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Automatic Distance Measurement of Abdominal Aorta for Ultrasonography-based Visceral Fat Estimation

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Abstract— **Ultrasonography-based visceral fat estimation is a promising method to assess central obesity, which is associated with metabolic syndrome. The key to this method is to measure three types of distance in the ultrasound image. The most important one is the distance from the skin surface to the posterior wall of the abdominal aorta. We present a novel automatic measurement method to calculate this distance using 1D ultrasound signal processing. It is different from the conventional 2D image processing based methods which have high failure rate when the target is blurred or partially imaged. The proposed method identifies the waveforms of the aorta along a group of ultrasound scan lines and a rating mechanism is introduced to choose the best waveform for distance calculation. The robustness and accuracy of the method were evaluated by experiments based on clinical data.**

I. Introduction

Unlike subcutaneous fat which builds up under the skin, visceral fat exists in the abdominal cavity and packs around internal organs. It has a negative impact on human health and excess visceral fat (central obesity) is associated with metabolic syndrome, which is a combination of medical disorders and increases the risk of cardiovascular diseases, insulin resistance, hypertension and type 2 diabetes. Waist circumference and body mass index (BMI) are usually used to assess obesity. However, they contain no direct information on fat amount and cannot distinguish between subcutaneous fat and visceral fat. The latter is strongly correlated with metabolic syndrome. The amount of visceral fat is therefore measured in medical diagnosis as an indicator for assessing the risk of metabolic syndrome.

Abdominal computed tomography (CT) scan has been considered as the most accurate method for visceral fat measurement [1, 2]. By virtue of the high CT image quality, visceral fat is segmented from the abdominal CT slice which is near the umbilicus and its area (visceral fat area, VFA, cm^2) is calculated. However, CT scan is costly and involves ionizing radiation problems. A variety of alternatives thus have been proposed to measure or estimate the amount of visceral fat in a direct or indirect way [3]. Among them, ultrasonography is a promising method owing to its real-time imaging, non-ionizing radiation, simplicity and low cost [4]. Because it is extremely difficult to directly segment the visceral adipose tissue from an ultrasound image, ultrasonography-based methods usually assess the visceral fat distribution by measuring three types of distance inside the abdominal cavity, which may have a strong correlation with VFA.

In our previous work [5], we proposed a fast and accurate ultrasonography-based method for visceral fat measurement, in which some distances in the abdominal cavity need to be measured on an ultrasound image. Our further study revealed a strong correlation between VFA and these distances. The most important one among the relevant quantities is the distance from the skin surface to the posterior wall of the abdominal aorta. The distance is currently measured manually by marking its two endpoints on a B-mode ultrasound image, which has three disadvantages: 1. Manual way is laborious and time-consuming. 2. The determination of the endpoints is somewhat ambiguous and varies among clinicians or even among different samples from the same measurement. 3. It is not suitable for batch processing.

In this paper, we propose an automatic measurement method based on an ultrasound image to calculate the distance from the skin to the posterior wall of the abdominal aorta. The idea is different from the conventional ones in that it does not need to identify the abdominal aorta in the 2D image (e.g., by line detection). That is because the abdominal aorta in the image is just a small irregular segment in some cases. Any shape-based detection method has a high failure rate in such case. The proposed method deals with the problem from a perspective of 1D signal processing. It analyzes a group of 1D ultrasound signals and detects the characteristic waveform of the target from each signal. A rating mechanism is involved to judge the "best" characteristic waveform and then the distance is calculated from the identified waveform. The paper is structured as follows: Section 1 introduces the relevant background; section 2 briefly describes the ultrasonography based visceral fat estimation; section 3 focuses on our automatic distance measurement method; section 4 provides experiments and evaluations and section 5 makes conclusion.

II. Ultrasonography-based Visceral Fat Estimation

Our previously proposed system [5] for visceral fat estimation consists of an ultrasound imaging system and a probe-holding belt, as shown in figure 1(a). The patient is in the supine position and the probe-holding belt is worn around the patient's waist centered at the umbilicus in order to standardize the following image acquisition and distance

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measurement steps. The clinician then identifies the abdominal aorta in ultrasound images taken from three different positions as depicted in figure 1(b). In each position, three distances are measured on the ultrasound image as illustrated in figure 1(c), where d_1 represents the distance from the skin surface to the posterior wall of the abdominal aorta; d_2 represents the thickness of subcutaneous fat; d_3 represents the distance from the internal surface of the rectus abdominis muscle to the posterior wall of the abdominal aorta. Because the shapes of the objects being measured are irregular, we require the clinician to measure the distances along the approximate central line of the field of view (FOV) of the probe as denoted by the vertical dot line in figure 1(c). Finally, nine distances measured on three images are available. A strong correlation between the nine distances and VFA was validated by the statistical results of clinical data in our further study. Therefore VFA can be estimated through the nine distances using a fitting function or a database matching method.

