VOL. 2020, NO. 2-3, 2021, 49-55
www.elektrika.utm.my
ISSN 0128-4428

ELEKTRIKA
Journal of Electrical Engineering

A Supervised Deep Feedforward Neural Network (SDFNN)-based Image Reconstruction Algorithm for Radio Tomographic Imaging

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Abstract: Radio tomographic imaging (RTI) is an emerging imaging technique that utilizes the shadowing losses on links between multiple pairs of wireless nodes within the sensing area to estimate the attenuation of physical objects. By using an image reconstruction algorithm, the attenuations caused by the physical objects will be transformed into a tomographic image. The tomographic image provides information about the shape, size and position of an object. However, the process of reconstructing a tomographic image from the RSS measurements is an ill-posed inverse problem, meaning that a small number of errors or variations in measurements will lead to a significant impact on the image quality. The existing linear inverse solvers provide fast reconstruction but the imaging results is non-satisfactory and inaccurate. On the other hand, the nonlinear inverse solvers produce a higher quality image but are computationally expensive. Studies of applying deep learning technique and neural networks in tomographic reconstructions to solve the ill-posed inverse problems have emerged in recent years. However, to the best of our knowledge, the studies conducted in solving the inverse problem of RTI system using deep learning technique are rare. Therefore, a supervised deep feedforward neural network (SDFNN)-based image reconstruction algorithm for the RTI system is explored in this study to determine the feasibility of deep learning technique in reconstructing a tomographic image using RSS measurements only.

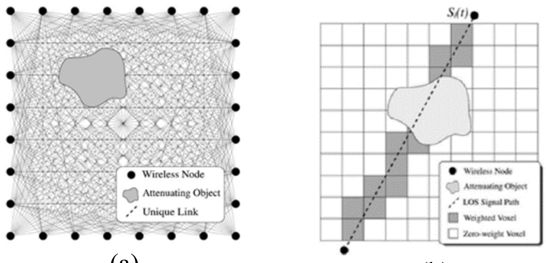
Keywords: Radio tomographic imaging, image reconstruction algorithms, deep neural networks, deep learning and wireless sensor networks

Article History: received 25 May 2021; accepted 12 June 2021; published 15 0ctober 2021.

1. INTRODUCTION

Radio tomographic imaging (RTI) is an emerging imaging technique that utilizes the shadowing losses on links between multiple pairs of wireless nodes within the sensing area to estimate the attenuation of physical objects. Figure 1(a) shows an illustration of the wireless sensor network (WSN) in the RTI system [1][2]. The black colour dots represent the radio frequency (RF) sensor that acts as transceivers. When the RTI system is operating, the transceivers in the sensor network will communicate with each other and formed a unique link. The object that enters the monitoring area at this time will absorb, diffract, reflect, or scatter some of the transmitted waveforms. Also, at the same time, the object will block some of the lines of sight (LOS) path of the unique links in the RTI system as shown in Figure 1((b) [1][2]. This caused the links between multiple pairs of RF nodes to experience shadowing losses. The shadowing losses is referred to the variations in the received signal strength (RSS) measurements which will be used for the reconstruction of the tomographic image. By using an image reconstruction algorithm, the attenuations caused by the physical objects will be transformed into a tomographic image. The tomographic image provides information about the shape, size and position of an object.

In recent years, RTI has gained huge interest from the researchers in the device-free localization (DFL) field due to its ability to generate an image to localize a stationary and moving target within the monitoring area using the RSS measurements only without any phase and timing information [1], [3]–[14]. Besides, the RTI system is suitable for localization applications that are concerned about privacy. This is due to the facts that the RTI system only detects the presence and location of targets; it does not identify the individual uniquely [15].



(a) (b)

Figure 1. An illustration of (a) the wireless sensor network (WSN) in the RTI system, (b) LOS path and the object in the RTI system [1][2].

However, the process of reconstructing a tomographic image from the RSS measurements is an ill-posed inverse problem for the RTI system, meaning that a small number of errors or variations in measurements will lead to a significant impact on the image quality [1], [2], [16]. Besides, the reconstructed image in the RTI system is low in quality due to the number of pixels of an image is always higher than the number of sensor measurements. To solve the ill-posed inverse problem of the RTI system, a technique known as regularization has been introduced by adding extra information to the mathematical cost model [16]. In this decade, there are various regularization methods have been proposed by the researchers to solve the inverse problem. The inverse problem solvers in the RTI system mainly can be classified into two categories: linear algorithms and nonlinear algorithms.

