Improving precision in air-leak detection using Machine Learning

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Summary

Air guns are reliable sources widely used in the seismic industry. When failures occur, air bubbles are released in the water and can distort the emitted signals. To ensure optimal data quality, source outputs are continuously monitored using near field hydrophones. The current detection methods are based on user experience to differentiate between air leaks and other disturbances in the water affecting the near field hydrophones. We chose to develop a light convolutional neural network since the aim is to have a fast detection tool running in real time during acquisition. Near field recordings from multiple surveys were used to train a robust and generic network. To confirm the accuracy of the network, extensive field tests were conducted using different source geometries operated at different depths.

Introduction

Air guns are widely used in seismic exploration. They are a reliable seismic source and produce highly repeatable signals. Air guns operate with high pressure air in harsh conditions and in a constantly changing environment. Any damage to the air guns or the air hoses can lead to small or large quantities of air leaking into the water. The outputs of all the air guns forming the source arrays are continuously monitored using near field hydrophones (NFH). Variations in the recorded traces are analyzed in real time to understand the cause and take action. An air leak can significantly distort the pressure signal emitted by the gun arrays and may degrade the quality of the recorded data. Quick action must be taken to ensure optimal data quality and minimal operational downtime.

Currently air leaks are identified by analyzing both the actual NFH recordings and an FFT deconvolution attribute in the frequency domain (Day and al., 2007). However, these detection methods require experience to be correctly interpreted. The main difficulty is the lack of differentiation between air leaks and other disturbances in the air/water flows around the NFH. Air leaks and disturbances both affect the recordings causing variations in amplitude, frequency, and time.

The characteristics of NFH recordings depend on the source configuration, the number of guns in the array, the towed depth, and the operating pressure, all of which cause variations in the shape and amplitude of the recorded traces. All the possible variations need to be taken into consideration to reliably detect air leaks.

Method

As soon as an air leak is detected, remedial action is taken that limits the number of shots that are affected. Consequently, recorded measurements of the effects of air leaks are rare. Despite this limitation, we managed to gather data from 22 surveys. These datasets contain a variety of source configurations, layouts and operating depths and have been recorded across the vessel fleet making them fit for training a reliable machine learning network. The data are prepared, and their dimensions reduced to allow for a single classification model. We chose a light convolutional neural network (Figure 1) since the aim is to have a fast detection tool running in real time during acquisition.

To ensure a generic detection method able to differentiate air leaks from the other disturbances, variety of records were used in the training set. The training data includes ‘good’ near field measurements with no air leak and limited noise, but also recordings of noisy measurements not caused by air leaks. To further increase the amount of data and their variation, data augmentation has been performed.

