Improving Earthquake Detection in Fibre-Optic Distributed Acoustic Sensors Using Deep-Learning and Hybrid Datasets

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Abstract *The capability of fibre-optic distributed acoustic sensing to detect earthquakes is enhanced using deep learning. A training approach combining fibre-optic and traditional seismic measurements is proposed to improve the classification performance of low SNR fibre-based seismic measurements. Results demonstrate up to 98.8% of accuracy. ©2022 The Author(s)*

Introduction

Distributed optical fibre sensing [1] has attracted great deal of attention due to its potential to monitor physical variables with spatial resolutions of a few metres along tens of kilometres of optical fibre. Among different technologies, distributed acoustic sensors (DAS) [1,2] have been widely studied in both academy and industry.

In recent years, the potential of using installed telecom optical fibres to perform spatially resolved monitoring of mechanical vibrations has motivated the use of DAS technology to develop distributed seismographic networks, exploiting existing worldwide optical communication cables [3,4]. Compared to conventional seismographs (typically separated over tens of kilometres), DAS can monitor seismic waves with a metre-scale spatial sampling. This corresponds to a huge improvement (about three orders of magnitude) in the spatial resolution provided by DAS, offering to specialist a new type of tool to monitor the propagation of earthquake waves.

The capabilities of DAS systems to identify specific vibration patters over optical cables can be significantly enhanced using machine learning tools [5,6]. In DAS-based seismology, the training of machine learning models needs a large number and diversity of earthquakes to be measured with DAS [7,8]. To cope with these requirements, a generative adversarial network (GAN) has been used to increase the training dataset [7]. More recently, the use of seismic waveforms obtained by traditional seismographs was proposed to train deep learning models for classification of real DAS measurements [8].

This paper proposes a training strategy based on seismic DAS measurements to improve the performance of deep learning models originally trained with conventional seismic data. Based on DAS measurements obtained over telecom and dedicated optical cables, results demonstrate that the proposed approach improves the classification of seismic records with low signal-to-noise ratio (SNR). This even includes cases when the seismic wave level is similar to the noise level (~0 dB SNR). Compared to deep learning models trained with only traditional seismic data, the use of a hybrid dataset improves the accuracy of the DAS earthquake detection up to 98.8%.

DAS seismic measurements for deep learning

The seismic DAS traces used in this work have been obtained at three worldwide locations. In all cases, different coherent Rayleigh-based phase-sensitive optical time-domain reflectometers (ϕ-OTDRs) are used. The first dataset is measured with a phase-demodulated DAS based on optical heterodyne detection, in a 41.5 km-long telecom optical cable installed offshore Toulon, France [9]. The second dataset comes from a phase coherent DAS system connected to an 8.7 km-long optical cable buried in a trench of 400 m depth at a geothermal site near the Brady Hot Springs, in Nevada, USA [10]. The last dataset is obtained with a chirped-pulse DAS over a 42 km-long optical fibre installed for offshore monitoring a power cable close to Zeebrugge, Belgium [11].

These DAS seismic datasets are combined with traditional seismic records obtained from the STanford Earthquake Dataset (STEAD) [12], which contains local earthquakes of different magnitudes and locations around the world.

Fig. 1 shows a comparison between seismic waveforms measured with DAS and a traditional seismometer. The similitude between traces has been the motivation of the approach proposed in this paper which uses a hybrid database that combines both types of records to attain improved earthquake detection deep learning models for DAS records. Note that DAS seismic traces are usually characterised by very low SNR, as shown in Fig. 2. As seen, in this case many traces with SNR around 0 dB are included in the processing. This denotes a fundamental difference compared to seismometer records. Hence, including DAS traces in the training is expected to improve the

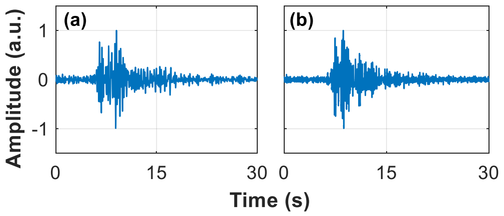

Fig. 1: Comparison of seismic records obtained with (a) a fibre-optic DAS and (b) a traditional seismometer

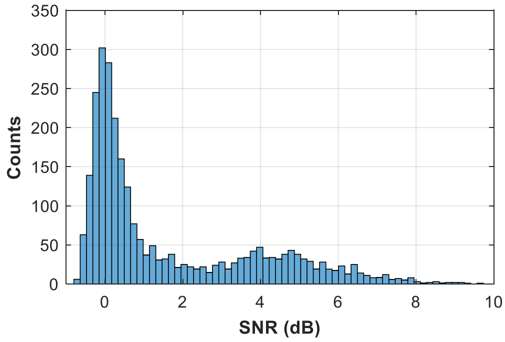

Fig. 2: Histogram of SNR distribution of DAS seismic traces

seismic classification performance of trained models, as will be shown hereafter.

