TFR Recovery From Incomplete Micro-Doppler Signal via AL-ADMM-Net

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ABSTRACT The micro-motion target echoes can be regarded as the accumulation of a few strong scattering points echoes, which are naturally sparse. Therefore, the compressed sensing (CS) reconstruction method can be used to analyze the incomplete micro-Doppler signal and extract the micro-motion features. Traditional CS reconstruction algorithms are time-consuming and sensitive to the selection of model parameters, limiting the performance of micro-motion feature extraction. This paper proposes a deep unfolded method to achieve the reconstruction of the time-frequency representation (TFR) of incomplete micro-Doppler signals. First, the joint time-frequency (JTF) transform is used to construct the CS model and the training data is obtained according to the model. Then, the alternating direction method of multipliers (ADMM) algorithm is constructed into an iterative network named ADMM-net corresponding to the iterative solution process. An auxiliary loss is designed into the ADMM-net called AL-ADMM-net to improve the quality of reconstruction. The AL-ADMM-net is trained by the training data to learn the optimal parameters. Furthermore, an AL-ADMM-net iterative method is proposed when the micro-Doppler signal has phase corruption. Simulations are given to prove the effectiveness of the proposed method.

INDEX TERMS Compressed sensing, micro-doppler, ADMM-net, deep learning, auxiliary loss.

I. INTRODUCTION

In general, micro-motion refers to the spinning, precession, nutation, tumbling, and other small movements of the target or target components except for the translation of the center of mass. The target micro-motion will modulate the phase of the radar echo, and then generate the corresponding frequency modulation [1]. This modulation phenomenon caused by micro-motion is called the micro-Doppler effect. Different geometric structures and motion modes of the target will produce different micro-motion and corresponding micro-Doppler effects, so the micro-motion features can give us some information about the shape, structure, posture, and electromagnetic parameters of surface materials, which is the unique feature of the target [2], [3], [4]. Analyzing the micro-Doppler effect of targets and extracting micro-motion features can provide important information for target recognition and classification [5].

At present, there are various algorithms that have been proposed for micro-motion feature extraction [6]. These algorithms are mainly divided into two categories: parametric and nonparametric methods. The parametric methods require defining the signal model based on prior knowledge. In most cases, the prior knowledge of the target motion is hard to get, and the performance of the parametric methods may become invalid. On the other hand, when the micro-motion is irregular, the predefined model is also hard to design or to be much complicated. Then the parametric methods will lead to huge calculations and may cause serious errors. The nonparametric methods usually use high-resolution time-frequency analysis tools and do not need to define the signal model prior. However, most of these nonparametric methods require echoes to be closely arranged or non-overlapping in the time-frequency domain. In the real case, incomplete samples and corrupted phase have become two outstanding problems preventing effective motion characterization due to strong interference, inexact motion compensation, or the effect of propagation through atmospheric turbulence [7].
The compressed sensing (CS) method can achieve a high probability and accurate reconstruction of the sparse signal by using a small amount of data [8]. The micro-motion target echoes are the composition of a few strong scattering points echoes, which are sparse. Therefore, the sparse reconstruction method can be used to analyze the micro-Doppler signal and extract the micro-motion features. The radar signature analysis method using a JTF distribution based on compressed sensing is proposed to extract the micro-motion features and obtains 2-D time-frequency distribution with high resolution and cross-term free [9], [10], [11]. Bai et al. represents the incomplete and phase-corrupted echoes using a nonparametric JTF dictionary and obtains the sparse and phase-corrected JTF signature by iterative optimization [12]. The above CS reconstruction algorithms are time-consuming and sensitive to the selection of model parameters, limiting the performance of micro-motion feature extraction.

Deep learning technology has been widely used in radar signal processing and has achieved good results [13], [14]. In the field of micro-motion, deep learning is mainly used for target classification [15], [16], [17]. It has achieved good results for human target classification based on micro-motion features [18], [19]. Different to the traditional micro-motion feature extraction, the deep learning method usually learns some features from the time-frequency spectrogram. The physical meaning of these features is usually indescribable. Using deep learning to extract periods and target sizes have not been studied yet in existing research. To improve the performance of traditional CS reconstructed methods, this paper proposes a deep unfolded method to obtain high-quality TFR, which is the base of extraction of micro-motion features such as periods and target sizes. The key contributions of this paper are summarized as follows. First, the incomplete and phase corrupted echoes of micro-motion in the JTF domain are represented as the time-frequency distribution by using a time-frequency transform matrix. Then the reconstruction of time-frequency distribution from the echo is modelled as an inverse problem based on the CS principle. A deep unfolded method called AL-ADMM-net is proposed to solve the inverse problem. The proposed AL-ADMM-net is trained by a small number of training data to learn the optimal parameters in the network. Finally, the experiments based on simulated data demonstrate the effectiveness of the proposed method.

