

# Paper Title\*

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**Abstract**—This document is a model and instructions for L<sup>A</sup>T<sub>E</sub>X. This and the IEEEtran.cls file define the components of your paper [title, text, heads, etc.]. \*CRITICAL: Do Not Use Symbols, Special Characters, Footnotes, or Math in Paper Title or Abstract.

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## I. INTRODUCTION

Deblurring is the task of estimating a sharp latent image, given a blurry image as input. It is not observable in the literature an algorithm for deblurring all objects. Thus, methods that exploit domain-specific knowledge have emerged for deblurring categories of objects, e.g., text, faces and motion images [1]. In oil exploration field, the seismic data acquisition and its inversion to acoustic impedance attribute typically generates blurry images of the subsurface, in such a way that it is not clearly observe the interfaces between different rock layers, geological structures such as channels, etc. 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 [2]. 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 [3], 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, cause 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.

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 [4] and the advances in Graphical Processing Unit (GPU) [5] allowed CNN to outperform state-of-the-art techniques in detection [49], [50], model-free tracking [6], classification [7]. With excellence in feature learning, CNN achieved notorious success in image and video classification [8], [9], action and speech recognition [10], [11]. Under the perspective of the 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 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 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. 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.

## II. THEORETICAL FOUNDATIONS AND RELATED WORKS

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 (1)

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

where,  $F$  is the investigated physical system, and relates a set of model parameters  $m = (m_1, m_2, \dots, m_n) \subset R^n$  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 (2)

$$r(t) = \frac{z(t + \delta t) - z(t)}{z(t + \delta t) + z(t)}, \quad (2)$$

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 (3)

$$d(t) = s(\tau) * \sum_{j=1}^N r(t - t_j) \delta(t - t_j) + e_d(t) \quad (3)$$

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 [14], 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 [15], [16]. Despite of the low-frequency model, the final model for acoustic impedance still lacks of high resolution details.

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

$$y = k \otimes I + n \quad (4)$$

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 [17]. For the last six years, considerable effort has been employed in single image [18]–[21] and multi-image [22], [23] 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 [18]. However, [24] show that deblurring methods based on this prior tend to favor blurry images over original latent images.

The Bayesian inference approach [24] 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 to represent 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 [25], 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 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 [26] suggest a generalization for the method proposed by [25], 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 [27] and take a severe computational cost [28]. 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 (5)

$$y = \sigma(I, p) \quad (5)$$

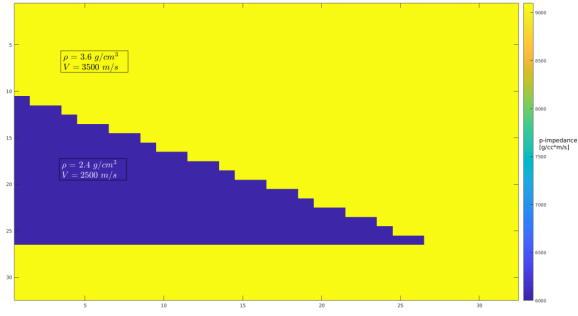


Fig. 1. Acoustic impedance model generation. Wedge with reference values for density and compressional velocity.

Learning-based methods focus on developing a model to learn the function  $\sigma$  [29] and to perform non-blind deblurring [28]. [30] learn a convolution neural networks (CNN) to recognize motion kernels and performs non-blind deconvolution in dense motion field estimate, in addition, [29] minimize regularized  $l_2$  in order to perform text deblurring.

### III. DATA AND METHODS

#### A. Acoustic Impedance Inversion

The experiments described in this paper perform on a set of synthetic acoustic impedance images. Using synthetic models to test and parametrize algorithms is a common practice in reservoir characterization [31]. It allows studying the results of the algorithms without external interferences and performing efficient interpretations and assessments. According to [32], wedge shaped models is a straight way to analysis the seismic model and inversion processes. It reproduces reservoir contexts such as stratigraphic refinements, edges and channel structures in a realistic manner.

The training set generation occurs in two steps. The first step creates a set of wedge shapes represented by images with size 32 x 32. The wedge shapes represent the reservoir and they randomly vary in width and length. The second step fills the lithology with values of petrophysical properties. In order to simplify the assessments and conclusions, we fill the lithology structures with constant reference values of rock densities and compressional velocity observed in the literature [33]. The acoustic impedance is calculated using the density and velocity models and the images in high resolution model are obtained, as illustrated in Fig. 1.

