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Automated Discrimination Method for Measuring the Thickness of Muscular and Subcutaneous Fat Layers Based on Tissue Elasticity

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Abstract— **The balance between human body composition, e.g. bones, muscles, and fat, is a major and basic indicator of personal health. This paper proposes a new discrimination method for measuring the thickness of subcutaneous fat and muscular layers based on tissue elasticity. The validity of the proposed method was evaluated in twenty-one subjects (twelve women, ten men; aged 20-70 yr) at three anatomical sites. Experimental results show that the proposed method can achieve considerably high discrimination performance.**

I. INTRODUCTION

The balance between human body composition, e.g. bones, muscles, and fat, is a major indicator of personal health, and its quantification is useful for evaluating obesity and muscular strength in the elderly. The effects of exercise and diet therapy can be also evaluated as an inspiration to promote our health in daily living.

Medical images obtained from X-ray computed tomography (CT) and magnetic resonance imaging (MRI) clearly recorded the thickness of subcutaneous fat and muscles in each part of the human body, and these techniques are useful for precisely evaluating body composition [1], [2]; however, these systems are not widely installed, except in medical institutions. Also, X-ray CT has a serious drawback in that the subjects are exposed to radiation.

On the other hand, ultrasound imaging devices are compact, safe, and inexpensive, and can observe each part of the human body in real time [3]. These advantages make the devices suitable for rapid and precise measurement. Because of these advantages, we have developed portable ultrasound imaging devices for evaluating human body composition [4]. This device is intended to be widely used not only in the medical field but also in healthcare. We have also tried to develop an automated discrimination function to support these measurements [5]. This discrimination method utilizes the statistical characteristics of the tissue image; however, the discrimination errors varied among individuals, increasing when the body size did not meet the standard.

This paper proposes a new automated discrimination method for measuring the thickness of muscular and subcutaneous fat layers. This method can discriminate tissue boundaries using a one-dimensional echo signal, so that the production cost of the device is significantly reduced. To achieve high discrimination accuracy, the system uses the characteristics of tissue elasticity, and the discrimination is conducted using a neural network.

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II. AUTOMATED DISCRIMINATION METHOD BASED ON TISSUE ELASTICITY

A. System Components

An overview of the measurement system is shown in Fig. 1. The system consists of a sensor unit, a main unit, and a personal computer with control software. Table I shows the specification of the measurement system. The main unit and sensor unit are compact, lightweight, and easily portable. The single element of the ultrasound transducer is attached to the head of the sensor unit. During measurement, the head of the sensor unit compresses the surface of the human body, and transmits ultrasound pulses repeatedly. The thickness of muscular and subcutaneous fat layers is measured based on the echo signals reflected at the tissue boundaries. The center frequency of the ultrasound pulse is 3 MHz, and the pulse repetition frequency is 3 kHz. The compression force is set to 10 N by an internal coil spring.

The compression of the coil spring is detected by two photo interrupters located beside it. Also, these two points are used as triggers of signal recording. The first and second triggers are set to 1 N and 10 N, respectively. Echo signals are temporarily stored in the buffer memory after the signal was digitized by an A/D converter with a sampling frequency of 24 MHz, and then transferred to the computer via USB.

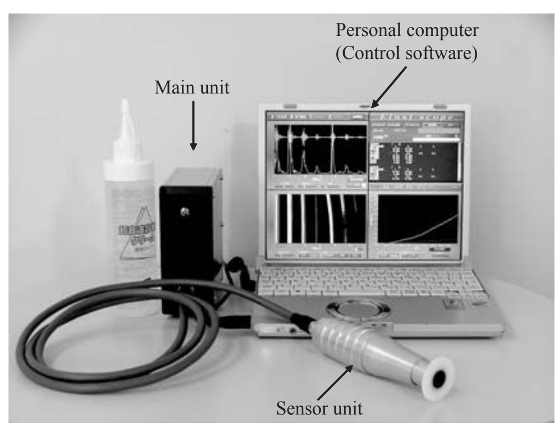

Fig. 1. Measurement system

TABLE I
SPECIFICATION OF THE MEASUREMENT SYSTEM.

