Through-the-Wall Radar Imaging Based on Deep Learning

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Abstract. High resolution image can be obtained with backprojection (BP) algorithm, but at the same time, significant grating lobes will be brought in radar image and reduce the quality of image. This paper presents a through-the-wall radar (TWR) imaging method based on deep learning to improve the quality of radar image. A convolutional neural network was designed for TWR imaging, the radar image can be obtained as the output of neural network. The simulation and real data experiments demonstrate the effectiveness of proposed method.

Keywords: Through-the-wall radar imaging ·
Convolutional neural network (CNN)

1 Introduction

To obtain high range and azimuth resolutions, the backprojection (BP) algorithm is employed to through-the -wall radar imaging. However, the process of energy integration will bring in grating lobes. Significant grating lobes may increase false alarms or even submerge the weak target near a strong target [4], and may effect the later process, such as target detection and identification. Thus, it is necessary to propose a new radar imaging method. Deep learning has been successfully employed to tackle several image tasks such as target detection

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and show better performance than traditional methods. In radar imaging community, the complex valued convolutional neural network (CCNN) has achieved a good result in enhancing radar imaging [2]. Neural network can learn features of images from training data, then it will optimize weights to be adaptive to training data. Finally, a trained model is obtained after many iterations, and can be employed to solve specific problem. In order to solve the problem of through-the-wall radar imaging performance, a new imaging method is proposed. Firstly, through-the-wall radar signal model and BP algorithm are analyzed, then we can generate training data via the signal model. Secondly, neural network are designed for through wall radar imaging. Finally, the trained neural network can be employed to obtain a better image than the image generated by BP algorithm. Simulation and real experimental results show that grating lobes are suppressed and the quality of image is improved.

2 Signal Model and BP Algorithm

2.1 Signal Model

For through wall radar, we analyze the signal model with one transmitter and N receivers. The position of antennas can be found in Fig. 1, where T is transmitter and Ri $(i = 1, 2, \ldots, N)$ is receivers.

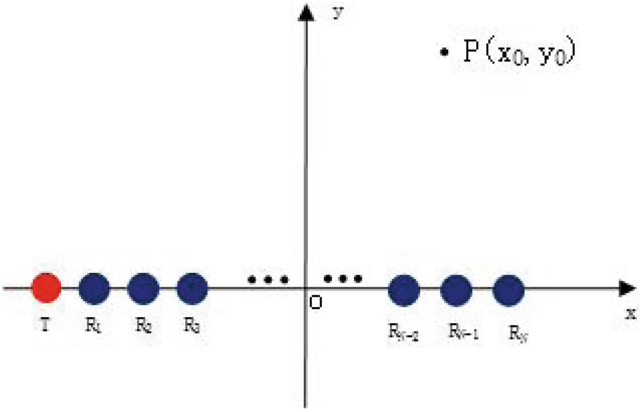

Fig. 1. Geometry of the scenario.

For through-the-wall radar, the transmitted signal can be expressed as follows:

$$s\left(t\right) = a\left(t\right) \exp\left(j2\pi f_c t\right) \tag{1}$$

where $a(t)$ is the waveform of transmitted signal, t is fast time, and f_c denotes carrier frequency. The echo signal can be written as

$$s_r\left(t_m, t\right) = a\left(t - t_m\right) \exp\left[j2\pi f_c\left(t - t_m\right)\right] \tag{2}$$

where t_m is the delay of transmitted signal and echo signal that can be written as follow

$$t_m = \frac{\sqrt{(x_0-x_m)^2-(y_0-y_m)^2}-\sqrt{(x_0-x_t)^2-(y_0-y_t)^2}}{c} \tag{3}$$

where (x_0, y_0) is coordinate of arbitrary point's, (x_m, y_m) is the mth $(m = 1, 2, \ldots, N)$ receiver's coordinate, and (x_m, y_m) is the transmitter's coordinate.

