Machine Learning Air-leak detection during active Acquisition for Seismic Air Gun arrays

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Summary

Air-driven marine seismic sources are a common means of providing a repeatable and reliable source of energy for reflection seismology. Mechanical or material failure of source components can lead to air leaking from the source into the water column, degrading source stability and performance. Monitoring for air-leaks can be done through recording and analysis of near-field hydrophones mounted on the source. Air-leaks manifest as incoherent signal distortion on these recordings. Inverting for signature variations introduced by different gun volume, depth, source layout and pressure through pre-processing of the near-field hydrophone recordings allows a single convolutional neural network to distinguish between air-leaks and other forms of signal deformation. An autoencoder was trained on supervised, curated, and augmented data, reaching a training accuracy of 96.5% on the validation dataset. Modification of the air-leak probability score before display on a non-linear color pallet allows for accurate, fast, and unambiguous determination an air-leak, facilitating remote shut-off of the air supply thereby avoiding forced and unplanned time to repair the source, increasing operational uptime.

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Introduction

Air-driven marine seismic sources are a common means of providing a repeatable and reliable source of energy for reflection seismology. Operating in a harsh environment, under high pressure in the presence of corrosive seawater and near constant wave action, marine sources are subject to substantial wear and tear. Faults do occur and air-leaks are no exception. Mechanical or material failure of hoses, connectors, gun seals (o-rings and cap-rings) or even the chamber or shuttle itself, are typically progressive. The performance of the source deteriorates unless the damaged part can be addressed. Near-field hydrophones are mounted on the sources to monitor their behavior. Degradation of the source manifests in several ways, typically: (1) reduction in peak-to-bubble ratio, reducing overall signal amplitude; (2) deviation from the designed tuned array response, altering the frequency spectrum of the signal; (3) perturbation on a shot-to-shot basis, giving greater than desired variability in the signature of the air gun array; and (4) additional noise recorded by near-field hydrophones near the location of the leak, degrading the source signature derived from the near-field recording. Figure 1 shows real examples of items 1, 2 and 3.

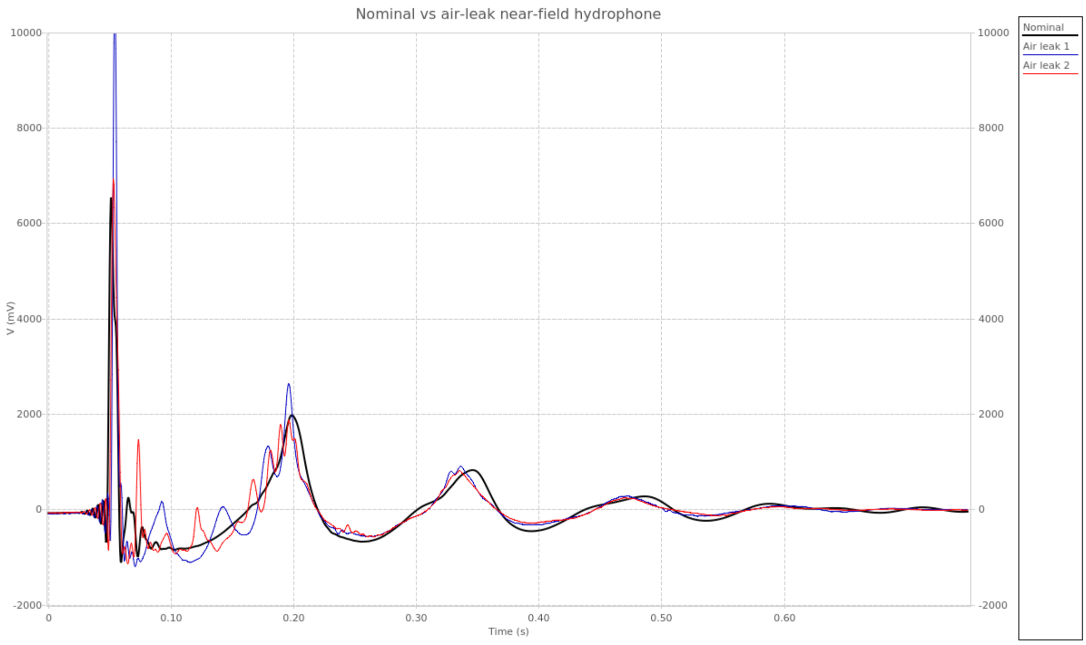

Figure 1 *Superimposed near-field hydrophone traces before and during an air-leak*

Due to these undesirable effects and the uncertainty in quantification of the immediate impact on the final data, all large and some smaller air-leaks are not tolerated in production, despite efforts to reduce their negative impacts. Modern gun controllers have remotely controlled shut-off valves allowing selective isolation of a subset of the aforementioned components. Shutting off the airflow to these can prevent both further deterioration of the failed part and stop the leak. If the gun in question can be omitted or can be substituted with a spare gun without unacceptable degradation of the source signature, then using the shut-off valve can allow acquisition to continue. This mitigating action avoids forced and unplanned time to repair the source, increasing operational uptime. To make the most of this technology, accurate, fast, and unambiguous determination of the presence of air-leaks is required.

