Deep-tomography guided by well-log velocity information

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Abstract

Deep-learning (DL) techniques are a new frontier for velocity model building since they can help alleviate the dependency on human curation, computational time, and inversion issues. The use of a neural network opens the possibility of combining data from different sources which represent different physical quantities in the same flow. In this work, we analyzed the effect of including well-log velocity information on a supervised deep-learning velocity model-building method. The method chosen was Deep-tomography (DT), which in its original implementation uses as input for a U-Net the subsurface offset panels migrated with an input model. The U-Net is trained in a supervised way to generate velocity updates which improve the initial model used to migrate the subsurface offsets panels. The use of input data in the image domain easily enables us to combine well information as a sparse image, with non-zero information just in the well positions. This image is then used as an extra channel in the input image for the U-Net. The preliminary results, for the last iteration of DT, shows that the inclusion of the well-log information improves the data fit and increases the structural similarity, enhancing the layer's contrasts.

Introduction

Velocity model-building flows based on DL techniques have been present in many recent studies [1]. In supervised learning tasks, some approaches investigated the ability of the DL flow to completely recover the velocity model from the seismic shots [2]. In this case, the shots are the input for the neural network, and the velocity model which generated the shots is the desired output, used during the training phase. Such approaches eliminate the iterative nature of conventional inversion tools (e.g. Tomography and Full-Waveform Inversion), however since they are a complex data transformation, from shots to model, they present some generalization issues, requiring a high similarity between the training data, and the data over which the method will be applied. Besides, the use of raw shot data imposes some additional questions, particularly when considering the data size of the 3D acquisition, that are much large than the modern GPU memories can handle.

Some recent works propose migrating the seismic shots using a constant velocity model to predict the complete velocity model [3]. Another similar approach is to update iteratively an initial model using DL tools [4]. Due to the iterative nature of model prediction, the process was called Deep-Tomography (DT) and is able to predict structurally complex models.

Of important aspect of DL is its ability to combine information from different sources, conciliating different amplitudes ranges and densities of representation. One important source of information about seismic velocity comes from the sonic well-log. In practical terms, after some processing, it is possible to obtain a localized high-resolution velocity model from the sonic well-log. Log information is sparse and hard to use in conventional inversion, one possibility is to use it indirectly as a regularizer [5]. However, for deep-learning, sparsity is not an issue, and the well-log information can be used as an extra channel for training, consisting of a panel entirely equal to zero unless the positions where there the sonic log info is available. The use of well logs as an extra channel of a neural network was previously investigated to enhance the resolution of velocity models generated using a low-frequency FWI [6].

In this work, we combined the idea of using the sonic log velocity information with the DT flow. The method was evaluated for the last iteration, which defines the velocity update to the true model and is more sensitive to prediction errors. We tested the proposed method for 2D synthetic data, comparing the predictions with and without the use of the well info, the test set and also for the Marmousi model [7].

Method

The migrated images used as input for DT are obtained with RTM (Reverse Time Migration) and a cross-correlation extended imaging condition [8]. For a 2D approach, this imaging condition can be written as

$$I(x, z, \lambda) = \sum_{shots} \sum_{t} W_s(x - \lambda, z, t)\, W_r(x + \lambda, z, t) \quad (1)$$

In equation (1), the parameter λ represents the subsurface offset. For each value of λ used, a different image is composed, with the property that the events migrated with the accurate velocity focalize to zero subsurface offset value, otherwise, the events will spread to the high values subsurface offsets. It was previously shown that focalization can be used as a measure to correctly update the velocity model [9]. For our application, we used fourteen subsurface offset values, with values in a range between zero and 280 meters. Maximum subsurface offsets were empirically chosen in order to capture the maximum offset where it was possible to observe coherent events.

Since it is a proof of concept work, we created a synthetic 2D data set, with 1000 velocity models with 3.5 km of depth and 9 km of lateral extension. The spatial sampling used was equal to 10m in both directions. The velocity models were created to represent a high structural complexity, simulating a system of deposition, folding, faulting, and erosion, which aims to be a simplified version of the actual geological process. For each velocity model, we defined up to four drilled positions to be used as an extra channel in the input image. For each model, we simulated a synthetic seismic acquisition by implementing the acoustic, isotropic wave equation. We used a Ricker wavelet with a peak frequency of 20 Hz to simulate the source. The acquisition was designed as a split spread acquisition, with a maximum offset equal to 3,5km and in order to have full coverage inside the model, which was laterally extrapolated to allow the full shot over the region of interest.

