Robust clutter suppression in heterogeneous environments based on multi frames and similarities

Jia Duan · Yifeng Wu · Xiaobo Deng · Yufeng Cheng · Jun Tang

Received: 1 February 2021 / Revised: 14 June 2021 / Accepted: 1 August 2021 / Published online: 9 September 2021

© The Author(s), under exclusive licence to Springer Science+Business Media, LLC, part of Springer Nature 2021

Abstract

A method of robust clutter suppression with space–time adaptive processing (STAP) for airborne radar in heterogeneous environments is proposed, which is based on multi frames and the similarity between the cell under test and each training sample. The proposed method deals with the problem of covariance matrix estimation for STAP in heterogeneous clutter. Firstly, the method expands the set of training samples by selecting similar training frames from past frames. Secondly, initial training samples are selected from the expanded training samples set, that are composed of the samples of the current frame and past frames. Thirdly, initial training samples which may be contaminated by target signal are discarded. Fourthly, the similarities between the cell under test and the remaining training samples are estimated, and training samples which are more similar to the cell under test are assigned higher weights in the estimation of the clutter covariance matrix. The proposed method overcomes the problems of training samples’ heterogeneity and insufficiency in the estimation of the clutter covariance matrix. The accuracy of the estimated clutter character is improved significantly, and thus the performance of clutter suppression is improved. Experimental results based on measured data demonstrate the performance of the proposed method.

Yifeng Wu
wuyf95@mail.sysu.edu.cn
Jia Duan
bifiduan119@126.com
Xiaobo Deng
45285883@qq.com
Yufeng Cheng
872180737@qq.com
Jun Tang
Tangj_ee@tsinghua.edu.cn

1 School of Electronics and Communication Engineering, Sun Yat-Sen University, Guangzhou 510275, People’s Republic of China
2 AVIC Leihua Electronic Technology Research Institute, Wuxi 214063, People’s Republic of China
3 Department of Electronic Engineering, Tsinghua University, Beijing 100084, People’s Republic of China
Keywords  Airborne radar · Heterogeneous clutter suppression · Space–time adaptive processing (STAP) · Covariance matrix estimation

Abbreviations

STAP  Space–time adaptive processing  
CUT  Cell under test  
NHD  Non-homogeneous detectors  
IID  Independent and identically distributed  
DOF  Degree of freedom  
CPI  Coherent process interval  
MSMI  Modified sample matrix inversion

1 Introduction

Airborne phased array radar is widely used to detect moving targets, while its performance degrades in clutter. Space–time adaptive processing (STAP) is adopted to suppress clutter (Li et al., 2019; Rangaswamy et al., 2004a; Wang et al., 2018a). It forms notches at the locations of clutter to suppress clutter. Generally, it is capable to suppress clutter efficiently in homogeneous environments, while its capability of clutter suppression degrades severely in heterogeneous environments (b; Lan et al., 2020a; Sun et al., 2011; Wang et al., 2017a). The clutter covariance matrix of the cell under test (CUT) is necessary for STAP, while it is unknown in the application. Normally, independent and identically distributed (IID) training samples are used to estimate the clutter covariance matrix of the CUT. To ensure its performance of clutter suppression, STAP needs enough IID training samples to estimate the clutter covariance matrix, and its performance of clutter suppression degrades severely when the number of training samples is less than two times the system’s degree of freedom (DOF) (Riedl & Potter, 2018; Yifeng et al., 2015; Zhang et al., 2018).

In heterogeneous environments, some of the selected training samples cannot represent the property of the clutter in the CUT, and the estimated clutter covariance matrix is not exact, which degrades the performance of STAP. To overcome the problem of clutter heterogeneity, numerous non-homogeneous detectors (NHD) have been proposed to remove nonhomogeneous training samples from the initial training samples set (Rangaswamy et al., 2004b; Wang et al., 2013; Zhao et al., 2018). However, these NHD methods do not take the property of the CUT into account, and the selected training samples cannot represent the CUT when the CUT is heterogeneous with most of the initial training samples (Tang et al., 2012; Yang et al., 2013). In this situation, the performance of STAP to suppress clutter degrades seriously. On the other hand, to ensure the accuracy of the estimated clutter covariance matrix, the number of training samples should be larger than 2 times the system’s DOF, while the number of training samples may not enough after the process of NHD, which degrades the performances of STAP to suppress clutter (Wang et al., 2018b).

