Transfer learning-based radar imaging with deep convolutional neural networks for distributed frequency modulated continuous waveform multiple-input multiple-output radars

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Abstract
Deep-learning-based radar imaging is developed with distributed frequency modulated continuous waveform multiple-input multiple-output (FMCW MIMO) radars in which a deep-learning approach based on the convolutional neural network (CNN) is proposed to achieve radar images robust to adverse circumstances. Differently from the existing deep-learning methods applied to radar object recognition, the deramped radar signal is exploited as the input of the proposed deep CNN (DCNN) without any processing related to the spectrogram transform and the subspace decomposition. To effectively train the proposed DCNN, the received signal is reformulated in terms of the reflection gain values in the (azimuth, range) patches in the image region of interest such that the output vector of the DCNN is composed of the reflection gain values in the associated patches. Furthermore, to overcome the limitations on the amount of training data and training time, the transfer learning approach is effectively applied to the distributed FMCW MIMO radar imaging. The proposed radar imaging is assessed with synthetic simulation data. Specifically, by transferring the pretrained DCNN model for a given reference radar to other distributed radars, the distributed radars can save about 52.4% in training time compared with a DCNN having the same architecture but without transfer learning.

1 | INTRODUCTION

To monitor the surrounding environment or detect targets with high reliability, distributed radars are deployed in intelligent vehicle systems and anti-drone systems [1–3] (and references therein). Furthermore, because radar imaging for such surveillance that is robust to harsh environmental conditions can be effectively achieved by exploiting frequency modulated continuous waveform multiple-input multiple-output (FMCW MIMO) radar with low implementation cost, the radar imaging with FMCW MIMO radar is extensively investigated [4–8].

To obtain a high-resolution radar image with the FMCW MIMO radar, two-dimensional multiple signal classification (2-D MUSIC) algorithms can be exploited [8, 9]. However, in such algorithms, the estimation of the covariance matrix of the received signal is required for the subspace-based signal processing. Accordingly, multiple FMCW pulses are collected at the receive antennas for the subspace estimation, which may incur a considerable latency to obtain radar images. In addition, when the FMCW MIMO radars are spatially distributed, each radar should perform the subspace estimation, which is not desirable for radars with limited computing resources. To avoid
the subpace estimation, compressive sensing (CS) based approaches have been investigated [10–15]. In [10], the reweighted L1 minimisation method is applied to radar imaging with a single antenna FMCW radar. In [11], greedy reconstruction algorithms such as orthogonal matching pursuit (OMP) or subpace pursuit are exploited to achieve the radar images, and in [12, 13], a sparse Bayesian learning algorithm is applied in the angle-of-arrival estimation. In [14, 15], sparse Bayesian pursuit has been applied to pulse-Doppler MIMO radar imaging and synthetic aperture radar imaging. In [16], to obtain a high-resolution radar image with distributed FMCW MIMO radars, Bayesian matching pursuit (BMP)-based imaging methods are proposed, in which a single FMCW pulse is transmitted from each transmit antenna, and the BMP is applied to the received signals collected from multiple receive antennas for the sparse radar image reconstruction. However, the CS-based radar imaging methods also require the iterative matched basis searching process. Especially in BMP-based algorithms [16], sequential computation of the likelihood metric for possible support candidates still requires considerable computational complexity.

When the distributed FMCW MIMO radars are exploited, radar imaging based on the deep convolutional neural network (DCNN) is proposed to achieve stable radar images in adverse circumstances without any iterative searching process. We note that deep neural networks have been successfully applied to image restoration/classification tasks because of their outstanding performances in adaptability and feature extraction [17, 18]. Furthermore, in [19], the CNNs for object recognition using micro-Doppler radar have been developed, where the spectrogram of the received radar signal is used as the input of the CNN. In [20], CS-CNN has been proposed for radar image restoration with a single MIMO radar, where low/high-resolution images obtained from conventional CS algorithms are exploited to train CNN. Unlike the existing deep-learning methods applied to radar object recognition and radar image restoration, the deramped radar signal is exploited as the input of our proposed DCNN without any processing related to the spectrogram transform and the matching pursuit process.

