IEEE Access
Multidisciplinary : Rapid Review : Open Access Journal

Received February 24, 2016, accepted March 12, 2016, date of publication March 30, 2016, date of current version April 29, 2016.

Digital Object Identifier 10.1109/ACCESS.2016.2547948

Application of Micro-Doppler Signatures for Estimation of Total Energy Expenditure in Humans for Walking/Running Activities

YOUNGWOOK KIM[1], (Senior Member, IEEE), SONGITA CHOUDHURY[2], AND HYOUN-JOONG KONG[3]

[1]Department of Electrical and Computer Engineering, Lyles College of Engineering, California State University at Fresno, Fresno, CA 93740, USA
[2]Division of Cardiology, Department of Cellular and Integrative Physiology, University of Nebraska Medical Center College of Medicine, Omaha, NE 68198-5850, USA
[3]Department of Biomedical Engineering, Chungnam National University College of Medicine and Chungnam National University Hospital, Daejeon 35015, South Korea

Corresponding authors: H.-J. Kong (e-mail: gongcop@cnu.ac.kr) and Y. Kim (e-mail: youngkim@csufresno.edu).

ABSTRACT We investigate the feasibility of estimating the total energy expenditure (TEE) of a human for walking/running activities with micro-Doppler signatures. Doppler radar can capture micro-Doppler signatures produced from limb motions when a human moves. As the micro-Doppler signatures contain information regarding limb movement, TEE can be estimated by analyzing the Doppler spectrogram. To understand the relationship between the TEE and micro-Doppler signatures, basic arm and leg motions are measured by the Doppler radar, whereas a respiratory gas analyzer measures the volume of exchanged respiratory gas (O_2 and CO_2) to obtain a reference TEE. The area of micro-Doppler signatures in a spectrogram has been suggested to serve as key information to estimate TEE. For the verification of the suggested approach, TEE was measured for seven human subjects, who performed walking and running activities on a treadmill at five different speeds using both the Doppler radar and the respiratory gas analyzer. We confirm that strong correlations exist between the micro-Doppler area and the TEE. Finally, a regression model for walking and running activities is developed for a person. Then, the model calculates the TEE under two scenarios, and we find that the estimation errors are 13.2% and 12.3%.

INDEX TERMS Human activity monitoring, indirect calorimetry, micro-Doppler, regression model, total energy expenditure.

I. INTRODUCTION

The demand for an accurate and reliable assessment of total energy expenditure (TEE) in humans has grown since the increase of chronic diseases due to the lack of regular exercise and high-calorie diets. Proper energy expenditure through physical activities can help not only in controlling weight but also in preventing obesity and many associated diseases such as stroke, hypertension, type-2 diabetes, coronary heart disease, and colon cancer. Because it is necessary to ensure that the recommended minimum calories are consumed by an individual on a daily basis, it is essential to track TEE using a precise and easy method when they exercise [1], [2].

TEE is composed of three major components: activity energy expenditure, diet-induced thermogenesis, and resting energy expenditure [3]. Energy expenditure can be most accurately measured by direct calorimetry, which is based on the measurement of the heat produced by a human in a sealed chamber. However, direct calorimetry is very impractical and expensive in a clinical setting. Therefore, several indirect approaches to estimate the human TEE have been proposed. Food intake and questionnaires are simple methods to calculate the TEE, although they suffer from high estimation errors. Alternatively, methodology utilizing instruments and sensors, such as mechanical pedometers, heart-rate recorders, accelerometers, calorimeters, and respiratory gas analyzers, have been researched. Although the respiratory gas analyzer is regarded as the gold standard for assessing the TEE in clinical settings, it requires special equipment that is expensive and bulky [2], [4].

Recent research has shown that the use of accelerometers could be an effective method because not only does a strong correlation exists between energy expenditure and accelerometer output in gait analysis [5], [6], but the sensor is relatively simple, portable, and accurate. Using the accelerometer output coming from body parts such as the waist, wrist, and ankle, the TEE is estimated using a regression model. However, the accelerometers need to be continuously attached to several parts of a body, which is quite cumbersome. Moreover, a data consistency issue exists because the estimation varies depending on the position and orientation of sensors. In addition, wearable sensors require batteries to be recharged. For these reason, several studies show that non-wearable type of sensors are preferable [7].

In this paper, we propose to estimate the TEE of a human subject for walking and running activities by remotely measuring the Doppler response using radar. The motion of a weffective and suppresses clutter while detecting a moving object. In particular, each part of the limb of a human body produces its own Doppler shift known as micro-Doppler. Micro-Doppler signatures have been extensively researched to analyze micro-motions of a radar target [8]–[10]. Especially for humans, human detection, gait analysis and human activity classification have been researched [11]–[14]. Therefore, we suggest the use of micro-Doppler signatures as the main component for estimating the TEE. The preliminary idea was presented by the authors in [15], but not fully investigated. This current research focuses on the investigation of the correlation between the TEE and micro-Doppler signatures. By measuring fundamental limb motions such as lifting an arm and a leg using Doppler radar, we study which characteristic of the micro-Doppler signatures are related to the TEE. We model the leg limb motion as a pendulum. Through changing the angle of the leg motion, we investigate the relationship between the micro-Doppler signatures and TEE. We suggest the area of the micro-Doppler signatures as physically meaningful features. For verification, measurements are carried out on human subjects when they walk and run on a treadmill because these activities are the most common and frequent exercises in daily lives. Based on the measurement, a regression model is constructed to estimate the TEE when Doppler information is provided. The maximum Doppler frequency and the frequency of a limb motion are extracted from the micro-Doppler signatures in the spectrogram. Finally, we estimate the TEE for the combination of walking and running activities using a trained model. The theory, measurements, data processing, and results are reported.

II. MICRO-DOPPLER SIGNATURES FROM HUMAN MOTIONS

When a human subject is illuminated by Doppler radar, an incident wave is reflected from the torso, head, limbs, and other parts. The Doppler shift from the torso determines the velocity of the subject, whereas those from the limbs produce a modulated signature in a spectrogram, as shown in Fig. 1. The signature is so unique that it could serve as a feature for detecting a human subject and even for classifying human activities [13], [14]. Because most energy expenditure occurs because of limb motions, we can possibly estimate the energy expenditure based on the Doppler signature of the limbs, especially for a walking/running activity.

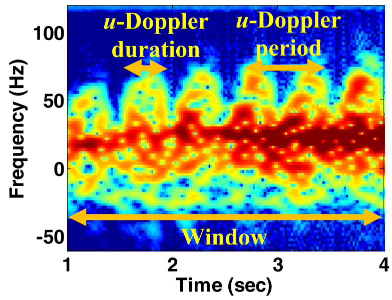

FIGURE 1. Doppler spectrum of a walking human.

