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Measurements of pedestrian's ioad using smartphones

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Abstract. The applications of smartphones or other portable smart devices have dramatically changed people's lifestyle. Researchers have been investigating useage of smartphones for structural health monitoring, earthquake monitoring, vibration measurement and human posture recognition. Their results indicate a great potential of smartphones for measuring pedestrian-induced loads like walking, jumping and bouncing. Smartphone can catch the device's motion trail, which provides with a new method for pedestrain load measurement. Therefore, this study carried out a series of experiments to verify the application of the smartphone for measuring human-induced load. Shaking table tests were first conducted in order to compare the smartphones' measurements with the real input signals in both time and frequency domains. It is found that selected smartphones have a satisfied accuracy when measuring harmonic signals of low frequencies. Then, motion capture technology in conjunction with force plates were adopted in the second-stage experiment. The smartphone is used to record the acceleration of center-of-mass of a person. The human-induced loads are then reconstructed by a biomechanical model. Experimental results demonstrate that the loads measured by smartphone are good for bouncing and jumping, and reasonable for walking.

Keywords: portable devices; embedded sensor; MEMS technology; human-induced model

1. Introduction

1.1 Background

The last decade has witnessed the tremendously quick development of smartphones and other portable smart devices in their ever-increasing user numbers and new abilities. In China for example, there are in total 1.3 billion registered cellphones by the end of 2015, which means 95.5 cellphones for every hundred people. Meanwhile, the cellphones are becoming 'smart' and 'multifunctional' with more and more integrated powerful sensors resulting from rapid development of micro-chip technology. Taking Apple® phone as an example, various sensors are packed into an iPhone such as accelerometer, gyroscope sensor, magnetometer and light sensor, to name a few. With a proper software, i.e., applications or APP, the records of all these embedded sensors can be acquired and analyzed to measure responses of a structure and to recognize the activities (walking, jumping, etc) of the phone's user. The smartphone with embedded-sensors was used as human activity recognition equipment (Khan *et al*. 2010), and as earthquake monitoring equipment (Reilly *et al*. 2013). IPod was also used as telegraph pole vibration monitoring equipment (Orai *et al*.2013). Finally, iPhone was used as bridge cable vibration monitoring equipment (Yu *et al*. 2015).

Dynamic loads will be generated when an individual or a group of people is walking/jumping/bouncing on a structure, which are termed as pedestrian-induced loads. Typical pedestrian loads include walking, jumping and bouncing. In this study, bouncing is defined as a rhythmic body movement that is similar to jumping action but the feet remain in contact with the ground. These loads can cause large vibration to structures when their frequencies are close to the natural frequencies of the structure. Large resonant structural vibrations can make people feel uncomfortable so that leads to the so-called vibration serviceability problem as already happened in structures like footbridges (Zivanovic *et al*. 2005), high-rise buildings, stadia (Jones *et al*. 2011) and long-span floors. At the design stage of a vibration-prone structure, a proper model for human-induced load is critical for assessing its performance when it is subjected to pedestrain-induced loads. To this purpose, researchers have conducted experiments to record human-induced loads by two methods: direct measurement and indirect measurement. The former utilizes devices as force plate instrumented treadmill or pressure insole to directly measure time history of the load (Fig. 1). The latter usually measures the responses of a stiff structure under human-induced loads. The load's properties are then identified by inverse dynamic analysis. The two test methods, however, are not suitable for long-duration individual load measurement and for crowd load measurement due to the limited number of devices or experimental space. The measurement of human-induced loads in real situation for individual and for a group of people remains a challenge.

The smartphone, the most ubiquitous electronic appliance in modern people's daily life, provides a significant opportunity to establish a new, low-cost and convenient way to measure pedestrian-induced loads of individual or a group in real situation. Inspired by this idea,

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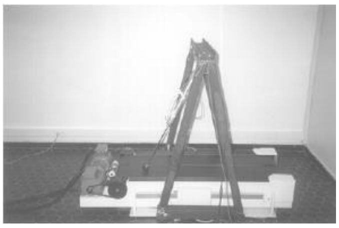
(a) Force plates



(b) Treadmill (Belli *et al*. 2001)

(c) Insole

Fig. 1 Measurement devices for individual walking load

we conducted feasibility study to verify the measurement accuracy of smartphones and their possibility for pedestrain-induced load measurements (Chen *et al*. 2016). We found that with the help of smartphone's powerful sensors, we can measure the acceleration of a person while he/she is walking or jumping. The corresponding loads can be reconstructed from the measured accelerations. The current paper improves this idea by proposing coordinate transition rules for smartphone's records, checking the dynamic load factors measured by smartphones and force plates, and extending this technique to crowd-load measurement.