Deep learning models for seismic DAS

In this work, the presence of seismic waves in DAS records is detected with the classical deep learning paradigms: fully connected artificial neural networks (FC-ANN), convolutional neural networks (CNN) and recurrent neural networks (RNN). In all cases, the input layer is designed to receive timeseries of 6000 samples. Meanwhile, the output layer is a single node with a Sigmoid function that gives the probability of the inputted DAS wave being a seismic waveform. Only hidden layers are different among the 3 models.

The implemented FC-ANN model has two hidden layers with 4000 and 3000 neurons each and a ReLu activation function. The CNN is composed of 8 hidden convolutional layers with a 1x3 kernel size, followed by a ReLu activation function and a batch normalisation layer (BatchNorm). Max-pooling layers are included to reduce the output size of some convolutional layers. The last hidden layer is linear and has 32 neurons. Finally, the third model is a combination of convolutional and recurrent networks inspired by the CNN-RNN Earthquake Detector (CRED) architecture [13]. This has 6 hidden convolutional layers with a 1x3 kernel size and ReLu functions, followed by 3 recurrent layers and 1 linear layer. The recurrent layers correspond to long short-term memory (LSTM) layers, so this model will be here called CNN+LSTM. More details on all these 3 models can be found in [8].

Training with hybrid seismic data

The first training stage uses 200,000 traditional seismograph records from the STEAD dataset,

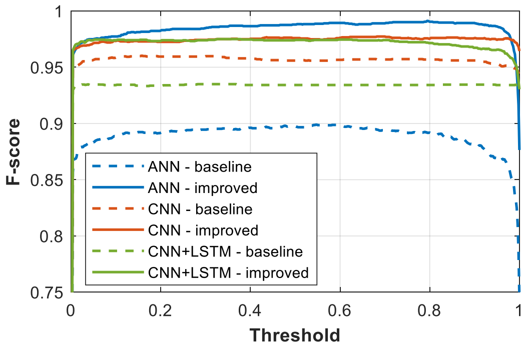

Fig. 3: F-score of baseline (dashed lines) and improved (straight lines) deep learning models vs threshold

which are distributed equally between seismic and noise waveforms. This leads to trained models that will be used as baseline to evaluate the performance improvement attained with the proposed hybrid training approach. The trained models are obtained minimising a binary cross-entropy loss function and updating the weights of the net with the Adam optimisation algorithm. In the second training stage, the network weights are updated using only DAS data. For all models, a conservative learning rate of 10^{-5} is used with an early stopping criterion to avoid overfitting.

Traditional and DAS seismic records are pre-processed, including detrending, resampling and amplitude normalisation between -1 and 1. This leads to 60 s traces with 6000 samples.

Results

Fig. 3 shows the F-score metric as a function of the classification threshold for the 3 implemented models. Dashed lines show the performance of the baseline models. These lines indicate that the CNN and CNN+LSTM models reach better F-score over the entire thresholds range, attaining a maximum of 96.0% and 93.5%, respectively, compared to the 89.9% of the FC-ANN model. On the other hand, straight lines in the figure show the performance obtained by the models trained with the hybrid dataset. It is observed that the proposed training improves the performance of all 3 analysed models, leading to a maximum F-score of 97.7%, 97.5% and 99.0% for the CNN, CNN+LSTM and FC-ANN models, respectively.

Results indicate that the largest improvement is provided for the FC-ANN model. This can be presumably explained by the larger number of parameters that are trained in this architecture, which allows for a better feature extraction of the seismic traces. On the other hand, it is worth mentioning that even with a reduced number of parameters, both CNN and CNN+LSTM models can reach similar (negligibly lower) performance.

Fig. 4 shows the histograms of the number of DAS traces classified as true positive (TP), false negative (FN), false positive (FP) and true

