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Data augmentation for training a neural network for image reconstruction in MPI

Anselm von Gladiss [a,*] · Ivanna Kramer [a] · Nick Theisen [a] · Raphael Memmesheimer [a] · Anna C. Bakenecker [b] · Thorsten M. Buzug [b,c] · Dietrich Paulus [a]

[a] Institute for Computational Visualistics, University of Koblenz-Landau, Koblenz, Germany
[b] Fraunhofer Research Institution for Individualized and Cell-Based Medical Engineering IMTE, Lübeck, Germany
[c] Institute of Medical Engineering, University of Lübeck, Lübeck, Germany
[*] Corresponding author, email: vongladiss@uni-koblenz.de

Abstract

Neural networks need to be trained with immense datasets for successful image reconstruction. Acquiring these datasets may be a difficult task, especially in medical imaging. Data augmentation techniques are used to enlarge an available dataset by synthesizing new data. In this work, it is proposed to use the single measurements of a system matrix measurement in magnetic particle imaging for training a neural network for image reconstruction. Before training, mixup augmentation is used to create linear combinations of the single measurements and thus, enlarging the training dataset. Image reconstruction results using neural networks trained with an augmented system matrix are compared to images that have been reconstructed using the conventional system-matrix-based approach.

I. Introduction

Magnetic Particle Imaging (MPI) is a tracer-based medical imaging modality that visualises the spatial distribution of super-paramagnetic iron oxide nanoparticles which serve as tracer material [1]. The tracer material is excited by oscillating magnetic fields along its non-linear magnetisation curve and the dynamic magnetisation of the tracer is measured via an induced voltage signal. A magnetic gradient field is applied for attenuating the magnetisation of the tracer but in a small volume and thus, spatial encoding is enabled. The measured voltage signal can be reconstructed into an image representing the spatial distribution of the tracer. For reconstruction, there are mainly two methods that are currently used, the system-matrix-based approach and x-space reconstruction.

A third approach to image reconstruction is based on neural networks, which have been used for reconstruction in medical imaging for different imaging modalities. Neural network architectures have been utilised for the fast and accurate reconstruction of 2D magnetic resonance (MR) images [2]. Convolution neural network models [3] have been applied for an end-to-end positron emission tomography (PET) image reconstruction [4]. Reconstruction of computed tomography (CT) images by utilizing neural networks has indicated a significant reduction of the image noise and improved contrast-to-noise-ratio compared to iterative reconstruction methods [5]. In MPI, convolutional neural networks have been used for reconstructing hybrid 1D and simulated 2D data [6, 7]. In [8] the architecture of a neural network has been used for regularising image reconstruction.

Before a neural network can be used for reconstruction, it needs to be trained employing sample input and output data, which are measured raw data and idealised or best-case reconstruction results. The performance of the neural network relies on an extensive amount of training data. Acquiring training samples is usually a challenging task especially in the medical imaging domain. A common solution to overcome the data scarcity issue is data augmentation - a set of techniques that expands the initial input space by creating new synthetic data based on the existing data. The objective of data augmentation is to act as a regularization method and to ensure that the model does not overfit the training data, which leads to a better performance and robustness of the network [9].

In this work, a hybrid 1D system matrix is used for training a neural network. The data is augmented using a mixup technique [10].

II. Methods and materials

The dataset used in this work is presented. It is explained how the dataset can be used as training data for a neural network. Then, the mixup technique for augmenting the dataset is introduced. Last, the neural network that is trained using the augmented data is presented.

II.I. Dataset

Two hybrid 1D system matrices have been measured in a magnetic particle spectrometer [11]. The dataset is described in [12] and has been used in [6, 12] to investigate the spatial resolution in MPI and for neural-network-based image reconstruction.

The dataset consists of two system matrices with 97 and 241 magnetic offset field positions, respectively, within the range of $[-12\,\mathrm{mT}, 12\,\mathrm{mT}]$. The first system matrix is used for training a neural network and for validating the training. The second system matrix is used for testing the image reconstruction by designing hybrid phantoms [12]. It features a higher discretisation than the first system matrix in order to represent partial volumes in the reconstructed images.

For training a neural network, the first system matrix is interpreted as 97 single measurements carried out at different emulated spatial positions. These single measurements serve as input data. As output data, 97 1D images are created that have intensity values of 0 except to the measurement position, where an intensity value of 1 is stored.

A hybrid three-dot phantom has been created using the second system matrix. Ground truth data is generated by mapping an intensity value of 1 for each single measurement to the 97 pixel-grid. Due to the higher discretisation of the second system matrix, the intensity value is split between the two nearest pixel-neighbours.

