Transactions of the Korean Nuclear Society Spring Meeting
Jeju, Korea, May 9-10, 2024

Seismic Signal Upsampling with Integration of Interpolation and LSTM

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***Keywords:** Upsampling, Interpolation, LSTM

1.Introduction

As of February 13, 2024, the total number of accelerometers installed by the National Earthquake Comprehensive Information System (NECIS) of the Korea Meteorological Administration (KMA) is 289, collecting data at sampling rates of 20 and 100. Initially, seismic data were recorded at a sampling rate of 20, suitable for determining the magnitude and location of earthquakes. With advancements in data transmission speeds and storage capacities, data are now also recorded at a sampling rate of 100.

To create models capable of distinguishing between P waves, S waves, and noise, it is essential to utilize high-frequency data from nearby strong seismic events. High frequencies attenuate more effectively over distance, meaning data from distant sources become diminished. However, Korea's predominant granite underground composition minimally affects attenuation, making local earthquake data particularly valuable for leveraging high-frequency information.

According to Nyquist's theorem [1], a sampling rate of 100 can only capture frequencies up to 50 Hz, limiting our ability to analyze higher-frequency seismic data. High-frequency data above 50 Hz are crucial for improving model accuracy in identifying seismic wave characteristics. By enhancing the sampling rate to 200, we can secure data in the 50 to 100 Hz range, significantly improving our model's ability to differentiate seismic wave types. Such refined models are instrumental in minimizing damage to critical infrastructure, including nuclear power plants, by providing more precise predictions.

Currently, Korea records seismic data at a sampling rate of 100, which restricts visibility into the higher-frequency spectrum essential for detailed analysis. Our research aims to elevate this rate to 200, enhancing model performance by incorporating a broader range of high-frequency data.

Interpolation is a method for upsampling seismic signals to estimate values between given data points. Linear Interpolation, which calculates the average of two adjacent values, is most effective when the sampling rate is doubled. However, the simplicity of linear interpolation limits the accuracy of seismic signal upsampling, necessitating the creation of a model that offers more precise predictions.

To address this limitation, we turn to Deep Learning. The RNN family of models, particularly the LSTM [2] has shown exceptional performance in predicting time series data, such as seismic waves, due to its ability to handle long-term dependencies with high accuracy.

We developed a new model by integrating Linear Interpolation and LSTM, referred to as 'Linear Interpolation + LSTM'. Initially, we created interpolated data at a sampling rate of 100 using Linear Interpolation. This interpolated data, along with existing target data at a sampling rate of 100, was then processed with the LSTM to produce trained data at the same rate. Subsequently, we combined the trained data with the original data at a sampling rate of 100 to achieve a final output at a sampling rate of 200. The performance of our model was compared to that of traditional interpolation methods (Linear Interpolation, Spline Interpolation) and LSTM model.

2. Methods

2.1 Traditional Interpolation

The first method of interpolation discussed is Linear Interpolation, which calculates the interpolated value by taking the average of two neighboring values, formulated as:

$$(1)\ \ y = y_0 + \frac{(y_1 - y_0)}{(x_1 - x_0)} \times (x - x_0)$$

Linear Interpolation determines the intermediate value between two data points along a straight line. The coordinates (x_0, y_0) and (x_1, y_1) are employed to approximate the y-value corresponding to any given x-value.

Another method, Spline Interpolation [3], employs higher-order polynomials for connecting data points with smoother, curved segments.

$$(2)\ \ S_i(x) = a_i + b_i(x - x_i) + c_i(x - x_i)^2 + d_i(x - x_i)^3$$

Here, $i = 0, 1, \ldots, n-2$ and, $S_i(x)$ represents the spline function over the interval $[x_i, x_{i+1}]$. The coefficients a_i, b_i, c_i, and d_i dictate the spline's curvature for the given segment. Spline Interpolation, thus, constructs a continuous, differentiable, and smooth curve through the dataset.

Figure 1 illustrates the application of both Linear and Spline Interpolation methods to original data. Linear Interpolation connects data points directly, forming linear segments, whereas Spline Interpolation creates a smooth, curved path through the points, demonstrating its capability to estimate values with greater continuity and smoothness.