The commonly used linear inverse solvers are linear back projection (LBP) [17], Tikhonov regularization (TR) [1], [2], [12], [17]–[25], truncated singular value decomposition (TSVD) [2], [23] and regularized least squares estimator [5], [26]–[33]. While for nonlinear algorithms are projected Landweber iteration [34], pre-iteration Landweber iteration (PLI) [22], Landweber iteration (LI) [22] and total variation (TV) [2], [35]. The existing linear algorithms provide fast reconstruction, but the imaging result is non-satisfactory and inaccurate. On the other hand, the nonlinear algorithms produce a higher quality image but are computationally expensive. Although various regularization techniques have been introduced to solve the inverse problem of the RTI system, however, the image produced using the existing image reconstruction algorithms still does not achieve a satisfactory result.

Studies of applying deep learning technique and neural networks in tomographic reconstructions for electrical impedance tomography (EIT) to solve the ill-posed inverse problems have emerged in recent years [36]–[40]. From the previous works done by the researchers in the EIT field using deep learning-based image reconstruction algorithms, it shown that deep learning approaches are capable to replace more complex and slower non-linear image reconstruction algorithms and avoid poor inverse solvers because they are good at mapping complicated nonlinear functions.

However, to the best of our knowledge, the studies conducted in solving the inverse problem of RTI system using deep learning technique are rare. Three studies have been published solving the ill-posed inverse problem of RTI system using deep learning techniques [41]–[43]. Due to low computation cost in training and execution, the initial works done by [41] have used convolutional neural networks (CNN) in their study to remove the artifacts caused by the limited number of sensors. Although both of the studies in [41] and [42] have used CNN to improve the reconstruction accuracy of the image and their network inputs are in image form, however, there are some differences in their design of network architecture. In [41], the authors used the images reconstructed using FBP algorithms as the network inputs and the ground truth images are regarded as the labels for the input data. While in [42], the RSS measurements are collected and remapped into the training data set generated by the forward model and selected as the network inputs.

Although works are done in [41] and [42] demonstrated that the CNN network is capable of improving the reconstruction accuracy by generalizing based on previous network training experiences. However, our investigations show that CNN is not practical with the resources available to us. This is because the reconstruction of a tomographic image is a multi-regression problem which is nonlinear and complex. Besides, the size of the pixels for a tomographic image usually very large, from 500 x 500 pixels up to 1280 x 1280 pixels. The large pixel size of the tomographic image will increase the computational cost during the training of the deep learning model. Therefore, a supervised deep feedforward neural network (SDFNN)-based image reconstruction algorithm for the RTI system is explored in this study to determine the feasibility of deep learning technique in reconstructing tomographic image using RSS measurements only.

In Section 2, the experimental setup for the RTI system will be discussed in detail as well as the network architecture and training process of the proposed SDFNN model. The preliminary results of the proposed SDFNN-based image reconstruction algorithm will be presented in Section 3. We conclude the paper and discuss the future work in Section 4.

2. SDFNN-BASED IMAGE RECONSTRUCTION ALGORITHM FOR RTI SYSTEM

In this section, the experimental setup for the RTI system is discussed in detail. Next, a supervised deep feedforward neural network (SDFNN)-based image reconstruction algorithm for the RTI system is modelled in this paper to study the feasibility of deep learning technique in reconstructing a tomographic image using RSS measurements only.

2.1 Experimental Setup for RTI System

The experimental setup for the RTI system in this study is as per our previous work in [44]. The eight units of RF sensors are mounted around the monitoring column with a diameter of 1m. Each of the RF sensors operates in transceiver mode in which they can transmit and receive sensor measurement sequentially. Figure 2 show an overview of the RTI system [44].

As mentioned in Section 1, when the RTI system is operating, the communication between multiple pairs of transceivers will form multiple unique links within the monitoring area. Also, since the connection between transceivers is two-way communication, thus, each of the individual links will have two measurements. The total number of unique links can be described as:

$$M = \frac{K\,(K-1)}{2} \qquad (1)$$

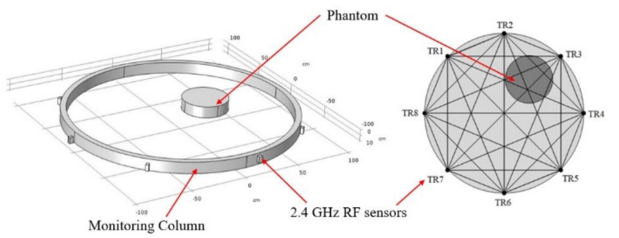


Figure 2. An overview of the RTI system [44].

