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A Machine Learning Approach for Structural Health Monitoring Using Noisy Data Sets

Ahmed Ibrahim, Ahmed Eltawil, *Senior Member, IEEE*, Yunsu Na, and Sherif El-Tawil

***Abstract*—Continuous structural health monitoring of civil infrastructure can be achieved by deploying an Internet of Things network of distributed acceleration sensors in buildings to capture floor movement. Postdisaster damage levels can be computed based on the peak relative floor displacement as specified in government standards. This article uses machine learning approaches to identify the status of buildings postevent based on accelerometer traces. Prior work in the field assumed the use of high-quality accelerometers for displacement estimation. In this article, we focus on using lower quality and cheaper accelerometers, while accounting for noise effects by incorporating noisy data sets in machine learning approaches for classification. A labeled acceleration data set of buildings response to earthquakes was created, where each sample is labeled with its corresponding damage severity. Sensor noise is included in the data set to model nonideal sensors. Classification performance of machine learning algorithms, such as support vector machine, K-nearest neighbor, and convolutional neural network, is presented. Techniques for addressing noise levels are proposed, and the results are compared with regular noise cancellation techniques that adopt high-pass filtering.**

***Note to Practitioners*—This article presents a methodology for automatic estimation of buildings status in the aftermath of a natural disaster, such as an earthquake. It focuses on using low-cost inertial sensors, such as accelerometers, to sense buildings' vibrations and then applying machine learning algorithms to detect damage. Utilizing the convolutional network approach, the proposed methods detect the building damage state with high accuracy. Since this article focuses on using cheap sensors, the cost of deploying a sensor network to monitor buildings is reduced significantly. Deploying this network enables rescue and reconnaissance teams to have a clear view of the most vulnerable structures.**

***Index Terms*—Convolutional network, interstory drift ratio (IDR), machine learning, structural health monitoring (SHM).**

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A. Ibrahim is with the Department of Electrical Engineering and Computer Science, University of California at Irvine, Irvine, CA 92697-2625 USA (e-mail: amibrah1@uci.edu).

A. Eltawil is with the Computer, Electrical and Mathematical Sciences and Engineering Division, King Abdullah University of Science and Technology, Thuwal 23955-6900, Saudi Arabia, and also with the Department of Electrical Engineering and Computer Science, University of California at Irvine, Irvine, CA 92697-2625 USA (e-mail: aeltawil@ieee.org).

Y. Na and S. El-Tawil are with the Department of Civil and Environmental Engineering, University of Michigan at Ann Arbor, Ann Arbor, MI 48109-2125 USA (e-mail: yunsu@umich.edu; eltawil@umich.edu).

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I. Introduction

In THE aftermath of a natural event, such as an earthquake, rapid and accurate information from structural health monitoring (SHM) systems enables first responders and reconnaissance teams to address the most vulnerable structures first, and consequently avoid loss of lives and property. Automated monitoring is achieved by using an Internet of Things (IoT) network of preinstalled sensors to capture the movement of a building during an event, enabling distributed, accurate, and instantaneous monitoring of structures [1].

Measuring instantaneous relative displacement of floors within a given building is used to calculate the interstory drift ratios (IDRs) for each floor of the building, where IDR is the ratio of the relative floor displacement to the floor height. Documents released by government agencies and civil engineering societies, such as the Federal Emergency Management Agency and the American Society of Civil Engineers (ASCE), relate IDR values to building damage level. These documents define two main critical thresholds of relative floor displacement of a given building, such that the building can be classified into one of three categories: immediate occupancy (IO), life safety (LS), or collapse prevention (CP), which indicate that the building is either safe, needs further inspection, or unsafe, respectively [2], [3].

A. Previous Work

In the last two decades, using machine learning algorithms to identify structural damage has been studied extensively. For instance, in [4], a Bayesian probabilistic approach is presented for smart structures monitoring based on the pattern matching approach, and neural networks are used for matching the damage patterns for the purpose of detecting damage locations and estimating their severity. The damage was defined as the reduction of interstory stiffness which induced changes in modal parameters. To add the effect of noise, white noise is added to the simulated acceleration time history of the structure subjected to wideband excitation. Similarly, in [5], a bilevel damage detection algorithm that utilizes dynamic responses of the structure was presented. The approach utilized a neural network as a classifier. Signal anomaly index (SAI) was proposed to express the number of changes in the shape of frequency response functions (FRFs) or strain FRF (SFRF). SAI was calculated by using the acceleration. The damage was detected from the magnitude of the SAI value, and the location of the damage was identified using the pattern matching achieved by the neural network. In addition, noise was added to prepare a large number of training sets and to examine how noise affects the damage detection results.

A damage identification method intended for steel moment-frame buildings was presented in [6]. The method was based on artificial neural networks and modal variables. The inputs of the network were the mode frequencies, and the outputs were the stiffness. After an earthquake, the damage index at each story was determined by comparing the stiffness to the initial one which is evaluated in the beginning, i.e., without damage. A simplified finite-element model was used to generate the data needed to train the nets. The method was simulated on a five-story office building under conditions as close as possible to reality. In addition, white noise was added to simulate the effect of sensor noise.

