Study on Robust Cascaded Time-Space Adaptive Reverberation Suppressing Method

Ma Quli, Zhan Haoke, Yuan Bingcheng, and Zhu Xi

***Abstract*—The cascaded time-space adaptive method usually use an inverse Reverberation Covariance Matrix calculation to obtain adaptive weights. Reverberation covariance matrix is singular matrix owing to limited IID sample number obtained by active sonar in non-stationary environment. Based on which, a robust cascaded time- space adaptive method is presented in this paper. The new method uses diagonal loading and conjugate after reversal arranging data to overcome the problem of limited sample number. In the scenario of limited sample number, the new approach can cancel the reverberation effectively. The sea trial results to verify its effectiveness are presented.**

***Index Terms*—Reverberation, space-time adaptive, diagonal loading, limited sample, reversal arranging data.**

I. Introduction

The research shows that Space Time Adaptive Processing (STAP) can eliminate the reverberation of active sonar effectively than conventional techniques [1], [2]. People are utilized to profit from the contribution of Brennan, Klemm, Baozheng [3]-[6] and so on. They present a great deal of lower rank space time approaches up to now. According to the working mode and complexity of the active sonar, the cascaded Time-Space Adaptive (TSA) method is more suitable for the reverberation suppression. TSA method filters the acoustical signal from each sensor of sonar array by using a group of Doppler filters. After that, the reverberation is suppressed by using the technology of adaptive beamforming. TSA usually use an inverse Reverberation Covariance Matrix (RCM) calculation to obtain adaptive weights. Accurate estimation of the RCM is the key step of TSA realization. In practice, the maximum likelihood estimate of RCM is calculated from the auxiliary samples, which is assumed Independent and Identical Distributed (IID) [7]-[10]. And the required size of the auxiliary samples is greater than 2 or 3 times of Degrees Of system Freedom (DOF) to guarantee an output Signal-Reverberation-Noise Ratio (SRNR) that is within 3 dB that obtained with the true statistics. In practical shallow water environment, The IID reverberation sample support requirements can no usually be satisfied. The performance of TSA is therefore degraded. How to reduce this requirement is an important problem. And RCM is singular matrix owing to limited sample obtained by active sonar in non-stationary environment.

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In order to overcome the above-mentioned difficulties, this paper use diagonal loading and conjugate after reversal arranging data to overcome the problem of limited sample number. This method avoids singular matrix which aroused by small eigenvalue with diagonal loading. In the scenario of limited sample number, the RCM can be estimated effectively, which can make the notch positions more accurate and the notch more deep, so as to cancel the reverberation more effectively. The simulation and sea trial results to verify its effectiveness are presented. Accordingly, this method possesses research future in active sonar practicality.

II. Improved TSA Method

TSA method filters the acoustical signal from each sensor of sonar array by using a group of Doppler filters. After that, the acoustical signal turns into a group of narrowband signals in frequency domain, then these narrowband signals is processed by the technology of adaptive beamforming.

Let us define $x_j(n)$ is the No. j(j=1, 2, …, K) signal sample from the No. n sensor. $X_t(n)=[x_1(n)\ x_2(n)\ \ldots\ x_K(n)]^T$ is the No. n sensor signal sampling vector. And then, The space-time 2-dimension data vector $X(NK\times 1)$ can express as $X=[X_t^T(1)\quad X_t^T(2)\quad \ldots\quad X_t^T(N)]^T$. Where N is the number of array sensor. Let us define $W_t(f_k)$ $(K\times 1)$ is the weight vector of the No. k Doppler frequency filter. Then we can obtain the output of the No. k Doppler frequency filter with each sensor , namely

$$Y\left(f_k\right)=[W_s^H\otimes W_t(f_k)^H]X \tag{1}$$

where, $W_s(N\times 1)$ is the adaptive space steering weight vector. $\otimes$ is Kronecker direct product.

Then, RCM R_k $(N\times N)$ of the No. k frequency channel is obtained as

$$R_k=E\left[Y\left(f_k\right)Y\left(f_k\right)^H\right] \tag{2}$$

where, H express conjugate transposed. So, the adaptive space weight vector of the No. k Frequency channel in detecting direction α which is obtained as

$$W_s=\mu R_k^{-1}s\left(\alpha\right) \tag{3}$$

where, $\mu=s^H\left(\alpha\right)R_k^{-1}s\left(\alpha\right)$, and $s\left(\alpha\right)$ is the space steering vector.

