An Auto-segmentation and Measurement of Visceral Adipose Tissue On Ultrasound Image

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Abstract. In order to effectively segment the visceral adipose tissue and help the doctors to rapidly diagnose the potential risks of metabolic syndrome, here we developed a deep learning-based method which is based on the U-net architecture for segmenting and measuring the visceral adipose tissue(VAT). And even no matter which orientation that the operator takes, the model can segment the visceral fat area and then use the appropriate outputs to compute the max thickness of VAT. One hundred and fourteen healthy volunteers were enrolled in this study. Ultrasound(US) was performed, and then the visceral adipose tissue was segmented and measured by the model that we use. We regard the distance behind the linea alba in the xiphoid process as the thickest visceral adipose tissue(VAT max). The dice score and accuracy are 3.46%, 96.44% respectively. In addition, compared with the manually outlined segmentation, the pearson correlation coefficient and the mean relative error (MRE) are R=0.9231 (P<0.001) and 10.12% in the measurement of the VAT max between original and output images. The auto-segmentation and measurement of visceral adipose tissue on ultrasound method demonstrate the accuracy of deep learning in segmentation and measurement of visceral adipose tissue.

1. Introduction

Metabolic Syndrome(MS) is well-known as a high risk disease which has a huge correlation with visceral adipose tissue. Imai A, Higuchi S and Clarisse Miranda Prado proposed that visceral fat had direct connection with Metabolic Syndrome, Type 2-diabetes, hypertension, gallstones, pulmonary hypertension and even some cancers are included [1-3]. Therefore, to effectively diagnose the high incidence of this disease in time, many novel methods by segmenting subcutaneous and visceral adipose tissue in medical images are put forward[4-12].

A huge number of studies have demonstrated that separating measurement of subcutaneous and visceral adipose tissue is effective[4-6]. In recently years, various methods are applied to measuring visceral and subcutaneous, but most of these methods are based on CT or MRI medical images, Steve C.N. Hui and Grainger AT had respectively proved that computed tomography (CT) and Magnetic Resonance Imaging (MRI) presented an accurate regions in total adipose tissue and they also segmented the region of visceral fat[4-6]. The limitations are:

1) Unavoidable-radiation; 2) Exorbitant-Price; 3) Time-consuming;

Taking these factors into consideration, in this paper, we choose ultrasound as a reliable, reproducible, accurate and safe way to segment visceral fat tissue and automatic measure the max
thickness\[8-12\].

Figure 1. (a) the transverse ultrasonic view of the upper abdominal wall and the linea alna line, which contains subcutaneous, muscle and visceral, (b) the longitudinal ultrasonic image was done from the xiphoid process to the umbilicus along the linea alba, which contains subcutaneous, muscle and visceral. (c) the ideal ultrasound image that with out muscle.

Segmentation of adipose in previous research performed as manual, semi-automated and automated segmentation and measurement. There is no denying that these methods solved the segmentation problem to some extent, but the limitations are following:

1) Manual segmentation and measurement: Whatever medical image we choose, we need an experienced professor to mark the VAT region and then measure the thickness by an automatic measuring tool. Obviously, the limitation is that it is the waste of time, the task seems tedious and we can not avoid the human factors.

2) Semi-automated segmentation: Hamagawa K used ultrasound to estimate the VAT, and explored the connection between coronary artery disease with SAT\[13\]. Unlike using MRI or CT medical image, it chooses Safety ultrasound. Measuring the distance that the max width in VAT region and the min width in SAT region. It proposed a suitable methodology that we can accurately measure the VAT and find the position of max thickness(Fig1.a and c). But through the actual operation we find that the ideal images can not easily be found, the ultrasound images with muscle(Fig1.b) are usually acquired. What is more, the max or min landmark exists human factors. So automatic segmentation seems more effective than it.

3) Automated segmentation: Grainger AT utilized the automatic segmentation of SAT, VAT, both of them are based on the traditional U-net architect and make progress in this area, analysed the relationship between VAT and BMI, and computed the square of the VAT by the output\[5-6\]. But as it is mentioned above, the injury of radiation, charge expensive and time consuming can not be avoided.

We combined with the advantage of these three methods and considerate their disadvantage. In this paper, we propose using a U-net\[14\] architecture with few annotated images that the network can be trained end-to-end and perform perfect to segment the VAT from the adipose tissue no matter which the orient that the operator takes, the model can segment the visceral fat area and then use the appropriate output to compute the max thickness of VAT.

2. Materials and Methods

2.1. Data Collection and Preparation
One hundred and fourteen healthy volunteers were enrolled in this study (man : 56 , woman : 58). The average age is 44 years old( range :20 to 72 years old). We choose the Insight 37C ultrasound machine. With a linear array probe L10 (38mm, 10 MHZ) . The probe was positioned parallel to the medial of the abdominal about 1-5cm above the umbilical. Hamagawa K is proofed that the abdominal adipose are consisting of three layer: subcutaneous adipose tissue(SAT), muscle tissue and visceral adipose tissue (VAT) (Fig.2.a). First of all, we parallel the probe to acquire the transverse ultrasonic view of the upper abdominal wall and the linea alna line (Fig.2.b). This area is divided into three areas and we can easily find that the media of this image is the connecting point with these three different regions. To find the max thickness of the VAT, we centered on that connecting point and rotated the probe to perpendicular the horizontal line to collect the longitudinal ultrasonic image was done from the
xiphoid process to the umbilicus along the linea alba (Fig.1.c)[13]. It almost consists of two regions that we can easily segment or measure the VAT. But sometimes the operator can not precisely find the perfect images that are without muscle. Fig.1.d and Fig.1.e that we supposed that the probe deflect to the right region slightly, it causes the muscle layer is also included, so it makes a great challenge to our segment task.

