Deep Generative Models for Distributed Acoustic Sensors (DAS)

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Abstract

This paper presents two solutions based on Deep Learning techniques to detect mechanical events in signals coming from distributed acoustic sensors (DAS). Specifically, two systems for this task are described. The first one is a deterministic solution based on the concept of autoencoder (AE), while the second system is a stochastic solution based on the idea of Variational Autoencoder (VAE). The signals used for the tests have been provided by Aragón Photonics Labs (APL).

Introduction

In recent years, techniques have been presented that make it possible to detect mechanical events in the physical environment of an optical fiber due to the impact they have on the propagation of light within the fiber (specifically Rayleigh scattering). The systems that develop these techniques are known as DAS (Distributed Acoustic Sensor) and provide information on whether an event has occurred at a specific spatial point and time instant. Their relevance lies in the multitude of applications they have. For example, it is possible to detect an intruder in a specific area, estimate the speed of a vehicle (due to its evolution in distance and time) or detect seismic activity. And all this can be achieved with a system that is invisible to the human eye, covering large spatial extensions of up to 50 km and independent of orography.

Unsupervised Anomaly Detection

To detect events in the signals coming from DAS systems, prior processing is necessary. For this purpose, unsupervised anomaly detection techniques are proposed. Unsupervised anomaly detection consists of identifying which events are not normal with a system trained only on anomaly-free data. Therefore, potential mechanical events that may occur will be considered anomalies. Deep Learning systems such as Autoencoders and Variational Autoencoders have been used for this task.

An autoencoder is a neural network that has two main parts: the encoder and the decoder, and whose objective is to make the input to the encoder and the output of the decoder as similar as possible by passing through a compressed version of the data. These structures have been proposed as a method for unsupervised anomaly detection [2]. For this purpose, the network is trained with a type of data in order to be able to accurately reconstruct this type of data. Thus, when in the inference stage, the network tries to process another type of data, the performance will be clearly worse.

Autoencoders do not allow to generate new data similar to the original, which is interesting for many applications. For this purpose, solutions such as Variational Autoencoders (VAE) [3] are proposed, which are models that allow to generate new data coming from the same probability distribution of the original data. Therefore, they are said to be generative models.

Data description

The information coming from the DAS sensor is a large matrix, since it contains information in time and distance. Thus, if $\boldsymbol{S} = (s_{ij}) \in \mathbb{R}^{L_t \times L_d}$ is the sensor output, s_{ij} contains information about instant i at position j, and L_t and L_d are the number of temporal and spatial samples, respectively.

The input to the network is not the large matrix $\boldsymbol{S}$, but smaller patches are taken within it. Thus, four parameters are defined: N_t and N_d, which are the patch length in the temporal and spatial dimensions, respectively, and M_t and M_d, which are the patch offset in the temporal and spatial dimensions, respectively. It follows that:

$$\boldsymbol{S^P} = \left(s^p_{i_t,i_d,j_t,j_d}\right) \in \mathbb{R}^{W_t \times W_d \times N_t \times N_d},\ s^p_{i_t,i_d,j_t,j_d} = s_{M_t(i_t-1)+j_t,\, M_d(i_d-1)+j_d}$$

where $W_t = \left\lceil \frac{L'_t - N_t}{M_t} + 1 \right\rceil$ and $W_d = \left\lceil \frac{L'_d - N_d}{M_d} + 1 \right\rceil$

Finally, a MinMax scaling is applied to each patch of size $N_t \times N_d$ and they serve as input to the network.

Models Evaluation

Both models are described and evaluated below.

Proposal 1 - Autoencoder

First system is an autoencoder with convolutional layers and is described in Figure 1. The cost function used is the mean quadratic error. The instantaneous quadratic error between input and output is taken as the anomaly marker:

$$A_k^{SE} = (a_{kij}) \in \mathbb{R}^{N_t \times N_d}, a_{kij} = \|x_{kij} - x_{kij}\|_2$$

When this marker takes values above a threshold, an anomaly is considered to be present.

Proposal 2 - Variational Autoencoder

In this case, the structure of the previous proposal is maintained and the latent space's dimension is 64. Furthermore, cost function is defined as the sum of the mean squared error between input and output, and KL divergence between $N(\mu_z, \sigma_z)$ and $N(0,1)$, where μ_z and σ_z are the vectors associated with the mean and standard deviation of the latent space, respectively. In addition to A_k^{SE}, a second anomaly marker is defined:

$$A^{KL} = \frac{1}{2}\sum_{j=1}^{64} (\mu_z)_j^2 + (\sigma_z)_j^2 - \log(\sigma_z)_j^2 - 1 \ \in \mathbb{R}$$

The advantage of this proposal lies in the fact that to calculate this anomaly marker, information has to be processed only through the encoder. Therefore, only when for a given input, this anomaly marker takes a value above a threshold, this input must be decoded.

Experimental Results

The objective is to obtain a system whose output is probabilities of normality. To achieve this, the anomaly markers are statistically modeled using maximum likelihood estimation. A^{SE} is modeled by an exponential distribution and A^{KL} using a normal distribution. For the experiments carried out, a 36.4km optical fiber was used in a controlled environment. To train the system, there were 15 minutes of non-event time. To evaluate the performance of the system, the following events were intentionally provoked: a hydraulic hammer chopping, the passage of heavy machinery and an excavator digging at 0 and 10 meters from the place where the fiber is buried. Table 1 shows a comparison of the results obtained in terms of the area under ROC curve (AUC) for some of these events. It shows that the anomaly marker A^{KL} performs worse, so it is recommended that the threshold be set at low values.

Conclusion

In this paper we have presented two techniques to detect events in signals from the DAS. The performance is similar in both, but the anomaly marker $\boldsymbol{A^{KL}}$ in the VAE allows to reduce considerably the amount of data to be processed.

REFERENCES

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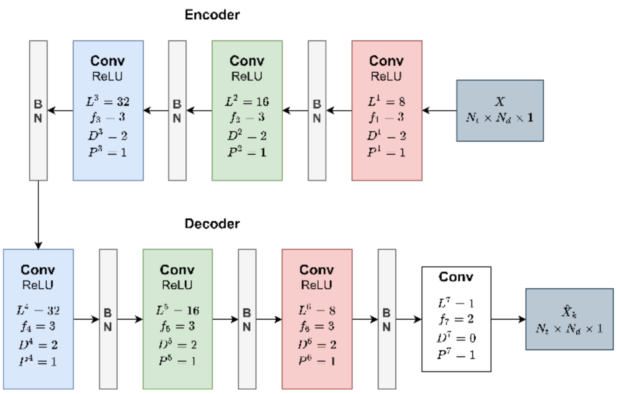

Fig. 1. Autoencoder design in proposal 1

Table 1. AUC in different signals in both proposals

	Hydraulic Hammer	Caterpillar advancing	Digging 0m	Digging 10 m
AE - A^{SE}	0.997	0.924	0.976	0.962
VAE - A^{SE}	0.994	0.937	0.978	0.958
VAE - A^{KL}	0.973	0.846	0.914	0.940