2.2 BP Algorithm

Before employ BP algorithm, demodulation and range compression should be done. For different transmitted signal, there are different methods to complete this process. For example, we can use a matched filtering implement range compression of linear frequency modulated (LFM) signal by operation of convolution. After range compression, we get the time domain signal as follows [3]

$$s_{rc}\left(t_m, t\right) = sinc\left[B\left(t - t_m\right)\right] \exp\left(-j2\pi f_c t_m\right) \tag{4}$$

where B is the bandwidth of transmitted signal. Then, the range compression signal can be projected onto Cartesian grids to form a through wall radar image which can be given by following integral [1,5]

$$I\left(x_0, y_0\right) = \int s_{rc}\left(t_m, t\right)|_{t=t_m} \exp\left(j2\pi f_c t_m\right) dt_m \tag{5}$$

Via BP integral, we can get BP image of arbitrary area. From Eqs. 4 and 5, we can found that there will be two conditions for a point whose coordinate is $P_1(x_1, y_1)$: (1) There is a target at this point, we can easily get the peak energy of echo signal that generated by the target will be accumulated. (2) There is nothing at this point or the transmitted signal cannot be reflected via this point, then side lobes of s_rc will be accumulated to this point, so it will generate grating lobes. If there is a weak target at P_1, whose accumulated signal energy is A_1, and assume that grating lobe energy is A_n, when $A_n < A_1$, the weak target will be defocused. If there are some strong target near P_1, it will be impossible that $A_n > A_1$, so the weak target is submerged by grating lobes.

3 Through-the-Wall Radar Imaging Based on CNN

In order to get through-the-wall radar image with high performance, we design a CNN to enhance imaging. The network structure can be found in Fig. 2.

First, the echo signal data input into the network, to get an initial image, we designed a fully connected layer which is achieved by BP algorithm. After getting a BP image, the absolute value image of BP image input into the next layer.

For generation of training data, we can define the expected target function as [2]:

$$O\left(x, y\right) = p\left(x, y\right) * \left|o\left(x, y\right)\right| \tag{6}$$

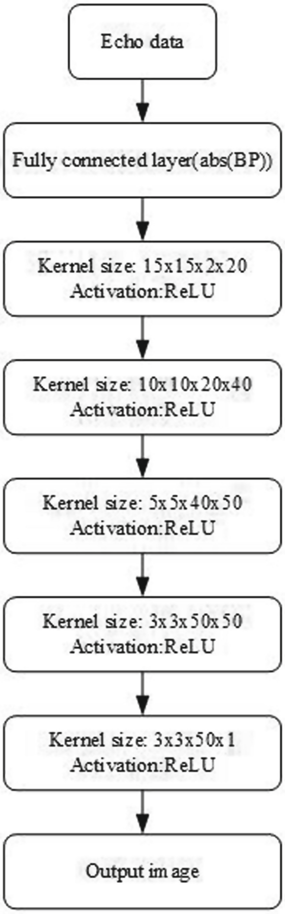

Fig. 2. Network structure.

where "*" represents operation of convolution, $o(x, y)$ is the scattering coefficients of target and $p(x, y)$ is ideal point spread function (PSF), which can be written as

$$p\left(x, y\right) = \exp\left(-\frac{x^2}{\sigma_x^2} - \frac{y^2}{\sigma_y^2}\right) \tag{7}$$

where σ_x, σ_y control the width of $p(x, y)$. To get high resolution image, the values of them are 0.012, 0.012 respectively.

We generate 10000 sets of reference images which include 4 12 points of random coordinates (x, y) within a square area by 6 and $o(x, y) = 1$. Then generate corresponding echo data as training data. The loss function is defined as:

$$E = \sum\left(O - f_o\right)^2 \tag{8}$$

where O denotes reference image and f_o is output image of neural networks. We employ the Adam algorithm as the method for stochastic optimization. The learning rate is 10e−4, batch size is 50. Training lasts for 10 epochs. Our implementation is based on TensorFlow and CPU.

4 Experiments

In this section, both simulations and real data of through-the-wall radar are presented and analyzed to identify the effectiveness of the proposed methods.

4.1 Simulation

For simulation data, we set 4 targets and the result of BP imaging can be found in Fig. 3.

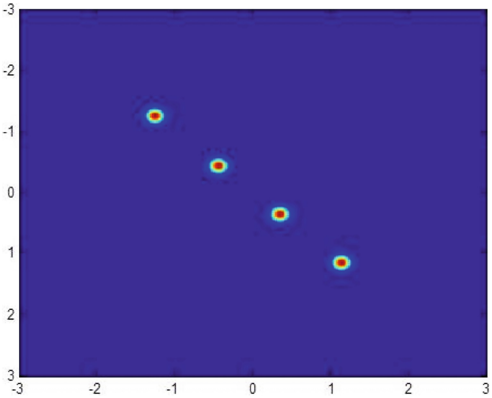

Fig. 3. The result of BP imaging.

