Generative Neural Networks in Nuclear Test Monitoring

Mikhail Rozhkov[1], Enrique Castillo[2], Ilya Dricker[1],
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INTRODUCTION AND MAIN RESULTS

We developed Temporal Generative Adversarial Neural Networks for producing quality multicomponent synthetic seismograms. By representing the data from a group of sensors as a single hypercomplex number, the network's operations become more expressive and parameter-efficient. It learns a single transformation on a richer mathematical object, instead of independent transformations on multiple real-valued channels.

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Objectives

Various nuclear test monitoring techniques require numerous waveforms and expect good spatial coverage of seismic source:

Master-Event-based hypocenter determination - aseismic areas and those lacking IMS sufficient coverage has no templates. Scarcity of nuclear explosion records for most test sites is an issue.

Imbalanced Learning – in detection and classification techniques nuclear explosions is an underrepresented class. Labeled data is extremely scarce. Need to minimizing the impact of imbalance - need efficient data augmentation. Without enough data, the network is likely to simply overfit to the few examples it has, failing to generalize to new, unseen events.

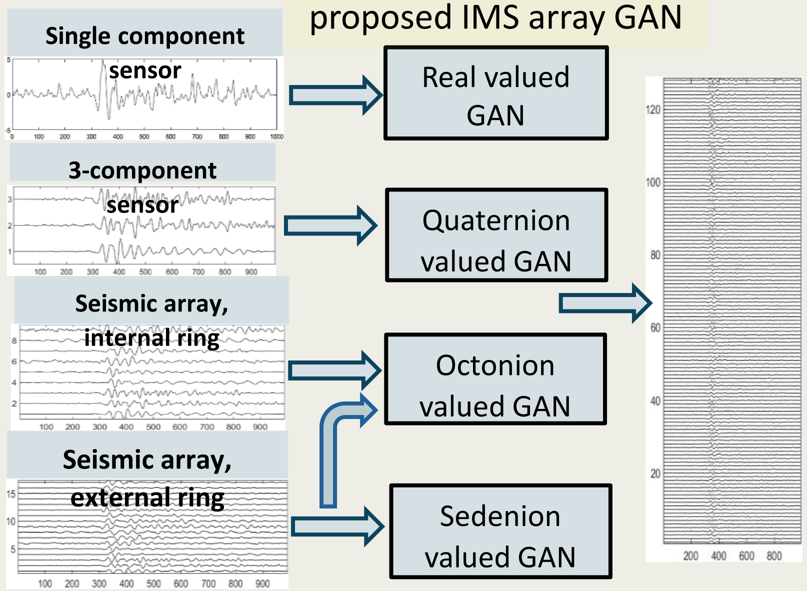
Generative Networks, GN – a novel way of producing realistic, high-quality synthetic metadata and time series. Low output diversity is an issue. Need to estimate different GNs, including multidimensional GNs.

This is where a hypercomplex approach offers a powerful and elegant solution. Instead of relying solely on the data to discover all the underlying patterns, we can embed known physical or geometric relationships directly into the network's architecture. This is a form of *hypercomplex inductive bias*, where we bake a knowledge of the problem into the model itself.

Methods

Specifically for the 3-component seismic array based CTBT monitoring, we learned a hypercomplex approach to seismic data deep learning, like we did before with the multilinear tensor constructions. By representing the data from a group of sensors as a single hypercomplex number (1D to 16D), the network's operations become more expressive and parameter-efficient. It learns a single transformation on a richer mathematical object, instead of independent transformations on multiple real-valued channels. This acts as a powerful regularizer, guiding the network to learn physically meaningful features and mitigating the overfitting that plagues data-scarce problems.

General structure of the proposed IMS array GAN



Results / Conclusion

We developed Hypercomplex (HC) Deep Model approach to seismic data augmentation and accessed it with data from 5 DPRK nuclear explosions recorded globally at the IMS arrays and single 3C stations. To achieve it, Deep Octonion and Sedenion* Generative Adversarial Networks were implemented based on 1->16 Cayley-Dickson construction, producing highly diverse data to mitigate the risk of bias in the further model's training and allowing to learn a broader range of seismoacoustic records, leading to greater location or discrimination accuracy and robustness. This innovation aligns with current research in geometrically-structured learning and physics-informed neural networks.

Generative Networks, especially HC adversarial branch, is as an important approach in seismic monitoring, since the IMS array's geometrical structure perfectly fits the HC numbers geometrical structure. They can produce sufficient number of synthetic waveforms based on empirical rather than known theoretical approaches.

CTBTO-hosted Expert Technical Analysis Spot Check Tool, SCT and tentatively ParMT (Moment Tensor Based Depth Determination) are among the consumers of the GN's products.

GNs are also a vital alternative to the known data augmentation techniques used in *Imbalanced Learning* for producing single and multichannel patterns.

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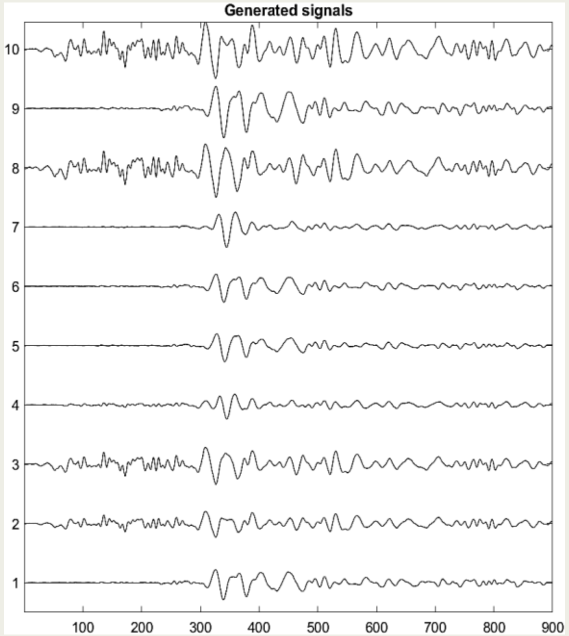
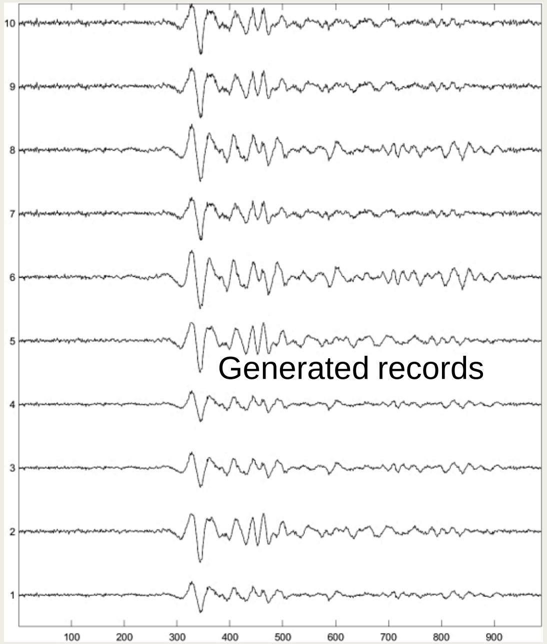
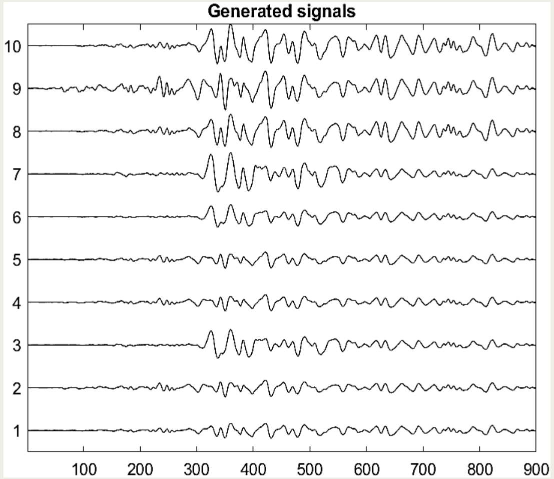
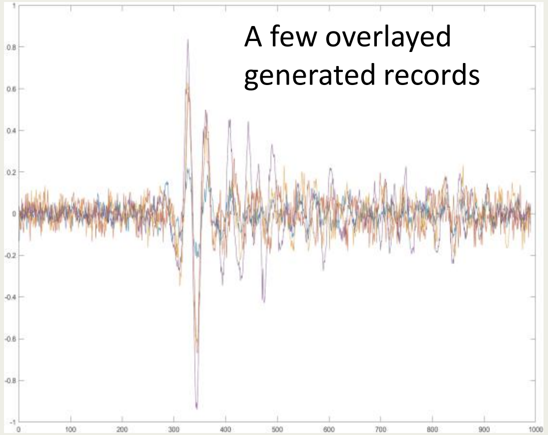
Comparing generated data of 1D TCCGAN with vanilla and LSTM GAN

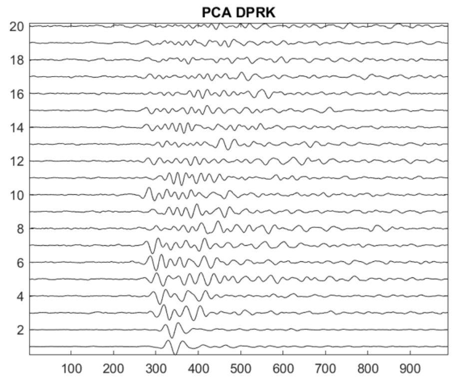


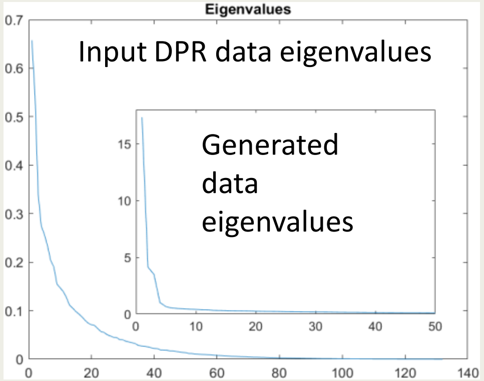


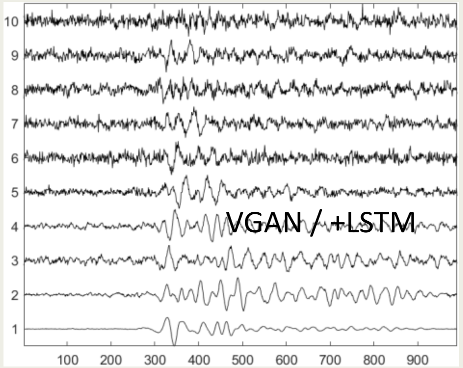


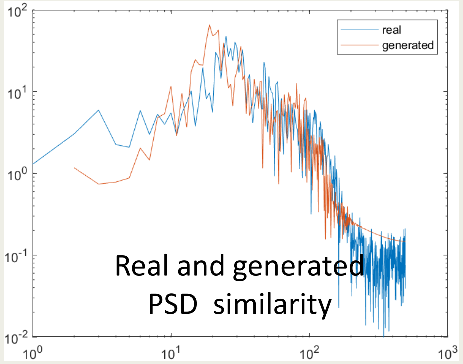


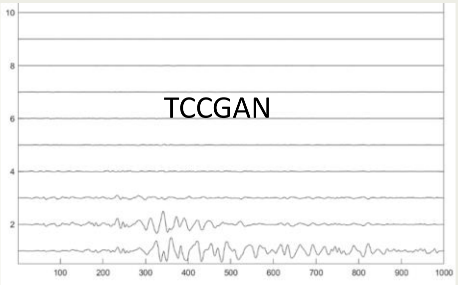
Principal components



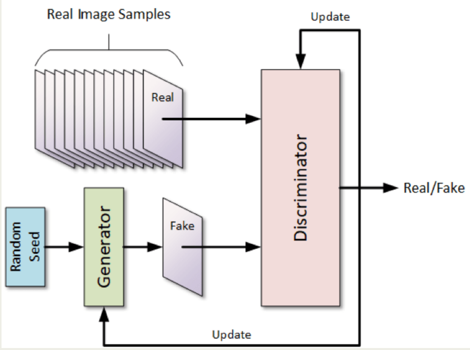








Data diversity of the fast dense vanilla GAN is even higher than the diversity of the more sophisticated Temporal Conditional Convolutional (TCC) GAN, but the output is a bit noisy. Still it's insufficient – see rapidly vanishing/degrading principal components). Compare with the DON-related slide.