Section 2 elaborates the measurement principle of smartphones and the coordinate's transition rules. Section 3 discusses validation experiments that are extensions of that in the feasibility study (Chen *et al*. 2016). In Section 4, smartphones are adopted to measure individual walking, jumping and bouncing loads. The measurements are compared with that by three-dimensional motion capture technique and force plates in both time domain and frequency domain. Crowd load measurements by smartphones are discussed in Section 5. Finally, the main findings of this study are summarized in Section 6.

2. Smartphone's measurement working principle

2.1 Smartphone's embedded sensors

The development of the phone's embedded sensors is the main distinction between the traditional phone and the smartphone. There are various kinds of sensors in a smartphone like accelerometer, gyroscope sensor, GPS, touch sensor, infrared sensor, magnetometer, temperature sensor and fingerprint sensor. The accelerometer and gyroscope sensor are the two mainly used sensors to record the motion trial of the smartphone.

The accelerometer and gyroscope sensor are all regarded as MIMU (Micro Inertial Measurement Unit), which integrates six-dimension inertia parameters together in a micro electronical unit to record tri-axial accelerations and

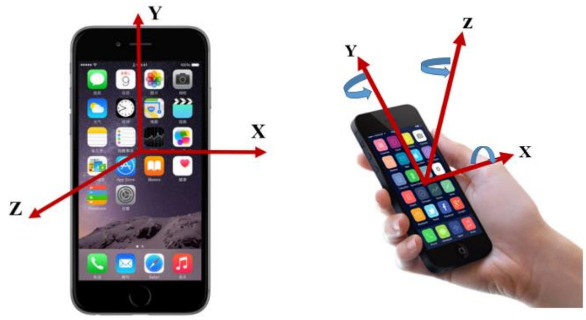


Fig. 2 The coordinate axis of the iPhone and the positive direction of the acceleration sensor

tri-axial angular velocity. The gyroscope's precision decides the smartphone's measurement precision. Factors that affect the accuracy of gyroscope include scale factor, zero-bias stability, measurement range, output noise, bandwidth, and resolution ratio. The accelerometer and gyroscope sensor in iPhone5s and the up (manufactured by Apple Inc.) are advanced and their measurement range (frequency and amplitude) covers that of the human activities (InvenSense® on-line website). We thus selected iPhone5s (and higher generations) for the following experiments.

2.2 Local coordinates and coordinates transformation

Fig. 2 shows the local coordinate system in order to describe a smartphone's motion. The built-in tri-axial accelerometer can measure acceleration of the phone in *x*, *y* and *z* direction. The tri-axial gyroscope sensor can measure the angular rotation velocity about the three axes. There are many Apps available for acquiring records of the two sensors. We adopted one called Sensorlog® in the following experiments because it can provide records of latitude, longitude, acceleration and gyro rotation data with a high sampling frequency of 100 Hz.

Suppose we know the orientation of a phone's local coordinates before using it for vibration measurement, e.g., *y*-axis is perpendicular to the ground and *x*-axis is parallel to the ground. This original position is defined as global coordinates. When using the smartphone to measure a person's movement, the orientation of the smartphone's local coordinates changes all the time. Therefore, coordinate transformation is necessary to convert smartphone's measurements from local coordinates to global coordinates. For transformation purpose, let's define the three-dimension angular velocities from gyroscope sensor as ϑ_x, ϑ_y, ϑ_z (unit rad/s), the acceleration measured by smartphone at time instant t is expressed as [$a_1(t)$, $a_2(t)$, $a_3(t)$] in local coordinates whose counterparts in global coordinate is [a_x, a_y, a_z].

