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An Adaptive Beamforming Algorithm for the LMS Array Problem

(LMS어레이의 문제점을 고려한 적응 빔 형성 알고리듬)

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要 約

LMS 기법을 이용한 적응 신호 처리상에서 복합적으로 제기 되어온 간섭신호 제거, 수렴속도, 오차 조정 및 기준신호 발생 등의 전체적인 문제점들을 합성적으로 고려한 하나의 적응 기법이 제시된다. 제안된 방법은 최소화 적응 처리를 하기전에 먼저 어레이 입력으로 들어오는 복합신호로 부터 표적신호를 분리하고, 기준신호를 제거한다.

본 기법은 적응처리기에 있는 잔유잡음의 정도에 제한을 둔다. 분석결과 본 기법은 코히어런트 또는 인코히어런트 간섭신호 제거에 효과적이며 특히, 수렴계수의 동적범위가 넓어 안정도가 좋고 수렴속도가 빠르며 평균자승오차가 매우적다. 또한, 기준신호발생이 필요없다는 장점이 있다. 시뮬레이션 결과는 이론적인 예측과 일치한다.

Abstract

An adaptive nulling technique is presented to synthetically overcome the integrated problems associated with the conventional LMS array in the performances of jammer rejection, convergence rate, misadjustment, and reference signal generation. The proposed method is to remove the target signal from the array input and to eliminate the reference signal prior to minimization processing. The algorithm is constrained to the residue noise level in adaptive processor. Analysis shows effectiveness of the algorithm for coherent and/or incoherent interference rejection, wide dynamic range of convergence factor, rapid adaptation rate, and small mean square error. Simulation results confirm the theoretical prediction.

I. Introduction

Conventional signal reception systems are susceptable to degradation in signal-to-noise ratio (SNR) performance in signal environments where deliberate or unintentinal interferences are smart and strong. The adaptive null steering array has been a useful means for reducing the vulnerability of the reception of a desired signal in the presence of interferences in radar, sonar, seismic, and communications systems. The Applebaum's adaptive array [1] and the least-mean-square (LMS) array of Widrow [2] have been most widely used for the suppression of interference in

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adaptive communications applications. Most adaptive arrays based on conventional optimization techniques assume that the desired signal is statistically uncorrelated with the interference signal and that the strength of the desired signal is weak compared to the interference. These basic two assumptions limit the performance of the adaptive array in practical situations where the coherent interferences exist at the receiving array and where the target signal power is strong compared to the interference as in usual communications systems.

There have been several significant problems to be considered in the conventional adaptive algorithms: inability of rejecting coherent interference [3]-[5], difficulty of generating a reference signal for the LMS array [6]-[8], the power inversion problem of the desired signal in the Applebaum type array [8], and slow convergence speed [9]. Any of these problems encountered in the adaptive nulling applications can cause a considerable degradation of the array performance. Most of these adaptive processors have been studied for the environment of individual problem, without considering the integrated problems mentioned above. Synthetic approach for these problems is thus considered here.

The purpose of this paper is to investigate the effect of the new adaptive array in the performance of synthetically overcoming the problems associated with the conventional LMS adaptive algorithm. The new array is basically a modified version of the LMS adaptive array. The architecture of the approach is to decorrelate target signal from the array input signal by means of prefiltering and to eliminate the reference signal during optimization processing. It will be shown that the new array have several advantages against the problems of the LMS algorithm: 1) reference signal is not required, 2) coherent and/or incoherent jammers are rejected, 3) dynamic range of convergence factor is wider and is independent of the level of the desired target signal power, 4) rapid convergence and small mean-square error (MSE) are achieved, 5) the strength of the desired target signal does not affect on the array output, i.e., no power inversion for the target signal occurs.

In section II the problems of the LMS algorithm are examined. In section III the proposed algorithm is derived and some constraints of the proposed method are described. In section IV the performances are compared. In section V computer simulation results are presented to verify the theoretical predictions. Section VI contains conclusions.