US probe frequency	3 MHz
Sampling frequency	24 MHz
Pulse repeated frequency	3 kHz
Diameter of the US element	14 mm
Compression mechanism	Coil spring (stroke 10mm)
Scan depth	Approx. 100 mm
Contact pressure	10 N
Communication method	USB1.1 (12Mbps)
Dimensions (main unit)	50(W) $\times$ 130(H) $\times$ 170(D) mm
Dimensions (sensor unit)	41(D) $\times$ 140(L) mm
Weight	Approx. 2.2 kg

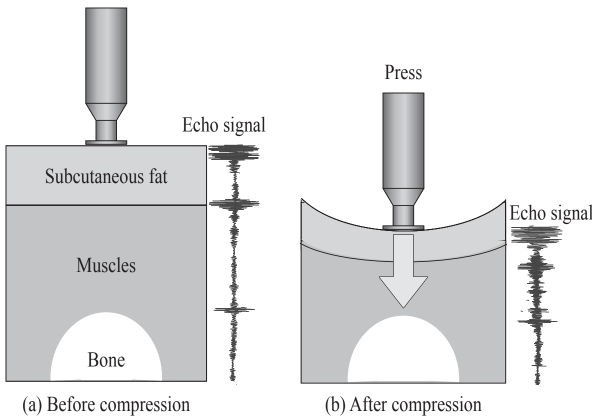

Fig. 2. Measurement principle of tissue elasticity

B. Discrimination Method

The measurement principle of tissue elasticity is illustrated in Fig. 2. The ultrasonic probe compresses the human body tissues, and measures one-dimensional echo signals repeatedly. The tissues are deformed as shown in Fig. 2(a)(b), and the deformation process is observed using echo signals. Figure 3 plots an example of the deformation process. In this figure, (i)(ii) indicate the subcutaneous fat and muscles, respectively. The horizontal axis is normalized according to total deformation. As shown in Fig. 3, the subcutaneous fat deforms rapidly at the beginning of compression, and then the deformation is saturated. On the other hand, the muscles deform gradually until the end of compression. We focused on this difference in tissue elasticity between subcutaneous fat and muscles, and applied it to the new automated discrimination method.

The structure of the proposed method is shown in Fig. 4 and consists of the feature extraction process and the discrimination process. In the feature extraction process, several candidate peaks are detected from the envelope of the echo signal using the appropriate threshold, and their depth is calculated. Then, the shift of the detected peaks is tracked while compressing the tissue. The strain between the skin surface and candidate peaks is calculated. Thus, "Depth" and "Strain" information is extracted and used as input data for the discrimination process. In the discrimination process, the neural network is used to deal with non-linear and multi-

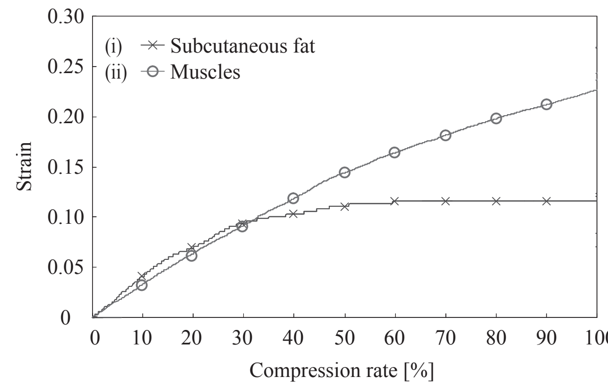

Fig. 3. Example of tissue elasticity of subcutaneous fat and muscles

dimensional feature data. Before discrimination, the network is trained using the training dataset. A detailed explanation is included in the following section.

