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# PRE-STACK SEISMIC DATA COMPRESSION USING U-NET BASED PREDICTORS

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## ABSTRACT

This paper explores the application of U-net-based predictors for compressing acoustic signals characterized by sound pressure and three-axis accelerations. These signals, generated in various geophysical and engineering applications, require efficient compression methods to address the challenges of high data volumes while preserving critical information. U-net, a deep learning model with an encoder-decoder structure and skip connections, demonstrates its potential for effectively compressing such data by capturing complex spatial and temporal patterns inherent in acoustic signals. The study evaluates the U-net's performance on data containing sound pressure and three-axis accelerations, focusing on maintaining data integrity essential for accurate analysis and interpretation. It integrates trace removal with U-net-based interpolation, fixed-point representation, and Discrete Wavelet Transform into a comprehensive compression framework. Performance metrics, including compression ratio, reconstruction error, and structural similarity index , are used alongside qualitative expert evaluations to assess the approach.The results aim to establish the U-net model as a robust solution for compressing multidimensional acoustic signals, reducing storage and transmission costs while ensuring high fidelity for advanced analysis and decision-making.

**Keywords:** *Seismic Data interpolation, Multidimensional data, Deep learning.*

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## 1. INTRODUCTION

Seismic data is an invaluable resource in the exploration and production of hydrocarbons, providing essential insights into subsurface geology and enabling informed decision-making for resource extraction. The increasing scale of seismic surveys, however, brings with it a significant challenge: the vast volumes of data generated can overwhelm traditional data storage, transmission, and processing systems. The sheer magnitude of seismic datasets, combined with the complexity of their structures and inherent noise, presents a unique set of difficulties for geophysicists and engineers. As such, effective seismic data compression methods are paramount to improving the efficiency of these processes, reducing the costs associated with data storage and transmission, and enhancing the overall workflow in geophysical analysis.

Compression techniques for seismic data typically fall into two categories: lossy and lossless methods. Lossy compression algorithms achieve higher compression ratios by approximating the data and sacrificing some fidelity, which may result in the loss of subtle but potentially crucial geological features. On the other hand, lossless methods retain the full accuracy of the original data but often with lower compression rates. Both approaches present trade-offs between compression efficiency and data integrity, underscoring the need for a method that balances these factors while maintaining the high standards required in seismic interpretation. Recent developments in machine learning, particularly deep learning models, have opened up new possibilities for improving the efficiency and effectiveness of seismic data compression. These models are capable of learning complex representations of data, enabling them to generate compressed formats that preserve essential features while achieving high compression ratios [1, 2].

Among the deep learning models, U-net has gained significant attention due to its impressive performance in image and signal processing tasks. Originally designed for biomedical image segmentation, the U-net architecture is based on an encoder-decoder structure with skip connections. This unique architecture allows the model to capture both local and global features in the data, enabling it to learn complex mappings between input and output even in highly structured data environments. The success of U-net in image segmentation and other fields has prompted its exploration in diverse areas such as medical imaging, remote sensing, and seismic data processing. In the context of seismic data, which is typically represented as multidimensional arrays with intricate patterns and varying levels of noise, U-net's ability to extract meaningful features from noisy, high-dimensional data makes it an ideal candidate for seismic data compression [3, 4].

Moreover, seismic data inherently exhibits high spatial correlation, particularly along the temporal or spatial dimensions of seismic traces. This spatial correlation means that adjacent seismic traces often carry redundant information, making trace removal a highly effective strategy for compression. The U-net architecture, with its encoder-decoder structure and skip connections, is particularly well-suited to this task. By learning the spatial relationships between adjacent traces, U-net can effectively reconstruct missing or removed traces, maintaining the fidelity of the data while reducing its size. This makes U-net a compelling approach for trace removal and interpolation in seismic data compression, leveraging the high spatial correlation present in the data to minimize loss and maximize compression efficiency [5, 6].

