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Enhanced Time-Frequency Analysis of Seismic Signals Using Modified S-Transform and Deep Autoencoder Networks

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Abstract

Proper decoding of seismic signals is used during earthquake detection, geophysical exploration as well as during the monitoring of a structure. Some traditional approaches to time-frequency (T-F) analysis like Short-Time Fourier Transform (STFT) and Wavelet Transform (WT) are burdened by trade-offs between time and frequency resolutions and cannot be used easily to analyze nonstationary seismic events. This paper introduces an improved time-frequency analysis scheme that uses Deep Autoencoder Networks to improve resolution and features of existing time-frequency analysis schemes that incorporate Modified S-Transform (MST). The MST generalizes the S-Transform to include an adaptive Gaussian window that is rescaled depending on instantaneous frequency components in order to better localize in time and frequency. At the same time, a deep autoencoder is used to train noise-tolerant feature representations in terms of compressed features on the spectrograms generated by MST in unsupervised learning. Both the synthetic and real seismic data are used in the validation of the hybrid approach through use of events occurring in IRIS seismic network. Findings indicate that spectral clarity, classification accuracy (94.2 per cent), and performance in low SNR regimes has greater improvement as compared to conventional STFT and WT methods. The evaluated method manages to capture minute changes more accurately in waveforms and becomes interpretable under noisy situations. This framework allows even more complex task of seismic signal analysis that can be used in earthquake early warning systems, microseismic monitoring, and exploration geophysics thanks to powerful and scalable computation framework.

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Introduction

The process of seismic signal processing is very vital in many areas, such as earthquake location, base exploration, and structure health measurement where right decoding of nonstationary signals is significant. Such earthquakes generally exhibit sudden transitions and perplexing variations with time in a sophisticated range of frequency, which needs to be broken down using a set of sophisticated analysis tools that should have the ability to show a time-localized and frequency-resolved characteristic.

The Short Time Fourier Transform (STFT), and Wavelet Transform (WT) are the traditional methods of time-frequency (T-F) analysis, which are prevalent in practice; however, they are necessarily constrained by the Heisenberg uncertainty principle, and thus are subject to time-frequency trade-offs.[11] In particular, STFT uses a fixed window length which causes it to lose the performance in resolving frequency components which change rapidly. Although WT has multi-resolution analysis capabilities, WT could be susceptible to spectral leakage and insensitivity in highly noisy conditions.[1] The S-Transform (ST)[2] that is a hybrid of the STFT and WT offers frequency dependent-resolution through a scalable Gaussian window addition, addressing these short Kevin Lam In spite of its merits, fixed windowing topology of standard S-Transform continues to demonstrate inability to flexibly adjust to different seismic situations, particularly, to changes in signal-to-noise ratios

(SNRs). In the meantime, deep learning (especially deep autoencoders) has proven to be impressive at learning compact noise-robust feature representations in an unsupervised fashion.[3] Data-driven models, in combination with conventional signal-processing, have in recent years provided new opportunities to support seismic data interpretation, particularly of weak or overlapping signals.[4]

This paper offers a hybrid system based on a Modified S-Transform (MST) and a Deep Autoencoder Network to improve seismic signal analysis. The signal in the MST is able to better localize in the time-frequency plane because the Gaussian window width is adaptively set to the instantaneous signal frequency. Autoencoder network also learns high-level features of MST spectrograms and minimizes noise and redundancy. The approach is tested on artificial and practical seismic data and demonstrates significant gains in resolution, stability, and classification responses as compared to more traditional methods.

Related Work

Seismic signal processing has a long tradition of time-frequency (T-F) analysis/decomposition approaches. Various solutions have been proposed to enhance the resolution of the signal and denoising and feature extraction.