In general, arm and leg motions are synchronized when a human walks or runs, and this make the micro-Doppler signatures overlap in the time domain in most cases. The micro-Doppler envelope has been reported to be mainly produced from leg motion owing to its longer length, making the micro-Doppler signatures from the arms exist inside the envelope [16]. In addition, the extent of limb motion is highly correlated because large leg strides cause large arm swings, and vice versa. Therefore, the micro-Doppler envelope itself can be an effective representation of the extent and frequency of the limb motion.

For the Doppler measurement, we use a continuous-wave Doppler radar, which is a low power, compact radar operating at a frequency of 7.25 GHz. It can detect a human subject from up to 20 m away. The average output power is −3 dBm. The system uses an onboard dipole-type antenna with a 60° beam width. The sensor output is a continuous coherent quadrature signal (I&Q) with a frequency that corresponds to the Doppler shift. This signal is converted into digital data using a data acquisition board (NI USB 6009, Austin, Texas) at a sampling rate of 1 *Ksps*. The sampled data are processed on a personal computer.

The time-varying behavior of the Doppler signal is investigated by a joint time–frequency analysis. We process the measured time-domain signal with a short-time Fourier transform [17].

$$S(t,f) = \int s(t') \cdot e^{-((t-t')/2\sigma^2)} \cdot e^{j2\pi f(t-t')} dt' = |\chi| \, e^{j\phi} \quad (1)$$

where $s(t)$ is the time-domain signal and σ is the width of the Gaussian window. In this study, the fast Fourier transform size is set to 256, and the overlapping time step is 10 ms, considering the velocity of human motions.

To extract the Doppler envelope, we process the spectrogram. Doppler signals have a higher signal-to-noise ratio than the Gaussian noise. Thus, we must set a boundary between the Doppler signal and noise to extract only the Doppler signal. As suggested in [14], we use the distribution of signal power to determine the threshold. The threshold is determined as the power when the Gaussian distribution from the noise is distorted, as shown in Fig. 2. After eliminating the noise,

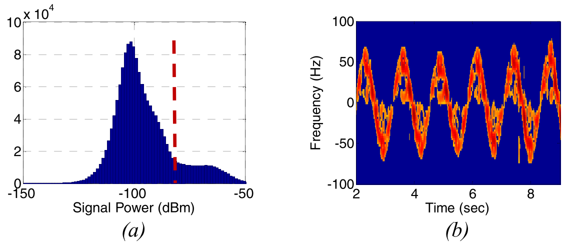

FIGURE 2. Doppler signal extraction using the distribution of signal power.

the Doppler envelope can be robustly detected. In the spectrogram, the velocity of target can be calculated from the Doppler frequency by $v = f_D \cdot c/2f_o$.

III. MEASUREMENT OF FUNDAMENTAL LIMB MOTION

To estimate the TEE based on the Doppler signatures, we need to extract a key feature of the micro-Doppler signatures that would serve as an independent variable for the estimation. The following measurements were carried out to understand the limb motion of a human and TEE. We expect the key feature to be obtained through these basic measurements. All human experimentation procedures were reviewed and approved by the Institutional Review Board, California State University at Fresno (IRB-0917-2014). Six participants (three males and three females) from the California State University and seven participants (three males and four females) from Seoul National University volunteered to participate in the study.

For the reference measurement of the TEE, we used a respiratory gas analysis system (Quark b^2, COSMED, Rome, Italy) during exercise and at rest. The energy expenditure was determined by continuously measuring the oxygen uptake (VO2) and carbon dioxide production (VCO2) in expired air. Given both VO2 and VCO2, the following equation can be used to precisely convert the gas exchanges to kilo-calorie per minute [18]:

$$\begin{aligned} &Energy\ expenditure\ (kcal/min) \\ &\quad = (VO2^{*}3.781) + (VCO2^{*}1.237) \end{aligned} \tag{2}$$

For ensuring accurate acquisition of the TEE, each subject took a break for approximately 5 min by sitting upright indoors before every measurement. The TEE in the following measurement includes the resting energy expenditure and the caloric cost due to the activity performed.

A. MEASUREMENT OF BASIC ARM- AND LEG-LIFTING MOTION

To investigate the correlation between the Doppler information obtained from the limb motion and the TEE, we performed basic measurements for arm/leg lifting. First, the fundamental arm and leg movements were measured in an indoor environment. The subjects participating in the measurement consisted of two males and two females. The participants sat on a stool 3 m from the radar. They raised one arm up to 90° and lowered it every 3 s for 5 min for a total of 100 times in the trials. The participants were positioned orthogonal to the radar, as shown in Fig. 3, so that the radial velocity of the arm and leg could be captured by the Doppler radar. To determine the effect of arm speed on the TEE, the movement was varied at three different levels from slow to medium to high at the subject's discretion. The total number of movements remained the same at 100 times. In addition, the participants were free to randomly alter both the speed and the frequency of arm motions and perform them 100 times. Each exercise was completed four times per person to validate data. During the activities, the participant wore a mask for the metabolic gas analysis system. The caloric cost of the exercises was measured by the system.

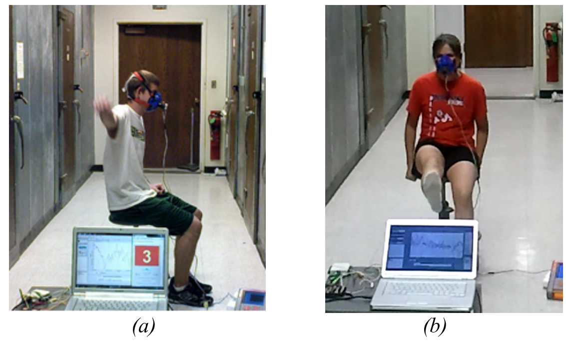

FIGURE 3. Measurement of (a) arm lifting and (b) leg lifting using respiratory gas analyzer and radar.

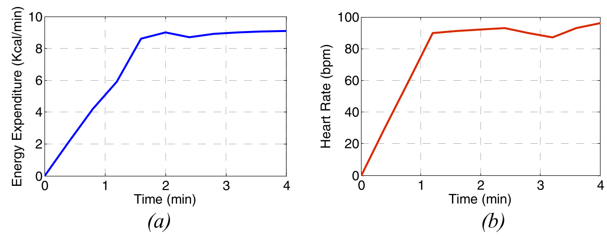

FIGURE 4. Example of measured (a) TEE per minute and (b) heart rate of basic limb lifting motion.