This paper presents an experimental design aimed at evaluating the effectiveness of U-net-based models in compressing seismic data, with a particular focus on seismic data from the Petrobras Data in the Jubarte Basin. The research seeks to demonstrate the ability of the U-net architecture to achieve high compression ratios while preserving the integrity of the seismic data, which is crucial for accurate geological and geophysical interpretations. The study contributes to the existing body of knowledge in seismic data processing by investigating a novel application of deep learning techniques, specifically U-net, in the compression of geophysical data.

The contributions of this paper are multifaceted. First, we propose the novel application of U-net for seismic data compression, leveraging its encoder-decoder structure with skip connections to learn efficient representations of seismic data that balance high compression ratios with the retention of critical features necessary for accurate interpretation. Second, we demonstrate the effectiveness of U-net for trace removal and interpolation by taking advantage of the high spatial correlation inherent in seismic data. Third, we present a comprehensive experimental framework for evaluating U-net's performance in seismic data compression. The methodology includes detailed steps for dataset preparation, model training, and validation, ensuring that the model is rigorously tested and its generalization capabilities are thoroughly assessed. Finally, we evaluate the performance of the U-net model using metrics such as compression ratio, reconstruction error, and domain-specific accuracy in seismic interpretation, providing insights into the potential of U-net for efficient seismic data handling [7].

The primary goal of this experiment is to evaluate the effectiveness of U-net architecture-based predictors (interpolators) for compressing seismic data, with a specific focus on active seismic data collected at the seafloor via Ocean Bottom Cables positioned in the Jubarte Basin, Brazil. This study aims to investigate whether U-net can successfully compress such seismic data while preserving essential features necessary for accurate geological and geophysical analysis.

The expected outcomes of this study include the following: determining the efficiency of U-net-based predictors in compressing seismic data; assessing the generalization capability of the model by comparing performance on training and validation datasets; and providing insights into potential improvements or alternative approaches for seismic data compression.

This comprehensive study aims to contribute to the ongoing development of seismic data compression techniques and demonstrate the applicability of deep learning models in this critical area of geophysical data processing.

## 2. EXPERIMENTAL SETUP

The experimental setup is pivotal in validating the use of machine learning models, particularly the U-net architecture, in seismic data prediction and compression. This section provides a comprehensive description of the methodos employed to prepare the datasets, define the U-net model architecture, to conduct the training procedure, and to evaluate the model's performance. The primary objective of this study is to investigate the potential of the U-net model for interpolating active seismic data taken from the Jubarte Basin, Brazil. By focusing on improving both seismic data compression and prediction accuracy, the study aims to contribute to advancements in geological and geophysical research, where high-fidelity seismic data is crucial for subsurface exploration and resource management.

### 2.1 Data Preparation

The success of machine learning models relies heavily on the quality and distribution of the datasets used for training and validation. In this study, seismic data extracted from the Jubarte Basin serve as the core foundation for model development. These data undergo preprocessing and are subsequently partitioned into two primary subsets: the training dataset and the validation dataset.

**Training Dataset:** The training dataset, denoted as $D_{\text{train}}$, is sourced from a specific area within the Jubarte Basin. The dataset includes active seismic traces that capture a wide array of geological features, reflecting the diversity of the subsurface conditions in the region. The seismic data are multivariate, incorporating sensor readings from various sources and configurations. This diversity in the training data allows the model to learn a broad set of features and provides a solid foundation for training the model.

**Validation Dataset:** The validation dataset, represented as $D_{\text{val}}$, is extracted from a geographically distinct zone within the Jubarte Basin. This spatial separation ensures that the validation data are independent of the training data, which helps in minimizing spatial bias and promotes a more generalizable model. The validation dataset is critical for evaluating the model's performance on unseen data, simulating real-world conditions where seismic data from new locations will be processed.