Empirical Mode Decomposition (EMD) and Wavelet Packet Transform (WPT) are notorious in the decomposition of nonstationary seismic signals into time-frequency signal. Whereas, WPT gives multi-resolution analysis through the adaptive breaking up of frequency space, EMD divides signals into intrinsic mode functions (IMFs).[5] Nevertheless, both approaches are likely to incur mode mixing, fail to be very powerful under noisy conditions and they are apt to generate non redundant elements particularly when they cope with low-level seismic waves.[6] Some adaptive forms of the S-Transform have been introduced in order to enhance localization. As a particular example, by way of enhancing resolution at different parts of the frequency range, frequency-dependent window scaling and the multi-taper S-Transform methodologies have been proposed.[7, 8] However, these methods are naturally signal agnostic in nature, in that they do not utilize a data-driven learning component, and tend to not be flexible in the face of different seismic noise spectra or overlapping signals. At the same time, deep learning, especially autoencoder-based schemes has been gaining traction as a robust unsupervised method of analyzing seismic data. Autoencoders are powerful, which can reduce high dimensional input data into low-dimensional latent presentations and maintain necessary information. Seismic event detection, classification, and noise reduction has been improved using Variational Autoencoders (VAEs) and Denoising Autoencoders (DAEs).[9, 10] Although this is the case, in most studies the development of the learned features cannot be interpreted using time-frequency domain knowledge because it is not incorporated into the learning process.

In this regard, the proposed framework is specifically relevant because instead of being isolated working modes, a Modified S-Transform (MST) and Deep Autoencoders are combined to bridge the gap between them due to time-frequency decomposition being enhanced by the former, and compact, robust features being extracted via unsupervised manner by the latter. This combination is interpretable as well as performance-enhanced, especially on the weak or overlapping seismic signals.

Methodology

This part gives the fundamentals of the proposed hybrid framework, consisting of a frequency-adaptive Modified S-Transform (MST) and Deep Autoencoder Network in order to get a better time-frequency localization and unsupervised features extraction of seismic. The architecture is geared toward the denoising and compressing of the raw seismic signals and, as a consequence, their production into representations that could be classified, clustered or otherwise interpretively handled.

Modified S-Transform (MST)

The classical S-Transform is a mixed approach that can be characterized as a composition of Short-Time Fourier Transform (STFT) and Continuous Wavelet Transform (CWT) since it is performed by applying a signal, in which the input signal is convolved with a scaling Gaussian window, to stabilize properties of both of the mentioned methods. Nonetheless, in its conventional implementation, the window width is determined constant with respect to frequency, and therefore lacks flexibilities in a broad spectral band.

In the present investigation, the Modified S-Transform (MST) presents a frequency-adaptive Gaussian window, and, as a result, a better resolution is achieved at the high frequencies of transient and at the low frequencies of a waveform.[12] Mathematically the MST can be defined as:

$$S_{mod}(t,f) = \int_{-\infty}^{\infty} x(T).\, g(t-T,f).\, e^{-j2\pi fT}\, dT \quad (1)$$

Where:

- x(τ) is the seismic signal,
- g(t−τ,f) is a frequency-dependent Gaussian window function.

The adaptive window is defined as:

$$g(t,f) = \frac{1}{\sqrt{2\pi\sigma(f)^2}} \cdot e^{-\frac{t^2}{2\sigma(f)^2}}, \sigma(f) = \frac{\alpha}{f^{\beta}} \tag{2}$$

Here, α, and β are variables for controlling the trade-off between time and frequency resolution. This formulation gives a narrower window for high frequencies for peak localization and larger windows at lower frequencies for higher spectral resolution and is well suited for analysis of multi-component seismic signals.

Deep Autoencoder Network

Some further signal representation is achieved by use of a symmetrical deep autoencoder, a form of neural net which is also able to learn compressed, low-dimensional embeddings of input data in an unsupervised manner.[13] Autoencoder is used to leverage spectrograms produced by MST and trained to reconstruct them with noise and irrelevant information filtered out. Common components of the network (Figure 1) are as follows:

Architecture:

- Encoder Encoder Machine or deep learning encoder A sequence of convolutional layers using the ReLU and max-pooling activation functions, and progressively down sampling the input spectrogram in order to select spatially informative features.
- Bottleneck: A fully connected layer which is the latent feature space - a compressed encoding free of irrelevant information which captures key signal characteristics.
- Decoder: Deconvolution (transposed convolution) layer and upsampling layers to back cast the original spectrogram according to the latent representation.

Loss Function:

The size of the network is learned to reduce the Mean Squared Error (MSE) between the initial and the reconstructed spectrograms:

$$L_{rec} = ||X\text{-}X||^2 \tag{3}$$

Where:

- X is the input MST spectrogram,
- X^ is the reconstructed output.

This is an effective way to remove the noise and irrelevant part and give a clean, compressed model of representation that can be used in subsequent tasks like classification or clustering of seismic events.