Generator G produces new samples from random noise which appear very similar to the real ones after training. It attempts to reproduce the probability distribution of real data. A second model called discriminator (D) distinguishes between real and fake data. In the end, the G learned so well the probability distribution of input data *pdata(x)* to produce a sample that the D is no more able to distinguish it from real ones

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Some Multidimensional/Multichannel Time-Series Generative Models considered

Quaternion GAN (QGAN): Handles multichannel or multidimensional time-series data, leveraging quaternion representations to capture dependencies between channels.

Multivariate TimeGAN: Extends TimeGAN to handle multivariate sequences by jointly learning dependencies across multiple time-series.

Multi-Channel RCGAN: A variant of Recurrent Conditional GANs adapted for data with multiple correlated channels.

Conditional VAE for Multivariate Data: Extends CVAEs to deal with multivariate time-series, conditioning on cross-channel data.

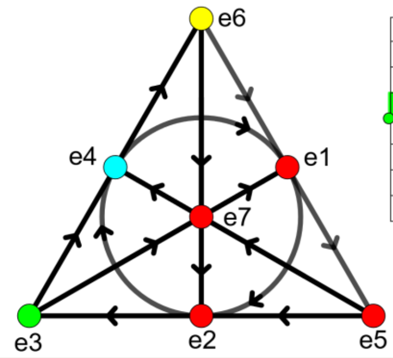
Multivariate Diffusion Models: Adaptations of diffusion-based approaches for multichannel time-series with complex dependencies.

Spatiotemporal GANs: Typically used for data with spatial and temporal characteristics, making them suitable for multichannel data that involves spatiotemporal dependencies.

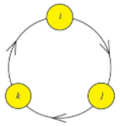
Multimodal Transformers: Transformer models adapted to learn across multiple time-series simultaneously, capturing dependencies between channels.

These models offer a range of approaches to handle both simple and complex time-series data structures. For multichannel or multidimensional time-series, ensuring the models can learn cross-channel relationships is key to maintaining fidelity in generated sequences.

Hypercomplex algebra



	e1	e2	e3	e4	e5	e6	e7
e1	−1	e4	e7	−e2	e6	−e5	−e3
e2	−e4	−1	e5	e1	−e3	e7	−e6
e3	−e7	−e5	−1	e6	e2	−e4	e1
e4	e2	−e1	−e6	−1	e7	e3	−e5
e5	−e6	e3	−e2	−e7	−1	e1	e4
e6	e5	−e7	e4	−e3	−e1	−1	e2
e7	e3	e6	−e1	e5	−e4	−e2	−1



Quaternion multiplication
$I^2 = J^2 = K^2 = IJK = -1$,

The octonions can be thought of as octets (or 8-tuples) of real numbers. Every octonion is a real linear combination of the unit octonions:

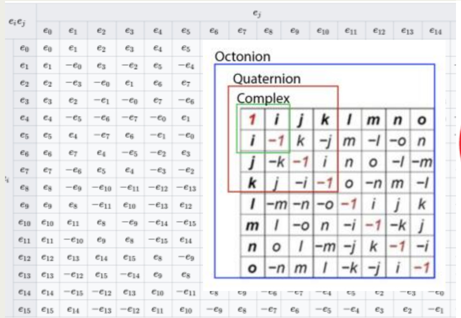
$$\{e_0, e_1, e_2, e_3, e_4, e_5, e_6, e_7\}$$

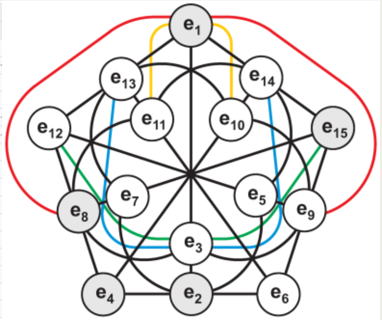
where e0 is the scalar or real element. That is, every octonion x can be written in the form

$$x = x_0 e_0 + x_1 e_1 + x_2 e_2 + x_3 e_3 + x_4 e_4 + x_5 e_5 + x_6 e_6 + x_7 e_7$$

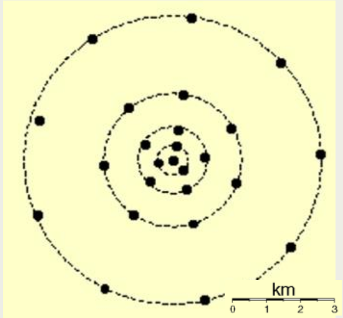
Sedenion is the 16-component number (1 Re and 15 Im)

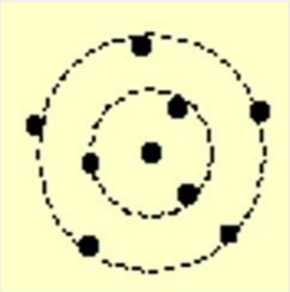
$$x = x_0 e_0 + x_1 e_1 + x_2 e_2 + \cdots + x_{14} e_{14} + x_{15} e_{15}$$





Physics- and Geometry-informed GAN: where algebra is mapped to physical array





The array geometry is projected directly to the octonion model, and the underlying wavefield related information is embedded into the GAN loss function related modules. For the shown above ARCESS IMS array (left), two outer rings can be described by the single sedenion or two octonion numbers, and the internal rings by octonions or quaternion models. SPITS array can be described by the single octonion + 1 quaternion. Since sedenions have a Null Divisor Problem (though we also embedded a sanity check with the depthwise separable convolution), scaling up to octonions is an option. The overall approach applies a strong inductive bias by embedding the physical correlations between sensors directly into the network's structure. This GINN/PINN would learn to generate synthetic waveforms that are not only realistic but also physically plausible given the unique geometry of the seismic network

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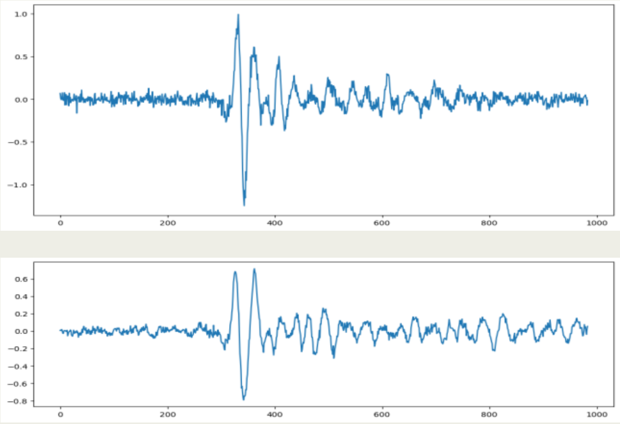
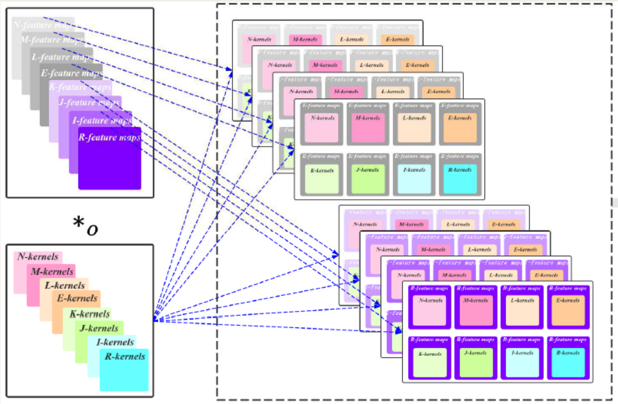
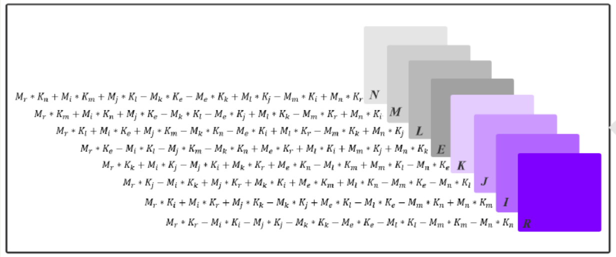
Vanilla Deep Octonion GAN output

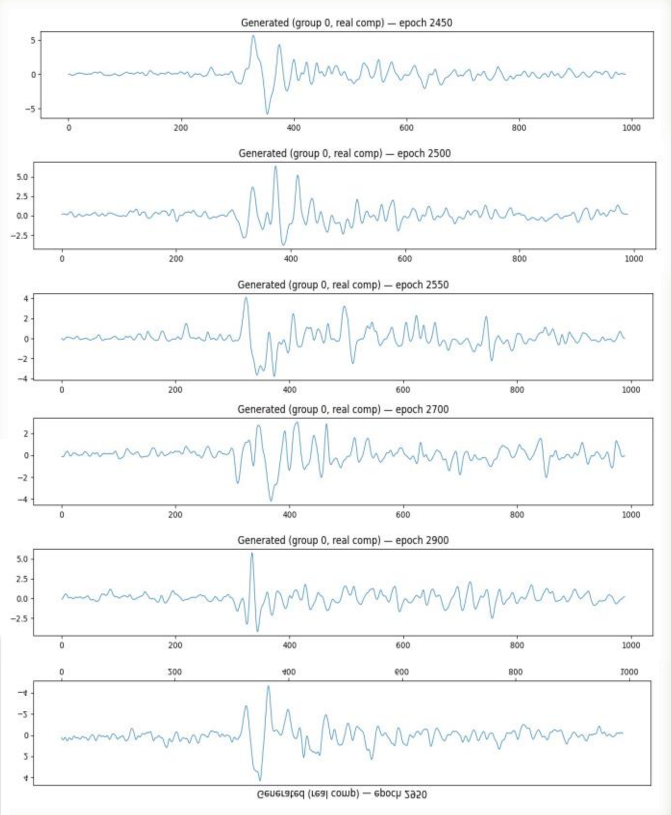




Octonion convolution block



Convolutional DOGAN output



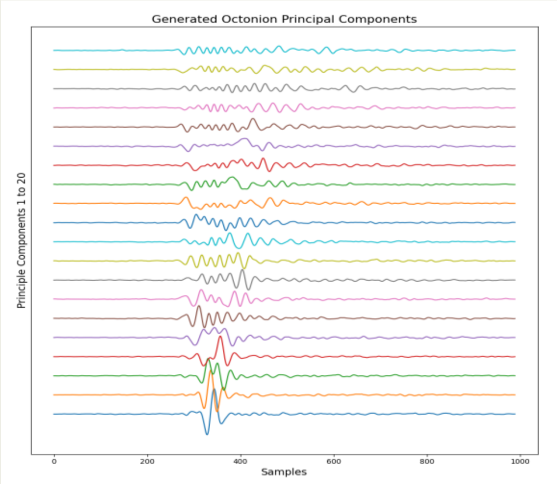
Convolutional Deep Octonion GAN generated data less noisy and more diverse.

