Training sample selection for space–time adaptive processing based on multi-frames

Chenxiao Zhang\textsuperscript{1}, Yifeng Wu\textsuperscript{1}, Mingming Guo\textsuperscript{1}, Xiaoobo Deng\textsuperscript{1}

\textsuperscript{1}AVIC Leihua Electronic Technology Research Institute, Wuxi, 100101, People’s Republic of China
\textsuperscript{E–mail: zhangcx1987@126.com}

Abstract: As training samples are not identically distributed with cell under test (CUT) in heterogeneous environments, the performance of space–time adaptive processing (STAP) to suppress clutter degrades. To improve the performance of STAP, this study proposes a novel training sample selection method for STAP based on multi-frames. The key feature of the new method is to overcome the deficit of independent and identically distributed (IID) training samples in heterogeneous environments. First, multi-frames are selected according to similarity from continuous frames; second, training samples which are IID to the CUT from current frame are selected; finally, combine the training samples of the current frame and same range samples in reference frame into final training sample set. The proposed method is applied to real-radar data, and experimental results demonstrate the effectiveness of the proposed method.

1 Introduction

Clutter suppression plays an important role in airborne radar when it detects moving targets in down-looking status. Generally, weak slow-moving target is obscured by strong clutter, which affects the detection performance. Space–time adaptive processing (STAP) \cite{1} is used in airborne radar system to suppress clutter. STAP needs clutter covariance matrix to calculate the adaptive weight. In practice, clutter covariance matrix is unknown and estimated from training samples which are adjacent to the cell under test (CUT). However the training samples may be contaminated by heterogeneous samples, such as dense buildings and land–sea boundary. First, clutter power may vary severely according to range; second, clutter is discrete owing to different terrains and inaccurate storage of terrain data would degrades the KA-STAP performance. It detects moving targets in down-looking status. Generally, weak slow-moving target is obscured by strong clutter, which affects the detection performance. Space–time adaptive processing (STAP) \cite{1} is used in airborne radar system to suppress clutter. STAP needs clutter covariance matrix to calculate the adaptive weight. In practice, clutter covariance matrix is unknown and estimated from training samples which are adjacent to the cell under test (CUT). However the training samples may be contaminated by heterogeneous samples, such as dense buildings and land–sea boundary. First, clutter power may vary severely according to range; second, clutter is discrete owing to different terrains and inaccurate storage of terrain data would degrades the KA-STAP performance.

In order to solve this problem, this paper proposes a novel training samples selection method for STAP based on multi-frames. This method employs less training samples than twice degree of freedom (DOF) from current frame in heterogeneous environments, and it selects training samples of the same ranges with the current frame from reference frame. As a result, the method could avoid the heterogeneity resulted by range and collect sufficient amount of homogeneous training samples. This paper is organised as follows: the signal model and conventional method are formulated in Section 2. In Section 3, the training samples selection method based on multi-frames processing is detailed described. Section 4 illustrates the experimental results based on real data. Finally, Section 5 concludes this paper.

2 Signal model

An linear array of airborne radar with \(N\) uniformly spaced elements is considered in this paper, and the inter-element space is \(d\). \(M\) pulses compose one coherent processing interval, the observed vector from the \(k\)th range gate is denoted as \(X(l)\)

\[
X(l) = a \ast s + e(l) + n
\]

where \(e(l)\) and \(n\) are the clutter signal and noise signal, respectively, \(s\) is the spatial-temporal steering vector of target, \(a\) is the amplitude of target. Let it suppose that \(\theta_l\) and \(\phi_l\) are the azimuth and elevate angle of the \(k\)th clutter patch in the \(l\)th range gate (Fig. 1).