II.II. Augmentation

The dataset is modified using three augmentation steps. First, random samples of the data are scaled using random factors in the range $[0, 1)$. Then, in order to train the neural network for partial-volumes, linear combinations of two neighbouring measurement positions are created. Last, linear combinations of randomly selected data in a batch are created which relates to the mixup augmentation technique [10]. The last step is applied multiple times and thus, the network is trained for measurements of sophisticated (phantom) data.

II.III. Neural network

A neural network featuring two dense layers and three convolutional layers has been created. As activation functions, exponential linear units have been chosen. Before the output layer, a rectified linear unit has been used for inhibiting negative intensity values.

For evaluating the augmentation method, the neural network has been trained three times for 250 epochs with the system matrix solely, the system matrix augmented using randomly scaled positions and partial-volume-augmentation, and last, using all the augmentation techniques. During training, 20 % of the data have been used for validating the training process.

III. Results

The neural network has been trained and validated using first the 97 original measurements, second an augmented dataset of 42,777 samples and third a mixup-augmented dataset of 130,545 samples. The hybrid phantom has been reconstructed using the trained neural networks and a conventional system-matrix-based approach. The reconstruction results are visualised in Figure 1. For comparison, the idealised ground truth is displayed.

Reconstructing the phantom with a neural network trained with a simple system matrix, a 1D image consisting of zero-value entries is obtained. Thus, the neural network has not reconstructed the phantom successfully.

Reconstructions are successful when the neural network has been trained with an augmented dataset. The single dots are reconstructed sharply. However, the intensity values do not match the ground truth data precisely in both cases. When augmenting the training set for partial volumes and scaling, the positions of the dots are not fully matched.

In comparison to the conventional reconstruction result using system-matrix-based reconstruction, the single dots fit intensity values and positions better when using neural network reconstruction with an augmented training dataset.

Background artefacts cannot be identified using neural network reconstruction in contrast to the conventional system-matrix-based approach.

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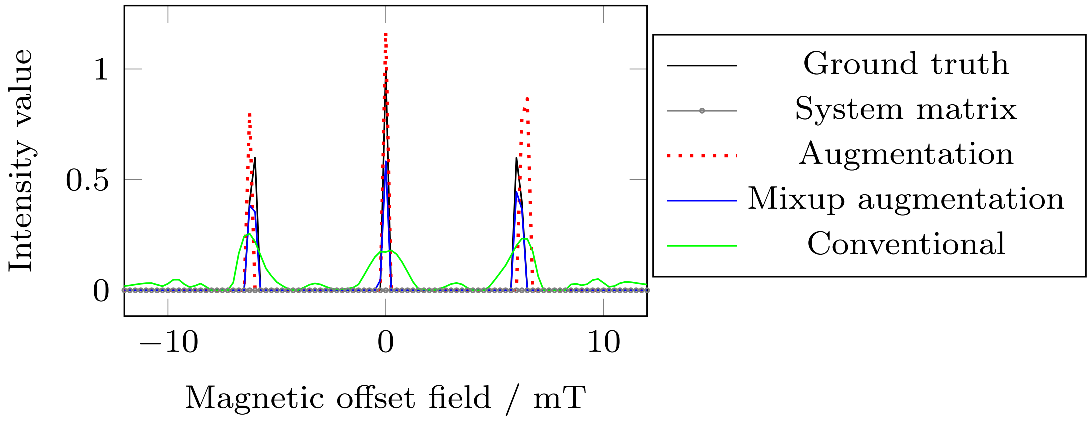

Figure 1: Reconstruction results of a three-dot phantom using neural networks trained with a system matrix (grey circles), a system matrix augmented regarding partial volumes and different intensity values (dotted in red), and a system matrix augmented using mixup techniques (blue). The ground truth and a conventional reconstruction result are visualised in black and green, respectively.

IV. Discussion and conclusion

A three-dot 1D-phantom has been reconstructed successfully with a convolutional neural network that has been trained with an augmented dataset.

Neural network reconstruction is a promising approach to image reconstruction in MPI. Reconstructed images may benefit from a higher quantifiability and spatial resolution in comparison to the conventional system-matrix-based approach. Furthermore, the image quality may improve as background artefacts are not present in the reconstructed images.

However, in this work only a three-dot 1D-phantom has been reconstructed. The generalisability of the neural network needs to be examined by using more sophisticated phantoms. Furthermore, neural network reconstruction of measured multi-dimensional datasets needs to be examined using the proposed method.

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Author's statement

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