But the IID auxiliary samples are not enough to calculate RCM in practical shallow water environment. This has effect on the Eq. (3).

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Now, let us define $Z(f_k)=JY^*(f_k)$, $Y^*(f_k)$ is the $Y(f_k)$'s complex conjugate, and J is r rank exchange matrix which is obtained as

$$J=\begin{bmatrix} 0 & .. & .. & 0 & 1 \\ 0 & .. & .. & 1 & 0 \\ . & .. & .. & .. & .. \\ . & .. & .. & .. & .. \\ 1 & 0 & . & 0 & 0 \end{bmatrix} \tag{4}$$

where, $JJ=I$. We can gain

$$R_k^{'}=E\left(Z\left(f_k\right)\cdot Z^H\left(f_k\right)\right)=JR_k^*J \tag{5}$$

So, the new RCM can obtain by

$$\hat{R}_k=\left(R_k^{'}+JR_k^*J\right)/2 \tag{6}$$

RCM $\hat{R}_k$ can be expressed as

$$\hat{R}_k=\sum_{i=1}^{p}\lambda_i u_i u_i^H+\sum_{i=p+1}^{LN}\lambda_i u_i u_i^H \tag{7}$$

where, λ_i is the No. i eigenvalue, u_i is the No. i eigenvector according to λ_i, p is the rank of RCM. Then,

$$\begin{aligned}\hat{R}_k^{-1}&=\sum_{i=1}^{LN}\frac{1}{\lambda_i}u_i u_i^H\\&=\frac{1}{\sigma_w^2}\left[I-\sum_{i=1}^{LN}\frac{\lambda_i-\sigma_w^2}{\lambda_i}u_i u_i^H\right]\\&=\frac{1}{\sigma_w^2}\left[I-A-B\right]\end{aligned} \tag{8}$$

where, σ_w^2 is the power of white noise,

$$A=\sum_{i=1}^{p}\frac{\lambda_i-\sigma_w^2}{\lambda_i}u_i u_i^H,\ B=\sum_{i=p+1}^{LN}\frac{\lambda_i-\sigma_w^2}{\lambda_i}u_i u_i^H\ .$$

If $\hat{R}_k$ is the true RCM, when $i>p$, we can draw a conclusion that $\lambda_i=\sigma_w^2$, namely B is zero. In other words, noise eigenvalue has no effect on the Eq. (3). In practice, the estimate of $\hat{R}_k$ is calculated from the training samples. IID samples are limited in general condition, and the estimate of $\hat{R}_k$ is not accuracy. When $i>p$, λ_i is fluctuate with σ_w^2, is not zero, which has effect on the Eq. (3). If λ_i is more less than σ_w^2, the value of B would be very big and RCM would be singular matrix. Now we can add a number closed to σ_w^2 onto all eigenvalue of RCM, namely

$$\hat{R}_{kDL}=\hat{R}_k+\lambda_{DL}I \tag{9}$$

where, λ_{DL} is the level of diagonal loading, there is $\sigma_w^2\le\lambda_{DL}<10\sigma_w^2$ commonly. How to select the DL level in practice that is demonstrated in Ref.[11], [12]. So

$$\hat{R}_{kDL}^{-1}=\frac{1}{\sigma_w^2+\lambda_{DL}}\left[I-\hat{A}-\hat{B}\right] \tag{10}$$

where, $\hat{A}=\sum_{i=1}^{p}\frac{\lambda_i-\sigma_w^2}{\lambda_i+\lambda_{DL}}u_i u_i^H$, $\hat{B}=\sum_{i=p+1}^{LN}\frac{\lambda_i-\sigma_w^2}{\lambda_i+\lambda_{DL}}u_i u_i^H$.

when $i<p$, λ_i is more bigger on which has been little effected by adding a little number λ_{DL}. When $i>p$, λ_i is more smaller which let $\hat{B}$ becomes smaller by adding a number λ_{DL}. Accordingly, $\hat{R}_{kDL}$ is closed to true R_k. Based on which we can get the TSA method by using $\hat{R}_{kDL}$ to replace R_k of Eq. (3).

