MONITORING UNDERGROUND POWER CABLES IN URBAN AREAS USING DEEP NEURAL NETWORKS AND DISTRIBUTED ACOUSTIC SENSING

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ABSTRACT

Distributed acoustic sensing is well-suited for monitoring underground power cables by measuring vibration signals along the cable. These signals can be used to detect mechanical activities that pose a risk to the infrastructure. We present an approach that performs this detection using deep neural network models. The models are evaluated on data from an installation site in an urban area that contains potentially disturbing signals from streets and construction sites. To assess the generalizability of the models they are evaluated on data from an installation site that is different to the sites used for training. Experimental results show that the models detecting excavator digging and jackhammer activity achieve an accuracy of 97.7% and 98.1%, respectively.

KEYWORDS

Distributed Acoustic Sensing, Deep Neural Networks, Power Cable Monitoring

INTRODUCTION

Distributed acoustic sensing (DAS) systems have a wide range of applications, above all real-time monitoring of power cables or infrastructure in oil and gas industry [1]. DAS uses a fiber optic cable (FOC) that is installed along the asset to capture the signal of vibrations near the cable. Buried infrastructure like power cables and pipelines can be damaged by third party activities. Using DAS, it is possible to detect and classify the third party intrusion (TPI) e.g., mechanical activities around buried assets and alarm on the threat [2].

Detecting TPI is a challenging task because the DAS data of mechanical activities depend on several factors like ground conditions and the tools that are used. Furthermore, signals that look similar to TPI signals caused by other activities should not trigger an alarm. To overcome these challenges an advanced machine learning method, namely deep neural networks (DNN), is used. A DNN can learn to detect signals of TPI activities based on data that were recorded in the past. Unlike threshold based approaches which depend on signal strength, DNNs take advantage of pattern recognition to classify activities.

Detecting TPI activities using DAS data and machine learning techniques has been proposed in previous works. In [3] a speaker is placed near a FOC and used to play back the acoustics of various activities including the sound of jackhammer in action. A convolutional neural network (CNN) is used to classify the signals. The work in [4] compares the performance of different machine learning algorithms to detect and classify excavator activities. To process the data, horizontal and vertical Sobel filters are applied. In [5] the Rayleigh backscattering traces are transformed to a gray scale image and used as the input to a CNN. A small CNN is used to achieve a high training speed. The work in [6] proposes a deep dual path network to classify TPI activities based on the spatial time-frequency spectrum. Data from seven classes are used, including excavator operation. The data are collected at three different railway lines.

In this paper, we present our approach to detect TPI activities using DNNs and DAS. Our system is installed in an urban area, where the power cables along with the fiber cable are buried under diverse active areas, including streets, bridges and construction sites. The DNNs we evaluate in this paper are trained using only data from installation sites that are different to the installation site used for evaluation. This approach is chosen in order to test our method in a scenario in which the detection system is used at a new installation site without adapting the DNNs to that site. We focus on two types of TPI namely: excavator digging and jackhammer activity. Since both are performed by heavy machines they may cause real damage to the power cable.

BASIC CONCEPTS

Distributed Acoustic Sensing

DAS is a technique to measure acoustic and vibration signals along a FOC using a single measurement device. When a laser pulse is sent into the fiber it is partially reflected along the fiber which results in a return signal that is measured. Depending on the application different wavelengths of the return signal are of interest, as can be seen in Fig. 1. For DAS the coherent Rayleigh scattering is used which is stimulated by strain changes in the fiber that are caused by acoustic and vibration activities. Like in a radar system the position of the vibration event is estimated by the traveling time of the laser pulse and the backscattered Rayleigh signal from the fiber.

