SCIENCE CHINA
Information Sciences

• LETTER •

May 2024, Vol. 67, Iss. 5, 159402:1–159402:2
https://doi.org/10.1007/s11432-023-3985-y

Unleashing potentials with deep learning: decoding the complex events for distributed fiber optic sensing applications

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Received 15 November 2023/Revised 15 January 2024/Accepted 19 March 2024/Published online 22 April 2024

After decades of research, distributed fiber optic sensors have become essential tools for precise long-distance measurements. They are applied across various sectors such as railway transportation, gas and petroleum, and smart grids. Signal processing, particularly in phase-sensitive optical time domain reflectometry (Φ-OTDR) event recognition and classification, is a primary research focus. Traditionally, the full potential of unlabeled data has not been harnessed, necessitating a large number of labels and considerable human effort to obtain a high-performance model.

To tackle this popular and critical issue, we propose employing semi-supervised learning (SSL) algorithms in distributed fiber optic sensors to utilize unlabeled data for auxiliary training purposes [1]. To effectively extract spatiotemporal features from vibration events, we comprehensively analyze and compare prominent semi-supervised deep learning methods, which are FreeMatch (EM) [2], FixMatch (XM) [3], MeanTeacher (MT) [4], and Self-training (ST) [5], with their corresponding supervised baselines. The semi-supervised algorithm and experimental results are shown in Figure 1. Experimental results show significant performance enhancement with the proposed semi-supervised model, especially in scenarios with limited labeled samples, indicating the substantial advantage of SSL for future distributed optical fiber sensing data processing.

The detailed contributions include the following.

(1) Comparative analysis of semi-supervised Φ-OTDR signal methods under label scarcity. We propose integrating the Fixmatch and FreeMatch semi-supervised frameworks with a high-performance disturbance classification network. The application of semi-supervised methods in the field of Φ-OTDR vibration event classification was comprehensively summarized. Even with only 12 Labeled samples in total, the proposed method achieves a classification accuracy of over 92%. Notably, employing self-adaptive class fairness regularization (SAF) results in faster convergence and better model generalization in label-scarce scenarios.

(2) Data augmentation study for narrow strip-shaped Φ-OTDR signals. Focusing on narrow strip-shaped Φ-OTDR signals, we explore more suitable data augmentation techniques to enhance semi-supervised processing, providing a robust foundation for signal analysis.

(3) Exploration of self-adaptive thresholds. This study explores global and local thresholds for self-adaptive thresholds (SAT). The global threshold correlates with the model's confidence in unlabeled data, reflecting the overall learning status and steadily increasing during training to ensure the proper discarding of erroneous pseudo-labels. Adaptive local thresholds consider intra-class diversity and potential class adjacency, adjusting the global threshold in a class-specific manner.

Semi-supervised algorithm. The choice of the primary network in a semi-supervised framework directly impacts the classification performance, as the design of the primary network significantly influences the representation and generalization of the model. To extensively and accurately acquire features of the Φ-OTDR data, we adopted and modified the ACNN-SA-BiLSTM (ACAB) network as shown in Figure A2(a) in Appendix A.2. The network uses convolutional neural network (CNN) to extract time domain features and BiLSTM to extract spatial features. We also introduced a dual attention mechanism consisting of channel attention and spatial attention to further enhance the classification performance. Introducing a channel attention mechanism in the temporal convolution involves incorporating a lightweight squeeze-and-excite (SE) module into the model. This is done to establish channel dependencies at a lower computational cost, compressing feature maps to integrate global context information throughout the model. Between CNN and BiLSTM, a spatial attention (SA) mechanism has been incorporated to focus the model on perturbation information while extracting spatial bidirectional relationships. We compared and analyzed four semi-supervised frameworks utilizing the ACAB as the primary network. These models are defined as ST-ACAB, MT-ACAB, XM-ACAB, and EM-ACAB. Among the four semi-supervised methods, the EM-ACAB model achieves the best performance.

