RESEARCH ON QUICK SEISMIC STRUCTURAL MONITORING AND DAMAGE EVALUATION TECHNIQUE USING SMARTPHONE

Jinke Li [(1)], Xuefeng Zhao [(2)]

[(1)] *No. 2 Linggong Rd., School of Civil Engineering, Dalian University of Technology, jinkeli@mail.dlut.edu.cn*
[(2)] *Professor, No. 2 Linggong Rd., School of Civil Engineering, Dalian University of Technology, zhaoxf@dlut.edu.cn*

Abstract

Nowadays, the city is bigger and bigger while earthquake is still a threat to the city buildings. However, most buildings except for few significant buildings don't have the structural health monitoring system. The assessment of buildings in the city region often depends on the traditional vulnerability analysis so that the real vibration time-histories of most buildings are unknown to engineers. On account of acquiring the real response of large amounts of buildings, GroundEye is proposed as a building structure monitoring and damage evaluation system based on smartphone. It can collect the displacement and acceleration of the building structure and assess the health condition of the buildings. This system is divided into two parts as monitoring part and damage assessment part. In the monitoring part, this system is based on smartphone which is a kind of developing sensor. As a smartphone is a collection of different sensors such as accelerometer, gyroscope, GPS, camera, and there are more and more applications of using smartphone as sensor in structural health monitoring. In the practical engineering, the floor acceleration could be acquired by the built-in accelerometer of smartphone easily. Besides, the inter-story drift could be monitored by the camera of smartphones through image processing algorithms. In the damage assessment part, the monitoring data acquired by smartphones could be uploaded to the database. Then, the monitoring data will be analyzed through code and different digital signal processing methods. And the analysis results will classify the structure into different damage levels. Besides, algorithms of artificial intelligence will be used to do data mining, which will show the advantage of big data. As a result, the building damage caused by a seismic in a city region could be obtained through crowdsourcing. In this paper, the principle of this system is introduced, and inter-story is taken as an example among all the parameters. Due to the fact that smartphone is not popularized in monitoring, multiple-degree-of-freedom shear model is used to simulate a seismic strike on a virtual city. After this, the identified results are used to categorize 5 damage levels, and artificial neural network is used to find the minimum number of smartphone monitoring systems in different structure types. As a result, this system could realize quick building damage evaluation within the city region through crowdsourcing.

Keywords: smartphone; damage evaluation; crowdsourcing; artificial neural network; city region.

1. Introduction

Nowadays, the city is becoming bigger and bigger. Once an earthquake strikes a city, due to the lack of monitoring sensors, the building real status couldn't be acquired in time. The most important factor is the high cost. Facing this problem, the usage of smartphone showed the possibility of low-cost monitoring, and smartphones had been used in seismic detection [1], pedestrian bridge vibration monitoring [2], cable force measurement [3]. Apart from these applications, smartphones have been verified in monitoring the building parameters, such as floor acceleration [4, 5, 6], inter-story drift [7], surface defects [8]. With the development of technology, the smartphone integrates different types of sensors which are continuously upgrading, and the smartphone has been popularised in the world. As a result, it is possibility to acquire large amounts data of buildings through smartphones. Once large amounts data are collected, the mathematical statistics, machine learning, deep learning and so on could be used to do data analysis.

Although the smartphone can acquire different kinds of data, in this study, the inter-story drift is chosen as the damage index for buildings. Inter-story drift is an engineering parameter, which is often used to assess the building structure damage [9]. In this study, using inter-story drift as the damage index, 5 building damage levels were categorised according to HAZUS [10].

At present, the fact is that smartphone is still not popularized in monitoring, so large amounts data couldn't be acquired. However, the scientific research about the city region damage need to be studied, such as building damage level among the city and the damage level statistics. In this study, in order to simulate the monitoring results during an earthquake, the multiple-degree-of-freedom (MDOF) shear model proposed by Lu [11, 12, 13] was used. Using this model, the nonlinear time-history analysis (NTHA) of thousands of different type building structures could be modelled during an earthquake. After the calculation, the max inter-story drift ratio (MIDR) could be stored.

Nowadays, machine learning and deep learning is developing fast, which is widely used in many fields, such as automatic drive, image processing, recommender system. The core of machine learning are the algorithms which can be used to process large amounts data such as support vector machine (SVM), artificial neural network (ANN), naïve Bayes [14, 15]. In this study, ANN was used to train the model.

