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Adaptive Moving Jammer Cancellation Algorithm with the Robustness to the Array Aperture

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Abstract

In moving jammer environments, the performance of conventional adaptive beamformer is severely degraded and the robust adaptive beamformer requires additional sensors to obtain desired performances. Therefore, it is necessary to develop efficient algorithm without any additional requirement of the number of sensors, etc. In this paper, we introduce a fast adaptive algorithm with variable forgetting factor, which does not have any additional requirements. From the computer simulations, we obtain the better performances than those of other techniques for the arrays with various aperture lengths.

Keywords: *Adaptive beamforming, Moving jammer, Variable forgetting factor*

I. Introduction

For decades, a number of adaptive beamforming algorithms have been investigated[1]. Recently, adaptive arrays should cope with a moving jammer problem as well as a fixed one. However, the conventional adaptive techniques cannot effectively cancel out the moving jammers because the weights are not able to adapt themselves sufficiently fast to the moving (nonstationary) jamming situations. Such degradation is caused by the fact that the rapidly moving interferers move away from the sharp notches of the adaptive beampattern. Therefore, the degradation is especially worse in small aperture array because of a small number of null points and wider space between the nulls.

To overcome these problems, Gershman *et al.* have proposed the robust beamforming algorithm with the derivative constraints[2]. The derivative constraints make the notches of the beampattern broad, so that the robust method has better results in the nonstationary situations than the conventional approaches. However, it must require additional sensors[3] and the does not guarantee good performance if the beamformer cannot have the sufficient number of sensors or has small aperture.

In this paper, we propose an adaptive beamforming algorithm with robustness for the number of sensors as well as the jammer motions. This algorithm introduces a variable forgetting factor to the RLS based algorithm. The variable forgetting factor makes the directional pattern effectively adapt to the nonstationary environments by updating at each snapshot, so that the arrays can cope with both the stationary and moving jamming situations without *any additional* sensors and *a priori* knowledge of the forgetting factor.

Computer simulations show that the proposed technique improves the output signal-to-interference-plus-noise ratio (SINR) for the several sizes of the array aperture.

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II. Problem formulation

We formulate the problem for a uniform linear array of N sensors. The complex adaptive beamformer output with the weight vector $\underline{w}$ at time t can be expressed as

$$z(t)=\underline{w}(t)^H\underline{y}(t) \tag{1}$$

and $(\cdot)^H$ stands for Hermitian transpose. Let a signal and q ($q < n$) narrowband jammers with much higher power than signal, impinge on the array from directions $\{\theta_1, \theta_2, \Lambda, \theta_q\}$ and from direction θ_s, respectively. Let the jammers be uncorrelated with each other as well as signal. In this array, the beamforming snapshot $\underline{y}(t)$ consists of a desired signal, jamming signals and background sensor noise, that is,

$$\begin{aligned}\underline{y}(t)&=s_s(t)\underline{a}(\theta_s)+\sum_{k=1}^{q}s_k(t)\underline{a}(\theta_k)+n(t)\\&=\underline{y_s}(t)+\underline{y_j}(t)+n(t)\\&=\underline{y_s}(t)+\underline{y_i}(t)\end{aligned} \tag{2}$$

where $s_k(t)$ and $s_s(t)$ are the k-th random jammer waveforms and the signal waveform respectively, and the jammer steering vectors $\underline{a}(\theta_1)$, $\underline{a}(\theta_2)$, Λ, $\underline{a}(\theta_q)$ and the desired signal vector $\underline{a}(\theta_s)$ can be modeled as plane waves:

$$\underline{a}(\theta)=[\exp(jx_1\xi),\exp(jx_2\xi),\mathrm{L}\ ,\exp(jx_n\xi)]^T, \tag{3}$$

where, $\xi=(2\pi/\lambda)\sin\theta$, λ is the wavelength, x_l is the coordinate of the l-th sensor, and T denotes the transpose. Assuming that all of three components, the desired signal, jammers, and background noise, are mutually uncorrelated, the optimal criterion for this jammer cancellation problem is maximizing the SINR and the optimal output SINR and weight vector are given by [1].

$$\mathrm{SINR}_{\mathrm{opt}}(t)=\frac{\sigma_s^2\left|\underline{w}_{\mathrm{opt}}^H(t)\underline{a}_s\right|^2}{\underline{w}_{\mathrm{opt}}^H(t)\mathbf{R}_i(t)\underline{w}_{\mathrm{opt}}(t)},\ \text{where}$$

$$\mathbf{R}_i(t)=\mathrm{E}\left\{\underline{y_i}(t)\underline{y_i}^H(t)\right\} \tag{4}$$

$$\underline{w}_{\mathrm{opt}}(t)=\frac{\mathbf{R}_i^{-1}(t)\underline{a}_s}{\underline{a}_s^H\mathbf{R}_i^{-1}(t)\underline{a}_s}, \tag{5}$$

where $\underline{a}_s=\underline{a}(\theta_s)$, $\mathrm{R_i}(t)$ is the interference (jammer plus noise) covariance matrix, and σ_s^2 is a signal power.