To effectively train the proposed DCNN for a single FMCW MIMO radar, the received signal is first reformulated in terms of the reflection gain values in the (azimuth, range) patches in the image region of interest such that the output vector of the CNN is composed of the reflection gain values in the associated patches. Furthermore, to avoid the I/Q transformation of complex-valued received signal without losing the phase information of the signal reflected from the target, a back-projection filtering-based preprocessing module is newly developed for the proposed DCNN for radar imaging with a single FMCW MIMO radar.

In the distributed FMCW MIMO radar environment, efficient transfer learning approaches are also proposed to overcome the small number of training data samples and the limited training time for distributed radars. The transfer learning has been effectively applied to radar object recognition with a limited training data set [18, 21]. Likewise, in our distributed FMCW MIMO radar system, the pretrained DCNN model for a given reference radar is transferred to other distributed radars, and the model mismatch can be quickly tuned in the distributed radars with a small number of training data samples. Two different transfer strategies are developed here according to the amount of available training data set. Specifically, all the model parameters are fine-tuned for a large training data set after loading the pretrained model parameters. For small training data set, a large portion of transferred DCNN model parameters is freezing, and the rest of the DCNN is trained. In addition, we have shown that by exploiting the output of the pretrained DCNN model as the training data set, the limitation of the training data set shortage in the distributed FMCW MIMO radar system can be overcome. The proposed radar imaging is assessed with synthetic simulation data. Specifically, by transferring the pretrained DCNN model for a given reference radar to other distributed radars, the distributed radars can save about 52.4% of training time over a DCNN having the same architecture but without transfer learning.

The rest of this paper is organised as follows. In Section 2, the distributed FMCW MIMO radar system model is introduced. In Section 3, DCNN-based radar imaging with a single FMCW MIMO radar is first proposed, and in addition, the transfer learning strategies for distributed FMCW MIMO radars are proposed. The simulation results of the proposed schemes with synthetic data are given in Section 4, and conclusions are made in Section 5.

2 | SYSTEM MODEL

Figure 1 shows the distributed FMCW MIMO radar system, where L FMCW MIMO radars are spatially distributed, and each radar is composed of Mt transmit (Tx) antennas and Mr received (Rx) antennas. Throughout this paper, Tx/Rx

Target 1

Target K

FIGURE 1 Distributed frequency modulated continuous waveform multiple-input multiple-output radar system
antennas in each radar are colocated and linearly parted by interelement spacing, $d_i$ and $d_j$ respectively. The FMCW signal transmitted from the $m$th Tx antenna of the $lth$ FMCW MIMO radar can be represented as

$$s_m^{(l)}(t) = \exp(j(2\pi f_c + \Delta f_0 + \Delta f_d(t-1))t + \pi n^2),$$

for $0 \leq t \leq T_{PR}$. The pulse duration of FMCW signal is denoted as $T_{PR}$ and the chirp rate is denoted as $\alpha$. The carrier frequency is denoted as $f_c$ and $\Delta f$ (respectively, $\Delta f_d$) is the frequency offset to avoid the interference among the Tx antennas in each radar (respectively, the interference from the other radars). The transmit signals are reflected in $K$ targets, and the received signal of the $m$th Rx antenna at the $lth$ radar is given as

$$r_m^{(l)}(t) = \sum_{k=1}^{K} \sum_{m=1}^{M} \gamma_k \gamma_m^{(l)}(t) + n_m^{(l)}(t),$$

where $\gamma_k$ is a coefficient aggregating the target reflection gain, the antenna gain at the $lth$ target, and the path-loss and $n_m^{(l)}(t)$ is the additive white Gaussian noise at the $m$th Rx antenna of the $lth$ radar. In addition, $r_{m,m,k}^{(l)}$ is the time delay for the signal transmitted from the $m$th Tx antenna at the $lth$ radar to be reflected on the $kth$ target and received by the $m$th Rx antenna at the $lth$ radar, given as

$$r_{m,m,k}^{(l)} = \frac{2}{c} \left( \frac{R_{m,k}^{(l)}}{2} - \frac{\nu_k^{(l)}}{2} - t \right),$$

