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Identifying the mechanical property of mortar using a solitary wave based deep learning

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ABSTRACT

This study proposes a real-time non-destructive evaluation technique for predicting the mechanical property of mortar using deep learning and highly nonlinear solitary waves (HNSWs). Of particular interest is to predict the elastic modulus of mortar via the convolution neural networks (CNN) architectures using HNSWs as input data. HNSWs are generated in a granular crystal sensor made of vertically aligned spherical beads in 1D chain. These generated and reflected HNSWs from mortar are used as input data. HNSW datasets for mortar samples at various water-to-cement (w/c) ratios and curing ages are collected for training and validation of the CNN architectures. The pre-trained CNN architectures showed high performance for identifying the elastic modulus of mortar with a variety of w/c ratios and days of hydration.

1. INTRODUCTION

A non-destructive evaluation (NDE) using HNSWs has been recently highlighted as an attractive alternative to existing NDE technologies because of its portability, low cost, and energy efficiency (Yang 2001 and Xianglei 2011). The NDE scheme uses HNSWs generated on a granular crystal sensor consisting of vertically aligned one-dimensional chains of spherical steel particles. Importantly, high sensitivity of HNSWs on mechanical and geometrical properties of various inspection media (Yang 2001, Sen 2008) has been demonstrated in a variety of applications. Examples include the characterization of the mechanical properties of materials (Schiffer 2020, 2019, 2018), the detection of defects (Sighal 2017, Yoon 2021, Yoon 2022, Yoon 2023, and Kim

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2022), and the assessment of bone quality (Yoon 2020, Yoon 2021, Yoon 2023, and Kim 2021). Moreover, the scheme has been applied for identifying the hydration time of fresh concrete (Rizzo 2014) and cement (Ni 2012), the presence of water on concrete surfaces (Rizzo 2016), and the stiffness of hardened concrete at different w/c ratios (Nasrollahi 2017).

Motivated by such successful applications of HNSWs on NDE, this research aims to develop a real-time HNSW-based NDE method using deep learning for the estimation of the mechanical property of mortar in a fast and reliable manner. The advantage of the proposed real-time NDE scheme is that it doesn't require the explicit analysis of the characteristics, such as wave speed and amplitude, of HNSWs reflected from an inspection medium. Among various DL algorithms, this study focuses on investigating the performance of predicting Young's modulus of mortar using three pre-trained CNN architectures, i.e., AlexNet, GoogleNet, and ResNet-18.

2. COLLECTION OF INPUT DATA

This section provides the process of collecting HNSW data for training and testing of the CNN architectures. We fabricated 5 cm cubic mortar samples for three w/c ratios of 0.4, 0.5, and 0.6 at the curing day of 7 and three curing days of 7, 14, and 28 at w/c = 0.5 with a water-to-sand ratio of 1:1. HNSW data are collected from the interaction between the mortar samples and a granular crystal sensor as shown in Fig. 1(a). The granular sensor is composed of vertically aligned 21 spherical particles made of AISI 52,000 steel. The incident HNSW is generated by dropping the 1st particle (striker) in the chain. Then, it propagates down through the chain and interacts with a mortar sample located at the bottom, resulting in reflected HNSWs as schematically shown in Fig. 1(b). These incident and reflected HNSWs are recorded in the sensor particle (11th particle) with an embedded piezoelectric ceramic disc, and they are converted into voltage and transmitted to the oscilloscope in real time as shown in Fig. 1(c).

