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A SELF-SUPERVISED TRANSFORMER FOR RF CAVITY SIGNAL DENOISING*

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Abstract

A frequent occurrence within industrial particle accelerator systems is electromagnetic noise accumulating within RF Cavity Sensor readings, attributed to their electromagnetically dirtier operating environments and production, with less of an emphasis on their performance optimization. This phenomenon prevents signals from accurately relaying information to beam operators and specialists and prevents data from successfully participating in feedback loops, making machine control much more difficult. Previous work has shown machine learning-based techniques as promising solutions for denoising that maintains signal quality and features. In this paper, we design, implement, and benchmark a self-supervised transformer-based machine learning algorithm that denoises In-Phase and Quadrature (I/Q) RF Cavity Signals without the need to reference a clean ground truth.

INTRODUCTION

Particle accelerators have seen wider use in areas other than scientific research. Industrial particle accelerators, specifically, have been used in a wide range of applications, such as polymer crosslinking, food irradiation, cancer treatment, and semiconductor manufacturing [1]. Due to their mass-produced nature, relaxed requirement for stability and beam quality, and high uptime requirements, particle accelerators with industrial applications undergo far less performance tuning than their research counterparts. This fact, coupled with recent advances in accelerator technology that have given way for more commercial applications with stricter tolerances to control, means that more attention must be paid to industrial deployment to improve system performance, specifically, the noise accumulated in sensor readings within these systems.

A problem that arises within industrial particle accelerators is that their operating conditions are far more electromagnetically "dirty," leading to their sensor readings accruing a lot of noise, which creates a set of data that does not clearly reflect the actual conditions that are occurring within the particle accelerator. The high amounts of noise in the readings from recording points, such as the inside of the RF cavity, greatly reduce the ability for machine operators to accurately control the accelerator. Our work is focused on the application of machine learning technology to improve signal processing for RF systems to achieve a higher degree of stability.

Previous research has shown machine learning algorithms to be viable solutions for a robust denoising process for RF signals. Our previous work has demonstrated the success of various autoencoder-based approaches, ones that use the latent space bottleneck to prevent the machine learning model from learning signal noise [2]. A limitation of this method was identified when the best performing Variational Recurrent Autoencoder (VRAE) of the previous study was applied to the IQ training data generated for this investigation. Numerous models were trained under different paradigms with limited success. Moreover, in all cases the models struggled to generalize, producing inconsistent results as the noise power spectrum was varied.

While researching alternative methods that were better suited to handle the feature space of the new training data, approaches that utilized transformers demonstrated promising results. A transformer is a type of machine learning algorithm that uses a mechanism called "attention" to assist the model in differentiating each part of a set of input data and how they relate to each other [3]. Although used mainly in supervised learning cases, transformer-based methods have been used to successfully denoise EEG and ECoG signals, gravitational wave data, and mechanical vibration signals [4–6].

Our work focuses on the design of a novel, transformer-based machine learning process to effectively denoise In-Phase and Quadrature (IQ) signals that are commonly seen in RF Cavity readings. This is done in a completely unsupervised fashion, meaning that the machine learning model never receives a reference of a clean, ground-truth signal in its training process. We see almost a 400 % improvement in MSE when comparing noisy signals and transformer reconstructions to the clean ground truth(s) available for training, and the transformer model achieving substantial denoising performance in signals frequencies past 0.15 MHz.

METHODS

Our approach is to utilize a transformer-based model to denoise signals but adapt the training mechanism of the model to handle the denoising in a self-supervised fashion. As in a realistic accelerator deployment environment there is no way to obtain a clean benchmark of the noisy signal that is sent for denoising, we must train the machine learning model to operate with no reference to a clean signal, and only use the ground-truth signal to benchmark and evaluate the robustness of the model we have trained.