II. The Problems of the Conventional LMS Adaptive Algorithm

The LMS algorithm of Widrow [2] finds the weight vector by minimizing the output mean-square error (MSE) between the array output and the locally generated reference signal. It is noted that the algorithm performances are closely dependent on the coherence of the input correlation matrix of each signal component, the estimated reference signal in the cross-correlation matrix, and the total input signal power of each signal. The basic requirements of the LMS algoirthm are: 1) estimated reference signal must be generated at each iteration, 2) the reference is statistically highly correlated with the target signal, 3) the desired target signal is not correlated with any of the interference signals, 4) the convergence factor must be chosen so that the mean value of the weight vector converges to the Wiener solution. If even one of these conditions is not met, the LMS algorithm can not be used in the desired manner. In practice the reference signal is not always available at the receiving array, the coherent jammers often exist with the target signal, and the input signal is rapidly changing. The problems associated with the LMS algorithm are considered next.

1. Coherent Signal Problem

The problem of this correlation exists due to the inherent property of the LMS algorithm. If the estimated reference signal is not correlated with the desired target signal, the cross-correlation vector becomes zero, causing a singular weight vector problem. If the jammer signal is highly correlated with the desired target signal, the correlation vector contains the coherent jammer signal components as well as the desired signal component. Thus, the adaptive processor even utilizing the estimated reference signal which is highly correlated with the target signal can not distinguish these two signal classes. This can cause an incorrect weight vector which cancels all or a portion of the desired target signal at the array output. This signal cancellation phenomena was previously examined by Widrow et al. [3], and some methods to combat these effects have been suggested. Duvall's [3] method uses the Frost [10] beamformer to separate the desired target signal from the interference signal. Spatial smoothing method was suggested by Shan and Kailath [4] to overcome the correlation between the jammer and the target signal, but this method requires a considerable amount of computation. Su [5] uses the so-called parallel spatial processing method to combat the coherent interference. This method requires a number of sub-beamformer for the desired performance. This vulnerability for the coherent jammer mainly comes from the interaction between the signal and the interference in the weight adjustment control loop.

2. Reference Signal Problem

The performance of the LMS array output is largely dependent on the quality of the generated reference signal. Ideally, the reference signal is required to be the desired target signal itself in order to give the maximum correlation. If the locally generated reference signal is not highly correlated with the desired signal, almost no array output is reproduced. Furthermore, in the changing environment where the desired target signal is often changing depending on the mission, a number of set of the reference signals must be generated and switched effectively. In practical situations the reference signal is not always available at the receiver and is not feasible for the receiving array to generate an exact replica of the desired signal for maximum correlation. Suitable reference signal generation methods have been suggested for a few types of communication system [6-7]. However, these techniques do not give a general solution for all applications. The power-inversion adaptive array was suggested by Compton, Jr. [8] to eliminate the reference signal, but this is useful only when the strong signal is non-coherent interference. Otherwise, the output signal-to-jammer noise ratio (SJNR) is degraded as the input SJNR increases.

3. Convergence Range and Speed Problem

The convergence rate of the adaptive algorithm is an important factor in real situations where the input signal is rapidly changing. It is shown that the convergence speed is dependent on the eigenvalue spread of the input correlation matrix and that the convergence range is strictly limited by the total signal power. It is observed that when the total input signal is much strong compared to the interference signal, the resultant range of convergence is narrower, so the system becomes more unstable. This phenomena can be a more serious when the number of jammers increase and the number of array is large. In cases where the convergence time is much longer than the radar dwell time or the hopping time of the spread-spectrum signal, the algorithm can not adapt to the rapidly changing input signal. One way to increase the convergence speed of the LMS algorithm has been discussed by Narayan et al. [9] in the transform domain. This method prewhites the input signal in order to compress the eigenvalue spread, but needs an additional time for the discrete Fourier transform.

From these points of view, it is concluded that the key factor governing the problems is the manipulation of the input correlation matrix of each signal prior to adaptation processing: 1) reduction of the total amount of input power entering the adaptive processor, 2) decorrelation of the target signal from the interference signal, 3) replacement of reference signal by the thermal noise level constant vector. This can be achieved by prefiltering the array input signal in frequency or spatial domain prior to adaptation processing. This is considered next.