The chosen architecture was a U-Net [10]. The U-Net is an encoder-decoder fully convolutional model typically used in computer vision-related tasks. Encoder-decoder models are often employed in these tasks because they often work with inputs and outputs of the same size, which is the for DT. Although encoder-decoder models are commonly used in classification or segmentation tasks, they can be repurposed with an adequate choice of the loss function and normalization of the input and output data. Since our task of generating velocity updates using the U-Net is closer to a nonlinear regression problem, we used the mean squared error between predicted and real velocity updates as a minimization objective for the training process of our network models.

Figure 1 represents the flow for the last iteration of DT. The subsurface offset gathers are treated as channels of the input image for the U-Net. The outputs used for training are calculated as the difference between the true velocity model and the velocity model used in migration. To define the iterative nature of the process, at each iteration, the model used for migration is the slowness smoothed using a Gaussian filter, which for the last iteration has σ =20. After the prediction, the result is summed over the model used in migration, to define the result. For the case where the well-info is used, there is an extra input channel, which is not equal to zero just in the well locations, where it assumes the values of the desirable velocity update in that position. The velocities used during the flow and its updates are scaled to km/s.

Results

The performance of each approach was evaluated over 100 velocity models, initially separated from the original set, and over the Marmousi model. We compared the results of training/predicting using the extra well-log data and not using this information. We evaluated Structural Similarity Index Method (SSIM) and the Relative Model Error (RME) over the 100 test models with and without the well-information. The observed mean SSIM without well-info was equal to 0.731, and with well-info was equal to 0.745, while the mean RME without well-info was equal to 2.890, and with well-info equal to 2.728. Despite being a small score difference, they made

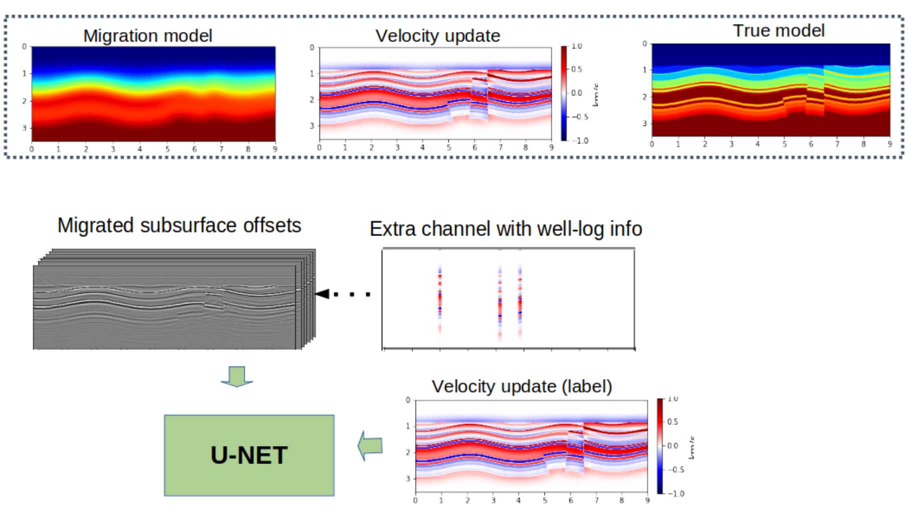

Figure 1: Representation of Deep-Tomography flow when using the information from the wells. In the top of the image we plotted the model used to migrated the seismic shots, which is a smoothed version of the true model. The extra channel inputs the desirable update for this initial model, as an extra channel with the migrated subsurface offset gathers.

