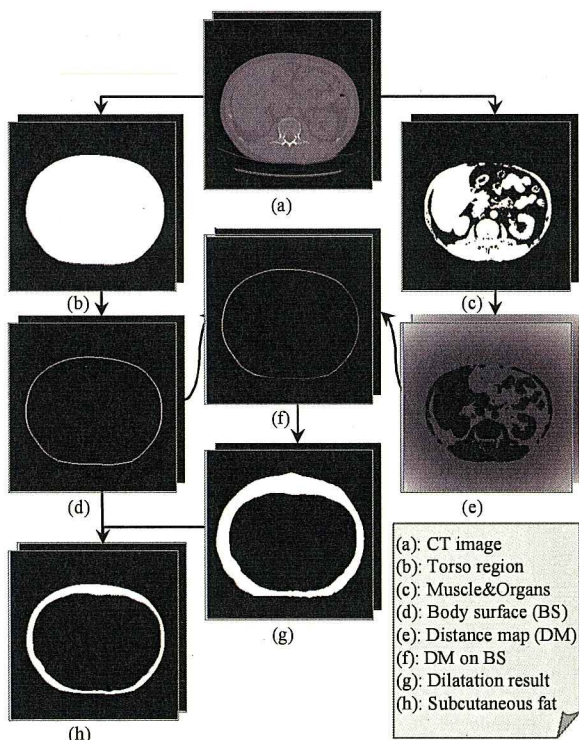s fat [Fig.2(g)] is decided by a binary dilatation processing from the body surface [Fig.2(d)] using a variable ball kernel which is adjusted for each voxel on the body surface based on its Euclidean distance value as shown in Fig.2(f). The subcutaneous fat region [Fig.2(h)] is decided by the region integration of human torso region [Fig.2(b)] and the range the of subcutaneous fat [Fig.2(g)]. At last, the fat tissue regions excepting the extracted subcutaneous fat are regarded as the visceral fat.

Lung surface division and model deformation

The lung regions are extracted using the shape of air regions inside of human body. The trachea and airway of bronchus are extracted by a 3-D region growing method [5] and removed from the air region firstly, and then the lung regions are extracted and divided into left and right lung based on a 3-D watershed method. The lung surfaces are extracted using a 3-D surface tracing algorithm and the diaphragmatic lung surfaces are identified based on the normal vector directions of lung surface [6]. The normal vector direction is calculated from a quadric that is fitted to each voxel on lung surface by the least squares method. We select the voxel on lung surfaces that has the normal vector directions bigger than a threshold value as the candidate points of diaphragmatic surface [Fig.3(a)] firstly, and then, identify the diaphragmatic surface [refer to Fig.3(b, c)] using a conditioned surface growing method from the candidate points. Finally, we estimate the diaphragm position [Fig.3(e)] by deforming a plate model [Fig.3(d)] to fit the diaphragmatic surface of lung [Fig.3(c)] based on a Thin-Plate Splines method [7]. The diaphragm region is extracted based on estimated diaphragm position [Fig.3(e)] and density information [Fig.3(f)].

(a): CT image
(b): Torso region
(c): Muscle&Organs
(d): Body surface (BS)
(e): Distance map (DM)
(f): DM on BS
(g): Dilatation result
(h): Subcutaneous fat

Fig. 2. The processing flow of the subcutaneous fat identification from torso CT images.
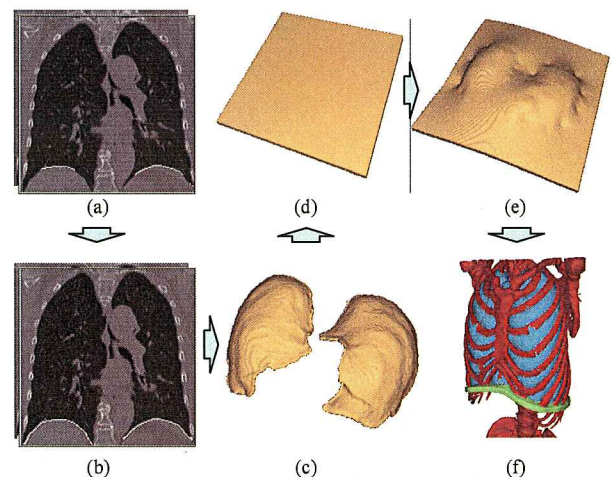

Fig. 3. Diaphragm identification based on lung surface analysis.
(a): Candidate points of diaphragmatic surfaces (white lines).
(b): Diaphragmatic surface of lungs (white lines).
(c): 3-D view of diaphragmatic surface of lungs.
(d): Prepared thin-plate model for diaphragm extraction.
(e): Estimated diaphragm region by deforming (d) to fit (c).
(f): A 3-D view of the final diaphragm inside the human torso.