### 2.2 U-Net Model Architecture

The U-net architecture is chosen for its proven effectiveness in a variety of image-to-image tasks, including medical image segmentation, where it has demonstrated superior performance. Given the complexity and noise characteristics inherent in seismic data, U-net's encoder-decoder structure with skip connections is likely to be well-suited for seismic data interpolation and compression.

The U-net architecture uses an encoder-decoder structure, where the encoder progressively downsamples the input data to capture high-level features, while the decoder works in reverse to reconstruct the data's spatial resolution. The skip connections that link corresponding layers of the encoder and decoder allow the model to retain fine-grained details at different scales. The output of the model, $\hat{Y}$, is predicted based on the input seismic data $X$ as follows:

$$\hat{Y} = \text{U-net}(X; \Theta)$$

wherein $X$ represents the input seismic data, $\Theta$ are the model parameters, and $\hat{Y}$ is the predicted output. This architecture is well-suited for seismic data as it excels at recovering fine details and contextual information despite the presence of noise or data irregularities.

### 2.3 Data Preprocessing

Prior to feeding the seismic data into the U-net model, several preprocessing steps are applied to standardize the data and enhance the model's convergence. The first step involves standardizing the seismic data $X$, ensuring that the input data has uniform characteristics. Standardization is crucial in helping the model learn more effectively, as it eliminates discrepancies in amplitude and offset across different seismic traces.

In addition to standardization, data augmentation techniques are employed to artificially expand the training dataset. Augmentation techniques such as random rotations, translations, and noise addition are applied to $D_{\text{train}}$ to simulate various real-world scenarios that may occur during seismic data acquisition. This augmentation ensures that the model is exposed to a diverse set of data, making it more robust and better equipped to handle unseen data during the training process.

### 2.4 Training Procedure

The training procedure is a critical aspect of the experimental setup and involves optimizing the U-net model's parameters to minimize the reconstruction error. The training dataset $D_{\text{train}}$ is divided into two subsets: one used for training the model and the other used for validation. A common partitioning strategy, such as an 80-20 split, is used to ensure that the model is evaluated at regular intervals throughout the training process.

The model is trained using a loss function, such as Mean Squared Error (MSE), which quantifies the difference between the predicted seismic data $\hat{Y}$ and the ground truth $Y$. The optimization process aims to minimize the following loss function:

$$\mathcal{L}(Y, \hat{Y}) = \frac{1}{N} \sum_{i=1}^{N} \|Y_i - \hat{Y}_i\|^2$$

where $N$ is the number of samples, $Y_i$ represents the ground truth, and $\hat{Y}_i$ is the predicted seismic data. The optimization is carried out using an appropriate optimizer, such as the Adam optimizer, with a specified learning rate schedule. The parameters of the model $\Theta$ are updated iteratively to minimize the loss function, yielding the optimized model:

$$\Theta^* = \arg\min_{\Theta} \mathcal{L}(Y, \text{U-net}(X; \Theta))$$

During training, early stopping is implemented to prevent overfitting. The model is also saved at regular intervals using checkpointing to ensure that the best-performing model, in terms of validation loss, is retained.

### 2.5 Validation and Performance Evaluation

Once the model has been trained, it is evaluated on an independent validation dataset, $D_{\text{val}}$, which is geographically independent from the training data. The validation dataset provides an unbiased estimate of the model's performance on new, unseen data. The evaluation focuses on key performance metrics, such as compression ratio, reconstruction error, and structural similarity.

**Compression Ratio (CR):** The compression ratio (CR) is a primary metric used to assess the model's ability to reduce data size while preserving key features of the seismic data. This ratio is calculated as the ratio of the original data size $S_{\text{orig}}$ to the compressed data size $S_{\text{compressed}}$, after applying the U-net model. Mathematically, the compression ratio is defined as:

$$\text{CR} = \frac{S_{\text{orig}}}{S_{\text{compressed}}}$$

A higher compression ratio indicates that the model is more efficient in compressing the seismic data, reducing both storage requirements and transmission costs. However, it is essential to balance compression with the preservation of essential seismic features to maintain the integrity of the data.

