Estimation of Indoor Physical Activity Level Based on Footstep Vibration Signal Measured by MEMS Accelerometer in Smart Home Environments

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Abstract. A smart home environment equipped with pervasive networked-sensors enables us to measure and analyze various vital signals related to personal health. For example, foot stepping, gait pattern, and posture can be used for assessing the level of activities and health state among the elderly and disabled people. In this paper, we sense and use footstep vibration signals measured by floor-mounted, MEMS accelerometers deployed tangent to wall sides, for estimating the level of indoor physical activity. With growing concern towards obesity in older adults and disabled people, this paper deals primarily with the estimation of energy expenditure in human body. It also supports the localization of footstep sources, extraction of statistical parameters on daily living pattern, and identification of pathological gait pattern. Unlike other sensors such as cameras or microphones, MEMS accelerometer sensor can measure many biomedical signatures without invoking personal privacy concerns.

Key words: Caloric energy expenditure estimation, Indoor activity detection, Localization of footstep source, MEMS accelerometer, Personal health care, Sensor networks, Smart homes.

1 Introduction

To promote personal health for the elderly and disabled, and to support independent living at reasonable cost, it is agreeable that a home based sensor network environment that collects various data and vital signs of the residents is a promising approach. In a smart home environment with pervasive intelligence, various vital signals can be measured by sensors such as vision sensor, microphone, electrode, pressure sensor and accelerometer, and can be processed to extract some information on mental and physical states of the resident. Then, the processed data and information can be used to diagnose their health conditions by medical doctors and caregivers.

Chronic diseases, such as diabetes, cardiovascular disease, respiratory disease, obesity, cancer and Alzheimer's disease, are currently leading causes of severe damage among the elderly and disabled people as well as the normal people in the United States. Table 1 shows leading causes of death due to chronic disease. Research on chronic diseases reports that the most common chronic conditions are high blood pressure, high cholesterol, arthritis and respiratory diseases like emphysema [13]. In addition, research on personal healthcare supports that increasing the level of physical activity decreases the risk of onset and developing the chronic illnesses [6][11].

A well-established smart home environment enables us to develop a sensor network-based chronic care management model, which makes it possible to prevent, delay, detect and control chronic diseases. This could be achieved by continuously measuring chronic-related outcomes and by periodically prescribing exercises to control the level of physical activity.

The pattern on the level of outdoor activity fluctuates with environmental changes on temperature, humidity, rainfall, and daylight length since the amount of time spent on outdoor leisure depends on the weather conditions [6][8][12]. The seasonal fluctuation of the outdoor physical activity affects health-related outcomes of the elderly and disabled people [6][8][9]. For example, the studies in [6][8][9][12] on the seasonal variation of blood cholesterol show that the seasonal variation of total physical activity levels in metabolic equivalent (MET)-hour/day is the range of 2.0-2.4 $MET \cdot h \cdot d^{-1}$ in men and women ages 20-70 year [8]. In the northern regions of USA, average total cholesterol peaks in men during the month of December and in women during the month of January when physical activity levels are lower [9]. This suggests that fluctuations on levels of physical activity across seasons may influence health-related outcomes positively or negatively [6][8]. Since the health-related outcomes fluctuates with environmental variations on seasons, controlling level of indoor physical activity adapting to conditions such as weather is conducive to maintaining better health state of the elderly and disable people.

For estimating levels of the indoor physical activity, the vital signs of walking (footsteps), gait pattern and posture are frequently measured via a sensor network-based environment. However, some sensors such as vision sensor and microphone may entail privacy problem despite high security levels of the sensor network itself.

For sensing user location in a smart home environment, we have adapted an unencumbered approach we refer to as smart floor localization and tracking [24]. This approach requires raised flooring (residential grade raised floor) and uses a grid of pressure sensors conditioned for use with psi of human body weight. The smart floor has been deployed at the Gator Tech Smart House (GTSH) [22][23], a real world house that is an assistive environment for R&D in use of pervasive technology for successful aging. The smart floor approach has several drawbacks including high deployment cost (due to required labor for wiring and connecting the sensors), and high complexity of the wiring and connections. The smart floor is also incapable of locating or discerning the locations of more than one user in the house.