To overcome the problems of training samples’ heterogeneity and insufficiency in the estimation of the clutter covariance matrix, this paper presents a robust clutter suppression method to improve the performance of STAP in heterogeneous environments. Past frames which share similar properties with the current frame are adopted to expand the initial training samples. Moreover, this paper takes the property of the CUT into account when it selects
training samples by the similarities between the CUT and initial training samples, and the similarities are estimated by the correlation coefficients between them. Training samples whose clutter is more similar to the clutter of the CUT are assigned higher weights in the estimation of the clutter covariance matrix. In this way, the proposed method estimates the property of the clutter in the CUT accurately and improves the performance of clutter suppression. Experimental results based on measured data demonstrate that the proposed method improves the performance of clutter suppression in heterogeneous environments effectively.

2 Signal model for STAP

Denote the observed vector of the CUT as $x_{k0,l0}$, where $k0$ and $l0$ are the frame index and range gate index of the CUT, respectively. The problem of target detection can be formulated as the following binary hypothesis test problem

$$
\begin{align*}
H_0 &: x_{k0,l0} = c_{k0,l0} + n_{k0,l0} \\
H_1 &: x_{k0,l0} = a_{k0,l0}s(\theta_0, f_0) + c_{k0,l0} + n_{k0,l0},
\end{align*}
$$

(1)

where $c_{k0,l0}$ and $n_{k0,l0}$ are the clutter and noise vectors of the CUT, respectively; and $a_{k0,l0}$ is the target amplitude, $s(\theta_0, f_0)$ is the target steering vector corresponding to the direction of $\theta_0$ and the Doppler frequency of $f_0$. To overcome the adverse effects of clutter on target detection, the clutter should be suppressed.

The problem of clutter suppression is described as minimizing the output of clutter power subject to a constant gain in the target direction. The optimum weight of STAP is given by the following mathematical problem (Wang et al., 2017b, 2018b)

$$
\begin{align*}
\min_{w_{k0,l0}} \quad & E\left[\|w_{k0,l0}^H x_{k0,l0}\|^2\right] \\
\text{s.t.} \quad & \left\|w_{k0,l0}^H s(\theta_0, f_0)\right\| = 1,
\end{align*}
$$

(2)

where $(\cdot)^H$ is the conjugate transpose, and $\| \cdot \|$ calculates the 2-norm of a vector or scalar.

According to formula (2), the adaptive weight of STAP is denoted as

$$
w_{k0,l0} = \frac{R_{k0,l0}^{-1}s(\theta_0, f_0)}{s(\theta_0, f_0)^HR_{k0,l0}^{-1}s(\theta_0, f_0)},
$$

(3)

where $R_{k0,l0}$ denotes the clutter covariance matrix of the cell under test (Wang et al., 2018c; Zhang et al., 2018). The STAP output of the cell under test is denoted as

$$
y_{k0,l0} = w_{k0,l0}^H x_{k0,l0},
$$

(4)

in which clutter is suppressed and the power of target keeps constant.

However, the clutter covariance matrix is unknown in practical application, and it’s normally estimated by independent and identical training samples which share similar properties with the CUT,

$$
\hat{R}_{k0,l0} = \frac{1}{L} \sum_{l=1}^{L} x_{k0,l}x_{k0,l}^H,
$$

(5)

where $x_{k0,l}(l = 1, \ldots, L)$ denotes the sample of the $k0$th frame at the $l$th range gate. To guarantee the performance of STAP, the number of training samples should be larger than 2.
times the dimension of $s(\theta_0, f_0)$. However, in heterogeneous environments, there may be no enough IID training samples that share the same property with the clutter of the CUT. In this situation, the clutter covariance matrix of the CUT cannot be well estimated, which degrades the performance of STAP.

