Image registration for distributed acoustic sensing acquired data using convolutional neural networks

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Abstract

We provide a brief overview of convolutional neural networks. Then we introduce a training set extracted from real data. We test the trained convolutional neural network on a portion of the training set to determine accuracy. Afterwards, we employ this trained convolutional neural network to identify events in data which contains walking and digging events. We then discuss our results which suggests that more than just the source of an event affects the way the event looks in the data.

Image Registration

Image registration is an important part of image processing or image recognition. It entails aligning two or more images into one coordinate system when the images are taken at different times, from different sensors, or from different viewpoints [2]. For example, features for a photograph of a person would include scaling and skewing the image as well as shifting, flipping, and rotating the person inside the image. For DAS-acquired data, the general shape of an event is hyperbolic. The features for image registration of such data would involve different methods for changing the shape or location of the hyperbolic response. Some clear attributes include scaling and shifting the response in the data. From [1], the velocity of the source changes the shape of the hyperbolic response as well as the size of the gauge length applied to the data. This experiment suggests that the pulse-repetition-frequency also affects the shape of the response.

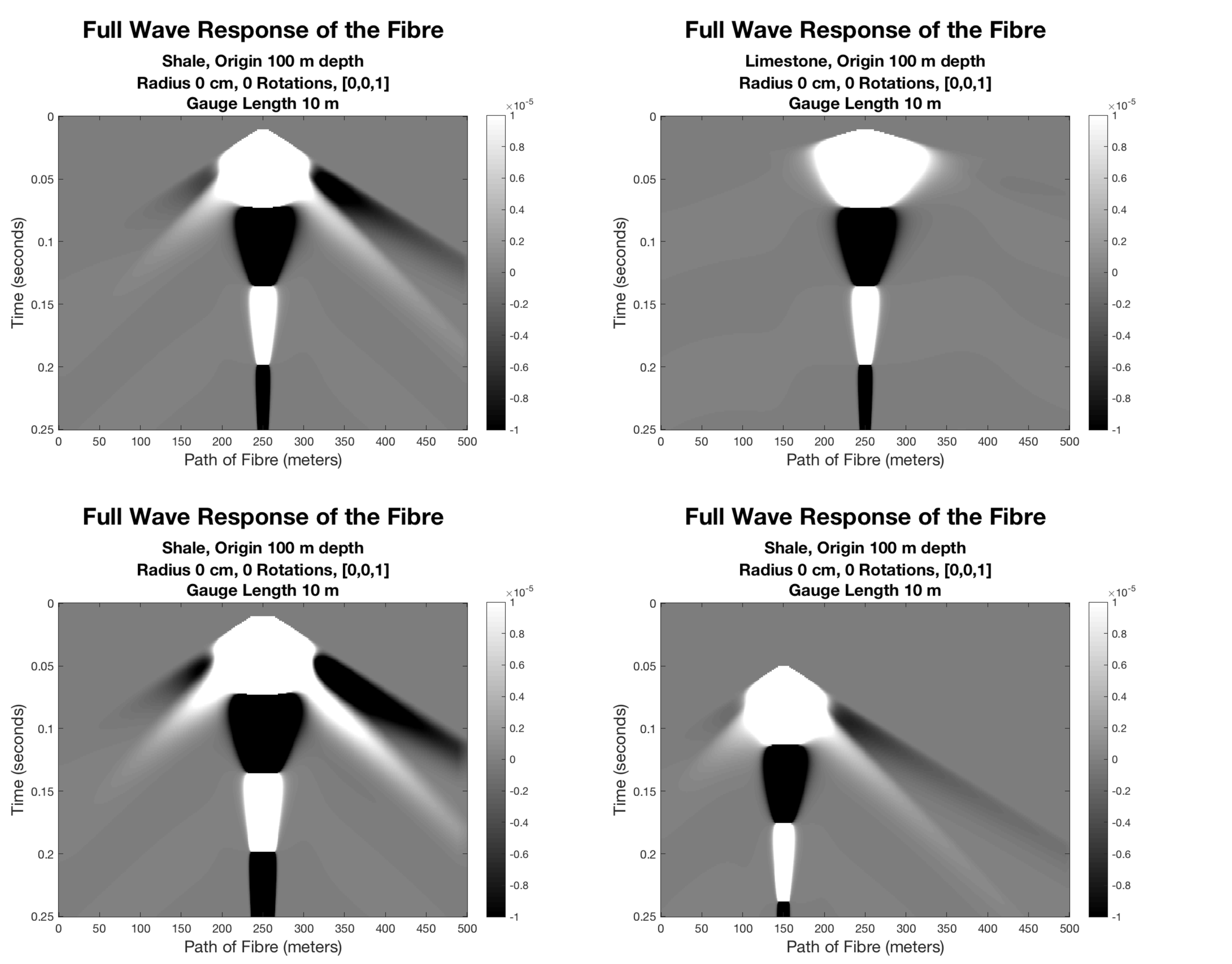

Figure: Synthetic examples of (Top row) signals from seismic waves moving at two different velocities. (Left column) signals acquired using two different gauge lengths. (Bottom right) signal from a shifted source location.