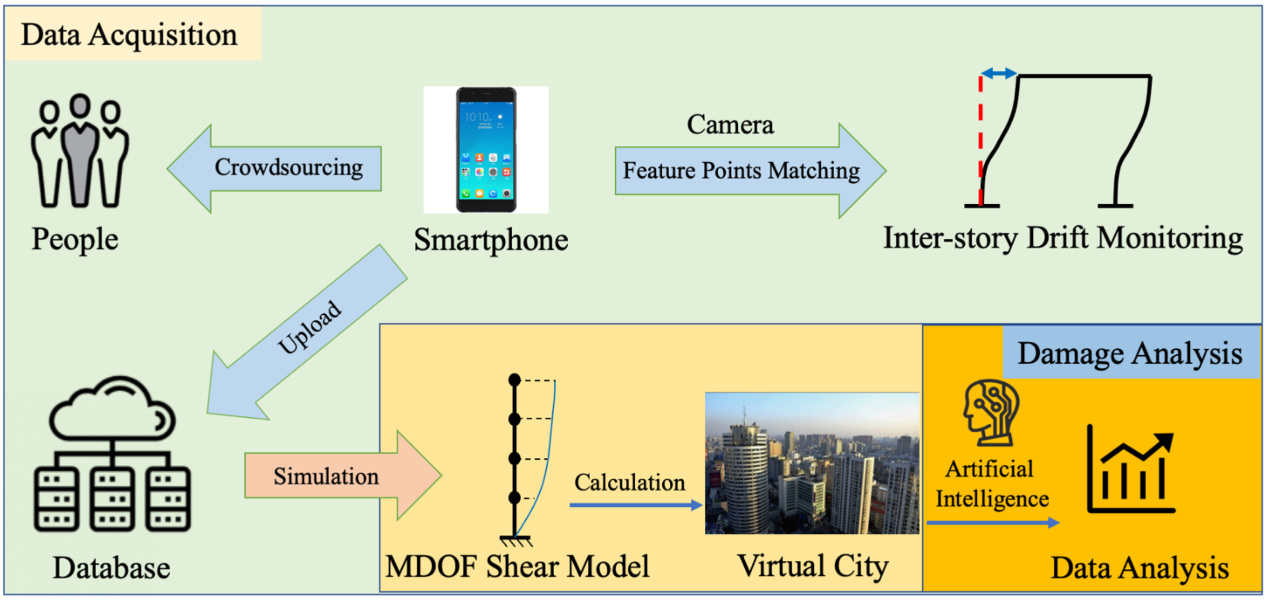


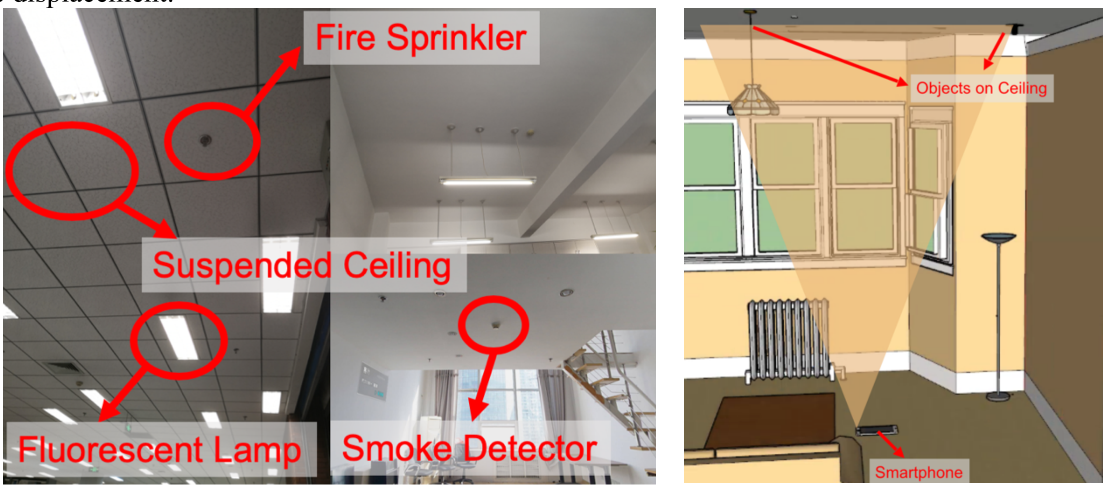
Fig. 1 – Schematic diagram of GroundEye in this paper.

