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Ultrasound Signal Processing Technique for Subcutaneous-Fat and Muscle Thicknesses Measurements

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ABSTRACT Accurate body-composition measurements are important for diagnosing health status. Devices used for body-composition measurement should be easily accessible for patient diagnosis whilst realizing high inter- and intra-operator accuracies for repetitive measurements. Dual-energy X-ray absorptiometry and magnetic resonance imaging (MRI) have been considered as a gold-standard method. However, these methods have disadvantages such as limited accessibility, high costs, and long scanning times. Ultrasound imaging is an alternative technique for body-composition measurement owing to its easy accessibility and convenience of use. Current ultrasound imaging techniques identify the interface between different tissue layers based on echogenicity changes observed in ultrasound images. Their measurement accuracies, therefore, depend on the ultrasound image quality and operator interpretation. Radio-frequency (RF) signals obtained directly from an ultrasound system ensure the reproducibility of measurements. However, RF signals contain substantial noise, and signal processing is fundamental in body-composition measurements. This study proposes an ultrasound signal processing technique to measure body composition. Backscattered RF signals in *ex vivo* swine-tissue samples were first acquired from an ultrasound system. Subsequently, interfaces of subcutaneous-fat, muscle, and bone were identified during RF signal processing. Next, subcutaneous-fat and muscle thicknesses were calculated based on the speed of sound through tissue. Lastly, the subcutaneous-fat and muscle thicknesses measured using ultrasound signals were validated using MRI scans. A strong linear correlation was observed between the proposed ultrasound method and MRI. Thickness correlations between ultrasound and MRI were observed to be 0.899 and 0.982 for subcutaneous-fat and muscle, respectively. The proposed technique, therefore, demonstrates clinical potential for body-composition measurements.

INDEX TERMS Body composition, signal processing, time of flight, acoustic attenuation, ultrasound.

I. INTRODUCTION

Accurate body-composition measurements are important for health-status diagnosis [1]. The changes of body-composition are associated with diseases such as sarcopenia, cachexia, atrophy [2], and pancreatic cancer [3]. Quantifying body-composition would aid clinicians to monitor progress of such diseases as well as develop weight-loss or weight-gain programs and assess the effectiveness of nutrition and exercise interventions [1]. Devices used for the measurement of body-composition must be easily accessible for the diagnosis of patients whilst realizing high inter- and intra-operator accuracies for repetitive measurements [4]. Skinfolds [5], [6], bioelectrical impedance [7], and anthropometric measurements [8] have been previously used for body-composition measurements owing to their convenience of use [1]. However, these techniques are typical indirect measurement methods, and their measurement accuracy is easily affected by the subject's physiological condition [4]. Dual-energy X-ray absorptiometry and magnetic resonance imaging (MRI) have been considered as a gold-standard method owing to their high image contrast [9], [10]. However, these methods have disadvantages such as limited accessibility, high costs, and long scanning times [9], [10].

Ultrasound imaging has been regarded as an alternative technique for body-composition measurements owing

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to its ease of accessibility and convenience of use [11]. Current ultrasound imaging techniques identify the interfaces of different tissue layers based on echogenicity changes observed in ultrasound images [1]. Their measurement accuracies, therefore, depend on the ultrasound image quality and operator interpretation. To ensure the reproducibility of measurements, backscattered radio-frequency (RF) signals directly obtained from an ultrasound system could be used for body-composition measurements [12]. Each subcutaneous-fat–muscle and muscle–bone tissue interface is characterized by different acoustic reflections and attenuations [1]; these interfaces can be identified based on RF signals. However, ultrasoundsignal acquisition is susceptible to factors such as temperature-based mechanical and electrical properties of the transducer. Moreover, reflected waves generally contain a substantial amount of noise [13], [14]. The signal processing of reflected waves, therefore, constitutes a fundamental function in the identification of interfaces between different tissue layers to facilitate body-composition measurements.