Body cavity extraction

Body cavity is constructed by thoracic cavity and abdominal cavity (including the pelvic cavity) from anatomical knowledge. The thoracic cavity is surrounded by the bone frame and closed by the diaphragm. The pelvic cavity is surrounded partly by the bones of pelvis and covered by the abdominal muscles in the front of human body. Our approach for body cavity extraction recognizes the range of chest and abdomen and pelvis roughly at first, and then, extracts the cavity regions in each part using the different methods. The details of this approach include five steps. (1) The torso region is divided into 3 parts (chest, abdomen, pelvis) using the area variety of circumscribed rectangle of bone frame slice by slice [Fig.4(a)]. (2) The initial thoracic cavity is extracted using a ball-kernel based region growing process limited by the spatial position of bone frame within the chest region identified in step1. The parameter of the ball kernel is calculated and decided automatically from the size of circumscribed rectangle of bone frame for each patient case respectively. (3) The same method of step 2 is also used for pelvic cavity extraction, the difference with the step 2 is that the subcutaneous fat is also used as the limitation of the region growing process except the bone frame [Refer to Fig.4(b)] and the two kinds of ball kernel are optimized and used for pelvic cavity extraction. (4) We expand the CT images to a thing plate based on the body contour slice-by-slice and identify the symmetrical pattern under the subcutaneous fat region as the muscle within abdominal cavity. The region other than muscle, subcutaneous fat and bone frame is regarded as the abdominal cavity. (5) The extraction results of steps 2, 3, 4 are composed to the final body cavity regions [Fig.4(c)].

Spatial division based on anatomical knowledge

We conclude the recognized results from the previous processing steps and generate the anatomical structure of human torso. Firstly, we use the diaphragm to separate human torso region into chest and abdomen parts as shown in Fig.5[a]. Secondly, the body cavity extraction result [Fig.5(b)] is added to separate the muscle and organ, subcutaneous fat and visceral fat regions using the spatial relations [Fig.5(c)]. At last, the region of a torso CT image is separated into the 13 parts: Region out of human body, skin, subcutaneous fat, visceral fat (in thoracic cavity and abdominal cavity), muscle, inner organs (in thoracic cavity and abdominal cavity), bone frame, diaphragm, lungs (includes left lung and right lung), trachea and bronchus that show the anatomical structure of human torso.
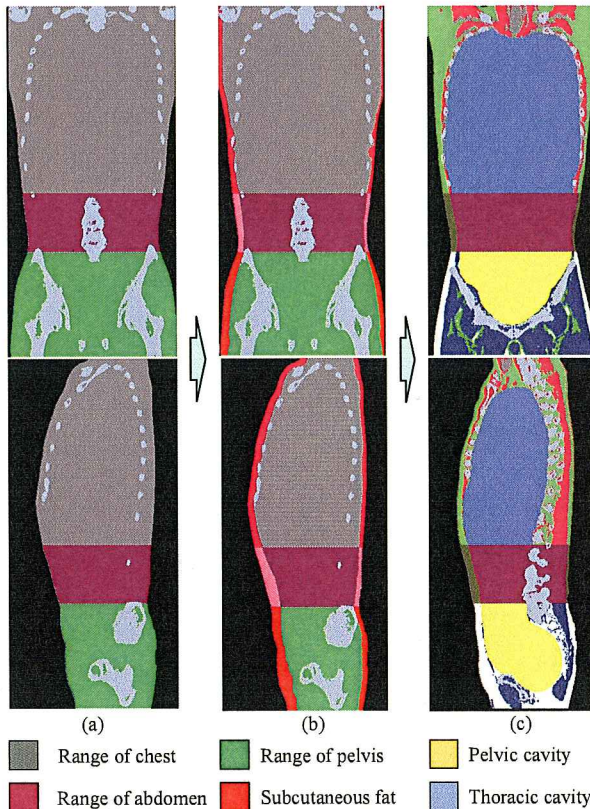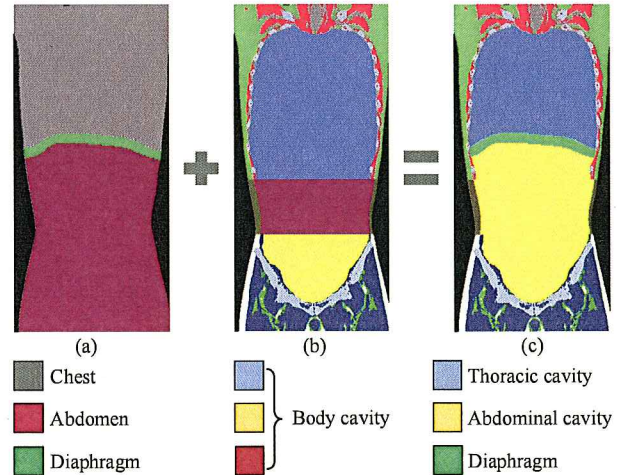
Fig. 5. Concluding the anatomical structure of human body in torso CT images (one coronal slice).
(a): The regions of chest and abdomen separated by diaphragm.
(b): Body cavity, bone frame, subcutaneous fat, and muscle regions
(c): Anatomical structure of human torso region.