An example of measured TEE per minute relative to time is shown in Fig. 4(a). Because the cardiopulmonary machine produces 1-minute averaged values at the beginning in the measurement setting, we can observe that the TEE had a transient period of approximately 1 minute until it stabilized. The heat rate also showed a similar trend with the TEE in Fig. 4(b). The measured spectrograms for two different speeds of motion are shown in Fig. 5. A slow arm movement generated a low Doppler frequency (around 52 Hz) in longer time duration, and a fast arm movement caused a high Doppler frequency (around 107 Hz) within shorter time duration. The caloric cost results of the arm lifting from the metabolic gas analysis system are listed in Table 1. The values were averaged among four measurements for each person. The result indicates no significant influence from the speeds of the motions when the number of motions was fixed.

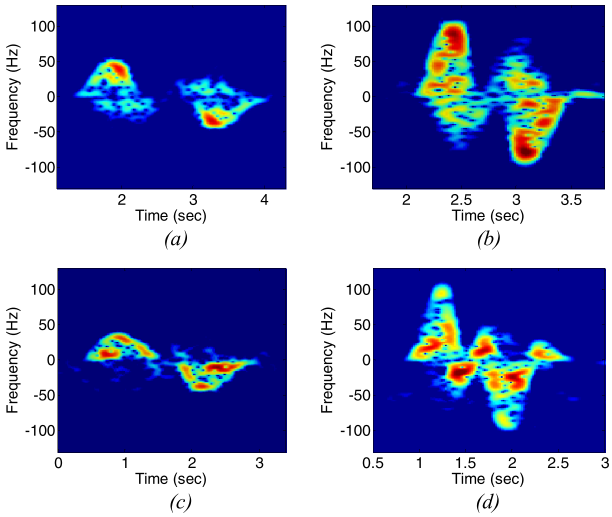

FIGURE 5. Measured spectrogram: (a) slow arm motion, (b) fast arm motion, (c) slow leg motion, and (d) fast leg motion.

TABLE 1. Measured TEE for arm lifting.

	Slow	Medium	Fast	Random
Subject 1 (female)	5 Kcal	5 Kcal	5 Kcal	5 Kcal
Subject 2 (female)	5 Kcal	5 Kcal	5 Kcal	5 Kcal
Subject 3 (male)	6 Kcal	6 Kcal	7 Kcal	6 Kcal
Subject 4 (male)	7 Kcal	7 Kcal	7 Kcal	7 Kcal

TABLE 2. Measured TEE for leg lifting.

	Slow	Medium	Fast	Random
Subject 1 (female)	9 Kcal	9 Kcal	8 Kcal	9 Kcal
Subject 2 (female)	8 Kcal	8 Kcal	8 Kcal	8 Kcal
Subject 3 (male)	7 Kcal	8 Kcal	7 Kcal	7 Kcal
Subject 4 (male)	10 Kcal	10 Kcal	10 Kcal	10 Kcal

The average caloric costs for leg lifting are listed in Table 2. The table also verifies that the caloric cost was not affected by the speed of the leg motions when the number of leg motions was fixed. Thus, we can conclude that the speed of motion has no strong correlation to the energy expenditure of the arm and leg lifting motions; however, the number of motions affects the TEE. This result is physically logical because the total work is calculated as a product of force and height displacement, which is not a function of time or speed. The maximum Doppler frequency and the Doppler duration become the key features in this measurement. However, we should note that the intensity of the three activities was categorized as easy; thus, the exercise did not reach the lactate threshold [19]. When the intensity of an exercise is above the lactate threshold, the caloric cost can nonlinearly change depending on the exercise intensity.

B. MEASUREMENT OF ARM-LIFTING ACTIVITY WITH DIFFERENT ANGLES

We measured the arm-swing activity that is a part of the actual motion of walking and running. The previous measurement was somewhat contrived because the arm and leg lifting was not natural in setting the lifting angle to 90°. In addition, the angle becomes negative owing to the back swing. As the swing speed changes, the angle also varies. The purpose of this measurement is to investigate the relationship between micro-Doppler signatures and energy expenditure when the swing angle is not set to 90°. We measured the Doppler signals and the TEE using a different swing angle θ. The swing time was not set; thus, the participant could naturally swing at his/her own pace. In this case, the swing angle represented the intensity of the exercise. The number of swings was fixed to 200 times to ensure that the time was sufficient to saturate the TEE. The measured maximum Doppler frequency and the TEE are listed in Tables 3 and 4 for the arm and leg motions, respectively. Example spectrograms are shown in Fig. 6.

TABLE 3. Measured TEE for the arm-swing movement.

Forward Angle (θ_1)	Back Angle (θ_2)	Maximum Doppler (Hz)	Period (s)	TEE per minute per swing (Kcal/min/swing)
30°	12°	72.4	1.24	0.0397
47°	18°	158.5	1.22	0.0529
76°	34°	194.2	1.27	0.0648

TABLE 4. Measured TEE for the leg-swing movement.

Forward Angle (θ_1)	Back Angle (θ_2)	Maximum Doppler (Hz)	Period (s)	TEE per minute per swing (Kcal/min/swing)
21°	16°	78.3	1.1421	0.0398
30°	24°	174.2	1.0625	0.0551
42°	35°	232.8	1.0714	0.0773

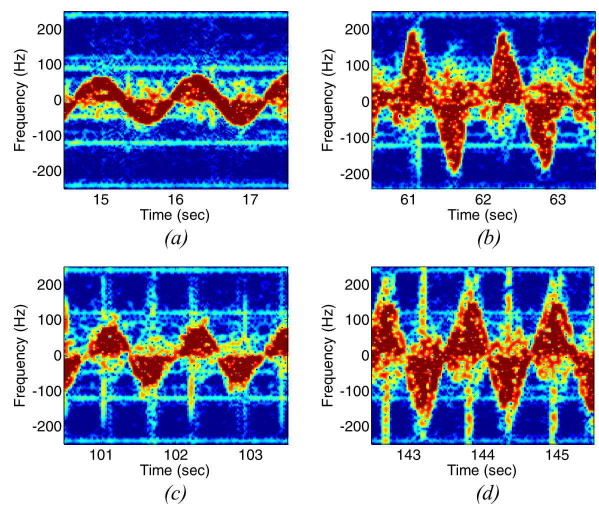

FIGURE 6. Measured spectrogram: (a) 15° arm motion, (b) 80° arm motion, (c) 15° leg motion, and (d) 45° leg motion.