The selection of the internal nodes activation functions of a neural network was addressed in [7]; the IASC-ASCE benchmark structure was used, and it was concluded that the best performance was achieved by training neural networks using modal parameters rather than Ritz vectors. Measurement noise is already included in part of the benchmark data set, specifically case studies 2, 4, and 5. In [8], SHM was achieved using a neuro-wavelet technique. The damage was detected based on the continuous wavelet transform. The input of the system was the mode shapes of structural elements. With respect to noise, Gaussian noise was added, and the neural network was trained with noisy and noise-free data. We use a similar approach; however, our system utilizes acceleration traces rather than deflection, since accelerometers are cheaper and already found in most smart devices nowadays. According to [9], it is expensive to increase the number of measurement points; hence, one way to address that issue is to predict the unmeasured mode shape data based on a limited number of measured data. A two-stage neural network was adopted, the first is used to predict the unmeasured mode shape and the second was used to localize and estimate the damage severity. In [10], combining neural networks with a genetic algorithm for damage detection was presented. A neural network was used to identify the structural main frequencies and mode shapes, and then a genetic algorithm was used to identify the damaged areas.

In [11], unsupervised learning approach for SHM self-organizing map (SOM) which is a class of neural networks that is used to create a 2-D representation of high dimensional data. SOM's training process relies only on the internal properties between the inputs and does not require input–output samples and, hence, a nonparametric damage detection algorithm was proposed, i.e., the algorithm does not depend on system parameters, such as modal frequency, and employ statistical approaches, such as machine learning, on raw acceleration traces and extract damage indicators.

In [12], an automated crack detection algorithm using image processing was presented. The algorithm used machine learning to automatically tune the threshold parameters to identify cracks more accurately. In [13], statistical procedures addressing the feature extraction process were used to identify features capable of detecting structural damage based on accelerometer data. Similarly, Boldt *et al.* [14] focused on automatic fault diagnosis for rotating machinery using machine learning, and recommended support vector machine (SVM) and K-nearest neighbor (KNN) algorithms for classification. In [15], several variants of KNN were proposed for SHM. Furthermore, in [16], an SVM was used for SHM, where the residual error (RE) of an autoregressive (AR) model of acceleration time series was used for damage detection. Moreover, in the same article, we used optimization algorithms to find the best parameter values of the SVM. In [17], an online version of an SVM for SHM was proposed. The input to the SVM is the statistical features of the acceleration, velocity, and displacement. Calculating velocity and displacement is done by numerical integration of acceleration, and low-frequency noise is canceled by a high-pass filter high-pass filter (HPF). In [18]–[20], convolutional neural network (CNN) was used to estimate damage severity based on accelerometer data. A CNN was used as a better alternative to other algorithms that depend on hand-crafted features. In addition, the same concept was applied to wireless sensors networks in [21] and [22]. The damage detection method operates directly on the raw vibration signals without filtering or preprocessing. A decentralized damage detection algorithm was proposed based on 1-D CNN, and it involved training an individual 1-D CNN for each wireless node.

Some of the prior work assumed the use of high-quality accelerometers to generate acceleration traces. However, a key point to note is that recently there has been a shift from using sparse, high-quality accelerometers, to using a larger number of distributed lower quality and cheaper sensors. For example, the feasibility of using smartphones to quantify seismic damage to buildings has been studied in [23] and [24]. In addition, in [25], the planar response of a smart device subjected to friction forces induced by an underlying moving plane due to an earthquake motion has been studied. In [26], built-in smartphones accelerometers were used to estimate buildings displacement during shaking. Since these accelerometers are low-quality consumer-grade ones, noise cancellation was achieved by using HPF. While filtering does improve system performance by reducing integrative noise, it comes at a risk of removing significant information from the signal as well.

Most of the prior work used to change in modal parameters to detect damage. In this article, we use IDRs as a damage indicator. We created a finite-element model of a four- and eight-story buildings, which is excited by historic earthquake traces and the response of each floor is simulated. Based on the IDRs, each floor is labeled by its damage level. We use the generated data set to train several machine learning classifiers. We also focus on the effect of noisy measurements on classification accuracy. We present alternative methods to mitigate the effect of noise, without resorting to HPF. Thus, the approach taken in this article can be summarized as follows.

1) Create a data set of buildings response to historical earthquakes and labeling the response of each floor as a sample according to its damage severity.
2) Demonstrate the effect of sensor noise on classification accuracy.
3) Use the traditional hand-crafted features and study the noise effect on them.
4) Present an approach to train classifiers using both ideal and noisy measurements to enhance accuracy.

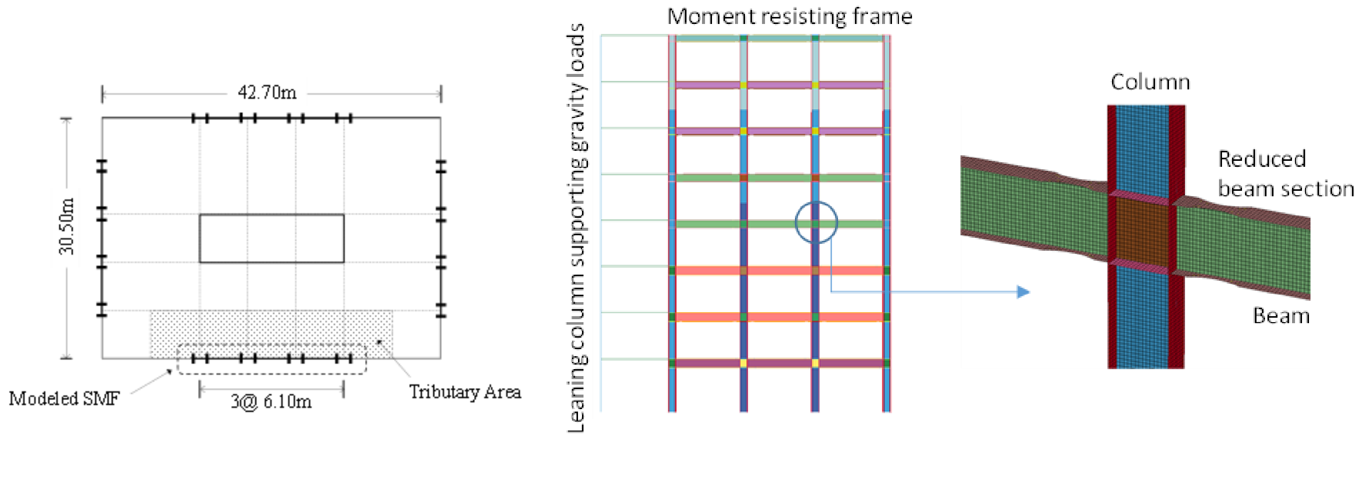

Fig. 1. Building plan and finite-element modeling details of perimeter frame. (a) Building plan. (b) SMF model.

