Segmentation of Computed Tomography Image with Potential Function Clustering for Assessing Body Fat

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ABSTRACT

CT scans are thin cross-sectional, radiographic images that can be obtained at any body level. CT images can describe the soft tissues with better clarity because it is more sensitive to slight differences in attenuation than standard radiography. Image segmentation is the key process to identify body fat in CT images. CT images at different body levels have different structures and hence different grayness histogram. Furthermore, the grayness histogram itself, in one CT image, has multiple peaks. Therefore, three segmentation methods, automatic threshold segmentation, morphological reconstruction segmentation, and potential function clustering segmentation, are used in this paper. Body fat contents and distributions are got according to segmented CT images. Experiment results show the effectiveness and stability of the multi-thresholds image segmentation method based on potential function clustering.

Keywords: image segmentation, potential function clustering, CT image, body fat

1. INTRODUCTION

Nowadays there is a growing interest in the study of body fat measurement, as obesity and its complications such as metabolic disorders, diabetes, hypertension, coronary heart disease, cardiovascular disease, etc. have aroused general concern. Some anthropometry-based methods\textsuperscript{1–3} including body mass index (BMI), waistline, skinfold, waist to femur ratio (WFR) and waist to hip ratio (WHR), etc. are straightforward and easy to be accomplished. But their accuracies have been questioned. Other popular methods such as underwater weighing (UWW)\textsuperscript{4}, bioelectrical impedance analysis (BIA)\textsuperscript{5–6}, and total body electrical conductivity method\textsuperscript{7} can estimate the content of body fat. But they cannot be used to measure parts of body fat, and are also expensive. Dual-energy x-ray absorptiometry (DXA)\textsuperscript{8}, computed tomography (CT)\textsuperscript{9}, magnetic resonance imaging (MRI)\textsuperscript{10} and Sonography\textsuperscript{11} can be used to measure parts of body fat. DXA cannot provide the depth information of the fat distribution, therefore cannot be used to analyze the distribution and content of intra-abdominal visceral fat and subcutaneous fat. Sonography is efficient for the measurement of regional fat, but its veracity is confined by the method itself, lower than CT and MRI. Although MRI can estimate body fat, the instrument is too expensive and the measure precision for subcutaneous fat is similar to CT, while the error is obvious as for intra-abdominal visceral fat. Also, the scanning time of MRI is longer than that of CT. Therefore; CT is currently an optimal technique, considering both the accuracy and expense to measure the content and distribution of body fat, especially in the analysis of the intra-abdominal adipose tissue. However, there is no system to measure body fat content and its distribution fully automatically and exactly.

CT scans are thin cross-sectional, radiographic images that can be obtained at any body level. Because CT makes use of different CT numbers derived from different attenuation coefficients of body tissues, which are expressed by different gray levels to build up image gray levels to reflect different tissues in a CT image. CT is much more sensitive to slight differences in attenuation than standard radiography and therefore depicts the soft tissues with better clarity\textsuperscript{12}. Also, body fat has a distinct grayness range compared with its neighboring tissues in a CT image. If pixels whose gray levels correspond to the range of CT number of body fat can be found out,

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\end{footnotesize}
identifying body fat becomes practical. In other words, the identification of body can be accomplished by the proper segmentation of CT image.

The purpose of image segmentation is to extract object information that needs to be studied from given images and to output this as a structure system. Segmentation is needed directly or indirectly for most of the operations done on images. It is also the most difficult and critical of all image operations. There has been numerous algorithm of image segmentation and hundreds of reports about it are published every year\textsuperscript{13-14}. Generally, making use of the differences between object and background can realize the segmentation of image based on gray levels. The choice of segmentation method strongly depends on the type and characteristics of CT image. In this paper, segmentation is used for recognition, to determine the whereabouts of the body fat in CT images.

CT images are noisy and have complex background. In order to get better results of body fat identification, three segmentation methods are used according to the characteristic of body fat gray levels. They are automatic image segmentation through a threshold based on grayscale, morphological reconstruction of image segmentation through a threshold, and potential function clustering segmentation. These methods are tested with CT images. After comparing their segmentation results on different CT images, potential function clustering segmentation method is proved to be practical.

