International Journal on Magnetic Particle Imaging
Vol 2, No 2, Article ID 1611002, 5 Pages

Infinite Science Publishing

Research Article

Basic Study of Image Reconstruction Method Using Neural Networks with Additional Learning for Magnetic Particle Imaging

Tomoki Hatsuda[a,*] · Tomoyuki Takagi[a] · Akihiro Matsuhisa[b] · Masahiro Arayama[b] · Hiroki Tsuchiya[a] · Satoru Takahashi[b] · Yasutoshi Ishihara[b]

[a]Graduate School of Science and Technology, Meiji University, Kanagawa 214-8571, Japan
[b]School of Science and Technology, Meiji University, Kanagawa 214-8571, Japan
[*]Corresponding author, email: ikuta.keisoku@gmail.com

Received 27 November 2015; Accepted 10 October 2016; Published online 1 November 2016

Abstract
In magnetic particle imaging (MPI), image blurring and artifacts occur in the reconstructed images because the magnetization signals generated from magnetic nanoparticles (MNPs) at the field free points (FFPs) are similar to those surrounding the FFP regions. While in the usual MPI approach, the system function utilized to perform the inverse-matrix operation is based on a point spread function (PSF) obtained on each point, in our study, we focus on considering the pattern information, which involves a combination of two or more PSFs (i.e., MPI system functions for multi-position MNP locations). However, since it is not practical to solve an inverse matrix considering all the combinations of PSFs, we propose a new reconstruction method introducing the method of additional learning with neural networks (NNs) in order to choose the required combination of PSFs. This method is expected to suppress image blurring and artifacts by learning the appropriate data sets, which consist of information on two or more combined PSFs in individual positions. Through numerical experiments, we find that the image blurring and artifacts are suppressed, and the image resolution is improved when compared with the conventional inverse-matrix solution.

I. Introduction

Magnetic particle imaging (MPI) has recently attracted attention as a noninvasive diagnosis technology. In the fundamental MPI reconstruction method [1, 2], a magnetic nanoparticle (MNP) location is reconstructed by detecting the odd harmonics generated from an MNP. In particular, using a reconstruction method based on an inverse-matrix solution [3], image blurring and artifacts are suppressed significantly. However, image blurring and artifacts still occur in reconstructed images because the magnetization signals generated from the MNPs at the field free points (FFPs) are similar to those in the vicinity of the FFP regions.

In order to overcome this problem, we previously proposed a reconstruction concept [4] based on neural networks (NNs) [5]. In this method, a data set comprising magnetization signal and MNP location pairs (i.e., point spread functions, PSFs) is used for learning in the NNs. If all possible data set combinations are learned, an accurate estimated result may be obtained. However, it is difficult to learn all the combinations within a reasonable time interval. Although the inverse-matrix operation is considered to be one of the solutions to this problem, this operation is not practical as all the corresponding combinations are excessively large for a large matrix size.

Thus, in this study, in order to address the combination-learning time-cost problem, we propose that the number of data sets learned in the first stage would be minimized. Additional learning with the use of appropriate data sets [6], which reduces the error between observed and estimated signals, should be performed. Image blurring and artifacts can be suppressed if the minimum number of required data sets is learned, even when the MNP magnetization is not sufficiently saturated, e.g., when an applied alternative magnetic field and/or a gradient magnetic field are/is weak. We performed numerical experiments to confirm the effectiveness of our proposed method.

II. Image Reconstruction Method

The concept of the image reconstruction method with the NNs is shown in Fig. 1. In our method, a typical NN architecture, which contains three layers, viz. input, hidden, and output [5, 7], is considered. The NNs learn the data set relations between the magnetization signals (see Fig. 1 (a)) and the MNP locations (see Fig. 1 (b)) as the input and output data, respectively, based on backpropagation. In the first learning process, a few thousand data sets are randomly selected from combinations of all the magnetization signal and MNP location pairs (normally, the combination of all the data sets yields an extremely large number of sets). After the first learning process, the iterative process comprising procedures (Proc. 1–6) is executed:

Proc. 1 (Fig. 1, stage 1 (Estimation)):
The observed signal (c) measured from an unknown MNP location is input to the NNs that have learned the original chosen data sets (shown in the box labeled "learning process"), and the MNP location (d) is estimated from the NN output. However, the estimated MNP location may differ from the actual unknown location, because the learning data sets may be insufficient. Hence, additional procedures (Proc. 2–6) are required.

Proc. 2 (Fig. 1, stage 2 (Analysis)):
The estimated signal (e) is calculated analytically from the estimated MNP location.