Numerous NHD methods have been proposed to select training samples, such as the generalized inner product (GIP) algorithm and loaded GIP algorithm (Rangaswamy, 2005; Rangaswamy et al., 2004b; Tang et al., 2012; Yang et al., 2013; Zhao et al., 2018), while these methods do not take the property of the CUT into account, and the selected training samples cannot represent the clutter of the CUT when the CUT is heterogeneous with most of the initial training samples. As a result, the performance of STAP to suppress clutter in heterogeneous environments suffers severely. On another hand, these NHD methods remove non-homogeneous samples which may result in training samples insufficiency. In this case, the estimated clutter covariance matrix is not accurate, and the performance of clutter suppression degrades.

3 Proposed method

To overcome the STAP performance degradation resulted from non-homogeneity and training samples limitation, this paper presents a robust covariance matrix estimation algorithm by introducing multi frames and weight factors into the process of clutter covariance matrix estimation, and the weight factors are calculated by the similarities between the training samples and the cell under test. The basic idea of the proposed method is that multi frames have more similar samples than the single frame, and the clutter property of the CUT can be well estimated by the training samples from multi frames, thus, STAP performance of clutter suppression improves. Firstly, the proposed method selects past frames that are similar to the current frame. The samples of the selected past frames and the current frame form the initial training samples set. Secondly, initial training samples which may be contaminated by target signal are discarded. Thirdly, the similarities between the remaining samples and the CUT are estimated, and the weights of training samples in the estimation of the covariance matrix are controlled by the corresponding similarities. Fourthly, the adaptive weight of STAP is calculated by the estimated clutter covariance matrix and applied to suppress clutter. The proposed method expands the initial training samples set and significantly improves the accuracy of clutter covariance matrix estimation, and thus the performance of clutter suppression improves. The detailed description is described as follows.

3.1 Multi frames selection

Since the ideal STAP weight is calculated according to the clutter covariance matrix of the clutter in the CUT, and it forms notches at the location of the clutter spectrum. Enough IID training samples which share the same property with the clutter of the CUT are needed. This Section expands training samples set by multi frames. In the process of extended frames selection, the past frames with the same system parameters and similar detection area are firstly selected. After that, the power spectrums of the selected frames areas estimated, and the past frames whose power spectrums are similar to the power spectrum of the current frame are selected.
The power spectrum of the current frame (its frame index is denoted as $k0$) is denoted as
\[ p_{k0}(\theta_i, f_j) = \| s(\theta_i, f_j)^H \tilde{R}_{k0}s(\theta_i, f_j) \|, \quad (i = 1, \ldots, I; j = 1, \ldots, J), \] (6)
where $s(\theta_i, f_j)$ is the scanning steering vector corresponding to the direction of $\theta_i$ and normalized Doppler frequency of $f_j$, $I$ and $J$ are the number of estimated direction and normalized Doppler frequency, respectively; and $\tilde{R}_{k0}$ is the covariance matrix estimated by the samples of the current frame,
\[ \tilde{R}_{k0} = \frac{1}{L} \sum_{l=1}^{L} x_{k0,l}x_{k0,l}^H, \] (7)
where $x_{k0,l}(l = 1, \ldots, L)$ is the training sample of the frame under test at the $l$th range gate.

The power spectrum of the $k2$th frame is denoted as
\[ p_{k2}(\theta_i, f_j) = \| s(\theta_i, f_j)^H \tilde{R}_{k2}s(\theta_i, f_j) \|, \quad (i = 1, \ldots, I; j = 1, \ldots, J), \] (8)
where $\tilde{R}_{k2}$ is the covariance matrix estimated by the samples of the $k2$th frame,
\[ \tilde{R}_{k2} = \frac{1}{L} \sum_{l=1}^{L} x_{k2,l}x_{k2,l}^H, \] (9)
where $x_{k2,l}(l = 1, \ldots, L)$ is the training sample of the $k2$th frame at the $l$th range gate.