2. BODY FAT CALCULATION BY CT IMAGE

2.1 Scientific theory of CT imaging\textsuperscript{15-16}

The CT technique uses X-rays that are collimated to provide a fan-shaped beam and it passes through the body, topographically scanning parts of body. In the process of scanning, the detector on the opposite side records the data, then the analog data are converted into digital ones for computer processing by a high-precision A/D. Then the digital data from individual profiles are stored. The second phase is reconstructed by one of the filtered convolution techniques followed by back projection and then image arrangement to give the corrected image data. Again these data are put into store. Finally the picture can be displayed in a number of different ways and various methods of picture processing can be applied.

The reconstruction of CT image is based on the attenuation coefficient at the X-ray. CT value is a relative value of the attenuation coefficient. The CT value of water is zero, and the CT value of air is -1000. The bone attenuation coefficient is twice as that of the water, so the CT value of bone is +1000. Then CT values of calcify or ossification tissue vary from 800 to 1000, crur from 30 to 85, blood from 25 to 65, soft tissue from 40 to 80, and fat tissue from -80 to -120.

2.2 CT Image Acquisition

The differences in CT image acquisition methods impact the result of body fat measurement. According to the CT imaging process, there are three methods to obtain the image\textsuperscript{17-18}: digital image acquisition based on DICOM 3.0, video collection, and film scanning. The first method farthest ensures the quality of CT image, but it is very expensive. As CT video signal is non-standard, extra-effort should be made for CT image acquisition via video collection. Film scanning is the primal way of CT image acquisition. In this method, the original CT data is firstly changed to CT video image. Then, the image is transformed to film by CRT (Cathode Radiation Camera). Finally, the film is scanned into a computer. This method has the most complex processes and the most artificial influence. But it is the most universal method and can be used to study old films. Therefore, it is used in this paper.

2.3 Body Fat Calculation by CT Image

CT scans are thin cross-sectional, radiographic images that can be obtained at any body level. CT is much more sensitive to slight differences in attenuation than standard radiography and therefore depicts the soft tissues with better clarity. In standard radiography, fat has lower attenuation than other tissues and hence has a distinct appearance on the CT image. Table 1 gives the CT values of different tissues in abdomen\textsuperscript{3}. It is very clear that fat has distinct CT values.
Table 1 The CT values of different visceral tissues and organs

<table>
<thead>
<tr>
<th>Tissue</th>
<th>Before using contrast medium</th>
<th>After using contrast medium</th>
</tr>
</thead>
<tbody>
<tr>
<td>Liver</td>
<td>40～70</td>
<td>60～90</td>
</tr>
<tr>
<td>Spleen</td>
<td>50～70</td>
<td>60～90</td>
</tr>
<tr>
<td>gallbladder</td>
<td>5～30</td>
<td>—</td>
</tr>
<tr>
<td>pancreas</td>
<td>40～60</td>
<td>50～70</td>
</tr>
<tr>
<td>Kidney</td>
<td>40～60</td>
<td>60～120</td>
</tr>
<tr>
<td>abdomen aorta</td>
<td>35～50</td>
<td>50～90</td>
</tr>
<tr>
<td>muscle</td>
<td>35～50</td>
<td>50～70</td>
</tr>
<tr>
<td>adipose</td>
<td>-80～-120</td>
<td>-80～-120</td>
</tr>
<tr>
<td>Bone</td>
<td>150～1000</td>
<td>150～1000</td>
</tr>
</tbody>
</table>

It is known that there are more than 2,000 grades in CT values. It is not possible for any display system to present this enormous range as discrete gray-tones without exhibiting some saturation effects or requiring picture processing. Even if the display could show all the details, the person viewing the image could not distinguish more than 20 values or so at any one time. To observe a range of CT values, which should be studied, a band of CT values can be selected by choosing a particular window position and width, and the CT values within the band can be displayed as a full range of gray-tones, which is called “window technology” as shown in Figure 1. Suppose that the band of CT values of organ or tissue from $M$ to $N$, $L$, which should be studied, is the position of the “window”, and it equals $(M+N)/2$, $W$ is called the wideness of the “window”, and it equals $N-M$. For the point $D$ inside the “window”, there is:

$$G/255 = DM/W$$  \hspace{1cm} (1)$$

As the CT values’ difference from $D$ to $M$ equals $D-(L-W/2)$, we have:

$$G = [D-(L-W/2)] \times 255/W$$  \hspace{1cm} (2)$$

After $L$ and $W$ are set, all the corresponding grayness in the “window” can be calculated. The grayness of CT value, which is above $N$, is set to 255. And the grayness of CT value which is lower than $M$ is set to 0.

