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Gamma Log Inversion of Seismic Data Based on Transformer with Stratigraphic Position Encoding

Yongjian Zhou, Haochen Qi, Wang Zhang, and Xiaocai Shan*

***Abstract*—As an indispensable part of geophysical exploration, seismic inversion can obtain the properties of subsurface media based on seismic data and available well-log information. With the nonlinear mapping ability, deep neural networks can map seismic data to well-log of interest. Interpreting gamma is crucial as it is essential for determining lithology and indicating sediment characteristics. Stratigraphic frameworks can approximate low-frequency trends in subsurface properties and are often used to guide well-log interpolation effectively. However, the existing deep neural network models cannot effectively explicitly fuse critical stratigraphic information, which will restrict the physical explainability and correctness of the seismic inversion. Thus, we propose a stratigraphic-encoded Transformer algorithm, named SeisWellTrans, to build a gamma log inversion model using horizon position encoding and seismic trace as inputs. Specifically, the incorporation of stratigraphic information from several horizons is crucial for improving the resolution of the output; and SeisWellTrans can efficiently model context in seismic sequences by capturing the interactions between horizon position encodings. We take the Volve field data as an example and use several gamma curves as training labels, numerical experiments demonstrate the geologically reasonable performance and high validation accuracy of this network and the crucial role that stratigraphic information plays. On the four validation wells, stratigraphic-encoded SeisWellTrans obtained an average correlation coefficient of 86%, exceeding 79% of stratigraphic-encoded CNN.**

***Index Terms*—Deep learning, Transformer, seismic inversion, gamma log, stratigraphic constraint.**

I. INTRODUCTION

SEISMIC data can characterize stratigraphic features and geological structures, while well-log curves can describe higher-resolution rock property information, such as impedance, lithology, and gamma. Seismic inversion can infer high-resolution rock properties in the subsurface at no-well locations, playing a significant role in building and characterizing subsurface reservoir models. Traditional seismic inversion assumes some forward physical and inversion models [1], [2], which is usually only an approximation and limits the accuracy of rock property estimation. Stratigraphic frameworks, such as horizons, faults, and unconformities, are usually taken as key additional constraints in building the initial or reference interpolation model in traditional seismic inversion [3]. Since stratigraphic frameworks can approximate the low-frequency trends of subsurface properties, it is critical for obtaining high-resolution rock properties.

In recent years, deep learning has attracted extensive attention in seismic inversion due to its excellent nonlinear mapping between inputs and outputs. In terms of seismic inversion, research on deep learning mostly focuses on elastic parameter or impedance inversion [3]–[14], other applications are inversion of gamma [3], porosity[3], [15], [16], fluid and lithology [17]–[20], etc. Seismic inversion of gamma, porosity, fluid, and lithology is more ill-posed and faces greater challenges than inversion of elastic parameters, which are more related to seismic waveforms. The deep learning networks used in the above studies are mostly Convolutional Neural Network (CNN) architectures, such as CNNs [3], [7], [14], [15], [18]–[20], Residual Attention Network [13], Autoencoders [8], U-Nets [6], [10], [16], and Temporal Convolutional Network [11]. There are also some Recurrent Neural Network (RNN) architectures, such as Long Short-Term Memory (LSTM) [17], and fusion architectures, such as CNN-Gate Recurrent Unit [4] and CNN-LSTM [9]. Yan et al. [3] input the initial interpolation results by relative geological time (RGT) volume into CNN together with the seismic data to invert several log curves, and achieves certain improvement. However, the calculation steps are relatively cumbersome, and the stratigraphic constraints are not directly embedded in the deep learning model. Therefore, it is necessary to design a deep neural network model to directly integrate stratigraphic constraints into the model, to test its effect on improving the inversion accuracy.

Originally proposed as a sequence-to-sequence model for machine translation, Transformer [21] is now a prominent deep-learning model widely adopted in various fields, such as natural language processing, speech processing, and computer vision. Transformer usually has a better performance and is more flexible than CNNs or RNNs since it is based on the multi-head self-attention mechanism and has few prior assumptions on the data structure [22]. Since Transformer does not introduce recurrence or convolution, it needs additional positional representation (especially for the encoder) to model the inner ordering of the input information. Few people have applied Transformer or its variants to seismic inversion. Recently, Wu et al. [5] input the original seismic data into a Fastformer and use the low-frequency model as the physical constraint label to predict brittle parameters. In the

Yongjian Zhou, Xiaocai Shan are with the State Key Laboratory of Deep Petroleum Intelligent Exploration and Development, Institute of Geology and Geophysics, Chinese Academy of Sciences, Beijing 100029, China.