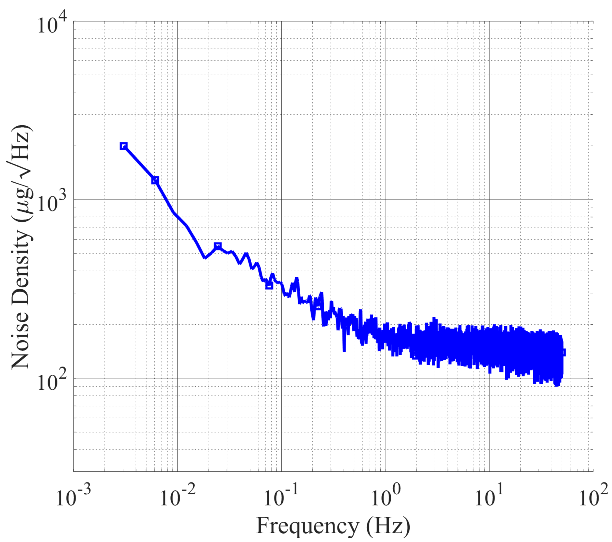

Fig. 2. Noise density of MPU6500 accelerometer.

5) Proposing classification using CNN that uses the raw input instead of extracted features and comparing with other techniques.

The rest of this article is organized as follows. In Section II, methodology of data set creation is presented. Section III describes the classification algorithms and how the features are extracted and selected. Results of the proposed techniques for accuracy enhancement are presented in Section IV. Finally, the conclusions are drawn in Section V.

II. Data Set Creation

According to government documents, buildings are classified per their damage state as IO, LS, or CP buildings. For instance, Table I lists the IDR limits for steel moment frame buildings which are stated in [2] and [3], and the corresponding physical tag used to identify the buildings' postevent condition. Hence, a building's status can be assessed by comparing its peak IDR to the predefined thresholds. Knowing the floor height, thresholds in IDR correspond to thresholds in relative floor displacement.

TABLE I
Relation Between IDR and Building State for Steel Moment Frame Buildings [2], [3]

IDR %	**Building State**	**Tag**
$< 0.7\%$	Immediate occupancy (IO)	Green
$0.7\% - 5\%$	Life safety (LS)	Yellow
$> 5\%$	Collapse prevention (CP)	Red

A. Buildings Simulation

Simulation of building response is conducted in order to generate training samples. We consider four- and eight-story buildings designed by National Institute of Standards and Technology (NIST) [27] in Seattle, WA, USA, to be representative of steel frame buildings. Three-bay perimeter steel special moment frames (SMFs) on each side of the building are used for the lateral load resisting system, as shown in Fig. 1(a) and (b). The SMFs are designed with reduced beam sections. With respect to the type of soil, we consider site class *D* which includes mixtures of dense clays, silts, and sands, which is the most common site class throughout USA [28]. Finite-element models of the SMFs are created using HyperMesh [29] and analyzed using the commercial code LS-DYNA [30]. The steel is ASTM-A992, and its engineering stress–strain properties are converted into true stress–strain data and then assigned to the finite elements. More details about the simulation setup are found in [31] and [32].

Based on the resulting IDRs, and using Table I, a data set is created that includes relative floor acceleration labeled with damage level, i.e., either IO, LS, or CP. In order to model real-cheap sensors, we have recorded the output noise of MPU6500 accelerometer chip [33] which is an off-the-shelf inertial sensor chip used in consumer devices, such as smartphones. Fig. 2 shows the power spectral density of the MPU6500 sensor. According to [32] and [34], we have assumed an additive noise model and added the recorded noise to the simulated acceleration data. Hence, two data sets are created: 1) nonnoisy data set and 2) noisy data set. For each

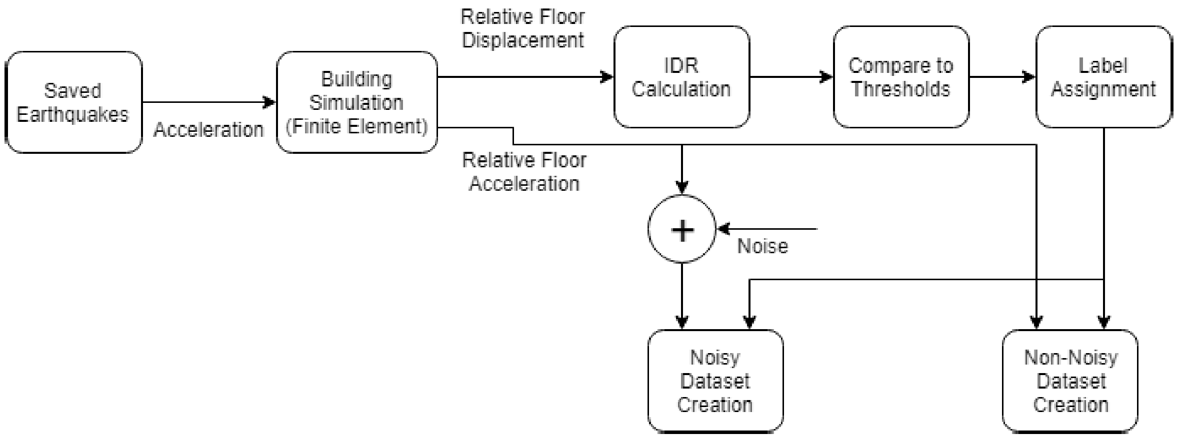

Fig. 3. Data sets creation block diagram.