1) Feature extraction: Here, the feature extraction for automated discrimination is explained. The raw echo signal is rectified and smoothed out using a low-pass filter with a cut-off frequency of 23 kHz, and N peaks, which have the intensity over the pre-specified threshold, are extracted from this envelope signal. In this study, the threshold is determined by trial and error. The extracted peaks are regarded as candidates of tissue boundaries among subcutaneous fat, muscles, and bone. Figure 5(a), (b) shows an example of the feature extraction process; Fig. 5(a) indicates the original echo signal and Fig. 5(b) indicates its envelope signal after rectification and smoothing out. Candidates for tissue boundaries are set at the beginning of compression ($m = 0$), and each candidate is defined as $D_{n,m}, (n = 1, 2, \cdots, N, m = 1, 2, \cdots, M)$. Here, n denotes the order of the extracted peak and m denotes the timing of the strain extraction. Timing m is normalized on the basis on the total strain of the whole tissue.

During compression, the shift of the extracted candidates is tracked and the strain $S_{n,m}$ of each candidate is calculated as,

$$\begin{aligned} S_{n,m} &= (D_{n,0} - D_{n,m})/D_{n,0}, \\ &\quad (n = 1, 2, \cdots, N, m = 1, 2, \cdots, M) \end{aligned} \tag{1}$$

As mentioned above, two kinds of information, the depth $D_{n,0}(n = 1, 2, \cdots, N)$ and strain $S_{n,m}(n = 1, 2, \cdots, N, m = 1, 2, \cdots, M)$, are extracted. The tissue boundaries among subcutaneous fat, muscles, and bone are discriminated using this information.

2) Discrimination: The discrimination process is conducted using the neural network. The input data calculated in feature extraction process is multi-dimensional, and the characteristics of tissue elasticity are nonlinear, as shown in Fig. 3; therefore, the neural network is adopted to deal with them. The neural network discriminates the type of tissue area with the candidate peaks. The input of the neural network is a multi-dimensional vector $(D_{n,0}, S_{n,1}, S_{n,2}, \cdots, S_{n,M})$, and the output indicates the type of tissue area (subcutaneous

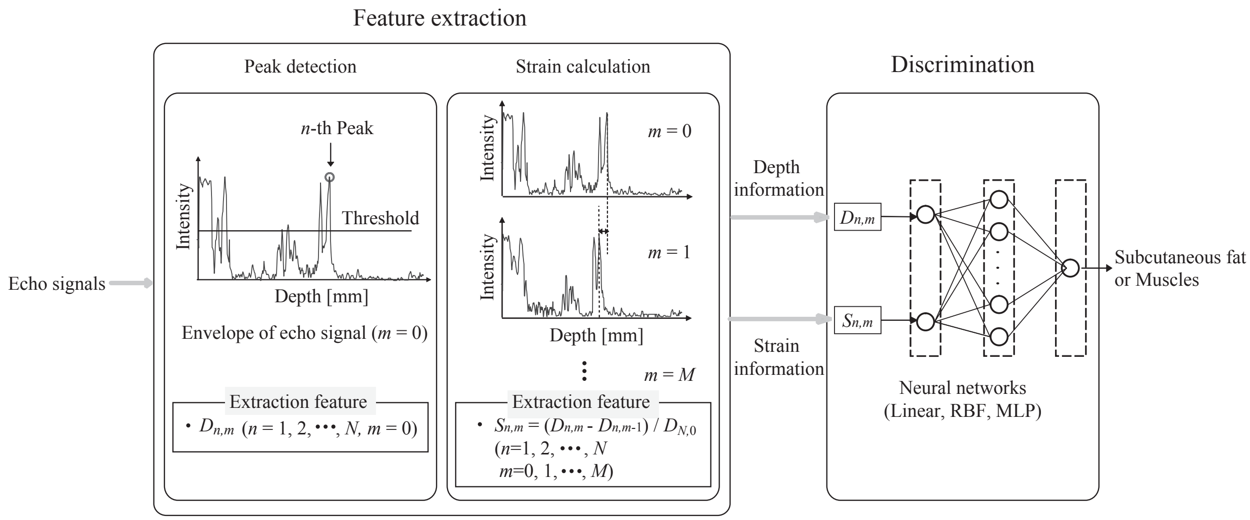

Fig. 4. Structure of the automated discrimination process.