In a real scenario, the blurry acoustic impedance is the result of an acoustic inversion method, such as Maximum *a posteriori* [15], [16], Sparse Spike [34] and Recursive Inversion [35], using seismic data with limited band-width. However, for experimental purpose, the acoustic impedance models were filtered and the high frequencies were removed to obtain the blurry images, as illustrated in Fig. 2. This way, the supervised learning is performed with the high resolution images and blurred images. To increase the number of examples in the training dataset we rotate the impedance models to establish the wedge structure in four different angles ( $0^\circ$ ,  $90^\circ$ ,  $180^\circ$  and

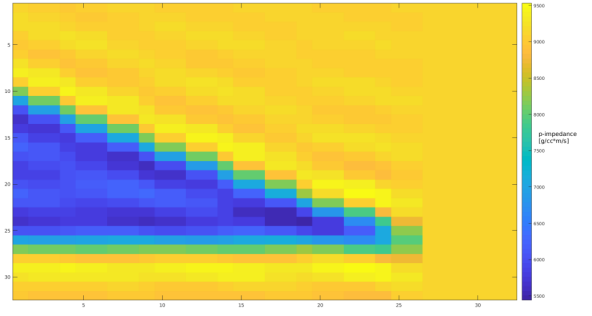


Fig. 2. Acoustic impedance blurred model.

$270^\circ$ ). This approach allows the model learning a wide edge variabilities in wedges images.

#### B. Proposed Architecture

The workflow of the proposed method consists of the following steps:

- Generate the synthetic impedance images;
- Blur the images through a low-pass filter;
- Train the convolutional model with the pair of high and low resolution images;
- Test the model with different blurry images;
- Assess the result for the testing output.

The CNN is a well established method for pattern recognition and image classification. Thus, an important breakthrough when applying CNN to deal with physical property images is developing a model capable to solve regression tasks. The model presented in this paper is able to solve two important problems related to deblurring images of physical properties : (1) learning the spacial patterns in the low resolution training images and (2) predicting each pixel intensity value in the new higher resolution image. To reach these two goals, our model, outlined in Fig. 3, comprises two major components that are combined to perform deblurring and physical property prediction jointly: (1) convolutional component and (2) regression component. The convolutional component is a two layer structure that maps a blurry image to a non-blurred model, while the regression layer is supposed to predict the continuous values of each pixel representing the acoustic impedance value. The state-of-the-art CNN models for image deblurring [1] and super-resolution [36] classify each pixel in the input image. Using these methods to solve the issue of deblurring continuous physical properties implies in discretization of each pixel in order to generate an image file. However, returning to the original data, results in information loss, what represents a serious inconvenient. Thus, combining the convolutional approach with the regression layer to deblur and predict the physics property represents a relevant advance.

#### C. Implementation Details

The model is implemented using the Deep Learning toolbox delivered in MATLAB R2017A. Our model comprises a simple architecture with two convolutional layers. Each one of them is configured with 50 kernels, sized 5 x 5 and stride 1,

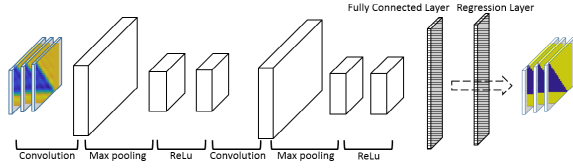


Fig. 3. Proposed model achitecture.

meaning that after each convolution operation the blur kernel is shifted one position in each direction. After each convolutional layer we proceed a maximum pooling operation to obtain the maximum value of small regions in the input image and obtain statistical summaries of these regions. We also apply rectified linear units (ReLU) after each pooling layer in order to speed up the training step and to learn sensible features from the images, following the proposal of [37]. After the second regularization layer, we add a fully connected layer, which maps the convolution layer's output to 1024 neurons. Finally, the output layer comprises a regression unit to predict the intensity of acoustic impedance in each pixel. The output vector is then resized to the original image dimension.

For training the network, we use a mini-batch with size of 32 training examples and we adopt an exponentially decreasing learning rate (initially set to 0.005), decreasing every iteration in a total of 100 iterations. It should be noted that, once the wedge shapes are randomly generated, every image is different and each one is introduced only once to the network, this way avoiding over-fitting. The network weights initialize randomly and the model performs a supervised learning through a dictionary containing pairs of low resolution and high resolution images. The Stochastic Gradient Descendant with Momentum (SGDM) [38] adjusts the network weights in every layer by minimizing the Mean Squared Error (MSE) in each batch of images. Thus, after the training phase, the model is capable to deblur any other wedge shaped acoustic impedance image not presented in the training dataset. The outputted image recovers the high frequencies and shows higher similarity to the high resolution image than to the blurred image, according to a established metric. The model was adjusted to deblur a wide variety of wedge shapes and impedance values. Those wedges which the model was unable to predict were added in the training set.