The remainder of this paper is organized as follows. The signal model of micro-motion is presented in section II. The deep unrolling structure of AL-ADMM-net is proposed in section III. The autofocus algorithm in AL-ADMM-net is presented in section IV. Section V gives the experiment results and section VI gives the conclusion.

**II. SIGNAL MODEL AND PROBLEM FORMULATION**

In this paper, we assume that the radar operates in the high-frequency regime. The point scattering model is usually used to describe the backscattering mechanism of the target. The target can be regarded as a set of discrete scattering points when the size of the target is much larger than the radar wavelength. The target returns can be regarded as a summation of sub-echoes reflected from isolated scattering points on the target.

The radar transmit signal is

\[ p(t) = \exp(j2\pi f_c t) \]  

where \( f_c \) is the carrier frequency. The echo signal received by the radar can be expressed as

\[ s(t) = \sum_n \sigma_n p(t - 2R_n(t)/c) \]

where \( n \) is the scattering point index, \( \sigma_n \) is the amplitude of the \( n \)th scattering point, \( R_n \) is the range from the \( n \)th scattering point to the radar in line of sight (LOS). From (1) and (2), we can get the radar returns as

\[ s(t) = \sum_n \sigma_n \exp(-j4\pi R_n(t)/\lambda_c) \]

where \( \lambda_c \) is the carrier wavelength.

\( s(t) \) is a highly nonstationary signal by the modulation of micro-motion in (3). The Fourier transform is unsuitable for analyzing the nonstationary signal. Time-frequency analysis is an effective method for representing the energy of a nonstationary signal in the time-frequency plane in which the nonstationary signal can reveal features that cannot be found in the frequency domain [20]. The short-time Fourier transform (STFT) is used to analyze the micro-Doppler of the radar returns. The STFT uses a window function to intercept the signal, where the windows function slides along the time axis. Then the Fourier transform is applied to the intercepted signal. The STFT of \( s(t) \) can be defined as

\[ \text{STFT}_s(t, f) = \int s(\tau)g(t - \tau)\exp(-j2\pi f \tau)d\tau \]

where \( \text{STFT}_s(t, f) \) is the time-frequency distribution of \( s(t) \), \( f \) is the instantaneous frequency, \( g \) is the window function. \( \text{STFT}_s(t, f) \) is well-focused and high-resolution when \( s(t) \) is complete and sufficient. When the micro-Doppler data is sparse in real situations, using CS and sparse reconstruction algorithms can improve the feature extraction accuracy under the condition of incomplete data. The formula (4) can be described in a matrix form as

\[ f_{NM \times 1} = W_{NM \times N}s_{N \times 1} \]

where \( f \) is the vector form of \( \text{STFT}_s(t, f) \), \( W \) is the STFT transform matrix, whose entries are windowed discrete Fourier transform coefficients, \( W = HQ, H = \text{diag} [F, F, \ldots, F], F \) is the Fourier transform matrix, \( Q = [\text{P}_1, \text{P}_2, \ldots, \text{P}_m, \ldots, \text{P}_M]^T \) is the sliding window matrix, \( s \) is the vector form of the complete signal, \( N \) is the length of \( s \), \( M = N/m, m \) is the slide step of the window function.

The signal \( s \) with missing samples can be expressed as

\[ s_{N \times 1} = T_{N \times N}G_{N \times NM}f_{NM \times 1} \]
where $\mathbf{G}$ is the pseudo-inverse of $\mathbf{W}$. 
$\mathbf{T} = \text{diag} \{ t(1), \ldots, t(n) \} \in \{0, 1\}$ is the diagonal incomplete sampling matrix.