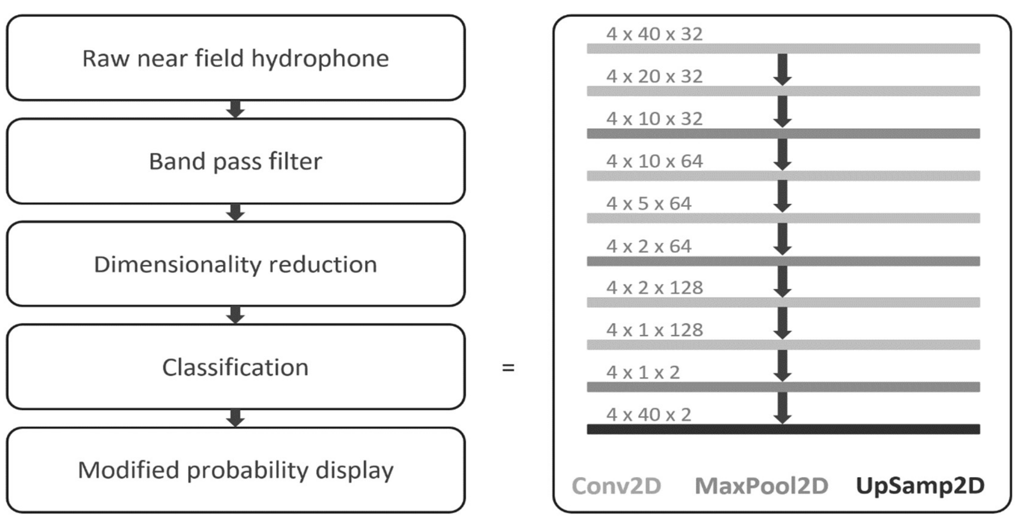

Figure 1 *Simplified process flow diagram and encoder model outline*

90% of the available data is used for training; the rest is used for validation. The accuracy of the training on the unseen data is 96,5%. For each trace, the algorithm outputs the probability that it is affected by an air leak. The probability is presented to the operator as a rolling map displaying the probability for all the active guns for the last 100 shots.
To confirm the accuracy of the new method, extensive field tests were conducted using different source geometries operated at different depths. The new machine learning detection was run in parallel with the FFT deconvolution. The machine learning detection runs in real-time on a single CPU core and the output was added to the usual QC displays (Figure 2).

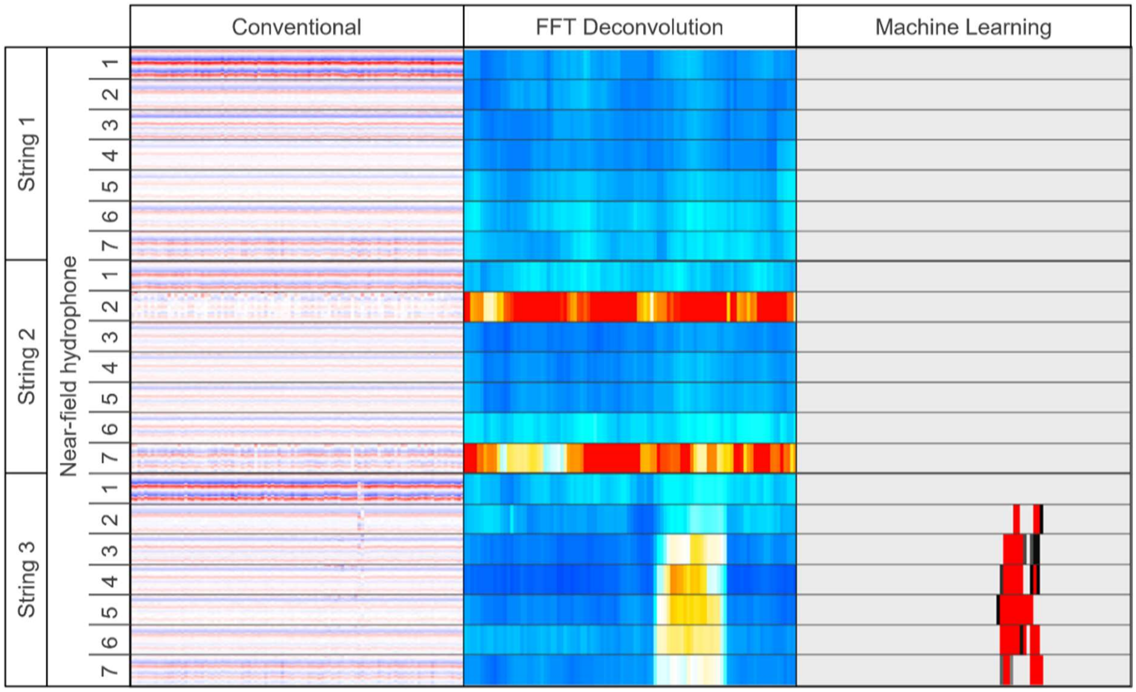

Figure 2 *Dual source acquisition configuration, showing a single source, three adjacent subarray strings each containing seven near-field hydrophones. The most recent shot is furthest right. NFH two and seven on string two are noisy, as can be seen in the layered near-field hydrophone date (left) and FFT deconvolution (central) displays. The ML display (right) is not affected, clearly showing only the air-leak on string three.*

Conclusions

Air leaks are a known problem affecting seismic sources requiring fast and reliable detection to be handled with minimal operational downtime. We have developed a convolutional network able to perform the detection of an air leak on near field recordings. The validation across the fleet confirms excellent performance of the network. It runs in real time and detects air leaks with superior confidence.

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References

Day, A.J., Hegna, S., Parkes, G. and Turnbull, N. [2007] Air–Leak Detection Using Frequency Domain Deconvolution, *69th EAGE Conference and Exhibition*, Extended Abstracts, B008