In this study, an experiment was carried out to collect the RSS measurements for training the proposed SDFNN network. Figure 3 shows an experimental setup for the RTI system. The experiments were conducted according to four phantom profiles design shown in Table 1. Three phantom design profiles (Design 1, 2 and 3) contain a single phantom; however, they are in different size and position.

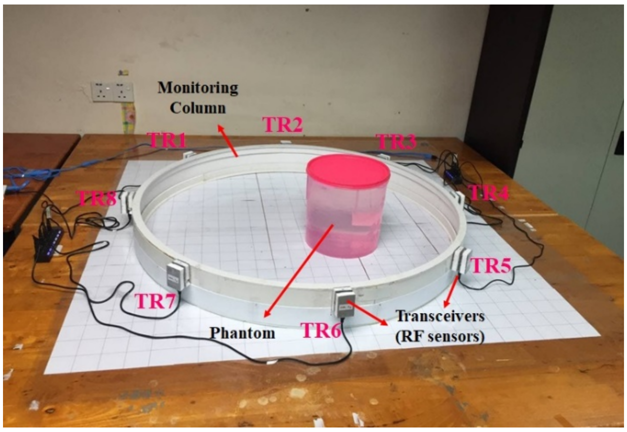


Figure 3. An experimental setup for the RTI system.

Table 1. Phantom Profiles Information

<table>
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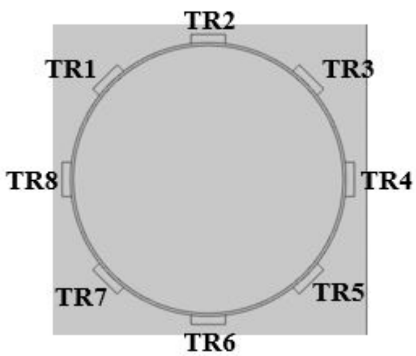
<tr><td>1</td><td>
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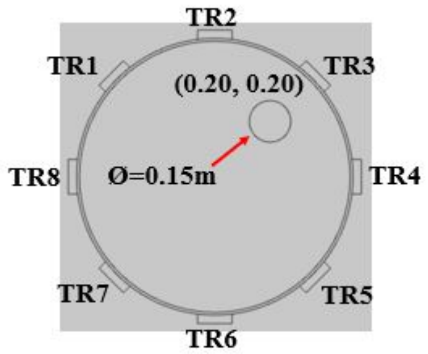
<tr><td>2</td><td>
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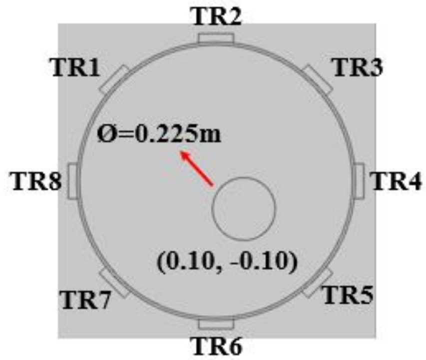
<tr><td>3</td><td>
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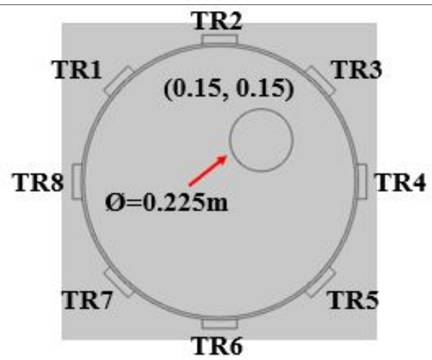
<tr><td>4</td><td>
</td></tr>
</table>

2.2 Network Architecture of Proposed SDFNN-based Image Reconstruction Algorithm

The main objective of tomographic reconstruction is to estimate the image vector, *x* from the measurements *y*, which is the inverse problem. The deep learning method that solves this problem is expressed in Equation 2, where x_n and y_n are datasets used to train this model. R is the network structure, which is used to learn the relationship between input and output. *l* and *g* denote cost function and regularization respectively. θ are the network parameters.