Based on the above definitions, the accumulated rotation angles about the three axes from time instant zero to t are as below

$$\varphi_t = \sum_1^n \vartheta_x \Delta t \tag{1}$$

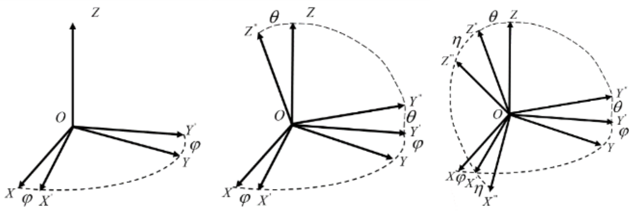


Fig. 3 Resolve the smartphone's motion condition in the order of *zxy*

$$\theta_t = \sum_1^n \vartheta_y \Delta t \tag{2}$$

$$\psi_t = \sum_1^n \vartheta_x \Delta t \tag{3}$$

where, n is the number of sampling points up to time instant t. The coordinate transformation can be expressed as

$$\left[a_x, a_y, a_z\right] = R\left[a_1, a_2, a_3\right]^T \tag{4}$$

where, R stands for the transformation matrix.

The transformation matrix can be derived based on the concept of *Eulerain Angle* through the procedure demonstrated in Fig. 3. Suppose the accumulated rotational angle at t is (φ, θ, ψ), we rotate the local coordinates in turn with the coordinate transformation matrix can be deduced as follow, where R,Z,N,Z', as shown in Eqs. (5), (6), (7) and (8), stand for operators which are used for the transformation between original coordinates and arbitrary coordinates.

$$Z'(\varphi) = \begin{pmatrix} \cos\varphi & \sin\varphi & 0 \\ -\sin\varphi & \cos\varphi & 0 \\ 0 & 0 & 1 \end{pmatrix} \tag{5}$$

$$N(\theta) = \begin{pmatrix} 1 & 0 & 0 \\ 0 & \cos\theta & \sin\theta \\ 0 & -\sin\theta & \cos\theta \end{pmatrix} \tag{6}$$

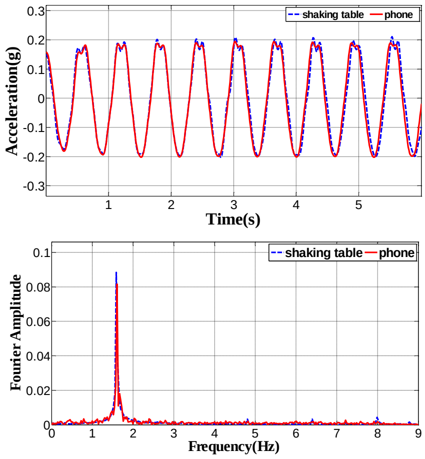
$$Z(\psi) = \begin{pmatrix} \cos\psi & \sin\psi & 0 \\ -\sin\psi & \cos\psi & 0 \\ 0 & 0 & 1 \end{pmatrix} \tag{7}$$

$$R(\varphi,\theta,\psi) = \begin{pmatrix} \cos\psi\cos\varphi - \sin\psi\sin\varphi\cos\theta & \sin\psi\cos\theta + \cos\psi\sin\varphi\cos\theta & \sin\varphi\sin\theta \\ -\cos\psi\sin\varphi - \sin\psi\cos\varphi\cos\theta & -\sin\psi\sin\theta + \cos\psi\cos\theta & \cos\varphi\sin\theta \\ \sin\psi\sin\theta & -\cos\psi\sin\theta & \cos\theta \end{pmatrix} \tag{8}$$

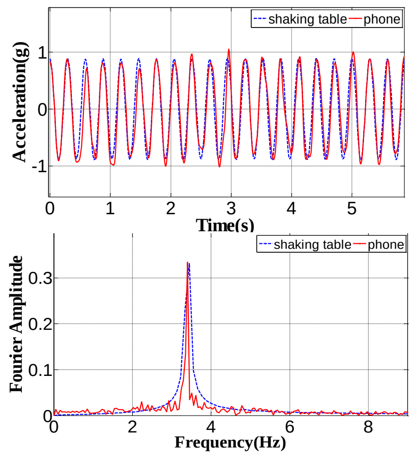
3. Application for periodic signal measurement

