Bare Demo of IEEEtran.cls for IEEE Journals

Michael Shell, *Member, IEEE,* John Doe, *Fellow, OSA,* and Jane Doe, *Life Fellow, IEEE*

***Abstract*—The abstract goes here.**

***Index Terms*—IEEE, IEEEtran, journal, LaTeX, paper, template.**

I. Introduction

THIS letter presents a deep convolutional approach for recovering high frequency components in post-inversion acoustic impedance models. The inversion of seismic data to obtain acoustic impedance is a frequently used technique because it offers several advantages: (1) it facilitates integrated interpretation, (2) stochastic inversion can improve data's vertical resolution, allowing sub-seismic features to be more precisely mapped, and (3) it optimizes the correlation between seismic and petrophysical properties of the reservoir. Using the seismic data in deep-water reservoir modeling leads to errors in estimating the reservoir properties because such data do not allow the wider understanding of the field under study [1].

Results from a typical post-stack or pre-stack seismic inversion are band-limited primarily due to missing low and high frequencies in the wavelet. Consequently, thin beds are generally poorly resolved [3]. The limited vertical resolution in the conventional seismic data is because the frequency of the data is limited in both the low frequencies and the high frequencies. The inversion process can add low frequencies to the seismic spectrum through constraint model. The seismic vertical resolution is the minimal thickness that can be resolved by seismic. The most accepted value is a quarter of the wave length (that means that only layers thicker than that will be detected by seismic acquisition). In larger depths that value can be as high as 20 meters, which may represent a significant amount of oil volume being under or overestimated or mitigate connectivity problems.

In deterministic inversion approaches, the vertical resolution remains constrained by the seismic bandwidth [4]. Deterministic inversion is mainly useful for deriving general trends and highlighting large features in an exploratory stage. On the other hand, stochastic investion uses random variation of parameters to reach results with vertical resolution that is superior to the conventional data. When working with multiple realizations, selecting the model that best characterizes the reservoir is difficult, since all of them are equally probable. Uniqueness problems are an issue mainly addressed by calculating the mean of different realizations. However, it has been proved that the mean solution is closer to a bandwidth limited solution, in such a way that the high frequencies characteristics are lost [5]. Another approach to deal with the high frequency impedance information outside the frequency band of seismic signal is assuming a blocked model for the earth's impedance [5]. This assumption is not always valid, and in some cases the high frequencies in the inverted impedance are ignored [6]. Very recent methods aim to enhance the seismic resolution and, by consequence, achieving an improvement in seismic inversion and reservoir characterization. [7] use wavelet frequency-dependent scaling to extends the amplitude spectrum of high- and low-frequency axes in time domain.

In this letter, we propose a new multichannel and multilayer Convolutional Neural Network (CNN) model to perform deblurring in post-inversion acoustic impedance. Each network layer maps higher level features originating in the previews layers through one-dimensional convolutional blur kernels. To perform this mapping, the kernels (also named weights) are adjusted by minimizing a loss function. The model enhances the resolution of acoustic impedance images trace by trace, resulting in sharp images with increased high-frequency bandwidth and lower noise. In order to train the model, we perform Maximum-a-Posteriori (MAP) inversion to obtain a band-limited acoustic impedance model. Then, the pairs of blur and latent images are normalized and presented to the network as input and target, respectively. The core concept of our architecture is the combination of the convolutional layers with regression layers, thus the convolutional layers learn the spatial structures existing in different acoustic impedance images, while the regression layer proceed the prediction of the property values. Thus, deblurring the acoustic impedance models, as a post-inversion refinement process, should lead to a more accurate interpretation of the impedance models.

The contributions of this work are threefold. First, according to our knowledge, it is the first to approach inversion resolution enhancement through a post-inversion refinement. Second, the proposed deep learning model effectively recovers the high frequency spectrum absent in the post-inversion acoustic impedance, yet correcting deformations existing in thin bodies caused by the inversion process. Third, it contributes ......

The remainder of this letter is organized as follows. Section II reviews the CNN, a popularly used deep-learning technique. Section III describes the proposed deblurring approach. Section II reports the experiments and results, and Section V concludes our work.

M. Shell was with the Department of Electrical and Computer Engineering, Georgia Institute of Technology, Atlanta, GA, 30332 USA e-mail: (see http://www.michaelshell.org/contact.html).

J. Doe and J. Doe are with Anonymous University.

Manuscript received April 19, 2005; revised August 26, 2015.