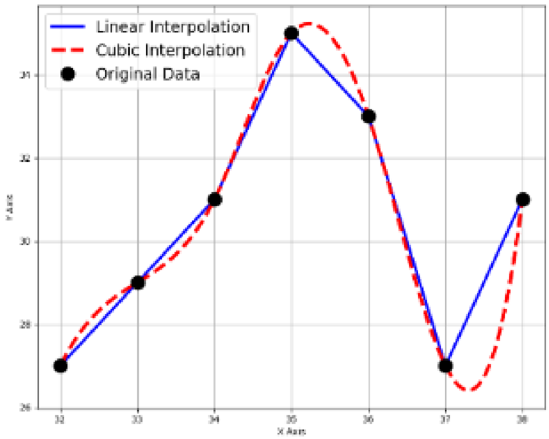

Fig. 1. Linear & Spline Interpolation

2.2 Linear Interpolation + LSTM modeling

Linear Interpolation, while a foundational method for data generation, is inherently limited in its accuracy as it merely averages two adjacent values. Employing deep learning to refine interpolation-generated data holds the potential for more precise predictions. The deep learning method we use focuses on the Long Short-Term Memory (LSTM) model, which is a key type of Recurrent Neural Network (RNN). The LSTM model was specifically designed to overcome the vanishing gradient problem encountered by traditional RNNs, enabling it to effectively retain information over extended periods. This characteristic is particularly advantageous for enhancing the analysis of time series data. By training an LSTM with time series data refined through interpolation, we significantly enhance the model's predictive capability.

The methodology of combining Linear Interpolation with LSTM modeling is depicted in Figure 2. The process unfolds as follows:

1. Before the process, we prepare the original data, which has a sampling rate of 200.

2. Initially, we extract only the odd-indexed data points from the original dataset, which has a sampling rate of 200, to create a downsampled dataset with a sampling rate of 100.

3. Linear Interpolation is then applied to this downsampled data to achieve an upsampling back to a rate of 200.

4. Subsequently, we extract only the even-indexed points from the interpolated data to serve as the training dataset.

5. The target dataset is formulated by extracting the even-indexed points from the original dataset.

6. An LSTM model is constructed and trained using the data at a sampling rate of 100 derived from step 4.

7. Finally, a new model is established by integrating the newly generated data, at a sampling rate of 200 from the LSTM, with the previously downsampled odd-indexed data.

In the integrated dataset, the odd-indexed points remain as they were in the original dataset, whereas the even-indexed points represent the LSTM-predicted values following interpolation.

3. Experiments and results

3.1 Dataset and preprocessing

This study utilizes a dataset comprising 188 days of mini-seed format data, observed at a sampling rate of 200 by Nanomatrix seismometers, spanning from November 24, 2022, to June 15, 2023. To enhance the data quality for training, detrending was applied to eliminate linear trends and mean values. Subsequently, the daily data were segmented into 1-minute intervals (equivalent to 60 seconds multiplied by a sampling rate of 200) for processing and analysis.

3.2 Training

3.2.1 Linear Interpolation + LSTM, LSTM Models

The dataset was stratified into three subsets for training, testing, and validation, distributed in a 6:2:2 ratio, respectively.

Table Ⅰ: Summary of dataset

Total	Training	Validation	Test
261,725	157,035	52,345	52,345

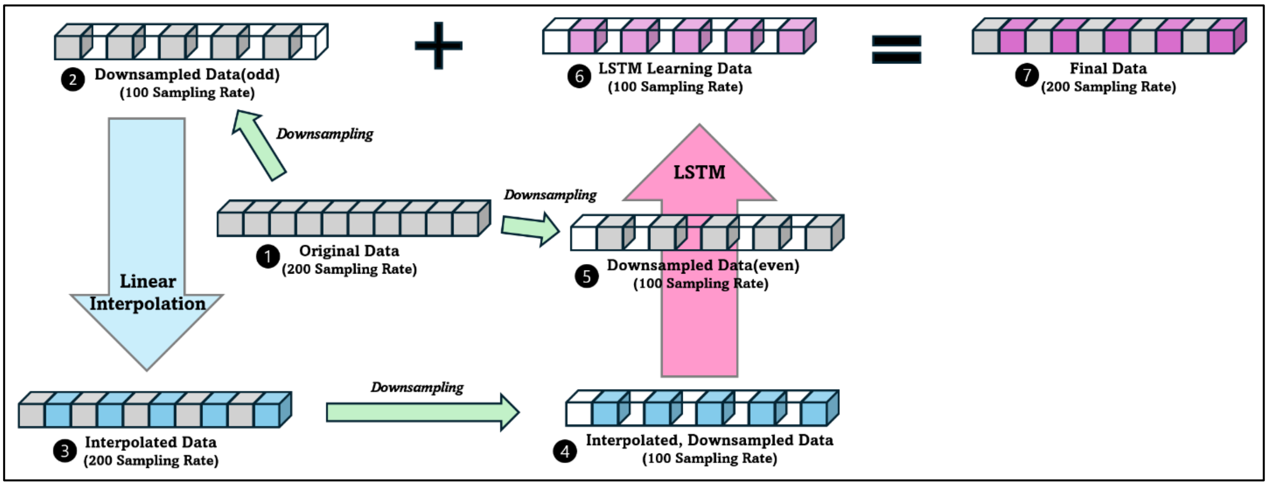

Fig. 2. Linear Interpolation + LSTM Modeling

For the optimization algorithm, the Adam optimizer was selected due to its efficiency in combining the benefits of Momentum[4] and RMSprop algorithms. This approach adaptively modifies the learning rates for individual parameters, facilitating quicker convergence and enhancing the stability of the learning process. The models were trained using a batch size of 32 across 25 epochs.