III. Proposed Adaptive Algorithm

In a practical adaptive system, the desired reference signal is not always available, smart coherent jammers and interferences often exist at the receiving array, and the input signal may be rapidly changing. In these situations, the conventional adaptive array may not perform in the desired manner. In this section a modified LMS algorithm with a residual noise constraint is presented to overcome the integrated problems associated with the conventional LMS adaptive algorithm.

1. Algorithm Derivation

A new model shown in Fig. 1 consists of the adaptive processor and the nonadaptive combiner. The adaptive processor is used for the weight vector generation to null the unwanted signals, while the nonadaptive combiner sums the

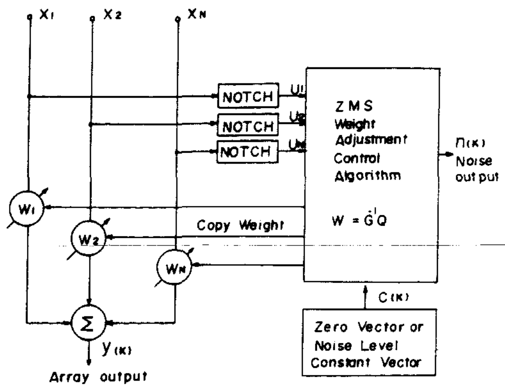

Fig.1. Proposed adaptive model.

weighted input signal utilizing the copied version of the weight vector from the adaptive processor. A new adaptive processor is basically a modified LMS combiner having a bank of notch filters (frequency or spatial) which can decorrelate the target signal components from the array input. Note that the reference signal has been eliminated and replaced by infinitesimal constant vector which may be neglected in the feedback loop. The element of this constant signal vector should be a small value equivalent to or less than the thermal noise level. In this case, the error signal e(k) with time index k can be approximated by array output itself in the adaptive processor. To avoid a loss of generality, however, by taking into account the noise-level constant vector, the error signal is

$$e(k) = c(k) - n(k) \tag{1}$$

where c(k) is a vector whose element is a small constant value of q and n(k) is the noise output of adaptive processor, i.e.,

$$c(k) = q\,[\,1\ 1 \ldots 1\,] \tag{2}$$

$$n(k) = \mathbf{W}^T(k)\,\mathbf{U}(k) \tag{3}$$

where **W**(k) is the adaptive weight vector at time k and **U**(k) is the input signal vector containing only prefiltered jamming signal and interfering noise. Assuming **W**(k) and **U**(k) are statistically independent, the mean-square error (MSE) is given by

$$\mathrm{MSE} = q^2 + \mathbf{W}^T(k)\,\mathbf{G}(k)\,\mathbf{W}(k) - 2\mathbf{Q}^T(k)\,\mathbf{W}(k) \tag{4}$$

where **G** denotes the input interference correlation matrix represented as

$$\mathbf{G} = E[\mathbf{U}(k)\,\mathbf{U}^T(k)]$$

$$= E\begin{bmatrix} U_1^2(k) & \ldots & U_1(k)\,U_N(k) \\ U_2(k)\,U_1(k) & \ldots & U_2(k)\,U_N(k) \\ U_N(k)\,U_1(k) & \ldots & U_N^2(k) \end{bmatrix} \tag{5}$$

and **Q** is the noise cross-correlation vector represented as

$$\mathbf{Q} = E[c(k)\,\mathbf{U}(k)] \tag{6}$$

where E[·] is the expectation. Using (2), (6) can be reduced by

$$\mathbf{Q} = q\,\mathbf{N} \tag{7}$$

where **N** = E[**U**(k)], the average input noise vector entering the adaptive processor. After taking e(k) itself as an estimate of the MSE in the adaptive processor, it can be shown that the estimated gradient vector of the MSE is

$$\nabla(k) = 2\,n(k)\,\mathbf{U}(k) - \mathbf{F}(k) \tag{8}$$

where **F**(k) = 2 c(k)**U**(k). Using the method of steepest descent and the estimate of the gradient in (8), the new weight updating equation is given by

$$\mathbf{W}(k+1) = \mathbf{W}(k) - 2\mu\,n(k)\,\mathbf{U}(k) + \mu\,\mathbf{F}(k) \tag{9}$$

where μ is a convergence factor which determines the step size and stability, **W**(k) is an old weight vector estimated at time k, **W**(k+1) is a new weight vector at time k+1. Note that this weight equation contains the additional term of F(k) which is the input interference signal vector scaled by a nonzero constant vector containing a noise level component.