In this paper, in order to introduce GroundEye, using smartphone to acquire inter-story drift is taken as an example. This paper is organised in the following sequence. First, the data acquisition using smartphones was introduced. Second, the virtual city was introduced, and the NTHA of the city buildings were calculated through MDOF shear model. In this process, the MIDR of all buildings could be identified. Third, these data were processed through an ANN model to make a regression of 5 damage levels. At last, the sensor placement advices could be concluded. Schematic diagram of GroundEye in this paper is shown in Fig. 1.

2. Data Acquisition

With the development of image processing, there are lots of algorithms to recognize the feature points in a picture such as scale-invariant feature transform (SIFT) [16], speeded up robust features (SURF) [17] and binary robust invariant scalable keypoints (BRISK) [18]. After this, the detected feature points could be used in other process such as drawing point cloud and three-dimensional reconstruction. These feature points can also be used in displacement monitoring, and there are already many applications in structural health monitoring. Monitoring the mid-span displacement of bridge [19] and experiment frame structure vibration [20] are two common instances among the applications.

As smartphone integrates camera, it's possible to use it to capture pictures indoor and analyse them. In a common building, there are many markers on the ceiling such as fire sprinklers, suspended ceiling supports, fluorescent lamps, and smoke detectors as shown in Fig. 2(a). Because there are lots of markers exist on the ceiling, it could be easy to stick a smartphone to the floor with the front camera on to shoot video of the ceiling as shown in Fig. 2(b). When an earthquake strikes an area, the videos shot by the smartphone could determine the inter-story drift. Then, the image process algorithm like SURF could be used to determine the relative displacement.

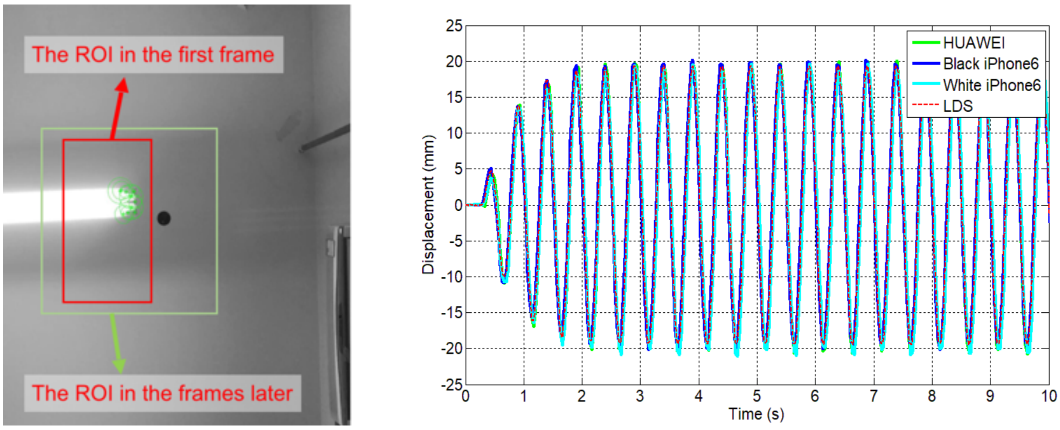


(a) (b)

Fig. 2 – (a) Ceiling markers. (b) A schamatic of using smartphone to monitor inter-story drift.

The inter-story drift could be identified through the following procedure. Before the smartphone installation, the scaling factor (SF), which is the ratio of physical length to the pixel length, should be calibrated. Then, a smartphone could be fixed to floor with front camera shooting video of the ceiling. In the image process, the first frame should be chosen as a reference, and relative displacements could be identified by subtract the feature points location in first frame. The region of interest (ROI) should be chosen carefully. As shown in Fig. 3 (a), it should guarantee that objects in one ROI should be on the same horizontal plane, under this condition, the scaling factor will be the same.

In the verification test, experiments were conducted on a shaking table, and the results of three smartphones and a laser device sensor (LDS) are shown in Fig. 3 (b). As the monitoring results of three smartphones agree well with LDS, the feasibility of using smartphone to monitor inter-story drift has bee verified.



(a) (b)

Fig. 3 – (a) The ROI selection and the detected feature points. (b) The results of different smartphones.

