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Abstract—The abstract goes here.

Index Terms—IEEE, IEEE
tran, 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 subseismic features to be more precisaly 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 convetional 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 inssue mainly adressed 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 charcteristics are lost [5]. Another approache to deal with the high frequency impedance information outside the frequency band of seismic signal is assuming a blocky model for the earth's

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J. Doe and J. Doe are with Anonymous University. Manuscript received April 19, 2005; revised August 26, 2015. impedance [5]. This assumtion 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 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 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, resulting in sharp images with increased high-frequency bandwidth and lower noise. In order to train the model, we blur a set of the synthetic acoustic impedance images to create a dictionary of images of high and low resolution. 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 postinversion 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 DBN, a popularly used deep-learning technique. Section III describes the proposed feature-selection method. Section IV II reports the experiments and results, and Section II concludes our work.

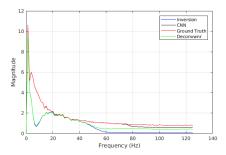


Fig. 1. .

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

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II. THEORETICAL FOUNDATIONS AND RELATED WORKS

III. PROPOSED METHOD

IV. EXPERIMENT AND DISCUSSION

A. Data Set

The high frequencies observed

V. CONCLUSION

The conclusion goes here.

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