**Reconstruction Error:** The reconstruction error is typically calculated using Mean Squared Error (MSE), which provides a quantitative measure of how well the model reconstructs missing or noisy seismic traces. MSE is defined as:

$$\mathcal{L}_{\text{MSE}} = \frac{1}{N} \sum_{i=1}^{N} \left(Y_i - \hat{Y}_i\right)^2$$

where $Y_i$ represents the ground truth seismic data, $\hat{Y}_i$ is the predicted seismic data, and $N$ is the number of samples in the dataset. A lower MSE indicates that the model is better at preserving the important features of the seismic data and is more accurate in its reconstruction.

**Structural Similarity Index (SSIM):** In addition to MSE, the Structural Similarity Index (SSIM) is used to evaluate the perceptual quality of the reconstructed seismic data. SSIM compares the structural similarity between the ground truth and the reconstructed data, taking into account luminance, contrast, and structural information. The SSIM index, $\text{SSIM}(Y, \hat{Y})$, is defined as:

$$\text{SSIM}(Y, \hat{Y}) = \frac{\left(2\mu_Y \mu_{\hat{Y}} + C_1\right)\left(2\sigma_{Y\hat{Y}} + C_2\right)}{\left(\mu_Y^2 + \mu_{\hat{Y}}^2 + C_1\right)\left(\sigma_Y^2 + \sigma_{\hat{Y}}^2 + C_2\right)}$$

where: - $\mu_Y$ and $\mu_{\hat{Y}}$ are the mean intensities of the ground truth and predicted data, respectively, - $\sigma_Y^2$ and $\sigma_{\hat{Y}}^2$ are the variances of the ground truth and predicted data, respectively, - $\sigma_{Y\hat{Y}}$ is the covariance between the ground truth and predicted data, - $C_1$ and $C_2$ are small constants to avoid division by zero.

The SSIM score ranges from -1 to 1, where 1 indicates perfect structural similarity between the ground truth and the reconstructed data, while a value closer to 0 indicates significant structural differences. A higher SSIM value signifies that the model maintains important spatial structures and patterns in the seismic data, making it more useful for geological interpretation.

**Overall Performance Evaluation:** The overall performance of the model is determined by considering a combination of the above metrics. A good model should achieve a high compression ratio, low reconstruction error (MSE), and high structural similarity (SSIM), while also satisfying the qualitative criteria set by domain experts. The balance between these factors is crucial to ensure that the model can effectively compress seismic data without sacrificing important geological and geophysical information.

By evaluating the model using both objective and subjective criteria, the experiment aims to provide a comprehensive understanding of the U-net model's ability to compress and reconstruct seismic data effectively.

### 2.6 Proposed Data Compression Methodology

The proposed data compression methodology consists of a sequence of processing stages aimed at minimizing the storage and transmission costs associated with seismic data, while preserving the essential information required for subsequent analysis. This framework incorporates the following components:

- **Trace Decimation and U-Net-Based Interpolation:** Seismic datasets typically exhibit redundancy due to the spatial correlation among adjacent traces. To exploit this redundancy, a subset of traces is deliberately removed. A U-Net model, characterized by its encoder-decoder architecture and skip connections, is then employed to reconstruct the missing traces. This structure effectively captures both local and global signal features, ensuring high-fidelity reconstruction despite partial data omission.

- **Fixed-Point Representation:** Upon interpolation, the seismic data—originally in floating-point format—is converted to fixed-point representation. This quantization process reduces memory usage by limiting numerical precision, making it particularly advantageous for deployment in resource-constrained environments. Despite the reduction in precision, this step maintains adequate accuracy for seismic analysis tasks.

- **Three-Dimensional Discrete Wavelet Transform (3D DWT):** The reconstructed dataset is further compressed using a 3D Haar wavelet transform with five decomposition levels. This process decomposes the data into hierarchical frequency subbands, enabling the isolation of significant signal features while discarding less informative components. The resulting multi-resolution representation is conducive to efficient and compact data encoding.