In ultrasound signal processing techniques, peak-signal detection methods have been utilized to identify tissue interfaces because strong acoustic reflection occurs between interfaces of different tissue layers [1]. By using peak-signal detection methods, subcutaneous-fat thickness has been measured in human tissues from the peak detected at the fat–muscle tissue interface [1], [15], [16]. However, current peak detection techniques are limited to the identification of the muscle–bone tissue interface, which is located deep in the tissues, because the attenuation of ultrasound signals critically reduces the signal-to-noise ratio. Moreover, there has been no report thus far on the simultaneous measurement of subcutaneous-fat and muscle thicknesses from backscattered ultrasound signals.

The present study proposes an ultrasound signal processing technique for body-composition measurements. In accordance with the proposed method, reflected ultrasound waves were first acquired from *ex vivo* swine-tissue samples. Subcutaneous-fat, muscle, and bone interfaces were then identified based on the results obtained from the RF signal processing of reflected waves. Next, the subcutaneous-fat and muscle thicknesses were calculated based on the speed of sound through the swine-tissue samples. Lastly, the fat and muscle thicknesses measured using ultrasound signals were validated in the light of MRI scans.

II. MATERIALS AND METHODS

This study comprises sample preparation, ultrasound signal acquisition, ultrasound signal analysis, and the validation of ultrasound results via MRI. Figure 1 presents an overview of the sample preparation as well as ultrasound and MRI measurements for *ex vivo* swine-tissue samples.

A. SAMPLE PREPARATION

Three fresh swine forearms were obtained from a local butcher shop, and 16 *ex vivo* swine-tissue samples were prepared by slicing these forearms into samples measuring 7 cm × 6 cm × 15 cm to include subcutaneous-fat, muscle, and bone layers. The skin of the swine-tissue samples was marked with a black-ink dot to perform measurements at the designated location by using an ultrasound transducer.

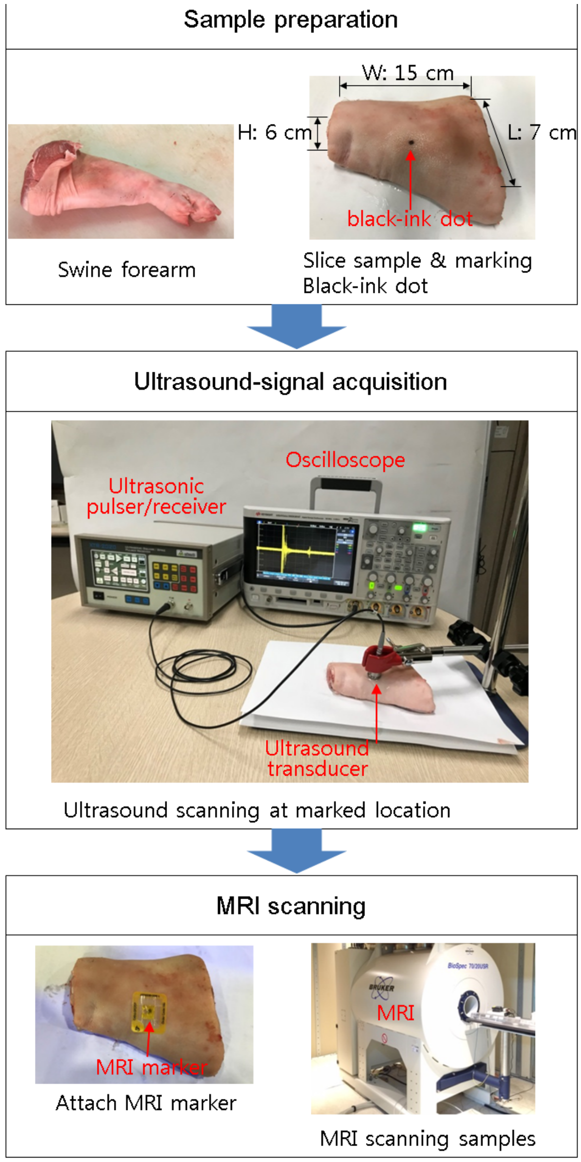

FIGURE 1. Overview of the sample preparation, ultrasound measurements, and MRI measurements for *ex vivo* swine-tissue samples.

