Bare Demo of IEEEtran.cls for IEEE Journals

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***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. However, the high frequencies...

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 paramethers 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 blocky 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.

We approach the post-inversion acoustic impedance deblurring through a Convolutional Neural Network (CNN) model. CNN is a framework of deep learning which has been used in a wide sort of machine learning tasks, with notorious success in image and video classification [8], [9], action and speech recognition [10], [11]. In reservoir characterization, CNN has been applied to lithofacies recognition [12] and calculation [13]. However, there is a lack of researches on improving the resolution of images resulting from inversion processes.

In this paper, we propose a new multilayer convolutional network model to perform deblurring in post-inversion acoustic impedance. Each network layer maps higher level features originating in the previews layers through unidimensional 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 band-width 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. In our approach, the domain-specific knowledge used in deblurring acoustic impedance impedance images is commonly obtained through training images containing geological knowladge. Generally, the images are obtained from a specialist's (geologist or geophysicist) knowledge about relevant characteristics of the reservoir for which one wishes enhancing the impedance images. 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 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 IV II reports the experiments and results, and Section II

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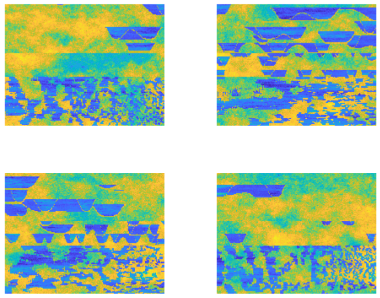

Fig. 1. Examples.

concludes our work.

II. Theoretical Foundations and Related Works

III. Proposed Method

IV. Experiment and Discussion

Here, we validate the proposed post-inversion deblurring method. First, a large-scale acoustic impedance model is introduced. Then, the inversion process that generates blurry images is described. Next, the parameters settings for the model training are presented. Finally, the experimental results are given for the proposed method, as well as the comparison methods.

A. Data Set

To evaluate the proposed frequency recovering 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 [14], 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

To build the training data set we perform the *Maximum-a-Posteriori* (MAP) [] inversion using the high resolution acoustic impedance. Initially, we created a Ricker wavelet with frequency band-width from $0Hz$ to $60Hz$. With the estimated wavelet (), the forward model is applied to obtain the synthetic seismic (). Additionally, the low frequency model () is calculated by applying a low-pass filter with $4Hz$ cutting frequency. Thus, applying the through the Eq. 2 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.

Text

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

[2] See [15] for more details about methodologies and model parameters.

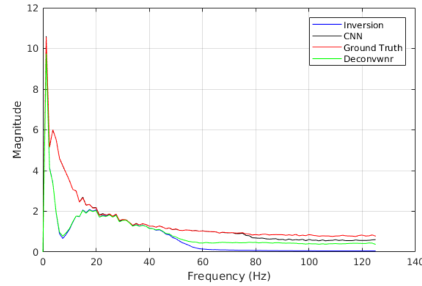

Fig. 2. .

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

B. Model Training

In order to train the CNN model, 80% of the acoustic impedance images is used to infer the blur filters. 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.

C. Acoustic Impedance Deblurring

V. Conclusion

The conclusion goes here.

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