Performance evaluation of the data involved the use of Mean Square Error (MSE)[5] and Log Spectral Distance(LSD) [6] metrics. These tools were employed to quantify errors both in the time domain and frequency domain, enabling a comprehensive assessment of model accuracy and efficacy.

3.2.2 Linear Interpolation & Spline Interpolation

Training utilized data from 188 days, processed in 1-day increments. We extracted only the odd-numbered data points from the original dataset, recorded at a sampling rate of 200, to create a downsampled training dataset at a sampling rate of 100. Subsequently, we performed upsampling back to a sampling rate of 200 using both Linear and Spline Interpolation techniques.

3.3 Experiment Results

3.3.1 Comparison Using MSE and LSD

The performance of the Linear Interpolation + LSTM model was compared against that of the Linear and Spline Interpolation methods, as well as a standalone LSTM model, utilizing Mean Square Error (MSE) and Log Spectral Distance (LSD) as evaluation metrics.

Table Ⅱ : Comparison with Models

Model	MSE	LSD
Linear Interpolation + LSTM	0.84	7.47
LSTM	3.11	7.55
Linear Interpolation	2.71	12.43
Spline Interpolation	2.89	23.83

Upon analyzing the interpolation results, Linear Interpolation demonstrated a mean square error (MSE) difference of approximately 0.18 and a log spectral distance (LSD) difference of around 11 when compared to Spline Interpolation. These findings indicate that the predictions made by Linear Interpolation, which employs the average of two adjacent data points, outperform those derived from the complex higher-order polynomial formula utilized in Spline Interpolation.

Further comparison between the Linear Interpolation + LSTM model and the performances of the standalone LSTM model and independent interpolation methods revealed that the Linear Interpolation + LSTM model exhibits superior performance in both MSE and LSD metrics. This suggests that preprocessing the training data with an effective method like interpolation to enhance learning efficiency, followed by subsequent LSTM training, leverages the strengths of both approaches. Specifically, it combines the high MSE performance of interpolation with the effective LSD performance of LSTM, thereby enhancing overall model efficacy.

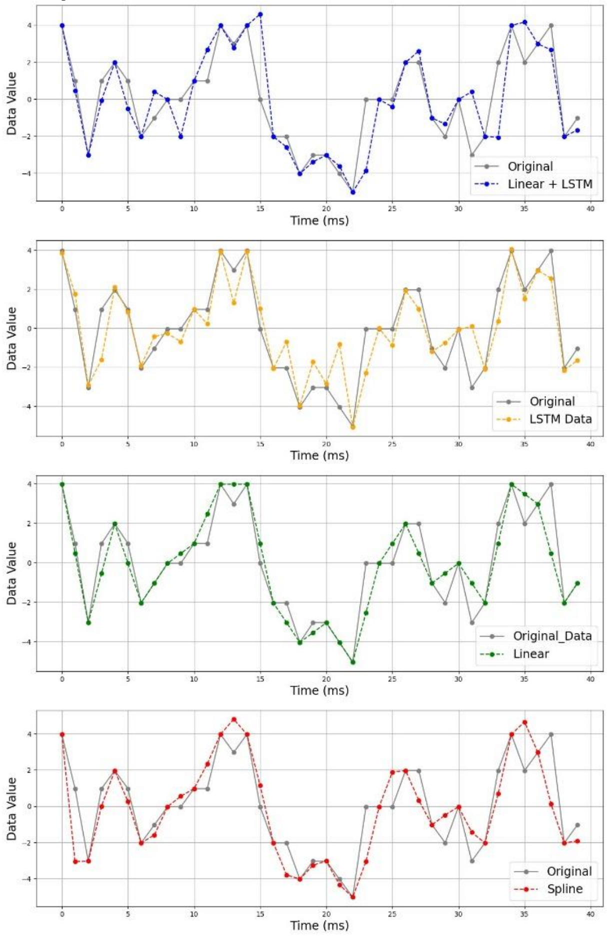

Fig. 3. Comparison of Original and Generated Data

3.3.2 Spectrogram Analysis

The spectrogram analysis for Linear Interpolation + LSTM, relative to the original data of an earthquake event occurring on April 30, 2023, at 19:03:29, 16 km east of Okcheon-gun, Chungcheongbuk-do, South Korea—with a depth of 6 km and magnitude of 3.1—reveals no significant disparities in decibel levels below 50 Hz. However, examining the frequencies above 50 Hz, it is observed that the amplitudes are mirrored, akin to a decalcomania, around the 50 Hz mark, amplifying the signal in both directions. Given the substantial amount of data below 50 Hz, it is imperative to focus on learning from more data above this frequency threshold to address these discrepancies effectively.