From Fig. 3, we found that the energy focus on the positions we set. Nevertheless the grating lobes degrade the quality of image. Near the target position, grating lobes energy cannot be ignored. When training neural network, the reference image is shown in Fig. 4.

It is clear that in the reference image the energy only focuses on the target position. During the training phase, the neural network will refine the weight matrix which can make, the output image close to this reference image. After training, the output image of neural network is presented in Fig. 5.

It is shown that the image quality of the output image is improved comparing to the BP image. The energy of grating lobes is decreased, and the energy focuses on the target.

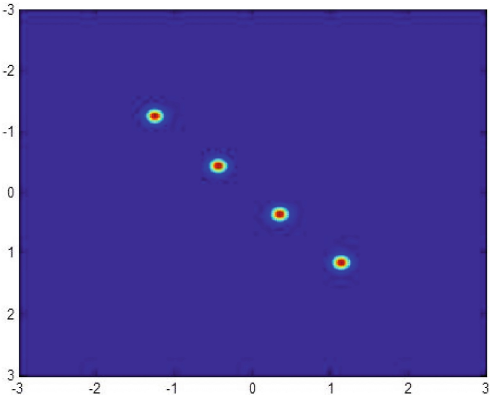

Fig. 4. Reference image.

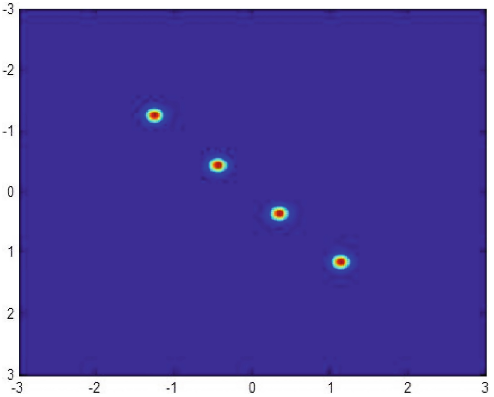

Fig. 5. The output image of neural network.

4.2 Real Data Experiment

The experiment scenario is a target behind wall and the radar antennas are placed at the another side. The BP image is shown in Fig. 6.

The quality of BP image is not good because of grating lobes. After putting echo data into the neural networks, we obtain the output image shown in Fig. 7.

The image quality has been improved significantly comparing to BP image, it is useful for following work such as target detection and identification.

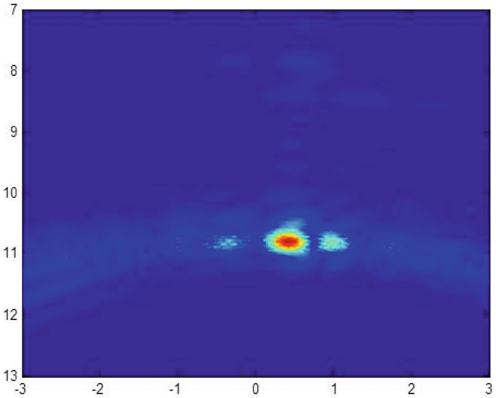

Fig. 6. BP image of real data.

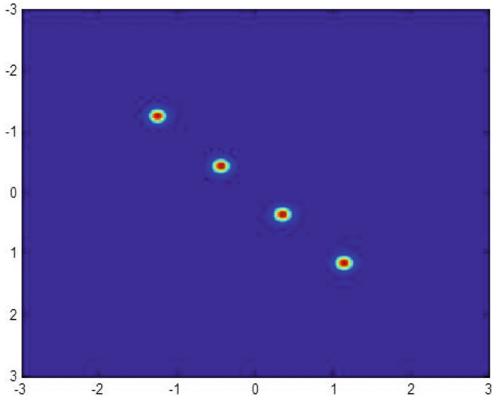

Fig. 7. The output image of neural network of real data.

5 Conclusion

A novel and effective neural network based through-the-wall radar imaging algorithm is proposed. Radar signal model and BP imaging algorithm are analyzed firstly. Then combining with CNN, we design the structure of neural networks. Finally, we obtain quality improved radar image with CNN. We believe neural network will bring more benefits to radar imaging in the future.

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