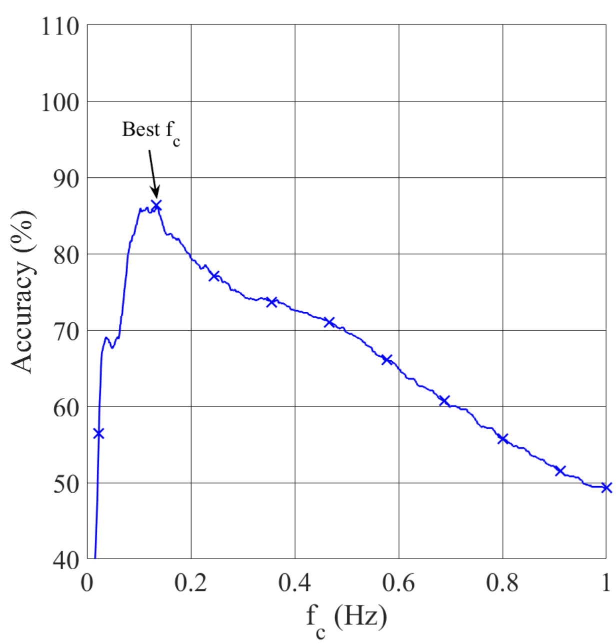

Fig. 4. Effect of changing HPF cutoff frequency on classification accuracy.

data set, 70% of the data is used for training, and 30% is used for validation.

Fig. 3 summarizes the proposed data set creation technique.

III. Classification Algorithms

A. Features Selection

Typically, acceleration data time series is represented by its discriminative features which are more convenient as inputs to classifiers. In [16], the following features were extracted from the RE of autoregressive (AR) model: maximum, minimum, difference of maximum and minimum, mean, mean of absolute, standard deviation, skewness, kurtosis, root-mean squared, form factor, crest factor, kurtosis factor, pulse factor, margin factor, and upper and lower control limits. The formulas needed to calculate each of them are mentioned in [16]. These features are assumed to be relevant to damage information. However, since in this article, we are concerned with additive noise that contaminates the measured acceleration. Hence, we propose three different methodologies to mitigate the effect of additive noise: 1) identification of noise-sensitive features; 2) using all the features while training using noisy and nonnoisy data sets; and 3) using raw noisy and nonnoisy data sets and allow the machine learning algorithm to identify the discriminative features that are immune to noise. The results of the proposed methods are presented in Section IV.

B. Classification Algorithms

Since the data set was created by comparing the peak relative displacement with certain standard thresholds, then the ordinary technique to estimate the damage label is to calculate relative displacement from relative acceleration, i.e., by double integration (DI), and then, compare the maximum value to the threshold. Ideally, without adding any noise to acceleration, that technique achieves 100% accuracy, which can be demonstrated by applying it to the nonnoisy data set. However, the same technique is not expected to achieve high accuracy when applied to the noisy data set, since DI of noise introduces large errors that severely reduce classification accuracy.

Machine learning classifiers have significant potential in processing noisy data. Several machine learning classifiers have been recommended for SHM in the literature. For instance, in [15], several variants of KNN were proposed. Besides, an SVM was used in [16] for damage detection where several optimization algorithms were used to find the best parameters of the SVM, and it was concluded grid search outperforms other searching algorithms.

As mentioned in [18] and [21], a CNN is an appropriate method to capture damage patterns in the response of buildings to vibration. In this article, we propose a CNN to classify buildings according to the level of damage based on relative floor acceleration. In addition, for the sake of comparison, we also use the grid search SVM algorithm described in [16], KNN algorithms and DI with HPF noise cancellation, which is shown later.

1) Proposed CNN Architecture: Based on earthquake strong-motion durations reported in [35], we assumed the maximum monitoring duration is 50 s, which indicates that the number of time samples is 5000 at 100-Hz sampling

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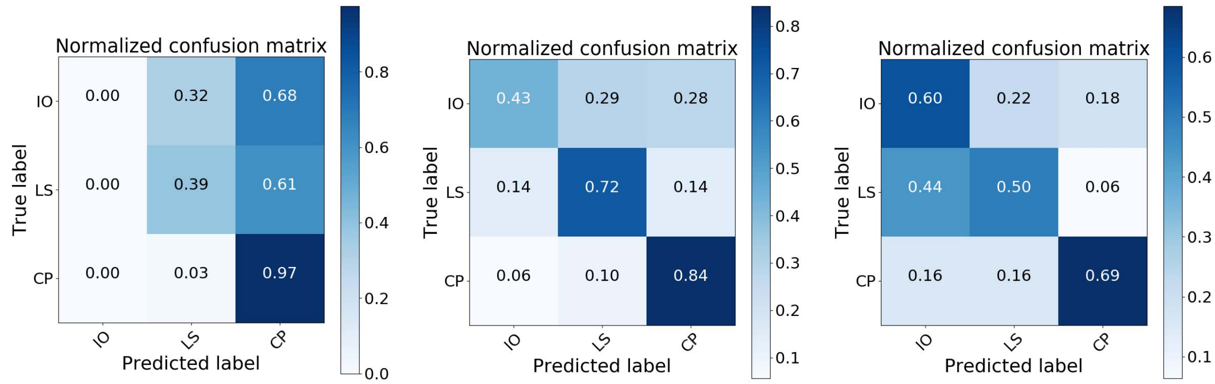

(a) (b) (c)

Fig. 5. Confusion matrices in the presence of noise without applying any noise cancellation technique. (a) Double integration (DI). (b) SVM. (c) KNN.