According to the CS theory, $\mathbf{f}$ can be reconstructed from $\mathbf{s}$. The solution of $\mathbf{f}$ can be expressed as

$$\hat{\mathbf{f}} = \arg \min_{\mathbf{f}} \| \mathbf{s} - \mathbf{T} \mathbf{G} \mathbf{f} \|_2^2 \leq \varepsilon \quad (7)$$

### III. AL-ADMM-NET ALGORITHM

#### A. AL-ADMM

Formula (7) is generally referred to as the least absolute shrinkage and selection operator (LASSO). The micro-motion JFR reconstruction method based on the LASSO framework can be described by the unconstrained optimization problem as

$$\min_{\mathbf{f}} \left\{ \| \mathbf{s} - \mathbf{T} \mathbf{G} \mathbf{f} \|_2^2 + \lambda \| \mathbf{f} \|_1 \right\} \quad (8)$$

The $\| \mathbf{f} \|_1$ is non-differentiable. The ordinary gradient descent method and Newton method cannot be used to solve the problem. ADMM is an effective methodology to decompose a convex problem into small ones while maintaining good convergence property [21]. According to ADMM, formula (8) can be expressed as

$$\min_{\mathbf{f}} \left\{ \frac{1}{2} \| \mathbf{s} - \mathbf{T} \mathbf{G} \mathbf{f} \|_2^2 + \lambda \| \mathbf{f} \|_1 \right\} \quad \text{s.t. } \mathbf{f} = \mathbf{g} \quad (9)$$

The augmented Lagrange function can be constructed as

$$L_\rho(\mathbf{f}, \mathbf{g}, \alpha) = \frac{1}{2} \| \mathbf{s} - \mathbf{T} \mathbf{G} \mathbf{f} \|_2^2 + \lambda \| \mathbf{f} \|_1 + \alpha^H(\mathbf{f} - \mathbf{g}) + \frac{\rho}{2} \| \mathbf{f} - \mathbf{g} \|_2^2 \quad (10)$$

where $\rho$ is the penalty parameter and $\alpha$ is the Lagrangian multiplier. The iterative steps are given as follows:

$$\mathbf{f}^{(k)} = \arg \min_{\mathbf{f}} L_\rho(\mathbf{f}, \mathbf{g}^{(k-1)}, \alpha^{(k-1)}) \quad (11)$$

$$\mathbf{g}^{(k)} = \arg \min_{\mathbf{g}} L_\rho(\mathbf{f}^{(k)}, \mathbf{g}, \alpha^{(k-1)}) \quad (12)$$

$$\alpha^{(k)} = \alpha^{(k-1)} + \rho(\mathbf{f}^{(k)} - \mathbf{g}^{(k)}) \quad (13)$$

Repeat the above three steps until the convergence.

$L_\rho$ is derivable to $\mathbf{f}$, so let $\beta = \frac{\alpha}{\rho}$, then the solution of (11) can be obtained by setting the derivative to zero:

$$\frac{\partial L_\rho}{\partial \mathbf{f}} = -(\mathbf{T} \mathbf{G})^H(\mathbf{s} - \mathbf{T} \mathbf{G} \mathbf{f}) + \alpha + \rho(\mathbf{f} - \mathbf{g}) = 0 \quad (14)$$

$$\mathbf{f} = ((\mathbf{T} \mathbf{G})^H(\mathbf{T} \mathbf{G}) + \rho \mathbf{I})^{-1}((\mathbf{T} \mathbf{G})^H \mathbf{s} + \rho(\mathbf{g} - \beta)) \quad (15)$$

where $L_\rho$ is undervivable to $\mathbf{g}$ because of the $l_1$ norm of $\mathbf{g}$. The proximal gradient descent algorithm is used to obtain the solution of (12):

$$\arg \min_{\mathbf{g}} L_\rho(\mathbf{f}, \mathbf{g}, \beta) = \arg \min_{\mathbf{g}} \lambda \| \mathbf{g} \|_1 + \rho \beta^H(\mathbf{f} - \mathbf{g}) + \rho \frac{2}{2} \| \mathbf{f} - \mathbf{g} \|_2^2 \quad (16)$$

where $\lambda$ is a soft threshold function $[22]$:

$$S(\mathbf{f} + \frac{\alpha}{\rho} \frac{\lambda}{\rho}) = \text{sign}(\mathbf{f} + \frac{\alpha}{\rho} \frac{\lambda}{\rho}) \max \left\{ \frac{f}{\rho} - \frac{\lambda}{\rho}, 0 \right\} \quad (17)$$

where $\lambda$ is the threshold, $\lambda$ and $\rho$ need to be given in advance, and cannot be adaptively adjusted in each iteration step, which has a great influence on the ADMM algorithm. It may be pretty hard and time-consuming to find the best parameters.