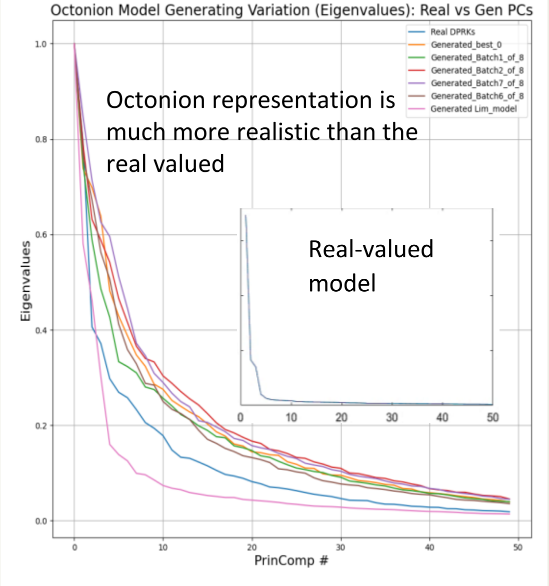
```python
def forward(self, x):
    B, Cin, T, O = x.shape; assert Cin == self.Cin and O == 8
    X = [x[..., i].contiguous() for i in range(8)]
    W = [self.weight[i] for i in range(8)]
    C = lambda w, xi: self._conv1d(xi, w)
    X0,X1,X2,X3,X4,X5,X6,X7 = X
    W0,W1,W2,W3,W4,W5,W6,W7 = W

    Y0 = C(W0, X0) - C(W1, X1) - C(W2, X2) - C(W3, X3) - C(W4, X4) - C(W5, X5) - C(W6, X6) - C(W7, X7)
    Y1 = C(W0, X1) + C(W1, X0) + C(W2, X3) - C(W3, X2) + C(W4, X5) - C(W5, X4) - C(W6, X7) + C(W7, X6)
    Y2 = C(W0, X2) - C(W1, X3) + C(W2, X0) + C(W3, X1) + C(W4, X6) + C(W5, X7) - C(W6, X4) - C(W7, X5)
    Y3 = C(W0, X3) + C(W1, X2) - C(W2, X1) + C(W3, X0) + C(W4, X7) - C(W5, X6) + C(W6, X5) - C(W7, X4)
    Y4 = C(W0, X4) - C(W1, X5) - C(W2, X6) - C(W3, X7) + C(W4, X0) + C(W5, X1) + C(W6, X2) + C(W7, X3)
    Y5 = C(W0, X5) + C(W1, X4) - C(W2, X7) + C(W3, X6) - C(W4, X1) + C(W5, X0) - C(W6, X3) + C(W7, X2)
    Y6 = C(W0, X6) + C(W1, X7) + C(W2, X4) - C(W3, X5) - C(W4, X2) + C(W5, X3) + C(W6, X0) - C(W7, X1)
    Y7 = C(W0, X7) - C(W1, X6) + C(W2, X5) + C(W3, X4) - C(W4, X3) - C(W5, X2) + C(W6, X1) + C(W7, X0)

    return torch.stack([Y0,Y1,Y2,Y3,Y4,Y5,Y6,Y7], dim=-1)  # [B,Cout,T,8]
```

PCA analysis





Deep octonion networks (DONs) as an 8-dimensional extension of Deep Network, the Deep Complex Network, and the Deep Quaternion Network (see Appendices). The main building blocks of DONs are octonion convolution, octonion batch normalization, and octonion weight initialization. The complexity of implementation holds it from wide dissemination so far. Recent tests showed better DON convergence, less parameters, and higher classification accuracy then the real, complex, and quaternion networks.

Hypercomplex deep learning offers significant benefits over traditional real-valued methods for processing multidimensional signals. These models provide a compact representation of multidimensional signals, enhancing generalization on unknown data.

Block diagram on the left is from: Wu, J., et al (2020). Deep octonion networks. Neurocomputing, 409, 218-232.

Appendices

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A Note on Octonions

- Octonions, eight-dimensional mathematical objects, have been explored as potential tools in physics, particularly in the context of the Standard Model, string theory and quantum gravity research as a potential framework for unifying quantum mechanics and gravity. They offer a way to describe a pre-spacetime, pre-quantum theory that could lead to a deeper understanding of the universe at its most fundamental level. Octonions, unlike real numbers, complex numbers, and quaternions, are non-commutative and non-associative. This non-associativity is crucial in the context of quantum gravity, where the very nature of spacetime at the quantum level is expected to be non-commutative.
- Non-commutative geometry, often used in conjunction with octonions, provides a mathematical framework for describing spaces where the order of operations matters, potentially mirroring the behavior of spacetime at extremely small scales.
- Penrose's twistor theory has a deep and evolving connection with octonions, particularly in attempts to find a complete theory of quantum gravity and to understand the Standard Model. While not an original part of the initial twistor formulation, the non-associative structure of octonions has been recognized by Penrose himself as potentially crucial for incorporating deeper symmetries and aspects of quantum gravity, with the algebra of bi-twistors providing a representation of split-octonions.
- However, the field is still under development, and many questions remain about the precise role of octonions in quantum gravity.

Why Octonions are Used?

- Algebraic Structure: The unique, non-associative nature of octonions aligns well with the fundamental symmetries and structures observed in physics, especially in higher dimensions.
- Unification: The octonions provide a mathematical tool for attempting to unify fundamental forces and particles in a single consistent theory, which is a major goal in theoretical physics.
- Geometric Properties: Their connection to geometric algebras and structures like the Fano plane offers new ways to visualize and understand the geometry of spacetime and particle interactions.

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Learning in Hypercomplex Domains

Hypercomplex deep learning leverages unique algebraic properties to improve learning operations and capture complex relationships in data.

- Hypercomplex algebras, such as quaternions and octonions, define specific mathematical operations that enhance learning.
- Learning operations in hypercomplex domains are influenced by the non-commutativity and non-associativity of these algebras.
- Hypercomplex layers, such as fully connected and convolutional layers, utilize domain-specific rules for multiplication and convolution.
- The ability to capture inter-channel and intra-channel correlations is enhanced in hypercomplex networks compared to real-valued networks.

Inductive Biases in the Hypercomplex Domains

Inductive biases in hypercomplex deep learning extend traditional biases by incorporating algebraic and geometric properties of hypercomplex numbers.

- Inductive biases can be categorized into relational and non-relational assumptions, influencing model generalization.
- Dimensionality bias emphasizes the strong correlations in multidimensional signals, aiding in effective representation and processing.
- Algebraic bias leverages unique properties of hypercomplex algebras to model complex interactions and relationships.
- Geometric bias utilizes the geometric properties of hypercomplex numbers to maintain structural integrity during transformations.

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Hypercomplex Number Systems in Deep Learning

Hypercomplex number systems, such as quaternions, enhance deep learning models by providing scale and viewpoint invariance.

- Hypercomplex systems can encode scale information, aiding in scale-invariant feature extraction.
- They are beneficial for tasks like object detection and image classification due to their perspective-invariant properties.
- Hypercomplex models can capture color invariance, improving model stability against noise and perturbations.
- Equivariance biases, such as rotation and translation, enhance robustness to random rotations and maintain informative transformations.

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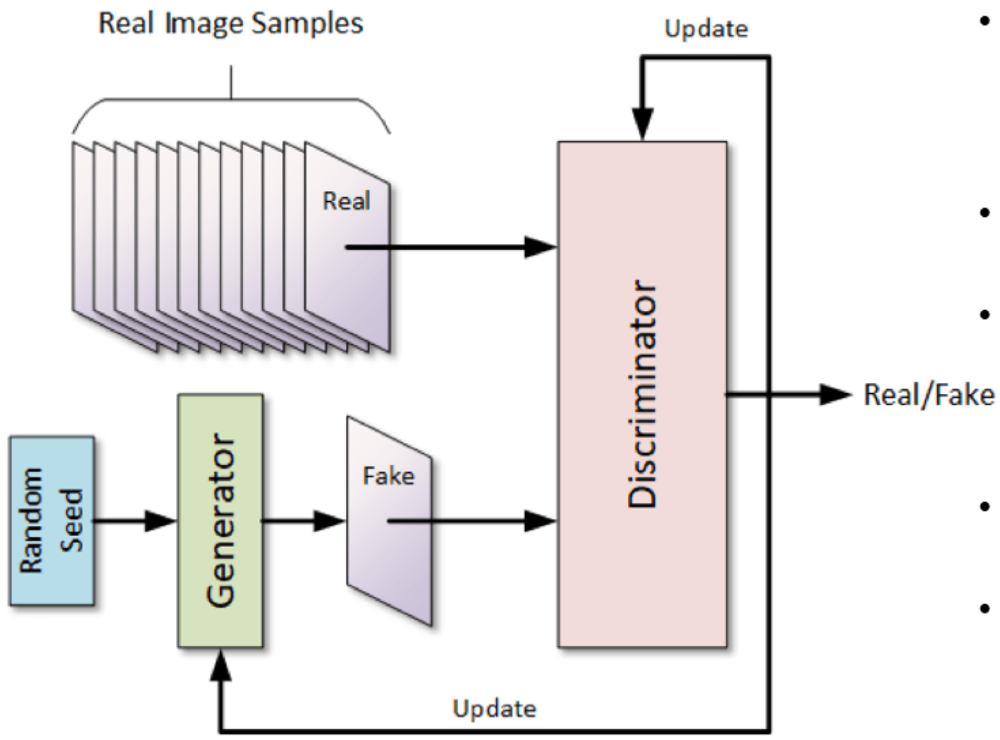
Basic GAN architecture



- A first model called generator (G) produces new samples from random noise which appear very similar to the real ones after training. It attempts to reproduce the probability distribution of real data.
- A second model called discriminator (D) distinguishes between real and fake data.
- In the end, the generator G learned so well the probability distribution of input data *pdata(x)* to produce a sample that the discriminator is no more able to distinguish it from real ones
- Thus, the optimal training of a GAN can be formulated as a minimax problem
- Through adversarial learning, GANs act as efficient generative models able to synthesize different but plausible artificial representations of any input data, by estimating their probability distribution

Figure: Bryon Moyer/Semiconductor Engineering

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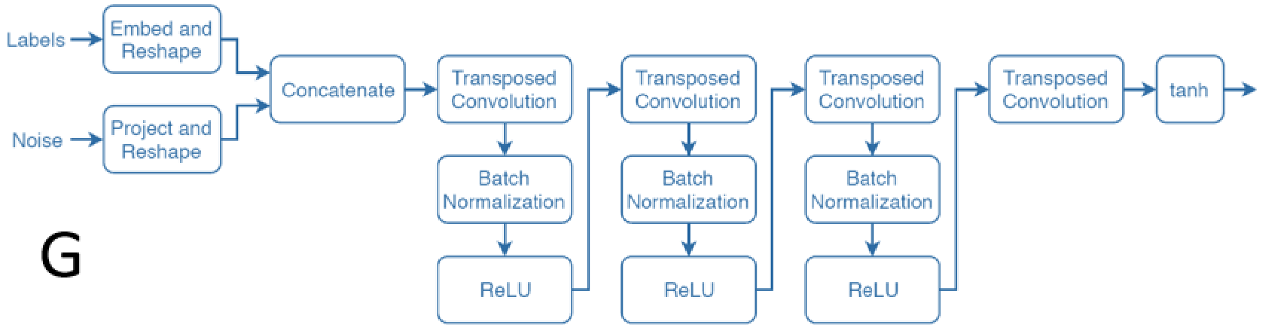
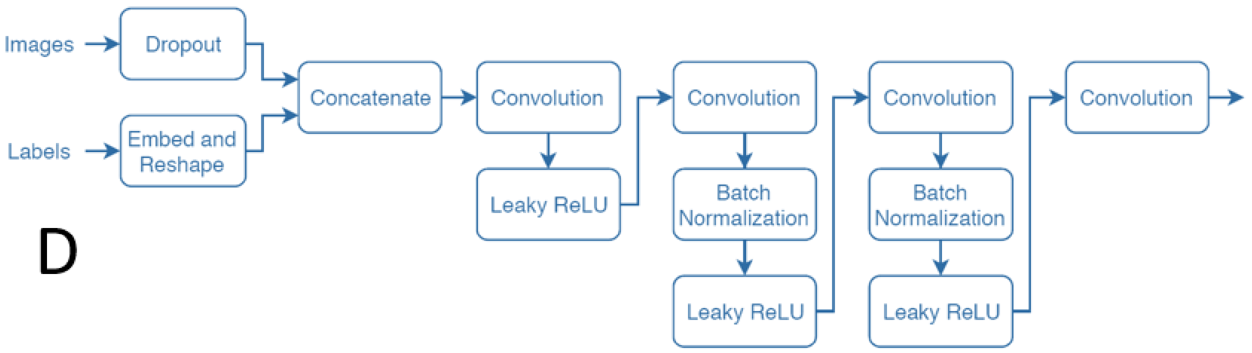
For seismic data, conditional convolution GAN was implemented



Generator network — Given a label and random array as input, this network generates data with the same structure as the training data observations corresponding to the same label. The objective of the generator is to generate labeled data that the discriminator classifies as "real."