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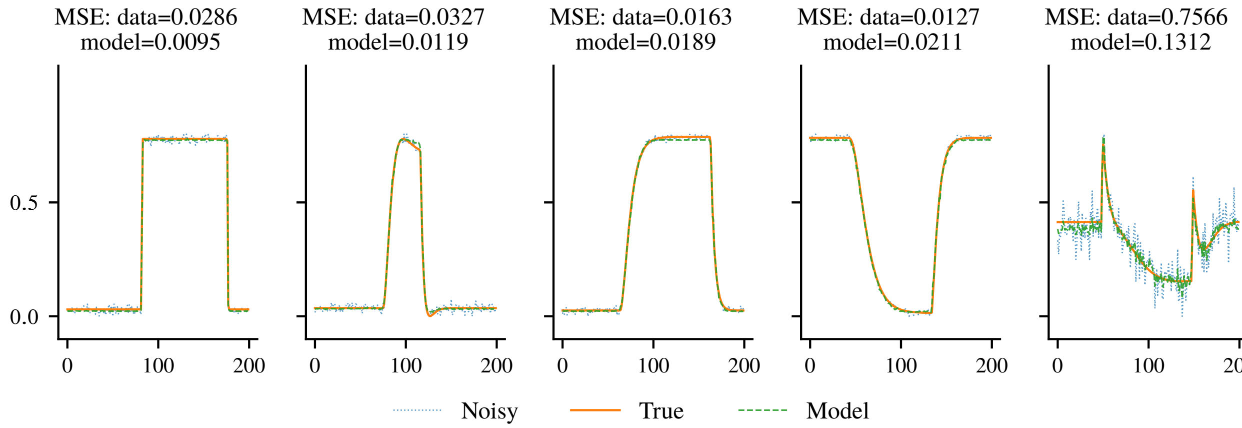

Figure 1: Model Mean Squared Error (MSE) calculations.

We do this by applying a similar method as described in "Noise2Noise" [7]. We feed a noisy batch $\mathbf{x}$ into the model, select a random value σ from a predefined range, generate an additional additive white Gaussian noise (AWGN) sample with noise amount σ. We add this to the original batch to generate an even noisier batch $\tilde{\mathbf{x}}$ which we then tell the model to reconstruct $\mathbf{x}$ from. By teaching the transformer to denoise the additional artificially applied noise, the model learns to identify and remove noise from the signal, outputting a denoised signal approximating the clean ground truth.

To ensure that the model is invariant to the amount of noise added and produces a consistent denoised output from the same noisy batch regardless of the noise amount, we implement a weighted consistency regularization term in the loss. This is done by taking the noisy batch currently participating in the training step, creating n more artificially noisy batches with different noise levels σ_n, generating the denoised signals based on these batches, computing their mean ($\bar{\mathbf{x}}$), and finally evaluating it's loss relative to the reconstruction of the original batch.

During testing, we saw that the mean on the consistency regularization term was de-attenuating the model's reconstruction shapes from the actual noisy reconstruction shape. This prompted us to implement a sharpening factor into the mean consistency signal loss. This is done by performing a convex combination between the mean consistency signal ($\bar{\mathbf{x}}$) and the original noisy batch that is fed into the model ($\mathbf{x}$). The sharpening factor β determines the relative weighting of each term:

$$y = (1 - \beta)\bar{\mathbf{x}} + \beta\mathbf{x}.$$

This approach instructs the model to retain the shape of the signal it is trying to denoise while also maintaining the noise invariance provided by the consistency regularization.

RESULTS AND ANALYSIS

The data for our studies were generated using an RF simulator that tracks In-Phase and Quadrature signals [8]. This approach takes advantage of a simple RLC cavity alongside a scattering matrix approach for propagation dynamics. We generated data from the simulator under a wide range of configurations including different couplings, de-tuning parameters, pulse lengths, pulse timings, and cavity quality factors.

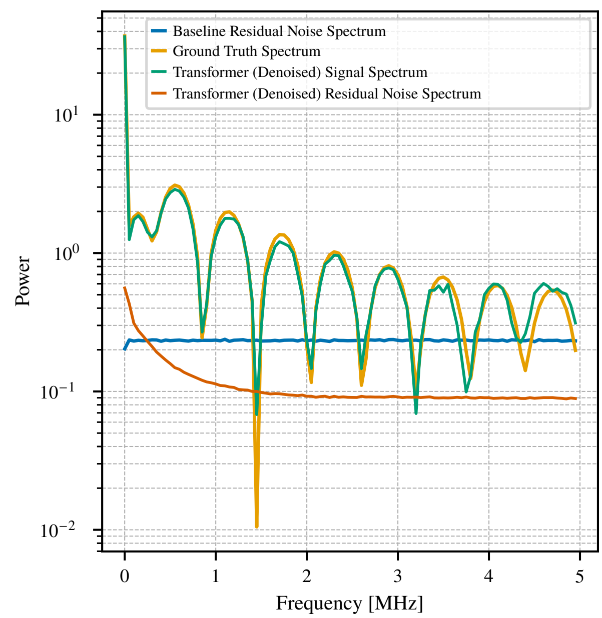

Figure 2: Power spectra plot.