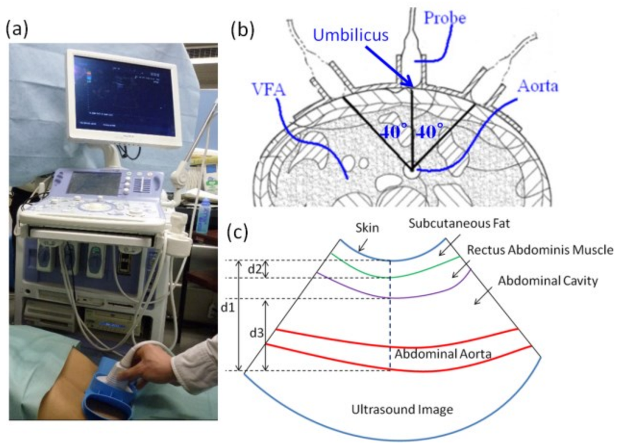

Figure 1. Our previously proposed system for visceral fat estimation. (a) System configuration. (b) Probe-holding belt. (c) Distance measurment.

III. AUTOMATIC DISTANCE MEASUREMENT

The key is to measure the three distances on an ultrasound image. Concerning d_2 and d_3, the measurement procedure could be automated by automatic image segmentation of the subcutaneous fat and the rectus abdominis muscle based on their positional and structural information, which is beyond the scope of the paper. This paper will focus on the automatic measurement of d_1, which is more challenging due to the uncertainties of the position and shape of the abdominal aorta in the captured ultrasound image. Figure 2 shows the manual distance measurement in clinical diagnosis. In the right image, the aorta is clearly imaged as indicated by the red rectangle. In contrast, the image of the aorta in the left image is only a small segment and unclear. It is even hard to identify the aorta in the static image by eyes, let alone measure the distance. Doppler ultrasound and visual cues caused by moving images can help clinicians in identifying the aorta in the manual measurement. Unfortunately, they do not work for static images. We propose a novel method to achieve automatic distance measurement, where the input of the algorithm is an image and the output is the desired distance.

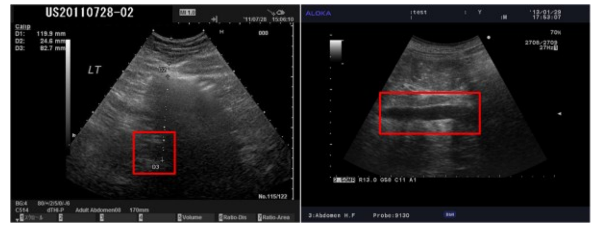

Figure 2. Mannual distance measurment in clinical diagnosis.

A. 1D Ultrasound Signal Extraction

Considering the uncertainties of the aorta image, we propose to detect the aorta by analyzing the signals along ultrasound scan lines. Figure 3(a) illustrates the ultrasound scan lines, where C is the scan line center. In order that the aorta is properly sampled, a group of scan lines at some angular interval within the range $[-\theta/2, \theta/2]$ are extracted. After the scan lines are determined, the intensity signal along each scan line is obtained by re-sampling the ultrasound image. Figure 3(b) shows one scan line in the ultrasound image. The green point represents the start of the scan line, which can be seen as the skin surface in our case. Figure 3(c) shows the corresponding intensity signal. Observation shows that the signal at the rear part of the scan line (i.e. under the aorta) consists of artifacts and noise. Hence the signal is reversed so that the green point becomes the end of the signal. Note that a minus pulse is evident in the extracted signal, which could be used to identify the aorta.