Discriminator network — Given batches of labeled data containing observations from both training data and generated data from the generator, this network attempts to classify the observations as "real" or "generated." The objective of the discriminator is to not be "fooled" by the generator when given batches of both rea[l] and generated labeled data.

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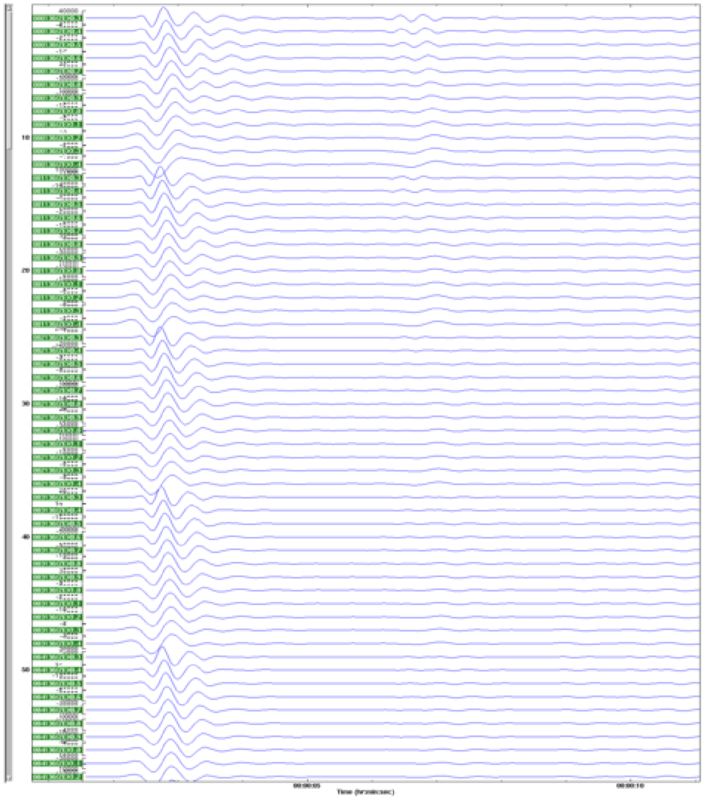
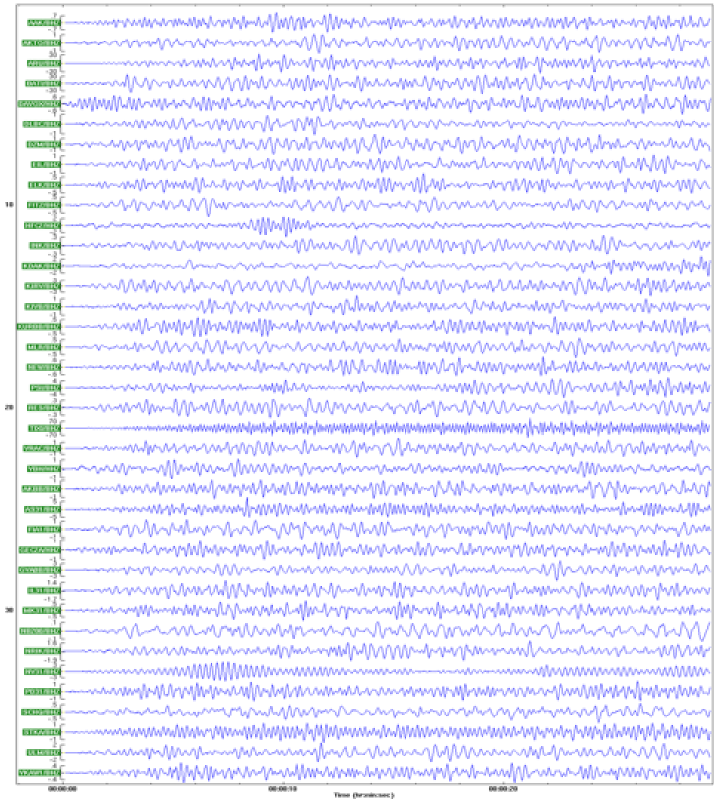
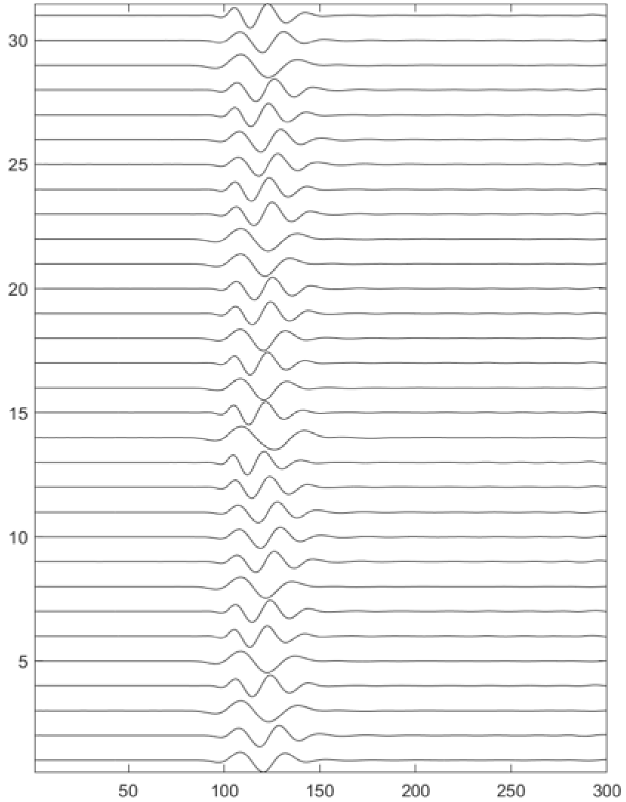
Synthetic test.



Calculated subset of the synthetic seismogram database, distance 30 degrees, different t* (0.3-1.4) and 3 depths (100-300 m) for 10 kT explosion in granite. Taken as a “true” signal.



Noise preceding explosions onsets at IMS stations, taken as a “false” signal



A subset of the faked generated data

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Generative Neural Networks in Nuclear Test Monitoring

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Mikhail Rozhkov[1], Enrique Castillo[2], Ilya Dricker[1],
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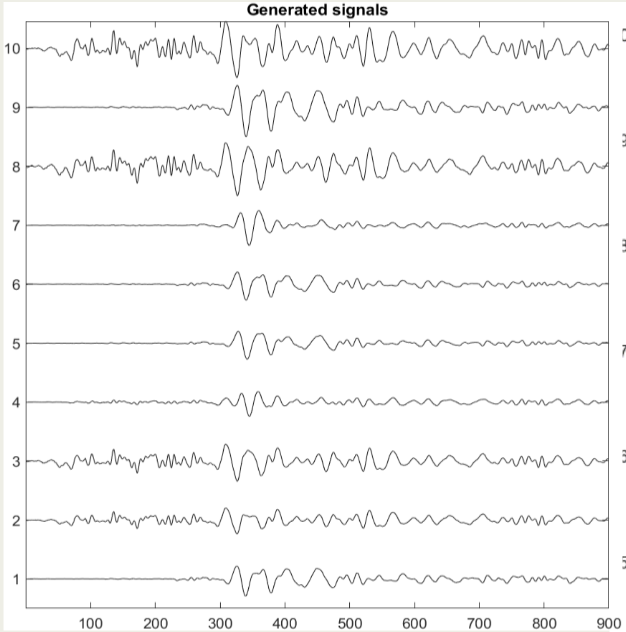
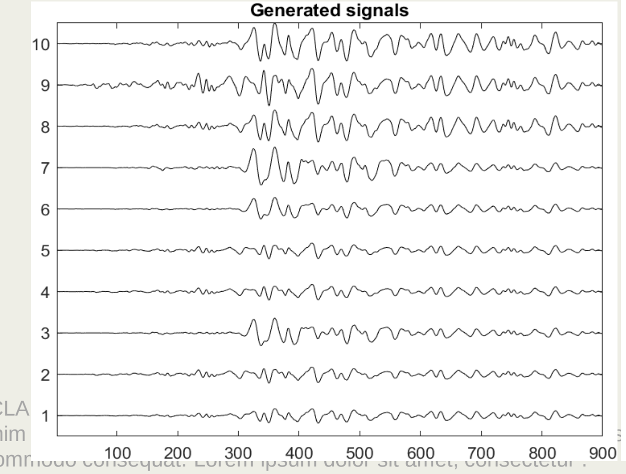
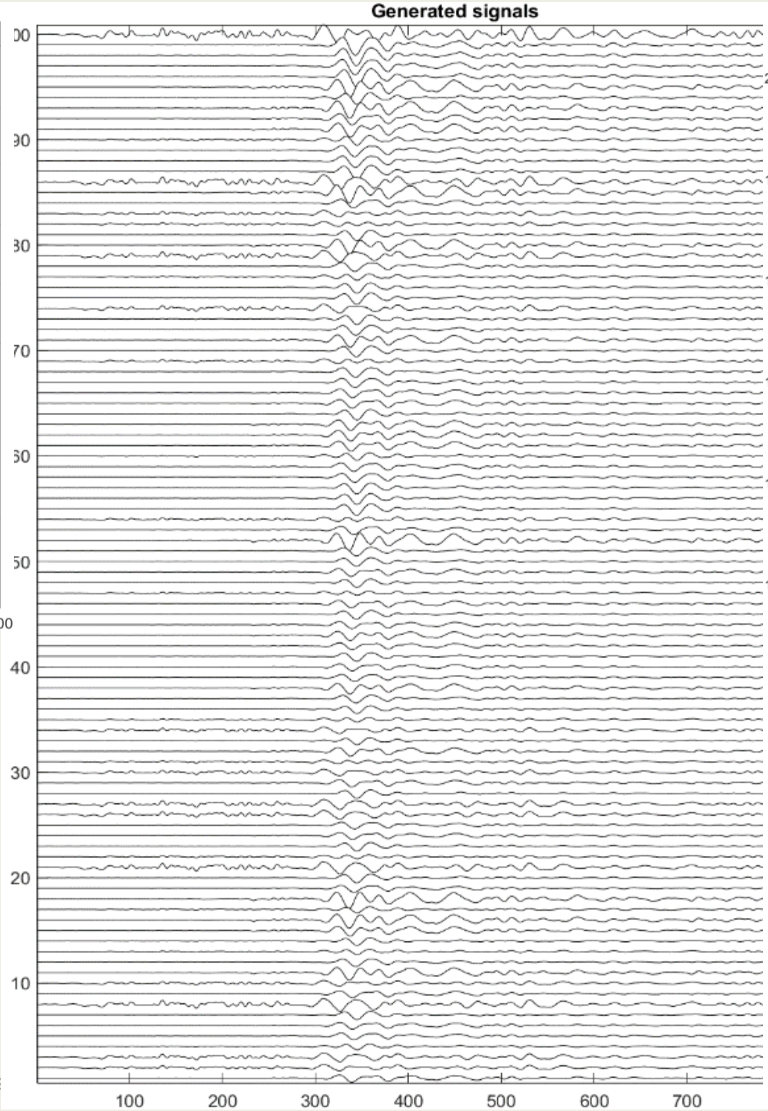
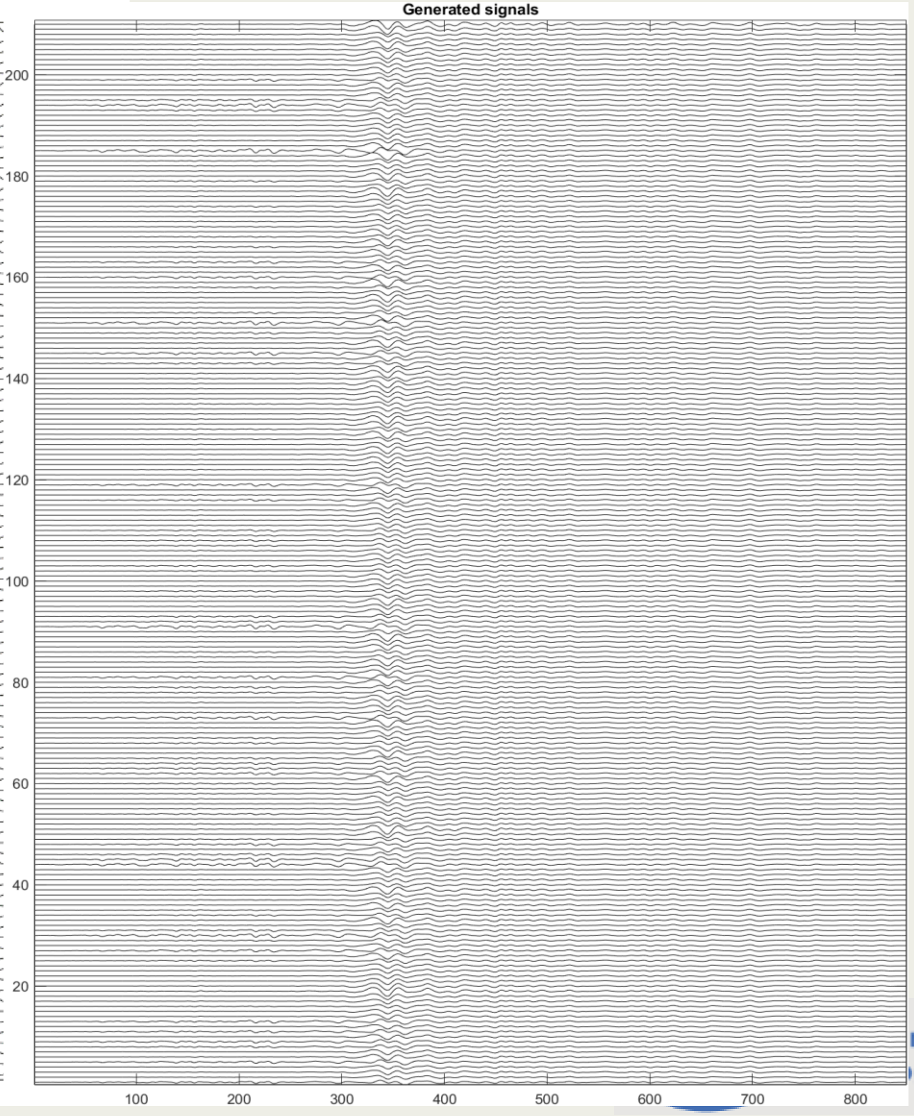
Convolutional GAN results: generated data from DPRK explosions training set