“Window technology” not only increases the resolution of CT, but also makes the CT value linear with the gray-tone value. From Table 1, it is found out that the CT values of fat have obvious differences with other tissues. Regions where the pixels have the gray-tone corresponding fat tissue can be picked out. Therefore, image segmentation plays a critical role in this process.
3. ALGORITHMS OF IMAGE SEGMENTATION

The choice of segmentation method strongly depends on the type and characteristics of an image. Due to the variety of medical imaging techniques, there is no universal segmentation method for all kinds of images. A simple thresholding method does not generate acceptable results for CT images, because they are noisy and have complex backgrounds. In this paper, therefore, three segmentation methods are used to identify body fat based on the grayscale characteristic of body fat stated above.

3.1 Automatic image segmentation through threshold based on gray-level

This algorithm comes from the method of thresholding based on gray-level\(^9\). Suppose the scope of image \(f(x, y)\) is \([z_1, z_2]\). First, \([z_1, z_2]\) is divided into target \(Z_1\) (fat in this paper), and background \(Z_2\). This is based on the upper and lower limits of fat grayscale, which are determined according to former experiences or knowledge or some other rules. And then, pixels in the image are classified by their grayscales: if \(f(x, y)\) belongs to \(Z_1\), then the pixel \((x, y)\) is regarded as target and marked as fat; if \(f(x, y)\) belongs to \(Z_2\), then the pixel \((x, y)\) is regarded as background.

Veracity of threshold directly affects the precision of segmentation and the validity of image analysis. The threshold can be decided by former experiences, the character of grayscale histogram or statistical decision method. In this study former experiences about CT image are not enough because of the un-uniform and complexity of CT images. So, the threshold can only be decided according to the character of grayscale histogram of a CT image. Its principle is that if the sizes of target and background areas are comparable and the two areas have certain differences in grayscale, grayscale histogram will have two peak values and a valley. One of the two peak values is central grayscale of the target, the other is of the background. The valley is used as the segmentation threshold.

Because of the differences of histograms of images, it is actually not simple to find the valley. Certain search rules must be designed. Figure 2 shows one method of searching the valley. On the assumption that \(h\) is the value of histogram, find the two regional peak values \(Z_1\) and \(Z_2\) first. Their interval must be larger than a certain value to avoid a point like \(Z_3\) being mistakenly marked as a regional peak value. Then find the minimum value \(Z_m\) between \(Z_1\) and \(Z_2\). \(h(Z_2)/\min(h(Z_1), h(Z_2))\) is used to assess the flatness of histogram. If it is small enough, it means that the histogram has two peaks and a valley. Thus, \(Z_m\) can be taken as threshold.

![Figure 2 A histogram with two pick values](image-url)
3.2 Morphological reconstruction of image segmentation

Although the range of fat grayscale can be found out by using the above method, the premise is that the CT image is marked by two peaks and a valley, the target and background areas are comparable, and the distribution of the grayscale histogram is normal or logarithm normal distribution. If one of these conditions is not satisfied, the segmentation results have errors. Therefore, morphological reconstruction method is used to improve the above method.

Morphological reconstruction method\textsuperscript{20} is an iterant extending operation process to an image by using certain mask mode. The focus of the method is to select a suitable mask mode that can emphasize the main subject of the image. Morphological reconstruction starts from the peak value of histogram of the image, and then is repeated until the pixel values are fixed. By making use of the result of the above segmentation method, the image can be classified as target Z1 and background Z2, which represent fat and background, respectively. Pixels in the image are classified into two classes. According to the classification, the scope of fat’s grayness is roughly determined and is used to build up the mask mode. Thus, exact fat distribution is got by using connectivity of pixel through reconstruction.

3.3 Image segmentation with potential function clustering

The above two methods are both based on single threshold segmentation. The segmentation results sometimes are not satisfied when a CT image’s histogram has multiple peaks due to complex background. To resolve this problem, a multi-thresholds image segmentation method based on potential function clustering\textsuperscript{21-22} is used.