There are several methods to estimate the similarity between matrixes, such as Euclidean distance and log-Euclidean distance. In this paper, the similarity between the frame under test and the $k$th frame can be calculated by their Euclidean distance of power spectrum (Wang et al., 2018c), which is denoted as $d_{k2}$.
\[ d_{k2} = \sqrt{\sum_{i=1}^{I} \sum_{j=1}^{J} p_{k2}(\theta_i, f_j) - p_{k0}(\theta_i, f_j)^2}. \] (10)

The Euclidean distance $d_{k2}$ reflects the similarity between the $k2$th frame and the current frame. Only the current frame and the past frames corresponding to the small $d_{k2}$ are selected as initial frames. The selected frames should share similar properties with the frame under test, and they are usually the nearest frames to the current frame. The samples of the selected past frames and the current frame form the initial training samples set, which contains much more samples than the current frame. In this way, the proposed method overcomes the problem of training samples limitation to a certain extent.

The sliding window method is adopted to further select training samples in the frame under test (Zhang et al., 2018), and the selected samples are close to the CUT. In the past frames, the training samples are also selected by the sliding window method. In this way, the initial training samples set are extended by samples of the current frame and past frames.

### 3.2 Discarding samples contaminated by target signal

Target signal in the training samples of clutter covariance matrix estimation may result in target-self-null, which must be avoided. Thus, the training samples which might be contaminated by target signal have to be discarded (Zhiqi & Haihong, 2016). Plenty of methods to discard samples contaminated by the target signal have been proposed (Wu et al., 2015), this
paper adopts the method of correlated coefficient to discard samples contaminated by target signal (Li et al., 2016). The correlated coefficient of the training sample $x_{k2,l}$ with the target steering vector is

$$c_{k2,l} = \frac{\|x_{k2,l}^H s(\theta_0, f_0)\|^2}{\|x_{k2,l}\| \|s(\theta_0, f_0)\|},$$

(11)

As shown in the above formula, the larger $c_{k2,l}$ is, the more similar the training sample with the steering vector is. Thus, to eliminate the effect of target-self-nulling, $\Delta k$ samples corresponding to the largest correlated coefficients are discarded from the initial training samples set. Denote the remaining samples set as $\Omega$, and the corresponding training samples are $x_{k2,l} \in \Omega$. In the next section, the clutter covariance matrixes are estimated by the remaining samples.

### 3.3 Similarity estimation and covariance matrix estimation

This section firstly estimates the similarities between training samples $x_{k2,l} \in \Omega$ and the CUT $x_{k0,l0}$. Then the clutter covariance matrix of the CUT is estimated based on the similarities. Plenty of methods to estimate the similarities have been proposed, this paper adopts the method of correlated coefficient which is similar to the method in the last section. The similarity between the CUT and $x_{k2,l}$ is denoted as

$$s_{k2,l} = \frac{\|\tilde{x}_{k2,l}^H \tilde{x}_{k0,l0}\|^2}{\|\tilde{x}_{k2,l}\| \|\tilde{x}_{k0,l0}\|}, \quad (x_{k2,l} \in \Omega),$$

(12)

where $\tilde{x}_{k0,l0}$ and $\tilde{x}_{k2,l}$ are the projection components of $x_{k0,l0}$ and $x_{k2,l}$ on the subspace orthogonal to the target subspace (which is mainly composed of the clutter subspace and noise subspace), respectively.

$$\tilde{x}_{k0,l0} = P x_{k0,l0},$$

(13)

$$\tilde{x}_{k2,l} = P x_{k2,l}, \quad (x_{k2,l} \in \Omega),$$

(14)

where $P$ is the orthogonal projection matrix of the target signal. $P$ can be denoted as

$$P = I - s(\theta_0, f_0)(s^H(\theta_0, f_0)s(\theta_0, f_0))^{-1}s^H(\theta_0, f_0),$$

(15)

where $I$ is the identity matrix.

According to the definition of $s_{k2,l}$, $s_{k2,l}$ is normally larger than 0 and smaller than 1. $x_{k2,l}$ is not similar to $x_{k0,l0}$ when $s_{k2,l} \rightarrow 0$, and $x_{k2,l}$ is similar to $x_{k0,l0}$ when $s_{k2,l} \rightarrow 1$. To better estimate the covariance matrix, training samples that are similar to the CUT are needed. Therefore, the training samples corresponding to large $s_{k2,l}$ are assigned heavy weights and training samples corresponding to small $s_{k2,l}$ are assigned light weights in the estimation of the covariance matrix. The estimated clutter covariance matrix of the CUT by the proposed method is

$$\hat{R}_{k0,l0} = \sum_{k2} \sum_{l} \frac{1}{s_{k2,l}} \sum_{k2} \sum_{l} s_{k2,l} x_{k2,l} x_{k2,l}^H, \quad (x_{k2,l} \in \Omega).$$