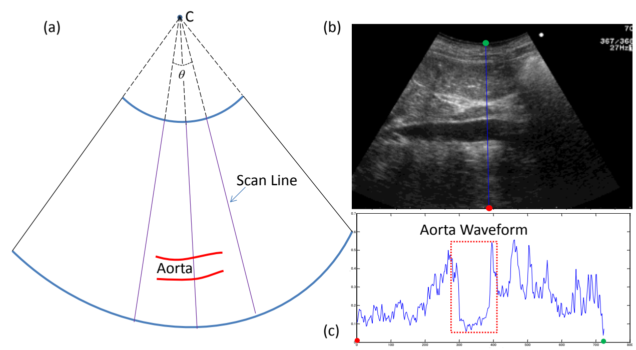

Figure 3. Scan line and intensity signal. (a) Ultrasound scan lines. (b) A scan line in the ultrasound image. (c) Intensity signal along the scan line.

The automatic signal extraction procedure is described as follows (see figure 4).

- The FOV of the ultrasound image is segmented from the background using a threshold method. Canny edge detection is performed based on the resulting binary image.
- Hough transform is performed on the edge image and two boundary segments B_1B_2 and B_3B_4 are picked up.
- The intersection point C (scan line center) of B_1B_2 and B_3B_4 is calculated and the radial lines which are originated from C and equally distributed within angle θ are extracted. The scan line starts at the place where $|CB_1|$ is far away from C. Every scan line has the same length $|B_1B_2|$ (or $|B_3B_4|$).

- Intensity signals are generated by interpolating the original image along the scan line (from its end to its start), with a sampling step being half of the original pixel spacing.

The above procedure is very effective for extracting the desired signals owing to the evident boundary of the FOV. In addition, the scan line extraction only needs to be run once if the FOV does not change. Assume we have M scan lines and N samples on each scan line. They can be represented by a $M \times N$ matrix $\boldsymbol{S}$ with S_j^i being the intensity of the sample j on the scan line i, where $i = 1,\cdots$ [illegible] $\cdots$. Next, the aorta is to be identified from the signal S^i.

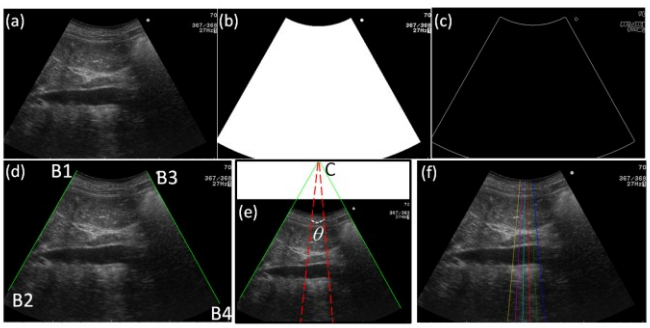

Figure 4. Automatic signal extraction. (a) Original image. (b) Segmented FOV. (c) Canny edge detection. (d) Boundary line detection. (e) Scan line center and range determination. (f) Extracted scan lines along which intensity signals are interpolated.

B. *Aorta Waveform Detection*

The ultrasound image of the aorta appears as an inner hypoechoic area with outer hyperechoic layers as shown in figure 5. Its waveform is ideally two separated peaks with peak-to-peak distance being the diameter of the aorta. The actual signal waveform is also shown in figure 5 and is separated into three parts according to their waveform characteristics: 1. Noise-like artifacts. As there is no evident organ appearing under the aorta in the image, this part of the signal looks like a noisy waveform. 2. Aorta waveform. It looks like two separated peaks which is our target waveform. 3. Waveforms of other organs. The task is to detect the aorta waveform from the signal.

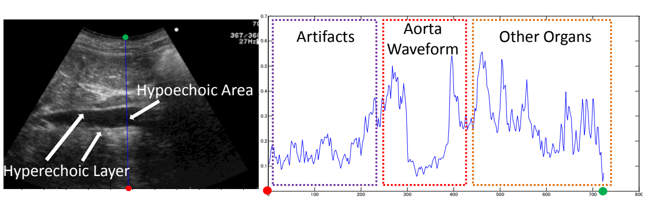

Figure 5. Intensity signal characteristics.