III. RESULTS AND DISCUSSION

We applied this method to 313 patient cases of torso CT images for anatomical structure recognition. Each patient case was imaged with a common protocol (120 kV/Auto mA) by a multi-slice CT scanner (UltraSpeed of GE Healthcare). Each CT image covered the whole human torso with about 1000 slices, isotopic spatial resolution of about 0.6 mm and density (CT number) resolution of 12 bits. Figure 6 shows an example of the recognized anatomical structure in 2D and 3D

Fig. 4. Results (upper: one coronal slice; lower: one sagittal slice) of body cavity identification from torso CT images.
(a): Deciding the range of chest, abdomen, and pelvis regions.
(b): Selecting subcutaneous fat and bone as the spatial limitation for region growing process.
(c): Deciding the body cavity region using a region growing method.

from the body surface to the inner organs. The accuracy of the body cavity segmentation results was evaluated by human observation. The thoracic cavity and pelvic cavity were the main targets in our evaluation. We confirmed that the body cavity had been extracted successfully in 88.8% (278/313) cases. The thoracic cavity had been identified successfully in 95.2% (298/313) cases and the pelvic cavity extraction was successfully in 93.2% (292/313) cases. Recognition of the diaphragm was successful in 80% (253/313) cases. The failure reason of body cavity extraction was that the accuracy of bone frame segmentation was not high enough especially in the case of contrast media enhanced CT images [8]. This problem can be solved by recognizing the detailed structure of bone frame to improve the segmentation accuracy in the future. The failure reason of diaphragm identification was that the diaphragm position was estimated based on the information of lung surfaces only which was insufficient in some cases. We found that using the surface of liver region can improved the accuracy of diaphragm identification from our additional experiment. However, the liver region segmentation was very difficult and had not been completely solved until now.

IV. CONCLUSION

A fully-automated scheme was developed for anatomical structure recognition from torso CT images. The density (CT number) distribution and spatial relation of the human tissue and organs were used in the recognition process. We confirmed that our scheme was feasible and effective for anatomical structure recognition by the evaluation using 313 patient cases torso CT images.

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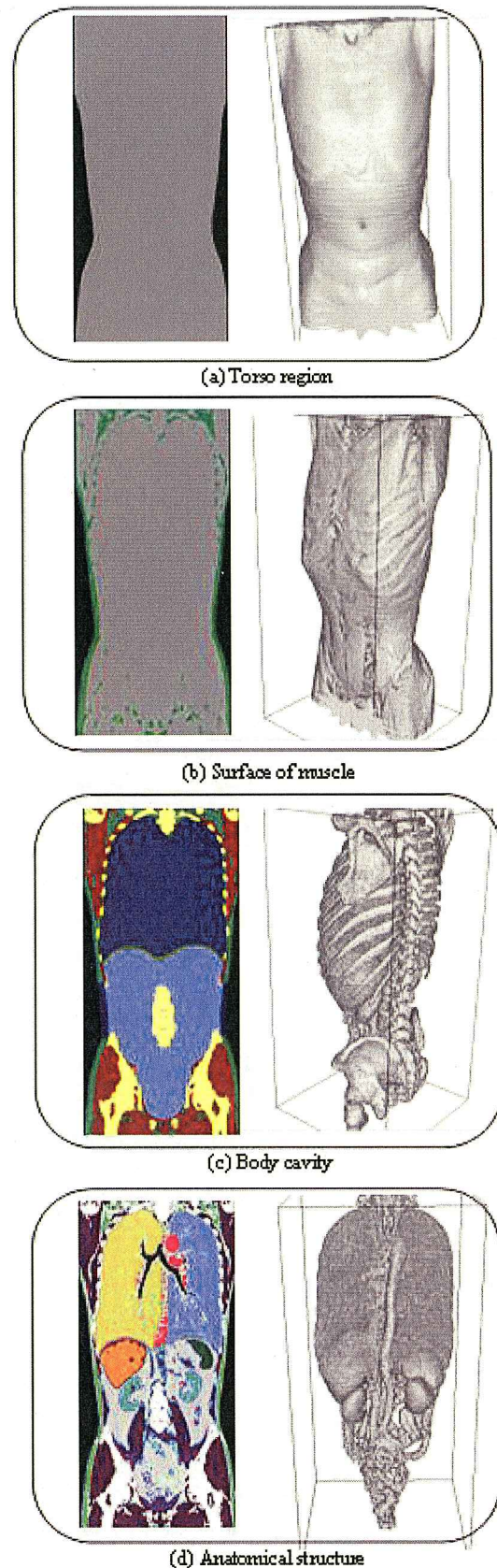
(a) Torso region

(b) Surface of muscle

(c) Body cavity

(d) Anatomical structure

Fig. 6 Visualization of the anatomical structures of human torso recognized from CT images. (Left: 2-D view of one coronal slice; Right: 3-D view).