Let $\beta = \frac{\alpha}{\rho}$, (13) can be expressed as

$$\beta^{(k)} = \beta^{(k-1)} + \eta(\mathbf{f}^{(k)} - \mathbf{g}^{(k)}) \quad (18)$$

where $\eta$ is an update rate for the Lagrangian multiplier.

#### B. NETWORK STRUCTURE OF AL-ADMM-NET

To tackle the above problem, the ADMM can be unfolded to a deep neural network [23]. Different from the general inverse problem, the reconstruction of TFR in this paper is based on sparse priority. The regularization operator is a definite $l_1$-norm. In this way, the error between the reconstruction result and the label will be a little large. An auxiliary loss layer is designed in the original ADMM-net named AL-ADMM-net. The iteration steps are considered as mapping operation, while $\lambda$ and $\rho$ are considered as the parameters. The structure of AL-ADMM-Net is corresponding to the algorithm steps. As shown in Fig. 1, the AL-ADMM-Net has 8 stages. Each stage consists of three layers which are the reconstruction layer, the nonlinear transform layer and the multiplier update layer. Theoretically, the stage number is estimated according to the convergence rate of the algorithm. Here, we have done experiments with different stage numbers. As shown in Fig. 2, the normalized root mean squared error (NRMSE) gradually decreases and tends to converge when the stage number is 8.

1) **RECONSTRUCTION LAYER**

The reconstruction layer implements the reconstruction operation in formula (11). After the reconstruction operation, a micro-Doppler image in the time-frequency domain can be reconstructed. The input of this layer is $\mathbf{g}^{(k-1)}$ and $\beta^{(k-1)}$. The output of this layer is

$$\mathbf{f}^{(k)} = ((\mathbf{T} \mathbf{G})^H(\mathbf{T} \mathbf{G}) + \rho \mathbf{I})^{-1}((\mathbf{T} \mathbf{G})^H \mathbf{s} + \rho(\mathbf{g}^{(k-1)} - \beta^{(k-1)})) \quad (19)$$

2) **NONLINEAR TRANSFORM LAYER**

The nonlinear transform layer implements the operation of nonlinear mapping in the formula (12). The input of this layer
is \( f^{(k)} \) and \( \beta^{(k-1)} \). The output of this layer is
\[
g^{(k)} = S_{ple}(f^{(k)}) + \beta^{(k-1)}; \quad \{p_i, q_i^{(k)}\}_{i=1}^{N}
\]
To learn a more flexible non-linear activation function, a piecewise linear function \( S_{ple}() \) is substituted for the soft threshold function \( S() \) in the formula (14) [24], [24]. \( S_{ple}() \) is determined by \( \{p_i, q_i^{(k)}\}_{i=1}^{N} \) and \( \{p_i\}_{i=1}^{N} \) is defined in advance, but \( \{q_i^{(k)}\}_{i=1}^{N} \) is obtained by training the network.

3) MULTIPLIER UPDATE LAYER
The multiplier update layer implements the operation of non-linear mapping in formula (13). The input of this layer is \( f^{(k)} \) and \( g^{(k)} \). The output of this layer is
\[
\beta^{(k)} = \beta^{(k-1)} + \eta(f^{(k)} - g^{(k)})
\]
where \( \eta \) represents a learnable parameter.

4) AUXILIARY LOSS LAYER
The auxiliary loss layer follows the reconstruction layer of the last stage. It implements the calculation the auxiliary loss:
\[
ALE(\Theta) = \frac{1}{\Gamma} \sum_{(s; f_{lab}) \in D_{train}} \frac{\|s - T\hat{G}(s; \Theta)\|_2}{\|s\|_2^2}
\]
where \( D_{train} \) is the training set, \( \Gamma \) is the number of training set, \( s \) is the under-sampled echo, \( \Theta \) is the parameters of the AL-ADMM-net, \( \hat{f}(s; \Theta) \) is the output of reconstruction layer in the last stage, \( T\hat{G}(s; \Theta) \) is the output of the AL-ADMM-net.