Haochen Qi and Wang Zhang are with the State Key Laboratory of Deep Petroleum Intelligent Exploration and Development, Institute of Geology and Geophysics, Chinese Academy of Sciences, Beijing 100029, China, and also with the College of Earth and Planetary Sciences, University of Chinese Academy of Sciences, Beijing 100049, China.

(e-mails: zyj@mail.iggcas.ac.cn, shxc@mail.iggcas.ac.cn, qihaochen@mail.iggcas.ac.cn, zhangwang@mail.iggcas.ac.cn)

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encoder, this scheme used the order constraints of seismic profiles but did not utilize the more detailed stratigraphic position constraints, which is essential for the inversion accuracy.

This letter presents a high-resolution gamma log inversion scheme based on the SeisWellTrans network, a Transformer with stratigraphic position encoding. Specifically, we take several horizons as the stratigraphic position encoding and take the corresponding seismic trace together as inputs to the SeisWellTrans. The network output is the predicted gamma log. There is a non-linear relationship between the outputs. On the public Volve data [23], we test and compare CNN and SeisWellTrans structures with and without stratigraphic position encoding as the input for seismic inversion. Compared with the CNN-based inversion method, SeisWellTrans achieves surprisingly better performance and generalization by efficiently modeling and capturing the interactive context in seismic sequences.

II. METHODOLOGY

A. Stratigraphic Position Encoding

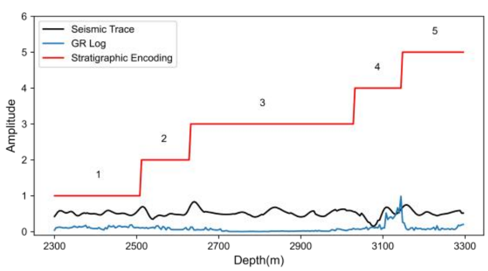

Fig. 1. The encoded stratigraphic information (red line) with normalized seismic trace (black line) and the corresponding gamma curve (blue line) form well 15_9-F-1-A in the Volve filed. The boundaries of stratigraphic encoding represent horizons of Ty, SHETLAND, BCU and Hugin_Base.

For field geophysical data, the well-log curves of the inversion target are sometimes missing at different depths, resulting in integrity inconsistencies of the log curves at different well locations. At the same time, the corresponding seismic traces are complete. As shown in Fig. 1, if discarding the stratigraphic formation constraint, the seismic waveforms at different depth areas are very similar, but the corresponding well-log curves are quite different. Thus, during the training process of deep learning models, if there is no stratigraphic constraint on the input layer, the model will confuse some samples with similar seismic waveforms but different log-curve labels, which is not conducive to its convergence.

Following feature engineering principles, neural networks may perform quite well with the input features chosen appropriately by the physical mechanism or expert experiences [24]. Stratigraphic information comprises the large-scale variation of the subsurface, which might help the inversion process converge to the global minima and improve the seismic inversion accuracy.

Therefore, similar to word position encoding in text modeling, it is critical to constrain seismic waveforms with stratigraphic order encoding as input. This is the key idea of the interpolation step in the traditional seismic inversion scheme, and it also conforms to the visual experience perception of geological interpretation experts in the actual workflow.

In this study, instead of only using the raw seismic trace as input, we extract several horizons as the stratigraphic information to constrain seismic trace and accelerate the convergence of the network training. The layers between several seismic horizons are positionally encoded as 1, 2, 3, …, N, which constitute the overall stratigraphic framework of the target area.