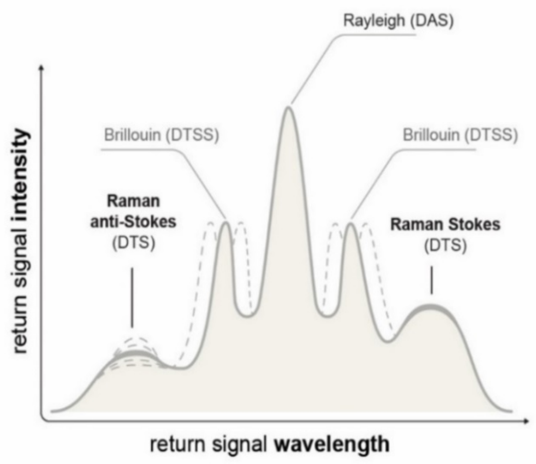

Fig. 1: Distribution of the return signal when a laser pulse is sent into a FOC

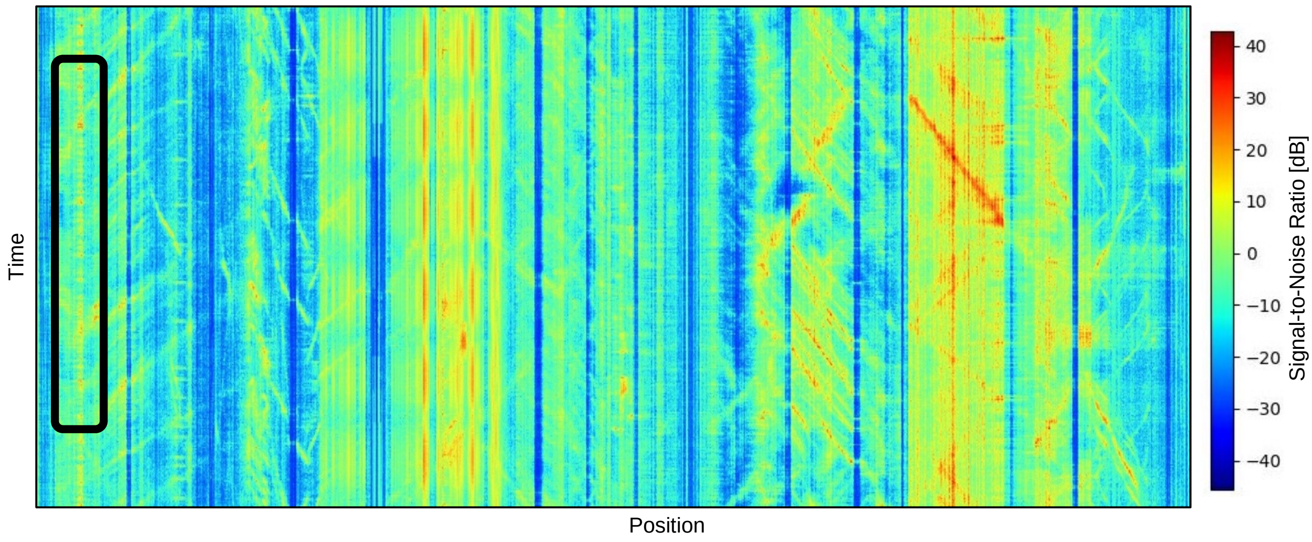

Fig. 2: Visualization of DAS data from the installation site used for evaluation

Deep Neural Networks

CNNs are machine learning tools especially well-suited for image classification tasks. A CNN consists of layers; if it has many layers it is named a DNN. Each of the layers gets the output of a previous layer as input and transforms it into an output. In our case the input to the first layer is an image of a signal captured by the DAS and the output of the last layer is a number between 0 and 1 that can be interpreted as the probability that the image contains the signal of a TPI activity. The transformation that a layer performs is defined by parameters which are set via training the DNN. In the training phase the DNN gets a large amount of signal images together with the information whether the image contains a TPI activity or not. The data are used to optimize the parameters in a way that the DNN minimizes the classification error on the training data. The optimization is done via a gradient descent algorithm.

EXPERIMENTAL SETUP

At the test site in this investigation the AP Sensing phase DAS model N5225B is used to interrogate the FOC. The DAS data are recorded with a repetition rate of 5000 Hz and a spatial sampling along the fiber of 5 m. The sensor cable is an extra FOC deployed close to the power cable. The high voltage cable and the FOC are buried in a depth of 0.5 to 2 m.

The data recorded by the DAS are so-called phase data. Instead of directly using this data as input to the DNN a preprocessing step is done by applying a fast Fourier transform (FFT) on the phase data and aggregating the energy in specific frequency ranges. Fig. 2 illustrates the processed data along a 12 km long fiber in an urban area. The colormap of Fig. 2 is also used for the other images showing DAS data in this paper.

The experiments focus on the detection of two different TPI classes, namely excavator digging and jackhammer activity. For each of these classes a DNN model is trained to classify whether an image of a signal shows the TPI activity or not. In a second step the trained DNN models are evaluated. Details of the training phase and the evaluation phase are given in the following sections.

Training

The DNN used for the TPI detection is not trained using data from the evaluation site but by feeding the DNN with DAS data measured at different installations. The various installations used for training the DNN differ in ground conditions as well as in depth of burial of the FOC. The goal of using diverse training data is to train a DNN that has a high generalizability and can therefore be used at a new installation site without retraining.

In Fig. 3 example signals from one of the installation sites used to collect training data are shown. The excavator digging signal has a characteristic pattern that is caused by the excavator shovel hitting the ground and moving through the soil. In comparison the signal corresponding to jackhammer activity looks very different. When the jackhammer has contact to the ground it creates a strong signal, when the jackhammer is lifted and has no contact to the ground the vibration is not transmitted to the FOC resulting in gaps in the pattern.