TABLE II
CNN NETWORK ARCHITECTURE

Layer	Type	Parameters	Activation
0	input	size = 5000	-
1	Conv1D	Kernel size=50 Filters=4	relu
2	Maxpooling	Pool size=20	-
3	Conv1D	Kernel size=10 Filters=10	relu
4	Maxpooling	Pool size=2	-
5	Flatten	-	-
6	Dense	Size=2	tanh
7	Dense	Size=3	tanh

rate. The CNN consists of seven layers that are described in detail in Table II. We also use one-hot encoding to the output, i.e., the three classes are represented by three output nodes. The network uses two convolutional and max-pooling layers.

2) Noise Cancellation Using HPF: For the sake of comparison, we show how HPF is used to minimize the effect of noise on classification using the ordinary DI method. As mentioned in [32], acceleration is contaminated with additive white noise. Evaluating displacement from acceleration requires DI, which amplifies the low-frequency noise significantly. Hence, using a HPF reduces the effect of noise in the DI method if a proper cutoff frequency is selected. We denote this method as DI+HPF. The higher the cutoff frequency, the more noise cancellation is achieved. However, increasing the cutoff frequency affects the signal and removes its low-frequency content, which in turn introduces an error.

Therefore, accuracy is expected to increase by increasing the cutoff frequency due to noise cancellation, and then, decrease when removing the low-frequency content of the signal becomes the dominant source of error. Fig. 4 shows the effect of changing the HPF cutoff frequency on the classification accuracy.

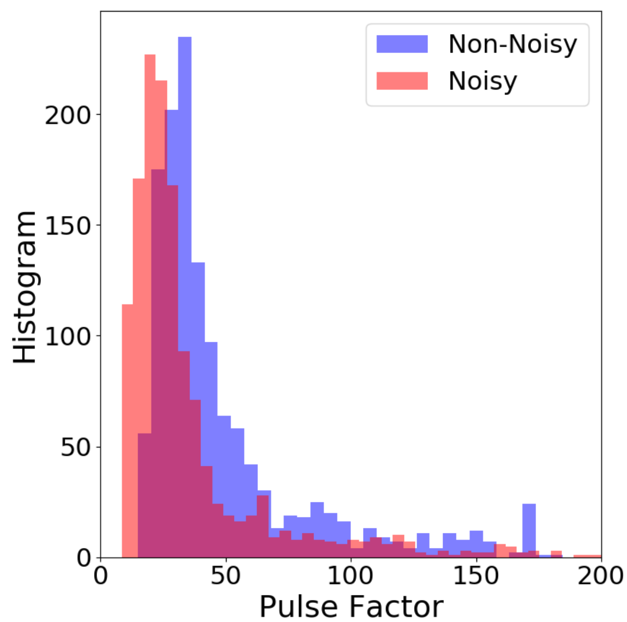

Fig. 6. Histogram of the pulse factor feature.

IV. RESULTS AND DISCUSSION

As expected, applying DI on the noisy data set results in low classification accuracy due to the accumulated error and is demonstrated by the confusion matrix, as shown in Fig. 5(a). In addition, training machine learning algorithms with the nonnoisy data set and validating using the noisy one results in poor performance as shown in Fig. 5(b) and (c). In the following, we discuss three different techniques to enhance the classification accuracy in the presence of noise.

A. Removing Noise Sensitive Features

As mentioned in [36], noise in measurements is hard to model and is, therefore, challenging to separate signal from noise. Specifically, for classification-oriented problems, such as activity recognition, appropriate features are derived from raw sensor data, which is then hand-crafted and fed into a classifier for training. This process is time consuming and requires extensive experiments to generalize well, besides

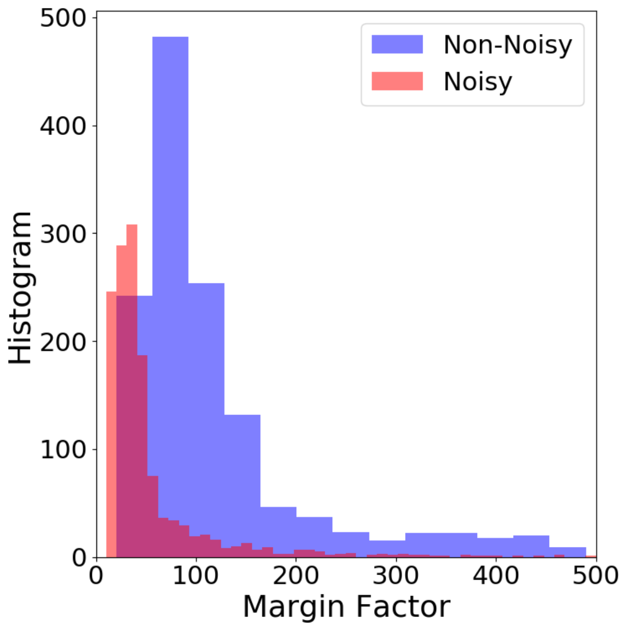

Fig. 7. Histogram of the margin factor feature.