B. ULTRASOUND SIGNAL ACQUISITION

A 2.25-MHz single-element focused transducer (BioSono Inc., USA) was excited by means of an ultrasonic pulser/receiver (Model XTR-2020, MKC Inc., Korea). Subsequently, the received RF signals were digitized through an oscilloscope (Model DSO1012A, Keysight Technologies, Korea) at a 20-MS/s sampling rate and stored in a personal computer for post-processing.

Sixteen *ex vivo* swine-tissue samples were used to perform ultrasound measurements. The ultrasound transducer coupled with sonogel was placed on the black dot marked on the swine-tissue samples. Subsequently, ultrasound measurements were performed by aligning the ultrasound transducer perpendicular to the skin surface. The RF echo signals backscattered from a tissue sample were acquired along the tissue thickness. Five scans per swine-tissue sample were performed at the same location, and the corresponding data were stored separately. Each sample measured by ultrasound was used for performing subsequent MRI scans.

C. ULTRASOUND SIGNAL ANALYSIS

Digitized RF signals were analyzed using MATLAB (Mathworks, Natick, USA). Figure 2 illustrates the steps involved in the ultrasound signal processing. The procedure involved the following steps.

	Goal	Method
Step 1	Reduce noise	• Segment averaging • Bandpass filtering
Step 2	Identify interfaces	• Envelope detection • Peak detection
Step 3	Classify tissues	• Attenuation coefficient estimation

FIGURE 2. Schematic steps of radio-frequency (RF) signal processing.

Step 1: Segment averaging was applied to multiple RF echo signals to reduce in-band noise for M segments:

$$s(n) = \frac{1}{M}\sum_{m=0}^{M-1} s_m(n), \quad n = 0, 1, \ldots, N-1$$

where $s(n)$ is the averaged RF signals, $s_m(n)$ is the m-th RF segment, M is the number of pulses per each measurement, and N is the number of digitized samples during the pulse repetition period. After the segment averaging, out-of-band noise was suppressed using a fifth-order Butterworth bandpass filter [17] with cut-off frequencies of 500 kHz and 5 MHz, and zero-phase filtering [18] was utilized to preserve the peak locations in the RF signals. Finally, Hilbert transform and log compression were performed to obtain log-compressed envelope signals [19].

Step 2: The tissue interfaces were identified by detecting local maximum values in the log-compressed envelope signals. The local maximum algorithm needs two parameters: minimum peak distance (MPD) and minimum peak prominence (MPP). The MPD determines the minimum separation between the detected peaks; therefore, it should be larger than the pulse duration. The prominence of a peak represents its intrinsic height relative to other peaks. By using an MPD of 1 μs and MPP of 10 dB, we could distinguish the strong peaks caused by reflection at tissue boundaries from the weak peaks generated from envelope fluctuation due to backscattering. The travel time of waves between the interfaces of subcutaneous-fat, muscle, and bone was determined using the detected strong peaks. Lastly, the subcutaneous-fat and muscle thicknesses were calculated by multiplying half the wave travel time by the speed of sound through the tissue (1547 m/s).

Step 3: The subcutaneous-fat, muscle, and bone were classified by measuring local attenuation coefficients for each tissue. The local attenuation coefficients were computed using a frequency-shift estimator [20] with a window size of 1 μs and 5 independent RF lines. The diffractive effects of the transducer were compensated with a homogeneous reference phantom having an attenuation coefficient of 0.511 dB/cm/MHz as measured from a tissue-mimicking phantom (Peripheral Vascular Doppler Flow Phantom; Model 524; ATS Laboratories, USA).