Under the condition that the convergence factor is chosen such that

$$0 < \mu < 1/g_{max} \tag{10}$$

where g_{max} is the largest eigenvalue of G, it can be shown that the mean value of weight vector converges to the optimal weight vector:

$$W_{opt} = G^{-1} Q \qquad (11)$$

For the noise-level constant vector, it can be rewritten by

$$W_{opt} = q\, G^{-1}\, N \qquad (12)$$

The minimum MSE is now obtained by sustituting W_{opt} from (12) for W in (4):

$$MSE_{min} = q^2 - q\, N^T\, W_{opt} \qquad (13)$$

For the special case that the input jamming and interfering noise signal is practically much stronger that the system thermal noise, the constant noise vector C(k) may be neglected in the weight adjustment control loop. In this case, the new weight updating equation from (9) is approximated by

$$W(k+1) = W(k) - 2\,\mu\, n(k)\, U(k) \qquad (14)$$

We call (9) the modified LMS algorithm with a residue noise constraint, while for the special case (14) is defined as the zero-mean-square (ZMS) algorithm in a practical system.

It is compared that the LMS algorithm always requires the estimated reference signal and that the amount of the minimum MSE mainly depends on the average power of the reference signal, while the proposed algorithm does not need reference signal generation and the amount of the minimum MSE is always less than the residual thermal noise level. For the ZMS case, the theoretical minimum MSE becomes zero. But in practical adaptive system with a finite adaptation time the minimum MSE can not become zero. It will be highly dependent on the residual noise level.

Fig. 2. shows the weight adjustment control loop for the ZMS algorithm. Note that the correlator receives only the interference and the jamming signal from the array input and output. For a practical use of adaptive algorithm, the finite time solution to weight vector is more important. Frqm (14), the average weight vector at adaptation time k is found to be:

$$E\,[W(k)] = M[I - 2\mu D]^k\, M^{-1}\, W(0) \qquad (15)$$

where W(0) is the initial weight vector, M is the modal matrix of G, and D is the diagonal eigenvalue matrix of G. As the iterative adaptation is progressed, the average weight vector get smaller as the iterative time increases and approaches residual noise level of the adaptive processor. For the worst case where the constant noise vector is eliminated, the average vector at adaptation time of infinity becomes zero. This theoretical zero vector causes a cancellation of the jamming and the interfering noise signals as well as the desired target signal. To avoid this theoretical singular solution problem, this algorithm is constrained to the residual noise level and to the adaptation time of convergence. In practice the adaptation time is not allowed to reach infinity, so this theoretical worst case may be of little concern. This is considered next.

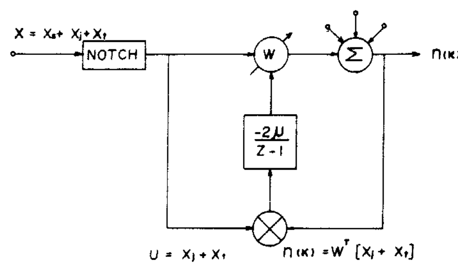

Fig.2. The ZMS algorithm control loop.

2. On the Constraints

Consider the rate of decrease of each signal component during adaptation processing to minimize the unwanted signals. The negative gradient for each signal can be expressed as

$$dP_j/dk \gg dP_t/dk \qquad (15.a)$$

$$dP_j/dk \gg dP_s/dk \qquad (15.b)$$

$$dP_s/dk \cong dP_t/dk \qquad (15.c)$$

where dP_j/dk, dP_s/dk, and dP_t/dk are the negative direction of gradients for the jammer, target signal, and thermal noise power, with respect to the small change of adaptation time, dk, respectively. Fig. 3 shows the gradient change for the jammer rejection. The jammer's power rapidly decreases with the gradient of dP_j/dk as compared