where $R_{m,k}$ (respectively, $R_{m,k}$) is the distance between the $m$th Tx (respectively, the $m$th Rx) antenna at the $lth$ radar and the $kth$ target. In addition, the relative velocity and the azimuth angle of the $kth$ target with respect to the $lth$ radar are, respectively, denoted as $v_k^{(l)}$ and $\theta_k^{(l)}$. The approximation in Equation (3) is from that the signal propagation path from the $m$th Tx to the $lth$ target plus the reflection path from the $lth$ target to the $m$th Rx can be approximated as the round-trip path between the virtual position of the middle of the Tx/Rx antennas and the $kth$ target. Here, $R_{l,k}^{(l)}$ is the distance between the reference element (i.e., the first element in the virtual array) in the $lth$ MIMO radar transceiver and the $kth$ target. In addition, $x_{lm}$ and $x_{km}$ are the relative positions of the $m$th Tx and $m$th Rx antennas with respect to the reference element of the $lth$ radar. Then, when the Tx/Rx antennas form a linear virtual array with interspersing $\lambda/2$ [22], by using the virtual element index $m$ instead of Tx/Rx indices, the time delay $r_{m,m,k}^{(l)}$ can then be expressed as

$$r_{m,k}^{(l)} = \frac{2}{c} \left( d(m-1) \sin \theta_k^{(l)} \right) + \frac{\nu_k^{(l)}}{c} - t,$$

where $R_{l,k}^{(l)} = 2R_{l,k}^{(l)}/c, m = 1, \ldots, M, l$. The approximation in Equation (4) is from the assumption that $\nu_k^{(l)} \ll c$. The received signals at each distributed radar are then multiplied with its transmitted signal and followed by the low-pass filter, given as

$$y_m^{(l)}(t) = LP\{r_m^{(l)}(t)\},$$

where $n_m^{(l)}(t) \sim \mathcal{CN}(0, \sigma_n^2)$. With a sampling frequency $f_s = \frac{1}{T}$, the de-ramped signal $y_m^{(l)}(t)$ can be sampled as

$$y_m^{[n]} = y_m^{(l)}(nT_s),$$

$$\approx \sum_{k=1}^{K} \gamma_k \exp\left\{ j(2\pi f_c r_{m,k}^{(l)} + 2\pi k \nu_k^{(l)} t - \pi k \nu_k^{(l)} ) \right\} + n_m^{(l)}(nT_s).$$

Because the de-ramped signal bears the range/azimuth angle information of $K$ multiple targets, the subspace-based estimation algorithms such as 2-D MUSIC [8, 9] have been applied to $y_m^{[n]}$, in which the de-ramped samples for several FMCW pulses are required to estimate the covariance matrix across array antenna elements.

3 | DEEP CONVOLUTIONAL NEURAL NETWORK FOR DISTRIBUTED FREQUENCY MODULATED CONTINUOUS WAVEFORM MULTIPLE-INPUT MULTIPLE-OUTPUT RADAR IMAGING

3.1 | Deep convolutional neural network for radar imaging with a single frequency modulated continuous waveform multiple-input multiple-output radar

Figure 2 shows the block diagram of our proposed DCNN for radar imaging with a single FMCW MIMO radar. Specifically, we first reformulate $y_m^{[n]}$ in Equation (5) and manipulate the
received signal through the preprocessing module, which enables easier DCNN learning. Then, the output of the preprocessing module is passed to the input layer of DCNN, which generates the desired radar image. Note that the proposed DCNN for radar imaging can be independently applied at each distributed radar.

3.1.1 Reformulation of the received signal

To apply DCNN for radar imaging, $y^{(l)}_m[n]$ in Equation (5) is reformulated in terms of the radar image. Specifically, we divide the image region of interest into $R \times P$ two-dimensional patches (range×azimuth angle) as Figure 3 and rewrite (5) as

$$y^{(l)}_m[n] \approx \sum_{p=1}^{P} \sum_{r=1}^{R} x^{(l)}(r,p) \exp \left \{ j4\pi f_c \left( \frac{R^{(l)}_r}{c} + \frac{1}{c} (d(m-1)\sin \theta^{(l)}_p) \right) + j4\pi k \left( \frac{R^{(l)}_r}{c} + \frac{1}{c} (d(m-1)\sin \theta^{(l)}_p) \right)nT_s \right \} + n_m^{(l)}[n], \tag{6}$$

where $R^{(l)}_r$ (respectively, $\theta^{(l)}_p$) is the range (respectively, the azimuth angle) of the target in the $(r, p)$th patch with respect to the $l$th radar and $n_m^{(l)}[n] \triangleq n_m^{(l)}(nT_s)$. See Figure 3. The coordinates of the reference antenna element in the first MIMO radar transceiver are set as the origin $(0, 0)$. In addition, the coordinates of the reference antenna element in the $l$th MIMO radar transceiver are denoted as $(a^{(l)}, b^{(l)})$. 