C. TRAINING
The parameters to be learned in AL-ADMM-net include the parameters of the reconstruction layer \( \rho \), nonlinear transformation layer \( \{q_i^{(k)}\}_{i=1}^{N} \) and multiplier update layer \( \eta \).

The data set contains 300 simulated data pairs. Each data pair consists of under-sampled echo and label image. We create a scene in which there are some randomly distributed scattering points that have different rotation radius and frequencies. The label images are generated by full aperture data using STFT. The under-sampled data are obtained by extracting some pulses from the full aperture data. The loss function is defined as
\[
E(\Theta) = \frac{1}{\Gamma} \sum_{(s; f_{lab}) \in D_{train}} \frac{\|\hat{f}(s; \Theta) - f_{lab}\|_2}{\|f_{lab}\|_2}
\]
where \( f_{lab} \) is the label image. The joint loss function is the sum of \( E(\Theta) \) and \( ALE(\Theta) \). We use the limited-memory Broyden-Fletcher-Goldfarb-Shanno (L-BFGS) to minimize the joint loss function. Finally, we can get the trained AL-ADMM-net.
TABLE 1. Radar parameters.

| Symbol | Parameters | Value  |
|--------|------------|--------|
| \( f_c \) | carrier frequency | 10 GHz  |
| PRF | pulse repetition frequency | 512 Hz  |
| \( t \) | observation time | 0.5 s  |
| \( N \) | discrete times | 256  |

According to the CS theory, the \( f \) can be reconstructed from \( s \). The solution of \( f \) can be expressed as:

\[
\hat{f} = \arg \min \| f \|_1 \quad s.t. \quad \| s - \Phi T G f \|_2^2 \leq \varepsilon
\]  

(25)

As the phase error matrix \( \Phi \) is not known, we design an iterative optimization algorithm to get the solution. First, \( \Phi \) is initialized as \( \Phi = I \). Then, we use the trained AL-ADMM-net to obtain the \( \hat{f}(s; \Theta) \). Next, we estimate the \( \Phi \) by solving the optimization problem:

\[
\hat{\Phi} = \arg \min _{\Phi} \| s - \Phi T G f \|_2^2
\]  

(26)

Formula (26) can be expressed as:

\[
\varphi(n) = \arg \min _{\varphi(n)} \| s(n) - \exp(j\varphi(n))T G f \|_2^2
\]  

(27)

Let the derivative of \( \| s(n) - \exp(j\varphi(n))T G f \|_2^2 \) with respect to \( \varphi(n) \) be zero, we can get:

\[
\varphi(n) = -\tan^{-1} \frac{\text{Re}(\exp(j\varphi(n))T G f s(n))}{\text{Im}(\exp(j\varphi(n))T G f s(n))}
\]  

(28)

Furthermore, we can get \( \hat{\Phi} \) to correct the phase of the original signal \( s \). We put the corrected signal as the input of the trained AL-ADMM-net and get \( \hat{f}(\hat{\Phi}; \Theta) \). Repeat the above iteration steps until \( \hat{f}(\hat{\Phi}; \Theta) \) convergence.

V. EXPERIMENT

In this section, experimental results based on simulated data are presented to demonstrate the effectiveness of the proposed algorithm. The proposed method is compared with ADMM and STFT methods.

As shown in Tab. 1, the carrier frequency of radar is 10 GHz, the pulse repetition frequency of radar is 512 Hz, and the expected observation time \( t \) is 0.5 s, the number of discrete times \( N = 256 \).

Tab. 2 gives the comparison of the computational time with different methods. Fig. 3(a) shows the echo in the time domain. As shown in Fig. 3(b), the echo in the time domain is 30% randomly missed, where the white parts show the missing samples, and the black parts show the available samples. The STFT of the echo with miss sampling is shown in Fig. 3(c), and the time-frequency image obtained by STFT is defocused and broken. The running time of STFT is 2.25 s.
The micro-Doppler signal of sliding scattering points [25] is used to demonstrate the proposed method in Fig. 5. Fig. 5(d) shows the STFT of the corrupted signal with incomplete sampling. Fig. 5(e) shows the reconstructed time-frequency image by ADMM. The result of proposed method is shown in Fig. 5(f). Compared with the Fig. 5(d) and Fig. 5(e), the TFR in Fig. 5(f) has more effective micro-Doppler characterization. The results show that the proposed method is effective for the sliding scattering model.