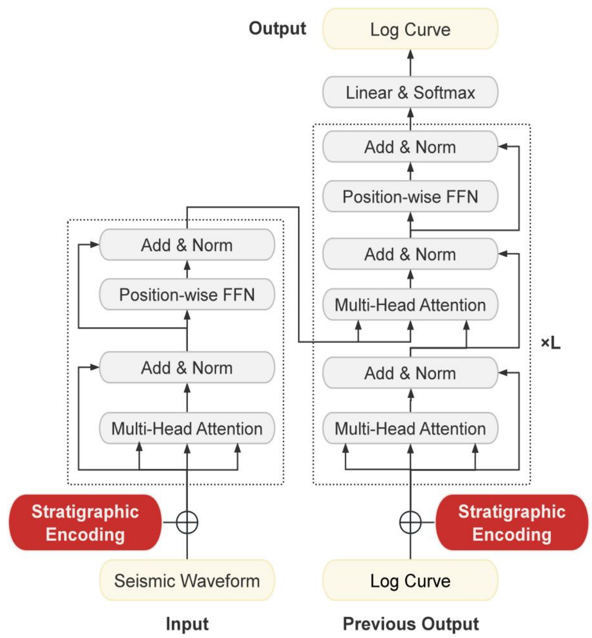

Fig. 2. The proposed architecture: SeisWellTrans with stratigraphic encoding.

B. Architecture of SeisWellTrans

Transformers, CNNs, and RNNs are all suitable for sequence data analysis and modeling, but Transformers are more universal and usually have better performances. To impose the inductive biases, CNNs use shared local kernel functions to track translation invariance and locality, and RNNs use Markovian structure to capture temporal invariance and locality. Different from CNNs and RNNs which inherently incorporate the inductive bias of locality, Transformer does not make any assumption on the data structure. As the central piece of the Transformer, self-attention can be viewed as a fully connected layer whose weights are dynamically generated from pairwise relations of inputs. On the one hand, self-attention has a constant maximum path length, enabling it to model long-range dependency. On the other hand, constant sequential operations make self-attention more parameter efficient, parallelizable, and flexible in handling variable-length inputs.

Fig. 2 shows the overall architecture of the proposed SeisWellTrans [21]. SeisWellTrans consists of an encoder and a decoder, each of which stacks *L* identical blocks. Encoder block is mainly composed of a multi-head self-attention (MHA) module and a position-wise feed-forward network (FFN). A residual connection and Layer Normalization are

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employed around each module. Decoder blocks furthermore insert cross-attention between the multi-head self-attention modules and the position-wise FFNs. Due to space limitations, the detailed mathematical formulas of each module can refer to [22], which is not expanded here. Like text modeling, this work uses a vector to represent the stratigraphic encoding (with dimension Len×d_embed), which is injected into the SeisWellTrans encoder together with the corresponding seismic waveform embedding (with dimension Len×d_embed). The output of the SeisWellTrans is the target gamma log curve (with dimension Len). We set Len as 250 and d_embed as 64. Compared with CNN structures, the structure in Transformer does not need to stack deep networks to obtain a global receptive field since the MHA module in encoder and decoder can model long-distance dependencies. Here, we stack 2 encoder and 2 decoder blocks with the head number of MHA module as 8. In the MHA module, the query (Q), key (K), and value (V) vectors are computed with dimensions of Len×d_embed, and are further split into 8 heads.

In this work, four models—CNN or SeisWellTrans with and without stratigraphic encoding in the input—are created to thoroughly assess the impact of network models and

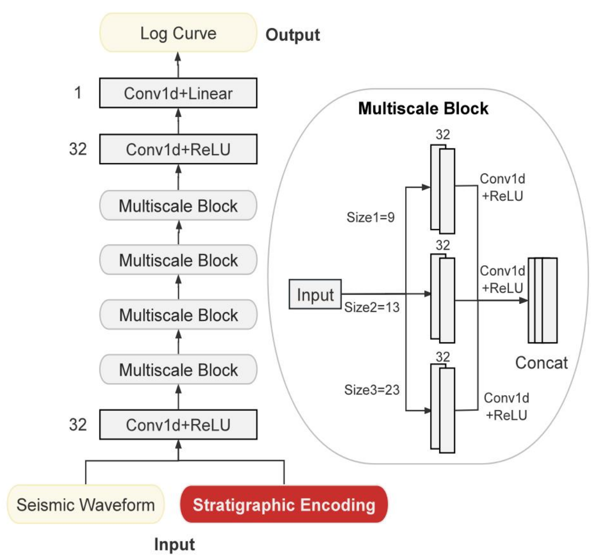

Fig. 3. CNN architecture with stratigraphic encoding used for comparison.

stratigraphic constraints on seismic inversion. For training the model, we use mean squared error (MSE) loss to measure the error between the true value and the prediction, and an Adam optimization to reduce the error. The CNN designed in this letter refers to the model architecture proposed by Yan et al. [3], as shown in Fig. 3. The difference is that Yan's model uses the RGT-interpolated log curve as a supplement to the seismic waveform, while we skip the interpolation step and directly use several seismic horizons as supplementary stratigraphic encoding input. From the level of information contained in the model input, compared to the initial interpolated curve, the seismic stratigraphic constraints can better represent the physical mechanism constraints and are more in line with the visual boundary features.