Proc. 3 (Fig. 1, stage 3 (Calculation)):
The error (f) between the observed and estimated signals is calculated.

Proc. 4 (Fig. 1, stage 4 (Detection)):
The error regions (g) depending on the error intensity at each FFP are detected. As a result, the "inside" and "outside" error regions are separated. Here, an error region is not extracted in terms of pixel units, but as a rough cluster region (for example, a cluster size of $\sim 5 \times 5$ pixels). This approach is used because the reconstructed image can be prevented from converging on the incorrect MNP distribution by defining the error regions using such cluster units.

Proc. 5 (Fig. 1, stage 5 (Creation)):
The new data sets comprising the magnetization signal and MNP location pairs (h) are generated analytically, both inside and outside the error regions. In an error region, various MNP locations are randomly generated as new output data. Further, although it may not be necessary to correct the estimated location in an outside region because of the small error in that region, MNP locations are also generated as new output data according to the estimated locations in order to reduce the error in the estimated distribution. That is, in this method, the occurrence probabilities are high in the vicinity of the estimated MNP positions, and low at positions where MNPs do not exist. Finally, the MNP locations generated inside and outside the error regions are combined, and new data sets comprising magnetization signals and MNP location pairs (h) are generated analytically.

Proc. 6 (Fig. 1, stage 6 (Addition)):
Additional learning is performed using the newly created data sets.

The above procedures are performed iteratively until the error between the observed and estimated signals is sufficiently reduced.

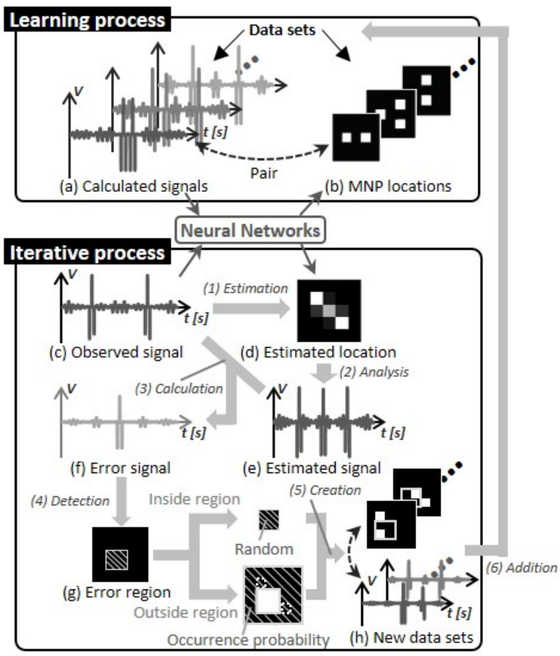

Figure 1: Concept of proposed method.

III. Numerical Experiment Methods

To confirm the effectiveness of the proposed method, we performed numerical experiments based on the basic MPI system shown in Fig. 2. In these numerical experiments, two coil pairs (diameter: 180 mm, distance to opposite coil: 180 mm) were considered. In addition, the field of view (FOV) was set to 11 mm×11 mm with a matrix size of 11 × 11, and the original MNPs (particle diameter: 20 nm) were located as shown in Fig. 3 (a). A gradient magnetic field of 3.0 T/m was generated along the x-direction, and an alternating field of 10 mT was applied with 122 Hz frequency in the same direction. Hence, we simulated conditions in which the MNP magnetization was insufficiently saturated.

In this study, a traditional three-layer NN with a sigmoid function was used. In total, 363, 242, and 121 neurons were used in the input, hidden, and output layers, respectively. In the first learning process, 10000 data sets were input to the NNs and 5000 additional data sets (size of cluster error region: 5 × 5 pixels) were generated in every iterative process. The learning and iterative processes were executed 20 times. To reduce the data input to the NNs, only the third, fifth, and seventh harmonics of the magnetization signals were used.

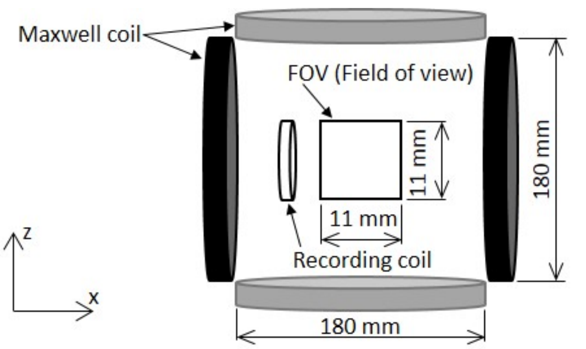

Figure 2: Basic magnetic particle imaging (MPI) system.