The steering vector of the clutter patch can be denoted as

\[
r_k = b(o_{lh}) \otimes a^T(o_{lh})
\]

where \(\otimes\) denotes the Kronecker product and \((\cdot)^T\) denotes transposition

\[
b(o_{lh}) = [1, e^{j2\pi \lambda \sin \phi_l \sin \theta_l}, \ldots, e^{j2\pi \lambda \sin \phi_l \sin \theta_l (M-1)}]^T
\]

Denote the \(M \ast 1\) temporal steering vector at normalised Doppler frequency \(o_{lh}\), and

\[
o_{lh} = \frac{2V}{f_c} \cos \phi_l \sin \theta_l
\]

where \(\lambda\) and \(f_c\) are the wavelength and pulse repeat frequency, respectively.
According to the algorithm of linearly constrained minimum variance, we have the following optimisation problem:

\[
\begin{align*}
\min_w & \quad w^H R w \\
\text{s.t.} & \quad w^H s = 1
\end{align*}
\]  

where \( w \) is optimum weight of STAP, \( R = E[XX^H] \) is the clutter covariance matrix of the \( h \)th range ring. \((\cdot)^H\) denotes the conjugate transpose. In practical application, \( R \) is unknown and normally estimated from the training samples around the \( h \)th range ring

\[ \hat{R}_h = \frac{1}{N_r} \sum_{i \in \Omega} X(i)X^H(i) \]  

where \( \Omega \) is the range cell index including every training samples, \( N_r \) is the number of training samples, to ensure the performance of estimation, \( N_r > 2\text{DOF} \). In order to improve the STAP performance in heterogeneous environment, conventional single-frame processing apply generalised inner product (GIP) algorithm [8] and power-selected training (PST) [9] to select samples for covariance matrix estimation.

However in the heterogeneous environment (e.g. dense buildings or land–sea boundary), training samples may be significantly non-homogeneous with each other. Thus, the covariance matrix estimated by (9) may be significantly different from the true covariance matrix of the CUT, which leads to the deteriorative performance of STAP [10]. The following section proposes a novel training samples selection algorithm based on multi-frames in heterogeneous environment.

3 Training sample selection based on multi-frames processing

In the multi-frames processing, the frame under test is called current frame, while other frames are called reference frames. The basic idea of the method is that multi-frames processing have more data sources to select training samples than the single-frame processing. So we could select less (<2DOF) training samples which are strictly IID with the clutter of the CUT in current frame; and then, combine ‘high similarity’ training samples from current frame and reference frame into final training samples.

To address this problem, we first dynamically select reference frames which are similar to the current frame, and optimise the training samples from the current frame; afterwards, we collect final training samples of ‘high similarity’ from multi-frames and calculate the adaptive weight. (Fig. 2)

3.1 Multi-frames dynamic selection

Since the STAP weight is calculated according to the power spectral density (PSD) of clutter in CUT, the reference frames whose power spectral densities are similar to the PSD of the current frame are selected.

Generally, the airplane exists posture tremble and location variation during flying. In this case, the PSD of the continuous frames may be different, we should select reference frames whose PSD are similar to the PSD of current frame. Now the number of total continuous frames is \( H \).

The power spectral density of the current frame can be expressed by

\[ q_h = \sum_{\omega, \nu} s(\omega, \nu)^H \hat{R}_{h_0} s(\omega, \nu) \]  

where \( h_0 \) is the number of current frame, \( \hat{R}_{h_0} \) is the estimated clutter covariance matrix around the CUT. The power spectral density of the reference frame is

\[ q_h = \sum_{\omega, \nu} s(\omega, \nu)^H \hat{R}_{h_0} s(\omega, \nu) \]  

where \( h \) is the number of reference frames, \( \hat{R}_{h} \) is clutter covariance matrix estimated from same range in the \( h \) frame. The PSD
To avoid weaker clutter nulls, PST selects stronger clutter samples homogeneous with each other.

Most airplane and interested targets are lower than 200 m/s; the frame period is about several milli-seconds, the velocities of reference frames are selected (Fig. 3). Training samples selection of multi-frames processing

Since the result of (12) is only influenced by $\hat{R}_h - \hat{R}_h$, the difference between the current frame and the reference frames can be estimated by $\hat{R}_h - \hat{R}_h$. In this paper, Euclidean distances between covariance matrices are adopted to estimate the similarities between covariance matrix of current frame and covariance matrix of reference frames. The Euclidean distance is defined by

$$g(h) = \sqrt{\text{tr}((\hat{R}_h - \hat{R}_h) \ast (\hat{R}_h - \hat{R}_h)^H)}$$  

(13)

where $\text{tr}(\cdot)$ is the sum of the diagonal elements of the covariance matrices, $g(h)$ is capable to reflect the spectral similarity between frames at a certain extent. PSD of current frame and reference frame are more similar when $g(h)$ approaches zero, so we can select several reference frames according to $g(h)$.