- **Entropy Encoding:** In the final stage, entropy encoding is applied to the quantized wavelet coefficients. By assigning shorter binary codes to more frequent patterns and longer codes to rare ones, methods such as Huffman or arithmetic coding achieve additional data compression. This step ensures a compact representation while preserving critical features necessary for interpretation.

Together, these stages form a robust and flexible compression pipeline that effectively balances storage efficiency and data integrity.

### 2.7 Experimental Results

Two compression configurations were evaluated to assess the performance of the proposed approach. Performance metrics included the compression ratio, mean squared error (MSE), and structural similarity index (SSIM), with frequency-band-specific analysis to better understand compression fidelity.

**Configuration 1: With 3D DWT.**The processing pipeline for this configuration includes Decimation 2:1, 3D DWT, Fixed-Point Conversion, and Entropy Encoding. It achieved a compression ratio of 3.80. In terms of overall performance, the Mean Squared Error (MSE) was 0.1606, and the Structural Similarity Index Measure (SSIM) was 0.9697. When broken down by frequency band, the results were as follows: for 0–20 Hz, MSE = 0.00078 and SSIM = 0.6756; for 20–80 Hz, MSE = 0.00158 and SSIM = 0.8841; for 80–150 Hz, MSE = 0.00333 and SSIM = 0.9348; and for 150–250 Hz, MSE = 0.0352 and SSIM = 0.9779. The wavelet-based configuration preserved key signal characteristics, particularly in the mid and high-frequency ranges, with minimal visual distortion. Detailed results across signal components can be seen in Figures 1–4.

**Configuration 2: Without 3D DWT.**This alternative pipeline consisted of Decimation 2:1, Fixed-Point Conversion, and Entropy Encoding, omitting the 3D DWT stage. It resulted in a lower compression ratio of 2.19. However, overall performance was slightly improved, with MSE = 0.1597 and SSIM = 0.9708. Frequency-band analysis revealed the following: for 0–20 Hz, MSE = 0.00078 and SSIM = 0.6792; for 20–80 Hz, MSE = 0.00156 and SSIM = 0.8936; for 80–150 Hz, MSE = 0.00327 and SSIM = 0.9412; and for 150–250 Hz, MSE = 0.0350 and SSIM = 0.9786. Although the compression ratio was reduced, the reconstruction fidelity—particularly SSIM—showed slight improvement. Visual inspections, as seen in Figures 5–8, confirm minimal degradation in signal quality, indicating that this simpler pipeline may be a viable option when computational efficiency is a priority.

These experimental results underscore the flexibility of the proposed compression framework. Depending on application requirements, one may prioritize compression ratio or computational simplicity without significant compromise in signal quality.

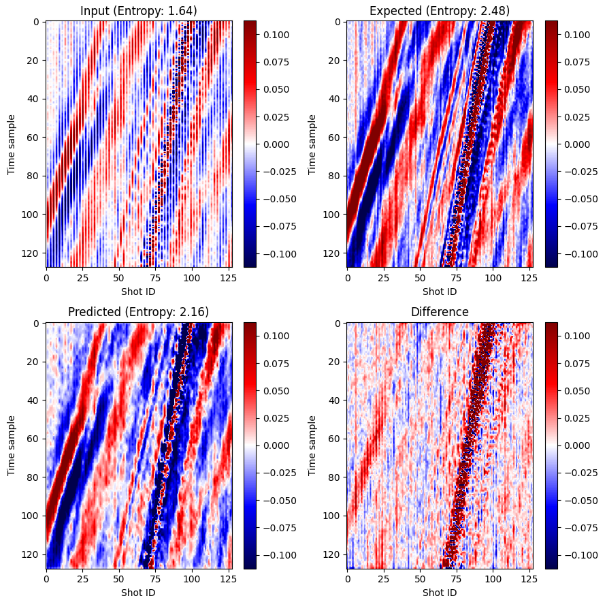


**Figure 1**. Compression results for sound pressure signal using decimation, 3D wavelet, float2fixed, and entropy encoding.