**FIGURE 2** Block diagram of the proposed deep convolutional neural network for radar imaging

**FIGURE 3** The $R \times P$ two-dimensional patches (range×azimuth angle)
Then, when the coordinates of \((r, p)\)th patch are given as \((a_{(r,p)}, b_{(r,p)})\), \(R_{(r)}^{(l)}\) and \(\theta_{p}^{(l)}\) in Equation (6) are respectively given as

\[
R_{r}^{(l)} = \sqrt{(a_{(r,p)} - a_{(l)})^2 + (b_{(r,p)} - b_{(l)})^2},
\]

\[
\theta_{p}^{(l)} = \tan^{-1}\left(\frac{a_{(r,p)} - a_{(l)}}{b_{(r,p)} - b_{(l)}}\right). (7)
\]

In Equation (6), \(x^{(l)}(r, p)\) is a coefficient aggregating the target reflection gain, the antenna gain at the \(l\)th radar, and the path-loss. That is, \(x^{(l)}(r, p) = y_{m}^{(l)}\) if the \(k\)th target is in the \((r, p)\)th patch, otherwise \(x^{(l)}(r, p) = 0\). By stacking the de-ramped signal \(y_{m}^{(l)}[n]\) for all virtual array elements and discrete time samples, we can have

\[
y^{(l)} = \begin{bmatrix} y_{1}^{(l)}[1], y_{2}^{(l)}[1], \ldots, y_{M}^{(l)}[1], y_{1}^{(l)}[2], y_{2}^{(l)}[2], \ldots, y_{M}^{(l)}[N] \end{bmatrix}^{T} = A^{(l)}x^{(l)} + n^{(l)}, (8)
\]

where \(A^{(l)} \in \mathbb{C}^{MN \times PR}\) is given as shown in Equation (9) at the top of the current page.

\[
A^{(l)} = \begin{bmatrix}
A(1, 1, R_{1}^{(l)}, \theta_{1}^{(l)}) & A(1, 1, R_{1}^{(l)}, \theta_{1}^{(l)}) & \ldots & A(1, 1, R_{1}^{(l)}, \theta_{1}^{(l)}) \\
A(2, 1, R_{1}^{(l)}, \theta_{2}^{(l)}) & A(2, 1, R_{1}^{(l)}, \theta_{2}^{(l)}) & \ldots & A(2, 1, R_{1}^{(l)}, \theta_{2}^{(l)}) \\
\vdots & \vdots & \ddots & \vdots \\
A(M, N, R_{1}^{(l)}, \theta_{1}^{(l)}) & A(M, N, R_{1}^{(l)}, \theta_{1}^{(l)}) & \ldots & A(M, N, R_{1}^{(l)}, \theta_{1}^{(l)})
\end{bmatrix} (9)
\]

with \(A(m, n, R_{r}^{(l)}, \theta_{p}^{(l)}) = \exp\left\{j4\pi f_{c}\left(\frac{R_{r}^{(l)}}{c} + \frac{1}{2}(d(m-1)\sin\theta_{p}^{(l)})\right) nT_{s}\right\} + j4\pi k\left(\frac{R_{r}^{(l)}}{c} + \frac{1}{2}(d(m-1)\sin\theta_{p}^{(l)})\right) nT_{s}\).}
where $X^{(i-1)}[m, n, k]$ is the $(m, n, k)$th element of $X^{(i-1)} \in \mathbb{R}^{m_{i-1} \times n_{i-1} \times k_{i-1}}$, the input of the $i$th layer and $f(\cdot)$ is an activation function. In addition, $W^{(i)}[p, q, k]$ is the $(p, q, k)$th element of the weight matrix $W^{(i)}$ at the $i$th layer and $b^{(i)}[k]$ is the $k$th element of a bias vector $b^{(i)}$. Note that, throughout the paper, ReLU function is used as the activation function of the CNN layers, which is given as