$$R_{learn} = arg\,min \sum_{n=1}^{N} l\,\{X_n, R_\theta(y_n)\} + g(\theta) \qquad (2)$$

In this study, a deep learning-based image reconstruction algorithm in reconstructing tomographic image is modelling using a supervised deep feedforward neural network as shown in Figure 4. The network contains three important layers: an input layer, three hidden layers and an output layer. The input vectors for the proposed SDFNN model consisted of 56 RSS measurements collected from eight units of transceivers in the RTI system as expressed in Equation 3. Each element contained a unique value. While the output vector contained 250,000 elements (500 x 500 pixels tomographic image) as expressed in Equation 4.

$$I = [x_1, x_2, x_3, x_4, x_5, \dots, x_{56}] \quad (3)$$

⍰ $= [y_1, y_2, y_3, \dots, y_{250,000}]$ (4)

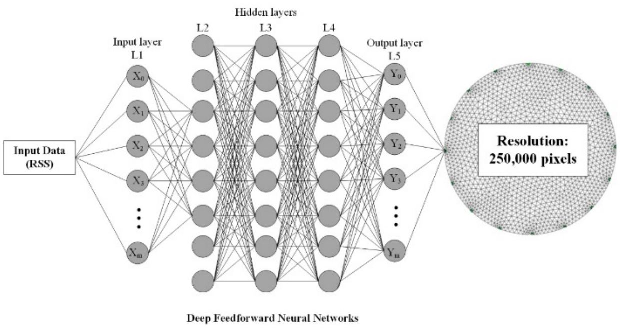


Figure 4. Network architecture of the proposed SDFNN-based image reconstruction algorithm for RTI system.

2.3 Network Training of Proposed SDFNN-based Image Reconstruction Algorithm

Before training the SDFNN model, we have a data preparation and data pre-processing process. Since we are using supervised learning, input and output data must be prepared and labelled. The input data which is the RSS measurements for the training of the SDFNN model are collected through conducting experiments. The RSS measurements are collected based on four designs shown in Table 1. While the labelled output data for the training of the SDFNN model is a 500 x 500 tomography image generated using a forward model. The four designs of a two-dimensional RTI system that have the similar setup to the designs shown in Table 1 are modelled and simulated using FEM. All the data are pre-processed before feeding it into the SDFNN model.

For the initial study, the proposed SDFNN model was trained using 300 datasets. All datasets were randomly divided into 3 sets: training, validating, and testing in 70:15:15. The training set was used to properly train each of the subsystems. While the validation set was used to determine the moment of stopping the iterative training process. The test set can be used for the independent assessment of network quality after the learning process.

Three phantom designs which are Design 1, Design 2 and Design 3 shown in Table 1 are applied in the training process of the SDFNN model. While Phantom Design 4 are not included in the training process of the SDFNN model. Phantom Design 4 are used to verify the feasibility of the proposed SDFNN model to reconstruct tomography image that not in the training process.

2.4 Working Principle of the Proposed SDFNN-based Image Reconstruction Algorithm for Radio Tomographic Imaging

The working principle of the proposed SDFNN-based image reconstruction algorithm for the RTI system consists of three parts as shown in Figure 5. The first part is the data collection and preparation section. The input data was collected through an RTI system, and the output data was generated using a forward model. Next, the SDFNN model was trained using prepared training datasets. Last, the predicted results from the SDFNN model will be used for image reconstruction.