EM is an improved version of FixMatch. SAT and SAF were applied in FreeMatch. SAT is a threshold adjust-

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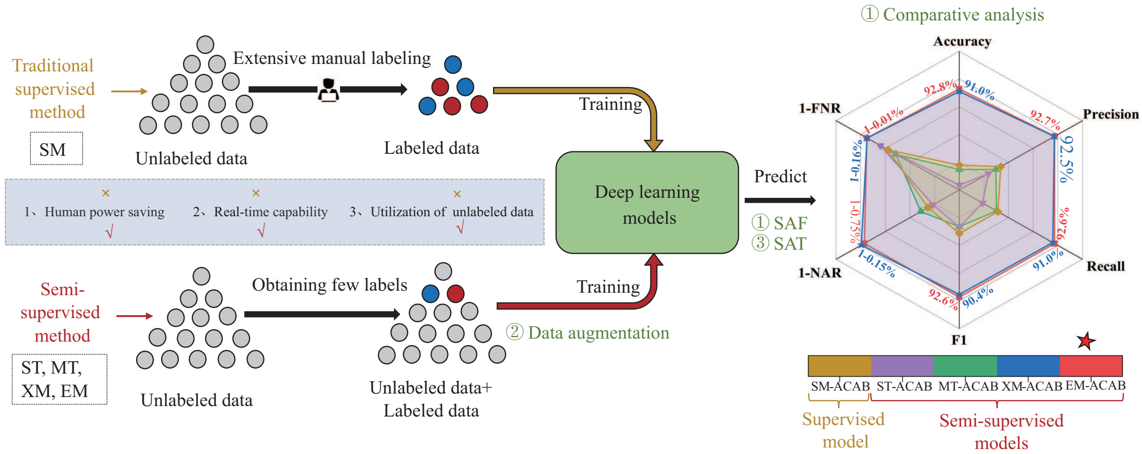

Figure 1 (Color online) Algorithm and experimental results (performance comparison of SSL frameworks with only 12 labeled training samples).

ment scheme that does not require manual threshold setting. Firstly, SAT estimates a global threshold as the exponential moving average (EMA) of the confidence from the model. Then, the adaptive SAT modulates the global threshold via the local class-specific thresholds estimated as the EMA of the probability for each class from the model. The design of the adaptive global threshold is guided by two principles. Firstly, the global threshold should be related to the model's confidence in unlabeled data, reflecting the overall learning state. Additionally, the global threshold should steadily increase during the training process to ensure incorrect pseudo labels are discarded. The adaptive local threshold is intended to adjust the global threshold in a class-specific manner, considering intra-class diversity and potential class adjacency. Furthermore, FreeMatch introduces SAF to encourage the model to make diverse predictions for each class, thus generating meaningful adaptive thresholds, especially under the settings where labeled data are rare.

XM and EM rely on the employment of both weak and strong augmentations. The data augmentation (DA) techniques employed in XM and EM can assist the model in harnessing information from unlabeled data, thereby enhancing its generalization capability. Gaussian noise with a mean of 0 and a variance of 1 is added to the raw sample as a weak augmentation. The strong augmentation involves a combination of three techniques, including Gaussian noise, flipping in spatial direction, and rectangular cutout. This approach is adopted considering the spatiotemporal attributes and temporal causality requirements of Φ-OTDR signals, as well as the narrow rectangular (12×10000) size of the Φ-OTDR signal.

Conclusion. Addressing the classification performance challenge in Φ-OTDR real-world applications due to the difficulty in obtaining enough labeled samples, we introduced and researched semi-supervised learning models tailored for Φ-OTDR event classification. Specifically, the XM-based models exhibit notable improvements in classification performance compared with the ST model based on pseudo-labeling and the MT model based on consistency regularization. The EM approach introduces the SAT mechanism and incorporates SAF to encourage the model to make more accurate predictions for each class. This strategy generates meaningful adaptive thresholds, leading to further performance improvement over the XM. The proposed semi-supervised methods in this study offer the potential to enhance the accuracy of disturbance event classification in environmental settings without increasing optical equipment costs or complexity. These methods exhibit fast convergence and ease of transfer ability. The rapid convergence, ease of transferability, and significant performance enhancements exhibited by these methods position them as promising technological pathways for advancing the field of Φ-OTDR event classification, suggesting their potential to play a crucial role in future research and applications.

Acknowledgements This work was supported in part by National Key Research and Development Program of China (Grant No. 2021YFB2900704) and Fundamental Research Funds for Central Universities (Grant No. 021314380211).

Supporting information Appendixes A–C. 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.

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