$$f(X^{(i)}) = \max(0, X^{(i)}).$$

Batch normalisation layer: The batch normalisation layers normalise the output of convolution layer through the batch normalising transform [25], where the batch mean is computed from the output of the convolution layer, and then it is subtracted from the output. Finally, the result of subtraction is divided by the batch standard deviation. The output of the batch normalisation layer is then given as

$$BN^{(i)}[m, n, k] = \frac{X^{(i)}[m, n, k] - \mu^{(i)}[k]}{\sqrt{(\sigma^{(i)}[k])^2 + \epsilon}}, \quad i \in \mathcal{L},$$

$$k = 1, \ldots, k_i; m = 1, \ldots, m_i; n = 1, \ldots, n_i$$

where $\epsilon$ is a constant added to the batch variance for numerical stability and $\mathcal{L}$ is a total set of layers. Here, $\mu^{(i)}[k]$ and $(\sigma^{(i)}[k])^2$ are the batch mean and variance of $X^{(i)}$, respectively. Note that, by using the batch normalisation, we can avoid overfitting problem during the training process for the proposed DCNN [25].

Flatten, fully connected (FC) layer: The flatten layer is used for converting the shape of output of convolution layer into the vector which is used as the input of FC layer. In the FC layer, the output of convolution layer is associated with a proper loss function such that the desired radar images are generated after the training. Throughout the paper, the binary cross-entropy (BCE) is used as the loss function which is given as

$$BCE(\hat{x}^{(l)}_{\text{out}}, \tilde{x}^{(l)}) = -\frac{1}{PR} \sum_{i=1}^{PR} \hat{x}^{(l)}[i] \log(\tilde{x}^{(l)}_{\text{out}}[i])$$

$$+ (1 - \hat{x}^{(l)}[i]) \log(1 - \tilde{x}^{(l)}_{\text{out}}[i]),$$

where $\hat{x}^{(l)}_{\text{out}} \in \mathbb{R}^{PR \times 1}$ is the output of FC at the $l$th radar and $\tilde{x}^{(l)}$ is the element-wise absolute valued vector of $x^{(l)}$ in Equation (8) with normalisation. That is, $\tilde{x}^{(l)} = \frac{x^{(l)}}{|x^{(l)}|}$ and its value implies the pixel intensity. More importantly, because $\tilde{x}^{(l)}[i] \in [0, 1]$, it can be regarded as the probability of a pixel being “on,” where the BCE loss function can be used to train
DCNN instead of using the mean squared error (MSE) loss function \([26, \ 27]\).

### 3.2 Transfer learning with deep convolutional neural network for distributed frequency modulated continuous waveform multiple-input multiple-output radars

For multiple distributed FMCW MIMO radars, the DCNN developed in Section 3 can be applied independently. However, when distributed radars have the same hardware specifications, the parameters in the DCNN can be highly correlated. Accordingly, the parameters in the DCNN for the distributed FMCW MIMO radars can be efficiently learnt by transferred parameters from the reference radar that has already finished the training process (i.e. pretrained DCNN model). As shown in Figure 6, two different transfer learning strategies are proposed. In Strategy 1, all the model parameters are fine-tuned after loading the pretrained model parameters, which is advantageous when a large number of data samples are available. In Strategy 2, by freezing large portion of transferred DCNN model parameters, the rest of the DCNN is trained with training datasets and is preferable when a small number of training data samples are available.

### 4 SIMULATION RESULTS

In order to verify the proposed DCNN for the radar imaging, we consider the distributed FMCW MIMO radar system as in Figure 7, where three FMCW MIMO radars are placed in a straight line with a distance of 10 m. In the simulations, we use 77 GHz as the centre frequency, 300 MHz as the operating bandwidth, and 3.33μsec as the pulse duration. The number of time samples is set as 2000 samples per pulse and FMCW MIMO radar is exploited with \(M_i = 2\) and \(M_t = 4\), where the transceiver antennas are placed such that virtual uniform linear antenna array is formed with interantenna spacing \(\lambda/2\), where \(\lambda\) is a wavelength.

