Estimation of microseismic source mechanisms from DAS data using unsupervised deep learning

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Summary

Distributed acoustic sensing (DAS) is a rapidly expanding seismic acquisition technology. It is increasingly applied in microseismic monitoring during hydraulic fracturing, and as a complement to broadband seismometers for measuring teleseismic waves generated by earthquakes. A key task in these DAS applications is determination of the source mechanism from information encoded in the direct arrivals. DAS acquisition generates very large volumes of data, and how to manage these volumes is an open question; also, DAS data comprise measurements of different aspects of the elastic field than those associated with geophones or seismometers, and consequently conventional moment tensor inversion does not transfer directly. To manage these issues, we formulated a deep learning algorithm for source mechanism estimation from DAS signals. The algorithm begins with a convolutional auto-encoder step, designed to extract features from DAS-microseismic data relevant to moment tensor characterization. The features are analyzed for moment tensor information using two additional deep learning techniques, based on clustering and generative adversarial networks (GAN). Clustering detects groups of input seismic events that share strongly correlated source mechanisms, allowing for moment-tensor-based grouping of seismic data. Finally, we developed a trained GAN which maps from feature space to moment tensor estimate, predicting source mechanisms from DAS-microseismic data.

Methodology

Hydraulic fracturing is a specialized reservoir treatment used to increase permeability by mechanically fracturing the reservoir rock. As these fractures propagate into the reservoir they act as sources for seismic energy which carries important information about the location and type of fracture that generated recorded microseismic data. For example, information encoded in the direct arrivals such as phase (Eyre and van der Baan, 2015), amplitude (Eaton et al., 2014; Eyre and van der Baan, 2015), or a combination of both (Eyre and van der Baan, 2015; Willacy et al., 2019) have been used to estimate the moment tensor. The moment tensor estimates can then be used to infer in-situ stress, fracture type (which can further be used to infer flow paths for hydrocarbons), occurrence of new fractures, and help optimize future treatments.

Moment tensor estimates are conventionally supplied through a family of processes known as moment tensor inversion (MTI). However, many of these algorithms are designed for multicomponent geophone data, and therefore do not transfer directly to DAS data, which measures a different portion of the elastic wavefield. Two main issues prevent the direct application of MTI to DAS data, (1) DAS supplies measurements of normal tangential strain along the fiber, and is thus a single component sensor, and (2) the expense of MTI restricts its application to very large datasets of the type DAS supplies (due to its very dense trace spacing).

To address these issues, we instead turn our attention to a practical approach for moment tensor estimation rooted in deep learning. Two motivations are present for a deep learning approach. The first is that deep learning algorithms tend to be data-hungry and thrive when they have access to large datasets from which to learn complex relationships. Second, we can view DAS data, and specifically the direct arrivals, as containing features relevant to the goal of moment tensor estimation such as amplitude and phase information. Machine learning algorithms are adept at learning complex structure within datasets and extracting meaningful features from the data (e.g. Ongsulee, 2017). A class of machine learning algorithm know as convolutional neural networks (CNN) are well-suited for processing and extracting information from image-type data. A special subset of these CNN, known as convolutional autoencoders (CAE) are fully unsupervised, and can learn to extract complex feature mixtures from input data absent a large labelled dataset (e.g Cheng et al., 2018). The convolutional autoencoder consists of two networks, the first is a conventional CNN that compresses the input images to a vector known as the feature space that represents the image by only its most important information or features. The second network, referred to as the decoder, is a mirror image of the first and consists of transposed convolutions (Pardede et al., 2018). Its goal is to use the feature space representation and learn a mapping that forms an accurate reconstruction of the original image. As training proceeds, this network learns how to extract only those features from the data relevant to image reconstruction. The CAE provides a means of compressing high-dimensional input images to a low-dimensional vector representation that contains only the most salient features in the input image.

Once the CAE is trained, we have access to an encoder network that can extract meaningful features from out input microseismic images. We then set up two additional algorithms designed to extract moment tensor information from the feature space representations of our data. The first is a clustering algorithm based on the density-based clustering with applications to noise (DBSCAN) algorithm (Ester et al., 1996). Clustering groups data based on shared characteristics. Clustering the feature space representations of the input data will group images that share similar feature spaces. If the feature space representations contain important information about moment tensor class, then images with similar feature spaces (occupying the same cluster) should also share similar source mechanisms. The second algorithm we construct is rooted in the idea of generative adversarial networks (GAN) presented by Goodfellow et al., 2014. GANs consist of two competing networks known as the discriminator and the generator. The generator takes input data (here feature space representations) and predicts a moment tensor label. The discriminator takes a feature-space and moment-tensor-label pair and tries to detect which pairs are authentic and which have been constructed by the generator. The generators goal is to make sufficiently accurate moment tensor predictions, such that the discriminator fails in its task. This procedure leads to a generator network that can form accurate predictions of the moment tensor given a feature space vector. Once trained, the generator network is extracted and used to form moment tensor predictions from feature space vectors.