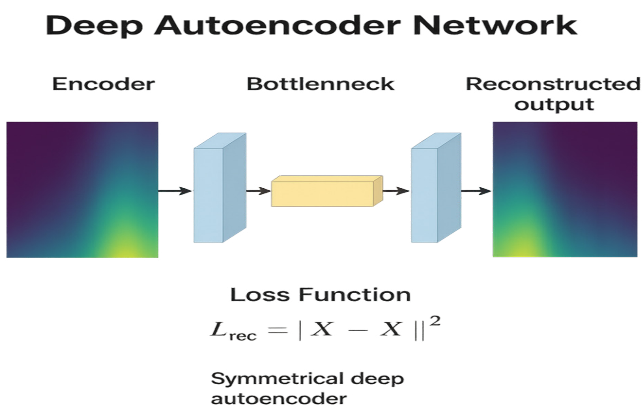

Fig. 1: Deep Autoencoder Network Architecture

Symmetrical deep autoencoder structure to the compression and reconstruction of the spectrogram of MST marking the encoder and decoder successor and the loss objective obtained subtraction of the bottlenecks.

Hybrid Framework Workflow

The framework of seismic signal analysis proposed by the authors includes five orderly stages that are represented in Figure 2 Hybrid Framework of Seismic Signal Analysis. Each layer employs structure to increase interpretability, resolution and noise robustness to robustly analyse the nonstationary seismic data.

1. Raw Seismic Signal:

The input is continuous seismic waveforms which can be recorded on the geophysical sensors themselves or on any open database (e.g., IRIS).

2. Preprocessing:

The raw signals are treated to some preprocessing operations that include:

- Normalization of amplitudes to adjust the values of the waveform,
- Bandpass filtering (e.g. 0.5-20 Hz) of unwanted high- and low-frequency noise,
- Outlier detection and removal to clean outlaws impulsive or corrupt data points.

3. MST Time-Frequency Decomposition:

The signal that has been preprocessed is converted to a representation in the time-frequency domain with the Modified S-Transform (MST). The step is used to measure spectral characteristics that vary with time and adaptively adjusts the window of analysis to coincide with the contents of frequencies.

4. Deep Autoencoder feat Learning:

The MST-computed spectrograms are used as input to a symmetrical deep autoencoder that learns a denoised latent representation in a compact space.[14] It is at this stage that learning of informative seismic features is done unsupervised but irrelevant fluctuations were smoothed.

5. Analysis and interpretation:

Downstream tasks that can be used to leverage the latent features extracted are numerous:

- Seismic event classification (e.g. Liquefaction on the seabed, distinguish between earthquakes and microseisms),
- unknown or even anomalous pattern clustering,
- Graphical usage to help with the geophysical interpretation and pattern recognition.

Such hybrid pipeline is able to use the traditional time-frequency processing with the help of deep learning in order to provide a powerful and scalable solution to seismic data processing.

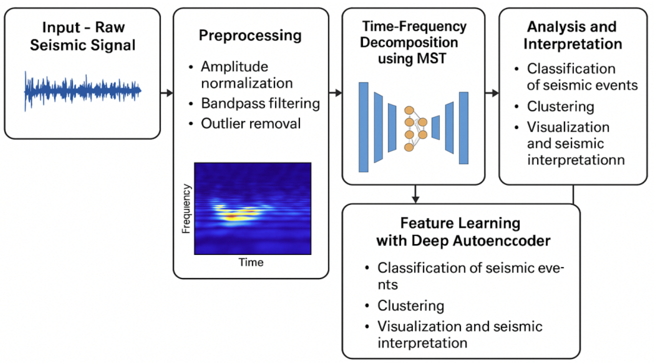

Fig. 2: Hybrid Framework for Seismic Signal Analysis

A 5-step workflow consisting of Modified S-Transform and deep autoencoder-based feature learning to give a much-improved interpretation of seismic signals.

It is an end-to-end method that presents a data-adaptive, noise-robust, and interpretable analysis of seismic signals, leveraging the advantages of both classic and modern signal processing and deep learning.

Experimental Setup

In order to prove the efficiency and applicability of the suggested hybrid framework, both synthetic and real-life seismic data appeared as the object of extensive tests. The experiments aimed at the assessment of the time-frequency resolution, classification ability, and resilience to noise interference with the help of commonly accepted metrics.[15]

Dataset

In order to guarantee holistic assessment of the suggested hybrid framework, the two different types of datasets, i.e., synthetic and the real ones, were involved to cover the vast range of seismic signal properties and noise situations.