Three metrics assess the performance of the convolution network: Fast Fourier Transform Index - FFTI (6), Rooted Mean Square Error - RMSE 7. The FFTI is a similarity metric calculated based on the fast fourier transform (FFT) of each image. It is introduced by [39] and calculates as

$$C = \frac{(\sum_{i=1}^N F_{1i} F_{2i} - N \bar{F}_1 \bar{F}_2)^2}{(\sum_{i=1}^N |F_{1i}|^2 - N \bar{F}_1^2)(\sum_{i=1}^N |F_{2i}|^2 - N \bar{F}_2^2)}, \quad (6)$$

where, for each frequency, an intensity value is calculated from the real and complex parts of the 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

FFTI is to 1, the higher the similarity between the images. The frequencies spectrum is additionally useful to present the graphic of frequency magnitudes in the images. The frequency magnitude graphic allows distinguishing what high frequencies were added to the acoustic impedance after the low resolution image is passed through the trained CNN.

$$RMSE = \sqrt{\frac{(\sum_{i=1}^N (x_i - y_i)^2)}{N}}, \quad (7)$$

#### IV. EXPERIMENTS

To build the training dataset we generate 500 images of random wedge. Because the last layer of the network is a regression unit, it is necessary the normalization of the images to values between 0 and 1, and the results are presented in terms of this normalization. The normalized images are then rotated according to the established angles mentioned in Section III, then comprising a total of 2000 images. By doing so, we present to the network the same lithologies in different positions and expect that the network identify general sorts of wedges in angles different from those with which the it was trained. The rotated images are blurred by applying a low-pass filter with cutting frequency  $4Hz$ , then the pairs of blurred and not-blurred images are used to adjust the model weights. It is relevant to mention that the images which are blurred with the same cutting frequency and that remain symmetric after the rotation, what means that rotating the images causes no changes in impedance values. In the following subsections we present the results divided into the cases we consider relevant to test. In the first case, we test the wedges rotated according to the established angles and with acoustic impedance values normalized to 0 and 1. In the second case we invert the impedance values in such a way that the wedges are set with normalized value equal to 1, and 0 out of it. In the third case we test images with impedance values normalized to the interval between 0.3 and 0.7, therefore, out of the range used during the training phase. In the fourth and fifth cases we test present to the model wedges rotated at random angles and with random shapes.

##### A. Integer Angles Rotated Wedges

We firstly test if the network is capable to correctly model the shape of the wedges and to deblur the edges and contours in a simple perspective. Thus, the training images and the test images have the same reference values for density and compressional velocity, they are different only by their shapes. Comparing the blurry image (Fig. 4b) and the CNN output (Fig. 4c) it is noticeable that the CNN output reached a sharp image and accurately predicted the pixel values. The RMSE for the network output in Tab. I is considerably less than the RMSE for the blurry image, while the FFTI slightly increases and indicates more similarity between the network outputs and the latent images, except for the first image, for which the IFFT shows not representative change. The frequency magnitude illustrated in Fig. ?? shows that the model precisely recovered the frequency spectrum of the original image.

