Real-time Seismic Attributes Computation With Conditional GANs

https://youtu.be/-OdvDIZYVTE

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Motivation/Summary

- Seismic data analysis is a crucial step for the Oil and Gas industry.
- It helps to define the most accurate place to drill production wells, with enormous commercial value.
- Seismic attributes are measurements over 3D volumes, that represents imaging snapshot of sub-surfaces [1].
- Seismic surveys can reach terabytes. Processing are expensive.
- We are proposing to train conditional GANs to learn how to compute seismic attributes.
- Using our approach, we're able to compute attributes over seismic blocks in real-time, with a **speedup of 80x**, in comparison with the classical formulation.

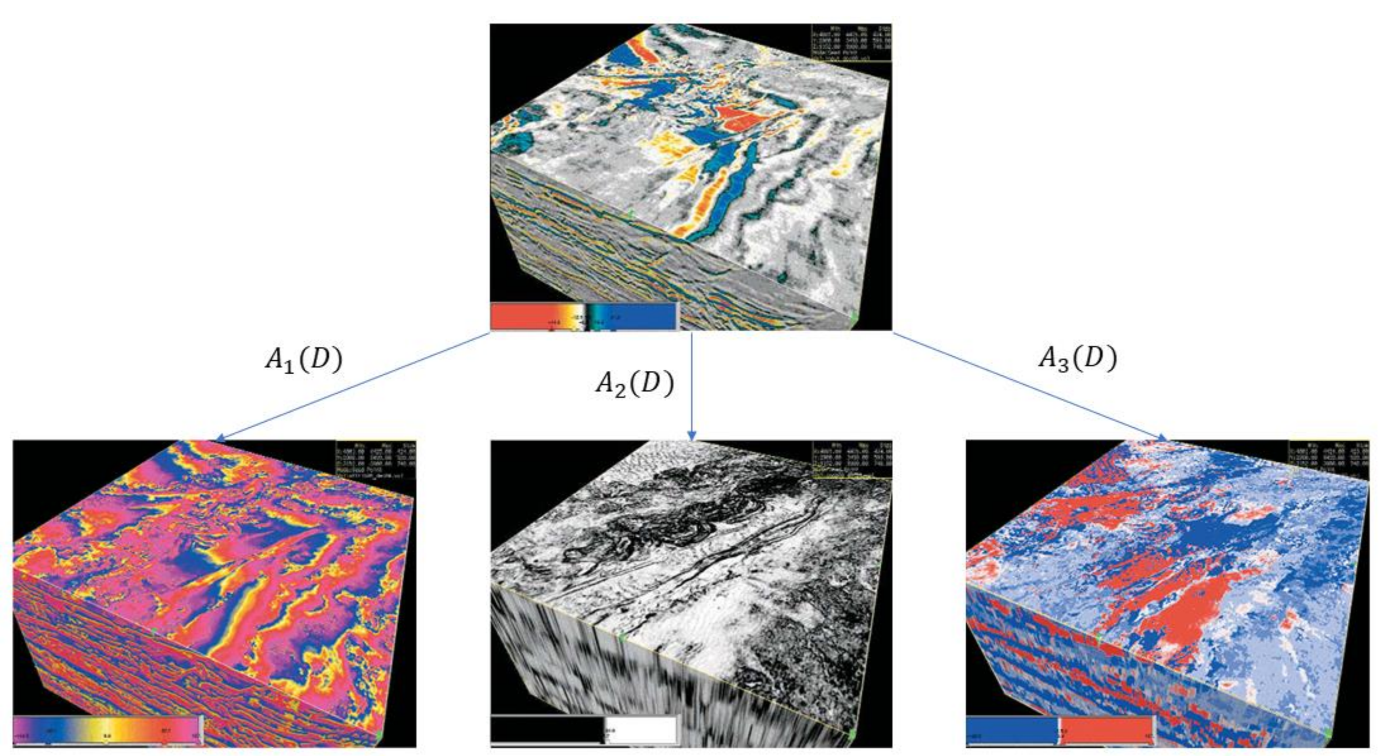


Figure 1 – A seismic attribute is a mapping between original volume D, and a mathematical transformation An