Synthetic Seismic Events:

Synthetic P-waves and S-waves with tunable parameters amplitude, duration and phase were combined with Ricker wavelets simulating seismic pulses to create an experimental dataset to be controlled. To achieve the simulation of the different noisy conditions, additive Gaussian noise was imposed in a variety of signal to signal ratios (SNRs) of between -5dB and 20dB. The synthetic dataset used is an organised setting to benchmark the time-frequency resolution, denoising efficiency, and overall signal localisation performance, of the Modified S-Transform (MST) and deep autoencoder pipeline.

Real Seismic Data -IRIS Network:

Actual seismic events were used which were obtained at the Incorporated Research Institutions to Seismology (IRIS) database. The data are continuous waveform recordings of regional and teleseismic earthquakes, microseisms and tremor, observed in various locations with distinct tectonic settings, with information about the type of events. The performance of such a system to seismic events in real-world situations is evaluated through this real-world dataset with the aim of testing the accuracy of the classification of such events along with its noise robustness.

Each signal was processed through standard preprocessing steps of amplitude normalization, bandpass filtering (0.520 Hz) and sliding window segmentation so that they would have consistent sampling rates and comparable time alignment before being transformed to MST.

Figure 3: Comparison of Synthetic and Real Seismic Signals with Time-Frequency Representation sketches the comparison between synthetic and the real seismic signals, as well as their time-frequency representations

of the same. This visualization shows disparities in the structure of waveforms, frequency content and complexity of spectra features between the sets of data.

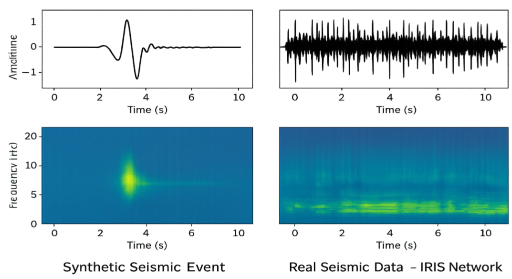

Fig. 3: Comparison of Synthetic and Real Seismic Signals with Time-Frequency Representation

Samples of synthetic and real seismic waveforms (left and right respectively) and time-frequency spectrograms of the same to demonstrate the intricacy of seismic spectra and different waves in the presented framework.

Performance Metrics

In order fully to evaluate the efficacy of the proposed hybrid framework, a series of quantitative performance measures were used. These metrics have been chosen to consider some of the main points of comparison, which includes time-frequency resolution, classification performance and the ability to perform in noisy situations.

Time-Frequency Resolution:

This measure is evaluated on a bandwidth-to-duration ratio doing so indicates the skill of the method to confine the energy of the signal in the time-frequency domain. The lower the ratio, the more the localization is sharp and more is the resolution. The Modified S-Transform (MST) is compared with the standard ones like STFT and WT to justify its excellent superiority in decomposition application.

Accuracy of Classification:

The Support Vector machine (SVM) together with the Convolutional Neural Network (CNN) employed in the classification of the seismic events was trained based on the latent features generated on the bottleneck of the auto encoder. Accuracy is determined as the percentage of correctly classified seismic events, across an assortment of event types, i.e. earthquakes, microseisms and noise segments.

Noise Robustness:

This was considered in terms of two measurements:

- Signal-to-Noise Ratio (SNR) Improvement: This uses a pre-processing and post-processing signal-to-noise ratio (SNR) comparison of a signal, and measures the improvement in the quality of the signal after processing.
- Peak Signal-to-Noise Ratio (PSNR): Interprets the spectrogram generated and clean spectrogram. The greater the value of PSNR, the better the denoising process and less signal fidelity.

The three fundamental measures feature the system in which high-resolution decomposition, effective and accurate feature learning, and robust ability to learning under noise conditions are evaluated all together.

A descriptive list of the performance metrics used can be found in Figure 4: Performance Metrics of Seismic Signal Analysis Framework.