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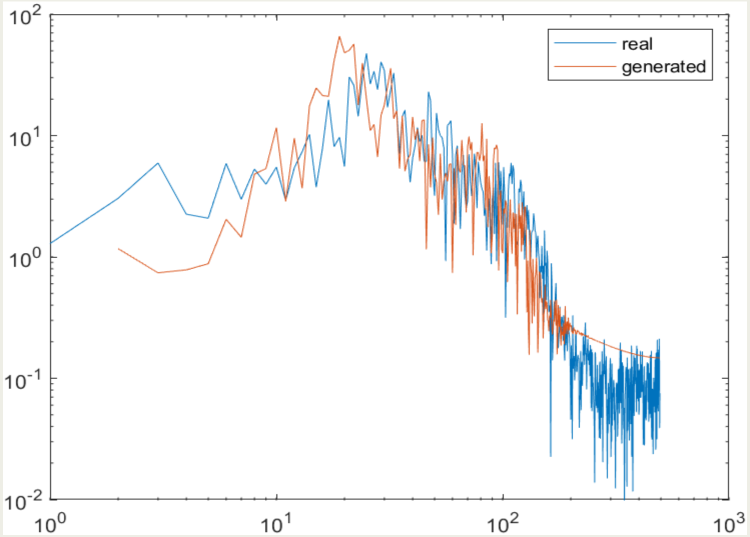
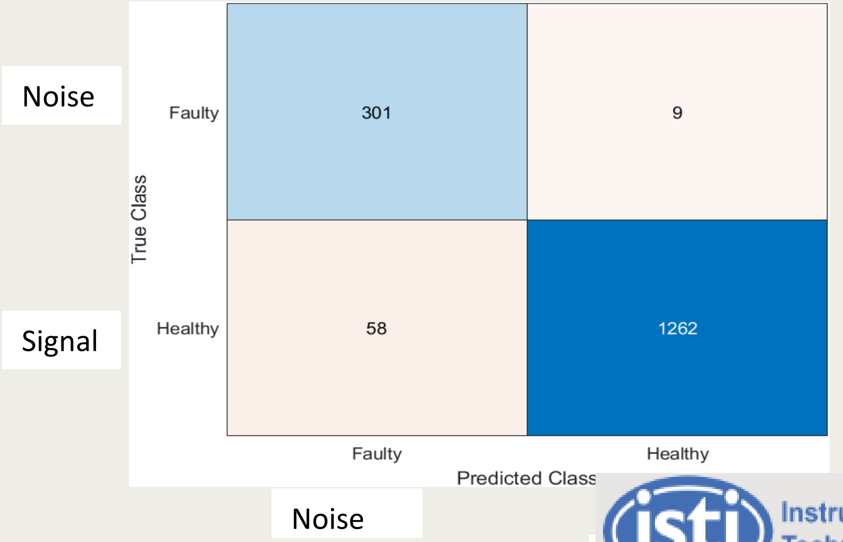
Analyzing results

To validate the results, the following was applied:

1. Principal component analysis (perform PCA on the features of the real signals and project the features of the generated signals to the same PCA subspace)
2. Comparing real and generated PCA latent behavior (eigenvalues slope - concavity) to estimate the diversity of generated data
3. Comparing the spectral characteristics of real and generated signals
4. Predicting labels of real signals. For example, train an SVM classifier based on the generated signals and then predict whether a real signal is healthy or faulty



The confusion matrix shows pretty good degree of accuracy. 1320 true signals were tested and 58 of them recognized as noise, while out of 310 noise signals only 9 were recognized as true.



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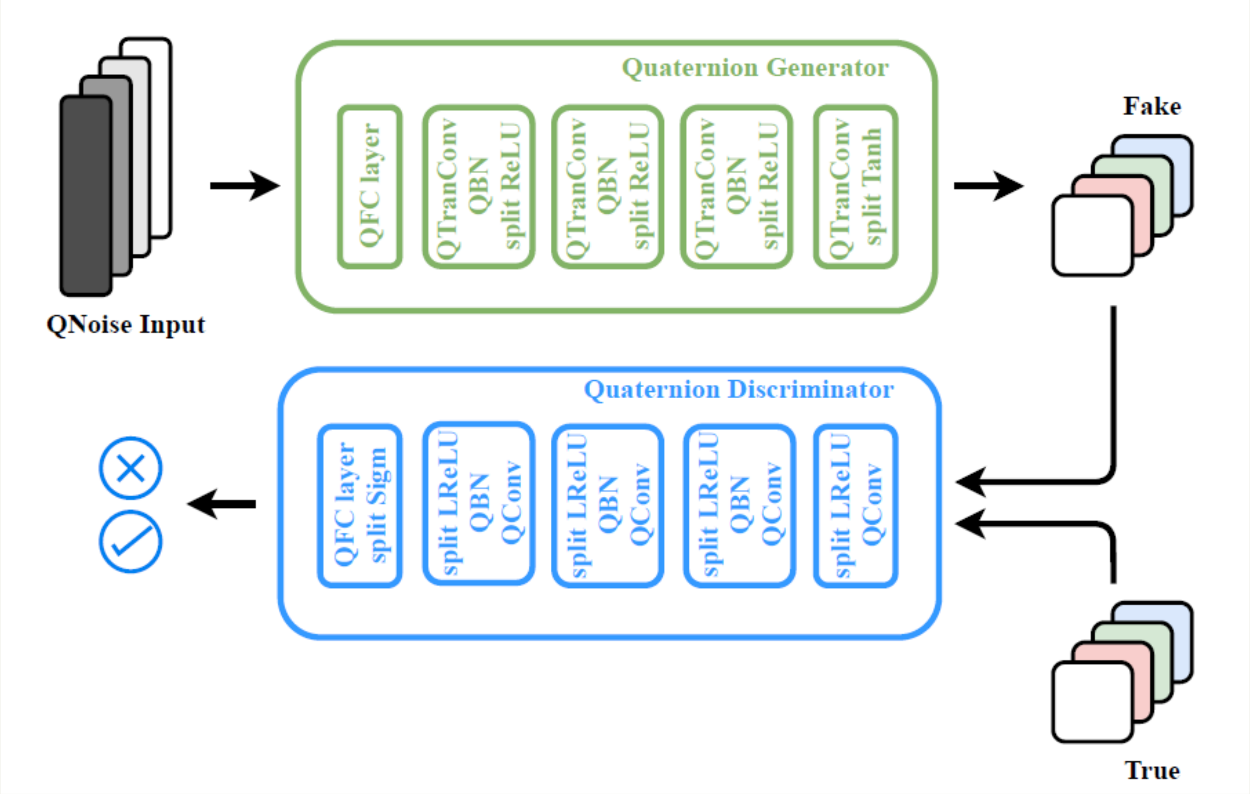
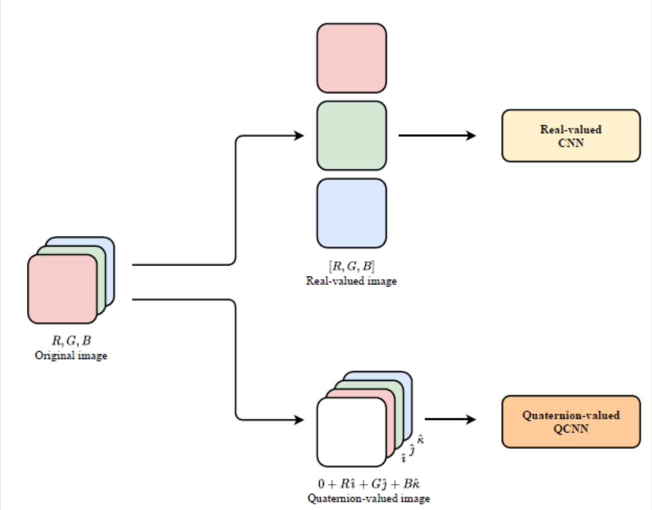
Quaternion Vanilla GAN architecture