III. EXPERIMENTS

A. Dataset Preparation

In June 2018 Equinor [23] released the Volve Data Village data set for research and study. The field data contains over 40,000 files, covering production data, well design, seismic data, well logs, geologic and stratigraphical data, etc. In this letter, we mainly use seismic, horizons, and well-log data. The seismic data are post-stack migration in the depth domain, called "ST10010ZC11_PZ_PSDM_KIRCH_FULL_D.MIG_FIN.POST_STACK.3D.JS-017536.segy." The horizon data contain some key horizons such as Ty_Fm, Shetland_Gp, BCU, and Hugin_Base. There are 20 wells with different curves, such as velocity, density, impedance, porosity, and gamma. Some wells lack specific log curves, but it is worth noting that every well contains a gamma curve, which is thus selected as the seismic inversion target here to test the proposed method.

The preparation of the data set includes the following four steps, extracting seismic traces beside wells, encoding stratigraphic positions, data normalization, and dividing the training and validation dataset.

(1) In the process of extracting seismic traces beside wells, since most of the wells in the Volve field are deviated, it is necessary to extract seismic traces by segments according to the well trajectory and smooth the joints of each segment.

(2) In the process of stratigraphic encoding, we selected four key horizons named Ty_Fm, Shetland_Gp, BCU, and Hugin_Base, and encoded the stratigraphic information as 1, 2, 3, 4, and 5, as shown in Fig. 1.

(3) Since the numerical levels of seismic and gamma log data are inconsistent, to accelerate model optimization, we perform maximum and minimum normalization on seismic and gamma log data respectively to uniform their amplitudes.

(4) After the above three steps, the input and output of each well sample are constructed. To verify the effect of the model and be consistent with the work of Yan et al. [3], samples from wells 15_9-F-1-A, 15_9-F-4, 15_9-F-11-A, and 15_9-F-15-A are set as blind validation datasets and samples of the remaining 16 wells are used as the training datasets.

B. Validation Results from Different Networks and Inputs

Fig.4 shows the true (blue curves) and predicted gamma curves by the stratigraphically encoded CNN (orange curves) and the stratigraphically encoded SeisWellTrans (purple curves) on the four validation wells. Under the constraint of stratigraphic encoding, the seismic-inverted gamma curves by both models generally follow the overall trend of the measured curves, particularly in regions with low and smooth variations of gamma values (outside the dotted boxes in Fig.4).

SeisWellTrans, however, reveals specific advantages over the CNN model in various aspects. At critical depths where the gamma values increase or decrease sharply (such as dotted boxes in Fig.4), the predictions of SeisWellTrans visually match the actual values quite well, especially in promptly portraying their ascending and descending trends and slopes. This indicates the high vertical resolution of the proposed

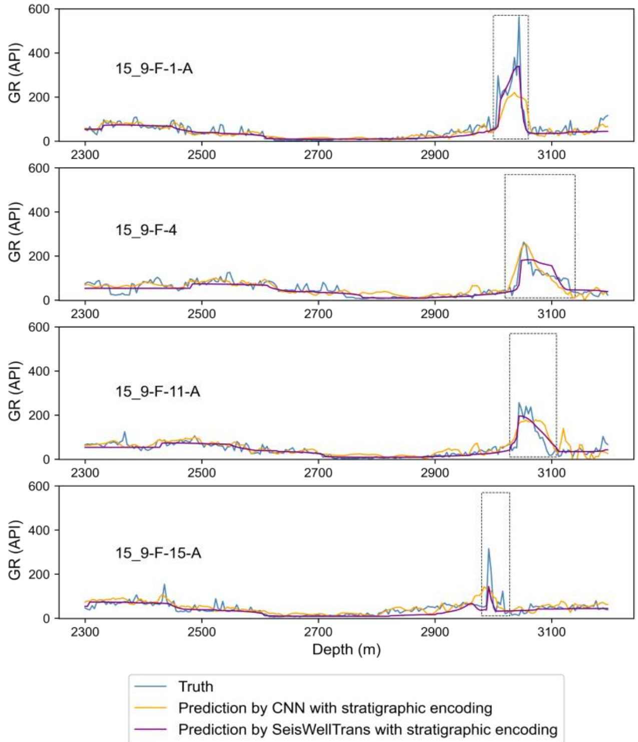

Fig. 4. The measured (blue curves) and predicted gamma curves by CNN with stratigraphic encoding (orange curves) and SeisWellTrans with stratigraphic encoding (purple curves) on the four validation wells.