Architecture of CNN

A convolutional neural network was built using the tutorial from [2] and [3]. Cost function and stochastic gradient descent is based on [5]. The CNN has a convolutional layer, a pooling layer, and a densely-connected output layer which feeds into a softmax regression with cost entropy. We applied the stochastic gradient method to a cost function.

Training Set

We extract images from real data for the training set. We employ 207 data sets: 96 contain walking events and 111 contain digging events. The training set contains 3232 images of size 128×128. The set has 1002 walking events, 1142 digging events, and 1086 noise events.

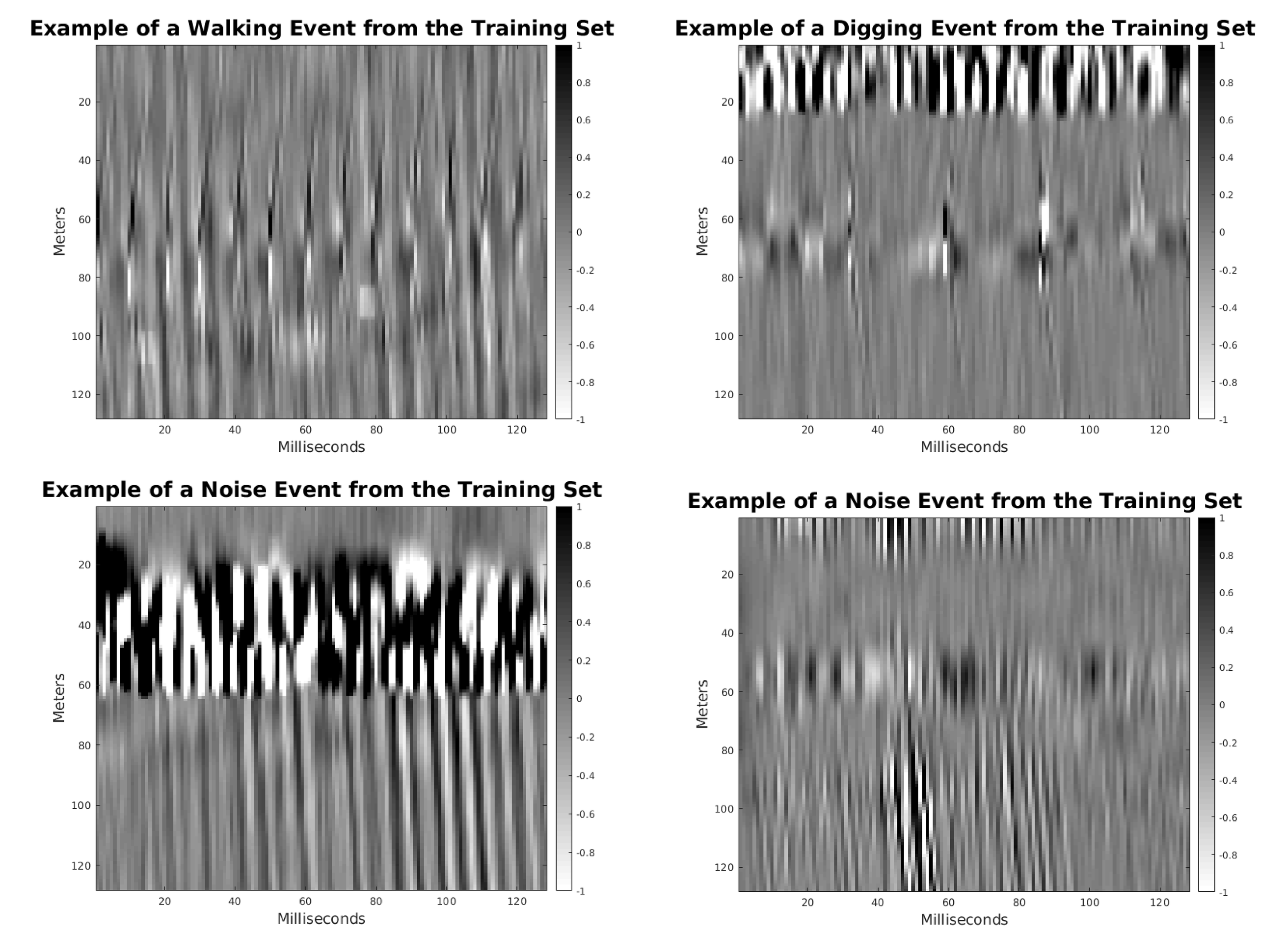

Figure: (Top left) An image of a walking event from the training set. (Top right) An image of a digging event from the training set. (Bottom) Examples of noise events from the training set.