Testing of the transformer denoising algorithm shows great promise and performance for denoising the more complex IQ RF Cavity signals. On the validation dataset, the model achieves close to a 395 % improvement in Mean Squared Error in comparison to the baseline noisy signal, going from a MSE of 586.2863 on the noisy dataset to 148.2969 on the transformer denoised dataset.

Furthermore, this improvement can also be seen in a sample of the model reconstructions compared to the ground truth seen in Fig. 1 . Even in the worst-case scenario where a very low signal-to-noise ratio exists, the model is able to remove a large part of the noise while maintaining the overall shape of the signal fairly well.

In order to better evaluate the robustness of the transformer to denoise signals, the mean spectra of both the

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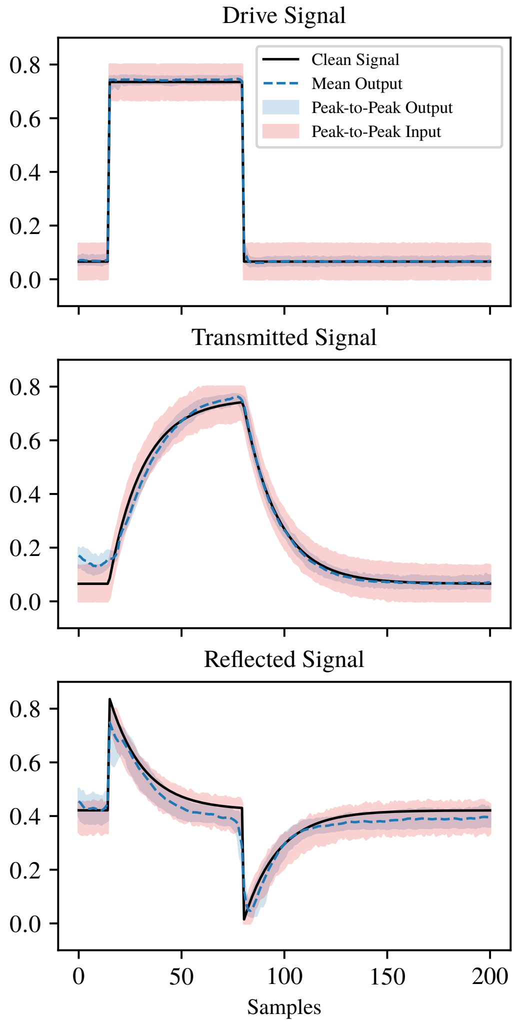

Figure 3: Variance test on in-phase RF signals.

transformer reconstructions and the residual noise of the validation dataset was plotted, alongside a single sample spectra of a transformer reconstruction and its respective ground truth signal in Fig. 2.

Our findings show that the transformer-based model successfully removes noise from the input signals past frequencies of 0.15 MHz. The spectra from a single sample of the transformer's reconstructions closely follow the shape of the ground-truth clean signal associated with it throughout all frequencies, demonstrating the model's ability to denoise signals while also preserving the signal's features effectively.

We also tested the model with signals from simplified RF model to determine it's peak-to-peak performance when integrated within a accelerator feedback loop. We did this by running the same input signal batch 100 times with different random noise profiles and then calculating the mean and variance of the model's reconstructions (Fig. 3). The results show that the peak-to-peak variance of the model's outputs are consistently far less than the noise of the input signals into the model, and that the mean reconstruction signal of the model follows the shape of the ground-truth input signals.

DISCUSSION

We have successfully developed a transformer-based RF Signal denoising model that has the capability to robustly reduce noise at almost all signal frequencies. Further work will investigate denoising performance of the same method with other colors of noise that are frequently found within RF Signals. More work will also be dedicated to creating a real-time hardware deployment of this model to be integrated within an operational particle accelerator in the near future.

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