D. MAGNETIC RESONANCE IMAGING

The Bruker Biospec 7T system (BioSpec 70/20 USR; Bruker, Germany) with a 72 mm quadrature volume coil was used to image *ex vivo* swine-tissue samples. Axial-plane images of tissue sample were acquired using a T2-weighted rapid imaging with refocused echoes (RARE) sequence with the following scanning parameters: repetition time = 2500 ms; echo time = 35 ms; slice thickness = 1.5 or 2 mm; RARE factor = 4; number of acquisitions = 2; matrix size = 256 × 192; and field of view = 8 × 8 cm. Oil-filled capsules (MR SPOTS MRI Skin Marker; ref. no. 185; Beekley Medical, Bristol, CT, USA) used as external markers were secured onto the black dot marked on the swine-tissue samples to identify corresponding sections measured via the ultrasound technique. The subcutaneous-fat and muscle thicknesses measured using the ultrasound technique were compared with those obtained via MRI.

E. STATISTICAL ANALYSIS

The correlation coefficients of thicknesses measured using the proposed ultrasound method and MRI were calculated. The coefficient of variation (CV) was also analyzed for repeated ultrasound measurements. In addition, Bland–Altman analysis was performed to further examine the relationship between the ultrasound and MRI measurements.

III. RESULTS

Figure 3 presents a stepwise illustration of the representative RF signal processing results and corresponding MR image of a swine-tissue sample. Figure 3(A) depicts the RF signal obtained from the swine-tissue sample as a plot of wave-travel time against voltage. Figure 3(B) presents the RF signal with wave-travel time along the horizontal axis and voltage along the vertical axis after segment averaging and bandpass filtering. Figure 3(C) depicts the log-compressed envelope signal including three prominent peaks: (a) 16.2 μs, (b) 25.0 μs, and (c) 66.2 μs. The first peak (a) was identified when the amplitude of the log-compressed envelope signals demonstrated a sharp increase to −8.7 dB. The second peak (b) was observed at an amplitude of −12.9 dB. Likewise, the third peak (c) was identified at an amplitude of

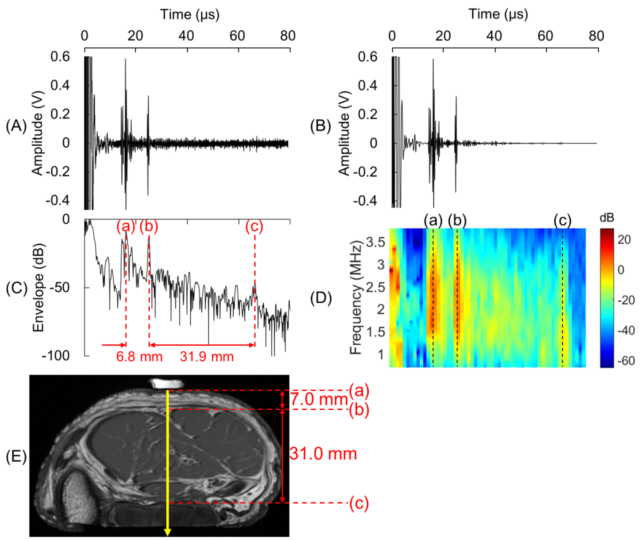

FIGURE 3. Stepwise illustration of the representative RF signal processing results and the corresponding MR image of a swine-tissue sample –(A) RF signal obtained from a swine-tissue sample as plot of wave-travel time against voltage; (B) RF signal with wave-travel time along horizontal axis and voltage along vertical axis after segment averaging and bandpass filtering; (C) log-compressed envelope signal with wave-travel time along horizontal axis and envelope along vertical axis; (D) time versus frequency map including the corresponding locations of three prominent peaks; (E) MR image obtained for a swine-tissue sample.

−45.8 dB. Note that the time of ultrasound-signal acquisition was delayed to approximately 10 μs to avoid near-field noise in the ultrasound transducer and the prominent peaks were chosen over wave-travel time of 10 μs. Figure 3(D) shows a time versus frequency map including the corresponding locations of the three prominent peaks. In the figure, red color represents high envelope values (dB) and the three prominent peaks were identified from the time versus frequency map. The attenuation coefficients of subcutaneous fat, muscle, and bone were computed from the time versus frequency domain based on the slope of the spectral centroid. With the proposed method, the subcutaneous-fat and muscle thicknesses measured for a swine-tissue sample were 6.8 mm and 31.9 mm, respectively. Figure 3(E) shows the MRI scan of this swine-tissue sample. The yellow arrow denotes the ultrasound-beam direction, and the corresponding locations of (a), (b), and (c) have been marked in the MR image. With MR imaging, the subcutaneous-fat and muscle thicknesses measured for the aforementioned swine-tissue sample were 7.0 mm and 31.0 mm, respectively.