From the measurements, we observed that the maximum Doppler frequency and TEE increased with the limb swing angle. In addition, a nonlinear relationship existed between the maximum Doppler and TEE. In terms of the period, the relationship was not deterministic.

IV. MODELING OF TEE FROM MICRO-DOPPLER SIGNATURES OF HUMAN LIMB MOTION

Based on the previous measurements, we proposed to use the micro-Doppler area as a main feature to estimate the TEE per minute because the area is calculated based on the maximum Doppler frequency, Doppler duration, and frequency of the limb motion when the time window is given. Therefore, the area extracted from a spectrogram is assumed to be a function of the TEE. The function can be linear or nonlinear depending on the activity type and its intensity under which the human subject is performing.

To verify and expand this idea, we modeled the limb movement as a pendulum and calculated the expected Doppler shift depending on the angular velocity. In the first measurement case presented in Section III *A*, assuming that the angular velocity is constant when a human swings its arms and neglecting a short duration for acceleration, the radial velocity relative to the radar is calculated as

$$v = r\omega \cdot \cos(\omega t) \tag{3}$$

where r corresponds to the limb length and ω is the angular velocity of the limb. The expected Doppler shift depending on ω while a limb is lifted to 90° and brought back to the original position is shown in Fig. 7(a). The micro-Doppler area for the quarter periods is calculated by

$$Area_{MicroD} = \int_{0}^{\pi/2\omega} r\omega \cdot \cos(\omega t)dt = r \tag{4}$$

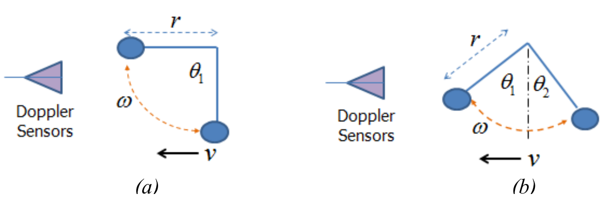

FIGURE 7. Limb model for the calculation of Doppler area, (a) when the arm lift is 90 degrees, and (b) when the arm lift is non 90 degrees.

This equation indicates that the estimated TEE depends only on r and is not a function of ω. This result implies that the micro-Doppler area can be a valid feature because the TEE should remain the same for the basic limb-lifting motion regardless of the arm speed, as listed in Tables 1 and 2. This result is physically reasonable because total work is determined only by the force and displacement that were constant in the measurement. For the verification, the calculated area of the micro-Doppler and TEE versus the speed of the limb is shown in Fig. 8(a) and (b). In this case, approximately a constant (linear) relationship is observed between the micro-Doppler area and TEE. However, the relationship might be nonlinear for different human activities.

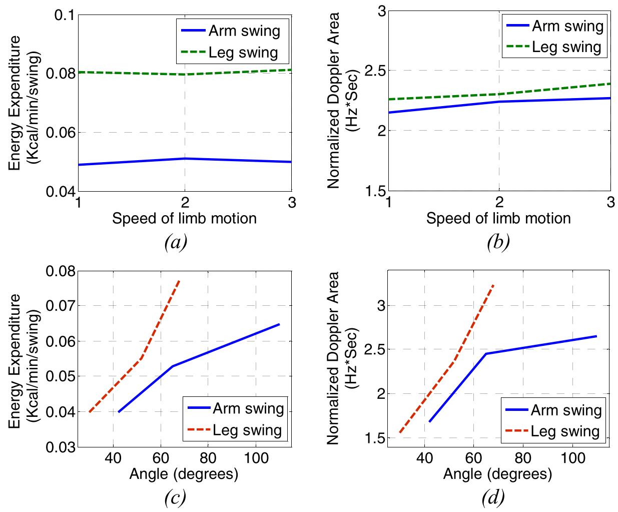

FIGURE 8. Measured TEE and micro-Doppler area, (a) TEE/min/swing of 90° arm and leg lifting for the arm, (b) MicroDoppler area for 90° arm and leg lifting for the arm, (c) TEE/min/swing of non-90° arm and leg lifting, and (d) MicroDoppler area for non-90° arm and leg lifting for the arm.

For the second measurement presented in Section III B, the lifting angle was varied as Fig. 7(b); thus, the Doppler area was calculated as follows:

$$Area_{MicroD} = \int_{0}^{\theta_1/\omega} r\omega \cdot \cos(\omega t)dt = r \cdot \sin(\theta_1) \tag{5}$$

From (5), the relationship between the micro-Doppler area and TEE becomes nonlinear because the total work done by the lifting motion should be proportional to the height displacement $r \cdot (1 - \cos(\theta_1))$. However, the two functions (Eq. (5) and $r \cdot (1 - \cos(\theta_1))$) have similar shape and monotonically increase with respect to θ_1. We have plotted the calculated the area of each micro-Doppler and TEE per minute versus the limb angle and shown it in Figs. 8(c) and 8(d). The micro-Doppler area and the TEE per minute show a strong correlation with the increase in the limb angle. Even though the nonlinear relationship can be confirmed by the graph, the TEE per minute can be expressed as a function of the micro-Doppler area. From the results of the two measurements, we set the micro-Doppler area as a key feature to estimate the TEE per minute.

V. MEASUREMENT OF TEE IN HUMANS FOR WALKING AND RUNNING ACTIVITIES ON TREADMILL

A. INVESTIGATION AND MODELING OF HUMAN LIMB MOTION

We study the limb motion in practical walking and running activities to investigate the relationship between the TEE and micro-Doppler signatures. The angle of the limb motion is not 90°, and the arm moves backward with respect to the torso. Furthermore, rather than the arm motion, the leg motion occupies a significant part in both micro-Doppler and energy expenditure. Usually, micro-Doppler signatures from the legs override those of the arms. Thus, to model the limb motion, we must investigate how the limb-motion frequency, limb angle, and angular velocity vary relative to the speed of a human, through measurements.