III. Performance Characterization

The output of the No. k *Doppler* channel after TSA method processing in detecting direction α can be expressed as [13], [14].

$$Z_{out}=\left(W_s^H(\alpha)\otimes W_t^H\right)X \tag{11}$$

where, $W_s(N\times 1)$ is the adaptive space steering weight vector; $W_t(K\times 1)$ is the weight vector of the No. k Doppler frequencies filter; $\otimes$ is Kronecker direct product.

When the RCM R is true in detecting direction α, the output $SRNR$ of the No. k Doppler channel after TSA method processing can be expressed as

$$\begin{aligned}SRNR&=\frac{|b|^2\left|W_s^H(\alpha)S(\alpha)\right|^2}{W_s^H(\alpha)RW_s(\alpha)}\\&=S^H(\alpha)R^{-1}S(\alpha)\end{aligned} \tag{12}$$

where, $S(\alpha)$ is the space steering vector, and b is the amplitude of signal echo. When the RCM R is estimated from training samples in detecting direction α, let us define $\hat{R}$ is the RCM estimated. Then the output $SRNR$ of the No. k Doppler channel after TSA method processing can be expressed as

$$\overline{SRNR}=\frac{\left(S^H(\alpha)\hat{R}^{-1}S(\alpha)\right)^2}{S^H(\alpha)\hat{R}^{-1}R\hat{R}^{-1}S(\alpha)} \tag{13}$$

So the loss of output $SRNR$ caused by $\hat{R}$ becomes

$$\begin{aligned}&SRNR_{loss}\\&=\frac{\left(S^H(\alpha)\hat{R}^{-1}S(\alpha)\right)^2}{S^H(\alpha)\hat{R}^{-1}R\hat{R}^{-1}S(\alpha)}\cdot\frac{1}{S^H(\alpha)R^{-1}S(\alpha)}\end{aligned} \tag{14}$$

Improved Factor (**IF**) is defined as the ratio of output and input $SRNR$ which can measure the performance of TSA method. See Eq. (15)

$$IF(\alpha, f_k) = \left\{ W_s^H S_Z(\alpha) \right|^2 (RNR+1)\sigma^2 \Big\} / W_s^H S(\alpha) W_s \quad (15)$$

where, *RNR* is the reverberation-noise-ratio, σ_w^2 is the white noise power.

IV. Experimental Results

Parameters connected in sea experiment is given: the line array has 40 sensors that is placed with half wave length uniform; the distance of array and seabed is 150 meters; the velocity of platform is 13 knot, the angle of array axis direction relative to direction of *V* is $\delta = 0^0$ (side looking); the carrier frequency is 2KHz with wide beam, the transmit pulse is 0.1s, The target appears in direction $\alpha = 50^0$, and the speed is 10 knot, towards the array stem for stem.

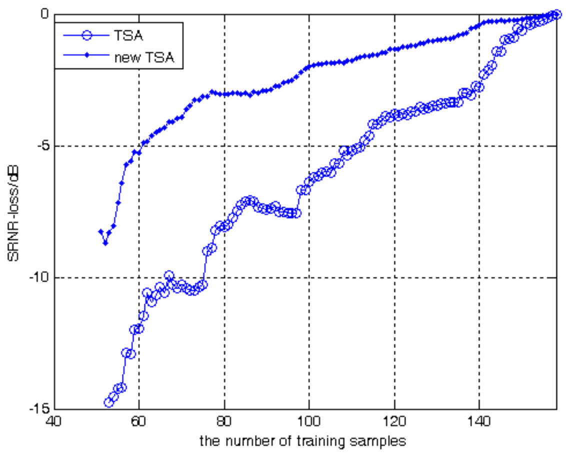

Fig. 1. Output $SRNR$ loss versus the number of training samples.

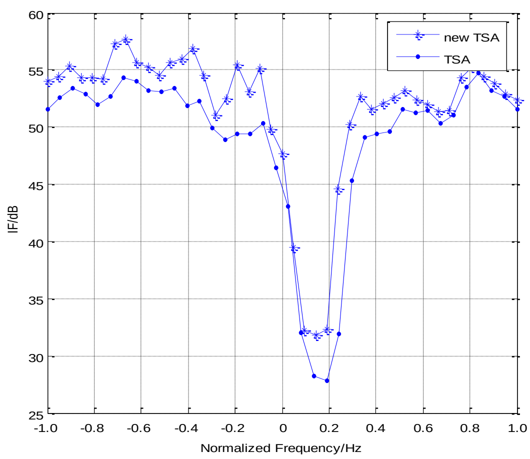

Fig. 2. IF varied with the new TSA and TSA.

