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Optical time-series signals classification based on data augmentation for small sample

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Dear editor,

The analysis of captured 1D time-series sequences has been a challenge in engineering research such as sensing for a long time. 1D time series often exhibit more abstract and complex characteristics in engineering. For example, continuous or pulsed ultrasound is often used in ultrasonic detection [1] to transmit and receive energy in the medium to assess the location of damage or the degree of wear in the workpiece to be measured. However, because small damage in the workpiece is often invisible, only the temporal signals received by the sensor can be used to detect and study the damage. Ultrasonic signals exhibit complex characteristics during the propagation of the workpiece. Therefore, analyzing the time-series signal effectively is the basis for improving the ability of sensing and monitoring.

Traditional methods of signal analysis are often based on complex physical models built manually [2, 3]. However, these methods may bring large errors, especially when the structure of the workpiece is very complex. With the development of deep learning, artificial intelligence networks are receiving increasing attention in the processing of time-series signals. The training of a good deep learning model often requires the support of big data [4] (easily collected and containing samples of tens of thousands of orders of magnitude), but this is difficult for some specific tasks. Damage detection, for example, is often an abrupt and lengthy process in reality. It is not realistic to collect thousands of samples. The overfitting problem in the deep learning model caused by limited data sets is a very common problem. Therefore, it is essential to consider data augmentation. Data augmentation has been demonstrated to be an effective method for improving model generalization and overcoming the overfitting problem.

Two data augmentation techniques, random scale-cropping and random erasing, are proposed to improve the performance of the classification model for complex signal sequences sampled in practice, in order to overcome the generalization challenges associated with insufficient training data and complex signal characterization. As shown in Figure 1, in order to acquire optical time-domain signals with complex characterization, a high-sensitivity fiber Bragg grating (FBG) sensing system is used to acquire ultrasound signals for different damage cases. Next, the collected data are processed for data augmentation, which is evaluated in the deep learning models.

The actual input signal is a combination of a series of short sequences of events. And types and sorts of events that occur on the sequence determine the class of signal. In practice, however, a well characterized sequence signal may not always be collected. Environmental noises and temperature variations can also affect the sensitivity of the sensor. The neural network might mistake the noise as a classification criterion and ignore the characteristics of the key events occurring sequence. In this situation, the model will get inaccurate results in the test set.

To overcome this problem, a strategy of random scale-cropping on the original samples is proposed in this study. It enables the resampling of a dataset. The model reads only a portion of the events for all samples as well as the sampling process is completely random. There are many sampling possibilities for each sample and hence the dataset can be expanded very large. For the test set, it will eliminate the situation that the test data sequence cannot be accurately identified due to incomplete performance. At this time, all the samples participating in the training are incomplete. The translation invariance of a one-dimensional convolutional neural network (1D-CNN) will pay more attention to the sequence of key events in training rather than simply remembering the exact time of them. Another advantage of the randomly cropped sequence is that the back-

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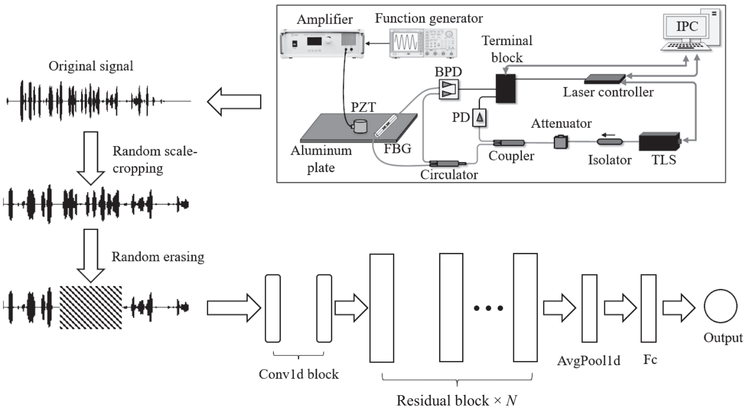

Figure 1 Schematic diagram of signal acquisition, signal enhancement, and model design.

ground noise is suppressed in some way. Low probability noise does not show up in all processed samples. The test samples will not be misclassified because they do not contain such noise.