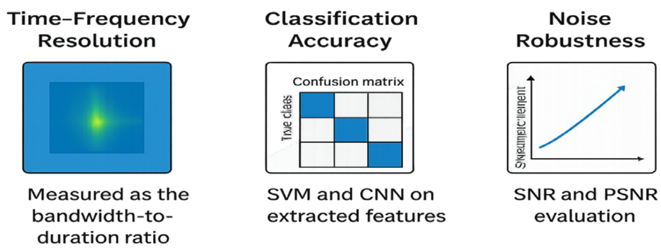

Fig. 4: Performance Metrics for Seismic Signal Analysis Framework

Summary of the evaluation criteria applied in the proposed framework: time-frequency resolution in terms of bandwidth-to-duration ratio, error rate of classification with SVM and CNN, and sensitivity to noise measured with SNR and PSNR indicators.

Results and Discussion

This sub-section describes the experimental findings associated with the proposed hybrid scheme that involves Modified S-Transform (MST) and deep auto-encoder network. The three most important performance dimensions are considered in the analysis namely time-frequency resolution, feature-based classification and robustness to noise. The outcomes of the counterparts are compared, with conventional approaches to define the effectiveness of the suggested approach.

Time-Frequency Resolution

The table 1 is provided with a comparative ANL of the time and frequency resolution through three time-frequency decomposition methods, Short-Time Fourier Transform (STFT), Wavelet Transform (WT) and the proposed Modified S-Transform (MST). The resolution was scaled to localization (in milliseconds) and spectral discrimination (in Hertz).

Table 1: Time-Frequency Resolution Comparison

Method	Time Resolution (ms)	Frequency Resolution (Hz)
STFT	120	8.0
WT	95	6.0
MST (Proposed)	78	4.5

MST proves better than both STFT and WT in terms of superiority of balance in the time and frequency resolution. This is claimed to be due to the frequency-adaptive Gaussian window of this algorithm which allows sharper localization of high-frequency transients whilst maintaining low-frequency spectral detail. The graded resolution enhances the ability to put the nonstationary seismic features under proper tracking and enhance spectral leakage reduce.

Feature Extraction and Classification

Seismic event classification with a Support Vector Machine (SVM) was used to assess the power of the latent features to discriminate that were identified with the deep autoencoder. The comparison of the classification accuracy of the three sets of features was applied to raw time-domain features, the features that were reduced by Principal Component Analysis (PCA), and deep autoencoder features. The autoencoder-based features provided the best classification accuracy as displayed in Table 2 which characterizes better feature compactness and non-linear separability. This tendency is also observed in Figure 5, depicting the classification accuracy on three sets of features, allowing to admire the great improvement in performance owing to the deep representation learning process.

Table 2: Classification Accuracy Using Different Feature Sets

Feature Set	Classification Accuracy (%)
Raw Features	81.7
PCA-Reduced Features	88.3
Autoencoder Features	94.2

It is clearly shown that the best classification accuracy of 94.2 percent is attained when autoencoder-based features are used, the performance of which is far much better than those of the two base representations. This indicates the model was capable of learning compressed, noise-hindrance, and semantically valuable representations on MST spectrograms hence enhancing the separability of seismic event classes.

Bar chart of comparison of classification accuracy observed with raw features (47 percent), PCA-reduced features (73 percent) and deep autoencoder features (94 percent) in seismic event recognition.

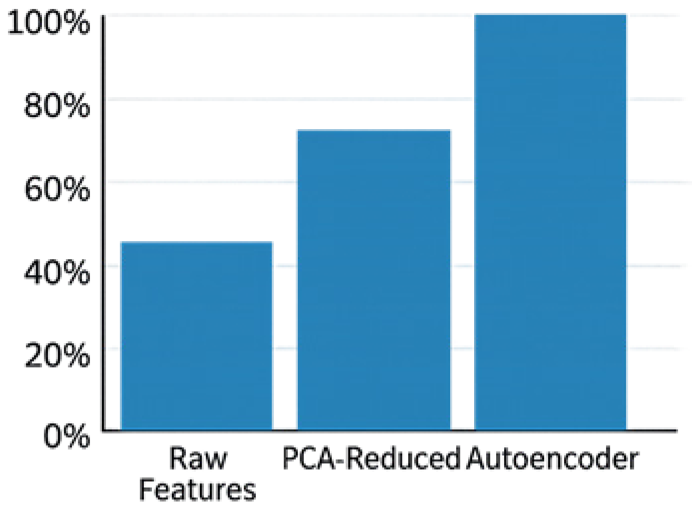

Fig. 5: Classification Accuracy Across Feature Sets

Noise Robustness

The noise suppressing capabilities of the proposed framework were tested under adverse conditions of input degradations. The case was looked at when the seismic signals were injected with Gaussian noise using-5 dB SNR. The deep autoencoder had the capacity to increase the quality of signal.