Suppose an image with $M \times N$ pixels is presented by $I = \{f(i,j)\}_{i=0}^{M-1,j=0}^{N-1}$; $f(i,j) \in [0,1,2,\ldots,G-1]$ is the grayness of pixel $(i,j)$, integer $G > 0$ is gray level of image $I$, then grayness histogram of $I$ is:

$$H(k) = \frac{1}{MN} \sum_{i=0}^{M-1} \sum_{j=0}^{N-1} \delta_{ij}(k), k \in \{0,1,2,\ldots,G-1\}$$

where

$$\delta_{ij}(k) = \begin{cases} 
1, & \text{if } f(i,j) = k; \\
0, & \text{otherwise} 
\end{cases}$$

Histogram potential function is calculated as:

$$P_{H}(k) = \sum_{g=0}^{G-1} \frac{H(g)}{1 + \alpha(g-k)^2}$$

Potential function is the term used in physics and engineering for a harmonic function. It is constructed by an iterative interpolation to the radix potential function $C(x)$ with histogram $H(k)$.

$$C(x) = \frac{1}{1 + \alpha x^2}$$

where $C(x)$ is a smooth function. So, $P_{H}(k)$ is much smoother than $H(k)$. When selecting proper $\alpha$ (in this paper $\alpha = 1$), $P_{H}(k)$ will have the same peak-valley characteristic with $H(k)$.

Generally speaking, near the peak of potential function, the histogram potential is always great. More far from the peak, the potential decreases. The first peak impacts the finding of the second one. To eliminate this effect, the first peak will be attenuated. Thus, surplus potential function is defined.
Set $P_0(i) = P_{ii}(i)$ as the histogram potential function of a CT image. Its $k^{th}$ step surplus potential function is defined as:

$$P_k(i) = P_{k-1}(i) - P^*_k \frac{1}{1 + f_d(i - x_k)^4}$$  \hspace{1cm} (7)

where $k \in \{1, 2, \ldots, C\}$, $i \in \{0, 1, 2, \ldots, G - 1\}$, $P^*_k = \max\{P_{k-1}(i) | i \in \{0, 1, 2, \ldots, G - 1\}\}$, $x_k = \{i; P_{k-1}(i) = P^*_k\}$, and $f_d$ is a factor to control the attenuation radius. If an image histogram has $C$ peaks, potential partition function group can be obtained by the following formula:

$$F_k(i) = P_{k-1}(i) - P_k(i)$$  \hspace{1cm} (8)

where $k \in \{1, 2, \ldots, C\}$ and $i \in \{0, 1, 2, \ldots, G - 1\}$.

From Equations (7) and (8), we have:

$$F_k(i) = P^*_k \frac{1}{1 + f_d(i - x_k)^4}$$  \hspace{1cm} (9)

where $k \in \{1, 2, \ldots, C\}$, $i \in \{0, 1, 2, \ldots, G - 1\}$. In fact, the partition function $F_k$ presented by Equation (9) is a $P^*_k$-tall four-power radix potential function, whose center is $x_k$.

$$C_d(x) = \frac{1}{1 + f_d x^4}$$  \hspace{1cm} (10)

In Equation (9), $F_k$ has three factors: $x_k$, $P^*_k$ and $f_d$. Among them, $f_d$ is the key one, because $f_d$ will determinate $x_k$ and $P^*_k$, if the histogram is changeless. $f_d$ is expressed as:

$$f_d = \left[ \left( \frac{D_H}{2} \right)^2 \cdot \frac{\beta}{C - 1} \right]^{-1}$$  \hspace{1cm} (11)

where $D_H = \max \{i; H(i) \neq 0, i = 0, 1, \ldots, G - 1\} - \min \{i; H(i) \neq 0, i = 0, 1, \ldots, G - 1\} + 1$. It represents the image gray depth (the difference between the max gray level and the min gray level). $C$ is the number of histogram’s peaks. $\beta$ is an empirical constant (in this paper $\beta = 4$).

For a certain kind of images, the number of clustering $C$ can be prearranged according to their characteristic. But to complex images, this job is difficult. An adaptive method can be used to determine the value of $C$. According to the definition of surplus potential function, the min surplus potential is set as $R_{PH} > 0$. When the number of clustering $C = k$, the $C$ step surplus potential is checked. If $R_{PH} \leq \max\{P_c(i), i \in \{0, 1, 2, \ldots, G - 1\}\}$, let $C$ equal $k + 1$. The surplus potential is iteratively updated until $R_{PH} > \max\{P_c(i), i \in \{0, 1, 2, \ldots, G - 1\}\}$ is met.
4. EXPERIMENTAL RESULTS

In order to assess the performance of the segmentation methods, experiments are made on the CT images of the abdomens of volunteers at L3-L4 vertebral level. All scans are made by using a Shimadzu SCT—4500 CT scanner located in the Department of Radiology, the General Hospital of Tianjin Medical University, Tianjin, China. All scans are performed in the supine position with a diameter of 400mm, and a thickness of 5mm. Images are generated with a 200mA, 120kV beam for a duration of 2s. CT films are then scanned by an UMAX Astra 4000U scanner into a computer.

