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Abstract. A smart home environment based on pervasive networked-sensors enables us to measure and analyze various vital signals related to personal health care. For example, the vital signals on footstep, gait pattern, and posture can be used for assessing the health state among the elderly and disabled people. In this manuscript, we use footstep vibration signals measured by network-based MEMS accelerometers attached on the bottom of wall for estimating the level of indoor physical activity that elevating the activity level is conducive to maintaining better health state of the elderly and disable people. The footstep vibration signal measured by MEMS accelerometer includes vital sign induced by human activities such as walking, sitting, sleeping, cooking and personal hygiene. With the purpose of developing a smart-home-based healthcare system for the elderly and disabled people, this paper deals with on estimation of energy expenditure level in human body, extraction of statistical parameters of daily living pattern, and identification of pathological gait pattern. Different from image sensor and sound sensor, MEMS accelerometer sensor can measure some biomedical signatures without entailing personal privacy problem.

Keywords. Personal health care, MEMS accelerometer, Energy expenditure level, Smart home, Sensor network, Localization of footstep.

1. Introduction

For a well-established smart house to be capable of promoting personal health in the elderly and disabled people to live independently with minimal medical expenditure, it becomes mandatory to implement a sensor-network environment that provide with the functions of collecting various data regarding current health state of the dweller. In a sensor-network environment with pervasive intelligence, various vital signals can be measured via networked-sensors, such as vision sensor, microphone, electrode, pressure sensor and accelerometer, and can be processed to extract some information on mental and physical state of the dweller. Then, the processed data and information can be used for diagnosing health conditions of the residents 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. Rresearches on chronic disease report that the most common chronic conditions are high blood pressure, high cholesterol, arthritis and respiratory diseases like emphysema [13]. In addition, researches on personal healthcare support that increasing the level of physical activity decreases the risk of onset and developing the chronic illnesses [6][11].

A well-established smart house 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, when chronic-related outcomes are measured and processed continuously for producing exercise prescription to control level of physical activity and information on the chronic conditions.

The pattern on the level of outdoor activity fluctuates with environmental changes on temperature, humidity, rainfall, and daylight length since the amount of time spending on outdoor leisure depends on the weather conditions [6][8][12]. The seasonal fluctuation of the outdoor physical activity affects on health-related outcomes of the elderly and disabled people [6][8][9]. For example, the studies [6][8][9][12] on the seasonal variation of blood cholesterol show that the seasonal variation is the amount of 2.0-2.4 MET $\mathrm{MET} \cdot \mathrm{h} \cdot \mathrm{d}^{-1}$ in men and women ages 20-70 year and some seasonal variation is observed in relation to blood lipid levels [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 in physical activity levels across seasons may influence health-related outcomes positively or negatively [6][8]. Since the health-related outcomes fluctuates with the weather conditions, controlling level of indoor physical activity adapting to the weather conditions is conducive to maintaining better health state of the elderly and disable people.

For estimating levels of indoor physical activity, the vital signals on footstep, 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 although the security levels of the network are very high and the computer has the log in procedure to prevent accessing by an undefined person.

For avoiding the possible privacy problem, in this paper, a MEMS accelerometer is used for estimating level on the indoor physical activity. The MEMS accelerometer attached on the bottom of wall measures vibrations induced by physical activities such as walking, opening and closing door, washing, eating meal, cooking, sleeping and watching TV etc. The output of the network-based MEMS accelerometer includes various noises caused by not only home appliances such as TV, radio and washing machine but also vehicles passing by the house. Table 2 shows some noise sources and spectral bands in a house.

The level of human activity depends on positively the level of energy expenditure (EEP). That is, high level of human activity means that the EEP is large. For example, a brisk exercise generates forceful large swing motions in the legs and which results in footstep vibration with large magnitude. Therefore, level of human activity can be estimated from the footstep vibration. Table 3 shows energy expenditure for some activities during daily living.