In this paper, MEMS accelerometer sensors are considered as a superior technology for location sensing and estimation of indoor physical activities. The MEMS accelerometers are mounted on the floor along side the walls - a constraint that simplifies deployment and that requires no home modifications. The MEMS accelerometers are networked and connected to the smart home computer using the Atlas sensor platform technology [20][21]. The sensors measure vibrations induced by physical activities such as walking, opening and closing doors, washing, eating a meal, cooking, sleeping and watching TV, among other activities. The output of the accelerometers includes various noises caused by not only home appliances such as washing machine and refrigerator with rotator but also vehicles passing by the house. Also, TV and radio may produce induced noise by loud sound pressure. Table 2 shows some noise sources and spectral bands in a smart home environment.

The level of human activity can be manifested by the level of energy expenditure. That is, high level of human activity means that the energy expenditure should be large. For example, a brisk exercise generates forceful large swing motions in the legs, which results in footstep vibration with large magnitude. Therefore, levels of human activity can be estimated from the footstep vibration signal. Table 4 shows energy expenditure for some activities of daily living.

With the purpose of developing a smart home-based healthcare system for the elderly and disabled people, this paper deals with the estimation of energy expenditure, localization of footstep sources, extraction of statistical parameters on daily living pattern, and identification of pathological gait pattern, based on connected MEMS sensors, which measures floor vibration induced by footstep on human activity. The purpose of this study is to use a MEMS sensor for localizing footstep source and computing correlation between the level of energy expenditure and the level of floor vibration. In this paper, a footstep vibration is modeled as a seismic signal composed of P-wave and S-wave, and mathematical analysis for localization is conducted based on a least square error method that fits a line of direction, in which 3 projected signals on acceleration to the x-axis, the y-axis and the z-axis are used for line fitting.

Table 5 shows some health-related information and outcomes easily obtainable from footstep localization and tracking. For example, a continuous monitoring based on tracking makes it possible to promptly detect a fall of a frail elderly person.

Table 1. Leading causes of death in chronic disease in the Unite States, 2005 [7][10].

Chronic Disease	Number of Deaths	Percentage(%)
Diseases of the heart	652,000	40
Cancer	559,000	34
Stroke	144,000	9
Chronic respiratory disease	131,000	8
Diabetes mellitus	75,000	5
Alzheimer's diseas	72,000	4

Table 2. Noise source and spectral bands.

Source	Spectral Band [Hz]
Vibration by sound pressure from TV and radio	10-22000
Vibration by home appliances with rotator	10-500
Road noise by vehicle	30-60
Impulsive noise induced by closing doors	Larger than 10

2 Footstep signature and gait pattern

A person walking on a floor generates a train of impulsive impacts, as the foot hits the floor, which propagates through the floor and produces a footstep vibration as shown in Fig. 1(a), which depends on structural dynamics and material characteristics of the floor in the house [1][2][3]. As shown in Fig. 1(b), a footstep movement is divided into two motion phases, which result in two characteristic spectral bands in the vibration responses of footstep as shown in Fig. 1(c). The footstep force normal to the supporting surface produces a low-banded signal below 500 [Hz] [1][2][3]. On the other hand, the tangential friction force generated by dragging the foot produces a high-banded signal above 1 [kHz] up to ultrasonic spectral range [1][2][3][4][5]. Rhythmic human activities, such as walking, dancing and aerobic introduce a distinct harmonic structure with quasi-periodicity to the resulting vibration responses of footstep. The harmonic structure includes valuable information for studying gait pattern.

The time-frequency representation of footstep vibration signal reveals some information on temporal and spectral variations of footstep and gait pattern. In general, a measured footstep vibration is contaminated by various noises. To clean the measured noisy signal, we can use the variable bandwidth filter, which suppresses noise between peaks without damaging peaks and introducing spurious signal in time-frequency domain. Since walking is one of the most important human activities, studying gait pattern is critical to the monitoring of ambulatory events in the elderly and disabled people [15][17]. Assessing different walking patterns can provide valuable information regarding an individual's mobility, energy expenditure and stability during locomotion [15][[17]. Classification on different walking patterns provides useful information leading to further understanding of both gait pattern and an individual's energy expenditure during daily living [15][17].