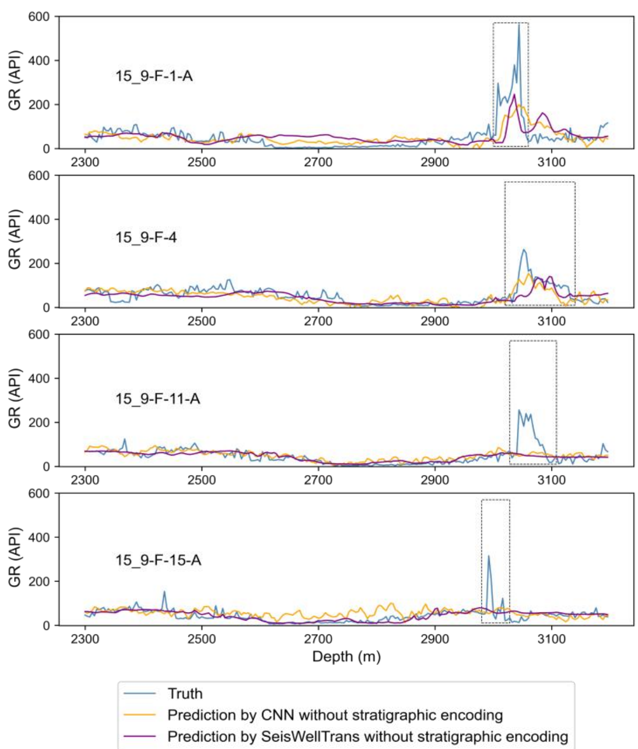

Fig. 5. The measured (blue curves) and predicted gamma curves by CNN without stratigraphic encoding (orange curves) and SeisWellTrans without stratigraphic encoding (purple curves) on the four validation wells.

seismic inversion approach. Table.1 shows that SeisWellTrans outperformed CNN in the high gamma areas (dotted boxes in Fig.4), low gamma areas (outside the dotted boxes in Fig.4) and whole areas of the four verification wells with the stratigraphic encoding. On the four validation wells, stratigraphic-encoded SeisWellTrans obtained an average correlation coefficient of 86%, exceeding 79% of stratigraphic-encoded CNN.

Fig.5 shows the true (blue curves) and predicted gamma curves by CNN without stratigraphic encoding (orange curves) and SeisWellTrans without stratigraphic encoding (purple curves) on the four validation wells. In the areas with low and smooth variations of gamma values (outside the dotted boxes in Fig.5), the predicted gamma curves by both models follow the general trend of the measurement curves. The predicted values of SeisWellTrans are relatively closer to the real values, while the predicted values of CNN have many weak fluctuations that do not match.

At critical depths where the gamma values increase or decrease sharply (dotted boxes in Fig.5), both models visually show significant differences from the true values, and neither of them can capture the ascending and descending trends and slopes. In wells 15_9-F-1-A and 15_9-F-4, the predicted values by CNN are slightly better than those by SeisWellTrans, which demonstrates that Transformer is somewhat more dependent on the stratigraphic position encoding.

Comparing Fig.4 and Fig.5 comprehensively, stratigraphic encoding has a great influence on the effect of CNN and Transformer models, which verifies that it is critical for the seismic inversion of log curves. When using stratigraphic constraints, seismic inversion by SeisWellTrans has higher resolution and accuracy than CNN, which benefits from Transformer's global perception ability and detail sensitivity with no prior structural assumptions.