Another problem will be brought out by the event complexity of the original signal sequence when measuring signals in practice, which also needs to be concerned. Some waveforms generated by different events may be overlapped with each other, leading to blurred signals. In addition, some of the events represented on the sequence are unnecessary (e.g., noise), so a strategy is intended to make the neural network focus on more general and important characteristics of the signal.

Random erasing of the input signal can overcome the above problem to some extent. When the input signal is poorly characterized by an event somewhere, random erasing some signals may prevent the model from overfitting to that feature by forcing it to learn other characteristics of the sequence. The model can decide on the most positive characteristics by "voting" on the entire training set. Let the input time-series sequence be represented as x and the output after the model as y. The probability distribution is jointly determined by the input sequence x and the mask vector μ:

$$\tilde{p}(y|x) = \sum_{\mu} p(\mu)p(y|x,\mu), \quad (1)$$

where the mask vector $\mu \sim p(\mu)$, which consists of two values 0 and 1. It acts on the input sequence x and randomly determines whether a certain part of the input is erased or not. The optimization objective of the model then becomes

$$J(\theta) = -\mathbb{E}_{x,y\sim\hat{p}_{\mathrm{data}}} \log \tilde{p}(y|x). \quad (2)$$

After random erasing, the inputs become sparse naturally. Events and characteristics with a high probability of occurrence throughout the representatively sparse training set will be more likely to be learned by the neural network model. The overfitting problem will be solved while a minority of characteristics is discarded.

Experiment and results. We have built the experimental setup shown in Figure 1 to acquire the ultrasound signal, and the main sensing unit used is the π-shift FBG with higher sensitivity. The central wavelength of the laser output is adjusted in real time through the method of proportional-integral-derivative control strategy to ensure that it is always in the linear region of FBG reflection peak [5]. The reflected light from FBG is detected by a balanced photodetector (BPD), which can effectively improve the sensitivity of the optical sensing system while suppressing the noise [6]. The experimental data were divided into a training set and a test set in the ratio of 8:2. The performance in the CNN model improved after data augmentation was applied, with the classification accuracy rising from 51.19% to 90.46%. The specific experimental setup and results are shown in Appendix B.

Conclusion. In this study, the problem of inadequate or uneven data collection is studied. A small sample dataset tends to cause overfitting of deep learning models, which limits the application of deep neural networks in engineering. To overcome this problem, data augmentation methods of random scale-cropping as well as random erasing are proposed. The results show that with the combination of the above methods, the model exhibits excellent classification performance with an accuracy of 90.46%. Further, the data augmentation methods proposed in the study have the potential to become general solutions in many fields besides fiber sensing, which guarantees that deep learning models can be effectively applied in engineering practices.

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Supporting information Appendixes A and B. The supporting information is available online at info.scichina.com and link.springer.com. The supporting materials are published as submitted, without typesetting or editing. The responsibility for scientific accuracy and content remains entirely with the authors.

References

1 Liang G L, Ma W, Wang Y L. Time-space transform: a novel signal processing approach for an acoustic vector-sensor. Sci China Inf Sci, 2013, 56: 042313

2 Lympertos E M, Dermatas E S. Acoustic emission source location in dispersive media. Signal Processing, 2007, 87: 3218–3225

3 Sousa K M, Dreyer U J, Martelli C, et al. Dynamic eccentricity induced in induction motor detected by optical fiber Bragg grating strain sensors. IEEE Sens J, 2016, 16: 4786–4792

4 Zhang W T, Jiang J W, Shao Y X, et al. Snapshot boosting: a fast ensemble framework for deep neural networks. Sci China Inf Sci, 2020, 63: 112102

5 Liu Z Z, Zhang X Z, Jiang J F, et al. Stabilization of high sensitivity optical fiber AE sensing for long-term detection. Optical Fiber Tech, 2021, 61: 102391

6 Wu Q, Yu F M, Okabe Y, et al. Application of a novel optical fiber sensor to detection of acoustic emissions by various damages in CFRP laminates. Smart Mater Struct, 2015, 24: 015011