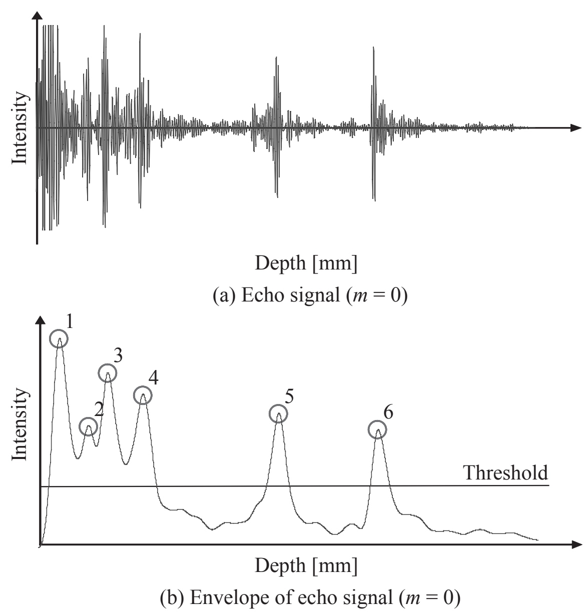

Fig. 5. Example of peak detection

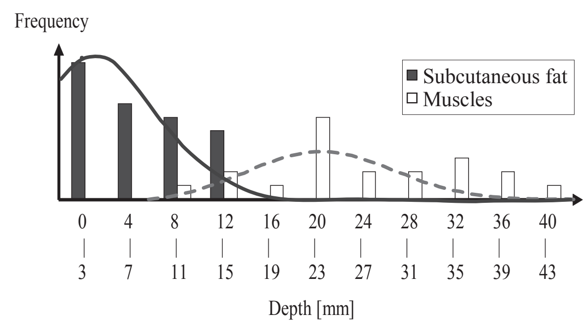

Fig. 6. Depth distribution of subcutaneous fat and muscle.

fat, muscles). The neural network is trained using the training dataset before discrimination.

III. EXPERIMENTS

Experiments were conducted to evaluate the accuracy of the proposed method. Twenty-one subjects (twelve women, ten men; aged 20-70 yr) participated in these experiments, and three anatomical sites (anterior upper arm, posterior upper arm and anterior thigh) were measured. These measurement sites are often used to measure the thickness of subcutaneous fat and muscular layers. The subject does not have to remove his/her clothes during the measurement. The parameter in the feature extraction was set as $M = 10$, and 204 samples (21 subject $\times$ 3 sites $\times$ N candidates) were extracted. Then, 141 samples were used for the learning of the neural network, and 63 samples were used for discrimination. Figure 6 presents the frequency distribution of 63 discrimination samples according to their boundary depth. Experienced observers examined them and discriminated the boundaries. As seen in this graph, the two groups overlapped and it was difficult to discriminate them using only depth information.

In this paper, statistical analysis software (STATISTICA, StatSoft, Inc.) was used to calculate the neural network. Three neural network models, a linear model, MLP and RBF, were compared. The linear model consisted of input and output layers, and the pattern space was divided using a linear function. On the other hand, the MLP consisted of the input layer, hidden layer and output layer. The sigmoid function was used as the transfer function. The RBF also consisted of the input layer, hidden layer and output layer. Gaussian function was used as the basis function. The number of units in the hidden layer of MLP and RBF was determined as 18 and 11 respectively by trial and error. MLP and RBF can construct a nonlinear model through learning.