The human activities like walking, jumping and bouncing are typically treated as periodic process. We thus adopted shaking table test to verify the measurement accuracy of smartphones for periodic signals. The experimental preparation is shown in Fig. 4. All the test phones were glued onto a plastic glass which was in turn fastened on the shaking table. Two arrangements of

Fig. 4 Smartphones fixed on the shaking table (horizontal (above) and 45 degree (below))



(a) Arrangement 1 and 1.6 Hz sine wave input (above: time history, below: spectrum)



(b) Arrangement 2 and 3.4 Hz sine wave input (above: time history, below: spectrum)

Fig. 5 Comparison of smartphone's measurement and shaking table's real input smartphones were considered: (1) y-axis of the phone was the same as and, (2) 45 degree to the shaking table's vibrating direction (Fig. 4). Sine waves and frequency sweeping waves were taken as input to the shake table. The accelerations measured by the smartphones were compared with that recorded by an embedded accelerometer in the shaking table.

There are in total seven sine waves were tested in the experiment whose frequencies are 1.2 Hz, 1.6 Hz, 2.0 Hz, 2.4 Hz, 2.8 Hz, 3.2 Hz and 3.4 Hz, covering the main frequency range of pedestrian-induced loads. Fig. 5(a) compares the smartphone's measurements with the real input for frequency 1.6 Hz and arrangement 1, the results for 3.4 Hz and arrangement 2 are shown in Fig. 5(b).

Note that for the above two cases the smartphone's measurements are close to that of the shaking table. The relative difference of peaks in time history is 3.1% and in amplitude spectrum is 3.0%. The main frequency of the smartphone's measurement is almost the same as the input sine wave. The dominant frequency and peak in amplitude spectrum are important for human-induced load. The above observations, together with that in previous study (Chen *et al*. 2016), demonstrate that the selected smartphones in this study is suitable to measure the low-frequency periodic acceleration with acceptable accuracy.

4. Application for individual load measurement

In this section, we apply the smartphone for individual load measurement. The methodology is that first we use the smartphone to measure acceleration of a person's body while he/she is walking, jumping or bouncing. The walking (or jumping/bouncing) load is then calculated using the acceleration measurements through a simple rigid model for walking. Investigation focusing here are placed on measurement accuracy, effect of smartphone's location and force conversion factors.

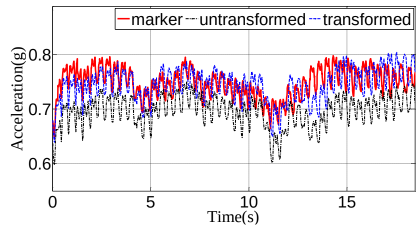
4.1 Measurement of a person's body movement by smartphone

To measure the movement of a walking person, we placed a smartphone on his/her waist by a belt (Fig. 6)

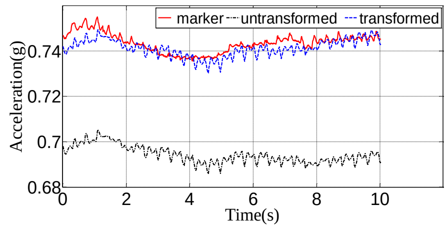
(a) Smartphone on the waist


(b) Orientation device

Fig. 6 The fixed method



(a) 1s RMS



(b) 10s RMS

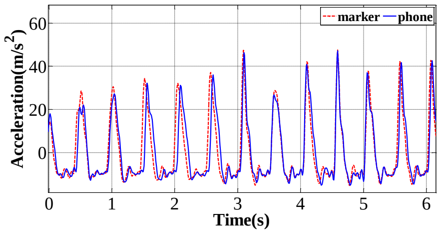
Fig. 7 Comparison of smartphone's records (with and without coordination transformation) with marker (bouncing, 2.0 Hz)

because the movement of this part could represent the whole body's movement. To learn the measurement accuracy of smartphone, we adopted three-dimensional motion capture technology (MCT) in the experiment. The MCT uses several infrared cameras to record three-dimensional special trajectories of a reflective point (termed as marker) attached to a moving subject. The system adopted in this study is the Vicon Motion Capture System which contains 12 cameras and four fixed force plates (AMTI Co.). More details about the experimental setup can be found in Pent *et al*. (2015). In the experiment, a marker was attached to the smartphone (Fig. 6(a)). The orientation of the smartphone's local coordinates was aligned with that of MCT through a specially-designed orientation device (Fig. 6(b)).