The attenuation coefficients of subcutaneous fat, muscle, and bone for 16 *ex vivo* swine-tissue samples are summarized in Table 1. The attenuation coefficients of subcutaneous fat and muscle were similar to the reported values of 1.6–2.7 and 1.0–1.2 dB/cm/MHz, respectively [21], [22].

Figure 4 depicts the relationship between tissue thicknesses measured via the proposed ultrasound method and MR imaging. Figure 4(A) depicts the correlation between the subcutaneous-fat thicknesses measured using the proposed ultrasound technique and MRI. The error bar represents the standard deviation, while the dotted line denotes regression.

TABLE 1. Attenuation coefficients of subcutaneous fat, muscle, and bone for 16 *ex vivo* swine-tissue samples.

Tissue	Attenuation coefficient (dB/cm/MHz)
Fat	1.8859±0.3599
Muscle	1.0982±0.3405
Bone	4.5703±0.8298

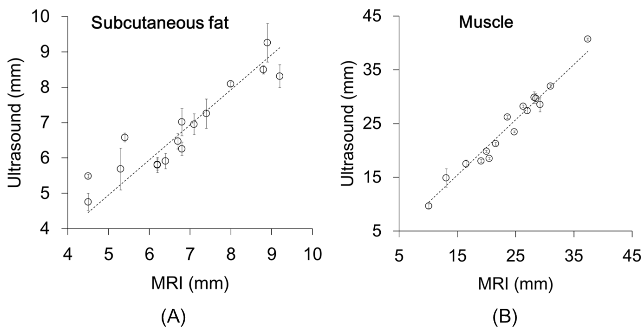

FIGURE 4. Relationship between tissue thicknesses measured via the proposed ultrasound method and MR imaging.

The thickness measured using the ultrasound technique correlates well with that measured using MRI (R = 0.899). The average value of CV was 3.9% when using the ultrasound technique for five successive independent measurements. Figure 4(B) shows a strong correlation (R = 0.982) between muscle thicknesses estimated using ultrasound and MRI. The average value of CV equaled 2.6% for five successive independent measurements performed using ultrasound.

Figures 5(A) and 5(B) depict Bland–Altman plots corresponding to the subcutaneous-fat and muscle thicknesses obtained using the proposed ultrasound technique and MRI, respectively. The middle red solid line indicates the mean difference of tissue thicknesses and the upper and lower red dotted lines represent 95% limit of agreement for the two measurements. The black dotted line denotes the regression line, and the correlation coefficients for the subcutaneous fat and muscle were 0.356 and 0.465, respectively.

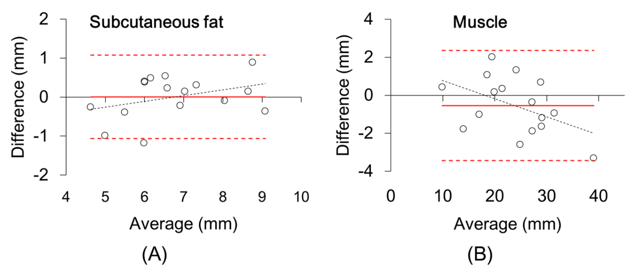

FIGURE 5. Bland–Altman plots obtained using proposed ultrasound technique and MRI for (A) subcutaneous-fat thickness and (B) muscle thickness.

IV. DISCUSSION

Our results demonstrate that a strong linear correlation exists between the proposed ultrasound method and MRI as regards the measurement of subcutaneous-fat and muscle thicknesses. When determining the subcutaneous-fat and muscle thicknesses, respectively, the correlations between the two techniques were 0.899 and 0.982. It was, therefore, inferred that the ultrasound signal processing technique proposed in this study demonstrated accuracy comparable to that of MRI in the measurement of subcutaneous-fat and muscle thicknesses.