Data

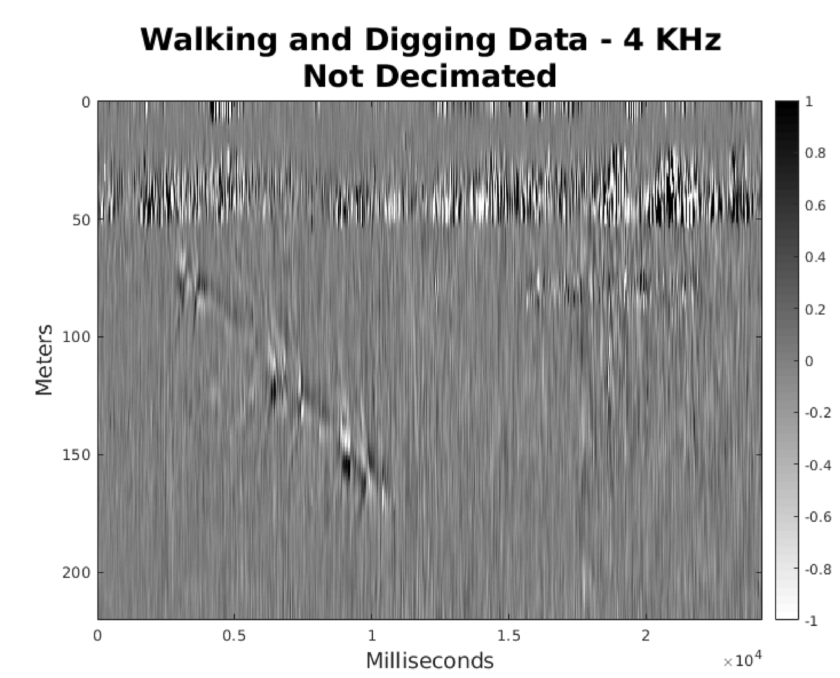

Figure: The 4kHz PRF data set which has not been decimated of someone walking next to the fibre and someone digging next to the fibre.

Data (cont.)

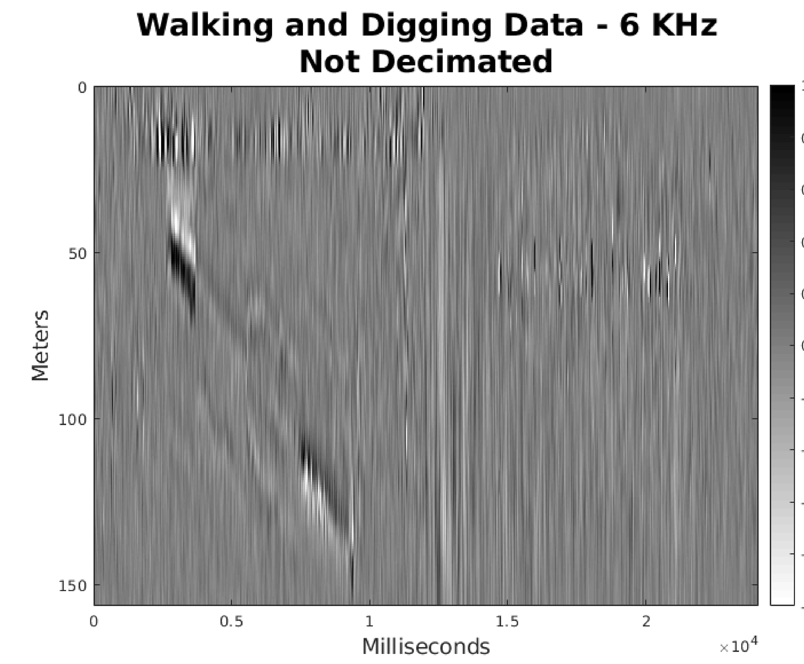

Figure: The 6kHz PRF data set which has not been decimated of someone walking next to the fibre and someone digging next to the fibre.

We glued a data set containing walking and a data set containing digging together for two data sets acquired at different pulse repetition frequencies (PRF) - 4kHz and 6kHz. We also apply the CNN to three different decimations of the two data sets — no decimation, decimation by 10 shots, and decimation by 50 shots.

Results

The CNN performed the best on the data decimated by 50 shots for both PRF data sets and was more successful with the data collected at 4kHz PRF.

Table: The accuracy of the convolutional neural network for each type of 4kHz PRF and 6kHz PRF acquired walking and digging data.

	No Decimation	10 Shots Decimation	50 Shots Decimation
4kHz	11%	34%	77%
6kHz	9%	0%	39%

Conclusions

- The CNN had approximately 80% accuracy when identifying events.
  It's necessary to consider how the DAS system collected the data when performing image recognition on DAS-acquired data, i.e. the PRF, the gauge length, etc.

References

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