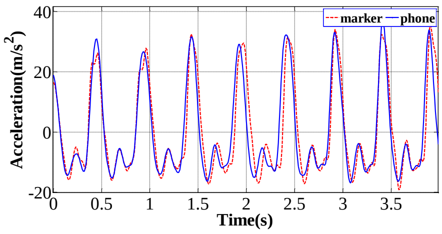
In the experiment, three test subjects walked, jumped or bounced to certain frequencies (guided by a metronome). The coordinates transformation was first applied to the smartphone's records using the methodology described in section 2.2. The resulting accelerations are then compared with that of markers. Taking 2.0 Hz bouncing test case as an example, Fig. 7(a) compares 1s running root-mean-square (1s RMS) curve of the marker's record (red solid line) with that of smartphone's original record (black dash line) and record after orientation transformation (blue dash-dot line), the comparison for 10s RMS of the three records is shown in Fig. 7(b). Note that after orientation transformation, the smartphone's measurements are very close to that of the marker. The same conclusion can be obtained for jumping and walking tests. Results for jumping test at 2.0 Hz are shown in Fig. 8.

4.2 The Influence of the Smartphone's position

In order to figure out whether the position of the smartphone could influence the measurement result or not, here three basic carrying methods were considered: putting it in the backpack causally, putting it in the front-pocket of



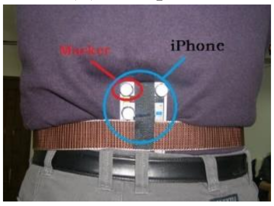
(a) Test subject 1



(b) Test subject 2

Fig. 8 Comparison of smartphone's records with marker (jumping, 2.0 Hz)

(a) Reference markers (b) backpack

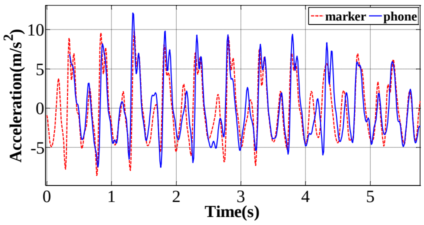


(c) Front-pocket (d) Waist

Fig. 9 Three different method to fix the smartphone

the skinny jeans, and fixing it on the waist by a belt. The 3D MCT were also adopted in the test. In particular, four markers are fixed on the test subject's head (Fig. 9(a)) to monitor the subject's movement. Moreover, for each carrying method additional markers was placed on the backpack (Fig. 9(b)) or on the smartphone (Fig. 9(c) and 9(d)), whose records are taken as reference for comparison.

Fig. 10 compares the marker's record with that of phone when the phone was in the pocket, while the comparison for phone on waist is shown in Fig. 8. Note that the smartphone's acceleration data in Fig. 8 are much closer to the marker's measurement than the results in Fig. 10. It can be inferred that the smartphone's fixed position decides the precision of the acceleration data and the waist-fixed method is better. When the phone was put in the backpack, however, the phone's records are different from that of the marker. Nevertheless, the dominant frequency and its amplitude of the phone's records are very close to that of the marker's, as demonstrated in Fig. 11 for free walking test. It can be inferred that the waist-fixed position is the most suitable location when recording the real human



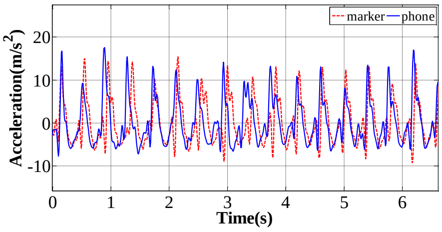


Fig. 10 The comparison of bouncing acceleration between smartphone sensor (front-pocket of the skinny jeans) and Marker (2.0 Hz bouncing (above) and 2.6 Hz bouncing (below))