After the experiment, it could be verified that smartphone type: HUAWEI Mate 10 Pro, iPhone 6 have a precision of 0.1664mm with distance 3000mm. This could satisfy the demand of inter-story drift monitoring. More details could be found in the paper [7].

3. Nonlinear Time-History Analysis (NTHA)

Due to the fact that smartphones have not been widely used in monitoring, the monitoring results should be simulated. In order to implement this task, the NTHA model proposed by Lu [11, 12, 13] was conducted to simulate the real earthquake response of buildings.

First, the city data were collected before calculation. The building properties needed include construction year, floor number, structure type, area, longitude and latitude. These data were based on a real city in China, while part of the data, which were difficult to acquire, were generated randomly. For example, the areas of different buildings were generated with an uniform distribution. Therefore, the virtual city was based on a real city. There are 46188 buildings in total in this city. Besides, there are 19 structure types in this virtual city according to Table 5.1 in HAZUS [10], and they are listed in Table 1.

Table 1 – Structure type list.

<table>
<tr><th>No.</th><th>Label</th><th>Description</th></tr>
<tr><td>1</td><td>S1L</td><td rowspan="3">Steel Moment Frame</td></tr>
<tr><td>2</td><td>S1M</td></tr>
<tr><td>3</td><td>S1H</td></tr>
<tr><td>4</td><td>S2H</td><td>Steel Braced Frame</td></tr>
<tr><td>5</td><td>C1L</td><td rowspan="3">Concrete Moment Frame</td></tr>
<tr><td>6</td><td>C1M</td></tr>
<tr><td>7</td><td>C1H</td></tr>
<tr><td>8</td><td>C2L</td><td rowspan="3">Concrete Shear Walls</td></tr>
<tr><td>9</td><td>C2M</td></tr>
<tr><td>10</td><td>C2H</td></tr>
<tr><td>11</td><td>C3L</td><td rowspan="2">Concrete Frame with Unreinforced Masonry Infill Walls</td></tr>
<tr><td>12</td><td>C3M</td></tr>
</table>

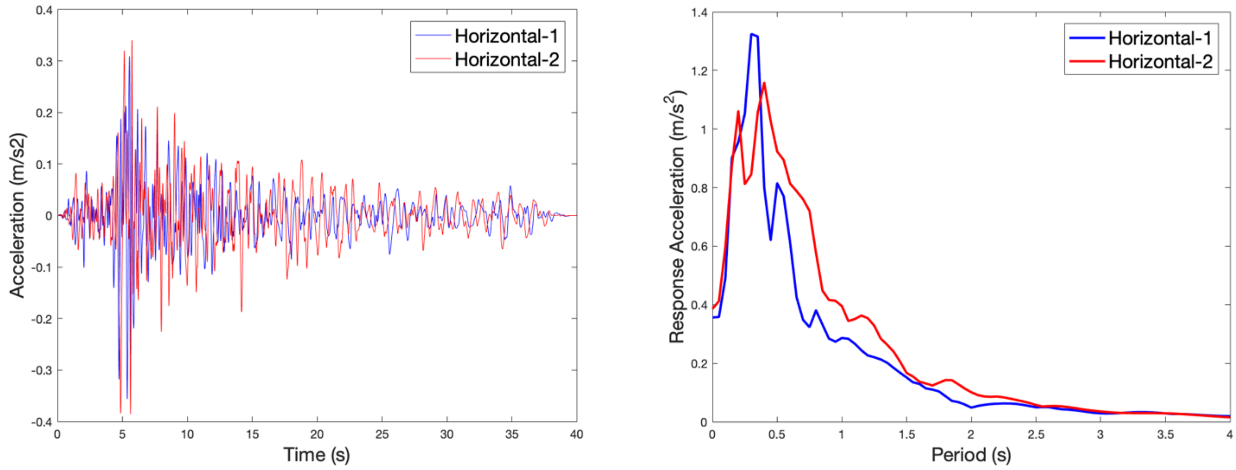
13	C3H	
14	RM2L	Reinforced Masonry Bearing Walls with Precast Concrete Diaphragms
15	RM2M	
16	RM2H	
17	URML	Unreinforced Masonry Bearing Walls
18	URMM	
19	MH	Mobile Homes

An earthquake was imported into this model, and the seismic wave was downloaded from PEER [21]. The information of the seismic wave is listed in Table 2.

Table 2 – Seismic wave information.