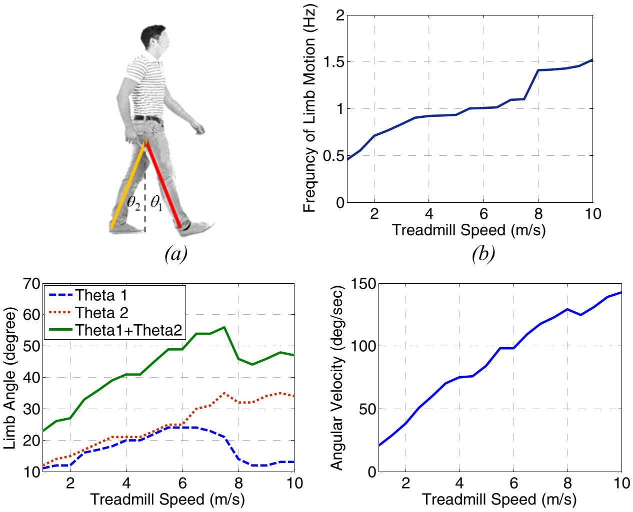

FIGURE 9. **(a) Limb model of walking/running activity. (b) Frequency of limb motion versus treadmill speed. (c) Limb angle versus treadmill speed. (d) Angular velocity versus treadmill speed.**

From the measurements obtained using a treadmill, example relationships are shown in Fig. 9. The frequency of the limb motion increases almost linearly with the treadmill speed, as shown in Fig. 9(b). A rapid change occurs at the speed of 8 m/s when the human subject starts to run. During running, the stride decreases, whereas the frequency of the limb motion increases. Fig. 9(c) shows that θ_1 and θ_2 increase with the treadmill speed while walking. When a human starts running, θ_1 decreases compared with when walking, whereas θ_2 keeps on increasing because the kinematics of walking and running are different in that running involves more vertical movement. However, the Doppler signatures come from θ_2, which is larger. The angular velocity of the leg also displays an approximately linear relationship, as shown in Fig. 9(d).

Based on the previous observation, the leg swing is modeled as symmetrical, and the maximum angle is a function of angular velocity ω to calculate the Doppler frequency. In this case, the Doppler area is calculated by (6) by assuming that the limb angle is modeled as a function of the leg angular velocity. When θ_1 and θ_2 are the same as θ

$$\begin{aligned} Area_{MicroD} &= \int_{-\theta(\omega)/\omega}^{\theta(\omega)/\omega} r \cdot \omega \cdot \cos(\omega t) dt \cdot \\ &= r \cdot \left(\sin(\omega \cdot \frac{\theta(\omega)}{\omega}) + \sin(\omega \cdot \frac{\theta(\omega)}{\omega}) \right) \\ &= 2r \cdot \sin\left(\theta(\omega)\right) = 2r \cdot \sin\left(\omega \cdot T_p\right) \end{aligned} \tag{6}$$

Here, T_p is the Doppler period. Angular velocity ω can be calculated by the maximum Doppler frequency using (3). Since $\theta = \omega \cdot T_p$, we have

$$Area_{MicroD} = 2r \cdot \sin\left(\omega \cdot T_p\right) = 2r \cdot \sin\left(\frac{f_{D\max} \cdot c}{2 f_c \cdot r} \cdot T_p\right) \tag{7}$$

The micro-Doppler area thus depends on the maximum Doppler frequency $f_{D\max}$ and the period of the Doppler signature when r is given. We observe that the Doppler area is not affected by ω. Now, when a certain human activity is consistent within a certain time window (T_D), the TEE can be modeled as

$$\begin{aligned} TEE &= Ac \cdot Sub \cdot K(T_p) \cdot Area_{MicroD} \cdot N \\ &= Ac \cdot Sub \cdot K(T_p) \cdot Area_{MicroD} \cdot \frac{T_D}{T_p} \\ &= Ac \cdot Sub \cdot K(T_p) \cdot 2r \cdot \sin\left(\frac{f_{D\max} \cdot c}{2 f_c \cdot r} \cdot T_p\right) \cdot \frac{T_D}{T_p} \end{aligned} \tag{8}$$

Here, Ac is a constant related to the activity type, Sub is a factor related to the individual human subject, and $K(T_p)$ is a factor associated with the intensity of the activity depending on the period of activity. N is the total number of micro-Doppler signatures within T_D, f_c is the carrier frequency of the Doppler radar, and $f_{D\max}$ is the maximum Doppler shift in the spectrogram. We should note that $K(T_p)$ is a constant for the basic arm- and leg-lifting motions because the intensity of the activity is not severe. However, the TEE would nonlinearly increase when the exercise reaches the lactate threshold. Therefore, including the factor that varies depending on the intensity of activity is reasonable. The relationship between the micro-Doppler area and TEE could be nonlinear and complex depending on the activity type and its intensity. Thus, the equation for the estimation of the TEE is generally formalized as

$$\begin{aligned} TEE &= f_1(Area_{MicroD}) \cdot N \\ &= f_2(Ac, Sub, r, T_p, f_{D\max}, T_D) \end{aligned} \tag{9}$$

This equation shows that the TEE is a function of the measured maximum Doppler frequency, micro-Doppler period, and total time duration. Therefore, instead of calculating the micro-Doppler area, the two Doppler features, namely, maximum Doppler frequency and frequency of the micro-Doppler in the spectrogram, need to be estimated. The maximum Doppler frequency and frequency of periodic signature in the spectrogram are more convenient and robust to identify. However, they suffer from the limitation in that the proposed method is only valid for activities in which the energy expenditure is mainly contributed by the limbs with a radial velocity. The orthogonal movement relative to the radar would not be captured by the Doppler radar.

B. *INVESTIGATION OF TEE AND MICRO-DOPPLER SIGNATURES OF A HUMAN*

To explore the relationship between the Doppler frequency and TEE, the participants were simultaneously measured by the radar and respiratory gas analyzer as the treadmill speed varied. During these exercises, the subject was always located within the detection range in front of the radar to receive the Doppler signal. The measurement setup is shown in Fig 10(a). Because a human torso does not produce a significant Doppler shift in the treadmill, micro-Doppler signatures from a limb motion can be easily identified. Seven participants (four males and three females) from Seoul National University volunteered to participate in the study. Prior to the measurement, the physical information of the participants, including age, height, weight, and sex, were recorded because this information is known to be a factor that influences the resting energy expenditure in the TEE [20]. The physical characteristics of the subjects are listed in Table 5.

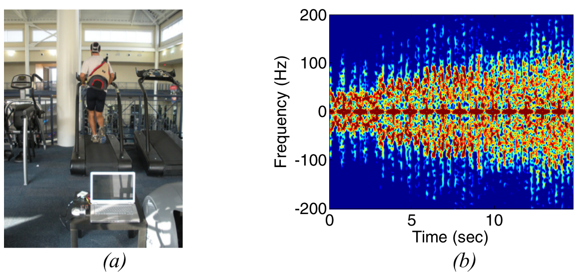

FIGURE 10. (a) Measurement setup at the treadmill and (b) measured spectrogram.

TABLE 5. Physical characteristics of subjects.