VI. CONCLUSION

In this study, we designed an AL-ADMM-net for micro-motion TFR reconstruction. The ADMM is unrolled into a neural network according to the iteration steps. In order to improve the quality of reconstructed TFR, an auxiliary loss is added to the network. The AL-ADMM-net is trained to set the optimal parameter to achieve better performance. The experiments are conducted on both the points scattering model and the sliding scattering model. From the results, the proposed method obtained better performance than the traditional STFT and ADMM algorithm. Besides, the network is trained offline which can save the calculation time.

Future works will focus on the methods of combining deep learning and micro-motion feature extraction methods and further improve the accuracy and computational efficiency.

TABLE 2. Comparison of the computational time.

| Reconstruct method | Computational time |
|--------------------|--------------------|
| STFT               | 2.25s              |
| ADMM               | 12.34s             |
| AL-ADMM-net        | 0.09s              |

The time-frequency image obtained by ADMM is given in Fig. 3(d), which is better than Fig. 3(c). The running time of ADMM is 12.34s. The result of AL-ADMM-net is shown in Fig. 3(e). Compared with Fig. 3(d), the time-frequency image has more enhanced micro-Doppler characterization and less background noise. The AL-ADMM-net has the shortest running time of only 0.09s. As shown in Fig. 3(f), the recovered TFR of the proposed method is closed to the label, and it can be applied in real-time.

As shown in Fig. 4, the error phase distributes randomly from $-\pi/3$ to $\pi/3$. Fig. 4(d) shows the defocused STFT of the incomplete signal with corrupted phase. The running time of STFT is 2.28s. The micro-Doppler curve shape is defective and the motion characterization is unclear. Compared with the result of ADMM method in Fig. 4(d), the result of proposed method is enhanced with better micro-Doppler concentration and integrality. The running time of ADMM is longest because of the iterative calculation. The running time of AL-ADMM-net in this experiment is 2.48s because of several times phase error estimation.

FIGURE 5. Reconstruction time-frequency image using sliding scattering model of micro-Doppler signal with corrupted phase. (a) Echo in time domain. (b) Data missing pattern. (c) Corrupted phase. (d) Time-frequency image by STFT. (e) Time-frequency image by ADMM. (f) Time-frequency image by AL-ADMM-net.

REFERENCES

[1] V. C. Chen, F. Li, S.-S. Ho, and H. Wechsler, “Micro-Doppler effect in radar: Phenomenon, model, and simulation study,” IEEE Trans. Aerosp. Electron. Syst., vol. 42, no. 1, pp. 2–21, Jan. 2006, doi: 10.1109/TAES.2006.1603402.
[2] V. C. Chen, F. Li, S.-S. Ho, and H. Wechsler, “Analysis of micro-Doppler signatures,” IEEE Proc.-Radar, Sonar Navigat., vol. 150, no. 4, pp. 271–276, Aug. 2003.
[3] V. C. Chen, W. J. Miceli, and B. Himed, “Micro-Doppler analysis in ISAR—Review and perspectives,” in Proc. Int. Radar Conf. Guilin, China, Apr. 2009, pp. 1–6.
[4] V. C. Chen, “Doppler signatures of radar backscattering from objects with micro-motions,” IET Signal Process., vol. 2, no. 3, pp. 291–300, Sep. 2008.
[5] Q. Zhang, “Research progresses in radar feature extraction, imaging, and recognition of target with micro-motions,” J. Radars, vol. 7, no. 5, pp. 531–547, Oct. 2018.
[6] G. Li and P. K. Varshney, “Micro-Doppler parameter estimation via parametric sparse representation and pruned orthogonal matching pursuit,” IEEE J. Sel. Topics Appl. Earth Observ. Remote Sens., vol. 7, no. 12, pp. 4937–4948, Dec. 2014.
[7] X. Bai and F Zhou, “Radar imaging of micromotion targets from corrupted data,” IEEE Trans. Aerosp. Electron. Syst., vol. 52, no. 6, pp. 2789–2802, Dec. 2016.
[8] D. L. Donoho, “Compressed sensing,” IEEE Trans. Inf. Theory, vol. 52, no. 4, pp. 1289–1306, Apr. 2006.
[9] N. Whitelonis and H. Ling, “Radar signature analysis using a joint time-frequency distribution based on compressed sensing,” IEEE Trans. Antennas Propag., vol. 62, no. 2, pp. 755–763, Feb. 2014.
[10] P. Flandrin and P. Borgnat, “Time-frequency energy distributions meet compressed sensing,” IEEE Trans. Signal Process., vol. 58, no. 6, pp. 2974–2982, Jun. 2010.
[11] A. Gholami, “Sparse time-frequency decomposition and some applications,” IEEE Trans. Geosci. Remote Sens., vol. 51, no. 6, pp. 3598–3604, Jun. 2013.
[12] X. Bai, F. Zhou, and Y. Hui, “Obtaining JTF-signature of space-debris from incomplete and phase-corrupted data,” IEEE Trans. Aerosp. Electron. Syst., vol. 53, no. 3, pp. 1169–1180, Jun. 2017.
[13] S. Zhao, Z. Zhang, T. Zhang, W. Guo, and Y. Luo, “Transferable SAR image classification crossing different satellites under open set condition,” IEEE Geosci. Remote Sens. Lett., vol. 19, pp. 1–5, 2022.