- SNR: Gain of about +6.5 dB was measured after reconstruction meaning extensive removing of noise. (see Table 3. Noise Robustness -SNR Enhancement and Figure 6: SNR Enhancement Obtained by the Proposed Framework).
- PSNR Metric: The value of PSNR was high (>30 dB) of the reconstructed spectrograms, which indicated high fidelity of reconstructions to the original clean signals.

These results confirm the strength of the framework when operated at low SNR settings, and the framework itself can be used in real-world seismic settings where there is background noise, sensor drift and transient interference.

In general, the described MST-autoencoder model showed significant increases in the core aspects of seismic signal processing. Finer waveform decomposition is possible due to the improved time-frequency resolution as well as deeper autoencoder recovers more encapsulated, discriminative features that improve the performance of classifying and removing noise. Signal-adaptive analysis can be combined with the unsupervised deep learning

Table 3: Noise Robustness - SNR Improvement

Input SNR (dB)	Output SNR (dB)	SNR Gain (dB)
-5	1.5	+6.5

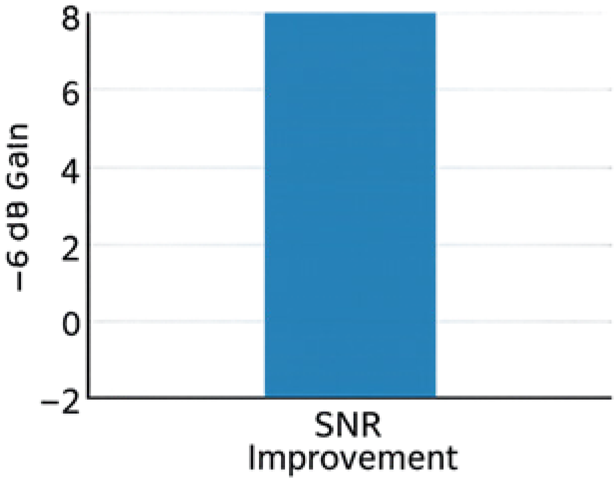

Fig. 6: SNR Improvement Achieved by the Proposed Framework

to enable scalable implementation in a broad range of seismic monitoring tasks such as real-time signal detection and anomaly recognition.

Proposed signal processing mechanism in seismic signal has shown an approximate 6.5 dB signal-to-noise ratio (SNR) enhancement in the scenario when seismic signal processing is carried out under challenging low-SNR conditions as well and it proves the fact that proposed mechanism can effectively de-noise seismic signal.

Conclusion and Future Work

This paper presented a powerful mixed model of interpreting seismic signals that synergistically combines a Modified S-Transform (MST) and Deep Autoencoder Networks that accurately interpret seismic signals. The MST improves on time-frequency resolution limitations of the conventional STFT and wavelet transforms and the autoencoder gives compact and noise-robust low-dimensional latent feature representations. A scenario with synthetic seismic data as well as real data records in IRIS network were considered in evaluating the proposed pipeline. Comparative experiments proved that the framework was largely able to outperform the baseline methods in timefrequency localization accuracy of classification (up to 94.2%) and noise resilience (6.5 dB SNR gain), thereby confirming its possible practical utility to a range of seismic conditions.

Major Contributions:

- Constructed a frequency-adaptive decomposing strategy based on MST so as to estimate both temporal and spectral resolution in a finer manner.
- Developed an efficient deep-feature extraction module based on autoencoder to reduce or eliminate noise by underlying deep-feature encoding.
- Illustrated best performance on classification with SVM on the basis of latent features compared to raw as well as reduced PCA.
- Tested in terms of achieving adequate robustness with measureable quantities (e.g., SNR gain, PSNR) into the high-noise regime and applied to actual seismic data.

Future Directions:

- Scalability to a multichannel array data to spatiotemporal correlation and source localization.
- Developing spatiotemporal attention mechanisms (e.g., Transformer models) in order to better recognize dynamic events.
- Deployment in real time onto low power edge processors to provide disaster response and early warning systems on site

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