Numerical Results

To facilitate training of these networks and validation of our results we create a dataset of 10,000 DAS microseismic images generated with random moment tensors constrained as being either compensated linear vector dipole, double couple, or tensile crack dominant. These images were used to train the CAE, where 8000 images were used for training and 2000 for validation. A feature space dimensionality of seven was selected through testing of many feature space dimensionalities and loss function monitoring. The feature spaces extracted with the CAE were then clustered using DBSCAN on a t-distributed stochastic neighbor embedding (van der Maaten and Hinton, 2012) from the feature space. Seven clusters were detected by DBSCAN. If the feature space representations encode important source information, then the data in each of the seven clusters should share similar source mechanics with other data in the same cluster. To evaluate this, we plot the moment tensor of each image in Hudson space (Hudson et al., 1989), and color it by the cluster to which it belongs. If the feature space contains important source information, then images in the same cluster should plot in a similar region of Hudson space. Figure 1a plots the clusters detected by DBSCAN, while Figure 1b plots the moment tensor for each image in Hudson spaced colored by its cluster. By-and-large images that are in the same

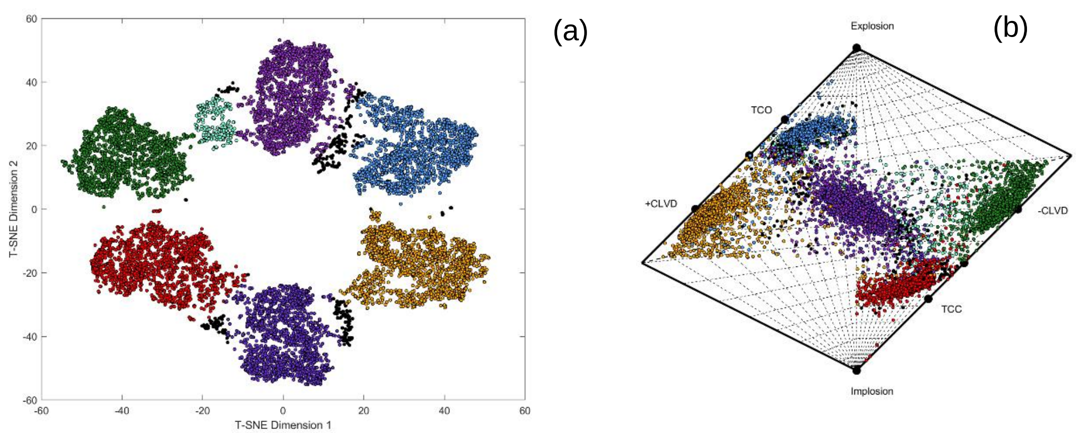

Figure 1: (a) The seven clusters detected by DBSCAN. Each point represents one of the 10,000 input images, and the colors indicate which cluster each point belongs to. (b) Hudson space representation of the moment tensor for each of the 10,000 images colored by the cluster in which they belong.

cluster also plot in a similar region of Hudson space. This suggests the CAE is extracting information relevant to the source mechanism, and that we can use this information to make predictions of the moment tensor.

Next, we employ the trained GAN to make predictions of the moment tensor. The feature space vectors are supplied to the trained generator and predictions of the Hudson space label associated with the feature space are computed. Figure 2a plots the true distribution of the Hudson space labels in purple and the predicted labels in yellow. Figure 2b plots the error in each component. The distribution of the predicted moment tensors is a good match to the true data.

This further suggests the feature space contains important source information, and that it can be used to make inferences of the source mechanism.

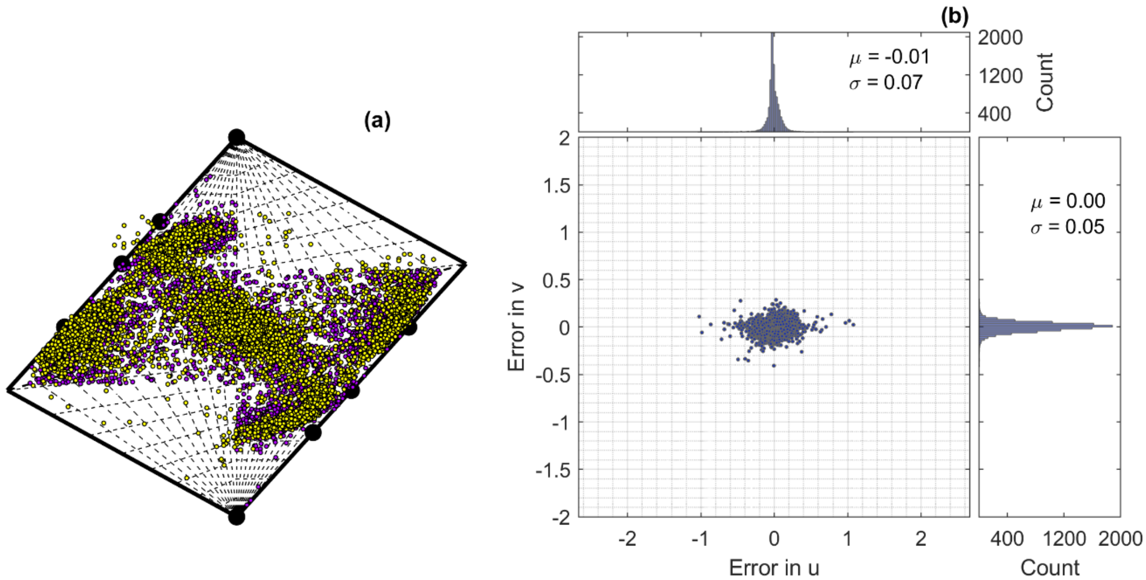

Figure 2: (a) Hudson space moment tensors for the true data in purple and the predicted moment tensors in yellow. (b) Error in each component of the Hudson-space moment tensor predictions.

Conclusions

Moment tensor estimation is an important procedure in microseismic data processing. Estimates of the moment tensor supply important information about the in-situ stress, fracture types, success of the treatment, and provides lessons for optimizing future treatments. DAS data is playing an increasingly important role in microseismic monitoring, and the development of algorithms for moment tensor estimation using DAS data is crucial. We present a novel approach, rooted in deep learning for extracting relevant source information from DAS microseismic data, and then further processing that information to make inferences of source mechanics. Both the clustering and GAN approaches shown here provide important source mechanism information from DAS microseismic data.

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