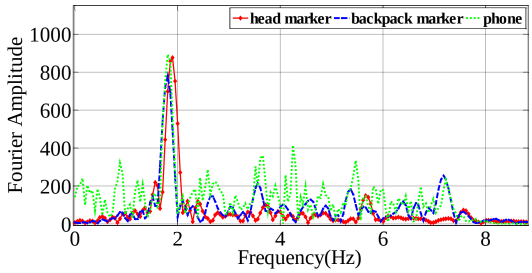


Fig. 11 The basic frequency of free walking load

activities in time domain. However, if only the frequency is needed, just putting the smartphone into the backpack casually can meet this requirement.

4.3 Conversion of Load from Acceleration

Eq. (9) is used to calculate the load induced by a person's activity using the smartphone's acceleration measurement. The equation assumes a single rigid-body model for a person.

$$G(t) = mg + mR\tilde{a}(t) \tag{9}$$

where, $G(t)$ is the load, m stands for body mass; g is gravitational acceleration (m/s^2); R stands for vibration participation coefficient of body mass, $\tilde{a}(t)$ is the acceleration measured by the smartphone. Due to the difference in different activity, the value of R is different for bouncing, jumping and walking. The best R can be determined by comparing the load calculated from Eq. 9 with the force plate data in able to make the mean error of the peak minimum by least square method. The best R value is influenced by many factors, like volunteer's exercise habit, limbs proportion, rhythm sensation, height, mass, ages or other factors which can influence the human activity. Some relative researches have shown that the BMI (Body Mass Index) can influence human's plantar pressure. We then design experiments to find the relationship between the best R and BMI. For bouncing activity, some of

Table 1 The best R for bouncing activity at different frequency (1.5 Hz)

Test subject's mass (kg)	Height (m)	Best R	Mean error of Peak
57.843	1.70	0.936	3.00%
58.778		1	4.44%
59.778		0.976	3.84%
61.450		0.890	4.76%
77.452	1.79	0.857	4.42%
78.309		0.728	8.24%
79.049		0.933	7.30%
80.098		0.870	7.82%
81.637		0.819	6.52%

Table 2 The best R for bouncing activity at different frequency (2.0 Hz)

Test subject's mass (kg)	Height (m)	Best R	Mean error of Peak
56.932	1.70	0.797	5.57%
57.870		0.898	3.63%
58.755		0.868	3.49%
59.686		1	3.49%
60.573		0.841	2.99%
78.228	1.79	0.780	9.11%
79.036		0.781	6.91%
79.919		0.815	6.77%
80.938		0.847	5.15%
81.832		0.807	5.18%

Table 3 The best R for bouncing activity at different frequency (2.5 Hz)

Test subject's mass (kg)	Height (m)	Best R	Mean error of Peak
56.949	1.70	0.855	4.48%
57.742		0.937	3.21%
58.808		0.936	3.899%
59.592		0.911	5.51%
60.576		0.855	4.75%
61.539		0.820	4.53%
77.394	1.79	0.862	5.65%
78.045		0.757	9.56%
79.157		0.821	9.74%
79.795		0.784	9.95%
80.679		0.77	8.71%
81.718		0.76	7.49%

the best R value we found for test cases with three frequencies (1.5, 2.0 and 2.5 Hz) are given in Table 1 to Table 3.

The associated peak error for these calculated R values varies in the range 3%-9.9%. A similar estimation error range was recently reported by Bocian *et al*. (2016). In their study, they utilized a wireless attitude and heading reference system which comprises a tri-axial accelerometers and gyroscopes, the same as a smartphone. The same procedure was applied to jumping test data to determine the