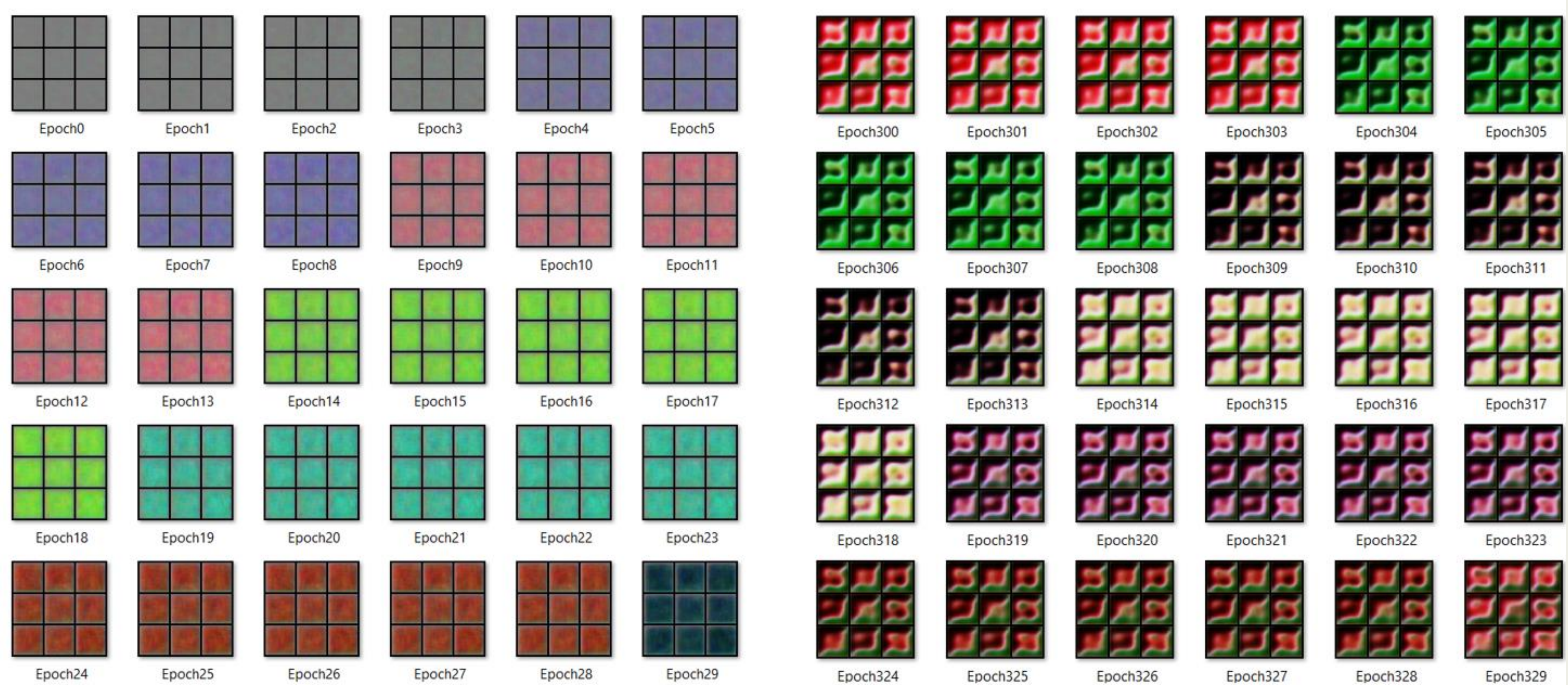




This is an alternative way to hypercomplex GAN implementation based on image processing. We converted our seismograms to the RGB images and learned the network with these images. Then we decoded our data and unpacked to the view compatible with the input dataset.

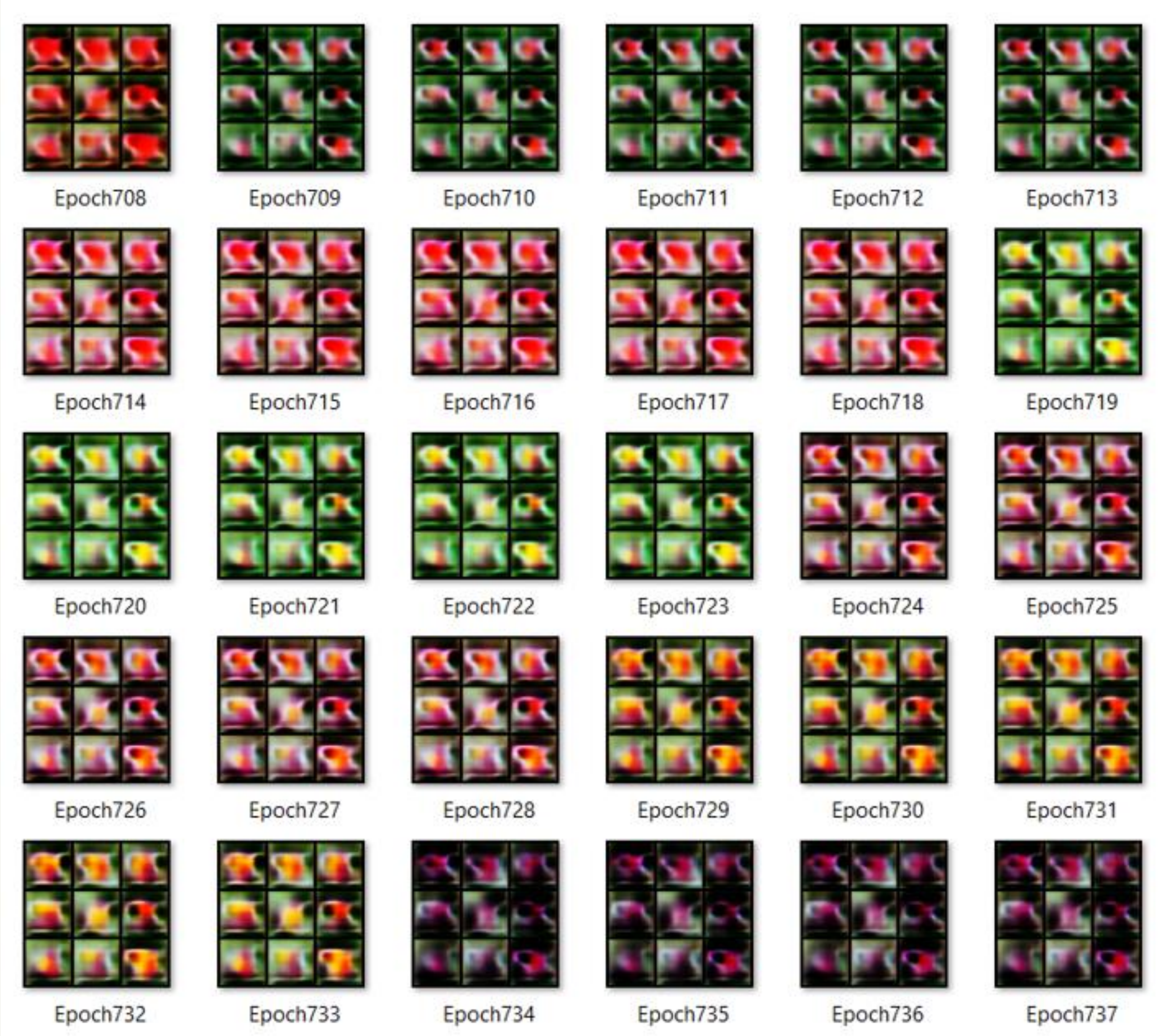
- In Quaternion Vanilla GAN architecture, each parameter including inputs, weights and outputs is a quaternion.
- The generator (green network) takes a quaternion noise signal and generates a batch of quaternion images with four channels.
- The discriminator tries to distinguish between fake and real quaternion samples exploiting the properties of quaternion algebra (Grassucci, et al, 2022)

How it works. Case “flowers”. Training process in Quaternion GAN image processing mode.



Epochs 0 to 329. Stages of generation. In the beginning there is mostly an RGB noise, though some forms start developing rather soon

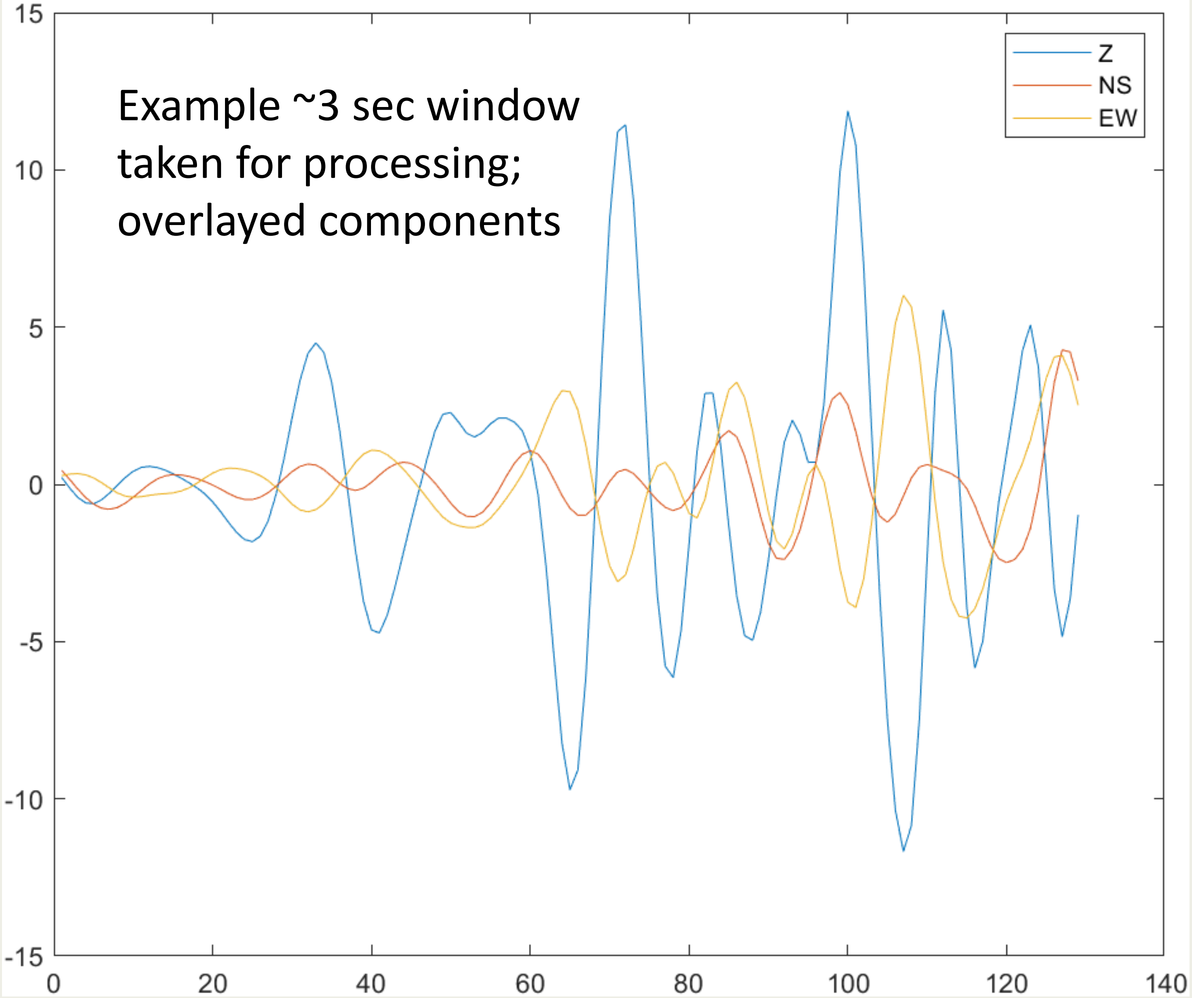
How it works. Case “flowers”. Further generation.