Figure 2. The abdomen superficial structure contains three layers(a), the transverse ultrasonic image of the upper abdominal wall and the linea alna line (b), which contains subcutaneous adipose tissue(SAT), visceral adipose tissue(VAT) and Muscle. The longitudinal ultrasonic image was done from the xiphoid process to the umbilicus along the linea alba (c). Careless operation that also cover some of the muscle tissue, move the probe to right side(d) and left side(e) slightly.

2.2. U-net Model
As we know, deep convolution networks are performing well in many yields. To realize the pixel classify that the FCN and SegNet are proved. However, the shortcomings are that a huge number of images must be needed to train the net and it is wasting a lot of time to accomplish this task. To overcome these deficiencies, we choose the U-net model[14] which can be trained end-to-end from very few images and outperform the prior best method.

2.3. Methods
2.3.1. Auto-segment
For precise segmenting the VAT, we asked experienced ultrasound professor manually outlined the VAT region in 350 longitudinal ultrasonic image. And then resize these images into 128*128, finally use the traditional U-net to train our model.

Figure 3. The overview of the segmentation method. First of all, acquire the original from the ultrasound equipment and then process the original images. Divide the data set into three parts(6:2:2) and then train using U-net model to get the output predicted segmentation.

The architect seems symmetrical, the front part using multiply 3*3 kernels to complete the convolution for extracting the visceral fat area features. And the max-pooling layers change the size of the images. These process named down-sampling. And the back half of the model similar to the font,
make use of the features and then de-convolution to the same size of the input. The whole process are present in Fig.3 Divide the original ultrasound images into three parts: training datasets, validation datasets and testing datasets. Manually label the training and validation datasets and then regard these samples as input, throw the four times convolution and the similar four times de-convolution to automatic acquire the results.

2.3.2. Measure the Max Thickness
To verify our segment results and propose a novel method to measure the max length of VAT, because it was proved important to the coronary artery disease that if the thickness over 6.9mm it can be regarded as the Independent predictor[18]. We use the segment results to compute the thickness. By counting the max number of the pixels in these results images and through the followed formula:

$$D = \frac{N}{96} \times 25.4$$

The N means the max number of the pixels or the Euclid Distance and the constant 96 means the resolution of the inputs are 96dpi, and the constant 25.4 means one inch is equal to 25.4 mm.

2.4. Manual measurement of VAT
To manually estimate the max length of the VAT, we use three methods.

1) Through the professional doctor to find the two points in the images and then compute the Euclid Distance to acquire the thickness.

2) Through the label image to count the max number of pixels and each pixel equal to a constant distance and then compute the length of max VAT.

3) Using the outputs of the model and use the same method with the second one to figure out the length.

2.5. The VAT Max Statistical Analysis
145 samples are used in this analysis, first of all, we estimate the original images length with method one, and then label the original images to automatic measure the length, finally according to the outputs from the U-net to compute the length.

We compare the three methods of the length (Fig.5(a,b)). And we also figure out the mean relative error (MRE). 12.51% and 11.95% are separately in results measurement with label and original images measurement.

2.6. The Relationship Between VAT Max With Age and BMI
For the further investigate the VAT max, we explore the age and BMI with the VAT, the result are in the Fig.5. (c,d) we can preliminary conclusion that there is no significant relationship between these parameters.
Figure 5. The relationship between the results and label images are shown in a (R = 0.9231, P<0.001). The correlation in the results and manual measurement are displayed in b (R = 0.9365, P<0.001). The relationship that VAT max with the age shown in a, the x-coordinate displays the VAT max, and the y-coordinate means the participants age distribution. And the relationship with the BMI (Body Mass Index= weight/height$^2$) are shown in b. the x-coordinate displays the VAT max, and the y-coordinate means the participants BMI distribution.

3. Discussion and Conclusion

3.1. Discussion

Adipose has become a major threat to human health. It consists of subcutaneous and visceral fat. Researches show that the visceral adipose tissue plays an important role. As is mentioned above, many methods are proposed to segment the VAT. In this task, we use the ultrasound image with deep learning to segment the visceral adipose fat. Compared with the MRI and CT methods, it is more convenient and time-saving. And on the basis of the segmentation, we use the predicted images to measure the max thickness of the VAT, which was proved to have a high relationship with the coronary artery disease. This measurement is faster and more precise than the manual way. Because the manual way can not avoid the human factors. The MRE between manual and automatic measurement is 11.95%.

During the research, we try to segment the subcutaneous adipose tissue at the same time, but if human has a relatively high BMI, we must add pressure to get the clear VAT, so that the SAT are not precisely. And we observed that if lipoma exits, this person always has a thick VAT. and we use the different gains (in reasonable range) to acquire the images as the inputs, the model also can perform well. Even more we use the different ultrasound facilities to get the images also can get good results.

3.2. Conclusion

In summary, the use of deep learning can accurately quantify visceral adipose tissue and then measure the max thickness of it in ultrasound images. Ultrasound equipment without radiation, time consuming, economize and the characteristics of real time imaging make this method more operational. If the SAT or the VAT is too thick that over 4cm (the facility range), we can not get clear ultrasound image which is a great challenge to our segment task. Therefore, the future work may focus on the follow tasks:

1) Improving the accuracy of the classification which including the triangular area and the parallel images.
2) Changing the linear array probe into convex array probe that can acquire the deep visceral fat.
3) Using the ultrasonic way to measure the area of the visceral fat.

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