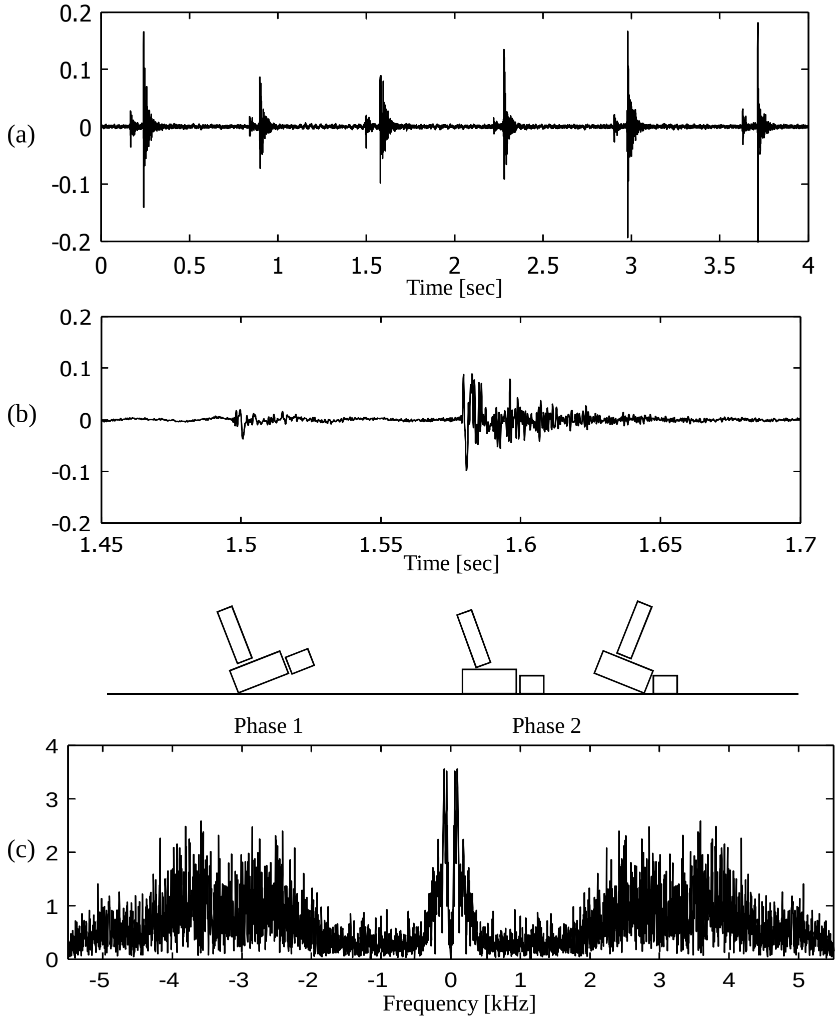

Fig. 1. Human footstep signal. (a) Time-history of vertical acceleration. (b) Two phase motions and corresponding footstep signal. (c) Fourier spectrum.

Patients with diabetes and peripheral neuropathy exhibit gait instability [15][16][17]. Gait unsteadiness has a strong association with depressive symptoms [15][16][17]. Abnormal walkers try to adapt a slower walking speed, shorter stride length, and longer double support time than normal walkers. Similar gait patterns are observed in patients with diabetes and peripheral neuropathy [15][17]. While patients with diabetes adapt a more conservative gait pattern to make them feel more stable, they remain at high risk of falls and injuries during daily activities [15][17].

3 Footstep source localization

In health monitoring in smart homes, it is important to obtain information on indoor location of a resident. For example, tracking indoor location is conducive to discriminating a fall of the elderly and disabled if positions of furniture such as couch and bed are known. Also by locating the user, the smart house can better support the user needs by activating certain monitoring and assistive applications that are location and area specific. Table 3 shows some available tools for localizing indoor positions of a subject. In this paper, we consider MEMS accelerometer to localize footstep source.

Table 3. Comparison of indoor localization tools.