III. Adaptive beamforming technique with variable forgetting factor

Generally, the optimal beamformer can be achieved by perfect knowledge of the second order statistics of the interference at the array. In practice, however, the realizable adaptive beamformer uses the approximated the covariance matrix.

The sample matrix inversion (SMI) adaptive algorithm estimates the covariance matrix $\mathrm{R_i}(t)$ using an L-sample sliding window as $\mathrm{R_{SMI}}(t)$ [1].

$$\mathbf{R}_{\mathrm{SMI}}(t)=\frac{1}{L}\mathbf{Y}_i(t)\mathbf{Y}_i^H(t), \tag{6}$$

where $\mathbf{Y}_i(t)=[\underline{y_i}(t)\quad \underline{y_i}(t-1)\quad \mathrm{L}\quad \underline{y_i}(t-L+1)]^H$.

Therefore, the SMI weight vector can be obtained by using the estimated covariance matrix in eqn. 4 instead of $\mathrm{R_i}(t)$. In the presence of moving interferences, the performance of the SMI algorithm degrades since it is based on the assumption that the interference is stationary in the L-sample window interval.

To improve the performance in the moving jammer environments, Gershman *et al.* have further developed the orthogonal projection onto the jammer subspace and proposed the robust algorithm. The robust method uses a higher order of the null in order to broaden the null width [2]. Robustness can be achieved by adding the derivative constraints to the covariance matrix. Therefore, in the robust SMI method with first-order constraints, the estimated covariance matrix can be expressed as

$$\mathbf{R}_{\mathrm{rob}}(t)=\mathbf{R}_{\mathrm{SMI}}(t)+\varsigma\mathbf{B}\mathbf{R}_{\mathrm{SMI}}(t)\mathbf{B}, \tag{7}$$

where ζ is real positive weight that determines the relative contribution of derivative data.

Assuming an array with N sensors, *p-th* order derivative constraints and q jammers, the robust method should satisfy that $N > (p+1)q$ and the higher order constraints are used, the more sensors are needed[3]. Even though $N > (p+1)q$, in practice, the performance is not guaranteed unless the number of sensors N is sufficiently large. Therefore, it is difficult to be applied to the adaptive beamformer with small numbers of sensors.

Table 1. Averaged output SINR values of optimal (OPT) and adaptive algorithms for the number of sensors [dB].

methods \ number of sensors	4	5	6	7	8	16	32
OPT	-2.1	-0.8	0.1	0.8	1.4	4.5	7.5
SMI	-15.9	-14.3	-12.7	-11.2	-9.8	-9.7	-10.4
GER	-35.0	-26.9	-18.8	-11.1	-7.5	0.9	3.1
VFF	-10.0	-7.9	-6.7	-5.5	-3.6	1.1	4.4

To obtain a good performance without additional sensors, we propose a fast adaptive beamforming algorithm based on the update equation of the correlation matrix $\hat{\mathbf{R}}_i(t)$

$$\hat{\mathbf{R}}_i(t) = \lambda(t)\ \hat{\mathbf{R}}_i(t-1) + \underline{y}_i(t)\underline{y}_i^H(t) \tag{8}$$

where $\lambda(t)$ is a variable forgetting factor (VFF) and $\underline{y}_i(t)$ is the undesired interference signal in eqn. 1. The variable forgetting factor is u
pdated at each sampling time and determined as the variance of estimation error $J(t)$, given by

$$\begin{aligned} J(t) &= \underline{w}(t)^H \hat{\mathbf{R}}_i(t)\underline{w}(t) \\ &= \underline{w}(t)^H (\lambda(t)\hat{\mathbf{R}}_i(t-1) + \underline{y}_i(t)\underline{y}_i^H(t))\underline{w}(t) \\ &= \lambda(t)J(t-1) + \underline{w}(t)^H \underline{y}_i(t)\underline{y}_i^H(t)\underline{w}(t) \end{aligned} \tag{9}$$

$$\lambda(t) = \frac{J(t)}{J(t-1)} - \frac{[\underline{w}(t)^H \underline{y}_i(t)]^2}{J(t-1)} \tag{10}$$

From eqn. 10, we derive forgetting factor update procedure under the assumption of the convergence in [4,5]. In sufficient convergence,

$$J(t) = J(t-1) = \mathrm{L} = J \tag{11}$$

$$\lambda(t) = 1 - \beta[\underline{w}(t)^H \underline{y}_i(t)]^2 \tag{12}$$

The scaling parameter β is a real positive constant. In eqn. 12, $\underline{w}(t)^H \underline{y}_i(t)$ is output sample value at time t, which it is sensitive to noise. To overcome this effect, we can use average value of $\underline{w}(t)^H \underline{y}_i(t)$ under the convergence assumption and eqn. 12 can be modified as

$$\begin{aligned} \lambda(t) &= 1 - \beta \mathrm{E}[\underline{w}(t)^H \underline{y}_i(t)]^2 \\ &= 1 - \beta \underline{w}(t)^H \hat{\mathbf{R}}_i(t)\underline{w}(t) \end{aligned} \tag{13}$$