IV. Results and Discussion

IV.I. Reconstructed Image Quality

Figure 3 (a) shows an original MNP location and Fig. 3 (b) and Fig. 3 (c) show the reconstructed images obtained following the use of the inverse-matrix solution [3] and the proposed method, respectively. With the proposed method, the error between the observed and estimated signals converged over 20 iterations. The number of data sets used for learning was suppressed to 110000, although the data set combinations reached the order of $1 \cdot 10^{36}$ for a reconstructed image with a matrix size of 11×11. These results show that the MNP distribution was reconstructed more precisely by the proposed method than by the inverse-matrix solution, which yielded some image blurring and artifacts in the middle of the reconstructed image. Thus, we confirmed that the reconstructed image quality was improved by considering additional information, which corresponds to two or more PSFs.

To evaluate the reconstructed image in Fig. 3 quantitatively, we used the mean squared error (MSE):

$$MSE_{image} = \frac{1}{XZ} \sum_{i=1}^{X} \sum_{j=1}^{Z} \left(I(i,j) - U(i,j) \right)^2 \quad (1)$$

Here, $I(i,j)$ represents the reconstructed image intensity, $U(i,j)$ the original image intensity, X the matrix size in the x-direction, Z the matrix size in the z-direction, and MSE_{image} the MSE of the reconstructed image. Table 1 lists the results obtained using the MSE. These results confirmed that our proposed method could estimate the MNP locations more precisely than the inverse-matrix solution even when the MNP magnetization was insufficiently saturated. Moreover, if an observed signal with noise is added, the proposed method is expected to estimate the MNP locations correctly, because magnetization signals generated from multi-position MNP locations are used in two or more combined PSFs. Thus, in future, we plan to examine the noise tolerance of the proposed method.

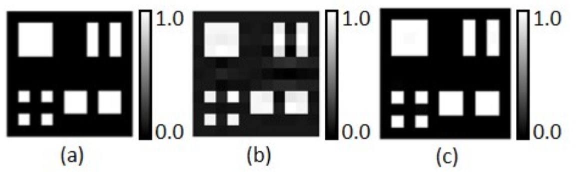

Figure 3: Numerical experiment results obtained using (b) inverse-matrix solution and (c) proposed method for (a) magnetic nanoparticle (MNP) location.

Table 1: Evaluation of numerical experiment results.

	Inverse-matrix	Proposed method
MSE	$1.24 \cdot 10^{-3}$	$4.31 \cdot 10^{-5}$

In addition, as many data sets that include the various MNP locations in the error regions are used for learning, the error between the estimated and unknown locations is reduced significantly. Thus, it is expected that a correctly reconstructed image can be obtained even if the magnetization signals generated from the MNPs at the FFPs are similar to those in the vicinity of the FFP regions.

IV.II. Convergence Properties

In the proposed method, many data sets are generated so that the appropriate data sets can be selected and used for learning in every iterative process. However, the number of iterations affects the reconstruction time, because considerable time is required to learn a large number of data sets. Therefore, we evaluated the convergence property of this method by performing numerical experiments under the same conditions as described above. We used the MSE (see Eq. (1)) for the reconstructed image and the MSE for the signal (MSE_{signal}):

$$MSE_{signal} = \frac{1}{XZN}\sum_{i=1}^{X}\sum_{j=1}^{Z}\sum_{t=1}^{N}\big(E(i,j,t)-O(i,j,t)\big)^2 \tag{2}$$

Here, $E(i,j,t)$ represents the estimated signal, $O(i,j,t)$ the observed signal, and N the number of sampling periods.

Figure 4 shows the convergence properties of our method. We found that MSE_{image} was stable after more than 10 iterations, and the MNP location could be estimated correctly. Moreover, it was found that MSE_{signal} was also stable after more than 10 iterations. Hence, to determine the learning process termination point, the MSE of the signal can be used as a decision-making criterion.

In the numerical experiments, the reconstruction time was ~16 min when a general computer (Quad core i7-3770 CPU, 3.40 GHz, 8.0 GB memory) was used to perform 20 iterations. Thus, to reduce the reconstruction time, it is important to determine the iteration process termination point.