Source	Information to be Extracted	Difficulty
Speech and sound	2D position	Shade, reverberation, privacy
Active sonar	2D position, orientation	Shade, reverberation
IR LED	3D position, orientation	Shade, cost
UWB	3D position, orientation	Shade, harmfulness
Vision, constellation	3D position, orientation	Complexity, illumination, privacy
Footstep vibration	2D position	Weak signal, space variance

On a floor, vibration signature of human footstep is a kind of seismic wave, which is induced by walking motions. An impact on a floor generates a vibration, which propagates like seismic wave as shown in Fig. 2. Generally, the footstep vibration is composed of two kinds of waves. One is P-wave whose particle motion is parallel to the propagation direction of wave. The other is S-wave whose particle motion is perpendicular to the propagation direction of the wave. A tri-axis MEMS accelerometer can measure projected versions in terms of acceleration on the P-wave and the S-wave with respect to the x-axis, the y-axis and the z-axis respectively. For localization of footstep source, we can use three kinds of physical quantities on amplitudes, arrival time differences and directions of particle motion on vibration as follows:

– Based on amplitude
  - Using triangulation

Table 4. Energy expenditure in activity, 160 lbs body mass [14].

Activity	Energy Expenditure [kcal/hr]
Sleeping	70
Lying quietly	80
Sitting	100
Standing at ease	110
Watching TV	110
Conversation	110
Eating meal	110
Strolling	140
Playing violin or piano	140
Housekeeping	150
Walking dog	316
Walking brisk	422

– Based on arrival time difference
  - Using cross correlation between amplitude signals
– Based on direction of particle motion
  - Using P-wave and S-wave vectors

When the decay characteristic on the wave amplitude is known, the trigonometric measure produces estimation on the position of footstep source if we use 3 amplitudes that are measured simultaneously at different places. Also, if we know the propagation speed of the wave, cross correlation of two measured signals at different places produces estimation on the position. Generally, the propagation speed of footstep vibration is larger than 1500 [m/sec]. If the speed of the wave does not depend on the amplitude of the wave, the wave equation that describes the vibration is linear. Therefore, at angular frequency $\omega = 2\pi f$, a zero-state response vector $\mathbf{A}(r,t;\omega) = [A_x(r,t;\omega)\ A_y(r,t;\omega)\ A_z(r,t;\omega)]^T$ for a footstep is represented by

$$\mathbf{A}(r,t;\omega) = \int_{r_s}^{r} \mathbf{H}(r,\sigma,t;\omega)\mathbf{F}(\sigma,t;\omega)d\sigma, \tag{1}$$

where $r = (x,y,z)$ is a position on the space domain and $\mathbf{F}(r,t;\omega)$ is a 3x1 footstep force vector as

$$\mathbf{F}(r,t;\omega) = [F_x(r,t;\omega)\ F_y(r,t;\omega)\ F_z(r,t;\omega)]^T \tag{2}$$

and $\mathbf{H}(r,t;\omega)$ is a 3x3 transition matrix that describes the propagation characteristics of the floor vibration as

$$\mathbf{H}(r,t;\omega) = \begin{bmatrix} H_{11}(r,t;\omega) & H_{12}(r,t;\omega) & H_{13}(r,t;\omega) \\ H_{21}(r,t;\omega) & H_{22}(r,t;\omega) & H_{23}(r,t;\omega) \\ H_{31}(r,t;\omega) & H_{32}(r,t;\omega) & H_{33}(r,t;\omega) \end{bmatrix}. \tag{3}$$

In general, a house floor is a non-isotropic inhomogeneous elastic medium of seismic waves. For example, a floor is a space-variant dynamic system when some furniture and facilities are on the floor. If a floor has a space-invariant property, that is, a floor is an isotropic homogeneous elastic medium, the matrix $\mathbf{H}(r,t;\omega)$becomes diagonal. An inverse Fourier transform of $\mathbf{A}(r,t;\omega)$ on the frequency domain produces therefore a time-history of 3x1 vector signals on acceleration.

Table 5. Information obtainable from localization.

Information and Outcome	Type	Observing Interval
Fall	Strength, tracking	Less than a half hour
Variation on living pattern	Tracking	More than one month
Variation on gait pattern	Strength, tracking	More than one month
Indoor activity level	Strength, tracking	One day
Personal hygiene	Tracking	One day
Habit on eating meals	Tracking	Less than three hours

Figure 3(a) shows a MEMS accelerometer located at $r = (0, 0, 0)$ and a footstep source at $r_s = (x_s, y_s, z_s)$ on the x-y plane, that is, on the floor. A vibration signature of footstep is composed of P-wave and S-wave. A particle subjected to P-wave moves in the direction that the wave is propagating. P-wave does not generate the vertical acceleration, that is, the z-axis component of acceleration. S-wave moves a particle up and down, or side-to-side, perpendicular to the direction that the wave is propagating. As shown in Fig. 3(b), the footstep source position $r_a = (x_s, y_s, 0)$ can be estimated from the horizontal accelerations, that is, the x-axis and the y-axis components of acceleration, induced by P-wave and S-wave in which directions of particle motion are parallel to the x-y plane.