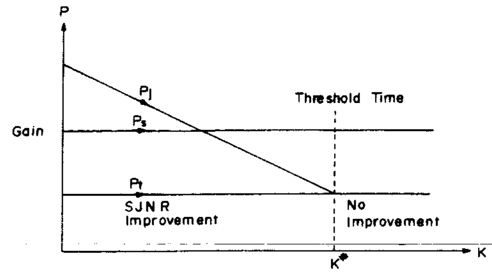

Fig.3. The gradient change for the jammer rejection in the ZMS algorithm.

to the other signal components. After a sufficient time of convergence has been elapsed so that the level of the jammer power at the processor output is equivalent to or less than that of the thermal noise power, the actual performance of the SJNR ratio is not improved further because the thermal noise power constantly exists with the small gradient of dP/t/dk. This point is defined as the "threshold time of convergence", k*, for maximum SJNR. This is the time when the level of the output jammer power is equivalent to the level of the thermal noise power. Thus, the adaptation time in the ZMS algorithm is constrained to the threshold time in order to avoid the theoretical singular problem. In this case, the constraints are subject to the residual thermal noise level of the adaptive system. At the threshold time of convergence, the output noise power at the adaptive processor is given by

$$P_n(k^*) = W^T(k^*)\,G(k^*)\,W(k^*) = P_t(k^*) \tag{17}$$

where P_n is the output noise power of the adaptive processor. Using (17), the relationship between k* and the suppressed noise power level is given by

$$P_n(k^*) = W^T(0)\,M\,A^{k^*}\,D\,A^{k^*}\,M^{-1}\,W(0) \tag{18}$$

where A= [I - 2μD]. Since A is the diagonal matrix whose elements are small values less than 1, A converges thermal noise level as time goes to infinity. Thus, the threshold time of convergence is controlled by the level of the thermal noise. The lower the noise level, the longer the adaptation time is required, but the output is less noise. Thus, the output SJNR is maximized at the threshold time of convergence where $P_j = P_t$:

$$\text{SJNR} = \frac{W^T(k^*)\,R(k^*)\,W(k^*)}{W^T(k^*)\,G(k^*)\,W(k^*)} = \frac{P_s^2}{2\sigma^2} \tag{19}$$

where **R** is the composite input signal correlation matrix of the nonadaptive combiner. Thus, by properly choosing the noise-level constant vector c(k), the adaptation time can be adjusted, and the output SJNR can be maximized.

In addition, the more accurate desired target signal from the adaptive system can be reproduced by subtracting the residual noise output n(k) of the adaptive processor from the nonadaptive combiner output y(k) each time. Because the residual noise output always works as an error difference between the desired noise level and the residual noise level at each time of adaptation. This suboptimal weight vector copied from the adaptive processor rapidly suppresses the undesired interference signal down to the level of the thermal noise, while it enhances the desired target signal to achieve the maximum SJNR.

IV. Performance Comparison

The convergence range of the algorithm is bounded by the largest eigenvalue of the input correlation matrix. It can be shown that

$$g_{max} < \text{tr}\,[\,G\,] \tag{20}$$

$$g_{min} > \det\,[\,G\,] \tag{21}$$

where tr [G] and det [G] denote the trace and the determinant of N by N square matrix **G**, respectively. Using (10) and (20), the convergence range of the ZMS algorithm is bounded by the total interference power P_j and the thermal noise power P_t, i.e.,

$$0 < \mu_{ZMS} < 1/[P_j + P_t] \tag{22}$$

where $P_j = \sum_{i=1}^{N} E[U_i^2(k)]$ and $P_t = \sigma^2 N$, while the convergence range of the LMS algorithm is governed by the sum of the array input signal component, i.e.,

$$0 < \mu_{LMS} < 1/[P_s + P_j + P_t] \tag{23}$$

where $P_s = \sum_{i=1}^{N} E[X_{si}^2(k)]$ = total target signal power. Note that the dynamic range of convergence factor in the ZMS algorithm is independent of the target signal power. Comparing (22) and (23), the dynamic range of the ZMS algorithm is always wider by a factor of the target signal power than that of the LMS algorithm. If the target signal power is much stronger than the interference signal power, the convergence factor in the LMS case must be chosen as small as possible because the large convergence factor around limit can cause the adaptive system to be unstable. Accordingly, small convergence factor causes long adaptation time. For this reason, the LMS algorithm is not effective when the receiver input signal-to-jammer ratio (SJR) is high. Since the convergence factor of the ZMS algorithm is not dependent on the target signal power and can be chosen from a wide range, the ZMS adaptive array can be more stable, faster, flexable, and have less output error.