With the purpose of developing a smart-home-based healthcare system for the elderly and disabled people, this paper deals with on estimation of EEP level, localization of footstep sources, extraction of statistical parameters in daily living pattern, and identification of pathological gait pattern, based on a MEMS sensor connected through WPAN, which measures floor vibration induced by human activity. The purpose of this study is to use a MEMS sensor for identifying the pathological gait pattern and correlation between the level of EEP and the level of floor vibration.

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 disease	72,000	4

Table 2. Noise source and spectral bands.

Source	Spectral Band [Hz]
Vibration by sound pressure from TV and radio	10-22000
Periodic vibration by washing machine	10-500
Road noise by vehicle	30-60

2. Footstep signature and gait pattern

A person walking on the 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 a house [1][2][3]. As shown in Fig. 1(b), a footstep motion 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 foot motion 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 to the vibration responses of footstep. The harmonic structure includes valuable information for studying gait pattern.

Since walking is one of the most important human activities, study on 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 on 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].

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 for falls and injuries during daily activity [15][17].

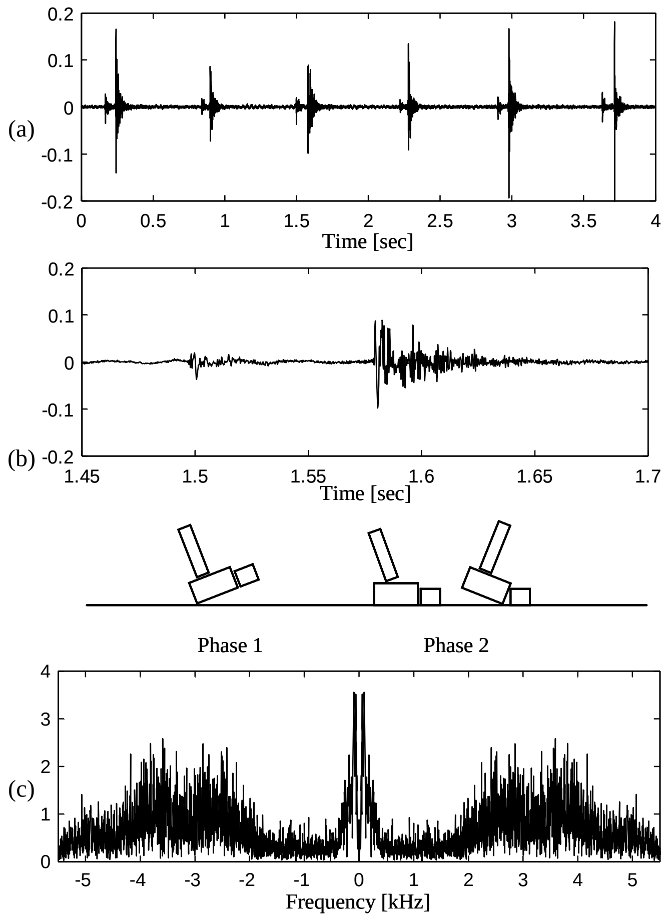

Fig. 1. Human footstep signal. (a) Time-history of vertical acceleration. (b) Two phase motions and corresponding footstep signal. (c) Fourier spectrum.

3. Footstep source localization

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. The other is S-wave whose particle motion is perpendicular to the propagation direction. A tri-axis MEMS accelerometer can measure projected versions 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 amplitude, time difference and directions of particle motion as follows:

- Based on amplitude
  - Using Trigonometric measure
- Based on time difference
  - Using cross correlation
- Based on direction of particle motion
  - Using P-wave and S-wave

If the decay characteristic on the wave amplitude is known, the trigonometric measure produces estimation on the position of footstep source. Also, if we know the propagation speed of the wave, cross correlation of two measured signals at different positions 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 a linear form. 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 floor in a house is a non-isotropic inhomogeneous elastic medium of seismic waves. For example, a floor is a space-variant dynamic system when some

Table 3. 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

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 a diagonal matrix. Inverse Fourier transform of $\mathbf{A}(r,t;\omega)$ on the frequency domain produces a time-history of 3x1 vector signals on acceleration.