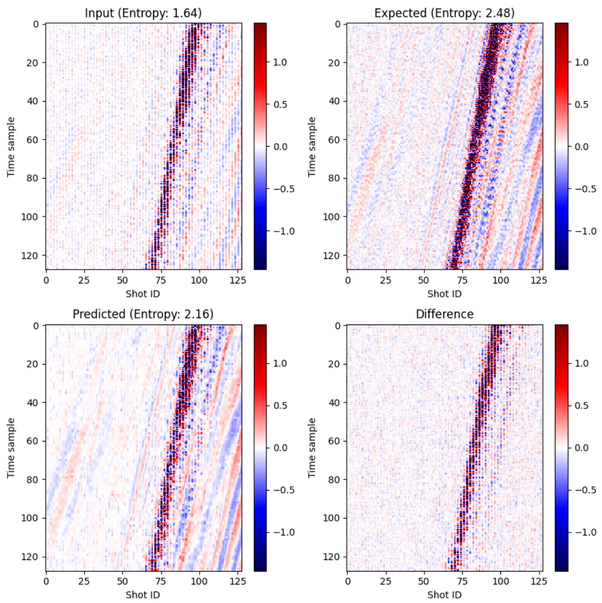


**Figure 2**. Compression results for vertical acceleration using decimation, 3D wavelet, float2fixed, and entropy encoding.

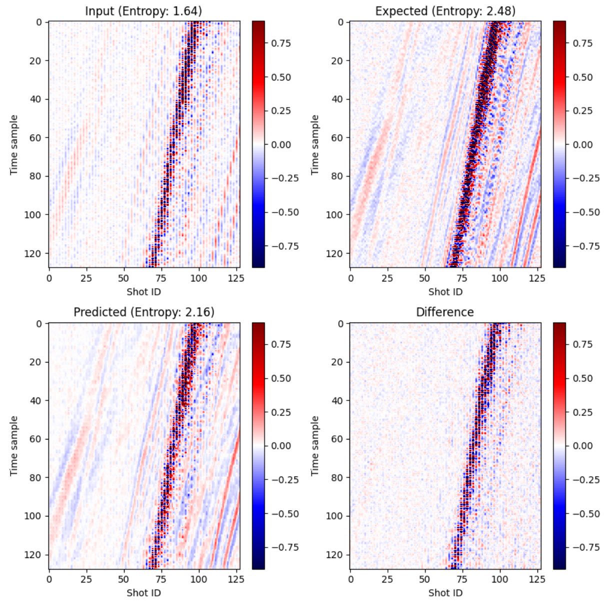


**Figure 3**. Compression results for crossline acceleration using decimation, 3D wavelet, float2fixed, and entropy encoding.

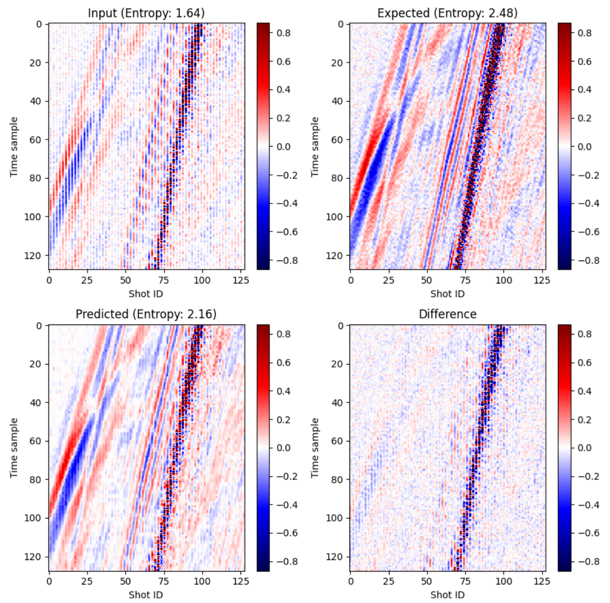


**Figure 4**. Compression results for inline acceleration using decimation, 3D wavelet, float2fixed, and entropy encoding.