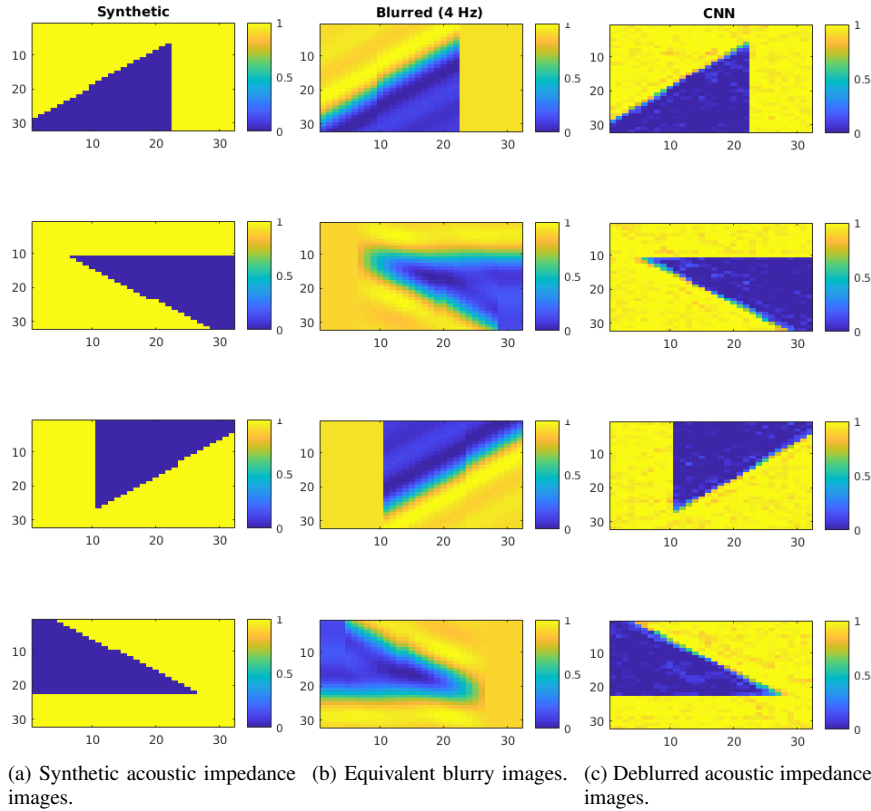


Fig. 4. First test case: the wedges are positioned in  $0^\circ$ ,  $90^\circ$ ,  $180^\circ$  and  $270^\circ$  and the acoustic impedance values are normalized to 0 and 1.

TABLE I  
METRICS VALUES FOR THE FIRST TEST CASE.

| Metrics   | Blurry Image (MSE - FFTI) | CNN (MSE - FFTI) |
|-----------|---------------------------|------------------|
| Example 1 | 0.1337 — 0.9773           | 0.0621 — 0.9724  |
| Example 2 | 0.1972 — 0.9464           | 0.0776 — 0.9747  |
| Example 3 | 0.1337 — 0.9773           | 0.0616 — 0.9861  |
| Example 4 | 0.1976 — 0.9498           | 0.0767 — 0.9771  |

TABLE II  
AN EXAMPLE OF A TABLE

| Metrics   | Blurry Image (MSE - FFTI) | CNN (MSE - FFTI) |
|-----------|---------------------------|------------------|
| Example 1 | 0.1294 — 0.9405           | 0.0675 — 0.9416  |
| Example 2 | 0.2033 — 0.8522           | 0.0765 — 0.9046  |
| Example 3 | 0.1294 — 0.9405           | 0.0701 — 0.9418  |
| Example 4 | 0.20335 — 0.8509          | 0.0763 — 0.9144  |

In the second scenario, we invert the impedance values of the lithology structures, that means, we fill the reservoir lithology with normalized impedance value equal 1 and the lithology around of the reservoir with value equal to 0. Even though the network outputs show lower RMSE and recover all the frequency spectrum (Fig. 5), the similarity between the CNN images is lower than the blurred images. This result is related to the fact that the model reconstruct the lithology structures, however they lack of thin details, what makes them slightly less similar to the latent image. The metrics for this case is in Tab. II

## V. EASE OF USE

### A. Maintaining the Integrity of the Specifications

The IEEEtran class file is used to format your paper and style the text. All margins, column widths, line spaces, and text fonts are prescribed; please do not alter them. You may

note peculiarities. For example, the head margin measures proportionately more than is customary. This measurement and others are deliberate, using specifications that anticipate your paper as one part of the entire proceedings, and not as an independent document. Please do not revise any of the current designations.

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Before you begin to format your paper, first write and save the content as a separate text file. Complete all content and organizational editing before formatting. Please note sections VI-A–VI-E below for more information on proofreading, spelling and grammar.

Keep your text and graphic files separate until after the text has been formatted and styled. Do not number text heads— $\LaTeX$  will do that for you.