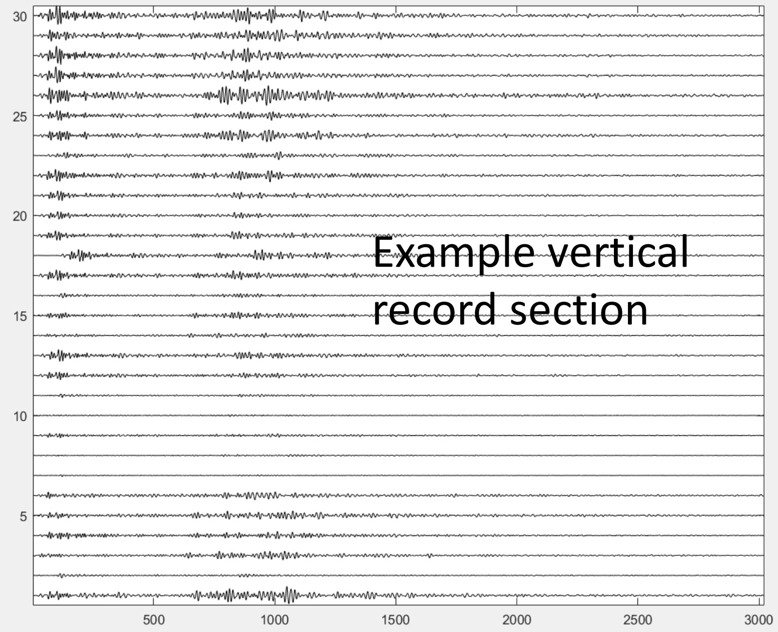


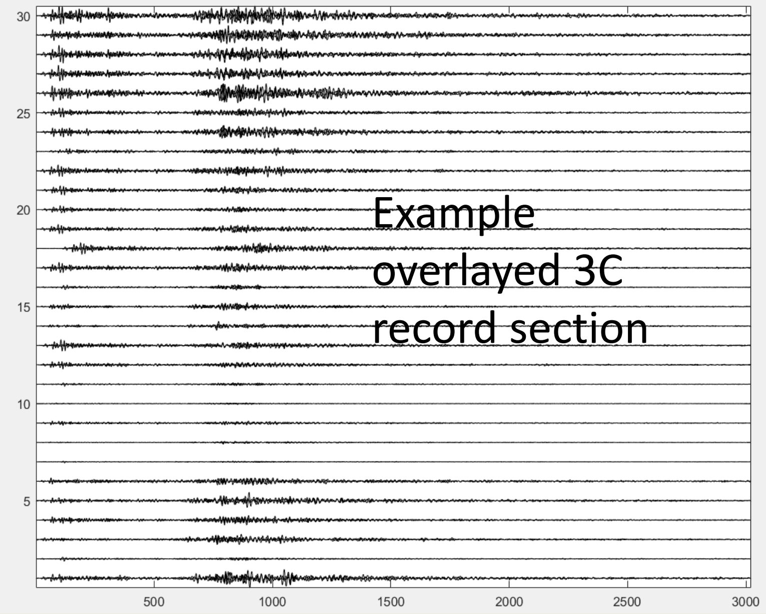
Training at 30% of total epoch time (left) and final “faked” flowers at epoch number more than 2000 and input image resolution 128x128. This implementation of QGAN produces 9 images per one file

Real data. Mining explosions

1536 3-component seismograms were processed following the procedure described above for synthetic signal.







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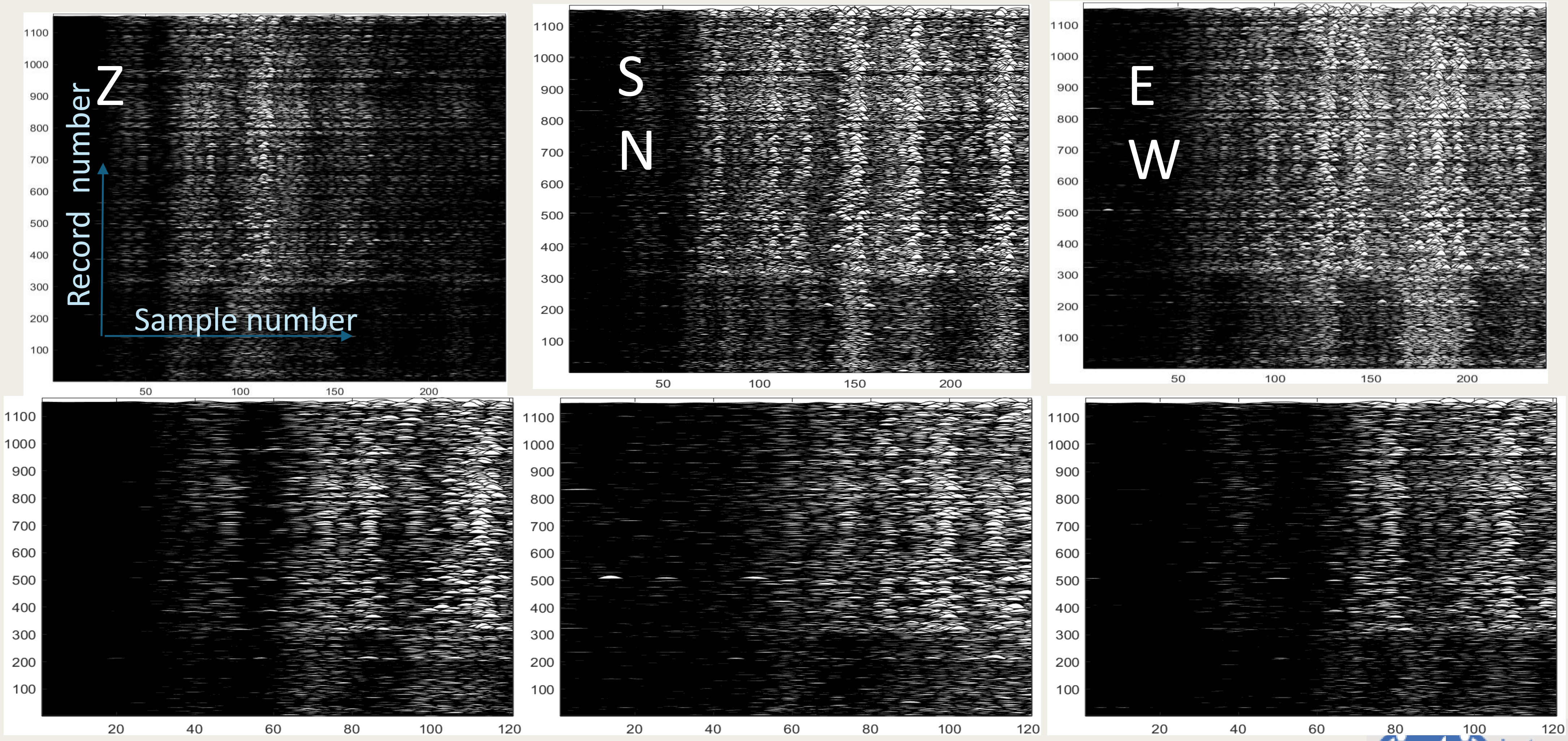
Input data Z, SN and NE data, views for 6 (up) and 3 (bottom) seconds



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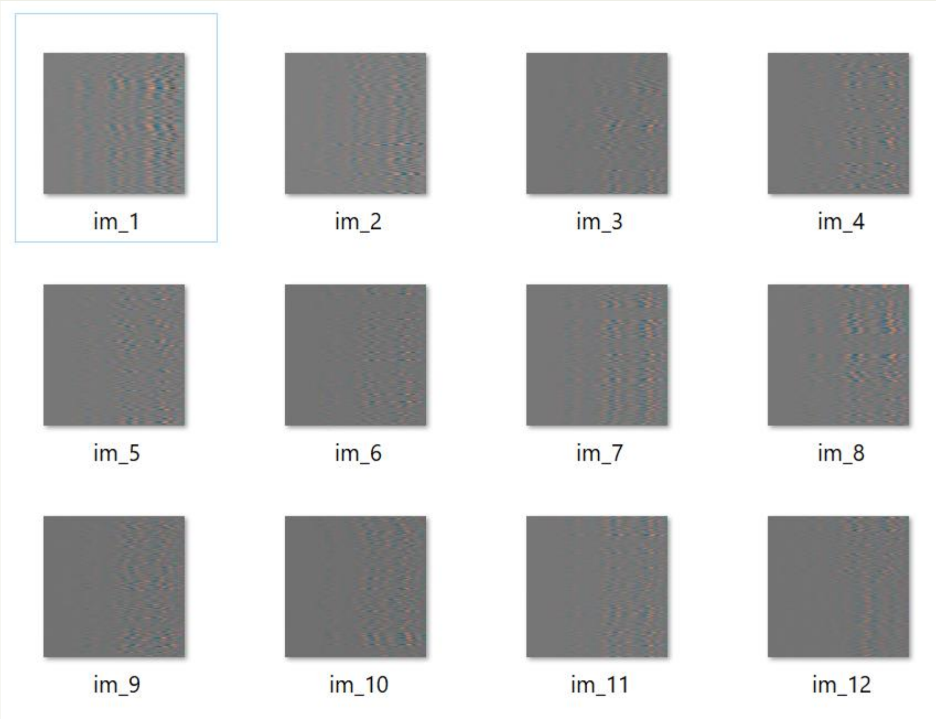
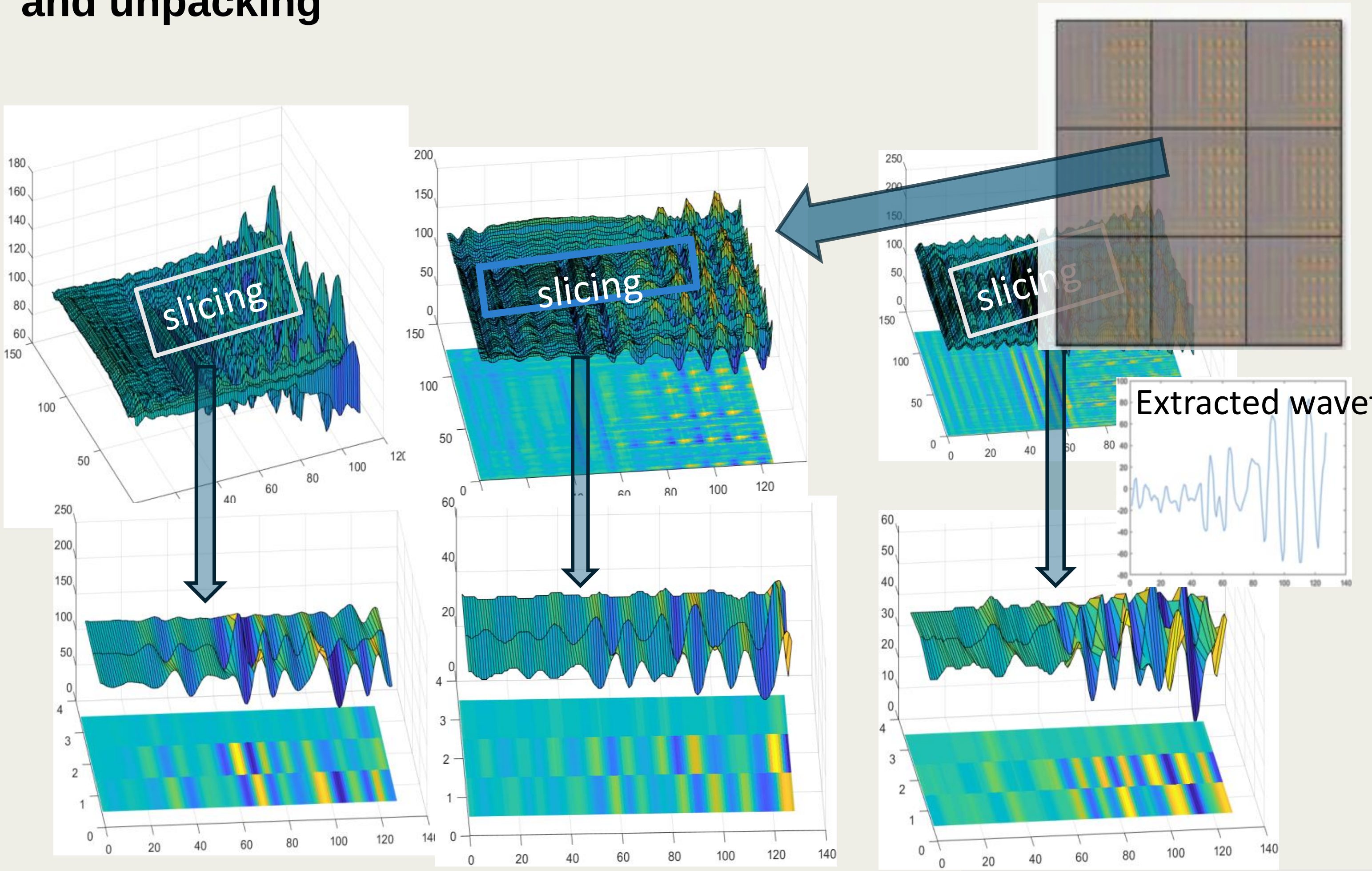
RGB maps of seismic data