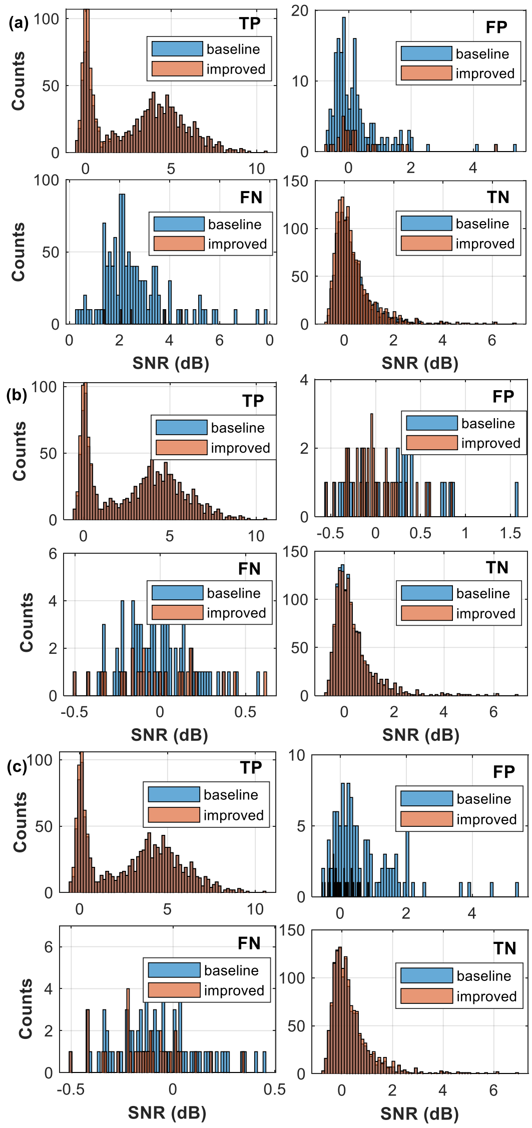

Fig. 4: SNR distribution of DAS traces organised according to classification metrics. Comparison of baseline and improved (a) FC-ANN, (b) CNN, and (c) CNN+LSTM models

negative (TN), as a function of the measurement SNR. The blue bars indicate the number of traces classified by the baseline models. Results point out that TP and TN, i.e., the correctly classified traces, are distributed in a large range of SNRs, whilst the FP and FN, corresponding to wrongly classified traces, are mostly distributed within low SNR levels (< 2 dB in all cases). The red bars in Fig. 4 show the results attained with the proposed training approach. The large reduction of FP and FN verifies that the use of a hybrid training improves the performance of the models.

Note that most traces are already correctly classified in all baseline models, leading to an accuracy of 89.7% for the FC-ANN, 96.2% for the CNN and 93.5% for the CNN+LSTM. These values are improved up to 98.8%, 97.7% and 97.5%, respectively, using the hybrid training.

Fig. 5 shows the output probability provided by each model for the first analysed DAS dataset. Fig. 5(a) shows the DAS strain recording as a function of time and fibre position. Clear sections with no acoustic signal (white coloured sections) are observed, which could have resulted from poor local strain transfer from the soil to the fibre cable. Note that the baseline models (blue curves) wrongly classify many of the timeseries measured at fibre sections with low strain response (output < 1). However, improved models (red curves) can successfully classify these traces in most of the cases. These results highlight the relevance of performing a training that adds DAS traces in the process, so that the models can learn from the specific features of seismic DAS measurements.

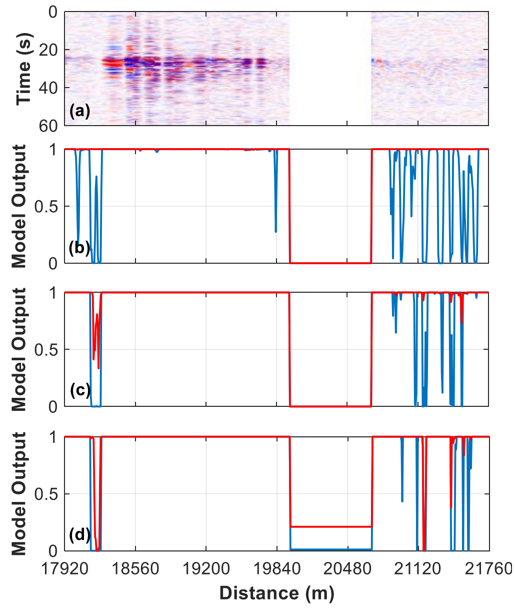

Fig. 5: (a) DAS strain as a function of time and fibre position. Comparison of output probability for baseline and improved (b) FC-ANN, (c) CNN, and (d) CNN+LSTM models

Conclusions

The proposed method has proven to improve the performance of deep learning models to classify earthquakes in low-SNR DAS traces measured over optical cables. Even though the improved CNN and CNN+LTSM models have resulted in slightly lower performance compared to the FC-ANN model, these former kinds of models are usually more suitable to process timeseries compared to FC-ANN models. It is therefore expected that CNN and CNN+LTSM models are more reliable for this kind of tasks, and the use of larger DAS datasets with more variety of features could still lead to better classification results.

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