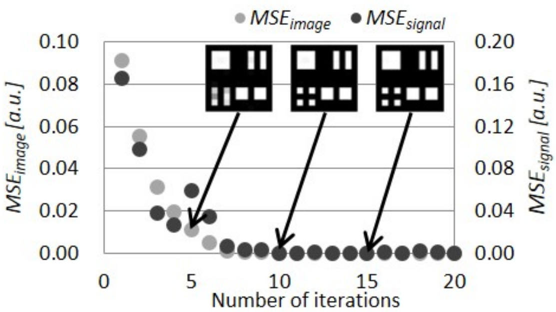

Figure 4: Convergence properties of our method.

IV.III. Harmonics used for Learning

In the evaluation of our proposed method, we used the third, fifth, and seventh harmonics of the magnetization signals to reduce the amount of data input into the NNs. The harmonics affect the reconstruction time and quality of the reconstructed image. Therefore, we determined the appropriate number of harmonics required for learning. We used the same numerical experiment conditions as discussed previously, and we used the expression for MSE_{image} (see Eq. (1)) to evaluate the image quality.

Figure 5 shows the differences in the results depending on the number of harmonics used in the learning process. We found that the MSEs differed significantly depending on the number of harmonics used, and many harmonics were required for accurate image reconstruction. However, as indicated in Table 2, the reconstruction time increased when many harmonics were employed. Hence, an appropriate number of harmonics is required. In this experiment, the third, fifth, and seventh harmonics were required for correct image reconstruction, and MSE_{image} remained constant after approximately 10 repetitions. However, the proposed method utilized a significantly longer processing time than the inverse-matrix method. Thus, in future, investigation of the appropriate number and order of harmonics is necessary to reduce the reconstruction time.

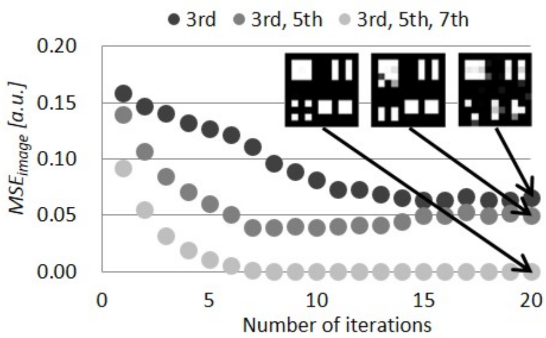

Figure 5: Evaluation of harmonics used in learning process.

Table 2: Reconstruction time.

	Inverse-matrix	Proposed method		
Harmonics		**3rd**	**3rd, 5th**	**3rd, 5th, 7th**
Time	1 min	10 min	13 min	16 min

V. Conclusion

We proposed a new reconstruction method using NNs subjected to additional learning. This method can reconstruct an image more clearly than the conventional method even when the MNP signals are insufficiently saturated because the proposed method can employ significantly more information than the conventional method. However, it may be difficult to reconstruct an accurate image when appropriate data sets are not selected for learning. Hence, in the future, we plan to improve the method by refining the data set selection process.

VI. Acknowledgments

This study was supported by a Grant-in-Aid for Scientific Research (B) (15H03038, 2015) and the Japan Society for the Promotion of Science (JSPS).

References

[1] B. Gleich and J. Weizenecker. Tomographic imaging using the nonlinear response of magnetic particles. *Nature*, 435(7046):1214–1217, 2005. doi:10.1038/nature03808.

[2] B. Gleich, J. Weizenecker, and J. Borgert. Experimental results on fast 2d-encoded magnetic particle imaging. *Phys. Med. Biol.*, 53(6): N81–N84, 2008. doi:10.1088/0031-9155/53/6/N01.

[3] J. Weizenecker, B. Gleich, and J. Borgert. A simulation study on the resolution and sensitivity of magnetic particle imaging. *Phys. Med. Biol.*, 52(21):6363–6374, 2007. doi:10.1088/0031-9155/52/21/001.

[4] T. Hatsuda, S. Shimizu, H. Tsuchiya, T. Takagi, T. Noguchi, and Y. Ishihara. A basic study of an image reconstruction method using neural networks for magnetic particle imaging. In *International Workshop on Magnetic Particle Imaging*, 2015. doi:10.1109/IWMPI.2015.7107046.

[5] D. E. Rumelhart, G. E. Hinton, and R. J. Williams. *Learning internal representations by error propagation.* MIT Press, Cambridge, 1986.

[6] T. Fukuda, S. Shiotani, and F. Arai. A new neuron model for additional learning. In *International Joint Conference on Neural Networks*, 1992. doi:10.1109/IJCNN.1992.287066.

[7] K. Funahashi. On the approximate realization of continuous mappings by neural networks. *Neural Networks*, 2(3):183–192, 1989. doi:10.1016/0893-6080(89)90003-8.