IV. Imulations

To compare the performance with the previous methods, we have carried out computer simulations about the same scenarios in [3]. We have changed the number of sensors from relatively small ($N = 4$) to large ($N = 32$). In all cases, we assumed one non-moving desired signal source and three moving narrow band jammers, and the beamformer consists of a uniform linear array of $\lambda/2$ sensor spacing. The simulated trajectories of angular jammer motion are $\theta_1(t) = -25°+10°\cos(t/20)$, $\theta_2(t) = 20°+5°\sin(t/15)$, $\theta_3(t) = -40°-10°\cos(t/15)$ and the DOA(direction of arrival) of the desired signal is known for $\theta_d = 0°$. We also assumed the signal-to-noise ratio (SNR) is –7.5 [dB] and the jammer-to-noise ratio (JNR) is 30 [dB]. We took $\zeta = 1.5$ and $\beta = 0.1$ in

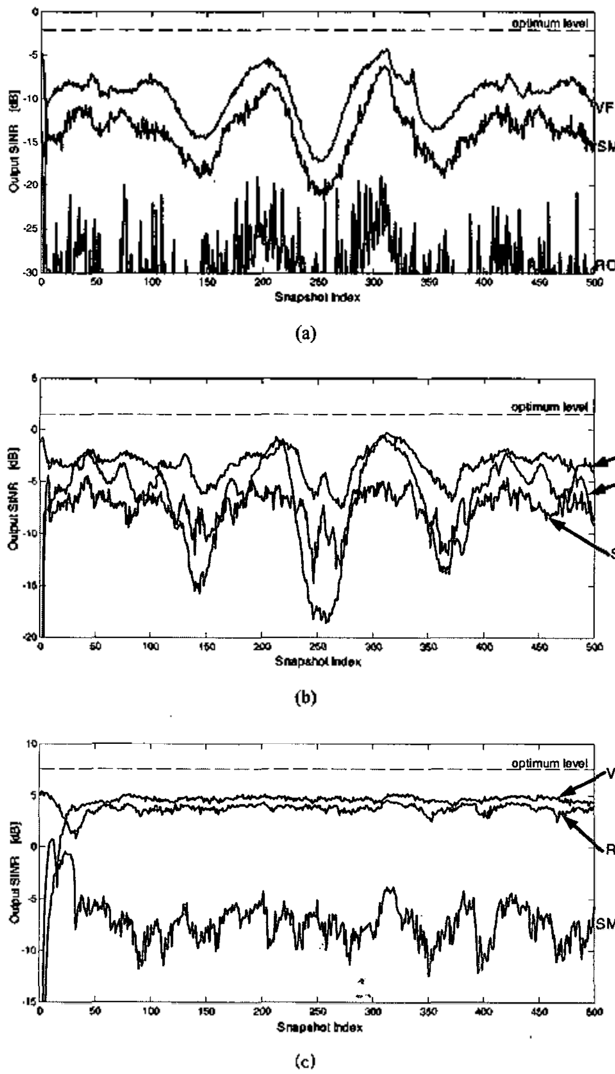

Fig. 1: Performances of adaptive algorithms (VFF: solid, SMI: dashed, ROB: dotted).
(a) $N = 4$, (b) $N = 8$, (c) $N = 32$

the robust method and the proposed algorithm, respectively.

We compared the results of the proposed algorithm (VFF) with those of the robust (ROB) and the conventional SMI (SMI) methods. In previous methods, we assumed that the length of the sliding window was same as the number of sensors ($L = N$). Figure 1 represent the output SINR versus snapshot index for $N = 4$, 8, and 32.

Simulation results show that the robust method completely fails in jammer cancellation for $N = 4$, whereas performs well for $N = 32$. We can see that the proposed algorithm performs better than others do for all situations. In Table 1, we summarize averaged SINR values of optimal and three adaptive algorithms for several numbers of sensors.

V. Conclusion

We proposed a new adaptive array technique using the variable forgetting factor. The result of computer simulations confirmed that the proposed method performs better than the conventional algorithms for both small and large array apertures.

Acknowledgment

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[Profile]

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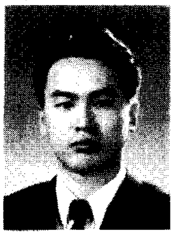

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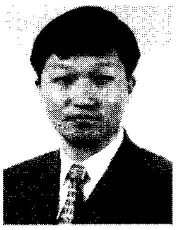

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