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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 an important problem in image processing. It seeks to remove distortions from a blurry image in order to recover the original image. Recovering the original image is possible if the the detail of the blurring method are known. In most cases, blurred images lack of enough information to uniquely recover a plausible image, this feature sets deblurring as an ill-posed problem. In this sense, deblurring images characterizes an inversion problem.

Geostatistical iversion techniques, such as Maximum-a-posteriori, produce blurred images. Deblurring is an important task in ps-inversion decision making.

Convolution Neural Network (CNN) is a topic of great interest in different research areas. The success of convolutional networks can be explained by its capacity to learn and generalize spacial patterns present in the training data. The primary studies on CNN are dated of 1980 and its application was mainly in image recognition. With the advances in Graphic Processing Unit (GPU) and the availability of training data, CNNs are successfully applied on image searching, self-driving mobiles and images classification [3].

We propose a new convolution network model to deblurre post-inversion impedance, in such a way that the resolution of the impedance image is enhanced through increasing the high-frequency band with small noise addition.

2. Related Work

Deblurring plays an important role in computer vision. Methods based on...However these methods lack of ...

Improving the resolution of sismic inversion is possible by adding high frequency in acquisition and processing seismic data. The seismic data is generally short of high and low frequencies and this phenomenon is caused by seismic acquisition, earth attenuation, high-frequency noise, etc., what negatively influence on geologic interpretations of seismic data [2]. Thus, we propose enhancing seismic impedance resolution through adding high-frequency post-inversion.

3. Convolution Neural Network

The approach adopted in this paper consists in training a CNN model to proceed deblurring over synthetic acoustic impedance images. The model is able to solve two important problems related to physical properties deblurring: (1) learning the spacial patterns in the low resolution training images and (2) predict each pixel intensity value in the new higher resolution image.

The model proceeds a supervised learning through the pairs of low and high resolution images. The optimization algorithm adjust the network weights in every layer by minimizing the Mean Squared Error (MSE) in each batch of images. Thus, after training phase, the model is capable to deblurr any other image not presented in training dataset. The output image must recover higher frequencies and, in advance, be more similar to the high resolution image than the blurred image.

Three metrics assess the performance of the convolution networks: fourier index (IFFT), frequency IFFT similarity metric, defined in Eq. 1,

$$C = \frac{(\sum_{i=1}^{N} F_{1i}F_{2i} - N\bar{F}_1\bar{F}_2)^2}{(\sum_{i=1}^{N} |F_{1i}|^2 - N\bar{F}_1^2)(\sum_{i=1}^{N} |F_{2i}|^2 - N\bar{F}_2^2)}, \quad (1)$$

where, for each frequency, an intensity value is calculated from the real and complex parts of fourier transform. F_{1i} represents the intensity value of i-th *pixel* in the first image and F_{2i} is the intensity value of i-th *pixel* in the second image. $\bar{F}_1$ e $\bar{F}_2$ are the mean frequencies in each image. The closer IFFT is to 1, the higher the similarity between the images. The frequencies spectrum is indeed useful to present the graphic of frequency magnitudes in the images. This approach makes possible distinguishing the frequency spectrum added by the proposed model. Additionally, the Root Mean Squared Error (RMSE), Eq. 2 is calculated in order to measure the global error in each pair of deblurred and high resolution images.

$$RMSE = \sqrt{\frac{(\sum_{i=1}^{N}(x_i - y_i)^2}{N}}, \tag{2}$$

The model architecture consists on two convolution layers, each one followed by one pooling layer and regularization layer. The second regularization layer is followed by a fully connected layer, which maps the convolution layer's output to 1024 neurons. The output model comprises a regression layer to predict the intensity value of each pixel.

4. Experiments

The proposed model aims to deblurr image representations of acoustic impedance. In this context, the model was first trained with a synthetic dataset. The dataset is composed by images representing two geological structures, in which one of them is in form of a

5. Conclusion

The conclusion goes here.

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