Earthquake Name	**Year**	**Station Name**	**Magnitude**	**Mechanism**
Humbolt Bay	1937	Ferndale City Hall	5.8	Strike slip

The seismic wave time history and elastic acceleration response spectra are shown in Fig. 4 (a) and (b) respectively.



(a) (b)

Fig. 4 – (a) Acceleration time history. (b) Elastic acceleration response spectra.

In order to verify the model could be competent under different seismic wave intensity, the peak ground acceleration (PGA) was modified 20 times from 0.56 m/s^2 to 11.11 m/s^2. After the parameters imported into the model, the MIDR of each building could be identified. Then, the damage level of each building (no damage, slight, moderate, extensive, complete) was identified according to HAZUS [10].

After the processes above, the monitoring results have been simulated through MDOF shear model. Then, these data could be gathered to be analyzed through an ANN model.

4. Artificial Neural Network (ANN) Model

In this study, an ANN model was built according to the city parameter characteristics. Assume all the buildings in this city experienced the same earthquake. One earthquake with a certain PGA was an independent model, so there were 20 models in total.

Among all the building property parameters: construction year, floor number, structure type, area, fundamental frequency and code type, 6 parameters were used as input. At the same time, 5 damage levels were chosen as output, which were no damage, slight, moderate, extensive and complete. Based on the experience, the designed model had two hidden layers in the model [14], and each layer has 9 units. The number of units were chosen as the sum of 2/3 of input units' number and output units' number [15]. In the hidden layers, the rectified linear unit (ReLU) was chosen as activation function.

Given the building structure parameters, the goal of this model is to identify which damage level the building is. Because there are 5 damage levels in this model, this problem is multiclass classification. The output layer has 5 units and a sigmoid activation function, and the optimizer is root mean square (RMS) propagation. In order to evaluate the performance, record 'accuracy' and 'mean square error' (Loss) value in the training history. The structure of designed ANN model is shown in Fig. 5.

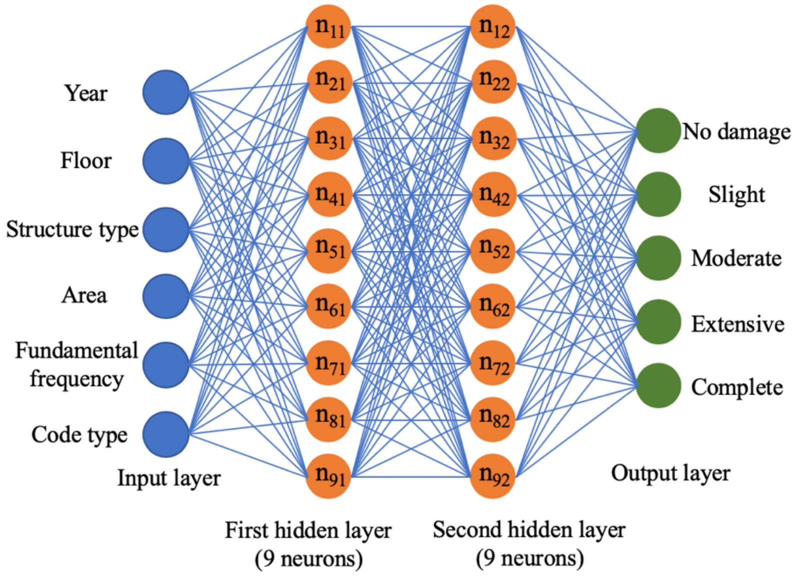


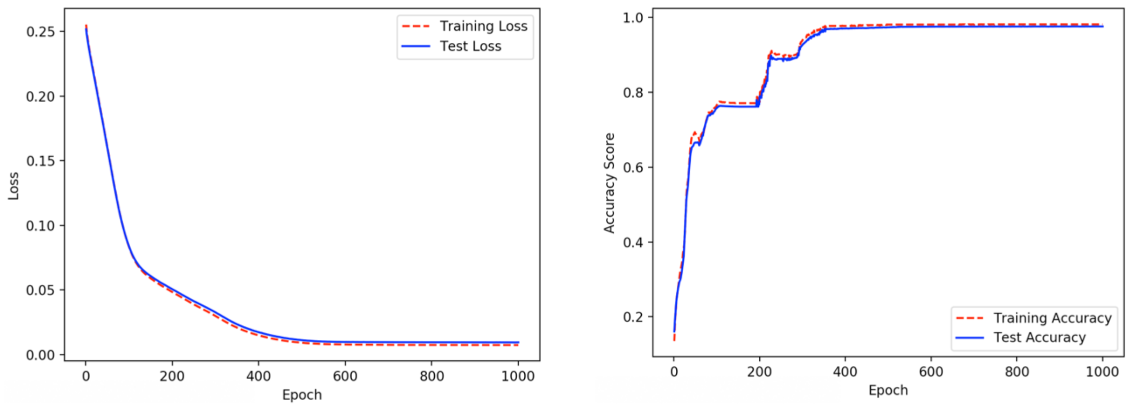
Fig. 5 – The designed ANN model.