A coarse-to-fine strategy is adopted for aorta waveform detection. The aorta waveform can be coarsely modeled by three local extrema: two adjacent maxima and one minimum between them. A moving average filter is used to smooth the original signal and then extrema detection is performed to obtain the local extrema of the signal which are used to locate the aorta waveform. In order to minimize the influence of noise, a threshold is set so that a detected maximum is larger than the adjacent minimum by at least the threshold. Similarly, a detected minimum is smaller than the adjacent maximum by at least the threshold. The threshold is determined adaptively by the characteristic of the "noise-like artifacts" waveform:

$$t_i = 3 \cdot \sigma_{S^i/2} \tag{1}$$

where t_i is the threshold for signal S^i and $\sigma_{S^i/2}$ is the mean length of all falling edges in the front half of signal S^i. Figure 6 shows the results of extrema detection with a threshold calculated by (1). Extrema in the "noise-like artifacts" waveform is successfully screened out. It is supposed that the first three detected extrema, the indices of which are denoted by p_1, v, and p_2, coarsely represent the target waveform.

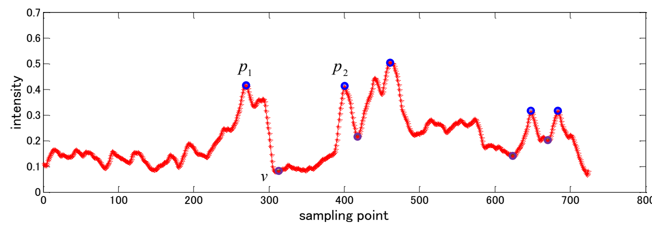

Figure 6. Extrema detection results.

After the three extrema are located, a more precise model is needed to characterize the aorta waveform. The transition zone from the hyperechoic layer to the hypoechoic area is reflected as a falling edge in the signal, so the aorta waveform can be further modeled by a falling edge followed by a rising edge at a distance equal to the aorta diameter. A refinement algorithm for identifying the aorta waveform is given as follows:

- All falling edges between p_1 and v are extracted and the one with a maximum decline is located, with its endpoint indices denoted by e_1 and e_2.
- All rising edges between v and p_2 are extracted and the one with a maximum rise is located, with its endpoint indices denoted by e_3 and e_4.
- The aorta waveform is thus characterized by the indices $\{e_1, e_2, e_3, e_4\}$, where $\{e_1, e_2\}$ and $\{e_3, e_4\}$ represent the posterior and anterior wall of the aorta, $\{e_2, e_3\}$ represents the interior of the aorta.

The distance d_i and the aorta diameter D_i are calculated by

$$\begin{aligned} d_i &= (N - e_1) \cdot sr \cdot ps \\ D_i &= (e_4 - e_1) \cdot sr \cdot ps \end{aligned} \tag{2}$$

where sr is the sampling rate (equal to 0.5 in our case), ps is the original pixel spacing which is read off from the ultrasound machine.

C. *Robustness Consideration*

We have given the algorithm for identifying the aorta from the intensity signal along a scan line. However, the algorithm may fail to find the right one, for example, in the case of the absence of the aorta in the scan line or some relative large fluctuations in the "noise-like artifacts" waveform. So signals along different scan lines are processed to find a collection of candidate aorta waveforms and then a "best" one is chosen as the final one. Initial screening is performed to detect the absence of the aorta according to the position and diameter ranges. A metric function is introduced to judge the quality of the remaining aorta waveforms.

A good aorta waveform should have high contrast and small ripples. High contrast reflects a large decline (rise) of $\{e_1, e_2\}$ ($\{e_3, e_4\}$). Small ripples means a small number of local peaks between p_1 (p_2) and v . Based on above analysis, we propose a metric function for rating candidate waveforms:

$$f^i = \left(S^i_{e_1} - S^i_{e_2} + S^i_{e_4} - S^i_{e_4}\right) - \left(S^i_{e'_1} - S^i_{e'_2} + S^i_{e'_4} - S^i_{e'_4}\right) \qquad (3)$$

where $\{e'_1, e'_2\}$ ($\{e'_3, e'_4\}$) is the falling (rising) edge with the second largest decline (rise) between p_1 (p_2) and v . f^i actually represents the altitude difference between the largest and the second largest falling (rising) edge. The aorta waveform with the largest f^i is chosen to calculate the desired distance.

IV. Experiment and Evaluation

Experiments were carried out to evaluate our method in two aspects: robustness of aorta waveform detection and distance measurement accuracy.

A. Robustness Evaluation

This aims to test whether the method can identify the aorta under various image qualities. Volunteers were recruited as the test subjects and 20 B-mode images were acquired as described in section II using the Prosound α10 ultrasound imaging system (Aloka, Japan). The scan line angle range was $\theta = 10^\circ$ with interval 1°. Our algorithm successfully identified aortas in all images and four typical cases (clear, blurred, partial aortas and strong echo artifacts) with the corresponding identified waveforms are given in figure 7.

