Automated Segmentation of Recuts Abdominis Muscle Using Shape Model in X-ray CT Images

N. Kamiya, X. Zhou, H. Chen, C. Muramatsu, T. Hara, R. Yokoyama, M. Kanematsu, H. Hoshi, and H. Fujita

Abstract—Our purpose in this study is to segment the rectus abdominis muscle region in X-ray CT images, and we propose a novel recognition method based on the shape model. In this method, three steps are included in the segmentation process. The first is to generate a shape model for the rectus abdominis muscle. The second is to recognize anatomical feature points corresponding to the origin and insertion of the muscle, and the third is to segment the rectus abdominis muscles based on the shape model. We generated the shape model from 20 CT cases and tested the model to recognize the muscle in 20 other CT cases. The average values for the Jaccard similarity coefficient (JSC) and true segmentation coefficient (TSC) were 0.841 and 0.863, respectively. The results suggest the validity of the model-based segmentation for the rectus abdominis muscle.

I. INTRODUCTION

RECENTLY, we are able to obtain high-definition CT images rapidly; however, the number of images increases to as many as a thousand slices per patient. This causes radiologists to overlook areas of no interest on the displayed images, when targeting specific diseases. Therefore, we have developed the computer-aided diagnosis (CAD) system to aid radiologists [1] in recognizing diseases otherwise ignored. In particular, in the CT images, the skeletal muscles are not much useful to doctors because their interest lies in the internal organs that are affected by diseases. Therefore, the effective use of image information is expected for the torso CT images, which were imaged not for the diagnosis of muscles but for the

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Naoki Kamiya is with the Department of Intelligent Image Information, Division of Regeneration and Advanced Medical Sciences, Graduate School of Medicine, Gifu University, Yanagido 1-1, Gifu 501-1194, Japan (phone: +81(58)-230-6515; fax: +81(58)-230-6514; e-mail: kamiya@ fjt.info.gifu-u.ac.jp) and also with the Department of Information and Computer Engineering, Toyota National College of Technology, 2-1 Eiseicho, Toyota Aichi, 471-8525, Japan.

Xiangrong Zhou, Chisako Muramatsu, Takeshi Hara, and Hiroshi Fujita are with the Department of Intelligent Image Information, Division of Regeneration and Advanced Medical Sciences, Graduate School of Medicine, Gifu University, Yanagido 1-1, Gifu 501-1194, Japan.

Huayue Chen is with the Department of Anatomy, Graduate School of Medicine, Gifu University, Gifu 501-1194, Japan.

Ryujiro Yokoyama and Masayuki Kanematsu are with the Department of Radiology Services, Gifu University Hospital, Gifu 501-1194, Japan.

Masayuki Kanematsu is with the Dept. of Radiology, Gifu University School of Medicine and Gifu University Hospital, Gifu 501-1194, Japan.

Hiroaki Hoshi is with the Department of Radiology, Division of Tumor Control, Graduate School of Medicine, Gifu Univ., Gifu 501-1194, Japan. other purposes (e.g. diseased organ). Since all torso CT slices contain muscle region, we propose an effective use of these images.

The goals of previous researches in the recognition of the skeletal muscles in CT images were to develop an anatomical database or to assist doctors in surgery. A systematic organ visualization method was proposed in the Visible Human Project [2] for CT images. This method could be used to identify some skeletal muscles, which were manually segmented. An atlas-based method for hip muscles was then proposed for the surgical planning for artificial joint surgery [3]. In this method, the shape model was found useful to obtain the region for the muscle. To accomplish the muscle recognition in CT, we have been developing a CAD system for the skeletal muscles in the torso region and have obtained some positive results in the automated recognition of the skeletal muscle in the chest and abdominal regions [4-6]. However, a recognition method, which considers the anatomical shape of the muscles, has not yet been realized except for a psoas major muscle region [6].

In this paper, we propose a novel method to automatically segment the rectus abdominis muscle in non-contrast torso X-ray CT images for the first time. This method is based on generating a shape model for the rectus abdominis muscles and applying it to a recognition process. Finally, we estimate the Jaccard similarity coefficient (JSC) and true segmentation coefficient (TSC) to compare the results of manual extraction and this method.

II. METHODS

We have already developed the muscle segmentation method based on the shape model in the psoas major muscle region [6]. The model-based approach was effective for segmenting the muscle region with a characteristic shape. The psoas major muscle has the spindle shape which we approximated its 3-D outer shape. In current method, we focus on the cross sectional shape of the rectus abdominis muscle and approximate it by using a quadratic function. In this paper, the proposed method is based on our advanced scheme; it generates the shape model, determines the anatomical feature point as landmark (LM), and generates the centerline connecting the LMs. Finally, the shape model is applied to segment the rectus muscle region.