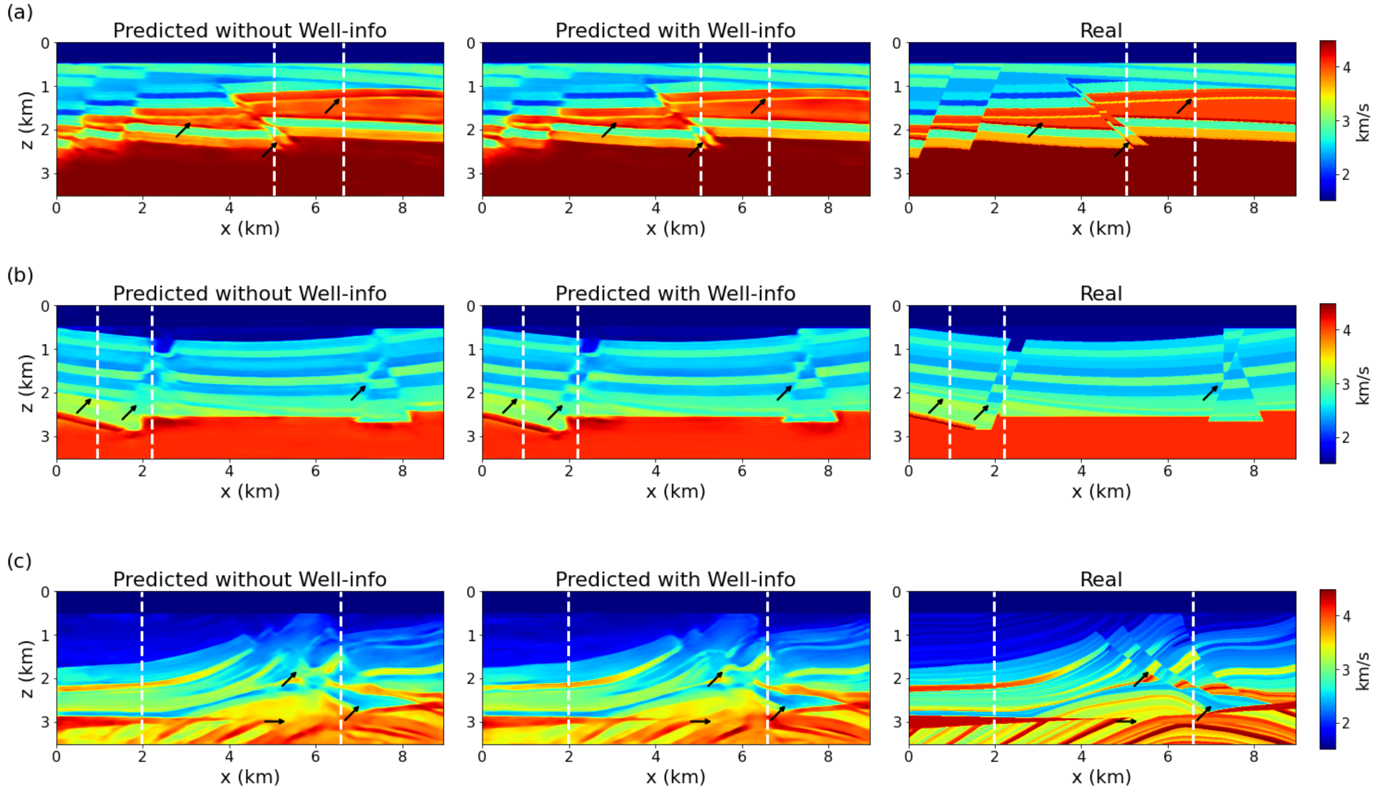

Figure 2: Plot of one test velocity model obtained without and with well-information, and the real expected model. Figure (a) and (b) accounts for two models from the test set, and Figure (c) for the Marmousi model.

significant differences in the structures of the final model.

Since generalization is an important question for deep-learning applications, we also evaluated the performances of DT for the Marmousi model. Figure 2 shows the predicted results for two models from the test set ((a) and (b)), and also for the Marmousi mode (c). The dashed white lines indicate the well's position, and we compared the prediction without and with well-info and the real expected model. It is important to mention here, that we have chosen models with two wells, however, the models used for training present the number of wells varying from one to four.