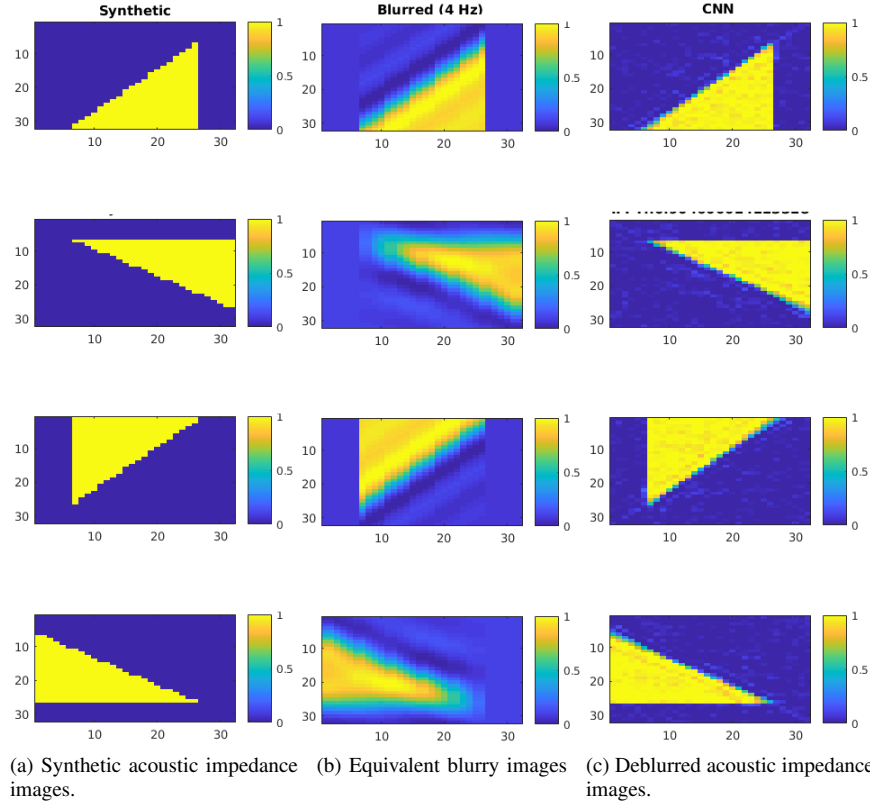


Fig. 5. Acoustic impedance models in which the physical property values are inverted in each lithology. The wedge, that represents the reservoir is filled with normalized impedance value equal to 1, while the lithology around the reservoir is filled with values equal to 0.

### A. Abbreviations and Acronyms

Define abbreviations and acronyms the first time they are used in the text, even after they have been defined in the abstract. Abbreviations such as IEEE, SI, MKS, CGS, ac, dc, and rms do not have to be defined. Do not use abbreviations in the title or heads unless they are unavoidable.

### B. Units

- Use either SI (MKS) or CGS as primary units. (SI units are encouraged.) English units may be used as secondary units (in parentheses). An exception would be the use of English units as identifiers in trade, such as “3.5-inch disk drive”.
- Avoid combining SI and CGS units, such as current in amperes and magnetic field in oersteds. This often leads to confusion because equations do not balance dimensionally. If you must use mixed units, clearly state the units for each quantity that you use in an equation.
- Do not mix complete spellings and abbreviations of units: “Wb/m<sup>2</sup>” or “webers per square meter”, not “webers/m<sup>2</sup>”. Spell out units when they appear in text: “. . . a few henries”, not “. . . a few H”.
- Use a zero before decimal points: “0.25”, not “.25”. Use “cm<sup>3</sup>”, not “cc”).

### C. Equations

Number equations consecutively. To make your equations more compact, you may use the solidus ( / ), the exp function, or appropriate exponents. Italicize Roman symbols for quantities and variables, but not Greek symbols. Use a long dash rather than a hyphen for a minus sign. Punctuate equations with commas or periods when they are part of a sentence, as in:

$$a + b = \gamma \quad (8)$$

Be sure that the symbols in your equation have been defined before or immediately following the equation. Use “(8)”, not “Eq. (8)” or “equation (8)”, except at the beginning of a sentence: “Equation (8) is . . .”

### D. L<sup>A</sup>T<sub>E</sub>X-Specific Advice

Please use “soft” (e.g., `\eqref{Eq}`) cross references instead of “hard” references (e.g., (1)). That will make it possible to combine sections, add equations, or change the order of figures or citations without having to go through the file line by line.

Please don’t use the `{eqnarray}` equation environment. Use `{align}` or `{IEEEeqnarray}` instead. The `{eqnarray}` environment leaves unsightly spaces around relation symbols.

Please note that the `{subequations}` environment in L<sup>A</sup>T<sub>E</sub>X will increment the main equation counter even when

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L<sup>A</sup>T<sub>E</sub>X does not work by magic. It doesn’t get the bibliographic data from thin air but from .bib files. If you use L<sup>A</sup>T<sub>E</sub>X to produce a bibliography you must send the .bib files.