Under the equal convergence factor, the convergence speed is dependent on the ratio of the maximum to minimum eigenvalue of the correlation matrix [9]. Using (21), the ratio g_{max}/g_{min} in the ZMS algorithm can be expressed as

$$r(\mathbf{G}) = tr\,[\mathbf{G}]/det[\mathbf{G}]. \tag{24}$$

For the LMS algorithm the ratio is given by

$$r(\mathbf{R}) = 1/\alpha.\ [tr\,(\mathbf{R}_s)/det\,(\mathbf{G}) + r\,(\mathbf{G})] \tag{25}$$

where $\mathbf{R}_s$ is the target signal correlation matrix and $\alpha = 1 + det\,(\mathbf{R})/det\,(\mathbf{G})$. When α is around 1, the eigenvalue spread of the LMS algorithm is always greater than that of the ZMS algorithm. Thus, the convergence speed of the LMS case is always slower than the ZMS case. When the target signal power is much stronger than the jammer power, the convergence speed of the LMS case will be much slower. When the jammer power is much stronger, the difference of the convergence speed becomes small.

As a measure of the degree by which the MSE exceeds the minimum MSE, misadjustment is defined by Widrow [2], i.e.,

$$M = \text{excess MSE}/MSE_{min} \tag{26}$$

It can be shown that for the ZMS algorithm

$$M = \mu\,[P_j + P_t] \tag{27}$$

and for the LMS algorithm

$$M = \mu\,[P_s + P_j + P_t] \tag{28}$$

Note that under equal input signal environments the misadjustment of the LMS algorithm is always higher than that of the ZMS algorithm. This means that an actual mean-square error of the ZMS case is always small, so the output jammer power decreases more rapidly. Therefore, at the finite equal adaptation time the output SJR of the ZMS case is always higher than that of the LMS case.

It is known that the signal cancellation problem occurs when the interference signal is correlated with the desired target signal. This phenomena occurs even if the interference signal just resides in the same signal space [3]. The correlator of the ZMS array receives the prefiltered interference signal components from the array input and output prior to adaptation processing. As long as the input filter can remove most of target signal components, the signal cancellation problem can be eliminated in the ZMS algorithm.

One advantage of the ZMS algorithm is the elimination of the requirement of reference signal generation in the weight adjustment control loop. Thus, the array performance is no longer influenced by the estimated reference signal and does not require even the desired signal information in the spatially notched ZMS array [11]. In terms of the computational efficiency and circuit complexity, the ZMS algorithm can be implemented easily, as far as the reference signal generation problem is concerned.

One disadvantage of the ZMS algorithm is the signal separation problem in the practical notch filtering. Signal leakage out of the notch filter can cause cancellation of the desired signal during adaptation processing. In the worst-case situation where the stochastic property of the interference is exactly the same as the target signal (i.e., same frequency), signal separation is not achieved by frequency-domain filtering method. For this case, one can consider spatial notch filtering using Duvall's [3] presubtractor based on the array structure. For other cases, frequency domain notch filtering can be realized using transversal filter. For a more protection, a combination of the spatial and the frequency domain filtering is desirable [12].

The ZMS adaptive null steering array minimizes the undesired signals by creating nulls for the interference signals in the off-look direction using the weight vector generated by the ZMS algorithm and maximizes the desired signal in the steered main beam direction. The ZMS adaptive array can be implemented in two ways depending on the type of input notch filter to remove the target signal from the array input during minimization processing. The spatially notch filtered ZMS array (SP-ZMS) is shown in Figure 4. It employs the spatial subtractor between the adjacent array signal. The frequency notch filtered ZMS array (FIR-ZMS) is shown in Fig.5. It employs the transversal finite-impulse-response (FIR) filter (FIR-ZMS). Details on the two types of ZMS arrays are presented in [12].