A. Shape Model Generation

The rectus abdominis muscle has a pathognomonic border

shape in its axial transverse section. Figure 1 (a) shows the image of the rectus abdominis muscle. The rectus abdominis muscle has a long flat shape and is located in front of the body [7]. Fig. 1 (b) shows the original CT image, and the arrows indicate the rectus abdominis muscle position in the transverse section. This section of rectus abdominis muscle displays an arching shape. In this method, we focused on its cross-sectional shape for model generation. As an initial examination, we considered the left and right rectus abdominis muscles the same, because of their symmetry. In addition, the difference in muscular thickness for different transverse sections from its origin to insertion is visually imperceptible. Therefore, the shape model of the rectus abdominis muscle is defined as the following quadratic function that approximates the border shape in the axial transverse section:

$$y = \alpha x^2 + \beta, \tag{1}$$

where y represents the arcate counter-shape in the axial transverse section, which is obtained by substituting the distance along the centerline for x. For the shape model of rectus abdominis, there are two parameters, α and β . The α is a fitting parameter that is automatically determined for each case in the following recognition process. Conversely, β is an outer shape parameter that corresponds to the thickness of the rectus abdominis, and is determined beforehand. The method for determining β is described below.

First, the thickness of the muscle is measured manually in twenty training cases. The proposed method has a single parameter β for each axial slice; we measure the thickness of the muscle from five slices equally spaced in the body axis direction. Next, a paired t-test is performed using these values to validate that the measured value is suitable for approximating the single parameter β . Table I shows that there was no statistical significant difference in the thicknesses at the five slices (p > 0.05). Therefore, 8.0, which was the mean value for muscular thickness that was obtained from twenty cases, were used for β in expression (1). The model function obtained by the above-mentioned procedure is represented by



Fig. 1. Rectus abdominis muscle (flesh colored and indicated by arrows): (a) long flat shape located front of the body, (b) transverse section of rectus sheath. The rectus abdominis muscle is enclosed in an aponeurotic tendinous sheath [7]

TABLE I
THE RESULTS OF PAIRED T-TEST FOR MUSCLE THICKNESS
RELATIONSHIPS

CROSS-SECTIONAL PAIR		Significance probability
Slice 1	Slice 2	0.092
	Slice 3	0.092
	Slice 4	0.945
	Slice 5	0.460
Slice 2	Slice 3	0.685
	Slice 4	0.336
	Slice 5	0.748
Slice 3	Slice 4	0.194
	Slice 5	0.395
Slice 4	Slice 5	0.161

the following expression:

Fig. 2 shows the diagram of the proposed method on the original CT image. The dotted line describes the shape model mentioned above.

B. Recognition of Anatomical Feature Points

 $v = \alpha x^2 + 8.0$

The process to recognize the landmarks (LM) is based on the anatomical positional feature. The anatomical positions where the rectus abdominis muscle is connected to skeleton are defined as origin and insertion. The correspondence between origin and insertion is shown in table II.

In the LM recognition process, the origin LM is obtained from one point on the crista pubica, and the LMs of the insertion are obtained from a total of four points located on the



Fig. 2. Diagram of shape model on the original CT image (dotted line)

TABLE II Correspondence between origin and insertion				
Region Origin		Insertion		
Rectus abdominis	Crista pubica	Xiphisternum Costa V Costa VI Costa VII		

xiphisternum and on costa V to costa VII. The targeted skeletons are selected from the segmented skeletal image [8], and each LM is determined on the selected skeleton.

C. Centerline Generation

In the centerline building process, we automatically connect the LMs that were determined above. The origin and its corresponding insertion are ordinarily connected by the shortest possible straight line. However, the shape of the abdomen differs greatly according to the body type. Therefore, the course of the muscle fiber cannot be simply expressed by the straightforward connection of origin and insertion. Therefore, a new additional LM that takes into account for the individual body shape is dynamically acquired on the basis of the LMs that were already set automatically. This process takes place as follows.

Let $L_m(x, y, z)$ be the newly set LM that is defined according to the following procedures. Here, the LM of the origin is assumed to be $L_o(i_o, j_o, k_o)$, and the LMs of the insertion are assumed to be $L_i(i_l, j_l, k_l)$, $(l=1, \dots, 5)$. First, the z and x coordinates of the new LM are determined by the midpoints of the origin and insertion.

$$z = \frac{1}{2}(k_o + k_l)$$
(3)

$$x = \frac{1}{2}(i_o + i_l)$$
 (4)