TABLE I

THE AVERAGE OF THE CORRELATION COEFFICIENTS OF THE FOUR VALIDATION WELLS

Models and Wells		CNN without stratigraphic encoding	SeisWellTrans without stratigraphic encoding	CNN with stratigraphic encoding	SeisWellTrans with stratigraphic encoding
Low GR area	15_9-F-1-A	0.38	0.32	0.81	0.84
	15_9-F-4	0.71	0.77	0.83	0.88
	15_9-F-11-A	0.80	0.84	0.79	0.89
	15_9-F-15-A	0.42	0.78	0.79	0.81
	MEAN	**0.58**	**0.68**	**0.81**	**0.86**
High GR area	15_9-F-1-A	0.85	0.85	0.89	0.94
	15_9-F-4	0.92	0.81	0.94	0.94
	15_9-F-11-A	0.80	0.81	0.91	0.96
	15_9-F-15-A	0.65	0.72	0.76	0.95
	MEAN	**0.81**	**0.80**	**0.88**	**0.95**
Whole GR area	15_9-F-1-A	0.64	0.51	0.83	0.91
	15_9-F-4	0.69	0.62	0.85	0.86
	15_9-F-11-A	0.51	0.55	0.81	0.90
	15_9-F-15-A	0.21	0.59	0.66	0.76
	MEAN	**0.51**	**0.57**	**0.79**	**0.86**

C. Test Results from Different Networks

Finally, we compared the crosswell seismic inversion results by CNN with stratigraphic encoding and SeisWellTrans with stratigraphic encoding. To view local details of prediction results, Fig.6a shows 2D seismic slices extracted from the 3D seismic volume. Fig.6b and Fig.6c show the gamma inversion results by CNN with stratigraphic encoding and SeisWellTrans with stratigraphic encoding, respectively. In Fig. 6b, high gamma areas are not well-defined and surrounded by artifacts. There are many subdivided small thin layers in the low gamma value area, but considering that the Pearson correlation coefficients of the stratigraphic-encoded CNN in the low gamma area in Table 1 are not higher than stratigraphic-encoded SeisWellTrans, this

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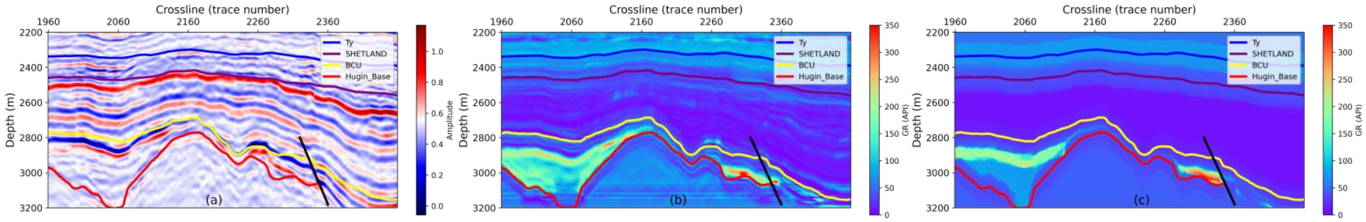

Fig. 6. A 2D seismic profile extracted from the 3D seismic volume (a). A comparison of inverted gamma profiles by (b) CNN with stratigraphic encoding and (c) Transformer with stratigraphic encoding.

thin layer information is not necessarily accurate. In Fig.6c, the target layer with a high Gamma value has clear boundaries and no artifacts around it. The boundaries of areas with low gamma values are clear, and the changes at different depths are depicted. This result can be used as a comparatively low-frequency initial model for further high-frequency detail inversion research.

The predicted gamma profile by SeisWellTrans shows more key features of gamma distribution compared to CNN, which proves that the multi-head self-attention mechanism can extract rich and precise seismic stratigraphic features and accurately map them into gamma information. In addition, the predicted transverse trend by SeisWellTrans is consistent and reasonable with the seismic structure. Compared to CNN, our inversion scheme in the fault area (black line in Fig. 6) is more consistent with the stratigraphic framework and structure.

V. Conclusion

In this study, we developed a Transformer network SeisWellTrans for high-resolution gamma inversion by integrating stratigraphic encoding along with seismic waveform. We analyze the enhancement effect of stratigraphic encoding and state-of-the-art deep learning model designing on seismic inversion. Test examples on the Volve field data show effective inversion performance and demonstrate that introducing stratigraphic encoding can help guide precise seismic inversion. More importantly, compared to CNN, SeisWellTrans has better precision benefits from its global perception ability and detail sensitivity with no prior structural assumptions. Our seismic inversion scheme is flexible and feasible for field seismic data applications with several wells. The proposed SeisWellTrans architecture with stratigraphic position encoding provides a promising reference for further research on the high-resolution inversion of other various logs, such as elastic impedance parameters, porosity, fluid, and lithology.

Acknowledgment

This research was supported by the National Key Research and Development Program Project (E41O5802). We thank all the editors and reviewers for their constructive comments and suggestions.

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