L<sup>A</sup>T<sub>E</sub>X can’t read your mind. If you assign the same label to a subsection and a table, you might find that Table I has been cross referenced as Table IV-B3.

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- The subscript for the permeability of vacuum  $\mu_0$ , and other common scientific constants, is zero with subscript formatting, not a lowercase letter “o”.
- In American English, commas, semicolons, periods, question and exclamation marks are located within quotation marks only when a complete thought or name is cited, such as a title or full quotation. When quotation marks are used, instead of a bold or italic typeface, to highlight a word or phrase, punctuation should appear outside of the quotation marks. A parenthetical phrase or statement at the end of a sentence is punctuated outside of the closing parenthesis (like this). (A parenthetical sentence is punctuated within the parentheses.)
- A graph within a graph is an “inset”, not an “insert”. The word alternatively is preferred to the word “alternately” (unless you really mean something that alternates).
- Do not use the word “essentially” to mean “approximately” or “effectively”.
- In your paper title, if the words “that uses” can accurately replace the word “using”, capitalize the “u”; if not, keep using lower-cased.
- Be aware of the different meanings of the homophones “affect” and “effect”, “complement” and “compliment”, “discreet” and “discrete”, “principal” and “principle”.
- Do not confuse “imply” and “infer”.
- The prefix “non” is not a word; it should be joined to the word it modifies, usually without a hyphen.
- There is no period after the “et” in the Latin abbreviation “et al.”.
- The abbreviation “i.e.” means “that is”, and the abbreviation “e.g.” means “for example”.

An excellent style manual for science writers is [46].

#### F. Authors and Affiliations

**The class file is designed for, but not limited to, six authors.** A minimum of one author is required for all conference articles. Author names should be listed starting from left to right and then moving down to the next line. This is the author sequence that will be used in future citations and by indexing services. Names should not be listed in columns nor group by affiliation. Please keep your affiliations as succinct as possible (for example, do not differentiate among departments of the same organization).

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Text heads organize the topics on a relational, hierarchical basis. For example, the paper title is the primary text head because all subsequent material relates and elaborates on this one topic. If there are two or more sub-topics, the next level head (uppercase Roman numerals) should be used and, conversely, if there are not at least two sub-topics, then no subheads should be introduced.

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a) *Positioning Figures and Tables:* Place figures and tables at the top and bottom of columns. Avoid placing them in the middle of columns. Large figures and tables may span across both columns. Figure captions should be below the figures; table heads should appear above the tables. Insert figures and tables after they are cited in the text. Use the abbreviation “Fig. ??”, even at the beginning of a sentence.

TABLE III  
TABLE TYPE STYLES

| Table Head | Table Column Head            |         |         |
|------------|------------------------------|---------|---------|
|            | Table column subhead         | Subhead | Subhead |
| copy       | More table copy <sup>a</sup> |         |         |

<sup>a</sup>Sample of a Table footnote.

Figure Labels: Use 8 point Times New Roman for Figure labels. Use words rather than symbols or abbreviations when writing Figure axis labels to avoid confusing the reader. As an example, write the quantity “Magnetization”, or “Magnetization, M”, not just “M”. If including units in the label, present them within parentheses. Do not label axes only with units. In the example, write “Magnetization (A/m)” or “Magnetization {A[m(1)]}”, not just “A/m”. Do not label axes with a ratio of



quantities and units. For example, write “Temperature (K)”, not “Temperature/K”.

#### ACKNOWLEDGMENT

The preferred spelling of the word “acknowledgment” in America is without an “e” after the “g”. Avoid the stilted expression “one of us (R. B. G.) thanks ...”. Instead, try “R. B. G. thanks...”. Put sponsor acknowledgments in the unnumbered footnote on the first page.

#### REFERENCES

Please number citations consecutively within brackets [40]. The sentence punctuation follows the bracket [41]. Refer simply to the reference number, as in [42]—do not use “Ref. [42]” or “reference [42]” except at the beginning of a sentence: “Reference [42] was the first ...”

Number footnotes separately in superscripts. Place the actual footnote at the bottom of the column in which it was cited. Do not put footnotes in the abstract or reference list. Use letters for table footnotes.

Unless there are six authors or more give all authors’ names; do not use “et al.”. Papers that have not been published, even if they have been submitted for publication, should be cited as “unpublished” [43]. Papers that have been accepted for publication should be cited as “in press” [44]. Capitalize only the first word in a paper title, except for proper nouns and element symbols.

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