3.2 Multi-frames combination clutter suppression

The frame period is about several milli-seconds, the velocities of most airplane and interested targets are lower than 200 m/s; therefore, target and clutter patches do not across range gates among several frame periods. The training samples selection process in current frame is similar with the single-frame process. To avoid weaker clutter nulls, PST selects stronger clutter samples for covariance matrices. GIP discards training samples containing outliers from the secondary data, final, the training samples are homogeneous with each other.

In this section, take three frames as one multi-frames unit, select $N_c$ ($N_c < 2\text{DOF}$) training samples from current frame $h_t$ like single-frame process, and the corresponding range gate of each selected sample is denoted as $T(j), (j = 1, 2, \ldots, N_c)$. The number of reference frames are $h_t$ and $h_c$. According to the corresponding range gate of each selected sample from the current frames, other training samples of same range from another two reference frames are selected (Fig. 3)

$$X_{h_t, \text{train}} = \{X_{h_t}(T(1)), X_{h_t}(T(2)), \ldots, X_{h_t}(T(N_c))\}$$  

(14)

$$X_{h_c, \text{train}} = \{X_{h_c}(T(1)), X_{h_c}(T(2)), \ldots, X_{h_c}(T(N_c))\}$$  

(15)

$$X_{h_c, \text{train}} = \{X_{h_c}(T(1)), X_{h_c}(T(2)), \ldots, X_{h_c}(T(N_c))\}$$  

(16)

The final training sample set is denoted as

$$X_{\text{train}} = \{X_{h_t, \text{train}} \ X_{h_c, \text{train}} \ X_{h_c, \text{train}}\}$$  

(17)

To ensure the performance of covariance matrix estimation, the amount of final training samples should be larger than twice the degree of freedom, that is $3N_c > 2\text{DOF}$. The final estimated clutter covariance matrix is

$$\hat{R} = \frac{1}{3N_c} \sum_{i=1}^{3N_c} X_{\text{train}}(i)X_{\text{train}}(i)^H$$  

(18)

4 Experimental results

To show the effectiveness of the proposed method, the proposed method is applied to real-radar data. The data was collected by a forward-looking airborne radar over different terrains which vary with range. The terrain of experimental real data is shown in Fig. 4, where red dotted line is the radar beam direction and black solid line is the samples data range. The colour bar demonstrates sea level elevation of every pixel.
Fig. 6 illustrates the system performance, which are indicated by the calculated improvement factor (IF). The IF is defined as the ratio of output signal-to-clutter-plus-noise-ratio (SCNR) against input SCNR. The proposed algorithm has a better performance than the single-frame process, which is because the proposed algorithm selects training samples whose property is similar to the property of clutter in the CUT.

CFAR detector is applied to process the real-radar data. One cooperation target is successfully detected after CFAR in multi-frames method (other one detected target is false alarm). The cooperation target locate in 0.32 normalised Doppler frequency and 96 range cell. Multi-frames method have better performance in false alarms ratio than single-frame method which detects five false alarms.

5 Conclusion

In this paper, a novel training sample selection method based on multi-frames is proposed to estimate the clutter covariance matrix of airborne radar STAP. First, the proposed method selects multi-frames dynamically according to reference frame similarity; second, training samples which are IID to the interference of the CUT from current frame are selected; finally, combine the training samples of the current frame and same range samples in reference frame into final training sample set, and the covariance matrix of the CUT are estimated by the final training sample set. The experiment based on real data demonstrates that the proposed method provides better clutter suppression performance than the single-frame STAP in heterogeneous environments. In addition, the proposed method could be applied to airborne phased-array radar easily.

6 References

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