Let $\mathbf{a}(t)$ be the measured output from a tri-axis MEMS accelerometer as follows:

$$\begin{aligned}\mathbf{a}(t) &= [a_x(t)\ a_y(t)\ a_z(t)]^T \\ &= \overline{\mathbf{a}}(t) + \mathbf{n}(t),\end{aligned} \tag{4}$$

where $\overline{\mathbf{a}}(t)$ is a signal on acceleration induced by human activities and $\mathbf{n}(t)$ is a white noise. In general, the P-wave is leading than the S-wave. Also, the P-wave and the S-wave are perpendicular each other.

As shown in Fig. 3, at a time instance t, for the P-wave, we obtain two equations as follows:

$$\begin{aligned}y &= (p_{y1}(t)/p_{x1}(t))x \\ &= k_1 x,\end{aligned} \tag{5}$$

and

$$\begin{aligned}y &= (p_{y2}(t)/p_{x2}(t))x - (p_{y2}(t)/p_{x2}(t))d \\ &= k_2 x - k_2 d.\end{aligned} \tag{6}$$

Then, the footstep position r_s is represented as follows:

$$r_s = (k_2 d/(k_1 - k_2), k_1 k_2 d/(k_1 - k_2), 0). \tag{7}$$

Using the measured time series on the P-wave, the slopes k_1 and k_2 are estimated by the least square approximation on line fitting. That is,

$$k_1 = \frac{E[p_{x1}(t)p_{y1}(t)] - E[p_{x1}(t)]E[p_{x1}(t)]}{E[p_{x1}^2(t)] - (E[p_{x1}(t)])^2} \tag{8}$$

and

$$k_2 = \frac{E[p_{x2}(t)p_{y2}(t)] - E[p_{x2}(t)]E[p_{x2}(t)]}{E[p_{x2}^2(t)] - (E[p_{x2}(t)])^2}, \tag{9}$$

where E means the expectation operation on the measured time series of the P-wave. Also, for the S-wave, we obtain two equations as follows:

$$y = (s_{y1}(t)/s_{x1}(t))x \tag{10}$$

and

$$y = (s_{y2}(t)/s_{x2}(t))x - (s_{y2}(t)/s_{x2}(t))d. \tag{11}$$

As shown in Fig. 3, the S-wave is perpendicular to the P-wave. Using the rotated version of (10) and (11), respectively $\pi/2$[rad] clockwise and $\pi/2$[rad] counter-clockwise, we can obtain a representation on the footstep position r_s from the S-wave.

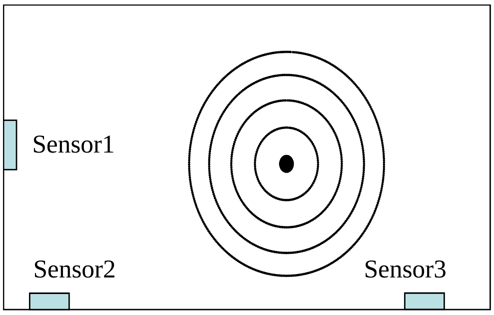

Fig. 2. Propagation of footstep vibration wave.

4 Estimation of energy expenditure level

The quantities $\overline{\mathbf{a}}(t)$ and $\mathbf{n}(t)$ in (4) are random variables. Therefore, we obtain that