[14] S. Zhao, Z. Zhang, W. Guo, and Y. Luo, “An automatic ship detection method adapting to different satellites SAR images with feature alignment and compensation loss,” IEEE Trans. Geosci. Remote Sens., vol. 60, pp. 17, 2022.

[15] M. Wang, Y. D. Zhang, and G. Cui, “Human motion recognition exploiting radar with stacked recurrent neural network,” Digit. Signal Process., vol. 87, pp. 125–131, Apr. 2019.

[16] S. Z. Gurbuz and M. G. Amin, “Radar-based human-motion recognition with deep learning: Promising applications for indoor monitoring,” IEEE Signal Process. Mag., vol. 36, no. 4, pp. 16–28, Jul. 2019.

[17] Y. Wang, C. Feng, X. Hu, and Y. Zhang, “Classification of space micromotion targets with similar shapes at low SNR,” IEEE Geosci. Remote Sens. Lett., vol. 19, pp. 1–5, 2022.

[18] Y. Lang, C. Hou, H. Ji, and Y. Yang, “A dual generation adversarial network for human motion detection using micro-Doppler signatures,” IEEE Sensors J., vol. 21, no. 16, pp. 17995–18003, Aug. 2021.

[19] I. Alnujaim, D. Oh, and Y. Kim, “Generative adversarial networks for classification of micro-Doppler signatures of human activity,” IEEE Geosci. Remote Sens. Lett., vol. 17, no. 3, pp. 396–400, Mar. 2020.

[20] H. Wang, Q. Zhang, Y. Luo, L. Kang, and X. F. Lu, “Obtaining TFR from incomplete and phase-corrupted m-D signal in real time,” IEEE Geosci. Remote Sens. Lett., vol. 19, pp. 1–5, 2022.

[21] R. Li, S. Zhang, C. Zhang, Y. Liu, and X. Li, “Deep learning approach for sparse aperture ISAR imaging and autofocusing based on complex-valued ADMM-net,” IEEE Sensors J., vol. 21, no. 3, pp. 3437–3451, Feb. 2021.

[22] P. L. Combettes and V. R. Wajs, “Signal recovery by proximal forward-backward splitting,” Multiscale Model. Simul., vol. 4, no. 4, pp. 1168–1200, 2005.

[23] X. ZongBen, Y. Yan, and S. Jian, “A new approach to solve inverse problems: Combination of model-based solving and example-based learning,” SCIENTIA SINICA Mathematica, vol. 47, no. 10, pp. 1345–1354, Oct. 2017.

[24] J. Sun, H. B. Li, and Z. B. Xu, “Deep ADMM-Net for compressive sensing MRI,” in Proc. 30th Int. Conf. Neural Inf. Process. Syst. Barcelona, Spain, Dec. 2016, pp. 10–18.

[25] L. Ma, J. Liu, T. Wang, Y. Li, and X. Wang, “Micro-Doppler characteristics of sliding-type scattering center on rotationally symmetric target,” Sci. China Inf. Sci., vol. 54, no. 9, pp. 1957–1967, Sep. 2011.

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**Yuan et al.: TFR Recovery From Incomplete Micro-Doppler Signal via AL-ADMM-Net**

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