V. Simulation Result and Discussion

Computer simulation results are presented to verify the effectiveness of the theoretical analysis of the proposed ZMS algorithm in comparison with the conventional LMS algorithm in the adaptive nulling applications. Several assumptions were made in this simulation including: the input signals are narrowband and the target signal's direction is known, but all interference's direction and spectral information are unknown. The arrays are linea, and all elements are isotropic and noninteracting. The performances of the ZMS algorithm were compared with that of the LMS array in terms of the jammer rejection capability in the incoherent and/or coherent directional jammers, the speed of null progress, the mean-square errors, the sensitivity to the signal leakage, and the array output performance.

Fig.6 compares the null gain progression for the LMS and ZMS algorithms, measured in the direction of the incoherent jammer arriving at -30 degrees from broadside. A 7-array element was used with an interelement spacing of half a wavelength at the target signal frequency of 0.2

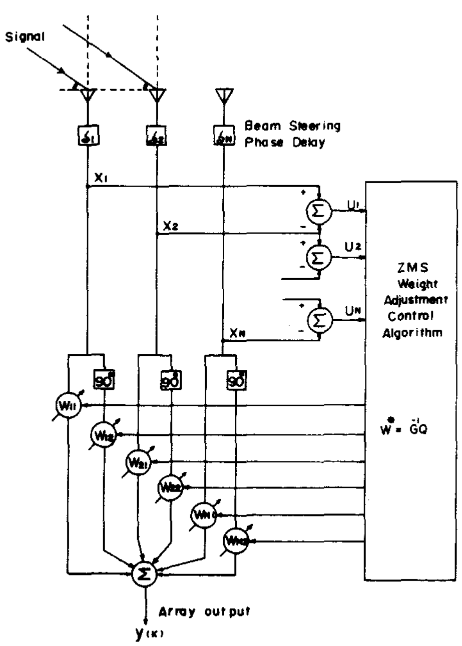

Fig.4. SP-ZMS array.

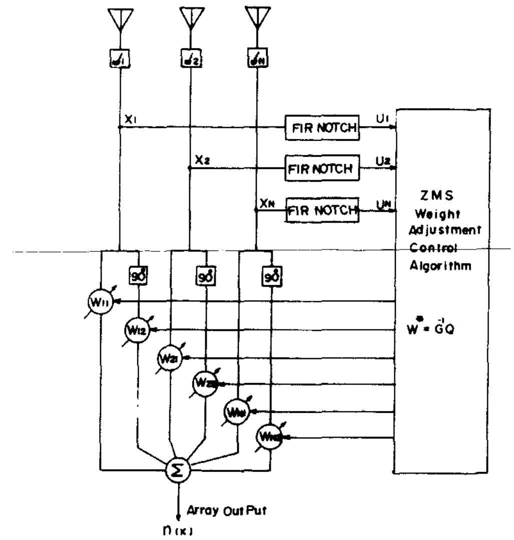

Fig.5. FIR-ZMS array.

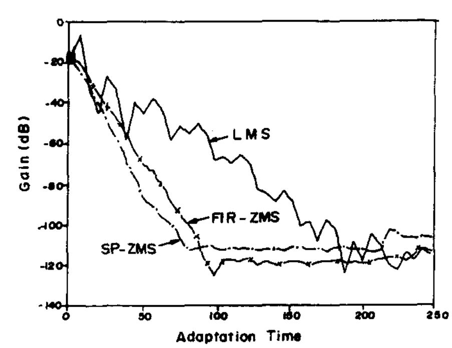

Fig.6. Adaptive null progress for the incoherent jammer No.1.

in normalized scale. The spatial angle of incidence from broadside for target signal was set to 30 degrees, and the incident angles for the jammer No. 1 and No. 2 were assumed to be-30 degrees and 70 degrees, respectively. The frequencies of jammer No.1 and No.2 were set to 0.4 and 0.13, respectively. The input SJR was - 6 dB. It is observed that under the equal convergence factor of 0.025 both of the ZMS arrays show much faster, deeper null progress to the steady-state gain with small fluctuations in the direction of jammer. But the LMS array shows a slow null progress, large fluctuation of null gain at the same adaptation time. As the theory indicates, depending on the amount of total input signal power entering the adaptive processor, the rate of adaptation varies. The less the total input signal power, the faster the speed of null progress.