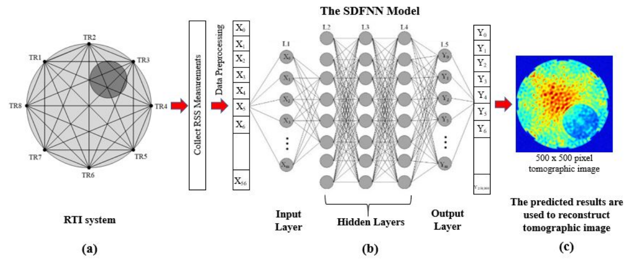


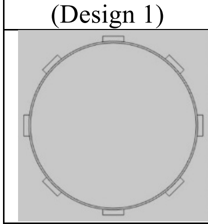
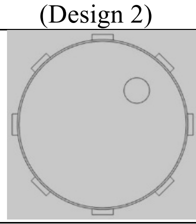
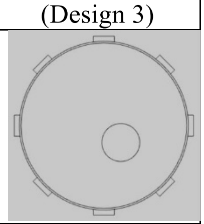
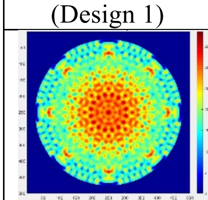
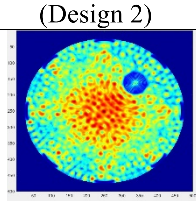
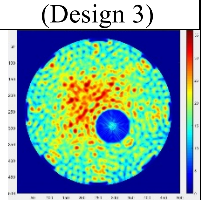
Figure 5. The working principle of the proposed SDFNN-based image reconstruction algorithm for Radio Tomographic Imaging. (a) RTI system used for the collections of RSS measurements. (b) Proposed SDFNN model. (c)The predicted results from the SDFNN model are used to reconstruct tomography image.

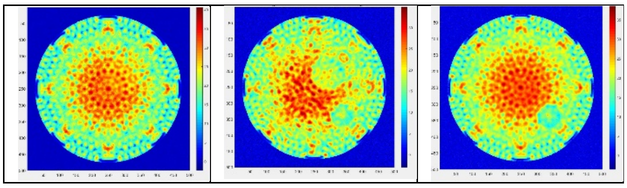
3. PRELIMINARY RESULTS

This section presents the preliminary results obtained by the SDFNN-based image reconstruction algorithm for the RTI system. Table 2 shows the reconstructed tomography image using a conventional linear image reconstruction algorithm: Linear Back Projection (LBP) algorithm for simulation and the proposed supervised deep feedforward neural network (SDFNN)-based image reconstruction algorithm.

Based on the obtained results, the feasibility of using the deep learning technique in reconstructing RTI image is proven. The SDFNN model is capable to reconstruct image for Phantom Design 1 accurately. Compared to the image reconstructed using LBP Simulation, the proposed SDFNN model able to localize the phantom in Design 2 and 3; however, the accuracy of the prediction on the size and position of the phantom needs further improvements.

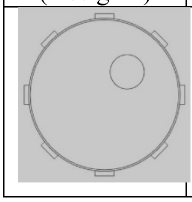
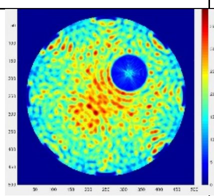
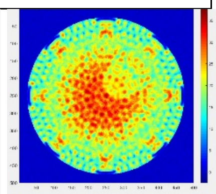
Table 2. Reconstructed image using Linear Back Projection (LBP) Simulation and Supervised Deep Feedforward Neural Network (SDFNN)-based Image Reconstruction Algorithm for RTI system.

Phantom Profiles (Design 1)	Phantom Profiles (Design 2)	Phantom Profiles (Design 3)
		
LBP Simulation (Design 1)	LBP Simulation (Design 2)	LBP Simulation (Design 3)
		
SDFNN Model (Design 1)	SDFNN Model (Design 2)	SDFNN Model (Design 3)



To verify the feasibility of the proposed SDFNN model to reconstruct tomography image that not in the training process, Phantom Design 4 are used in the testing process. Based on the result obtained in Table 3, the SDFNN model able to localize the phantom within the monitoring area. However, the size and shape of the phantom cannot be predicted accurately.

Table 3. Feasibility of SDFNN model to recognize unknown phantom design.

Phantom Profiles (Design 4)	LBP Simulation (Design 4)	SDFNN Model (Design 4)
		

4. CONCLUSIONS

In this paper, we proposed a supervised deep feedforward neural network (SDFNN)-based image reconstruction algorithm for the RTI system. The preliminary results showed the proposed SDFNN model able to reconstruct a tomographic image using RSS measurements only. However, the prediction on shape, size and position of the phantom needs further improvement. In the future study, the performance of the proposed SDFNN-based image reconstruction algorithm and the algorithm tuning parameters such as weight initialization, learning rate, activation functions, network topology, training batches, regularization and optimization will be explored to improve the quality of the reconstructed image.

ACKNOWLEDGMENT

This research was financed by the Collaboration Research Grant UTM-UniMAP 2018 (Grant No. 9023-00002). The authors gratefully thank Universiti Malaysia Perlis (UniMAP) for the facilities and technical support.

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