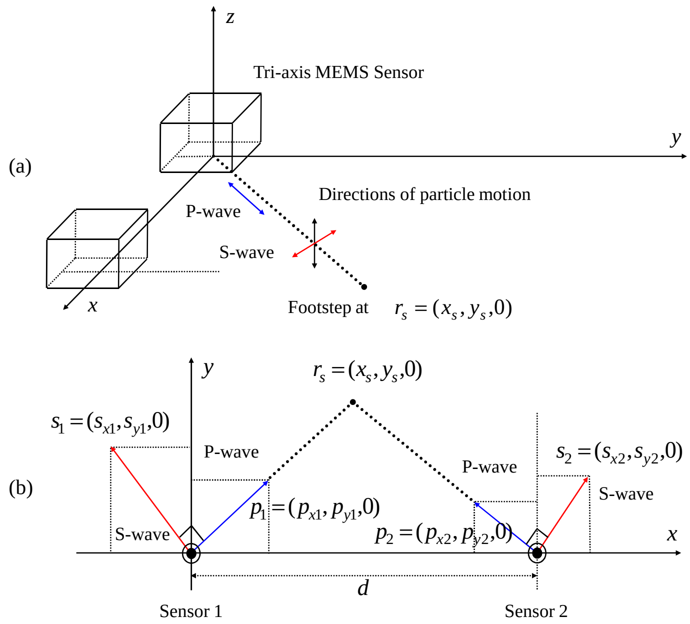

Fig. 3. Configurations for footstep localization. (a) P-wave and S-wave, and corresponding particle motion directions. (b) Localization of footstep source.

$$E[\mathbf{a}(t)\mathbf{a}(t)] = E[\bar{\mathbf{a}}(t)\bar{\mathbf{a}}(t)] + E[\mathbf{n}(t)\mathbf{n}(t)] + 2E[\bar{\mathbf{a}}(t)\mathbf{n}(t)], \tag{12}$$

where E means the expectation operation for a random variable. We assume that $\bar{\mathbf{a}}(t)$ and $\mathbf{n}(t)$ are uncorrelated each other and whose expectation values are equal to zero. Also, we assume that an individual's energy expenditure is proportional to the energy of vibration signal measured by a MEMS accelerometer sensor. Then, from the first assumption, we obtain that

$$E[\bar{\mathbf{a}}(t)\mathbf{n}(t)] = 0.$$

Therefore, (12) is represented by

$$E[\mathbf{a}(t)\mathbf{a}(t)] = E[\bar{\mathbf{a}}(t)\bar{\mathbf{a}}(t)] + E[\mathbf{n}(t)\mathbf{n}(t)]. \tag{13}$$

Let L_A denote an individual's energy expenditure by activities. In general, the quantity $E[\bar{\mathbf{a}}(t)\bar{\mathbf{a}}(t)]$ is a function of the energy expenditure L_A by human activity, that is,

$$E[\bar{\mathbf{a}}(t)\bar{\mathbf{a}}(t)] = f(L_A). \tag{14}$$

Then, from the second assumption, we obtain a linear relation as follow:

$$E[\bar{\mathbf{a}}(t)\bar{\mathbf{a}}(t)] = \alpha L_A, \tag{15}$$

where α is a constant. Combining (13) and (15), we obtain that

$$E[\mathbf{a}(t)\mathbf{a}(t)] = \alpha L_A + E[\mathbf{n}(t)\mathbf{n}(t)]. \tag{16}$$

As another form, we obtain that

$$\alpha L_A = \frac{1}{\alpha}E[\mathbf{a}(t)\mathbf{a}(t)] - \frac{1}{\alpha}E[\mathbf{n}(t)\mathbf{n}(t)]. \tag{17}$$

In (16) and (17), $N_0 = E[\mathbf{n}(t)\mathbf{n}(t)]$ represents noise power. If we know the constant α and the noise power $E[\mathbf{n}(t)\mathbf{n}(t)]$, then the energy expenditure L_A can be computed from (17) since $E[\mathbf{a}(t)\mathbf{a}(t)]$ is known. The constant $N_0 = E[\mathbf{n}(t)\mathbf{n}(t)]$ can be estimated from $\mathbf{a}(t) = \overline{\mathbf{a}}(t) + \mathbf{n}(t)$ if $\overline{\mathbf{a}}(t)$ is equal to zero.

5 Variation of gait pattern

Negative correlations between age and walking speed, and between age and stride length are observed in the elderly people [18][19]. The relative stance phase duration is correlated positively with age within the elderly people [18][19]. Slow speed is related to low daily activity, reduced muscle power, and diminished balance ability [18][19]. Long stance phase duration and slow speed in the elderly could be an adaptive characteristic in response to impaired balance [18][19].

