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Unsupervised deep-learning approach for time domain signal denoising in MPI

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Abstract

Denoising is crucial in Magnetic Particle Imaging (MPI) since the measured signals are inherently affected by noise and distortions that degrade the reconstruction quality. This work explores an unsupervised deep-learning approach for time-domain denoising of real-world MPI data, which is based on a Wasserstein Generative Adversarial Network (WGAN). The results show that unsupervised deep learning-based denoising can enhance the signal quality of 1D MPI data by increasing the sensitivity and reducing reconstruction artifacts.

I. Introduction

Image acquisition in Magnetic Particle Imaging (MPI) relies on the detection of nanoparticles injected into the subject. The acquired signal often suffers from a low Signal-to-Noise Ratio (SNR) and a common strategy to increase the SNR is to apply denoising after the signal acquisition. Typically, this is adressed by averaging, while this work explores an unsupervised deep-learning approach based on a Wasserstein Generative Adversarial Network (WGAN) model trained on real-world 1D MPI data. An unsupervised approach was chosen since high-quality data with clean ground truth labels rarely exists in MPI. The goal is to use only measured noisy signals together with empty background measurements as noise samples during training.

II. Materials and Methods

The WGAN architecture is based on a design proposed by Dittmer et al. [1]. The generator is implemented as an autoencoder for data denoising. Its output is evaluated by two discriminators: The first discriminator adds noise back to the denoised signals and attempts to distinguish the results from real measured samples. The second discriminator subtracts the denoised signals from the noisy input signals and tries to distinguish the results from real noise samples. To enforce the Lipschitz constraint required for the WGAN training, the gradient penalty method used by Dittmer et al. [1] was replaced with spectral normalization [2], since this has demonstrated improved training stability in our experiments. The dataset consists of real-world MPI data measured with the Bruker preclinical MPI system using point samples of 5 µl. Each sample contains Perimag nanoparticles diluted in deionized water. The concentrations are logarithmically distributed between 0.85 mg/ml and 85 ng/ml and the samples were placed at positions between −11 mm and 11 mm with a step size of 1 mm. The data was measured in x-direction with a gradient of $G_x = 1.25\,\mathrm{T/m}$ and a drive field of $H_x = 14\,\mathrm{mT}$. The model was trained on every second concentration and every second position, while the remaining data were used for testing.

III. Results and discussion

In the following, the denoised signals are compared to both noisy data (single periods of 40 µs) and reference measurements that were obtained by averaging 1000 measurements. No background correction was applied to any data. At the reconstruction process, the FFT was calculated by using 10 signal periods. When evaluating Figure 1, it can be observed that the amplitude linearity is well preserved for the higher concentrations. The drop at the highest concentration occurs, because this concentration is higher than the ones used during training, meaning the model generalizes well only in between the known concentration range.

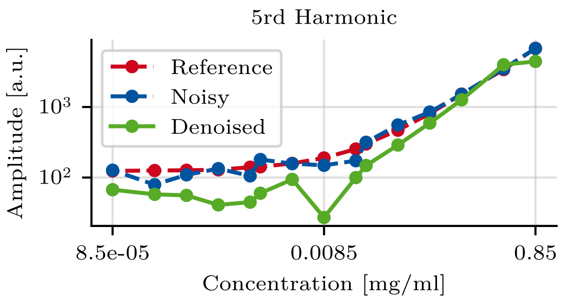

Figure 1: Amplitude of the 5th harmonic over particle concentration.

The reconstructions visualized in Figure 2 were done using the Kaczmarz algorithm with $N_K = 5$ iterations and a regularization parameter of $\lambda = 0.8$. For concentrations of 8.5 µg/ml and below, similar reconstruction artifacts appear in both the noisy and reference data, but are absent in the denoised results. Adjusting the reconstruction parameters did not eliminate these artifacts. This indicates that the denoising approach is able to increase sensitivity in MPI, by reducing the impact of the reconstruction algorithm and making the reconstructions more reliable. To evaluate the reconstruction quality, a Position Error (PE) was used. It measures the distance between the position of the maximum value in the reconstruction and the ground-truth position of the sample. The average PE and its standard deviation over all test samples (5 concentrations and 10 positions) was improved from 2.78 ± 3.44 mm for the reference signal to 1.87 ± 2.12 mm for the denoised signal. Moreover, the PE is more stable across different parameter settings, meaning that the reconstructed particle distribution is less dependent on the reconstruction algorithm (Figure 3).

IV. Conclusion

In this work, we presented an unsupervised deep-learning approach for denoising 1D MPI signals. This

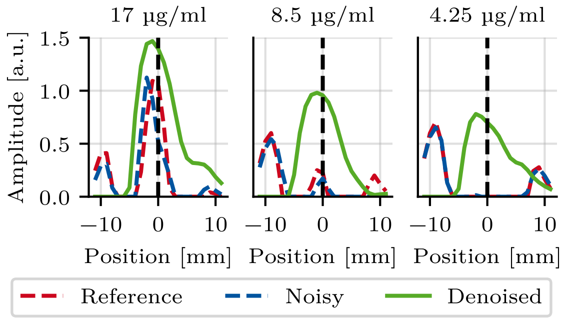

Figure 2: Reconstruction of point samples placed at the center of the field of view.

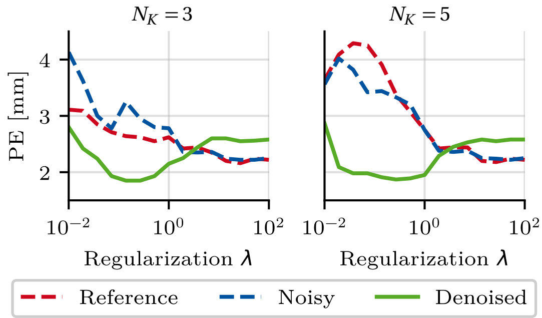

Figure 3: PE over different regularization parameters λ and number of Kaczmarz iterations N_K.

approach removed reconstruction artifacts at lower concentrations and made the reconstruction algorithm less dependent on the parameter settings, enabling improved comparability between different studies. At the same time, the measurement time was reduced significantly, since less averaging is required. For future work, a larger dataset and the extension of the approach to 2D and 3D MPI data will be explored.

Author's statement

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