It is possible to observe in Figure 2 that the well-info predicted models with more continuous layers and details in general and better-represented faults closer to the well. One important aspect is that the well-information improves the result, and the resolution of the velocity layers, even far from the well-position.

We also analysed the SSMI of the predicted models when compared with the true ones. The SSMI for the model in Figure 2 (a) is equal to 0.766 for the case without well-info, and is equal to 0.797 for the case with well-info. For the model in Figure 2 (b) the SSMI is equal to 0.778 for the case without well-info and is equal to 0.808 for the case with well-info. And for the Marmousi model the SSMI with the real model is equal to 0.467 for the case without well-info, and is equal to 0.481 for the case with well-info. Despite the final error for the Marmousi being larger than the one observed for the test set, the predictions obtained would be a good initial model for FWI. In this case, it is also possible to observe the benefits of using well-log velocity information.

Figure 3 shows the velocity profiles for the models in Figure 2 extracted exactly at the well's positions. As it is observed when analysing the models, the well-information is able to improve the predictions, defining with better resolution the velocity contrasts.

Conclusions

The use of deep learning algorithms for velocity model building has attracted great research interest. The use of input in the same domain as the output of the neural network opens a series of possible data uses. This works shows that combining migration images with localized, sparse, and accurate velocity information improves the overall deep-tomography resolution and structural features around the wells. This work shows that deep-learning inversion can benefit from sparse information from the direct use of sonic well-log

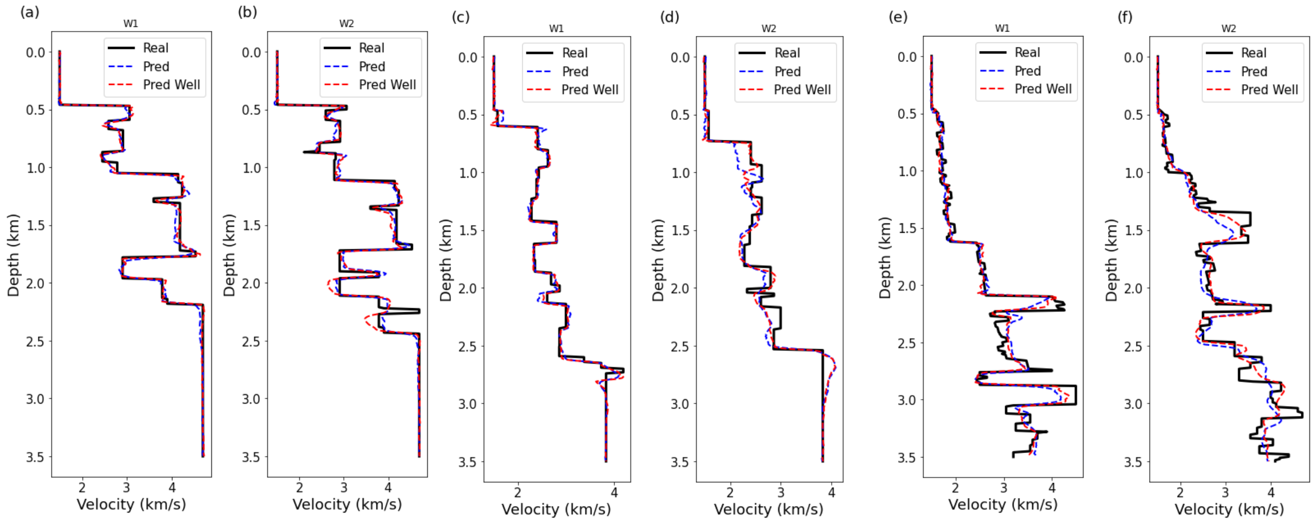

Figure 3: Velocity profiles extracted over the positions of the wells in the models in Figure 2. W1 accounts for the position in the left and W2 for the position in the right of the model. (a) and (b) show the profiles for models in Figure 2(a), (c) and (d) for models in Figure 2(b), and finally (e) and (f) for the Mamoursi model which is in Figure 2(c).

information and is able to improve predictions, even outside the well-log positions.

The use of the extra channel must be investigated for the complete flow of deep-tomography, in order to measure the effect over the final model when the starting model is a simplified horizontal gradient of the true model.

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