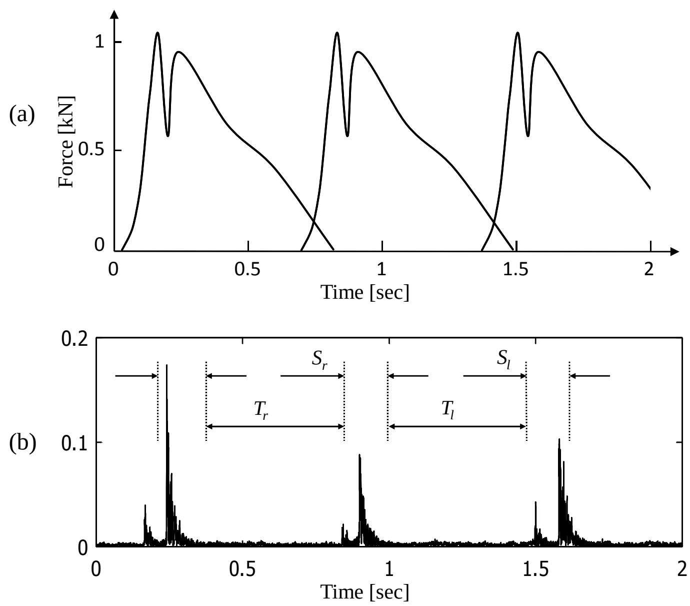

Fig. 4. Human footstep signature. (a) Vertical footstep force. (b) Parameters on one cycle footstep signal.

Table 6. Parameters on gait pattern.

Parameter	Description
Duration of stance in sec	S_R, S_L
Cycle duration in sec	$C_D = T_R + S_R + T_L + S_L$
Cycle duty	$C_R = (T_R + S_R)/(T_L + S_L)$
Normalized stride interval	$NS_R = T_R/C_D, NS_L = T_L/C_D)$
Energy of footstep signal	$E_R, E_L, E_T = E_R + E_L$
Normalized energy	$NE_R = E_R/E_T, NE_L = E_L/E_T$
Velocity, footstep/sec	$V_R = 1/(T_R + S_R), V_L = 1/(T_L + S_L)$

Figure 4 shows human footstep signature on footstep force and some parameters. As shown in Fig. 1(b), the two phase motions produces two distinct vibration, one is generated by the heel motion normal to the ground and the other is generated by dragging motion tangential to the ground. Parameters, such as duration of stance, footstep cycle and footstep energy, are used for observing variation of gait pattern. From footstep signal (4), we compute an analytic signal to obtain amplitude of (4) as follows:

$$\mathbf{q}(t) = \mathbf{a}(t) + iH[\mathbf{a}(t)], \tag{18}$$

where H is the Hilbert transform and $\mathbf{q}(t) = [q_x(t)\ q_y(t)\ q_z(t)]^T$. Then, we compute amplitude $|q_z(t)|$, as shown in Fig. 4(b). Table 6 shows parameters, which are used for identifying variation of gait pattern in this paper. Duration of stance, stride interval and energy on right and left foot motion are considered. It can be seen in the amplitude in Fig. 4(b) that the number of walking steps can be easily calculated by using thresholds. The threshold value is chosen as one third of the maximum peak within that frame.

6 Statistics on daily living pattern

Figure 5 shows experimental setup for extraction of statistical parameters on daily living pattern. The relation (17) between energy expenditure and indoor activity level enables us to extract parameters for daily, weekly and monthly charts describing an individual's activities. Based on 24-hour continuous monitoring, generation of statistics on temporal and spatial activity level helps a medical doctor to write exercise prescription of weakness and strength on activities to promote personal health concerns. The difference between exercise prescription recommended by a medical doctor and actual activity level can be estimated based on energy expenditure level and staying time in each space such as bedroom, living room, toilet and kitchen, and on statistics of onset and end of staying interval. Two-dimensional activity map of density on staying time in each living space with temporal information can be constructed for identifying some variation on living pattern.