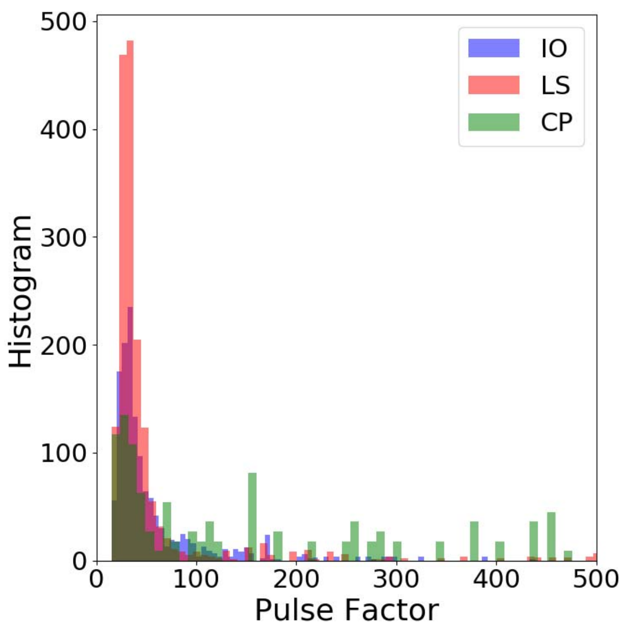

Fig. 8. Histogram of the pulse factor feature across the three classes.

being data dependent, i.e., features selection must be repeated if the data set is changed.

Hence, we apply the same approach of hand-crafted features, and each of the features mentioned in Section III-A is studied in the absence and presence of noise to identify those most sensitive to noise. The study includes the distribution of the data represented by its histogram. We focus on two main things in the histogram: 1) the effect of additive noise on the feature distribution, which is indicated if there is a significant change in the histogram of the feature with and without noise, and 2) the ability of the feature to discriminate between classes, and this is indicated by comparing the histograms of the feature across classes. This methodology is applied to the SHM data set created in Section II and the two most affected

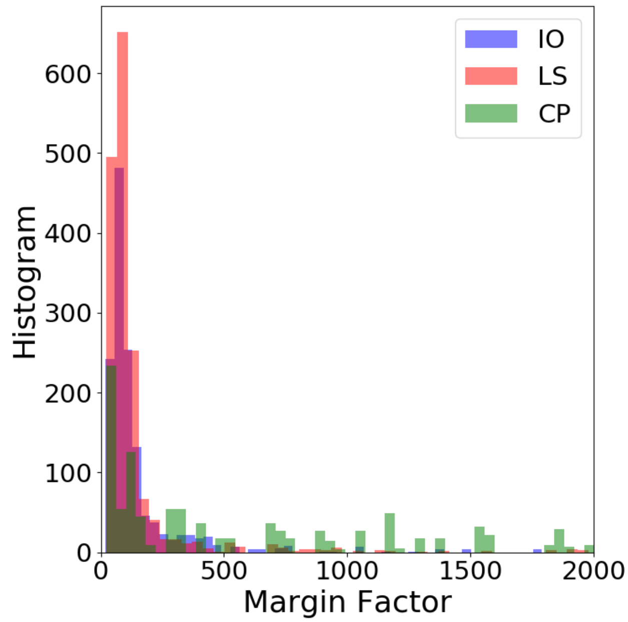

Fig. 9. Histogram of the margin factor feature across the three classes.

features by adding noise are pulse factor and margin factor which are calculated by (1) and (2), respectively, where N is the window size [16]. Histograms of these features are shown in Figs. 6 and 7, respectively. By removing these features from the features list, better immunity to noise is achieved without much loss in classification accuracy since these features are slightly discriminative, as shown in Fig. 8 and 9. It is clear that these two features are not well differentiating between IO and LS classes, while marginally useful to identify CP class

$$\text{PulseFactor} = \frac{\max(\text{RE}) - \min(\text{RE})}{1/N \sum_{i=1}^{N} |\text{RE}_i|} \tag{1}$$

$$\text{MarginFactor} = \frac{\max(\text{RE}) - \min(\text{RE})}{[1/N \sum_{i=1}^{N} \sqrt{|\text{RE}_i|}]^2}. \tag{2}$$

The SVM and KNN are trained using the nonnoisy data set after removing the noise-sensitive features, and then, validated by the noisy one. This technique results in performance enhancement, as shown in Figs. 10 and 11, respectively. The performance enhancement is clear by comparing Figs. 10 and 11 with Fig. 5(b) and (c).

B. Training Using Both Data Sets

Another approach is to train the classifier using both noisy and nonnoisy training data sets, and validate using the noisy validation data set. In this case, the classifier automatically ignores the noise-sensitive features while keeping the discriminative ones. The validation confusion matrices of the SVM and KNN are shown in Figs. 12 and 13, respectively. It is clear that training using both data sets results in better performance when compared with the base case; however, manually removing the noise-sensitive features results in better accuracy.

C. Proposed CNN

The CNN network described in Section III-B is trained using both data sets similar to the approach mentioned in

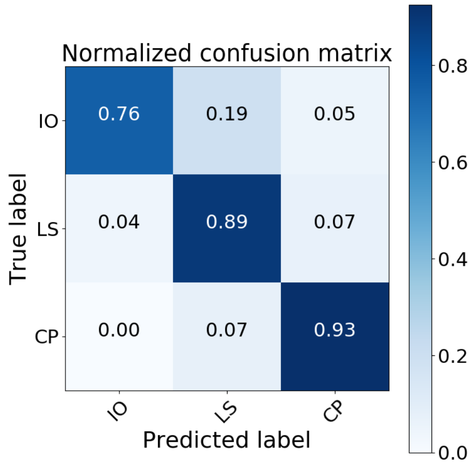

Fig. 10. Confusion matrix of SVM after removing the sensitive noise features. Algorithm is trained using the nonnoisy training data set and validated using the noisy validation one.