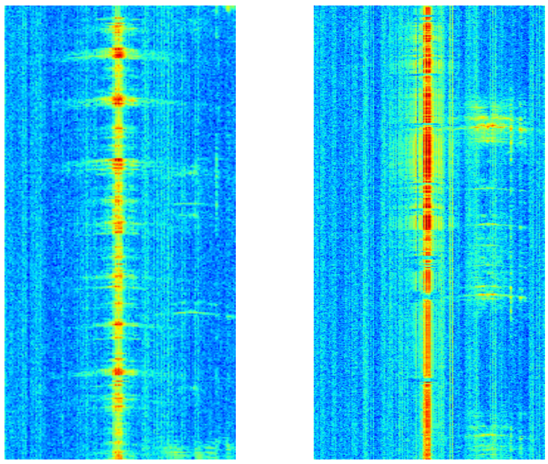

Fig. 3: Example signals from a site used for training corresponding to excavator digging (left) and jackhammer activity (right)

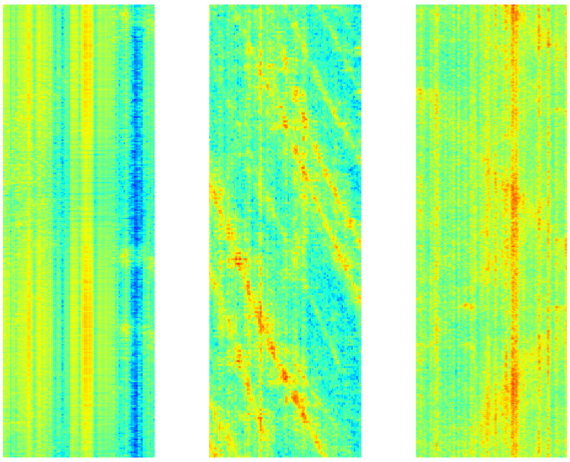

Fig. 4: Example signals from the evaluation site not corresponding to TPI activities

Evaluation

The data for evaluating the models are collected at a DAS installation site that is different to the installation sites of the training data. Fig. 2 shows the visualization of some data recorded by the DAS along the 12 km long fiber. Because the FOC is located in an urban area there are many strong signals along the cable making it more challenging for the models to correctly distinguish between the signals that correspond to TPI activity and the signals that correspond to no TPI activity. The black box on the signal visualisation in Fig. 2 marks an excavator digging close to the beginning of the cable. It can be seen that along the fiber there are signals with a higher intensity than the excavator signal, indicating that a simple threshold based approach is not sufficient to detect TPI activities.

The data that contain no TPI activity are collected by randomly selecting 2500 images during eight hours. We call a sample containing no real TPI signal a negative sample. Fig. 4 shows example signals from the installation site used for evaluation. Although the signals do not correspond to TPI activities they do contain patterns making it challenging for the models to correctly classify the signals as belonging to the negative class.

The excavator digging data are collected at two different positions along the fiber, at the first position eight minutes of digging is performed, at the second position 14 minutes of digging is performed. From these data 2500 images are randomly selected. In Fig. 5 an example of an excavator digging signal from the evaluation site can be seen. Compared to the excavator digging signal in Fig. 3 from a site used for training, the background noise is on a higher level. This difference between the training data and the evaluation data illustrates that it is important to train a model that can generalize well.

The data that contain jackhammer activity are collected at one position with a duration of 14 minutes. From these data 2500 images are randomly selected. Fig. 6 shows a signal of jackhammer activity from the evaluation site. In comparison to the example jackhammer activity signal from the training site in Fig. 3 there are more gaps in the pattern and the pattern is wider.

For both cases, excavator digging and jackhammer activity, the DNN models are evaluated by using acoustic background data (negative data) with excavator data and jackhanner data, respectively. This paper assesses the performance of the excavator model and the jackhammer model separately. Therefore, the excavator DNN model is not evaluated with the jackhammer data and the jackhammer DNN model is not evaluated with the excavator data.

To assess the performance of the models we use the metrics accuracy, precision and recall which are defined in the following. Let TP denote the number of true positives, i.e. images that are correctly classified as showing a TPI signal, FP denote the number of false positives, i.e. images that are incorrectly classified as showing a TPI signal, TN denote the number of true negatives, i.e. images that are correctly classified as showing no TPI signal, and FN denote the number of false negatives, i.e. images that are incorrectly classified as showing no TPI signal. The preceding definitions assume that an image with the signal of a TPI activity corresponds to the positive class and an image that contains no TPI signal corresponds to the negative class. However, it is also possible to switch the roles of the positive and negative class. In this case the definitions of TP, FP, TN and FN change accordingly.