Method

Source monitoring and anomaly detection has existed for a significant period. The approach of Day et al. (2007), though an excellent method for detecting source problems in general, can be improved upon with respect to both speed and specificity when it comes to air-leaks.

Near-field hydrophones are mounted at each air gun or cluster gun location, approximately 1m above, centrally along the array. The pressure of the main air feed line is also monitored to identify the presence of air-leaks. However, unless the air-leak is exceptionally large, experience shows that the compressor capacity is sufficient to keep the feed line at pressure within nominal tolerances. We propose using a Machine Learning (ML) based workflow that relies solely on near-field hydrophone measurements to detect the air-leak in real time. Air-leaks, when occurring in a dynamic environment such as on a towed array behind a seismic vessel, distort the primary signal recorded by the near-field hydrophones. This incoherent signal distortion is difficult to define using classical methods but lends itself well to Machine Learning (ML) applications whereby distinct examples of near-field hydrophone records with and without air-leaks are used to train a classification model.

To meet survey requirements, source parameters such as gun volume, type, depth, layout, and pressure are varied. The near-field signal depends on all of these parameters. Training a reliable ML network that can infer an air-leak when the input data is so variable is challenging. The dimensionality problem can be overcome through attribute calculations performed on the near-field signals, similar to Day et all. (2007), allowing implementation of a universal ML processing flow and use of a single classification model. Figure 2 outlines the overall process.

The deep learning network is an autoencoder which, thanks to its limited size, runs in real time on a single CPU core (Figure 2). The output is the probability score of a trace showing air-leak-like behaviour. To further reduce ambiguity, the tail end of the output air-leak probability score is flattened before being displayed using a non-linear colour pallet.