	Female (n = 3)	Male (n = 4)
Age (years)	28.3 ± 5.1	30.2 ± 9.2
Height (cm)	161.7 ± 5.9	177.1 ± 5.6
Weight (kg)	51.3 ± 4.0	72.8 ± 9.5
BMI (kg/m^2)	19.6 ± 0.3	23.1 ± 1.8

Each human subject ran for 20 min, and the treadmill speed was set to 3, 5, 7, 9, and 11 km/h for 4 min. The Bruce protocol [21] is the most commonly used; however, we did not employ it because it changes the slope as well as the speed of the treadmill to control the intensity of the activity. We only controlled the speed of the treadmill to vary the exercise intensity. The measured spectrogram from one subject is shown in Fig. 10(b) as an example. We observe that the maximum Doppler frequencies were 41.6 Hz at 3 km/h, 68.9 Hz at 5 km/h, 96.2 Hz at 7 km/h, 110.6 Hz at 9 km/h, and 141.8 Hz at 11 km/h. As the speed increased, the observed maximum Doppler frequency increased approximately in a linear manner. The recorded VO2 and VCO2 are shown in Fig. 11(a), and the TEE per minute calculated based on (2) is shown in Fig. 11(b). We observe that the recorded VO2 and VCO2 were strongly correlated, and they increased by a step with a lagging time. The TEE and TEE per minute relative to time are shown in Figs. 11(c) and 11(d). We observe similar phenomena for all seven participants.

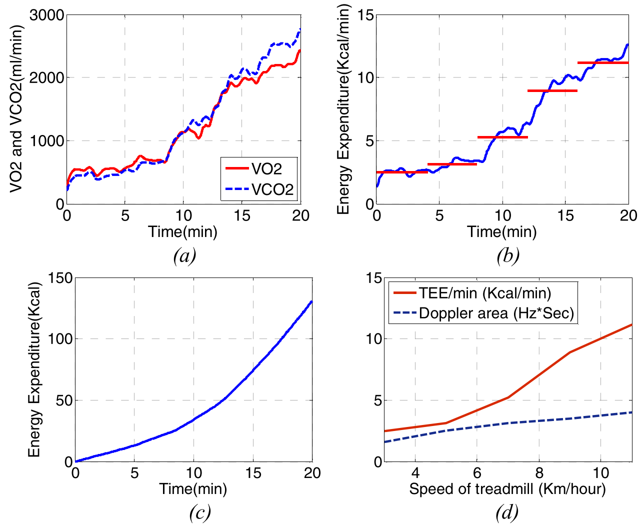

FIGURE 11. (a) Measured VO2 and VCO2 after low-pass filtering. (b) Measured TEE per minute and the averaged value for five steps. (c) Measured TEE. (d) Treadmill speed versus TEE per minute and sin $(f_{D\max} \cdot c \cdot T_p/(2f_c \cdot r))\,/T_p$ of the participant.

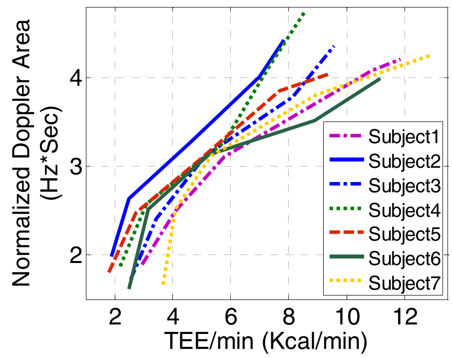

FIGURE 12. TEE per minute and sin $(f_{D\max} \cdot c \cdot T_p/(2f_c \cdot r))\,/T_p$ of the seven participants.

From (8), we can use the maximum Doppler and its period, instead of the micro-Doppler area, to estimate the TEE. Finally, the relationship between $\sin(f_{D\max} \cdot c \cdot T_p/(2f_c \cdot r))/T_p$ and TEE per minute for each participant are shown in Fig. 12, verifying that the TEE per minute is strongly correlated with the micro-Doppler area, and they have a nonlinear relationship. Each participant has a specific curve. If a nonlinear model is constructed based on several measurements, then the TEE can be estimated using the micro-Doppler area.

VI. ESTIMATION OF ENERGY EXPENDITURE DURING WALKING/RUNNING USING A REGRESSION MODEL

On the basis of the previous results, we estimated the TEE of a participant who performed two different protocols. Because the relationship between the area of the micro-Doppler and the TEE per minute was determined for five points, as shown in Fig. 11, the curve could be interpolated with a regression model using a smoothing spline that consisted of

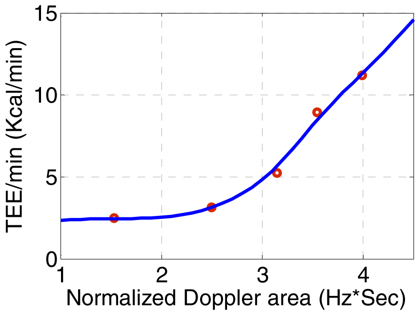

FIGURE 13. Regression between the micro-Doppler area and TEE for the seventh participant.

piecewise polynomial. The fitted curves are shown in Fig. 13 using a smoothing parameter of 0.99. The curve would be used to estimate the TEE per minute when the Doppler area is given. For the verification of the model, the TEEs for two experiment protocols were estimated.

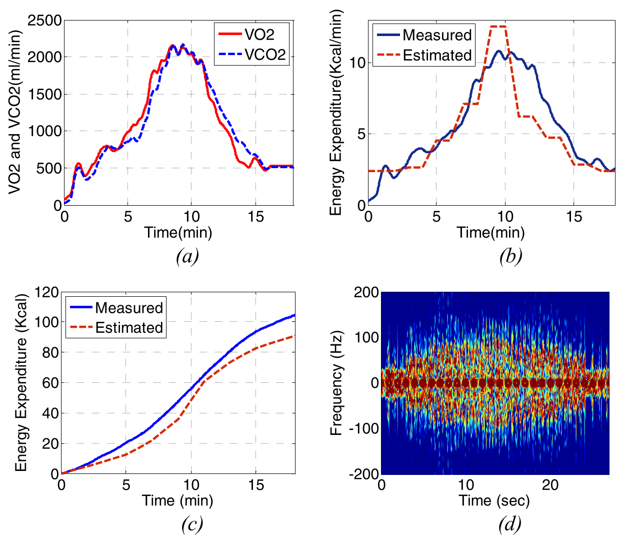

FIGURE 14. (a) Measured VO2 and VCO2 after low pass filtering. (b) Measured TEE per minute and the averaged value for five steps, (c) Measured TEE. (d) Measured spectrogram.