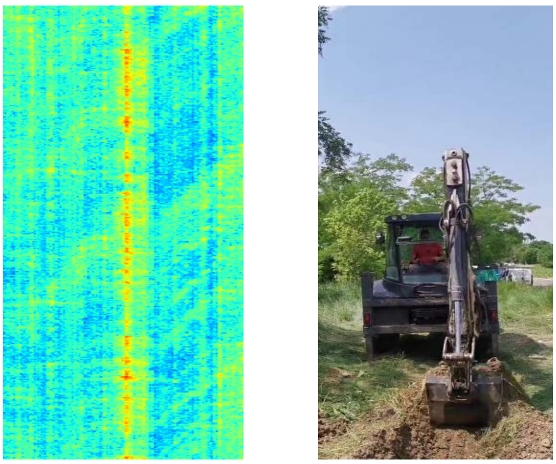

Fig. 5: Signal of excavator digging (left) and image of the excavator (right) from the evaluation site

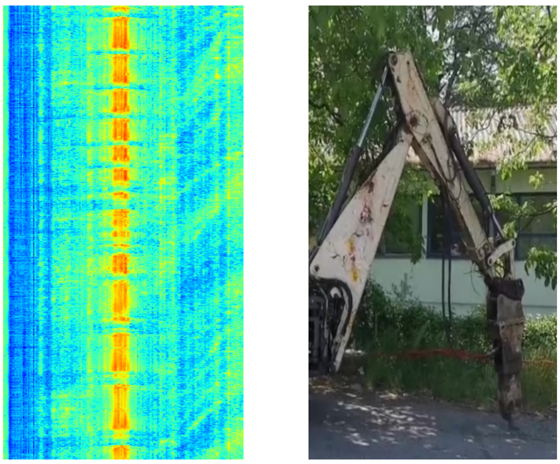

Fig. 6: Signal of jackhammer activity (left) and image of the jackhammer (right) from the evaluation site

a) Excavator model		
Class	**Precision [%]**	**Recall [%]**
Negative	98.9	96.6
Excavator	96.6	98.9
Overall accuracy: 97.7%		

b) Jackhammer model		
Class	**Precision [%]**	**Recall [%]**
Negative	98.3	97.9
Jackhammer	97.9	98.3
Overall accuracy: 98.1%		

Tab. 1: Results of excavator and jackhammer model

Accuracy is defined as the number of correctly classified images divided by the number of all images:

$$accuracy = \frac{TP + TN}{TP + FP + TN + FN} \; .$$

Precision is defined as the fraction of images classified as positive that are correctly classified:

$$precision = \frac{TP}{TP + FP} \; .$$

Recall is defined as the fraction of images from the positive class that are correctly classified:

$$recall = \frac{TP}{TP + FN} \; .$$

RESULTS

The results of the excavator DNN model are shown in Tab. 1a. The accuracy of the model is 97.7%. For the negative data the model achieved a precision of 98.9% and a recall of 96.6%. For the excavator data the precision is 96.6% and the recall is 98.9%.

Tab. 1b shows the results of the jackhammer DNN model. The accuracy of the model is 98.1%. For the negative data the model achieved a precision of 98.3% and a recall of 97.9%. For the jackhammer data the precision is 97.9% and the recall is 98.3%.

In our evaluation the excavator DNN model and the jackhammer DNN model have a comparable classification performance. Considering that the models have been evaluated on data from an installation site different to the installation sites of the training data the good results indicate that the models are generalizing well.

The results of this paper can be used as a starting point for further research. In this paper we assessed the performance of models that are trained without using data from the evaluation site. Future work may evaluate how much a customized model which incorporates data from the actual evaluation site in the training dataset boosts the performance over a generalizing DNN model.

CONCLUSION

In this paper we have presented our approach to detect TPI using deep neural networks in combination with distributed acoustic sensing. We trained DNN models on data from multiple DAS installation sites and applied the trained models to data measured at a different installation site located in an urban area. We evaluated a model that is trained to detect excavator digging and another model that is trained to detect jackhammer activity, achieving accuracies of 97.7% and 98.1%, respectively. The results demonstrate that DAS measuring technology in combination with DNN models can accurately detect mechanical threats to underground power cables deployed in noisy urban areas. Future work may investigate how the classification performance can be improved by using a model that is adapted to the evaluation site.

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GLOSSARY

CNN: Convolutional Neural Network
DAS: Distributed Acoustic Sensing
DNN: Deep Neural Network
FFT: Fast Fourier Transform
FOC: Fiber Optic Cable
TPI: Third Party Intrusion