Direct velocity estimation for seismic imaging using deep neural network

Stuart Farris, sfarris@stanford.edu; Vishal Das, vdas2@stanford.edu; Abhishek Tapadar, atapadar@stanford.edu;

Stanford SCHOOL OF EARTH, ENERGY & ENVIRONMENTAL SCIENCES

1a. What Is The Big Picture? Finding Earth's Elastic Properties

- Predict acoustic wave velocity of the earth's subsurface from seismic data.
- Data (Fig 1b) is collected in a survey (Fig 1a) to predict subsurface (Fig 1c).
- Classically, this inverse problem is solved using the wave equation and many assumptions[1] in a time consuming process, as much as half a year.
- We train a neural network once, which can then supply results within seconds.

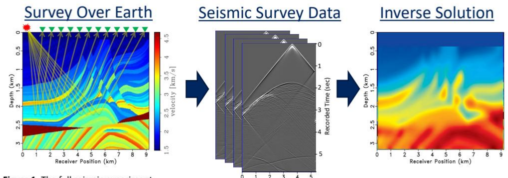


Figure 1. The full seismic experiment.

1b. What are we solving here? Inputs and Outputs

Input: A single seismic survey gather (2D image)

Output: A one dimensional wave velocity prediction (1D vector)

- To ease the problem above, assume the earth consists of flat, homogeneous layers.
- Assuming this, we predict the 1D velocity profile from a single gather

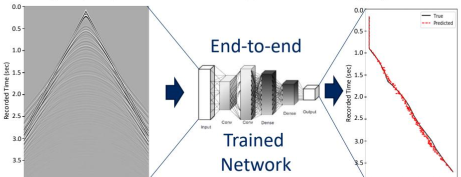
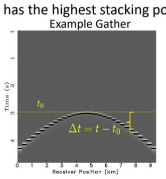


Figure 2. Desired project workflow.

2. What Is Our Baseline? Classic Velocity Analysis

- Normal Moveout Velocity Analysis[2] (NMO Analysis)
- Based on assumed hyperbolic moveout, scan over velocity values and compute stacking power in offset direction. From semblance scan, **hand pick velocity** that has the highest stacking power.



Hyperbolic moveout equation

$$t^2 = t_0^2 + \frac{x^2}{v^2}$$

1. Pick zero time, t_0
2. Scan over RMS velocities, v
3. Stack over offset
4. Plot stacking semblance
5. Hand pick trend

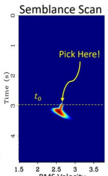


Figure 3. Baseline approach (Classic Velocity Analysis).

3. Generating Training Data

The Earth is Intrinsically Unlabeled!

- Use prior knowledge to create realistic labels. From these make realistic data.

Generate 10,000 synthetic data/label pairs

- **Labels:** Flat earth models with varying velocity layers and profile. Take 1D profile.
- **Data:** Deterministic wave propagation[4], we simulate the seismic experiment.

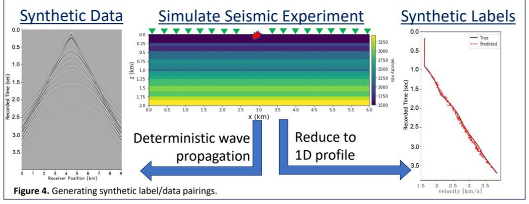


Figure 4. Generating synthetic label/data pairings.

4. Neural Network Architectures

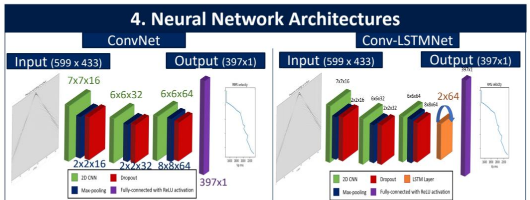


Figure 5. Architecture of deep neural networks: (I) Conv-Net with fully connected layer, (II) ConvLSTM-Net with LSTM layer.

