Seismic resolution enhancement using a conditional diffusion model

Haoran Zhang, Yang Liu, Gui Chen, China University of Petroleum-Beijing & National Key Laboratory of Petroleum Resources and Engineering, and Yuhang Sun, China University of Petroleum-Beijing at Karamay & Northeast Petroleum University*

SUMMARY

Seismic resolution enhancement of post-stack data is helpful for delineating subsurface structures as well as improving inversion accuracy. Deep-learning-based methods for resolution enhancement (e.g., Li et al., 2022; Chen et al., 2023; Gao et al., 2023) have shown promising performance in terms of the effectiveness and simplicity of applications compared to some conventional methods that rely on specific assumptions and elaborate algorithm designs. Diffusion models (DM), as a type of generative models, show superior capabilities to generative adversarial networks (GANs) on generating data that adhere to a learned distribution in many tasks. However, there is little reference about DM-based seismic resolution enhancement. Drawing inspiration from an application in seismic denoising (Durall et al., 2023), we develop a scheme based on a conditional denoising diffusion probabilistic model (DDPM) (Ho et al., 2020), which is conditioned on the seismic data in low resolution (LR), to reconstruct corresponding high-resolution images. The optimization objective in our approach differs from previous deep learning-based implementations. For network training, we propose practical procedures to acquire massive training data based on the generated pseudo-wells. Subsequently, we apply the diffusion model on both synthetic and field datasets. The experimental results demonstrate not only effective seismic resolution enhancement, but also additional denoising achieved by the conditional diffusion model.

METHODOLOGY

A diffusion model includes diffusion and denoising processes. The model training contains both of the processes, while only the denoising process is conducted in the inference stage. As depicted in Figure 1 with red arrows, the diffusion process reflects the probability distribution of the data $\mathbf{x}_t$ at any step t given the original high-resolution (HR) data $\mathbf{x}_0$, i.e. $q(\mathbf{x}_t|\mathbf{x}_0)$:

$$\mathbf{x}_t = \sqrt{\bar{\alpha}_t}\mathbf{x}_0 + \sqrt{1-\bar{\alpha}_t}\varepsilon, \quad \varepsilon \sim \mathcal{N}(\mathbf{0},\mathbf{I}), \tag{1}$$

where α_t is the hyper-parameter at step t and $\bar{\alpha}_t := \prod_{i=1}^{t} \alpha_i$.

As for denoising process $p_\theta(\mathbf{x}_{t-1}|\mathbf{x}_t,\mathbf{y})$ (the path with blue arrows in Figure 1), the network is forced to possess the ability of predicting Gaussian noise with the input noisy $\mathbf{x}_t$ conditioned on the LR seismic data ($\mathbf{y}$), according to the optimization objective:

$$\|\hat{\varepsilon}_\theta(\mathbf{x}_t,\mathbf{y},t) - \varepsilon\|_2^2, \quad \varepsilon \sim \mathcal{N}(\mathbf{0},\mathbf{I}), \tag{2}$$

where $\hat{\varepsilon}_\theta$ is the network output. Finally, we derive $\mathbf{x}_{t-1}$ through

$$\mathbf{x}_{t-1} = \frac{1}{\sqrt{\alpha_t}}\left(\mathbf{x}_t - \frac{1-\alpha_t}{\sqrt{1-\bar{\alpha}_t}}\hat{\varepsilon}_\theta(\mathbf{x}_t,\mathbf{y},t)\right) + \frac{(1-\alpha_t)(1-\bar{\alpha}_{t-1})}{1-\bar{\alpha}_t}\mathbf{z}, \tag{3}$$

where $\mathbf{z} \sim \mathcal{N}(\mathbf{0},\mathbf{I})$, from $\mathbf{x}_{t=T}$, till the ultimate HR result $\mathbf{x}_0$.

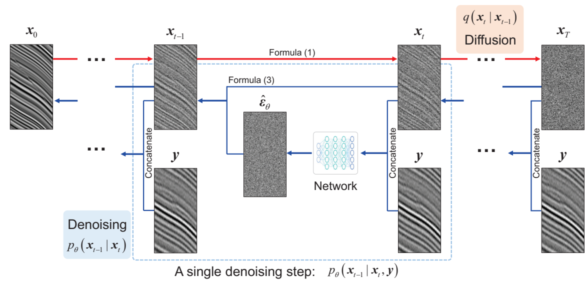

Figure 1: The proposed conditional diffusion model.

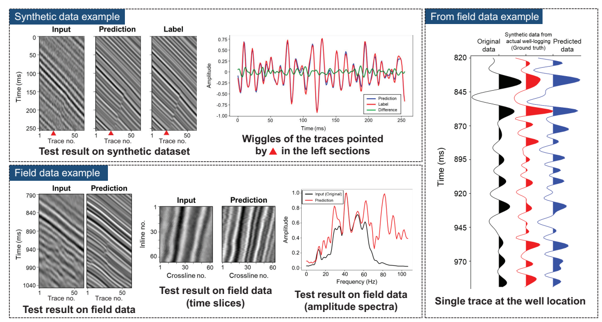

Figure 2: Test results from synthetic and field data examples. The introduction for each graph is given inside the figure.

EXAMPLES

Regarding data preparation, we first establish the relationship between P-wave velocity v_P and rock density ρ based on well-logging data from the target seismic survey. Subsequently, we randomly sample v_P and determine corresponding ρ using this established relationship to generate numerous pseudo-wells. By employing a geological modeling workflow (Wu et al., 2019) with the pseudo-wells, we obtain a wealth of synthetic data that closely resemble the features found in the field data. The synthetic LR data, along with their corresponding HR data, are used as the conditional inputs and the labels, respectively. We then train the diffusion model for 20000 iterations with 2000 diffusion steps. As illustrated in Figure 2, the results demonstrate significant resolution enhancement when comparing the sections, time slices, and spectrum of the predicted data to the original LR data. The single trace comparison at well location further validates the scheme effectiveness.

ACKNOWLEDGMENT

We thank Ricard Durall from Fraunhofer ITWM in Germany for helpful discussion and public codes. We also thank BGP Research & Development Center for supplying the field data.