To obtain training data samples, we have collected the received signal when three clusters of scatterers are randomly distributed within the image region of interest as in Figure 7. Here, the image region of interest (range×azimuth angle) is set as \([20, 60] m \times [−30, 30]^°\) and each cluster has a size of \(4 \times 1 m\), in which 85 point scatterers are regularly contained. Note that, for the scatterers, we choose a large arbitrary number, but it can be applicable to any arbitrary random number.

The DCNN architecture for the radar imaging consists of convolution layers, batch normalisation layers, and FC layer as in Figure 5. The learning rate is set as 0.0004 and the batch size is 100. The DCNN parameters are updated by using the existing adaptive moment estimation (Adam) method.
4.1 | Results with a single frequency modulated continuous waveform multiple-input multiple-output radar

In Figure 8, the radar image is obtained by the proposed DCNN when three clusters of scatterers are distributed as in Figure 8(a) (i.e. three targets are located at (−12.5, 45), (2.5, 40), (12.5, 45)m) and the received SNR is set as 20 dB. Here, the DCNN is trained with 6000 training data samples. For comparison purpose, the radar image is obtained from back-projection method as in Figure 8(b). Here, the radar image (i.e. \( x_{bp} = (A^{(1)})^H y^{(1)} \) obtained from (10) with a single FMCW MIMO radar. In Figure 8(b), the image around targets is severely blurred with poor resolution in both azimuth (i.e. cross-range) and range directions. In contrast, from Figure 8(c), the proposed DCNN gives results similar to those of the original target image.

![Radar Images](image)

**FIGURE 8** Radar images obtained through a deep convolutional neural network with a single frequency modulated continuous waveform multiple-input multiple-output radar

4.2 | Results with distributed frequency modulated continuous waveform multiple-input multiple-output radars

To see the validation of the proposed transfer learning strategies for distributed FMCW MIMO radars, the loss curves for the training data and the validation data with different numbers of training data samples are displayed in Figures 9 and 10. Specifically, the pretrained DCNN model is trained in the radar located at (0, 0)m with 5000 training data samples. Then, the weights of the pretrained model are loaded to the radar located at (10, 0)m and finely trained with different transfer learning strategies (i.e. Strategies 1 and 2 in Figure 6). For both Figures 9 and 10, the validation rate is 0.3. For comparison purposes, the loss curve for the DCNN without transfer learning is also evaluated. In

![Loss Curves](image)

**FIGURE 9** Loss curves (a) for the training datasets (b) for the validation datasets with 2000 training data samples
FIGURE 10  Loss curves (a) for the training datasets (b) for the validation datasets with 200 training data samples

FIGURE 11  Radar images at the distributed radar (a) without transfer learning, 2000 training data samples (b) with Strategy 1, 2000 training data samples (c) with Strategy 2, 2000 training data samples (d) without transfer learning, 200 training data samples (e) with Strategy 1, 200 training data samples (f) with Strategy 2, 200 training data samples
In Figure 9, the DCNN of the FMCW MIMO radar at \( (10, 0) \) \( m \) is trained with 2000 training data samples. In Figure 9(a), the loss decreases with the increase in training epochs because the DCNN is well trained for 2000 training data samples. Accordingly, in Figure 9(b), the loss of all training strategies for the validation datasets decreases as the number of epochs increases, regardless of the training strategy. In Figure 10, the DCNN at the FMCW MIMO radar at \( (10, 0) \) \( m \) is trained with 200 training data samples. It can also be found in Figure 10(a), the loss decreases with the increase in training epochs because the DCNN is well trained for 200 training data samples. However, in Figure 10(b), the loss for the validation datasets without transfer learning is much higher than those with transfer learning strategies. That is, insufficient training data sets incur the overfitting to the training data set, exhibiting poor generalisation performance. Interestingly, for a small number of training data samples, Strategy 2 (i.e. freezing a large portion of transferred DCNN model parameters) exhibits lower validation loss than Strategy 1 (i.e. finely tuning all the model parameters).

In Figure 11, radar images are obtained from the distributed radar located at \( (10, 0) \) \( m \) when the received SNR is set as 20 dB. From Figure 11(a), 11(b), 11(e), the three targets appear clearly in the radar image with 2000 training data samples. However, in Figure 11(d), with 200 training data samples, the targets are severely blurred in the radar image without transfer learning. In contrast, with insufficient training data samples, three targets are more clearly found in Figure 11(d) and 11(e) than that without transfer learning, which coincides with the observation of validation loss in Figure 10.