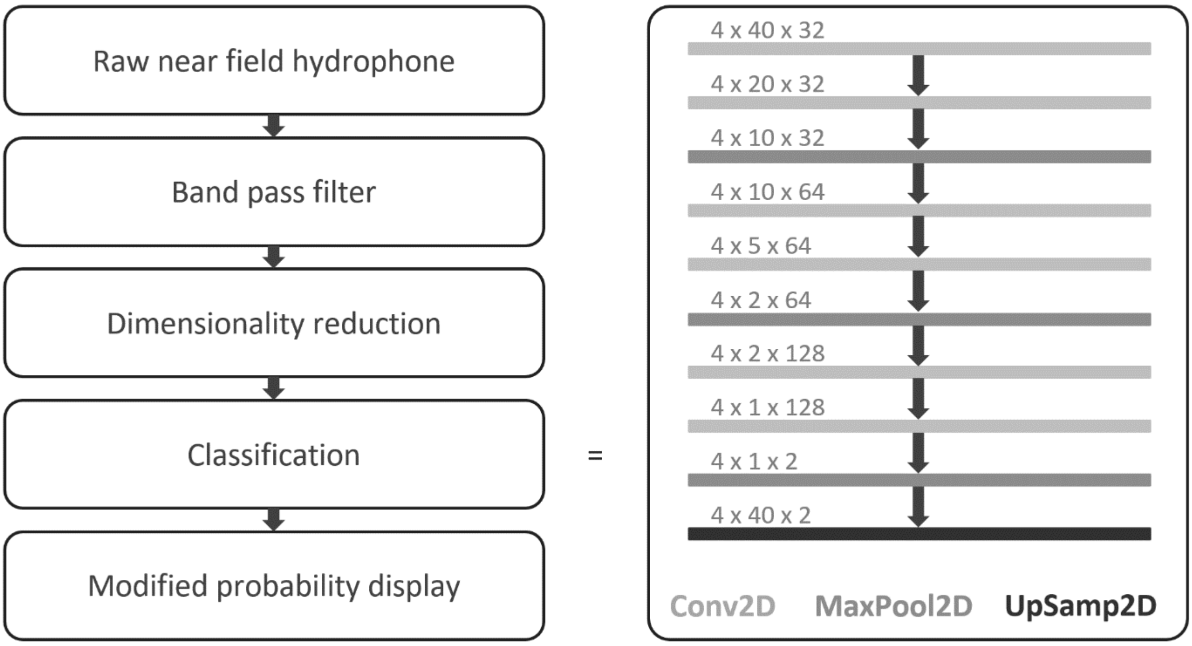

Figure 2 *Simplified process flow diagram and Autoencoder model outline*

The autoencoder was trained using supervised data. Machine Learning algorithms benefit from the size and quality of the training dataset. This immediately presents us with several issues. (1) Offshore operations are costly, and we want to acquire only good data. Hence, as soon as an air-leak is discovered and confirmed, the acquisition sequence is terminated, and the source repaired. This means that datasets containing confirmed air-leaks are very rare. (2) Data acquired with an air-leak is typically classified as Not To Be Processed and thus only available on field tape. This further reduces the datasets available for training since the raw field data is often not easily accessible. (3) Some air-leaks are small and their manifestation on the near-field data is minimal at best. Small air-leaks, such as those identified by the end-of-line drop test, whereby the sources are isolated for several minutes and the pressure drop monitored, can at times not manifest themselves on the near-field data at all. (4) Near-field hydrophones are indiscriminate in their recording. Other in-sea events, such as turbulence generated by towing the array through water, can generate signatures comparable to genuine air-leaks simply because the response of the near-field hydrophone is the same.Through the following actions and decisions these challenges have all been addressed:

A fleet-wide call for datasets over an extensive period yielded 22 datasets that were used during training. To further increase the size and variety of data with air-leaks in the training datasets, data augmentation techniques have been applied. Datasets containing small air-leaks that did not manifest on the near-field hydrophone data were discarded from the training dataset. Some of the datasets used for training contained noisy near-field hydrophone records where disturbances were not related to an air-leak. Therefore, any disturbances with a different signature than air-leak would be learnt by the network as data with no air-leak. Training data were split into 90% for the training and 10% for the validation. Training accuracy reached 96.5% on the validation dataset. Most of the false classifications were false positives related to noisy near-field hydrophone traces where no air-leak was present. Such false positives usually manifest on single isolated hydrophones as opposed to air-leaks which usually manifest on several adjacent hydrophones.

Implementation

Field trials of the method have been carried out on several acquisition vessels. The ML algorithm output was displayed adjacent to the conventional scrolling displays of the near-field hydrophone data and FFT deconvolution calculated using the method of Day et al. (2007) (figures 3 and 4), to allow direct comparison of the methods and gather user feedback. The ML algorithm performed equally well on single, dual, and triple source acquisition configurations.