The first protocol increased the treadmill speed and gradually decreased it every 2 min for 18 min. The speeds were 2, 4, 6, 8, 10, 8, 6, 4, and 2 km/h. The measured VO2 and VCO2 are shown in Fig. 14(a). The measured TEE per minute is shown in Fig. 14(b), and the TEE relative to time is shown in Fig. 14(c). The final TEE was 104.6 Kcal. We observe that the TEE per minute also gradually changed with the same pattern as that of the intensity of the activity. The spectrogram of a 3-s cropped example for each speed is shown in Fig. 14(d). We extracted the maximum micro-Doppler frequency, limb-motion frequency, and time-window size where the limb frequency persisted from the spectrogram. Using the developed regression model, we estimated the TEE per minute and TEE relative to time. They are shown in Figs. 14(b) and 14(c) by the red dotted graph. We can observe that a delay existed between the measured and estimated TEE per minute. The estimated TEE was 90.8 Kcal. The TEE estimation error was 13.2%.

The second protocol emulated a dynamic exercise by increasing, decreasing, and increasing the speed again. Between the measurements of the two protocols, the participant took a break for at least 10 min to ensure that a normal heart rate returned. The speeds were varied five times every 4 min, resulting in a total of 20 min. The speeds were 2, 6, 10, 4, and 8 km/h. The measured VO2 and VCO2 are shown in Fig. 15(a). The measured TEE per minute is shown in Fig. 15(b), and the TEE relative to time is shown in Fig. 15(c). The final TEE was 127.5 Kcal. We observe that the TEE per minute also gradually changed with the same pattern as that of the intensity of the activity. We extracted the maximum micro-Doppler frequency and the time duration when the frequency persisted from the spectrogram shown in Fig. 15(d). Using the interpolation model, we estimated the TEE per minute and the TEE relative to time, which are shown in Figs. 15(b) and 15(c), respectively. The estimated TEE was 111.8 Kcal. The TEE estimation error was 12.3%.

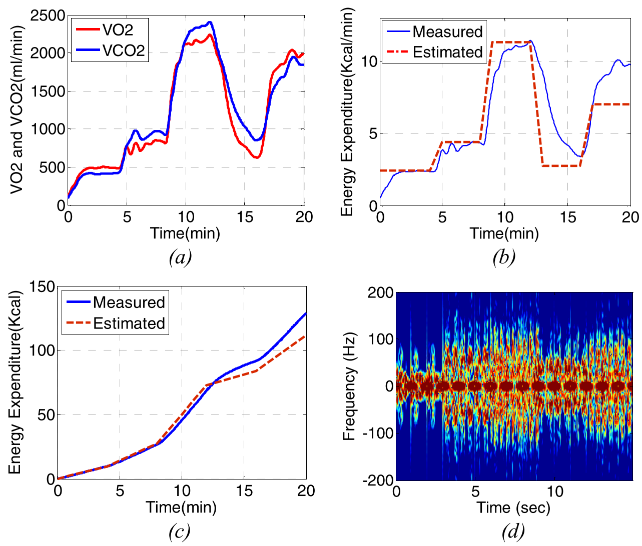

FIGURE 15. (a) Measured VO2 and VCO2 after low-pass filtering. (b) Measured TEE per minute and the averaged value for five steps. (c) Measured VO2 and VCO2 after low pass filtering. (d) Measured TEE per minute and the averaged value for five steps.

VII. DISCUSSION

The purpose of this study was to investigate the feasibility of estimating TEE using a radar system. Rather than using sensors to attach to a human body, the authors proposed an alternate method for remote estimation of human TEE based on micro-Doppler analysis. The results of the present study shows that similar performance in the estimation of energy expenditure was obtained compared with the accelerometer-based method reported by Lester *et al.* [22].

However, few points need to be addressed. This study suffers from limitations that come from the small sample size used to build a regression model. If the treadmill speed increases with more steps, the estimation could become more accurate by avoiding extrapolation. In addition, to construct a general regression model and not for a specific subject, a number of human subjects with diverse sex, age, weight, and height groups should be investigated. The other limitations of this study include the radar setup used. It did not capture vertical motions that are a significant part of energy expenditure, especially for the running activity. Further, multiple-sensor topology would be necessary to measure the three-dimensional movement. As far as the micro-Doppler measurement is concerned, occasionally, it was not clear in identifying the maximum value of the micro-Doppler signatures for the running activity due to their spread, whereas it was clearly detected in the walking activity. Higher carrier frequency radar with a higher analog-to-digital sampling rate is desired for robust measurement.

VIII. CONCLUSION

We proposed to estimate the TEE by performing remote measurement of the Doppler response of a human performing walking or running activities using radar. From several measurements, we found that the micro-Doppler area played a significant role in estimating the TEE because a strong correlation exists between them. Based on the obtained data of when a human subject walks/runs on a treadmill at different speeds, a regression model was constructed so that the TEE could be estimated when the micro-Doppler area is given. The area was approximately calculated using the maximum Doppler frequency and the period of the micro-Doppler signatures. For the two verification protocols, the TEE estimation errors were 13.2% and 12.3%.

REFERENCES

[1] T. C. Wong, J. G. Webster, H. J. Montoye, and R. Washburn, "Portable accelerometer device for measuring human energy expenditure," *IEEE Trans. Biomed. Eng.*, vol. BME-28, no. 6, pp. 467–471, Jun. 1981.

[2] C. V. C. Bouten, K. T. M. Koekkoek, M. Verduin, R. Kodde, and J. D. Janssen, "A triaxial accelerometer and portable data processing unit for the assessment of daily physical activity," *IEEE Trans. Biomed. Eng.*, vol. 44, no. 3, pp. 136–147, Mar. 1997.

[3] D. C. Nieman *et al.*, "Validation of Cosmed's FitMate in measuring oxygen consumption and estimating resting metabolic rate," *Res. Sports Med., Int. J.*, vol. 14, no. 2, pp. 89–96, Apr. 2006.

[4] H. A. Haugen, L.-N. Chan, and F. Li, "Indirect calorimetry: A practical guide for clinicians," *Nutrition Clin. Pract.*, vol. 22, no. 4, pp. 377–388, Aug. 2007.

[5] K. Dongwoo and H. C. Kim, "Activity energy expenditure assessment system based on activity classification using multi-site triaxial accelerometers," in *Proc. IEEE Eng. Med. Biol. Soc.*, Aug. 2007, pp. 2285–2287.

[6] S. W. Su, L. Wang, B. G. Celler E. Ambikairajah, and A. V. Savkin, "Estimation of walking energy expenditure by using support vector regression," in *Proc. 27th Annu. Int. Conf. Eng. Med. Biol. Soc. (IEEE-EMBS)*, 2005, pp. 3526–3529.