II. Theoretical Foundations and Related Works

Deblurring is generally modeled as the convolution of a blur kernel k with a latent image I:

$$y = k \otimes I + n \tag{1}$$

where n is the noise. Since k, I and n are unknown, the problem is highly ill-posed and admits infinite solutions for k and I. Blind deconvolution refers to the inference of the sharp image I, given only the blurry image y, without any knowledge regarding the kernel k and the noise n [8]. In contrary, if k is assumed to be known, the approach is called non-blind deconvolution [10]. Applying blind deconvolution generally implies in making assumptions on blur kernels and/or on latent images. For example, assuming sparsity of blur kernel or that natural images have super-Gaussian statistics. The second assumption leads to the use of image priors on inference process and, consequently, to the maximum *a posteriori* (MAP) estimation [9]. However, [11] show that deblurring methods based on this prior tend to favor blurry images over original latent images.

The Bayesian inference approach [11] outperforms the MAP based methods. It marginalizes the image from the optimization step, while estimating the unknown blur. According to [12], defining a gradient prior, by itself, is not sufficient to reach a sharp image, instead, they search in a data set for a prior that densely correspond to the blurry image similar to a sharp image. Even though [13] suggest a generalization for the method proposed by [12], it still requires a similar reference image, which is not always available.

The methods described previously fail when applied to real world blurry images [14] and take a severe computational cost [15]. In contrast, the learning-based methods have gained attention with the resumption and recent advances in convolutional neural networks (CNN). The adequate hyper-parameter adjustment allows CNN to learn non-linear function or blur kernels. Thus, deblurring becomes a function of a blurry image I and a set of parameters p as 2

$$y = \sigma(I, p) \tag{2}$$

Learning-based methods focus on developing a model to learn the function σ and to perform non-blind deblurring [15]. [16] teaches a CNN to recognize motion kernels and performs non-blind deconvolution in dense motion field estimate, in addition, [17] minimize regularized l_2 in order to perform text deblurring.

III. Data and Methods

A. Data Set

To evaluate the proposed deblurring method, an acoustic impedance data set is collected. [1] The data set contains a cube of acoustic impedance values from the updated Stanford VI reservoir [19], which is represented by a three-dimensional regular stratigraphic model. The cube contains 150x200x200 cells and the dimensions of each cell are 25 meters horizontally and 1 meter vertically. The model represents a fluvial channel system composed of three layers: the lowest one represents deltaic deposits (layer 3), the middle layer represents meandering channels (layer 2) and the first layer sinuous channels, deposited in the fluvial channel system. [2] Some sample images from Stanford VI are shown in Fig. 1 Even though the data has been synthetically generated through flux simulation, the layers represent geological bodies of high importance in reservoir characterization, such as channels connections and theirs discontinuity...

[1] Available at https://github.com/SCRFpublic/Stanford-VI-E/tree/master/Acoustic%20Impedance

Fig. 1. Examples.

Fig. 2. Examples.

In a realistic scenario, the number of hard data available for training and validating supervised models is scarce. In order to address this common issue, we performed experiments restricting the amount of training data set to 50%, 30% and 10% of the available data. The results using 50% and 30% did not show significant difference in the frequency spectrum, whereas 10% showed more significant discrepancies in the amplitude recovering and additional noise in higher frequencies (Fig. 2). Therefore, for the following experiments we adopted 30% of available data as training data set, once we observed it as the minimum amount of data to keep the model learning capability.

To build the training data set we carry out the *Maximum-a-Posteriori* (MAP) [21], [22] inversion using the high resolution acoustic impedance. In order to proceed the inversion, we created a Ricker wavelet with frequency band-width from $0Hz$ to $60Hz$, with which the synthetic seismic was calculated through the forward model. Additionally, a low frequency model is calculated by applying a low-pass filter with $4Hz$ cutting frequency. Thus, the inverted acoustic impedance cube is calculated and the pair of truth and inverted images compose the training data set. As expected, the inverted acoustic impedance band-width is restricted to the wavelet band-width with addition of the frequencies existing in the low frequency model. Due to the 1D convolution adopted in this work, the available data set contains 30000 trace samples with 200 cell along the depth.

B. Proposed Architecture

We propose a four-layer multichannel CNN architecture for deblurring post-inversion acoustic impedance images and recovering high frequency of thin layers. The model takes in each input channel the trace of the blurred acoustic impedance and the respective seismic data. By doing so, the network is able to learn with the acoustic impedance data associated with the local high frequency seismic. The model consists of one convolutional layer and one locally connected layer, each one of them followed by max pooling. The output of the locally connected is flatted and two fully connected layers are added in the end (Fig.).