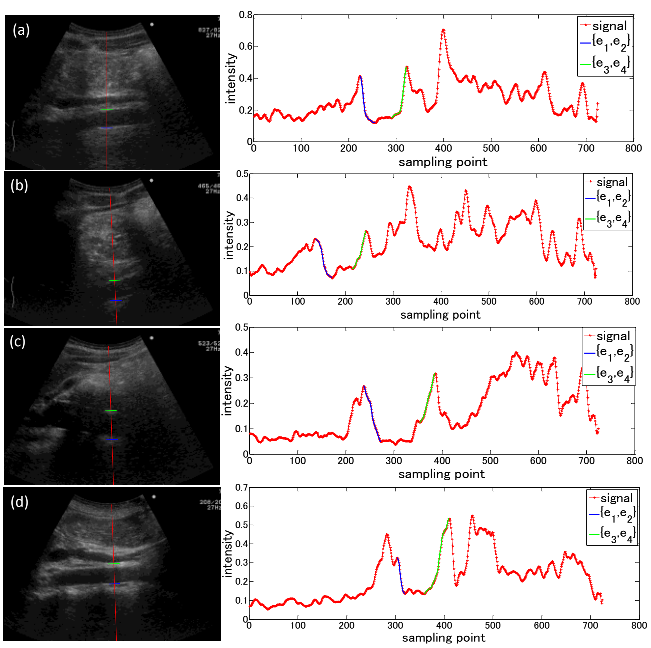

Figure 7. Aorta waveform detection results. (a) Clear aorta. (b) Blurred aorta. (c) Partially imaged aorta. (d) Strong echo artifacts near the aorta wall.

B. Distance Measurement Accuracy Evaluation

Clinical data were collected in Hiraka General Hostpital, Japan, for accuracy evaluation as shown in figure 8. We compared the distances measured by clinicians in a manual way with those obtained by our method. In total, 54 ultrasound images of patients were collected and 10 results with the largest errors (differences with the manual results) are listed in table 1. The average error of the 54 measurements is 0.53 mm.

Figure 8. Clinical examination and manual distance measurement.

TABLE I. 10 RESULTS WITH THE LARGEST ERRORS

Image No.	Manual Measurement (mm)	Automatic Measurement (mm)	Error (mm)
1	45.7	49.30	3.60
2	47.3	50.33	3.03
3	47.1	50.00	2.90
4	58.6	61.47	2.87
5	86.7	89.50	2.80
6	93.6	96.25	2.65
7	46.5	49.12	2.62
8	86.7	89.00	2.30
9	67.3	69.57	2.27
10	61.4	63.66	2.26

V. Conclusion

This paper proposed an automatic distance measurement method based on 1D ultrasound signal processing, which could identify the aorta in the ultrasound image even when it is blurred or partially imaged. The rating mechanism enhances the robustness of the algorithm. The robustness and accuracy have been validated by experiments based on clinical data. The proposed method is planned to be integrated into our ultrasonography-based visceral fat measurement system for fast and accurate central obesity diagnosis.

References

[1] S. Rössner, et al., "Adipose tissue determinations in cadavers--a comparison between cross-sectional planimetry and computed tomography," *Int. J. Obesity*, vol. 14, pp. 893-902, 1990.

[2] M. D. Jensen, et al. "Measurement of abdominal and visceral fat with computed tomography and dual-energy x-ray absorptiometry[1-3]," *Am. J. Clin. Nutr.*, vol. 61, pp. 274-282, 1995.

[3] K. Kooy, J. C. Seidell, "Technique for the measurement of visceralfat: a practical guide," *Int. J. Obes. Relat. Metab. Disord.*, vol. 17, pp. 187-196, 1993.

[4] F. F. Ribeiro-Filho, et al., "Methods of Estimation of Visceral Fat: Advantages of Ultrasonography," *Obes. Res.*, vol. 11, pp. 1488-1494, Dec. 2003.

[5] Y. Zhou, et al., "Fast and accurate ultrasonography for visceral fat measurement," in *Proceedings of Medical Image Computing and Computer-Assisted Intervention -MICCAI2010*, vol. 6362, Springer, 2010, pp. 50-57.