(16)

In the proposed estimation method, the proposed method considers the property of each training sample and takes the training sample property into consideration when it estimates the
covariance matrix of the CUT. Thus, the proposed method improves the accuracy of the clutter covariance matrix estimation, and the robustness of clutter suppression in heterogeneous environments improves.

The flowchart of the proposed algorithm is shown in Fig. 1, and the algorithm can be summarized as follows.

- **Step 1:** select the extended frames according to the waveform, interested region, and spectrum property et.al, and only frames whose property are similar to the frame under test are selected.
- **Step 2:** select initial training samples which are nearby the CUT, excluding the CUT and guard samples to prevent the target self-nulling effect, and the training samples of the frame under test and extended frames form the initial training samples set.
- **Step 3:** discard samples that might be contaminated by the target signal to avoid the target-self-nulling effect.
- **Step 4:** estimate the correlated coefficients between the selected training samples and the CUT, and the correlated coefficients are adopted to measure the similarities between the training samples and the CUT.
- **Step 5:** estimate the clutter covariance matrix of the CUT, and the weight of each training sample in the estimation is calculated according to the similarity between the training sample and the CUT.
- **Step 6:** calculate the adaptive space–time adaptive weight and process the CUT with the STAP weight.

![Flowchart of the proposed method](image)
4 Results and discussion

4.1 Experiment results

To demonstrate the performance of the proposed method, the proposed method and the classical method based on single frame and GIP are applied to measured data which was collected in a heterogeneous clutter environment. One coherent process interval (CPI) of the measured data contains 64 pulses, and a cooperated target was injected at the 200th range gate with 0.3 normalized Doppler frequency. The range-Doppler plot of the measured data is shown in Fig. 2, which shows the non-homogeneity of the environment. Figure 2a shows the clutter of the past frame and Fig. 2b shows the clutter of the current frame. Comparing the clutter in Fig. 2a, b, it shows that the clutter in the two frames looks the same.

The STAP based on a single frame adopts the classical GIP method to discard no-homogeneous training samples. The STAP result of the classical method based on a single frame is shown in Fig. 3. The result of the proposed method is shown in Fig. 4. Comparing Fig. 4 with Fig. 3, the clutter residue of the classical method in the black rectangle is 49 dB, and the clutter residue of the proposed method in the same black rectangle is 44 dB. At the same time, the power of the injected target remains the same. It shows that the proposed method improves the performance of clutter suppression.

A modified sample matrix inversion (MSMI) test statistic is plotted versus range bin for each of the results obtained at the normalized Doppler of 0.3 in Fig. 5. The value of range averaged statistic value was one of our performance measures in this paper, which demonstrates the superiority of clutter suppression. STAP results of a classical method based on a single frame are plotted at the normalized Doppler of 0.3, and the range averaged statistic value is 53 dB. The result of the proposed method at the same normalized Doppler is also plotted, it illustrates that the range averaged statistic value is 49 dB, which is 4 dB lower than the classical method. Experimental results show that the residual power of the proposed method is lower than that of the classical method, which demonstrates the performance of the proposed method.

Figure 6 shows the statistical output of the signal-to-clutter-plus-noise ratio (SCNR) against the input SCNR. The result of each input SCNR is statistically averaged by 200

![Fig. 2 Range-Doppler plot of different frames](image)
trails, in which different simulated targets are injected. The result of Fig. 6 shows that the output SCNR of the proposed method is 3 ~ 4 dB higher than that of the classical method, which illustrates the performance improvements of the proposed method.