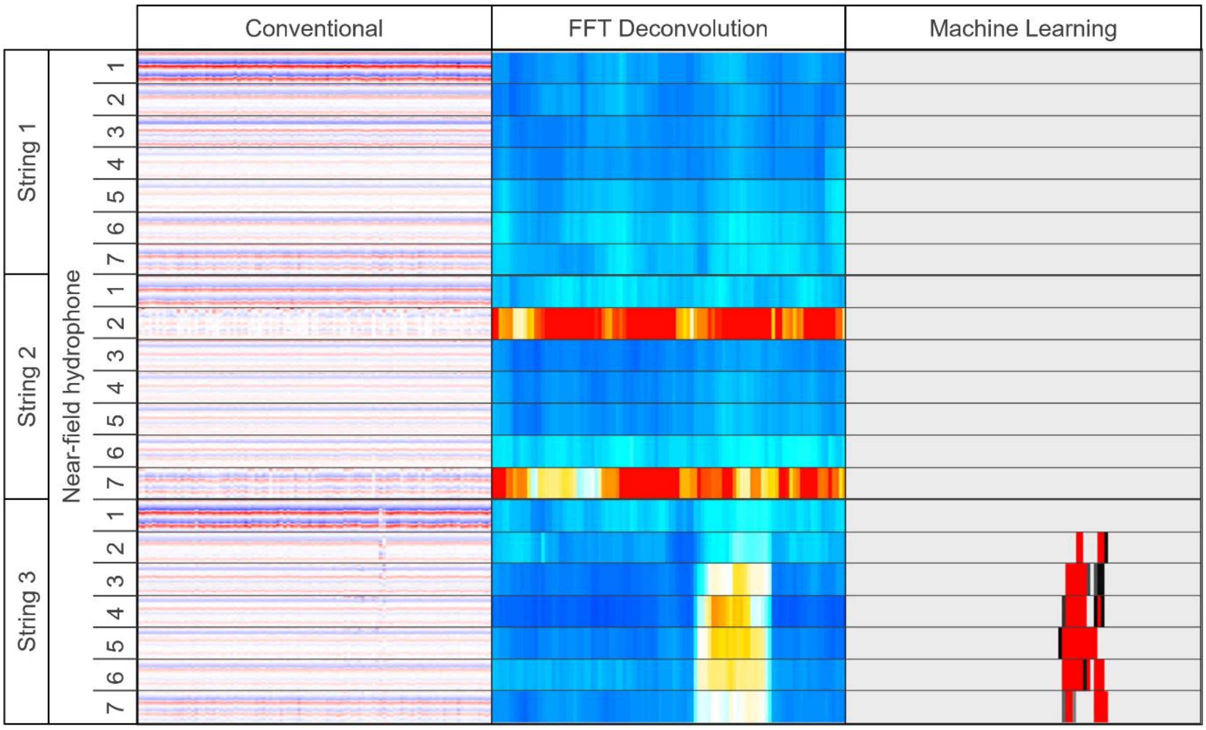

***Figure 3** Dual source acquisition configuration, showing a single source, three adjacent subarray strings each containing seven near-field hydrophones. The most recent shot is furthest right. Near-field hydrophones two and seven on string two are noisy, as can be seen in the layered near-field hydrophone date (left) and FFT deconvolution (central) displays. The ML display (right) is not affected, clearly showing only the air-leak on string three.*

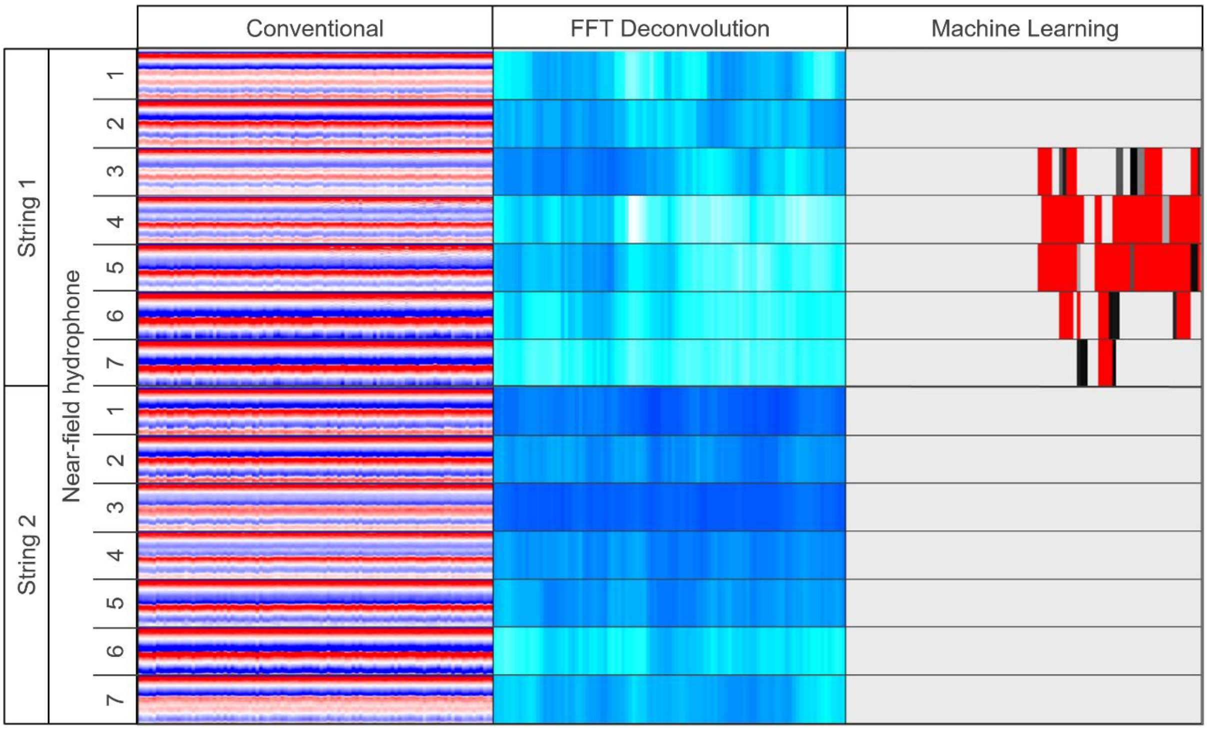

Figure 4 *Triple source acquisition configuration, showing a single source, two adjacent subarray strings each containing seven near-field hydrophones. The most recent shot is furthest right. The air-leak developing on string one is difficult to spot on both the layered near-field hydrophone (left) and FFT deconvolution (central) displays. The ML display (right) clearly shows only the air-leak occurring under near-field four of string one.*

Conclusions

Air-leaks manifest as distorted signals recorded by near-field hydrophones. Through dimensionality reduction, a single convolutional neural network can be trained to recognize such distortions, distinguishing between air-leaks and other forms of signal deformation. The implemented model is an autoencoder trained on supervised data. The combination of normalization, the small autoencoder and a flattened probability profile allows real-time and more precise air-leak detection on a single CPU core. Field trials indicate that, with this knowledge and a modern gun controller supporting remote shut-off valves, air-leaks can be quickly identified and isolated, reducing operational downtime.

Acknowledgements

We would like to thank the crews of the various test vessels for their assistance during initial field testing. We also thank PGS for permission to publish these results.

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