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***Abstract*—In this paper we will present a new convolution neural network model to deblurr post-insversion acoustic impedance images.**

1. Introduction

Deblurring is the task of estimating a sharp latent image, given a blurry image as input. Recovering the original image is possible if the details of the blurring method are known, but in most cases, blurry images lack of enough information to recover a unique image. It is not observable in the literature an algorithm for deblurring all objects. Thus, methods that exploit domains-specific knowledge have emerged for deblurring categories of objects, e.g. text, faces and motion images. Similarly, the focus of this work is in post-inversion acoustic impedance deblurring. Obtaining high resolution acoustic impedance images, through seismic inversion methods, is a critical part in oil reservoir characterization. Despite the notorious efficiency of the inversion methods, post-inversion images deblurring has not received much attention.

Reservoir characterization aims to determine a multidimensional structure and properties of an oil field. To achieve this goal, it is essential to combine, through an inversion algorithm, the informations, knowledges and available data about the field, in such a way that it is possible to make the quantitative predictions about the reservoir behavior [8]. The seismic data is widely used in inversion processes because of its facility and precision in interpreting the acoustic impedance property. To succeed in seismic inversion, it is necessary to include strategies to deal with multiple sources of uncertainties. Specifically, the limited band-width of the seismic data leads to a misinterpretation of the resulting acoustic impedance models. According to [2], improving the resolution of seismic inversion is possible by adding high frequency in acquisition and processing seismic data. However, the earth attenuation, high-frequency noise and other sources, causes the lack of high and low frequencies in seismic data. Thus, deblurring the acoustic impedance models, as a post-inversion refinement process, should lead to a more accurate interpretation of the impedance models.

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 infinity solutions for k and I. Several works have developed different deblurring methods for specific purposes. Blind deconvolution methods are widely investigated in image processing [25]. For the last six years, considerable effort has been employed in single image [17], [26], [33], [34] and multi-image [35], [36] blind deconvolutions. 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 [26]. However, [16] show that deblurring methods based on this prior tend to favor blurry images over original latent images.

The Bayesian inference approach [16] outperforms the MAP based methods. It marginalizes the image from the optimization step, while estimating the unknown blur. The authors show that it is possible to define a class of prior image based on natural image statistics, suitable enough for representing sharp images features. This prior formulation makes possible to use Bayesian inference in the estimation of the unknown image and the blur kernel. According to [27], defining a gradient prior, by itself, is not sufficient to reach a sharp image, instead, they search in a dataset for a prior that densely correspond to the blurry image that is similar to a sharp image. This search is an iteratively optimization over the correspondence between the images, the kernel and the sharp image estimation. Although [28] suggest a generalization for the method proposed by [27], it still requires a similar reference image, which is not always available.

The optimization methods previously described use a set of priors based on generic image statistics or domain-specific priors. It has been demonstrated that these methods work properly on synthetic blurs. However, newly studies show that they failure when applied to real world blurry images [29] and take a severe computational cost [30]. In contrast, the learning-based methods have gained attention with the resumption and recent advances in neural networks. The adequate hyper-parameter adjustment allows neural network 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

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

Learning-based methods focus on developing a model to learn the function σ [31] and to perform non-blind deblurring [30]. [32] learn a convolution neural networks (CNN) to recognize motion kernels and performs non-blind deconvolution in dense motion field estimate, in addition, [31] minimize regularized l_2 in order to perform text deblurring. We approach the acoustic impedance deblurring through a CNN model. CNN is a framework of deep learning which has been used in a wide sort of machine learning tasks. The availability of benchmarks [11] and the advances in Graphical Processing Unit (GPU) [3] allowed CNN to outperform state-of-the-art techniques in detection [12], [13], model-free tracking [14], classification [15]. With excellence in feature learning, CNN achieved notorious success in image and video classification [18], [20], action and speech recognition [19], [21]. Under the perspective of the reservoir characterization, CNN has been applied to lithofacies recognition [4] and calculation [5]. 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 convolution network model to perform deblurring in post-inversion acoustic impedance. Each network layer maps higher level features originated 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 band 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. The core concept of our architecture is the combination of the convolution 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.

2. Theoretical foundations

Inversion theory is used in several areas to infer parameters values related to physical processes based on experimental data. Inversion modeling refers to using the current measurements of observable physical parameters in order to infer the current model parameters (not observable). The inversion problem is described as (Eq. 3)

$$m = F^{-1}(d) \tag{3}$$

where, F is the investigated physical system, and relates a set of model parameters $m = (m_1, m_2, ..., m_n) \subset R^n$ estimated through the observed data $d \in R^s$. Geophysical methods frequently involve the solution and assessment of inversion problems. Studying these problems allow inferring physical properties distributions in the earth subsurface, using measured data. Among these data, the seismic data is mainly used in seismic inversion, which plays an important role in reservoir characterization. From a practical perspective, solving seismic inversion problems improves the exploration and management in oil industry, once the seismic data is highly correlated to petrophysical properties, e.g., density and porosity in subsurface.

The offshore seismic data is the main observable data used in seismic inversion. To perform seismic acquisition, one sends pulses through a controlled artificial source and captures the vertical component responses in function of time. The seismic data is a composition of the wave pulse used in the acquisition, named wavelet, and the characteristic of the interfaces between rock layers, on which the wavelet reflects. This rock layer characteristic is called reflectivity coefficient and it is calculated as

$$r(t) = \frac{z(t+\delta t) - z(t)}{z(t+\delta t) + z(t)}, \tag{4}$$

where, $z(t)$ is the acoustic impedance, in function of time t, defined as $z(t) = \rho(t)v(t)$, where $\rho(t)$ is the rock density and $v(t)$ the propagation velocity of acoustic wave. Therefore, the seismic data $d(t)$ is modeled as a discrete convolution operation $*$ of the wavelet s with the reflectivity coefficient r as

$$d(t) = s(\tau) * \sum_{j-1}^{N} r(t - t_j)\delta(t - t_j) + e_d(t) \tag{5}$$

where, N is the number of subsurface layers, $e_d(t)$ is a random noise in function of time. One ideal wavelet is a delta pulse with all the frequency band-width, however, in practice wavelets have their band-width generally limited from $6Hz$ to $65Hz$. By consequence, the images resulting from the seismic inversion will keep their frequency spectrum limited.

According to [7], a good acoustic impedance model contains more information than the seismic data, because the inversion process contains additional information originated from well-logs, for exemple, a low-frequency model. The well-logs are real data measured in wells spread along the field. With the local acoustic impedance it is possible to calculate the low-frequency model by interpolation between wells [37], [38]. Despite of the low-frequency model, the final model for acoustic impedance still lacks of high resolution details.

3. Conclusion

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