The slice position is determined by expression (3), and the position of the surface of the body in the slice section is determined by expression (4). Next, the y coordinate is determined. The y coordinate that describes the position from the surface of the body to the centerline is determined by the following expression:

$$y = \max\left\{j; \quad 0 < j < \frac{1}{2}h, \quad f(x, j, z) \in \text{subcutaneous fat}\right\}, (5)$$

where *h* is the size (number of pixels) of the input image in anterior-posterior direction, and *f* is the density of the input coordinate. Because of the facility in classifying subcutaneous fat from the other tissue using a CT value, the boundary coordinates between the subcutaneous fat and rectus abdominis muscle can be obtained by expression (5). The determined $L_m(x, y, z)$ is assumed to be a midpoint. Therefore, three points—the midpoint, the starting point $L_o(i_o, j_o, k_o)$, and the end point $L_i(i_l, j_l, k_l)$, $(l=1, \dots, 5)$ —are connected by a straight line to generate the centerline. Fig. 3 shows a 3-D image of a skeleton with anatomical centerlines.

D. Recognition Process

In the model fitting process, an appropriate fitting parameter is obtained from the input image by using the model function of expression (2). Further, the area represented by the generated function is assumed to be a mask image, from which the candidate region is obtained. Finally, the muscle region is determined from the peripheral region, if necessary. Details of the method of determining the fitting parameter and the



Fig. 3. 3-D image of skeleton with anatomical centerlines. Each color indicates different anatomical centerlines. Four centerlines on each side of rectus abdominis muscle.

recognition technique are discussed below.

In the recognition of rectus abdominis, fitting parameter α is determined in expression (2). Because the shape model of the rectus muscle of abdomen models the cross sectional shape, this fitting parameter is determined in each section as well. The α can obviously be determined from expression (2) by the coordinate pair of *x* and *y*. Here, the left and right ends of the centerline in each slice (indicated by arrow in Fig. 2) are given by $L_{\text{left}}(i, j, k)$ and $L_{\text{right}}(u, v, w)$, respectively. The value calculated by the following expression (6) is substituted for expression (2).

$$(x, y) = \left(\left| \sqrt{\left(i - \frac{i+u}{2}\right)^2 + \left(j - \frac{j+v}{2}\right)^2} \right|, 0 \right)$$
(6)

As a result, α that is appropriate for the test case for recognizing the muscle is obtained. This function is assigned to the centerline, and the region enclosed by the curve will become a mask image (Fig. 4). Finally, the area of the rectus abdominis is recognized by using the CT value in this mask image. In the mask region, it is comparatively easy to recognize the torso tissues by using the CT values, because the tissue in the mask region is composed of the muscle, subcutaneous fat, and visceral fat regions, which are easy to



Fig. 4. Shape model of the rectus abdominis muscle

separate. Fig. 4 shows a mask image generated by the shape model function. The two colors represent the masks of the left and right sides of the model.

III. RESULTS AND DISCUSSION

We applied this scheme to 20 CT cases of non-contrast torso X-ray CT images and evaluated the accuracy of the segmentation results. The results were evaluated by the overlap rate between the recognized and manually extracted regions created by an author under the guidance of the anatomical specialist. The Jaccard similarity coefficient (JSC) [9] and true segmentation coefficient (TSC) [10] were used to evaluate the proposed method. The former is calculated by $(A \cap B)/(A \cup B)$, and the latter by $(A \cap B)/A$. A and B are the regions of the gold standard and recognition results, respectively. The test database consisted of CT images from 10 males and females. The method was implemented in a computer with two 2.99 GHz clock CPUs.

The average JSC value was 0.841, and the average TSC value was 0.863. Fig. 5 shows the recognition results. Here, the 2-D recognition results are displayed in the slice images at the bottom of the limb section (a) and umbilicus section (b). The green region was extracted with our proposed scheme. The minimum and maximum value of the JSC was 86.4% and 92.0%, respectively. The standard deviation of the results was 6.4%. In the proposed technique, the boundary of the muscle was distinguished by using the shape model even if the rectus abdominis muscle touches the area of the intestines. The results indicate the possibility of using the model for automatic recognition of the rectus muscle of abdomen extending to abdominal cavity boundary.

In the proposed method, it can be said that the anatomical shape could be reproduced by few parameters. However, in order to verify the validity of this method, it is necessary to apply this method to database with larger variability. The processing time required for the proposed technique was about 5 min per case. This reduces the muscle segmenting and measuring workload of the radiologist considerably. For instance, when the author completely segmented muscle manually, 30 min or more were needed.

IV. CONCLUSION

We proposed a fully automated method based on the shape model to segment rectus abdominis muscle in non-contrast torso X-ray CT images. This method was applied to 20 CT cases. The average values for the JSC and TSC were 0.841 and 0.863, respectively. The results were satisfactory in generating the muscle shape model for segmenting rectus abdominis muscle. However, an improvement in accuracy is needed using a large dataset.

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Fig. 5. Recognition results (green region) on the original CT image: Transverse section at the bottom of the limb (a) and at the umbilicus (b)

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