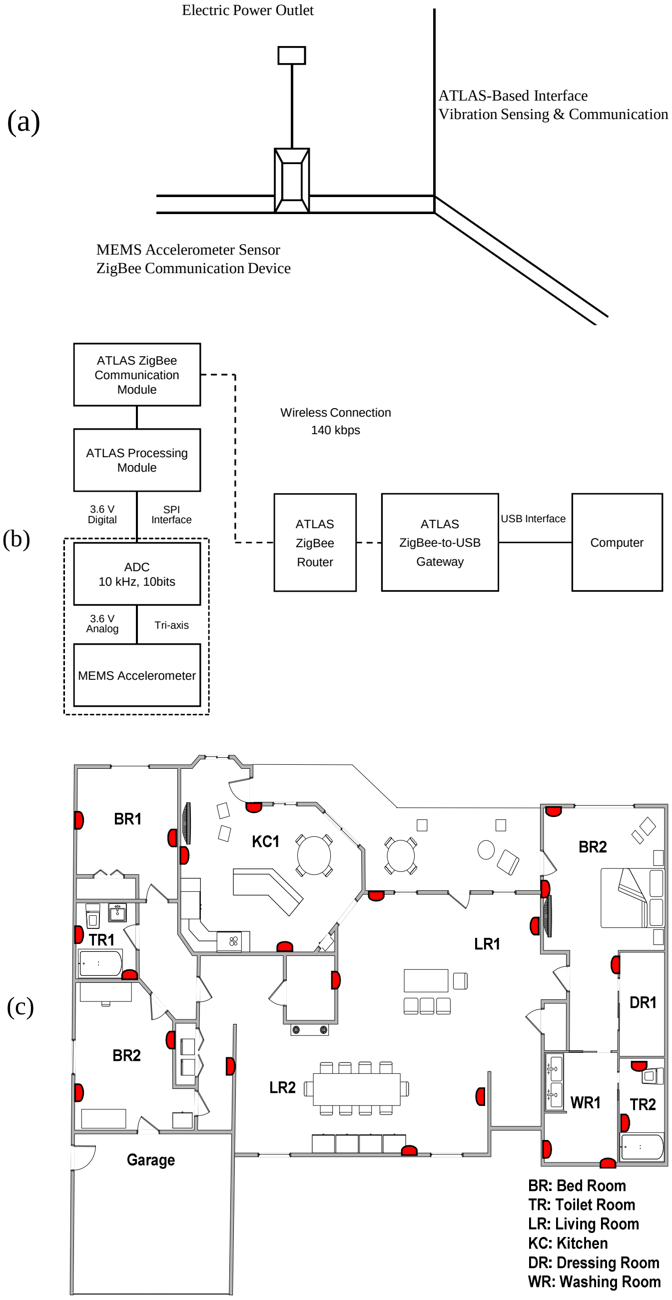

Fig. 5. Experimental setup. (a) A networked MEMS accelerometer attached on the bottom of the wall. (b) Block diagram of the networked MEMS accelerometer. (c) A smart house with network-based MEMS accelerometers connected using the Atlas sensor platform [20][21].

7 Conclusions and further studies

In this paper, a mathematical formulation on localizing footstep source is conducted in which footstep vibration signal is modeled as a seismic wave composed of P-wave and S-wave, where footstep vibration is measured by tri-axis MEMS accelerometers. Since particle motions on P-wave and S-wave include some information of propagation direction, the mathematical formulation enables us to estimate position of footstep source if the number of MEMS sensors for measurement is more than two. To reduce estimation error, the least square error method is used for fitting directional line from footstep source to MEMS sensor location.

Based on MEMS accelerometer, also, we analyze a relation between energy expenditure level and indoor activity level, with the purpose of maintaining personal health conditions among the elderly and disabled people regardless of seasonal variations on weather that affects on personal health-related outcomes such as blood pressure and cholesterol levels.

The long-lasting illness and disability caused by chronic disease decreases quality of life and restricts activities in the elderly and disabled people. The number of steps taken per day is correlated negatively with age in the elderly. Although the elderly are very active, their daily activity is appeared to reduce with age. Slow walking speed is related to daily activity. Long stride length and high speed may be related to muscle power. The main purpose of the system under considering is on estimation of energy expenditure level to promote personal health condition with the help of some networked sensor environments. In the system, the variations on living pattern are measured for on time detection of ambulatory health conditions, based on the statistical parameters extracted from footstep signature and tracking footstep source. Another purpose of the system is to collect continuously some basic bio-signals for transferring to medical doctor.

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