4.2 Discussion

Experimental results show that the capability of clutter suppression of the proposed method is better than that of the classical method. This is due to the classical method may not have enough IID training samples in the estimation of the covariance matrix, which degrades the
performance of clutter suppression. On another hand, the classical method does not consider the property of the CUT, thus, the selected training samples might not share the same property with the CUT in heterogeneous environments, and the estimated covariance matrix is not correct when the clutter of the CUT is heterogeneous with most of the initial training samples. In this case, the ability of STAP to suppress clutter degrades. The proposed method expanded the initial training samples set and considers the property of the CUT. It selects enough training samples which are IID with the CUT, and improves the estimated performance of the clutter property, thus, it improves the performance of STAP in heterogeneous environments.

The proposed method overcomes the performance degradation of STAP resulted from training samples insufficiency and heterogeneous, which adopts past frames and training samples similarities. The selected past frames should be measured from the same zone with the frame under test, otherwise, the proposed method cannot select past frames to extend the training samples set. On another hand, the proposed method estimates the similarity between the CUT and each training sample, and its calculation is larger than the classical method.
5 Conclusions

Based on the traditional STAP method, a weighted method is proposed, which is based on multi frames. After comparing with a traditional single frame and NHD method, it has been proven that the proposed method can achieve a good clutter suppression performance. Firstly, it uses past frames to expand the set of training samples. Secondly, training samples that are heterogeneous with most of the initial training samples are discarded by the classical NHD method. Thirdly, the similarity between the cell under test and each selected training sample is estimated. Then, the clutter covariance matrix is estimated according to the similarities. Since the proposed method expands the set of initial training samples and takes the property of each sample into account, it improves the performance of the clutter covariance matrix estimation. Thus, the proposed method can effectively suppress clutter in heterogeneous environments. Experimental results based on real data demonstrate the effectiveness of the proposed method.

Acknowledgements

This study was supported by the China Postdoctoral Science Foundation funded project Under Grant Number 2019M651994 and the Aviation Science Foundation of China Under Grant Number 2017Z2007002, and the Postdoctoral Science Foundation of Jiangsu Province Under Grant Numbers 2018K048C and 2019Z101, as well.

Authors’ contributions

Jia Duan and Yifeng Wu proposed the main idea. The work of Xiaobo Deng was mainly about experiments. The work of Yufeng Cheng and Jun Tang was mainly about the problem of discarding samples and the discussion.

Funding

The China Postdoctoral Science Foundation (grant number 2019M651994) and the Postdoctoral Science Foundation of Jiangsu Province (grant numbers 2018K048C and 2019Z101) support the study, and the Aviation Science Foundation (under grant number 2017Z2007002) supports the data of the study.

Declarations

Conflict of interest

The authors declare that they have no conflict of interest.

References

Lan, L., Liao, G., Xu, J., Zhang, Y., & Liao, B. (2020a). Transceive beamforming with accurate nulling in FDA-MIMO radar for imaging. IEEE Transaction on Geoscience and Remote Sensing, 58(6), 4145–4159.
Lan, L., Xu, J., Liao, G., Zhang, Y., Fioranelli, F., & So, H. C. (2020b). Suppression of mainbeam deceptive jammer with FDA-MIMO radar. IEEE Transaction on Vehicular Technology, 69(10), 11584–11598.
Li, R., Li, J., & Zhang, W. (2016). He Z (2016) Reduced-dimension space-time adaptive processing based on angle-Doppler correlation coefficient. EURASIP Journal on Advances in Signal Processing, 1, 97.
Li, Z., Zhang, Y., Guo, Y., Zheng, G., & Zhou, H. (2019). A robust STAP approach for airborne FDA radar with multiple possible prior information constraints. Multidimensional Systems and Signal Processing, 30, 2147–2166. https://doi.org/10.1007/s11045-019-00647-6.
Rangaswamy, M. (2005). Statistical analysis of the nonhomogeneity detector for non-Gaussian interference backgrounds. IEEE Transactions on Signal Processing, 53(6), 2101–2111.
Rangaswamy, M., Michels, J. H., & Himed, B. (2004a). Statistical analysis of the non-homogeneity detector for STAP applications. Digital Signal Processing, 14(3), 253–267.
Rangaswamy, M., Michels, J. H., & Himed, B. (2004b). Statistical analysis of the non-homogeneity detector for stap applications. Digital Signal Processing, 14(3), 253–267.
Riedl, M., & Potter, L. C. (2018). Multi-model shrinkage for knowledge-aided space-time adaptive processing. IEEE Transactions on Aerospace and Electronic Systems, 99, 1–1.
Sun, K., Meng, H., Wang, Y., & Wang, X. (2011). Direct data domain STAP using sparse representation of clutter spectrum. Signal Processing, 91(9), 2222–2236.
Tang, B., Tang, J., & Peng, Y. (2012). Detection of heterogeneous samples based on loaded generalized inner product method. *Digital Signal Processing, 22*, 605–613.