1536 x 3C input seismograms converted to RGB images

128 x 3C seismograms in each image

Inverse transformation: RGB to vector conversion and unpacking



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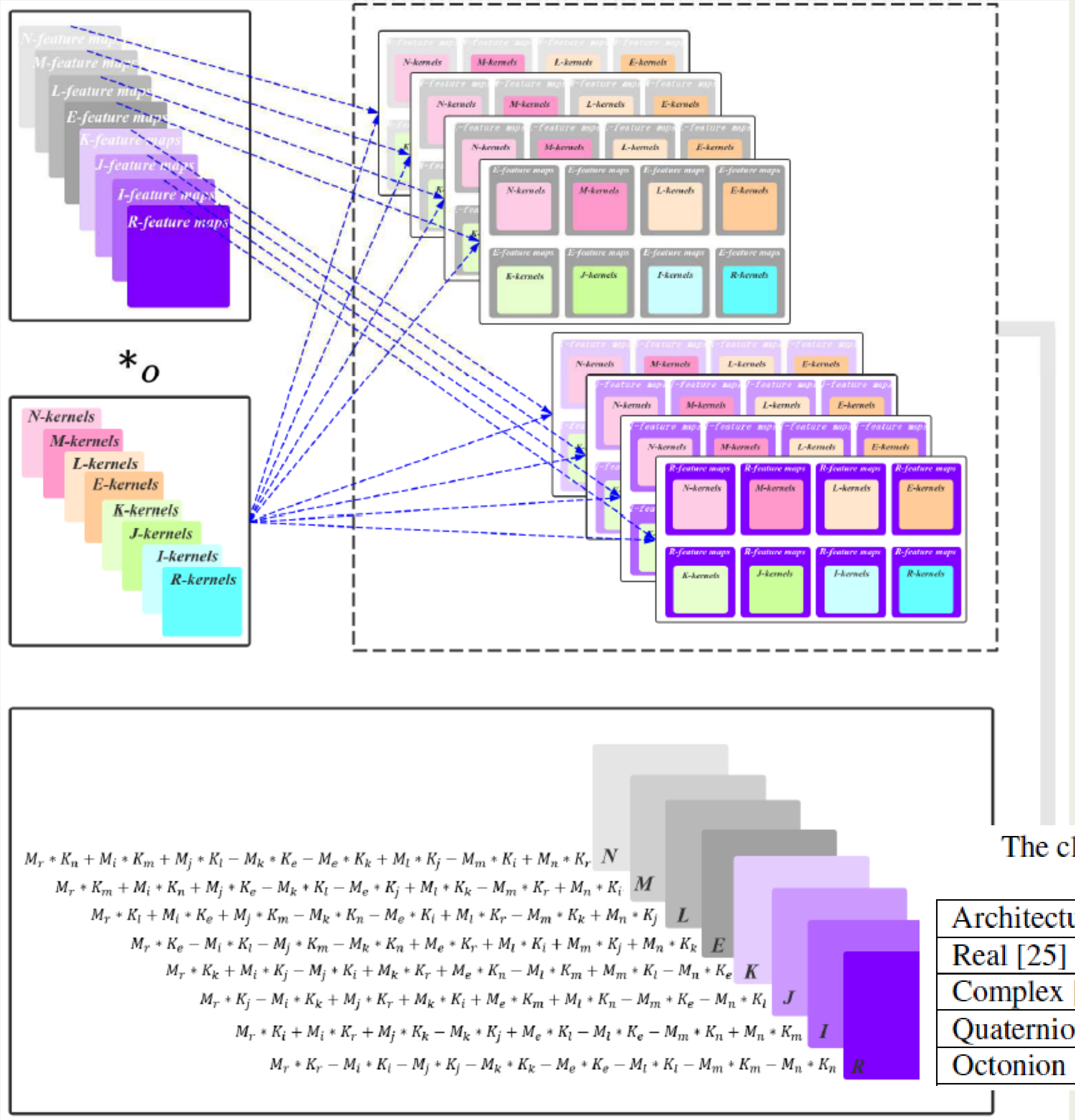
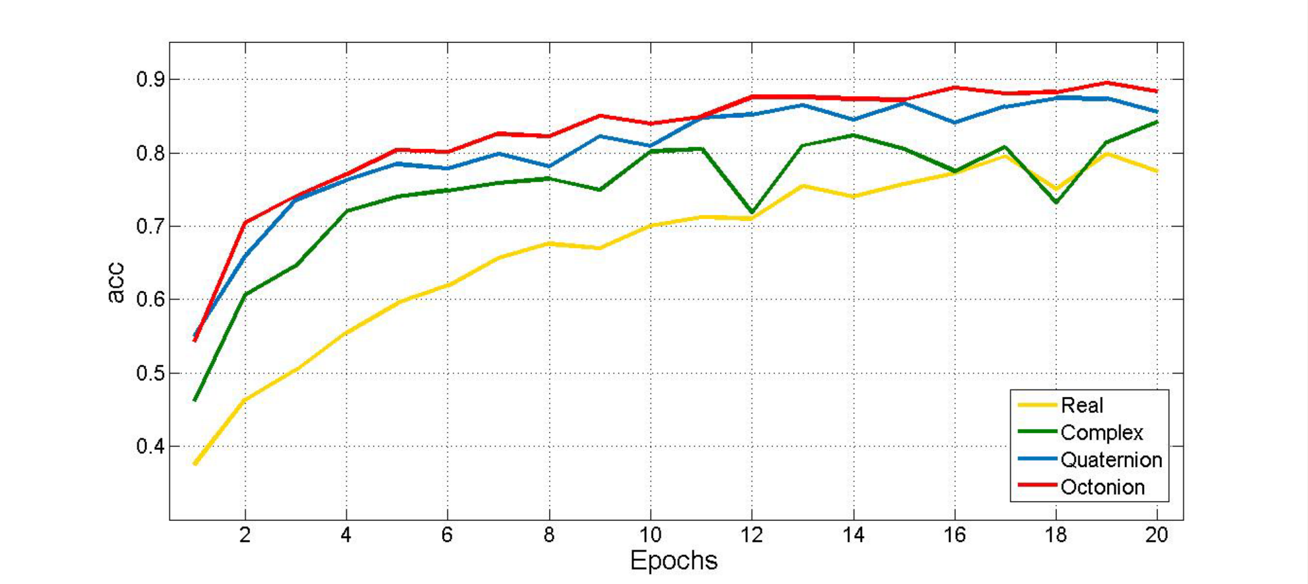
Deep Octonion Networks (DON) and overall performance

Deep octonion networks (DONs) as an 8-dimensional extension of DRNs, the DCNs, and the DQNs. The main building blocks of DONs are octonion convolution, octonion batch normalization, and octonion weight initialization. The complexity of implementation holds it from wide dissemination so far. On the left is the octonion convolution. Recent tests showed better DQN convergence, less parameters, and higher classification accuracy then the real, complex, and quaternion networks: Figures are from Wu, J., et al (2020). Deep octonion networks. Neurocomputing, 409, 218-232.





The classification error rate of three models in two types of datasets. FLOPs and MACCs denote floating point operations and multiply-accumulate operations, respectively.

Architecture	Params	FLOPs	MACCs	CIFAR-10	CIFAR-100
Real [25]	3,619,844	1081,333,248	340,380,416	6.37	-
Complex [65]	1,823,620	541,132,288	270,273,792	5.60	27.09
Quaternion [67]	932,792	271,922,688	135,662,848	5.44	26.01
Octonion	**481,150**	**137,350,144**	**68,368,896**	**5.35**	**24.60**

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Generative Networks and Imbalanced Learning

- We have trained the conventional GAN with the several realizations of the 6 DPRK explosions recorded at different distances by the IMS seismic arrays and single 3-component stations.
- The generated signals are statistically close to the learning patterns.
- We did the same exercise for more complex structures – Quaternion (Hypercomplex) GAN based on the CNN image processing and showed that this is possible to generate not only single component seismograms, but a 3-component seismogram based on the 3-component learning patterns, thus utilizing this way the entire volumetric information of the vector-sensor. More network adjustment required.
- Moving on to the wider perspective, the hypercomplex approach can be extended to the array of seismic channels and to the arrays of 3-component stations aggregating higher dimensions of hypercomplex algebra with the tensorial generalization.
- This approach can be naturally extended to solving the **imbalance problem**. Since most machine learning algorithms assume balanced class distributions, target class imbalance becomes a problem. Training classifiers on imbalanced data naturally bias models towards the majority class. Thus, machine learning applied to the IDC products and waveforms could be improved by balancing the data and metadata related to the natural and artificial seismoacoustic sources.

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Generative Networks in Imbalanced Learning

Waveform augmentation based on GAN (or other generative network) would allow producing sufficient number of nuclear explosion data to infer the imbalanced dataset from the insufficient dataset as it is now.

Need to use more explosion data:

1. PIDC data and other historical data, inc. analogue digitized
2. IRIS/FDSN
3. National databases, LLNL as a good candidate

Approaches to extend/upgrade feature set

- As in (Hyeongki, et al, 2022), use the imbalance learning with 1D frequency-domain features (e.g. FFT), but using GAN instead of ADASYN
- As in (Rozhkov, 2006), use the features made, e.g. of the wavelet packet decomposition which worked more efficiently than the conventional Fourier-based spectrogram. Special spectrogram mappings can also be used (Rozhkov, et al, 1998)
- Using GAN for generation of the synthetic seismograms of the minority class (techno-events) thus removing the imbalance problem at all. Or, using this approach just reduce the imbalance (if huge population is desired to be processed, and the real available seismograms would not be enough to generate by GAN sufficient number of “fake” explosions of significant variance).

Quantum time-series-augmentation

Quantum generative networks, including Quantum GANs (QuGANs), are being explored for applications in time-series generation and augmentation. While specific large-scale applications of quantum generative networks for time-series data are still in development, their potential lies in the ability to exploit quantum superposition and entanglement, allowing them to represent and process high-dimensional data more efficiently than classical GANs. This could be particularly advantageous in generating or augmenting time-series data with complex dependencies

Quantum GAN variants

- Fully Quantum GANs
- Hybrid Quantum–Classical GANs
- Tensor-Network-Based GANs
- Quantum Conditional GANs
- Quantum Wasserstein GANs
- Quantum Patch GANs Using Multiple Sub-Generators
- Quantum GANs Using Quantum Fidelity for a Cost Function
- Hamiltonian quantum generative adversarial networks (2024)

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