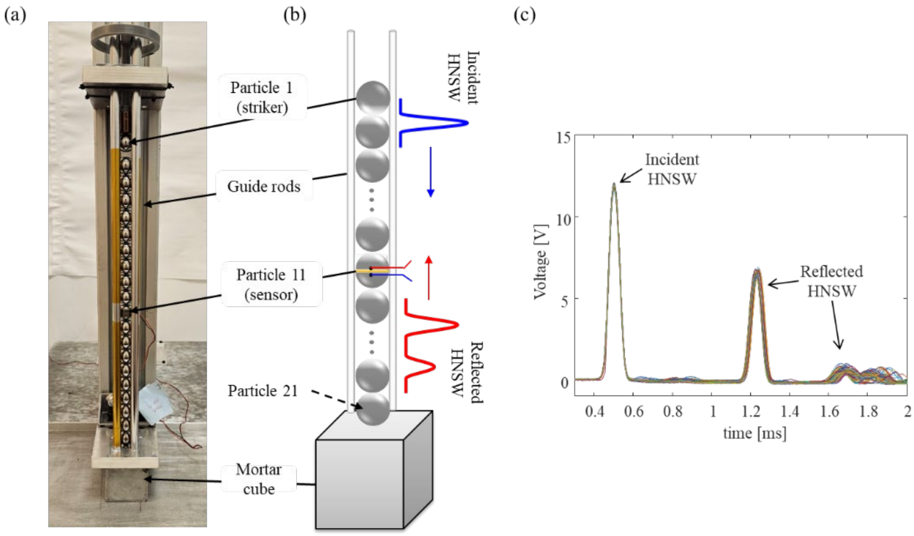

Fig. 1 (a) An experimental setup and (b) the schematic diagram of the granular crystal sensor and (c) incident and reflected HNSWs recorded from the sensor.

To predict Young's modulus using HNSWs via supervised learning, we established the relationship between Young's modulus and the PRW delay using a discrete element method (Yang 2011 and Schiffer 2020), i.e.,

$$y = \frac{ax^2+bx+c}{x+d} \tag{1}$$

where y represents the PRW delay, x is Young's modulus, and a=-0.0473, b=1.1066, c=0.2609, and d=0.09978 are fitting parameters obtained from a least square fit. Notice that the PRW delay is the arrival time difference between incident and the first (primary) reflected HNSWs, called PRW delay (see Fig. 2a). We collected a total of 600 HNSW data consisting of 100 HNSW signals for each specimen at three w/c ratios and three curing ages. Young's moduli for these HNSW data were obtained by substituting their PRW delays into Eq. (1) for supervise learning. For convenience, these input data were divided into 7 classes at intervals of 0.15 GPa, and 75% of the total data was used for training and 25% for testing.

3. RESULTS AND DISCUSSION

We employed three CNN architectures, i.e., AlexNet, ResNet-18, and GoogleNet, to predict Young's modulus using HNSW signals. AlexNet (Krzhevsky 2012) is the first CNN architecture that improves the CNN learning ability by increasing depth and implementing multiple parameter optimization strategies. GoogleNet (Szegedy 2015) is an architecture designed to achieve high levels of accuracy while reducing computational costs based on several small convolutions to drastically reduce the number of parameters. ResNet (He 2016) was designed to achieve large deep networks free of the vanishing gradient loss problems with "skip connections" and features heavy batch normalization. For training of all three architectures, we used the learning rate of 0.001 and the batch size of 128 and the stochastic gradient descent with momentum as an optimizer.

Three CNN architectures were trained and tested using HNSW input signals. For more accurate prediction of Young's modulus, we developed a new softmax regression, called a multiple mode testing scheme (Yoon 2023), that classifies the outputs using multiple HNSW input signals. The performance of the multiple mode testing scheme was compared with the single mode testing scheme which is the traditional softmax regression classifying the outputs with only one HNSW input signal. Table 1 shows the classification accuracy, recall, and precision of three CNN architectures for single and multiple mode testing schemes. Accuracy measures the overall classification accuracy. Precision measures the accuracy in classifying the specimen as positive. Recall measures the ability to detect positive specimens. With the use of the multiple mode testing, the classification accuracy increased from 89.3 % to 93.6 % for AlexNet, from 92.7 % to 97.9 % for ResNet-18, and from 89.3 % to 95.7 % for GoogleNet. ResNet-18 shows the highest classification accuracy of 97.9% in the multiple mode testing, which is 4.3% higher than AlexNet and 2.2% higher than GoogleNet. The comparison of the accuracy of the multiple and single mode testing schemes for all three models is graphically illustrated in Fig. 3. Moreover, relatively higher precision and recall were obtained for ResNet-18 than others. The lower accuracy of GoogleNet and AlexNet can be explained by the slope of the training accuracy shown in Fig. 4. Higer training accuracy is observed for ResNet-18 than GoogleNet and AlexNet. The training accuracy of ResNet-18 rapidly increases with increasing the number of training iterations, while the accuracy of GoogleNet and AlexNet increases slowly and the gradient gradually decreases.