Dataset

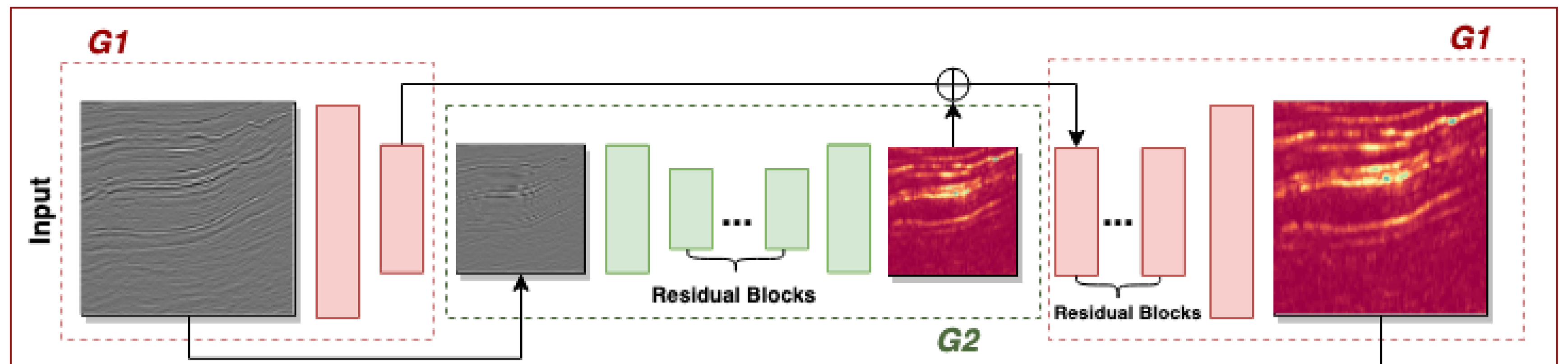
- Seismic data are represented as 3D volumes.
- Each voxel is an amplitude response (32-bits floating-point).
- We collected data at SEG [2] and USGS [3] repositories, from different parts of the world (Table 1).

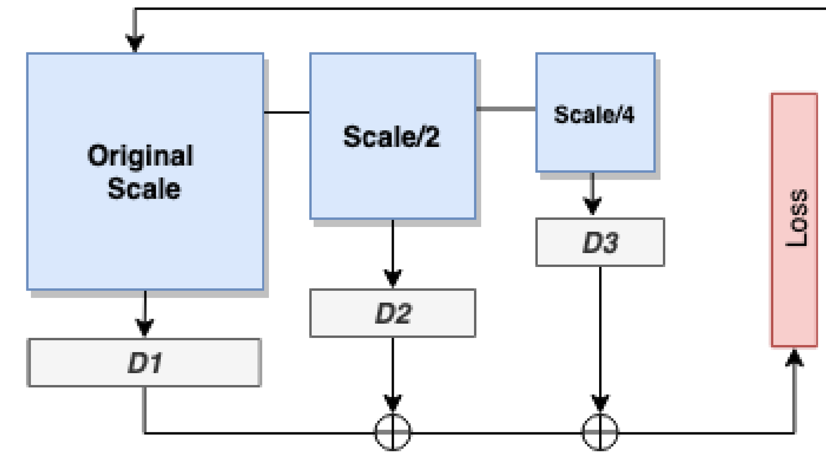
Dataset Name	Geography	Size (GB)	Grid Dimension
Poseidon3D	Australia	5.2	$(583 \times 2351 \times 945)$
Parihaka3D	New Zealand	3.9	$(870 \times 1040 \times 1080)$
SantaYnez3D_1	United States	2.1	$(389 \times 1074 \times 1260)$
SantaYnez3D_2	United States	1.5	$(262 \times 1163 \times 1176)$
NorneFiled2006	Netherlands	1.1	$(321 \times 1001 \times 851)$

Table 1 – Seismic surveys.

- We used the interpretation software OpenDetect [4] to generate the attributes and build our supervised learning pipeline.
- We generated a grand total of 55GBs of data, stored as SEGY [5] files.

Model





Loss Function [6]

$$\min_G \max_{D_1,D_2,D_3} \sum_{k=1,2,3} \mathcal{L}_{GAN}(G, D_k)$$

$$\mathbb{E}_{(\mathbf{s},\mathbf{a})}[\log D_k(\mathbf{s},\mathbf{a})] + \mathbb{E}_{\mathbf{s}}[\log(1 - D_k(\mathbf{s}, G(\mathbf{s})))]$$

- **Coarse-to-fine-generator:** Global generator ***G2*** and local enhancer ***G1.***
- **Multi-scale Discriminator:** Discriminator ***D1***,***D2***, and ***D3*** operates on different image scales.

Results

Training Setup

- We trained dozens of networks from scratch, for three attributes (Phase, Energy and Semblance) and selected the best models.
- The complete training cycle takes 2 days on NVIDIA DGX-1 servers (8x Tesla V100 GPUs – 32GBs).

Inference Results

- Average time to compute attributes with the classical formulation: 62 seconds.
- Our approach inferring conditional GANs: **0.78 seconds**.

Dataset	Phase	Energy	Semblance	OD Average Time	Ours	Speedup
NorneField2006	59s	25s	84s	56.22s	0.70s	**80.47**
SantaYnez3D_2	67s	27s	110s	68.11s	0.86s	**79.57**

Table 2 – Computation time for exact and DL approaches.

- The presented architecture may operate as a universal attribute calculator, with some restrictions.
- For a high-quality numerical reconstruction, we must specialize the model.

Attribute	MSE (RGT)	PSNR (RGT)	MSE (Ours)	PSNR (Ours)	SSIM (Ours)
Semblance	1×10^{-2}	17.06	1×10^{-3}	29.64	0.94
Phase	6×10^{-2}	11.65	9×10^{-3}	20.31	0.93
Energy	1×10^{-3}	28.8	8×10^{-5}	40.82	0.98

Table 3 – Quantitative results and comparison with the U-Net architecture from [7].