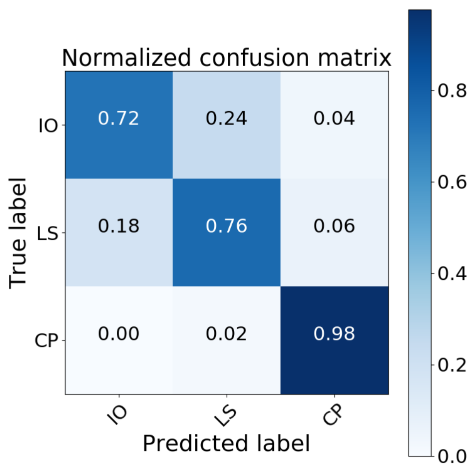

Fig. 11. Confusion matrix of KNN after removing the sensitive noise features. Algorithm is trained using the nonnoisy training data set and validated using the noisy validation one.

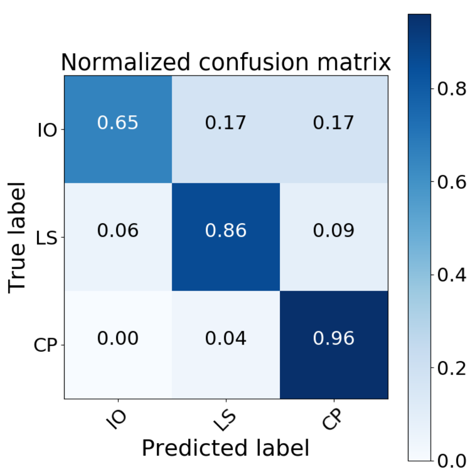

Fig. 12. Confusion matrix of SVM trained using the noisy and nonnoisy training data sets and validated using the noisy validation one.

Section IV-B. However, instead of training using features, the raw input data is used. The CNN network is assumed to be capable of identifying the discriminative features automatically. As shown in Fig. 14, the proposed algorithm outperforms the other techniques mentioned earlier.

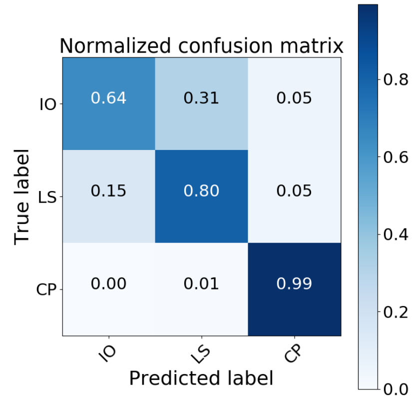

Fig. 13. Confusion matrix of KNN when trained using the noisy and nonnoisy training data sets and validated using the noisy validation one.

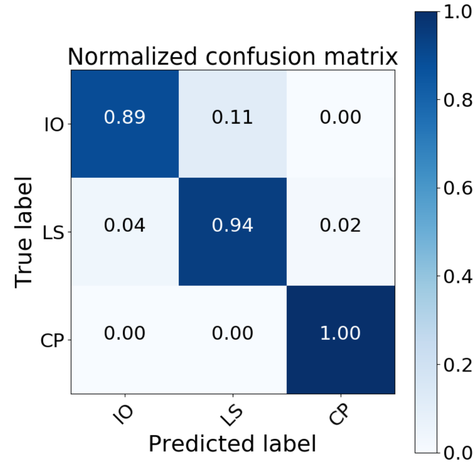

Fig. 14. Confusion matrix of the proposed CNN when trained using the noisy and nonnoisy training data sets and validated using the noisy validation one.

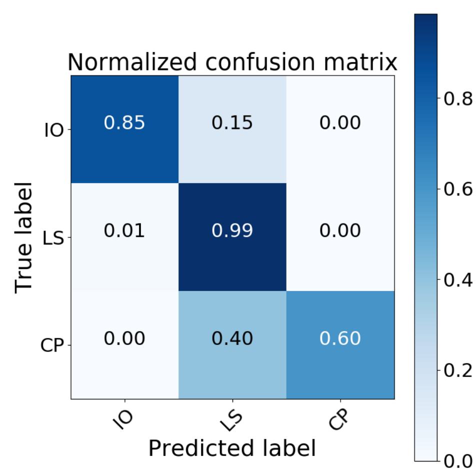

Fig. 15. Confusion matrix of DI method after applying HPF to remove noise.

D. HPF Noise Cancellation

As mentioned in Section III-B, HPF can be used for noise cancellation. Then, regular DI is performed on the filtered data to calculate displacement, which is directly used for classification. Fig. 15 shows the confusion matrix after applying this technique when using the optimal cutoff frequency.

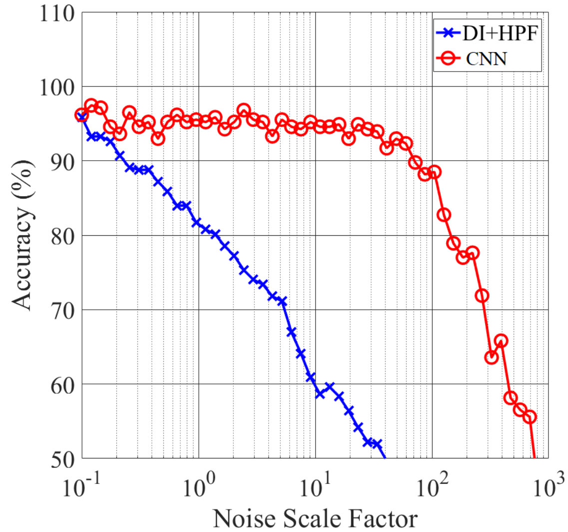

Fig. 16. Classification accuracy versus noise scale factor for the HPF and the proposed CNN techniques.