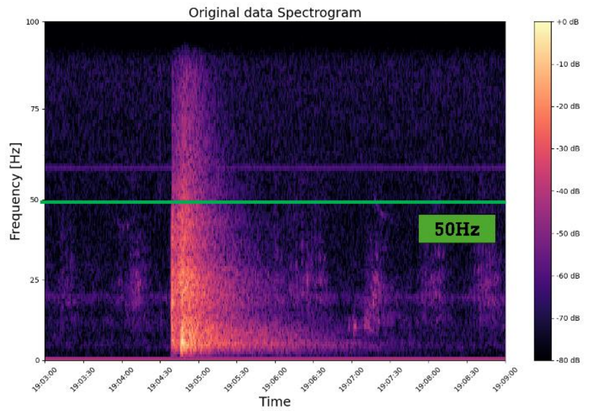

Fig. 4. Spectrogram of Original Data

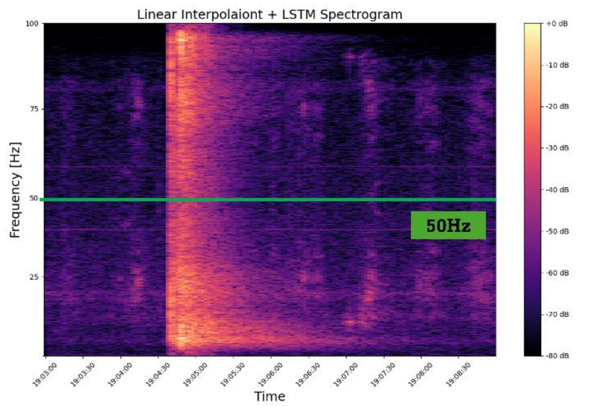

Fig. 5. Spectrogram of Linear Interpolation + LSTM

3.Conclusion

This study presents a new approach to upsampling seismic signals, showing that combining suitable data processing methods with the right deep learning model can exceed the performance of traditional interpolation techniques or standalone deep learning models.

Our new method, which integrates the Linear Interpolation + LSTM model, has shown to outperform both interpolation and LSTM models alone, achieving improvements of approximately 2 in mean square error (MSE) and 0.1 in log spectral distance (LSD). Despite these advancements, the comparison of the spectrogram with the original data highlighted a challenge: the predominance of data values below 50Hz compared to those above, indicating a limitation in capturing data above 50Hz effectively.

This method holds promise for enhancing the processing of seismic data collected by the Korea Meteorological Administration. We anticipate that the improved upsampling technique will facilitate the acquisition of higher-quality data, crucial for further research endeavors. Among these is the development of Smart Seismic Sensors[7], which we are currently underway at a sampling rate of 200, and the study of Seismic Data Processing and Prediction (SDPP). This work paves the way for more sophisticated analyses and applications in the field of seismology, leveraging advanced deep learning to enhance earthquake preparedness and response strategies.

4.Future Work

In our study, we enhanced performance by synergizing interpolation and deep learning models. Nonetheless, there exists potential for further improvements through various factors such as time slicing, choice of interpolation type, and selection of deep learning models. Throughout this research, data was segmented into 60-second intervals. The performance and processing time can differ based on the duration of these segments. Exploring optimal time slices beyond the 60-second framework may influence the efficiency and accuracy of upsampling.

Moreover, our investigation primarily focused on linear interpolation, chosen for its superior standalone performance. However, alternative interpolation methods might yield better results when combined with deep learning techniques. Future studies could explore a wider array of interpolation strategies to ascertain the most effective combinations.

The choice of deep learning model also plays a crucial role in performance variation. While this study utilized RNN-based LSTM models, exploring other architectures such as 3D Convolutional Neural Networks (CNNs), which account for spatial dimensions, or generative AI models, could lead to significant advancements. Investigating these alternatives may pave the way for developing more accurate and efficient models for seismic signal processing.

ACKNOWLEDGEMENT

This work was supported by the National Research Foundation of Korea (NRF) grant funded by the Korea government (Ministry of Science and ICT) (No. RS-2022-00144482)

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