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 $r_s=(x_s,y_s,0)$ 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:

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

where $\bar{\mathbf{a}}(t)$ 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:

$$\begin{aligned}y&=(p_{y1}(t)/p_{x1}(t))x\\&=k_1x,\end{aligned} \tag{5}$$

and

$$\begin{aligned}y&=(p_{y2}(t)/p_{x2}(t))x-(p_{y2}(t)/p_{x2}(t))d\\&=k_2x+k_2d\ .\end{aligned} \tag{6}$$

Then, the footstep position r_s is represented as follows:

$$r_s=(k_2d/(k_1-k_2),\,k_1k_2d/(k_1-k_2),\,0)\,. \tag{7}$$

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

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

Using the rotated version of (10) and (11), respectively $\pi/2$ [rad] clockwise and $\pi/2$ [rad] counterclockwise, we can obtain a representation on the footstep position r_s.

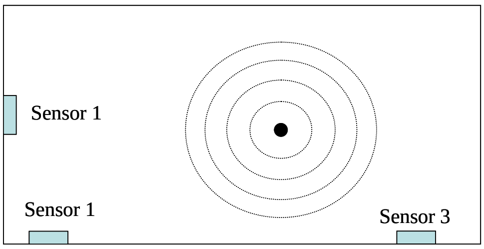

Fig. 2. Propagation of footstep vibration wave.

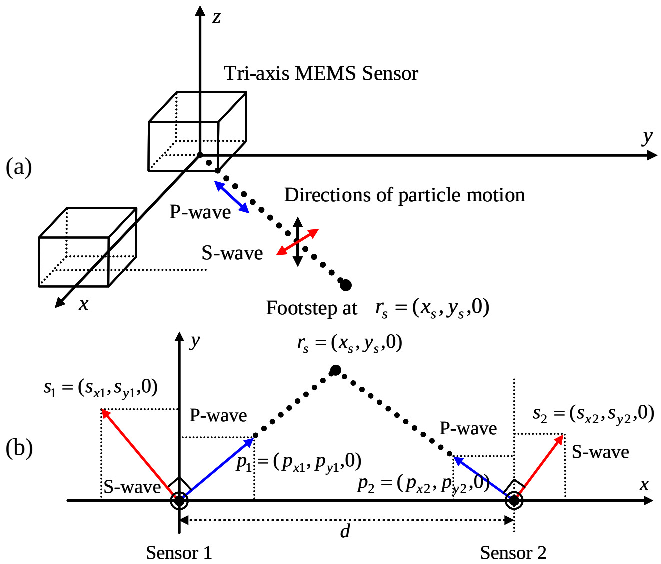

Fig. 3. Configurations for footstep localization. (a) P-wave and S-wave, and corresponding particle motion directions. (b) Localization of footstep source.

4. Estimation of energy expenditure level

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

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

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

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

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 $\mathbf{a}(t) = \bar{\mathbf{a}}(t) + \mathbf{n}(t)$ if $\bar{\mathbf{a}}(t)$ 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 group. The relative stance phase duration is correlated positively with age within the elderly group. Slow speed is related to low daily activity, reduced muscle power, and diminished balance ability. Long stance phase duration and slow speed in the elderly could be an adaptive characteristic in response to impaired balance [18][19].

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

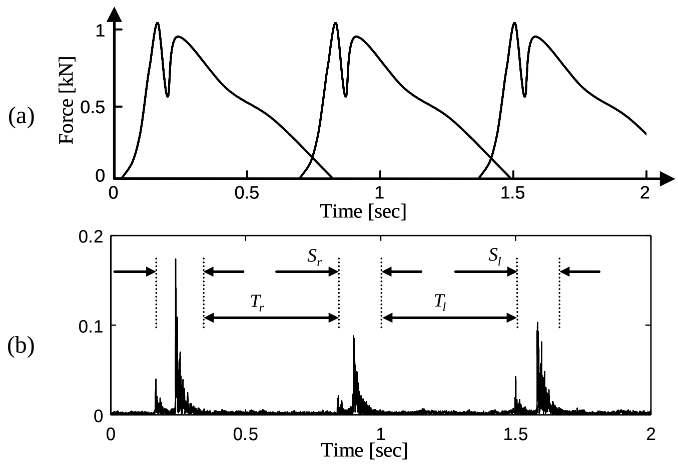

Fig. 4. Human footstep signature. (a) Vertical footstep force. (b) Parameters on one cycle footstep signal.

