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Sequence-to-Image Reconstruction in Magnetic Particle Imaging: A BiLSTM Proof of Concept

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Abstract

Magnetic Particle Imaging (MPI) produces voltage signals that are periodic and highly correlated across time. Classical deep-learning reconstruction methods generally treat these signals as static feature vectors. In this work, we explore a purely data-driven sequence-to-image approach using a bidirectional long short-term memory (BiLSTM) network followed by a lightweight convolutional neural network (CNN). The model directly maps 1D MPI-signals to 2D images. We evaluate performance using a synthetically generated, trajectory-encoded augmented MNIST dataset, and analyse robustness under different signal-to-noise ratios (SNR). Results demonstrate that the BiLSTM architecture successfully reconstructs image structure and remains robust even at low SNR levels, highlighting the potential of sequence modelling for future MPI reconstruction.

I. Introduction

In MPI, time-varying voltage signals are detected that are induced by the dynamic magnetization of nanoparticles within oscillating magnetic fields. These signals exhibit strong temporal dependencies and periodic structure due to the continuous motion of the low-field area used in MPI. Most learning-based reconstruction approaches in MPI ignore this sequential character and instead process flattened signal vectors using convolutional [1] or fully connected networks [2]. Recurrent neural networks in general leverage temporal dependencies in times-series data. LSTM networks are well-suited to capture long-range dependencies.

We propose a hybrid image reconstruction network based on a BiLSTM network and a CNN, that learns the mapping from complete voltage trajectories to 2D images. To allow systematic evaluation, we simulate MPI signal trajectories using an augmented MNIST dataset. An SNR study quantifies reconstruction robustness.

II. Methods and materials

II.I. Dataset

Inspired by the work of Koch et al. [1], we use the MNIST database consisting of 70.000 2D images of handwritten digits. We interpolate the images to a size of 40×40 pixels and augment the dataset by applying three random rigid transformations to each image.

We simulate corresponding MPI signals using the Langevin theory, excitation frequencies of $f_x = 24.51\,\text{kHz}$, $f_y = 26.04\,\text{kHz}$ and excitation amplitudes of $A_x = A_y = 20\,\text{mT}$. We add simulated normal distributed noise to achieve datasets with SNR = 20, 10, 5 dB.
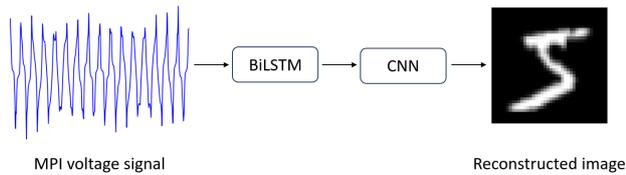
Figure 1: Visualisation of the hybrid model approach. A BiLSTM network reconstructs MPI signal to a vectorised non-uniformly sampled image. A following CNN performs gridding and interpolation steps to output the final image.

Table 1: Test results using datasets of different SNR levels. For training the hybrid model, data with an SNR of 20 dB have been used.

SNR in dB	20	10	5
SSIM in %	96.8 ± 1.1	96.7 ± 1.1	96.5 ± 1.2
NRMSE in %	4.49 ± 0.85	4.55 ± 0.85	4.68 ± 0.85

II.II. Network architecture and training

Our hybrid model consists of a BiLSTM network featuring three layers and 256 hidden units each and a CNN with a linear layer and seven convolutional layers producing an output image of 40×40 pixels, see Figure 1. We use the voltage signal and information about the signal trajectory as features for the BiLSTM model.

We sample our ground truth images with a Gaussian kernel along the signal trajectory to create surrogate images that we use for evaluating the BiLSTM network. We choose a combined loss function of first, the Charbonnier loss to evaluate the performance of the BiLSTM model, second and third, MSE and SSIM to evaluate the overall output image.

We train our hybrid model with the images of the 20 dB showing all digits but '5' (approx. 255.000 images in total) and use a 20 % split for validation. We test the model using all images the digit '5' from the datasets of different SNR (approx. 25.000 images each).

III. Results and discussion

We have successfully trained our model and applied it on the test data as described. We provide our test results in Table 1. Using the same SNR level for testing as for training, we achieve a high SSIM of 96.8 % ± 1.1 % and a low NRMSE of 4.49 % ± 0.85 %. When lowering the SNR of our test data, we notice only a small change in SSIM (decrease down to 96.5 % ± 1.2 %) and NRMSE (increase up to 4.68 % ± 0.85 %). The reconstructed images show no background artefacts and bear a close resemblance to the ground truth images, as visualised in Figure 2. However, some details such as the outlier in the upper part of the phantom (upper row) are lost.

The results confirm that our hybrid model consisting of a BiLSTM network and a CNN can reconstruct MPI
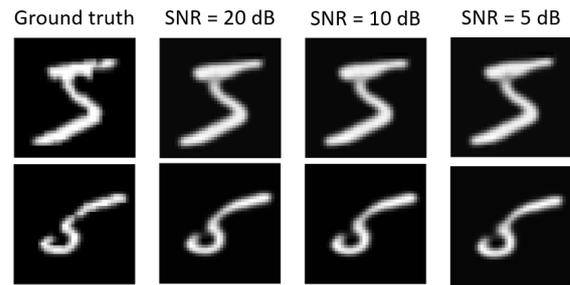

Figure 2: Reconstruction results of two test images (rows) with different SNR levels (columns).

images. Temporal correlations between signal samples carry sufficient information to infer coarse spatial structure, which the CNN converts into a refined image. The SNR study indicates that our approach is robust to noise.

In this work we have tested simulated MPI data. As MPI signals are sensitive to particle characteristics and the actual magnetic field, the generalisation ability of our method may be limited. However, we have used imaging parameters similar to those used in pre-clinical MPI scannners.

IV. Conclusion

We presented a hybrid BiLSTM-based and CNN-based model to reconstruct 2D images from simulated MPI voltage signal. Our model remains robust across different SNR levels. These results encourage further investigation of recurrent networks for MPI reconstruction.

Acknowledgments

Author's statement

Conflict of interest: The corresponding author is with the editorial board of *International Journal on Magnetic Particle Imaging*. Otherwise, authors state no conflict of interest.

References

[1] P. Koch, M. Maass, M. Bruhns, C. Droigk, T. J. Parbs, and A. Mertins, Neural Network for Reconstruction of MPI Images, in *International Workshop on Magnetic Particle Imaging*, 39–40, 2019.

[2] T. Hatsuda, T. Takagi, A. Matsuhisa, M. Arayama, H. Tsuchiya, S. Takahashi, and Y. Ishihara. Basic Study of Image Reconstruction Method Using Neural Networks with Additional Learning for Magnetic Particle Imaging. *International Journal on Magnetic Particle Imaging*, 2(2), 2016, doi:10.18416/IJMPI.2016.1611002.