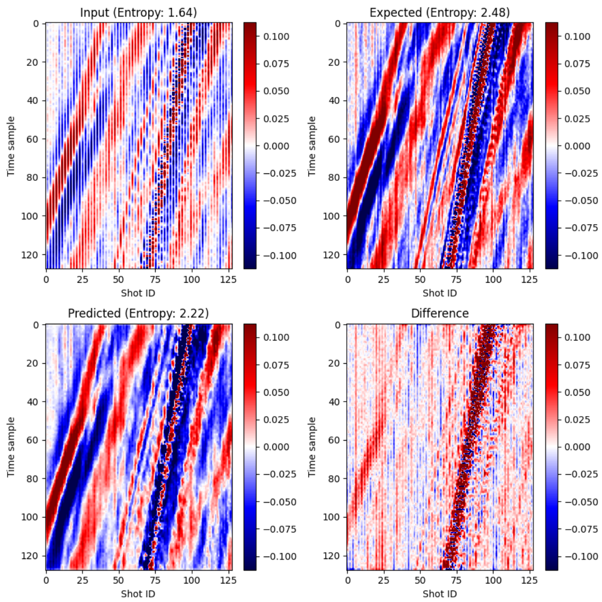


**Figure 5**. Compression results for sound pressure signal using decimation, float2fixed, and entropy encoding.

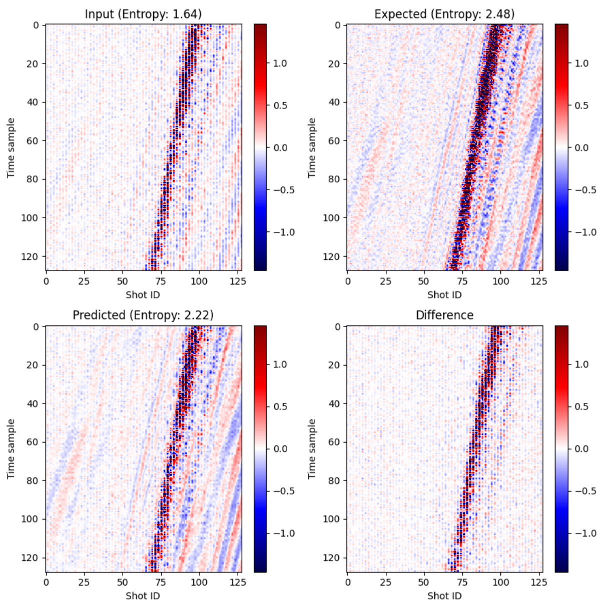


**Figure 6**. Compression results for vertical acceleration using decimation, float2fixed, and entropy encoding.

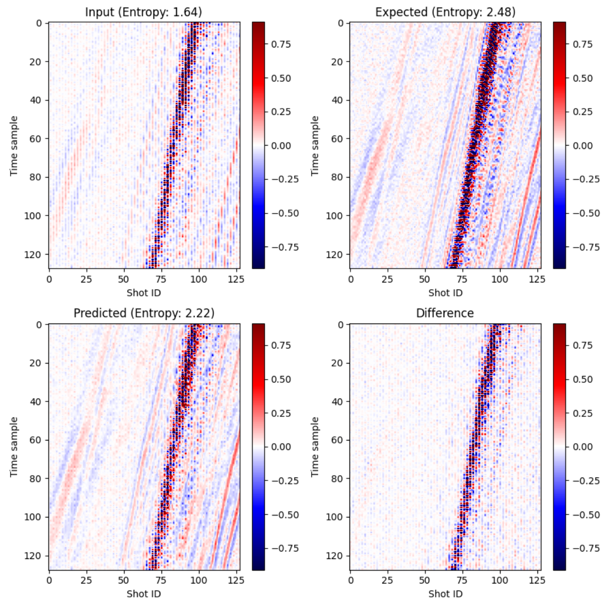


**Figure 7**. Compression results for crossline acceleration using decimation, float2fixed, and entropy encoding.

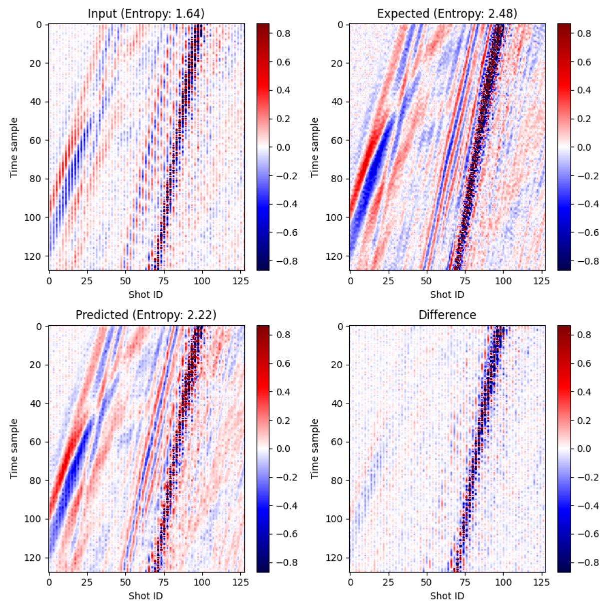


**Figure 8**. Compression results for inline acceleration using decimation, float2fixed, and entropy encoding.

## 3. CONCLUSION

U-net effectively reconstructs missing traces based on the spatial patterns and dependencies present in the data. This ability to perform high-quality trace interpolation is critical to reducing data size without sacrificing essential seismic information. By exploiting the U-net's encoder-decoder architecture and skip connections, the proposed framework accurately recovers missing traces while maintaining structural coherence in the data, thus enabling aggressive decimation without compromising interpretability.

A key contribution of the proposed compression approach lies in its ability to balance reconstruction quality with compression efficiency. This balance is achieved through the integration of multiple complementary techniques: fixed-point representation, three-dimensional discrete wavelet transform, and entropy encoding. Fixed-point representation reduces storage requirements by limiting numerical precision, while maintaining sufficient accuracy for seismic analysis. The 3D DWT enables multi-scale analysis and compression by isolating salient features in the data, and entropy encoding efficiently captures redundancy in the transformed signal.

Empirical evaluations demonstrate that the full compression pipeline achieves a compression ratio of up to 3.80, while preserving high fidelity in the reconstructed signals. Notably, the structural similarity index (SSIM) remains above 0.96 across the full bandwidth, with further improvements observed at higher frequency bands. This indicates that essential seismic features are retained, making the compressed data suitable for further processing and interpretation. Additionally, an alternative configuration without the 3D wavelet transform yields a lower compression ratio of 2.19, but achieves slightly better SSIM, highlighting the inherent trade-off between data compactness and reconstruction quality.

These findings emphasize the flexibility of the proposed method. Users may adjust individual components of the pipeline depending on the specific demands of the application—whether prioritizing maximum compression for transmission and storage efficiency, or favoring high-fidelity reconstruction for detailed seismic analysis. The modular nature of the approach ensures it can be tailored to various operational constraints and performance requirements.

In conclusion, the proposed multi-stage compression framework offers a robust, scalable, and adaptable solution for seismic data reduction. By achieving an effective compromise between compression ratio and reconstruction quality, it supports both efficient data management and high-resolution interpretation, making it suitable for applications ranging from real-time field acquisition to long-term archival storage.

## 4. ACKNOWLEDGMENTS

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