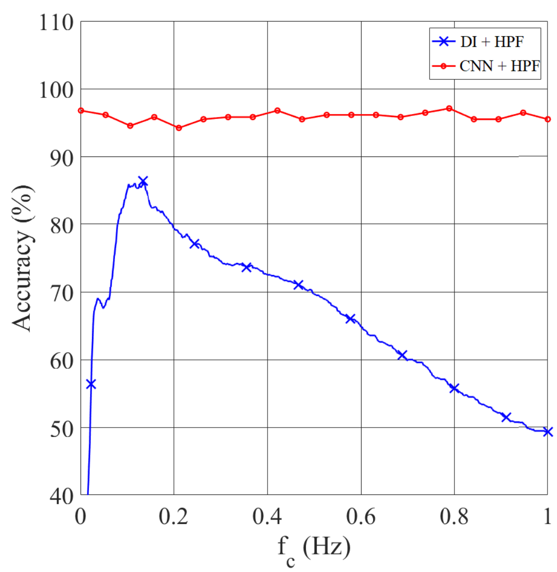

Fig. 17. Classification accuracy versus HPF cutoff frequency with and without using the proposed CNN method.

E. Effect of Noise Level on Classification Accuracy

It is clear that the proposed CNN method outperforms other methods. We demonstrate how changing the noise power affects the classification accuracy in the proposed CNN and the traditional DI+HPF techniques by multiplying the additive noise by a scale factor, as shown in Fig. 16. It is clear that the accuracy of the DI+HPF technique is less than but comparable to the proposed CNN technique at low noise levels. However, at high noise levels, the proposed CNN method results in better classification accuracy and is more resilient.

The CNN method achieves high accuracy regardless of filtering the training data. As shown in Fig. 17, HPF the data prior to training results in almost the same accuracy regardless of the HPF cutoff frequency, which outperforms the DI+HPF method.

V. Conclusion

Monitoring structural health of buildings during and after natural disasters is crucial, and directly impacts public safety. Buildings can be added to an IoT network by deploying inertial sensors in civil infrastructure, which facilitates post-disaster identification of structurally unsound buildings. In this article, we illustrated how machine learning techniques can be employed to identify buildings damaged state based on accelerometer readings in the presence of noise. We demonstrated how to address the effect of noise by using machine learning methods, such as SVM and KNN, and that removing the noise-sensitive features enhances the classification accuracy. In addition, we proposed a CNN method that is applied directly on raw data instead of the extracted features which outperformed the KNN, SVM, and traditional HPF noise cancellation methods.

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Ahmed Ibrahim received the B.Sc. degree (Hons.) in electrical engineering from Ain Shams University, Cairo, Egypt, in 2008, the M.Sc. degree in microelectronics system design from Nile University, Giza, Egypt, in 2014, and the Ph.D. degree in electrical engineering and computer science from the University of California at Irvine, Irvine, CA, USA, in 2019.

From 2008 to 2014, he was a Digital ASIC Design Engineer with Si-Ware Systems, Cairo, where he was involved in designing MEMS sensor interfaces. His research interests include signal processing, machine learning, sensor networks, and sensor fusion.

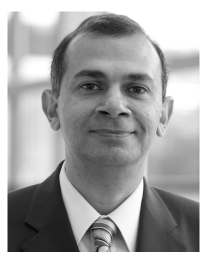
Ahmed Eltawil (S'97–M'03–SM'14) received and the B.Sc. and M.Sc. degrees (Hons.) from Cairo University, Giza, Egypt, in 1997 and 1999, respectively, and the Ph.D. degree from the University of California at Los Angeles, Los Angeles, CA, USA, in 2003.

Since 2005, he has been with the Department of Electrical Engineering and Computer Science, University of California, Irvine, CA, USA, where he was the Founder and the Director of the Wireless Systems and Circuits Laboratory. Since 2019, he has been a Professor with the Computer, Electrical, and Mathematical Science and Engineering Division (CEMSE), King Abdullah University of Science and Technology (KAUST), Thuwal, Saudi Arabia. His research interests are in the general area of low-power digital circuit and signal processing architectures with an emphasis on mobile systems.

Dr. Eltawil has been on the technical program committees and steering committees for numerous workshops, symposia, and conferences in the areas of low power computing and wireless communication system design. He received several awards, as well as distinguished grants, including the NSF CAREER grant supporting his research in low power systems.

Yunsu Na received the B.S. and M.S. degrees from Yonsei University, Seoul, South Korea, in 2011 and 2013, respectively, and the Ph.D. degree in civil and environmental engineering from the University of Michigan at Ann Arbor, Ann Arbor, MI, USA, in 2019.

His research interests include earthquake engineering, computational simulation, reconnaissance system, and signal processing.



Sherif El-Tawil received the B.S. and M.S. degrees from Cairo University, Giza, Egypt, in 1989 and 1991, respectively, and the Ph.D. degree from Cornell University, Ithaca, NY, USA, in 1996.

He is currently the Antoine E. Naaman Collegiate Professor of Civil and Environmental Engineering with the University of Michigan at Ann Arbor, Ann Arbor, MI, USA. His research interests include earthquake engineering, community resilience, disaster management, and computational simulation as applied to these topics.