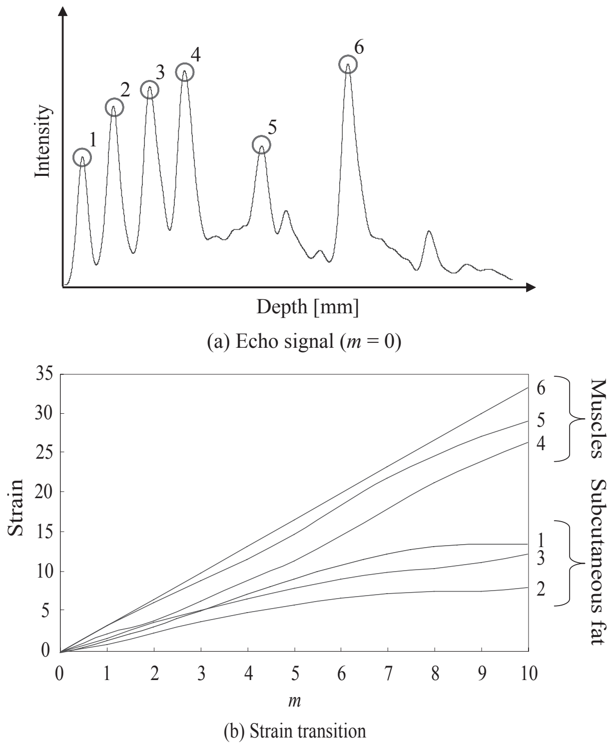

Fig. 7. Discrimination example.

A. Discrimination Example

An example of the discrimination result is shown in Fig. 7. The neural network model is MLP. Figure 7(a) shows the envelope of the measurement echo signal. Six candidate peaks were chosen using the pre-specified threshold. As shown in this figure, the depth information obtained based on the intensity is not sufficient to discriminate the type of tissue. On the other hand, Fig. 7(b) shows strain information for each candidate peak during compression. The strain characteristics are different between each candidate peak. The discrimination results by the neural network are also shown in the graph. The proposed method accurately discriminated the type of tissue based on tissue elasticity.

B. Evaluation of Accuracy

To verify the effect of the proposed discrimination method, comparison experiments were conducted under three conditions. The conditions used only depth information, depth information and strain information(m=5), and the proposed method. Also, three neural network models were investigated, and discrimination accuracy is shown in Table 2. In this table, discrimination accuracy was improved using strain information. Also, MLP and RBF, which are nonlinear models, seem to be more effective than the linear model.

Finally, the depth of tissue boundaries was calculated using the discrimination result by the proposed method. The difference from the manual discrimination result by an experienced observer is evaluated in Table 3. Here, manual discrimination was conducted using not only one-dimensional echo signals but also ultrasound images. The proposed method was compared with the situation using only depth information. The highlighted cells in the table indicate improved precision using strain information. We can confirm that the depths of tissue boundaries can be calculated precisely using the proposed method. In particular, cases with a large error have considerably improved accuracy.

TABLE II
DISCRIMINATION ACCURACY [%].

	Depth only	Depth and Strain(m=5)	Depth and Strain(m=1,$\cdots$,10)
Linear	88.9	90.7	94.4
RBF	-	92.6	95.3
MLP	-	92.6	94.4

TABLE III
DISCRIMINATION ERROR [mm].

Subjects	Anterior upper arm		Posterior upper arm		Anterior thigh	
	1	2	1	2	1	2
A	0.0	0.0	8.3	3.9	2.0	0.2
B	0.0	0.0	4.9	4.9	0.0	0.0
C	0.2	0.2	0.4	0.4	0.3	0.3
D	2.6	0.2	0.5	0.5	0.5	0.5
E	7.2	0.3	0.3	0.3	0.5	0.5

1:Using Depth information
2:Using Depth and Strain information(m=1,$\cdots$,10)

IV. CONCLUSIONS

In this paper, a new automated discrimination method was proposed to measure the thickness of subcutaneous fat and muscular layers. The proposed method discriminates the tissue boundary based on the characteristic of tissue elasticity. In the experiments, the performance of the proposed method was confirmed.

In future research we would like to improve the feature extraction process and the neural network model to expand the discrimination ability to other applications.

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