Draw two pictures (loss-epoch and accuracy-epoch) to view the loss and accuracy variance history to prevent overfitting. For each model, 1000 epoch was set firstly, and the batch size was set 1000.

5. Conclusion

When large amounts of monitoring data are collected, lots of things could be done just analysing big data. In this study, the minimum number of buildings with installed monitoring system was studied. There are all 46188 buildings in the virtual city. These specimens were categorised into training set and test set. This problem will change into finding a smallest number of training set with relatively high accuracy. As a result, the training set percentage was changed many times to ensure the test accuracy over 95%. After trail and error, the minimum value of training set percentage was identified.

An example of training history is shown in Fig. 6. It could be concluded that the loss starts to converge after epoch 500. Because training loss and test loss continues decreasing, and training accuracy and test accuracy continues increasing, the model is not overfitting.



(a) Traning loss and test loss history. (b) Accuracy history.

Fig. 6 – Training history of PGA =10m/s2, training set proportion = 3%, epoch = 1000.

The results of 20 experiments are collected in Table 3.

Table 3 – The size, accuracy and loss of each test in the last epoch.

PGA (m/s^2)	**Training Set Percentage (%)**	**Building Number**	**Training Accuracy**	**Training Loss**	**Test Accuracy**	**Test Loss**
0.56	3	1385	1.000	0.000	1.000	0.000
1.11	3	1385	0.978	0.009	0.973	0.010
1.67	3	1385	0.981	0.007	0.978	0.008
2.22	1	461	0.976	0.013	0.957	0.020
2.78	4	1847	0.982	0.006	0.974	0.008
3.33	4	1847	0.982	0.011	0.981	0.012
3.89	2	923	0.990	0.004	0.990	0.004
4.44	2	923	0.996	0.002	0.996	0.002
5.00	2	923	0.990	0.007	0.980	0.010
5.56	2	923	0.979	0.009	0.979	0.009
6.11	2	923	0.969	0.018	0.968	0.019
6.67	4	1847	0.975	0.010	0.970	0.012
7.22	4	1847	0.968	0.013	0.960	0.016
7.78	3	1385	0.958	0.020	0.951	0.022
8.33	2	923	0.989	0.010	0.981	0.013
8.89	4	1847	0.959	0.017	0.952	0.019
9.44	3	1385	0.978	0.011	0.976	0.012
10.00	2	923	0.981	0.010	0.973	0.012
10.56	2	923	0.985	0.006	0.977	0.009
11.11	2	923	0.983	0.008	0.978	0.010

A conclusion could be drawn that the minimum number of 4% of all buildings in the city, which is 1847 out of 46188 buildings, could predict the whole city building damage levels with accuracy higher than

95% within one earthquake. In other words, about 98 buildings at least in one building structure type should have monitoring system, then the damage level of whole city buildings could be predicted.

In this model, only the building parameters and the damage levels were needed, the parameter of earthquake did not involve in the calculation. It could be seen, once an earthquake strikes an area, if the earthquake intensity within the city is the same, part of the monitoring data could predict the whole city buildings' damage level.

However, the earthquake waves are not the same with different soil conditions, so the buildings in the city experience different earthquake. As a result, it needs further research on adding earthquake parameters to the model.

All in all, GroundEye system utilizes smartphones as sensors to monitor the building vibration, which will be potential to acquire large amounts data. Then, these data could be analyzed through data processing method such as machine learning. Therefore, it will be possible for quick building damage assessment within city region via crowdsourcing.

6. Acknowledgements

Funding: This work was supported by National Key research and development program (2016YFE0202400) and National Key R&D Program of China during the 13th Five-Year Plan Period (2016YFC0802002).

