Determining the Added Value of Surface Distributed Acoustic Sensors in Sparse Geophone Arrays using Transfer Learning in a Convolutional Neural Network

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SUMMARY

INTRODUCTION

Distributed acoustic sensing (DAS) is a technology that uses Rayleigh scattering in a fiber-optic cable to detect elastic signals when the particle motion is parallel to the sensing fiber (Hornman et al., 2013). The two main components used in distributed sensing are the interrogator unit and the fiber-optic cable. The interrogator unit works as a light source and receiver. It sends a known pulse of light down the fiber. Nearly any type of existing fiber-optic cable can be used in conjunction with an interrogator unit. Small imperfections within the fiber causes backscattering of light. The fiber undergoes a strain when a seismic wavefield approaches and a scattering of light is produced that is different from base conditions. The interrogator unit is able to measure the Rayleigh backscattering that is produced and relate it to the local strain along the fiber by recording the time of arrival and the phase-lag of the returning light signal (Parker et al., 2014).

Although DAS is utilized mainly in borehole acquisition, it has been shown repeatedly that the technology is capable of recording seismic data in surface acquisition (Daley et al., 2013; Yavuz et al., 2016; Jreij et al., 2018). Both Daley et al. (2013); Yavuz et al. (2016) concluded that observing P-wave reflections in a single DAS fiber is difficult. The issue that is apparent in their experiments is that short offset P-waves arrive perpendicular to the DAS fiber. DAS, however, is limited by its broadside insensitivity, or in other words, the fiber is most sensitive to waves that have particle motion parallel to the orientation of the fiber. In a geophone, this directional insensitivity is observed as well, but by recording multiple components, the insensitivity can be minimized.

DAS has many advantages in various industries. One of the most notable is that DAS enables seismic surveys to be acquired with dense sampling (as small as 10-centimeter receiver spacing) at large distances (tens of kilometers long). Achieving even 1-meter sampling with conventional geophone is expensive and logistically difficult. Deployment of DAS in surface acquisition is as simple as trenching the fiber in the ground and recording using an interrogator unit.

This paper is inspired by the PoroTomo survey geometry shown in Figure 1. The geophone acquisition has 238 geophones spaced anywhere from 50 meters to 150 meters apart. This receiver spacing is much greater than a conventional reflection seismic surveys which leads to aliased data as there is not enough spatial sampling. Fortunately, the PoroTomo survey also included about nine kilometers of DAS cable. The experiments presented in this paper utilize the dense spatial sampling of broadside insensitive DAS fiber and the broadside sensitivity of sparse, multi-component geophones. The energy norm imaging condition is to create an image of sparse, multi-component geophones by themselves and an image of sparse, multi-component geophones in combination with dense, DAS fiber.

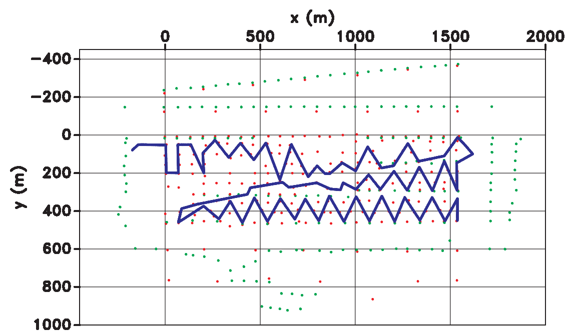

Figure 1: Sources (shown in green), multicomponent receiver (shown in red), and distributed acoustic sensing (shown in blue) geometry used in the PoroTomo survey.

The example shown in this paper are numerical examples which allow for quantitative analysis. All of the experiments presented in the paper can be qualitatively analyzed and discussed, but qualitative analysis is always different between people due to different biases and perspectives. A method to quantitatively analyze the experiments is needed to do effective comparisons.

Convolutional Neural Network

Machine learning is a field within computer science that focuses on the ability of computer systems to learn patterns within data without being explicity programmed for these patterns (Samuel, 1959). Machine learning has had a large boom in the geophysics industry within the last 10 years. The reasons for this are quite apparent: geophysicist work with large amounts of data, the geophysics field needs more quantitative analysis rather than qualitative, and machines are much better at identifying weak or high-dimensional patterns than humans are.

There are a variety of machine learning algorithms that can be utilized based on the problem that needs to be solved. One of the most powerful machine learning algorithms is the neural network. Neural networks are inspired by the biological neural networks that constitute human brains or at least how humans perceive they work (Gerven and Bohte, 2018). They consist of many layers in parallel and every layer consists of a number of nodes. All neural networks consists of at least two layers: the input layer and output layer. All the extra layers in between the input and output layers are the hidden layers. The nodes of every layer are like neurons in the brain. Every neuron has its own activation function that determines whether it should be "fired" or not similar to how a neuron in the brain behaves. Each layer receives the output from the previous layer based on if the previous neuron is fired or not.

Convolutional Neural Networks (CNN's) in particular are at the core of most state-of-the-art computer vision solutions for a wide variety of tasks. One of the most accurate CNN image classifiers is the Inception-v3 model (Szegedy et al., 2015). The original Inception-v3 model is trained and tested on the 2012 ImageNet Large Scale Visual Recognition Challenge (Russakovsky et al., 2015). The training dataset consisted of 10,000,000 labeled images that depicted 10,000+ object categories. The Inception-v3 model was able to perform with 3.5% top-5 error and 17.3% top-1 error. Top-1 error means that the class with the highest probability classification is the same as the target label, whereas top-5 error means that the target label is within the top-5 probability classifications. A top-1 error of 17.3% means the Inception-v3 model is able to perform with high accuracy, making it a top contendor for a geophysics image classification problem.

SURVEY DESIGN

METHODOLOGY & THEORY

Common Receiver Gathers

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