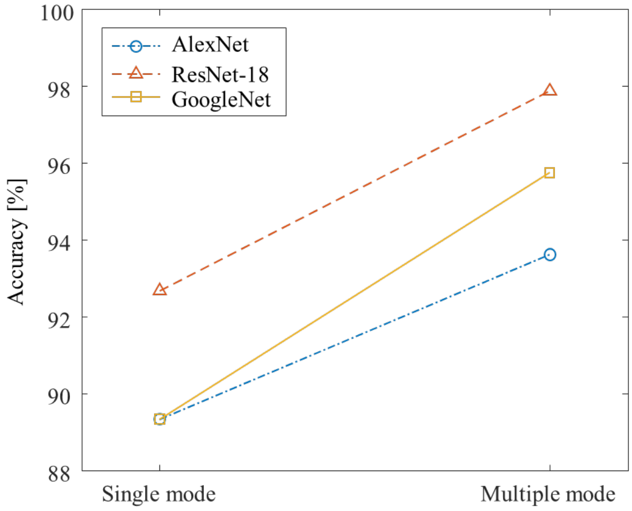

Fig. 3 Accuracy of multiple and single mode schemes for three CNN architectures.

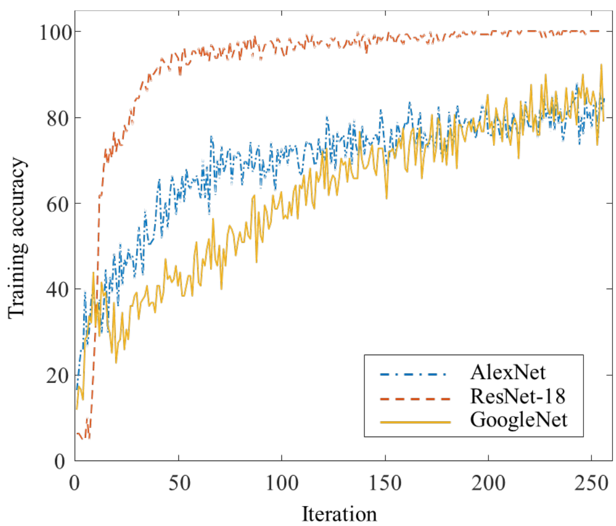

Fig. 4 Training accuracy of AlexNet, ResNet-18, and GoogleNet.

CNN model	AlexNet		ResNet-18		GoogleNet	
Mode	Single	Multiple	Single	Multiple	Single	Multiple
Accuracy [%]	89.33	93.62	92.67	97.87	89.33	95.74
Recall	0.883	0.922	0.938	0.993	0.883	0.944
Precision	0.771	0.911	0.862	0.952	0.865	0.958

Table. 1 Performance of the CNN architectures for the classification of Young's modulus for all three CNN architectures in single and multiple mode testing schemes.

4. CONCLUSION

In this study, we proposed a real-time HNSW based NDE method using three CNN architectures for classification of Young's modulus of mortar. To efficiently apply the HNSW signal data to the CNN architectures, the HNSW signals were mapped with Young's modulus through a mathematical relationship with the PRW delay obtained from a previously proven discrete element method. Approximately over 90% of accuracy was obtained for all three CNN architectures. Furthermore, we applied a multimodal approach to maximize the performance of these architectures. In multiple mode, classification accuracy increased by up to 6.4% compared to the general architecture (i.e., single mode), lowered the possibility of misclassification, and showed better performance. These results demonstrate the applicability of the HNSW based real-time NDE technique to predict and classify Young's modulus of mortar in real time.

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