Fig. 13 Crowd-load experiment

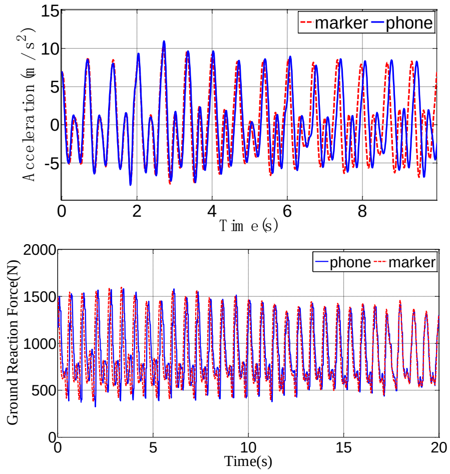


Fig. 14 Acceleration time domain and the comparison of the ground reaction force between the phone and the marker (1.5 Hz bouncing)

best R value. Again, it was found the R value was individual-depended and it varied in a range of 0.88-1.0. For walking test cases, however, it was difficult to obtain such R values because only single footfall forces (but not continuous force time history as jumping and bouncing) were recorded in the experiments.

The relation between the best R and BMI in bounce case can be represented below by binomial fitting (Eq. (10)).

$$R = \begin{cases} -0.18BMI^2 + 7.28BMI - 73.79 \\ (19.5 \le BMI \le 22) \\ -0.14BMI^2 + 7.23BMI - 89.12 \\ (24 \le BMI \le 28) \end{cases} \quad (0.5 \le R \le 1) \qquad (10)$$

After statistical analysis on all the experimental data, we suggest using R=1.0 in Eq. (9) for calculating jumping force. As for bouncing activity, using Eq. (10) to calculate the best R and then apply the best R to Eq. (9).

Fig. 12 compares the time histories of calculated force with that of the force plates for bouncing activity at 1.5 Hz and jumping activity at 2.0 Hz. The mean error of the peak are 5.05% (1.5 Hz) and the 4.38% (2.0 Hz).

5. Application for crowd-load measurement

Using smartphone to measure the crowd load is perhaps

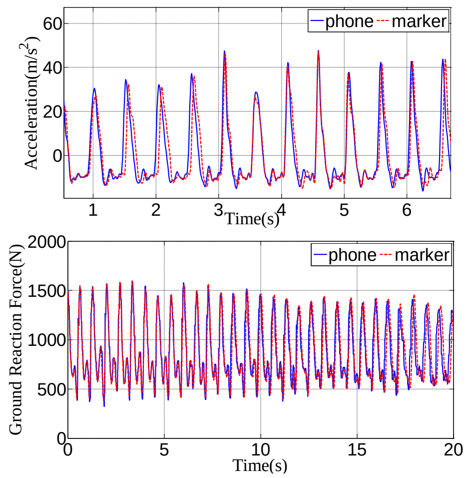


Fig. 15 Acceleration time domain and the comparison of the ground reaction force between the phone and the marker (2.0 Hz jumping)

the most attractive application of the device. As shown below (Fig. 13), we conducted a preliminary crowd-load experiment by employing 48 volunteers. Each of them carried an iPhone 6/6s on his/her waist by a belt. We also used 3D MCT in the experiment which consists of 18 cameras. Each test subject had three markers whose trajectories were monitored by 3D MCT. Test subjects were asked to bounce and jump to different frequencies in the experiment.

Fig. 14 and 15 compares the forces computed by marker's record and smartphone's record for bouncing and jumping test, respectively. The error in peak load value is 8.74% and 4.58% for bouncing and jumping. The results demonstrate the ability of smartphone for the crowd load measurements.

6. Conclusions

In order to verify the application of the smartphone measurement for pedestrian-induced loads, this paper carried out shaking table experiment, individual and crowd-load measurement. In the shaking table experiment, the smartphone can record the sine wave acceleration accurately in time domain and frequency domain. The time domain features of the sweep wave acceleration can also be obtained precisely. With the help of 3D MCT, it is found that the smartphone can measure an individual's movement which is in turn converted to human-induced load by a rigid body model. Preliminary experiments show that this methodology can be directly used in crowd load measurement. The accuracy of the load measurement depends on the installation manner, location of the smartphone and also the mass participation coefficient in the biomechanical model. Results in this study show that the load measurement errors in peak values for bouncing and jumping are within 10% for the suggested rigid model and suggested coefficient. More experimental data are necessary for determining a proper partition coefficient for walking activity.

Acknowledgements

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