[2] See [20] for more details about methodologies and model parameters.

Fig. 3. Examples.

The first convolutional layer deblurs the lower features in the input traces. Following, higher features are deblurred and individualized through a locally-connected layer [], which performs a one-dimensional convolution with unshared weights. Thus, instead of performing standard convolution, the weights of the learned kernel matrices are not shared across the input. The number of filters in the convolutional and locally connected layers is 50 and 100, respectively. As long as the number of filters increases from the first to the second layer, the size of each filter decreases from 20 to 10. This way, we note that the network learns thinner geological bodies in the second layer.

We used rectified linear unit (ReLU) function that is one of the most popular and efficient activation functions for CNNs. There are advantages of using ReLU such as efficient computation, and gradient propagation. The network uses Adam to optimize the loss function. This algorithm combines the AdaGrad and RMSProp methods and converges more efficiently in comparison to gradient descent, stochastic gradient descent, AdaGrad and RMSProp [18]. The Mean Absolute Error (MAE) is the loss function minimized in the training process. Additionally, we use a batch size of 10 traces.

IV. Experiment and Discussion

Here, we validate the proposed post-inversion deblurring method. The parameters settings for the model training are presented. Next, the experimental results are given for the proposed method, as well as the comparison methods.

A. Model Training

In order to train the CNN model, 80% of the acoustic impedance images is used to infer the blur filters and 20% of the images is used as validation samples. Due to the predefined hyperbolic tangent sigmoid (*tansig*) transfer function in the last layer, we normalized the acoustic impedance to values between 0 and 1, and the results are presented in terms of this normalization.

B. Deblurring Post-Inversion Acoustic Impedance

The results show a frequency spectrum very similar to the raw data. The deblurred images show a good recovery of high frequency events (thin layers), which are better noticed in the intersections between two channels (Fig. 3). It should be pointed out that the horizontal resolution seem to be better enhanced when compared to the vertical resolution, which can be an effect of the wavelet signature and/or the deconvolution process. The increase in the horizontal resolution is particularly important, since that's the situation where the layers get thinner and the porosity decreases, thus decreases the impedance contrast and, therefore, its seismic response. The vertical resolution improvement is essential to evaluate the vertical connectivity in the reservoir (thin layers of shale may act as barriers for the water injection and affect the production and pressurization of the reservoir). Besides significant improvements in the resolution, the model managed to correct some geometric deformations created during the inversion process (Fig. 4), which usually occurs in smaller depositional features (smaller channels).

Fig. 4. Examples.

TABLE I
Table of metric values for wedges with acoustic impedance normalized to 0 and 1.

Image Section	***Wiener Filter (dB)***	***Our (dB)***
Inline Section	0.1	0.1
Crossline Section	0.1	0.1

V. Conclusion

In summary, we showed that the CNN has Moreover, we introduced a simple architecture that combines convolutional, regression and locally connected layers. We demonstrated that the CNN achieved reasonable results regarding the high frequency recovering in seismic inversion data. The methodology is promising for deblurring post-inversion acoustic impedance due to its capability to learn one-dimensional blur kernels and recovering two-dimensional geometric features (such as deposition borders and thin layers). One suggestion for the workflow input data is using the shallower portion of the seismic, since most geological features tend to repeat themselves (fractal) where the frequency spectrum is broader in the high frequencies (the frequency amplitude decreases exponentially with depth, due to attenuation and dispersion effects during propagation). This way we could get a more realistic and comprehensive training data.

Acknowledgment

The authors would like to thank Conselho Nacional de Pesquisa e Desenvolvimento, Fundao de Amparo Pesquisa e Inovao do Estado de Santa Catarina and Petrobras for their support and availability during the work.

References

[1] S. S. Sancevero, A. Z. Remacre, R. S. Portugal, "O papel da inverso para a impednicia no processo de caracterizao ssmica de reservatrios." in Revista Brasileira de Geofsica, p. 495-512, v. 24, 2006.

[2] X. Xiaoyu, L. Yun, S. Desheng, G. Xiangyu, and W. Huifeng, "Studying the effect of expanding low or high frequency on post-stack seismic inversion," in SEG Technical Program Expanded Abstracts 2012, pp. 1-5, September 2012.

[3] R. Zhang and M. K. Sen and S. Phan and S. Srinivasan, "Stochastic and deterministic seismic inversion methods for thin-bed resolution", Journal of Geophysics and Engineering, V. 9, N. 5, 2012.