[7] E. E. Stone and M. Skubic, "Fall detection in homes of older adults using the Microsoft Kinect," *IEEE J. Biomed Health Informat.*, vol. 19, no. 1, pp. 290–301, Jan. 2015.

[8] B. Yuan, Z. Chen, and S. Xu, "Micro-Doppler analysis and separation based on complex local mean decomposition for aircraft with fast-rotating parts in ISAR imaging," *IEEE Trans. Geosci. Remote Sens.*, vol. 52, no. 2, pp. 1285–1298, Feb. 2014.

[9] P. Suresh, T. Thayaparan, T. Obulesu, and K. Venkataramaniah, "Extracting micro-Doppler radar signatures from rotating targets using Fourier–Bessel transform and timeŰfrequency analysis," *IEEE Trans. Geosci. Remote Sens.*, vol. 52, no. 6, pp. 3204–3210, Jun. 2014.

[10] P. van Dorp and F. C. A. Groen, "Human walking estimation with radar," *IEE Proc.-Radar, Sonar Navigat.*, vol. 150, no. 5, pp. 356–365, Oct. 2003.

[11] Y. Ding and J. Tang, "Micro-Doppler trajectory estimation of pedestrians using a continuous-wave radar," *IEEE Trans. Geosci. Remote Sens.*, vol. 52, no. 9, pp. 5807–5819, Sep. 2014.

[12] C. Karabacak, S. Z. Gurbuz, A. C. Gurbuz, M. B. Guldogan, G. Hendeby, and F. Gustafsson, "Knowledge exploitation for human micro-Doppler classification," *IEEE Geosci. Remote Sens. Lett.*, vol. 12, no. 10, pp. 2125–2129, Oct. 2015.

[13] D. Tahmoush and J. Silvious, "Radar micro-Doppler for long range front-view gait recognition," in *Proc. IEEE 3rd Int. Conf. Biometrics, Theory, Appl. Syst.*, Sep. 2009, pp. 1–6.

[14] Y. Kim and H. Ling, "Human activity classification based on micro-Doppler signatures using a support vector machine," *IEEE Trans. Geosci. Remote Sens.*, vol. 47, no. 5, pp. 1328–1337, May 2009.

[15] S. Choudhury and Y. Kim, "Application of Doppler radar for the estimation of total energy expenditure of a human subject," in *Proc. IEEE AP-S/URSI*, Chicago, IL, USA, Jul. 2012.

[16] S. S. Ram, C. Christianson, Y. Kim, and H. Ling, "Simulation and analysis of human micro-Dopplers in through-wall environments," *IEEE Trans. Geosci. Remote Sens.*, vol. 48, no. 4, pp. 2015–2023, Apr. 2010.

[17] V. C. Chen and H. Ling, *Time-Frequency Transforms for Radar Imaging and Signal Analysis*, 1st ed. Norwood, MA, USA: Artech House, Jan. 2002.

[18] M. Elia and G. Livesey, "Energy expenditure and fuel selection in biological systems: The theory and practice of calculations based on indirect calorimetry and tracer methods," *World Rev. Nutrition Dietetics*, vol. 70, pp. 68–131, 1992.

[19] J. L. Dantas and C. Doria, "Detection of the lactate threshold in runners: What is the ideal speed to start an incremental test?" *J. Human Kinetics*, vol. 45, no. 1, pp. 217–224, Mar. 2015.

[20] M. Malavolti *et al.*, "A new device for measuring resting energy expenditure (REE) in healthy subjects," *Nutrition, Metabolism Cardiovascular Diseases*, vol. 17, no. 5, pp. 338–343, Jun. 2007.

[21] T. A. Strzelczyk, D. A. Cusick, P. B. Pfeifer, M. D. Bondmass, and R. J. Quigg, "Value of the Bruce protocol to determine peak exercise oxygen consumption in patients evaluated for cardiac transplantation," *Amer. Heart J.*, vol. 142, no. 3, pp. 466–475, Sep. 2001.

[22] J. Lester, C. Hartung, L. Pina, R. Libby, G. Borriello, and G. Duncan, "Validated caloric expenditure estimation using a single body-worn sensor," in *Proc. 11th Int. Conf. Ubiquitous Comput.*, Orlando, FL, USA, 2009, pp. 225–234.

YOUNGWOOK KIM (S'03–M'08–SM'14) received the B.S. degree in electrical engineering from Seoul National University, South Korea, in 2003, and the M.S. and Ph.D. degrees in electrical and computer engineering from the University of Texas at Austin, USA, in 2005 and 2008, respectively. He is currently an Associate Professor with the Department of Electrical and Computer Engineering, California State University, Fresno. His research interests are in the area of radar signal processing, antenna design, and RF electronics. He has authored over 50 technical papers. His primary topic of research lies in radar target classification with machine-learning techniques, remote detection, monitoring, and analysis of human motions using EM wave. He is a recipient of the Provost's New Faculty Award from California State University, the A.D. Hutchison Fellowship from the University of Texas at Austin, and the National IT Fellowship from the Ministry of Information and Communication, South Korea.

SONGITA CHOUDHURY received the B.S. degree in electrical engineering from California State University, Fresno, in 2011. She is currently pursuing the M.D. degree with the University of Nebraska Medical and the Ph.D. degree with the Department of Cellular and Integrative Physiology under the guidance of Dr. T. Porter. Her current research interests include the ranostic ultrasound, ultrasound contrast agents, and medical devices. She is a member of Tau Beta Pi and Eta Kappa Nu.

HYOUN-JOONG KONG received the B.S. degree in electrical engineering and the M.S. and Ph.D. degrees in biomedical engineering from Seoul National University, Seoul, South Korea, in 2000, 2003, and 2009, respectively. From 2001 to 2009, he was a Research Member with the Department of Biomedical Engineering, Seoul National University Hospital (SNUH), Seoul, where the major research activities were the development of electronic instrumentation and intelligent algorithm for medical and biological applications including telemedicine, telemetric urodynamic system, electronic stethoscope, and retinal image analysis. From 2009 to 2012, he was a Post-Doctoral Researcher with the Department of Anesthesiology and the Pain Medicine and the Department of Plastic and Reconstructive Surgery, SNUH. From 2013 to 2016, he was a Research Assistant Professor with the Office of Hospital Information, SNUH, where the major research interests were medical informatics and hospital information system. He joined as a Faculty Member with the Division of Medical Informatics, College of Medicine, Chugnam National University Hospital, in 2016, where he is currently an Assistant Professor. He is a member of the Korea Society of Medical and Biological Engineering and the Korean Society of Medical Informatics.