Fig. 1 shows the relationship of output $SRNR$ loss and the number of training samples. From the Fig. 1, we can draw a conclusion that the required size of the training samples for the estimate of RCM which is about greater than 140 to guarantee an output $SRNR$ that is within 3 dB that obtained with the true statistics. After DL and conjugate after reversal arranging data processing, the required size of the training samples is about 70 to guarantee that. Namely, the degree of dependence on the training samples is reduced. But when the number of training samples is continue reducing, the output $SRNR$ loss is increase, because that the information of reverberation is continue reducing with the decrease of training samples.

Fig. 2 shows IF varied with the new TSA and TSA. From the picture, we can draw a conclusion that the performance after new TSA processing is the better than that after TSA processing.

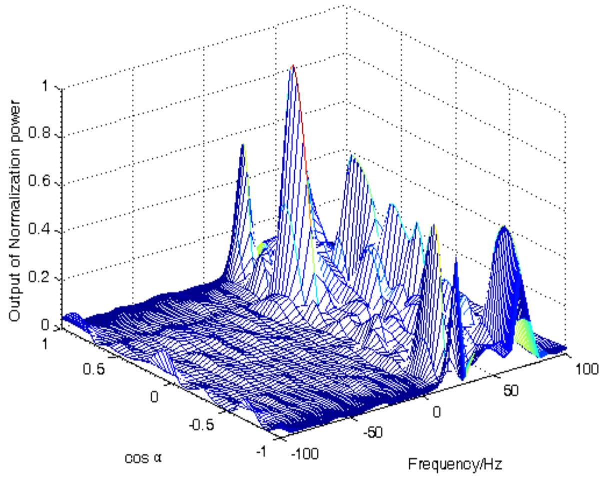

Fig. 3. The output of TSA processing.

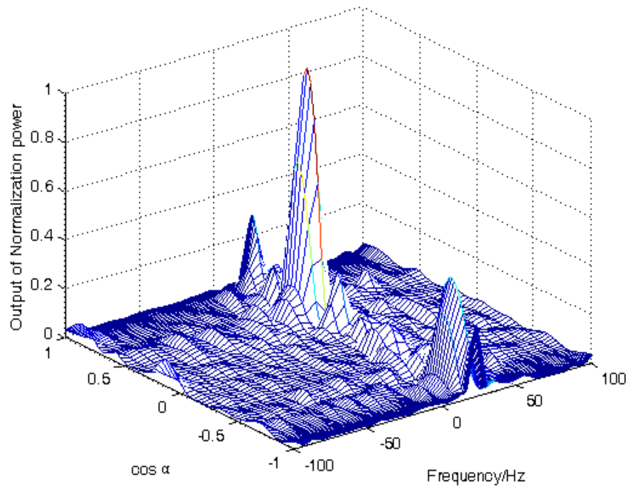

Fig. 4. The output of new TSA method.

Fig. 3 shows that output after processing of TSA method and Fig. 4 shows that output after processing of new TSA in the same training samples number (80) environment. We can draw a conclusion that the old method has bad performance compared with the new method, and we can see the target clearly after new method processing, the effects of reverberation can be eliminated by and large.

V. Conclusions

In order to overcome the difficulty of which RCM is singular matrix owing to limited IID sample in non-stationary environment, this paper presents a TSA method with DL and conjugate after reversal arranging data processing. The new method avoids singular matrix which aroused by small eigenvalue. From sea trail results, we can draw a conclusion that the degree of dependence on the training samples is reduced. But when the number of training samples is continue reducing, the output *SRNR* loss is increase, because that the information of reverberation is continue reducing with the decrease of training samples. Compared with old method, the new method enhances the performance of active sonar detecting weak targets greatly and that of robust. The sea trail results to verify its effectiveness. Accordingly, this method possesses research future in active sonar practicality.

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