Qualitative Results

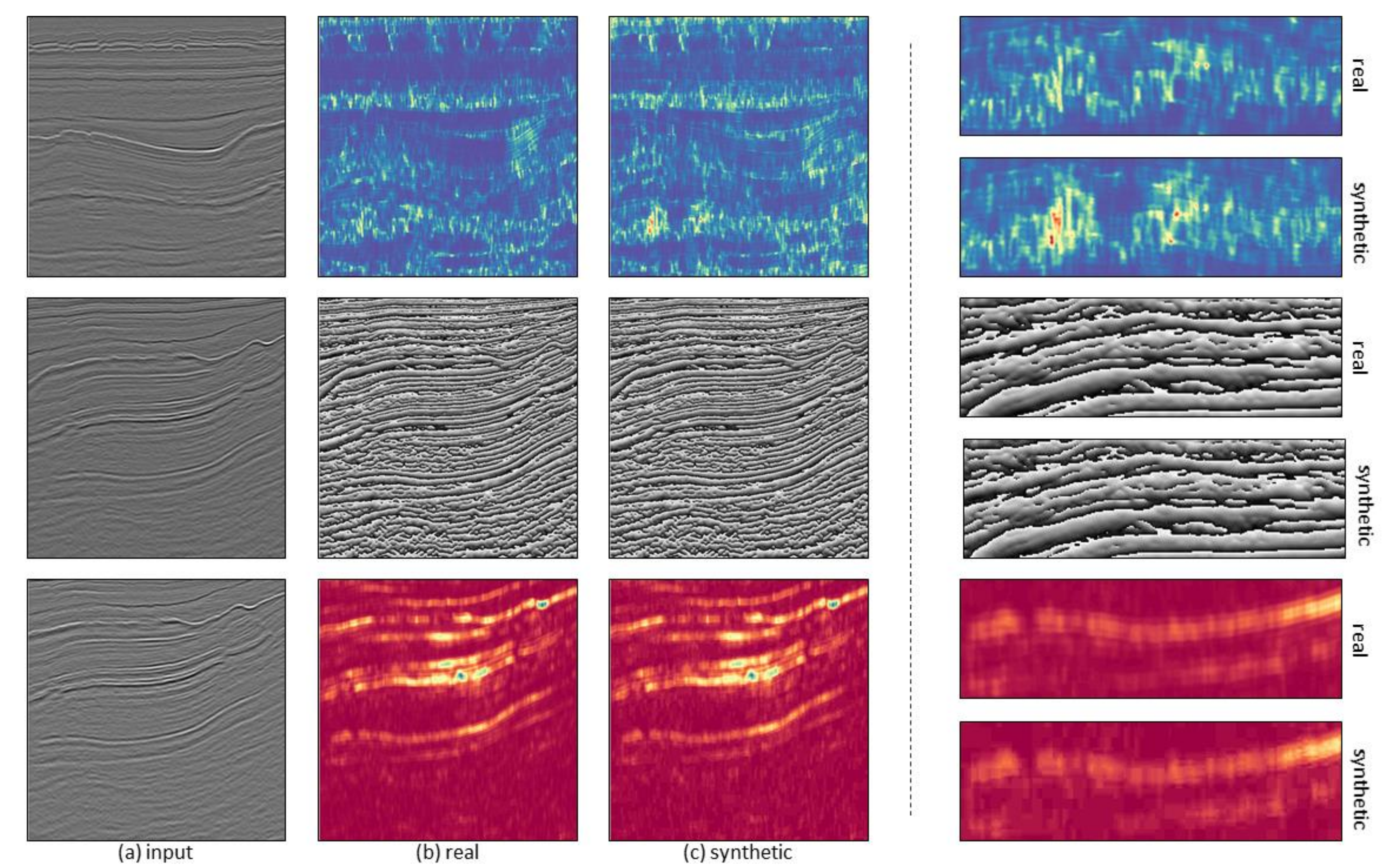


Figure 3 – Conditional GANs trained to compute Semblance (top), Instantaneous Phase (middle) and Energy (bottom) attributes.

- The overall image structure is well captured.
- Local features presented minor differences in expanded regions of interest (Figure 3, right panels).

Conclusions

- We conclude that conditional GANs can successfully approximate the computation of seismic attributes, with high visual fidelity, and minor numerical differences. The goal was achieved, and attributes over entire seismic blocks could be computed in real-time, with an **80x speedup**.
- The presented architecture may operate as a universal attribute calculator, with some restrictions.
- For a high-quality numerical reconstruction, we must specialize the model and properly adjust the architecture and tune the hyperparameter space to fit each data.
- For future work, we want to perform architectural modifications and explore 3D convolutions.
- **Acknowledgment** I would like to thank **Vineet Sai Kosaraju** for the insightful comments during the development of this work.

References

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