Table 4. Parameters on gait pattern.

Parameter	Description
Duration of stance, sec	S_R, S_L
Cycle duration, 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	$V_R=1/(T_R + S_R)$, $V_L=1/(T_L + S_L)$

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. Then, we compute amplitude $|q_z(t)|$, as shown in Fig. 4(b). Table 4 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 the amplitude in Fig. 4(b) that the number of walking steps can be easily calculated by threshold. 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 parameters on daily living pattern. The relation (17) between EEP and 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 present activity level can be estimated based on EEP level and staying time in each space such as bedroom, living room, toilet and kitchen, and statistics on onset and end of staying interval. Two-dimensional activity map of density on staying time in each space with temporal information can be constructed for identifying some variation on living pattern.

7. Conclusions and further studies

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

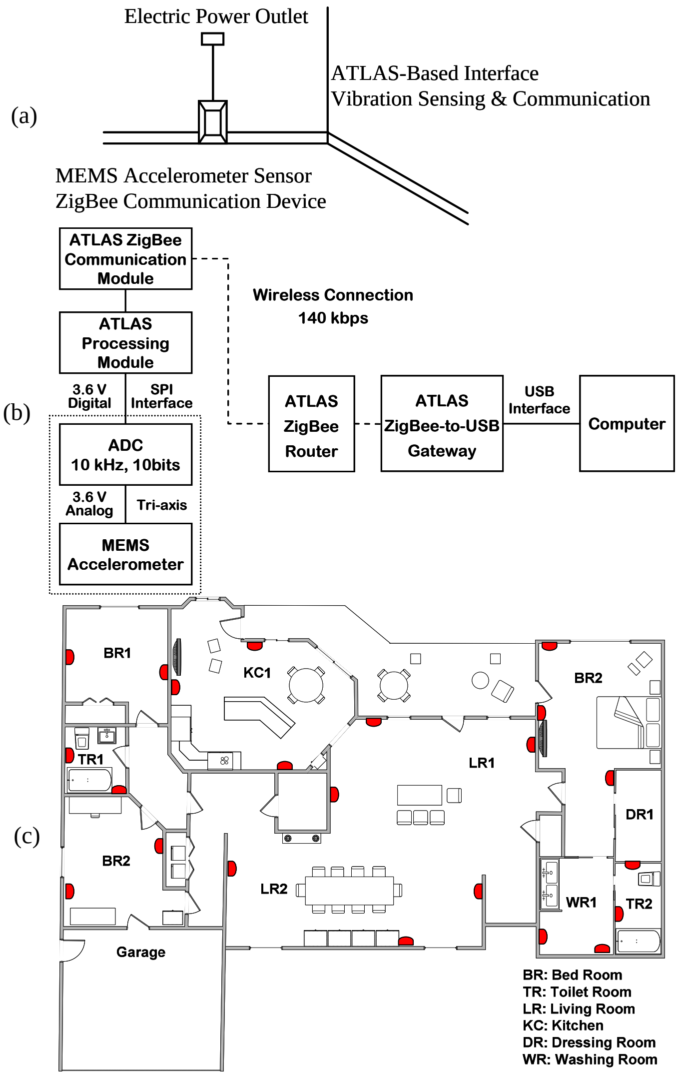

Fig. 5. Experimental setup. (a) A networked MEMS accelerometer attached on the bottom of the wall. (b) Block diagram of the networked MEMS accelerometer. (c) A smart house with network-based MEMS accelerometers connected through wireless personal area network.

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