The proposed ultrasound signal processing technique produced small variations when performing repeated tissue-thickness measurements. The average CV values equaled 3.9% and 2.6% for subcutaneous fat and muscle, respectively. This indicates that the ultrasound technique would have high reproducibility when used in the determination of subcutaneous-fat and muscle thicknesses.

The tissue samples were sliced to measure less than 7 cm $\times$ 7 cm $\times$ 17 cm in volume to facilitate their placement inside the quadrature volume coil used in the MRI system. To determine the size effect on the ultrasound-measurement accuracy, Altman analysis was performed. The Bland–Altman plots, depicted in Figure 5, demonstrate that the ultrasound signal processing technique produced accurate measurements regardless of the tissue-sample size. The maximum differences between subcutaneous-fat and muscle thicknesses measured using ultrasound and MRI equaled 1.2 and 3.3 mm, respectively. It was, therefore, expected that the proposed ultrasound technique would produce accurate measurement results for larger tissues.

In this study, a sample thickness of less than 7 cm was utilized when performing ultrasound measurements. The thickness of subcutaneous fat usually exceeds this value in obese human patients. The echo signal-to-noise ratio decreases with increase in tissue depth due to the attenuation of ultrasonic energy caused by soft tissues [23]. Thus, use of a higher transmitting voltage or gain increase would be necessary when performing ultrasound measurements for obese patients to identify the location of muscle–bone interfaces underneath thick subcutaneous fat.

The frequency-shift estimator has been utilized to measure local attenuation coefficients of fat, muscle, and bone in the swine-tissue samples. In the frequency-shift estimator, the window size should be small enough for sufficient spatial resolution to measure thin tissue layers. In contrast, the window size should be large enough to reduce estimation variance [24]. In this study, the window size was selected as 1 μs, which is larger than two pulse waves length and produced accurate and precise acoustic attenuation values for swine-tissue samples, as summarized in Table 1. However, the acoustic parameters of human tissues are different from those of swine tissues [25]. Therefore, the optimum window size should be investigated for measuring the attenuation of human tissues.

The present study has several limitations. First, a source of potential error in the ultrasound measurements is the application of transducer-based pressure on the skin, which results in the compression of underlying tissues. In this study, the ultrasound transducer was maintained slightly attached to the skin surface to minimize the compression of underlying tissues. In a future study, the applied compressive load may need to be measured to validate the accuracy of ultrasound measurements. Secondly, the thicknesses of tissue layers were measured based on the assumption that the ultrasound-transducer was aligned perpendicular to the skin surface. However, the orientation of the human body changes with the body parts considered [26]; thus, such an ultrasound-transducer alignment would not be ideal for use in clinical applications. In a future study, the authors intend to establish a geometric model for each part of the human body, and the optimal ultrasound alignment would be investigated for measuring the thickness of tissue layers constituting those parts. In addition, the magnitude of measurement errors caused by misalignment of the ultrasound transducer need to be further investigated. Moreover, subcutaneous-fat and muscle thicknesses determined in this study were computed by assuming a constant speed of sound (1547 m/s) throughout the tissue sample. However, the speed of sound varies between fat and muscle layers [25], and this would affect the computation of tissue thickness. The speed of sound in subcutaneous fat is 1478 m/s [25], causing a reduction of approximately 6% in the subcutaneous-fat thickness estimated using the proposed ultrasound technique.

V. CONCLUSION

The proposed ultrasound signal processing technique demonstrated accuracy comparable to that of MRI in tissue-thickness measurement. Additionally, the size of the ultrasound device can be reduced using A-line RF signals, making it portable. As a portable imaging device capable of making fast regional estimates of body composition, the proposed ultrasound technique is an attractive assessment tool for use in circumstances where other methods offer limited utility. The authors believe that proposed ultrasound technique has potential for use in clinical applications involving body-composition measurements, and thus, further extensive clinical investigations of the same are warranted.

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