Three groups of CT images are got. The first group contains five CT images of one volunteer to test reliability of segmentation methods. The width of the window is 1KH, and the center of the window is 150H. Figure 3 shows one of the five original CT images and its segmenting results by using automatic threshold segmentation, morphological reconstruction segmentation, and potential function clustering segmentation, respectively. Table 2 gives the results of fat contents of the five CT images.

![Figure 3(a) The original image](image1)

![Figure 3(b) Result of automatic threshold segmentation](image2)

![Figure 3(c) Result of morphological reconstruction segmentation](image3)

![Figure 3(d) Result of potential function clustering segmentation](image4)

**Figure 3** An example of 1st image group

<table>
<thead>
<tr>
<th></th>
<th>Image 1a</th>
<th>Image 1b</th>
<th>Image 1c</th>
<th>Image 1d</th>
<th>Image 1e</th>
</tr>
</thead>
<tbody>
<tr>
<td>automatic threshold segmentation</td>
<td>52.18%</td>
<td>52.16%</td>
<td>51.50%</td>
<td>51.10%</td>
<td>51.71%</td>
</tr>
<tr>
<td>morphological reconstruction segmentation</td>
<td>48.26%</td>
<td>51.95%</td>
<td>48.16%</td>
<td>45.35%</td>
<td>47.50%</td>
</tr>
<tr>
<td>potential function clustering segmentation</td>
<td>59.99%</td>
<td>59.22%</td>
<td>57.62%</td>
<td>58.17%</td>
<td>60.74%</td>
</tr>
</tbody>
</table>
It can be seen from Table 2 that all of the three algorithms accomplish the task of fat segmentation. But some pixels whose grayscale are higher than that of fat are taken as fat when morphological reconstruction segmentation is used. The segmentation results with the other two methods are better.

In order to compare the influence of the width and the position of the window on the segmentation methods, the second group of CT images is scanned. They are four continuous scanning of L3-L4 of the same volunteer. But, now the window’s width is 500H, its position is 50H. Figure 4 shows one of the original images and its segmentation results. It can be seen from Figure 3 that when automatic threshold segmentation is used, some pixels that belong to fat are wrongly taken as background.

To test the stability of the three algorithms to different individuals, the third group of images is taken. This group of nine images comes from nine volunteers at different windows’ widths and positions. An example image of this group and its segmentation results are shown in Figure 5. Table 3 gives the content of fat in the third group of CT images.
It can be gotten from Table 3 that during the segmentation some failures (marked with “\”) happen and only happen for automatic threshold segmentation and morphological reconstruction segmentation. It is also found out that potential function clustering segmentation is stable and credible.
5. CONCLUSION

As the content and distribution of body fat have been suggested to play an important and etiologic role in the diagnoses obesity, a lot of fat assessment methods have been developed. Among them, CT is the best one, considering both the accuracy and expense.

CT scans are thin cross-sectional, radiographic images that can be obtained at any body level. As it is more sensitive to slight differences in attenuation than standard radiography, CT image depicts the soft tissues with better clarity. Also, body fat has a distinct grayness range compared with its neighboring tissues in a CT image. Hence, image segmentation is the key process to identify body fat.

CT images at different body level have different structures and hence different grayness histogram. On the other hand, the variety of obesity leads to diverse grayness histogram distributions of CT images. Furthermore, the grayness histogram itself in one CT image has multiple peaks. Therefore, three segmentation methods, automatic threshold segmentation, morphological reconstruction segmentation, and potential function clustering segmentation are used in this paper. Body fat contents and distributions are got according to segmented CT images.

In order to assess the performance of segmentation methods, experiments are made on the CT images of the abdomens of 9 volunteers at L3-L4 vertebral level. Three groups of CT images are got. The first group contains five CT images of one volunteer to test reliability of segmentation methods used. Four continuous CT scans of L3-L4 of the same volunteer are made in order to compare the influence of the width and the position of the window on the segmentation methods. To test the stability of the three algorithms to different individuals, the third group of images is taken from nine volunteers at different windows’ widths and positions. Experiment results show the effectiveness and stability of the multi-thresholds image segmentation method based on potential function clustering.

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