Wang, F., Li, H., & Himed, B. (2013). A Parametric moving target detector for distributed MIMO radar in non-homogeneous environment. *IEEE Transactions on Signal Processing, 61*(9), 2282–2294.

Wang, T., Zhao, Y., Chen, S., & Zhang, K. (2017a). A cascaded reduced-dimension STAP method for airborne mimo radar in the presence of jammers. *Radio Engineering, 26*(1), 337–344.

Wang, Z., Xie, W., Duan, K., & Wang, Y. (2017b). Clutter suppression algorithm based on fast converging sparse Bayesian learning for airborne radar. *Signal Processing, 130*, 159–168.

Wang, W., Zou, L., Wang, X., & Yang, Y. (2018a). Deterministic-aided single dataset STAP method based on sparse recovery in heterogeneous clutter environments. *Journal on Advances in Signal Processing, 2018*(1), 24.

Wang, W., Zou, L., Wang, X., & Yang, Y. (2018b). Deterministic-aided single dataset stap method based on sparse recovery in heterogeneous clutter environments. *Journal on Advances in Signal Processing, 2018*(1), 24.

Wang, W., Zou, L., Wang, X., & Yang, Y. (2018c). Deterministic-aided single dataset STAP method based on sparse recovery in heterogeneous clutter environments. *Journal on Advances in Signal Processing, 2018*(1), 24.

Wu, Y., Wang, T., Wu, J., & Duan, J. (2015). Training sample selection for space-time adaptive processing in heterogeneous environments. *IEEE Letters on Geoscience and Remote Sensing, 12*(4), 691–695.

Yang, X., Liu, Y., & Long, T. (2013). Robust non-homogeneity detection algorithm based on prolate spheroidal wave functions for space-time adaptive processing. *IET Radar, Sonar & Navigation, 7*(1), 47–54.

Yifeng, W., Tong, W., Jianxin, W., & Jia, D. (2015). Robust training samples selection algorithm based on spectral similarity for space–time adaptive processing in heterogeneous interference environments. *IET Radar, Sonar & Navigation, 9*(7), 778–782.

Zhang, W., He, Z. S., & Li, H. Y. (2018). Linear regression based clutter reconstruction for STAP. *IEEE Access, PP*(99), 1.

Zhao, X., He, Z., Wang, Y., & Sun, G. (2018). Reduced-dimension STAP using a modified generalised sidelobe canceller for collocated MIMO radars. *IET Radar, Sonar & Navigation, 12*(12), 1476–1483.

Zhiqi, G., & Haihong, T. (2016). Robust STAP algorithm based on knowledge-aided sparse recovery for airborne radar. *IET Radar Sonar & Navigation, 11*(2), 321–329.

**Publisher’s Note** Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.

**Jia Duan** was born in Jiangxi Province, China, in 1989. She received the Ph.D. degree from Xidian University in 2015. Her research interests include radar system, ISAR imaging and automatic target recognition.
Yifeng Wu was born in Anhui Province, China, in 1988. He received the Ph.D. degree from Xidian University in 2016. He is currently an associate professor of Sun Yat-Sen University. His research interests include target detection, array signal processing.

Xiaobo Deng was born in Hunan Province, China, in 1982. His research interests include radar signal processing, waveform design, and array signal processing.

Yufeng Cheng was born in Jiangsu Province, China, in 1973. His research interests include radar system and airborne radar.
Jun Tang received the Ph.D. degree in electrical engineering from Tsinghua University, China, in 2000. He is currently a Professor with the Department of Electronic Engineering, Tsinghua University. His research interests include array signal processing, information theory and MIMO radar, and compressive sensing in radar application.