5. Results

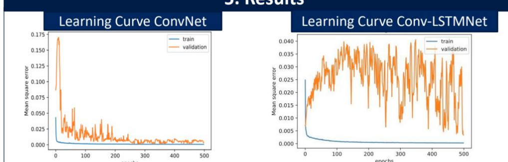


Figure 6. Learning curve for 500 epochs for ConvNet and ConvNet-LSTM. (Note change in scale between two plots)

Training data	700 samples
Validation data	100 samples
Test data	200 samples

Optimization	Adam
Learning rate	0.001
Cost function	Mean square error

6. Example: Root mean square velocity from seismic gather

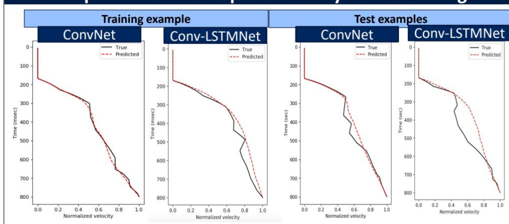


Figure 7. RMS velocity prediction using deep neural network for training and test sets for Architecture 1 and 2 respectively.

7. Summary: Hyperparameter Tuning

Sensitivity to CNN layers

# CNN layers	Train MSE	Test MSE
3 (Base)	6.86e-4	0.0033
2	3.19e-4	0.0181
1	0.0873	0.0846

Sensitivity to #CNN filters

# CNN filters	Train MSE	Test MSE
16, 32, 64	6.86e-4	0.0033
32, 64, 128	0.0023	0.0095
8,16, 32	0.0015	0.013

Sensitivity to CNN filter width

Filter width	Train MSE	Test MSE
7, 6, 6	6.86e-4	0.0033
14, 10, 8	6.14e-4	0.006
5, 3, 3	0.0015	0.0054

Sensitivity to CNN layers in Conv-LSTM Network

# CNN layers	Train MSE	Test MSE
3	0.0021	0.0002
2	0.0051	0.0003
1	0.0125	0.0133

8. Discussion

- **Deep learning approach to predict RMS velocity from seismic gathers works!**
- **Conv-LSTMNet has the least mean square error on the test dataset.**
- **Each epoch in Conv-LSTMNet took 5x computation time compared to ConvNet.**
- The robustness of the network needs to be systematically tested before deployment.[3]
- Some subtle fluctuations in the RMS velocity in the test dataset could not be predicted.
- This deep learning technique can hugely impact the turnaround time for seismic data processing.[5]

9. Future

- Perform robust hyperparameter tuning for optimum network architecture.
- Compare the results with velocity picks from industry experts (and define Bayes error).
- Use 3D volume of seismic gather to capture more information in the predictions.
- Apply the method to a real 3D seismic dataset and compare the results with current method.
- Optimize Conv-LSTMNet for faster computations.

10. References

[1] O. Yilmaz. Seismic Data Processing, Investigations in Geophysics. Society of Exploration Geophysicists, Tulsa, OK, 1987.

[2] Jon F Claerbout. Basic Earth Imaging. Technical report, 2010. URL http://sepwww.stanford.edu/sep/prof/bei11. 2010.pdf.

[3] V. Das, A. Pollack, U. Wollner, and T. Mukerji. Convolutional Neural Network for seismic impedance prediction. SEG Technical Program Expanded Abstracts 2018, 2071-2075

[4] Gabriel Fabien-Ouellet and Bernard Gloaguen, Erwan Giroux. Time-domain seismic modeling in viscoelastic media for full waveform inversion on heterogeneous computing platforms with OpenCL. Computers and Geoscience, 2016.

[5] S. Farris, M. Araya-Polo, J. Jennings, B. Clapp, and B Biondi. Tomography: a deep learning vs full-waveform inversion comparison. EAGE Workshop on High Performance Computing, sep 2018. ISSN 2214-4609. doi: 10.3997/2214-4609. 201803073. URL http://www.earthdoc.org/publication/publicationdetails/?publication=94580.