7. References

[1] Kong Q, Allen RM, Schreier L, Kwon YW (2016): MyShake: A smartphone seismic network for earthquake early warning and beyond. *Science Advances*, **2** (2), e1501055–e1501055.
[2] Feng M, Fukuda Y, Mizuta M, Ozer E (2015): Citizen sensors for SHM: Use of accelerometer data from smartphones. *Sensors (Switzerland)*, **15** (2), 2980–2998.
[3] Zhao X, Han R, Ding Y, Yu Y, Guan Q, Hu W, et al (2015): Portable and convenient cable force measurement using smartphone. *Journal of Civil Structural Health Monitoring*, **5** (4), 481–491.
[4] Shrestha A, Dang J, Wang X (2018): Development of a smart-device-based vibration-measurement system: Effectiveness examination and application cases to existing structure. *Structural Control and Health Monitoring*, **25** (3), e2120.
[5] Xie B, Li J, Zhao X (2019): Research on damage detection of a 3D steel frame model using smartphones. *Sensors (Switzerland)*, **19** (3), 1–17.
[6] Zhao X, Han R, Yu Y, et al (2017): Smartphone-Based Mobile Testing Technique for Quick Bridge Cable – Force Measurement. *Journal of Bridge Engineering*, **22** (4), 1–9.
[7] Li J, Xie B, Zhao X (2019): Measuring the interstory drift of buildings by a smartphone using a feature point matching algorithm. *Structural Control and Health Monitoring*, e2492.
[8] Wang N, Zhao X, Zhao P, Zhang Y, Zou Z, Ou J (2019): Automatic damage detection of historic masonry buildings based on mobile deep learning. *Automation in Construction,* **103** (July 2018), 53–66.
[9] Morfidis K, Kostinakis K (2017): Seismic parameters' combinations for the optimum prediction of the damage state of R / C buildings using neural networks. *Advances in Engineering Software*, 106, 1–16.
[10] FEMA (2012a): Multi-Hazard loss estimation methodology-earthquake model technical manual (HAZUS- MH 2.1). Federal Emergency Management Agency, Washington, DC.
[11] Lu X, Han B, Hori M, Xiong C, Xu Z (2014): A coarse-grained parallel approach for seismic damage simulations of urban areas based on refined models and GPU/CPU cooperative computing. *Advances in Engineering Software*, 70, 90–103.
[12] Xiong C, Lu X, Guan H, Xu Z (2016): A nonlinear computational model for regional seismic simulation of tall buildings. *Bulletin of Earthquake Engineering*, **14** (4), 1047–1069.
[13] Xiong C, Lu X, Lin X, Xu Z, Ye L (2017): Parameter Determination and Damage Assessment for THA-Based Regional Seismic Damage Prediction of Multi-Story Buildings. *Journal of Earthquake Engineering,* **21** (3), 461–485.
[14] Albon C (2018): *Machine Learning with Python Cookbook: Practical Solutions from Preprocessing to Deep Learning.* O'Reilly Media.
[15] Kirk M (2017): *Thoughtful machine learning with Python: a test-driven approach.* O'Reilly Media.
[16] Lowe DG (2004): Distinctive Image Features from Scale-Invariant Keypoints. *International Journal of Computer Vision*, **60** (2), 91–110.

[17] Bay H, Ess A, Tuytelaars T, Van Gool L (2008): Speeded-Up Robust Features (SURF). *Computer Vision and Image Understanding*, **110** (3), 346–359.
[18] Leutenegger S, Chli M, Siegwart RY (2011): BRISK: Binary Robust invariant scalable keypoints. *Proceedings of the IEEE International Conference on Computer Vision,* 2548–2555.
[19] Lydon D, Lydon M, Rincon JM Del, Su T, Robinson D, O'Brien E, *et al.* (2018): Development and field testing of a time-synchronized system for multi-point displacement calculation using low cost wireless vision-based sensors. *IEEE Sensors Journal*, **18** (23), 9744–9754.
[20] Choi I, Kim JH, Kim D (2016): A target-less vision-based displacement sensor based on image convex hull optimization for measuring the dynamic response of building structures. *Sensors (Switzerland)*, **16** (12), 1–17.
[21] PEER NGA Database. *Pacific Earthquake Engineering Research Center.* http://peer.berkeley.edu/nga/. Accessed on January 27, 2020