In Figure 12, the radar images of the distributed radars at \( (10, 0) \) \( m \) and \( (-10, 0) \) \( m \) are displayed, where the proposed DCNN with transfer learning (Strategy 2) is exploited, and the output of pretrained DCNN at the reference radar (located at \( (0, 0) \) \( m \) ) is used as the desired output image for the distributed radars. Here, the received SNR is set as 20 dB. It can be found that the targets are clearly found in both radar images is obtained from the radars located at \( (10, 0) \) \( m \) and \( (-10, 0) \) \( m \), compared with the original target image in Figure 12(a). That is, when the original image is not available, the output of the pretrained DCNN at the reference radar is exploited to generate the training datasets associated with the received signal at the distributed radars.

In Table 1, we compare the average training time per epoch at the distributed radars according to the different transfer learning strategies. The proposed DCNN is implemented by exploiting Keras framework with NVIDIA GeForce RTX 2060 6GB and Intel(R) Core(TM) i5-3570 CPU@3.4GHz. Here, the DCNN module is given in Figure 5, and 2000 training data samples are exploited. From the table, the average training time per epoch for the DCNN without transfer learning requires 2.95 s, which is almost similar to that for the DCNN with transfer learning strategy 1. In contrast, for transfer learning strategy 2, the distributed radars can save about 52.4% training time compared with the DCNN without transfer learning.

### Mean squared error comparison

In Figure 13, the Monte Carlo simulation is carried out to present the performance of the proposed algorithms with two

### Table 1 Training time according to model

| Model                                      | Average training time per epoch (sec) |
|--------------------------------------------|--------------------------------------|
| Proposed DCNN without transfer learning    | 2.95                                 |
| Proposed DCNN with strategy 1 in Figure 6  | 2.97                                 |
| Proposed DCNN with strategy 2 in Figure 6  | 1.37                                 |

Abbreviation: DCNN, deep convolutional neural network.
different transfer learning strategies (i.e. Strategy 1 (fine-tuning) and Strategy 2 (freezing) in Figure 6). Here, 45 points scatterers are randomly distributed in the area of interest. As performance measure, we evaluate the MSE (i.e. $E||\hat{x} - x||^2$) of radar image vector. For comparison purposes, MSEs of the DCNN without transfer learning and the OMP-based radar imaging [11] are also provided. In Figure 13(a), we evaluate the MSE when the DCNNs are trained (a) with 6000 training data samples, and it can be found that the DCNN-based radar imaging methods exhibit lower MSE than the OMP-based radar imaging. Interestingly, Strategy 1 outperforms other methods at high SNR because the DCNN is finely trained with enough training data samples. In Figure 13(b), we evaluate the MSE when the DCNNs are trained (a) with 200 training data samples, and the DCNN without transfer learning exhibits the worst MSE performance to the lack of data samples. In addition, when the training data set is small, it is advantageous to take transfer learning strategy 2, which also coincides with the observation of validation loss in Figure 10.

5 | CONCLUSIONS

Deep-learning-based radar imaging algorithms are proposed for FMCW MIMO radars that are spatially distributed. In the proposed DCNN radar imaging algorithm, the deramped radar signal is exploited as the input of the DCNN without any processing related to the spectrogram transform, the subspace decomposition, and the matching pursuit process. To effectively train the proposed DCNN and avoid the I/Q transformation of complex-valued received signal without losing the phase information of the signal reflected from the target, a back-projection filtering-based preprocessing module is newly developed. In addition, efficient transfer learning approaches are also proposed to overcome the small training data set and the limited training time for distributed radars. Specifically, according to the number of available training samples, two different transferring strategies are proposed, in which all the model parameters are fine-tuned after loading the pretrained model parameters for a large training data set. A large portion of transferred DCNN model parameters are freezing, and the rest of the DCNN is trained for a small training data set. We confirm through the computer simulations that the proposed DCNN-based radar imaging gives high-resolution radar images as its output without any complicated iterative process. Furthermore, by transferring the pretrained DCNN model for a given reference radar to other distributed radars, the distributed radars can save about 52.4% training time compared with a DCNN having the same architecture but without transfer learning.

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