[4] S. S. Sancevero and A. Z. Remacre and R. de S. Portugal and E. C. Mundim, "Comparing deterministic and stochastic seismic inversion for thin-bed reservoir characterization in a turbidite synthetic reference model of Campos Basin, Brazil", The Leading Edge, v. 24, num. 11, pp. 1168-1172, 2005.

[5] D. Cooke and J. Cant and A. Santos and P. Wa, Australia, "Model-based Seismic Inversion: Comparing deterministic and Probabilistic approaches". CSEG Recorder, 2010.

[6] S. Yuan and S. Wang and C. Luo and Y. He, "Simultaneous multitrace impedance inversion with transform-domain sparsity promotion", Geophysics, pp. 71-80, v. 80, n. 2, 2015.
[7] S. Chen and Y. Wang, "Seismic Resolution Enhancement by Frequency-Dependent Wavelet Scaling," in IEEE Geoscience and Remote Sensing Letters, vol. PP, no. 99, pp. 1-5.
[8] H. Zhang, D. Wipf and Y. Zhang, "Multi-image Blind Deblurring Using a Coupled Adaptive Sparse Prior," 2013 IEEE Conference on Computer Vision and Pattern Recognition, Portland, OR, 2013, pp. 1051-1058.
[9] S. D. Babacan, R. Molina, M. N. Do, and A. K. Katsaggelos, "Bayesian blind deconvolution with general sparse image priors." in Proceedings of European Conference on Computer Vision (ECCV), pp. 341355, 2012.
[10] C. Wang, L. Sun, Z. Chen, S. Yang and J. Zhang, "High-quality non-blind motion deblurring," 2009 16th IEEE International Conference on Image Processing (ICIP), Cairo, 2009, pp. 153-156.
[11] A. Levin, Y. Weiss, F. Durand, and W. T. Freeman. "Understanding and evaluating blind deconvolution algorithms." In IEEE Proceedings of International Conference on Computer Vision and Pattern Recognition (CVPR), pp. 19641971.
[12] Y. Hacohen, E. Shechtman, and D. Lischinski, "Deblurring by example using dense correspondence." In IEEE Proceedings of International Conference on Computer Vision (ICCV), pp. 23842391, 2013.
[13] J. Pan, Z. Hu, Z. Su, and M. H. Yang, "Deblurring face images with exemplars." In Proceedings of European Conference on Computer Vision (ECCV), pp. 4762. Springer, 2014.
[14] W.S. Lai, J. B. Huang, Z. Hu, N. Ahuja, and M. H. Yang, "A comparative study for single image blind deblurring." In IEEE Proceedings of International Conference on Computer Vision and Pattern Recognition (CVPR). IEEE, 2016.
[15] A. Chakrabarti, "A neural approach to blind motion deblurring." In Proceedings of European Conference on Computer Vision (ECCV), pp. 221235. Springer, 2016.
[16] J. Sun, W. Cao, Z. Xu, and J. Ponce, "Learning a convolutional neural network for non-uniform motion blur removal." In IEEE Proceedings of International Conference on Computer Vision and Pattern Recognition (CVPR), pp. 769777, 2015.
[17] M. Hradis, J. Kotera, P. Zemck, and F. Sroubek, "Convolutional neural networks for direct text deblurring." In Proceedings of British Machine Vision Conference (BMVC), 2015.
[18] D. P. Kingma and J. Ba. Adam: A method for stochastic optimization. Unpublished paper, 2014. [Online]. Available: https://arxiv.org/abs/1412.6980
[19] Lee, J. and Mukerji, T., 2012, "The Stanford VI-E reservoir: A synthetic data set for joint seismic-EM time-lapse monitoring algorithms": 25th Annual Report, Stanford Center for Reservoir Forecasting, Stanford University, Stanford, CA.
[20] Castro, S., Caers, J., and Mukerji, T., 2005, The Stanford VI reservoir: 18th Annual Report, Stanford Center for Reservoir Forecasting, Stanford University, Stanford, CA.
[21] A. Buland, and H. Omre, "Bayesian linearized avo inversion," In Geophysics, 2003, pp. 185–198.
[22] L. P. Figueiredo, M. Santos, M. Roisenberg, G. Neto, and W. Figueiredo, "Bayesian framework to wavelet estimation and linearized acoustic inversion," in Geoscience and Remote Sensing Letters, pp. 1–5, 2012.