Fig.7. compares the null gain progression for coherent jammer No.1 under the two types of adaptive arrays. For the worst case consideration, the frequency of the jammer No.1 was set equal to the target signal's frequency for a maximum correlation with the target signal. The frequency of the jammer No.2 is very close to the target signal's frequency for high correlation. These curves show clear differences in their coherent jammer rejection capabilities. The ZMS arrays continue to decrease, rejecting even a coherent jammer and rapidly approaches the steady-state null gain. The LMS array does not show the capability of rejecting a coherent jammer. Fig.8 compares the adaptive null directivity for the coherent jammer. Fig.9 shows the output mean-square errors under an equal convergence factor

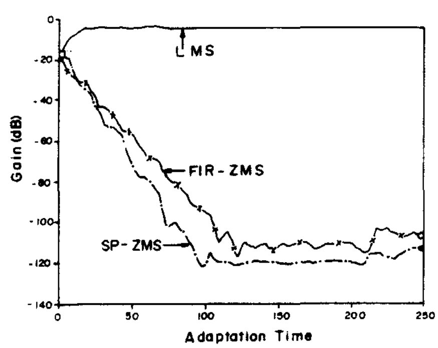

Fig.7. Adaptive null progress for the coherent jammer No.1.

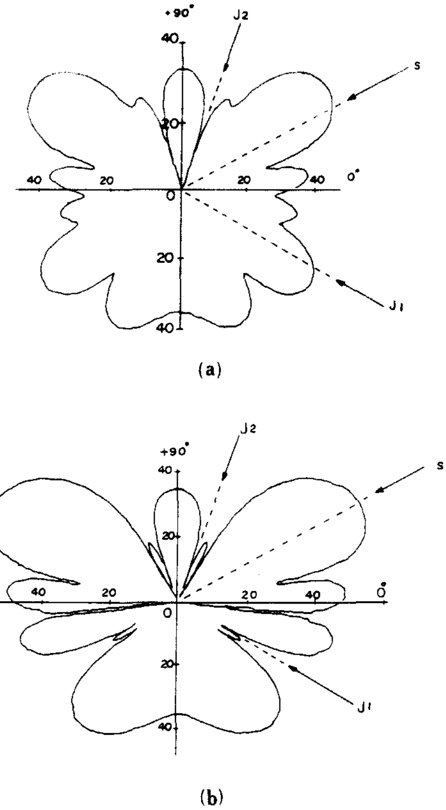

Fig.8. Adaptive null steering for the coherent jammer No.1: (a) LMS beamformer, and (b) ZMS beamformer.

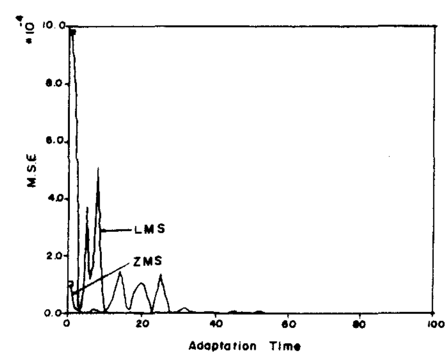

Fig.9. Output mean-square error.

of 0.025. The amount of the MSE for the LMS case is almost 10 times that for the ZMS case, and the convergence time to reach the equal level of MSE for the LMS case is almost three times greater than that of the ZMS case. Fig. 10 compares the output error performances. Both ZMS arrays are superior to the LMS case. The main reason for this is that the trace of the input signal correlation matrix for the ZMS case is greatly smaller than that of the LMS array. Using the ZMS array having 79-tap FIR notch filter, the array output spectrum is plotted in Fig. 11. The target signal is completely recovered, but the degree of jammer rejection is dependent upon the coherency with the target signal. Fig. 12 shows the directional gain change for two jammers as the signal separation ratio increases. It is seen that the main-beam gain is almost unchanged, but the directional gain change for two jammers gradually increases as the signal leakage increases.

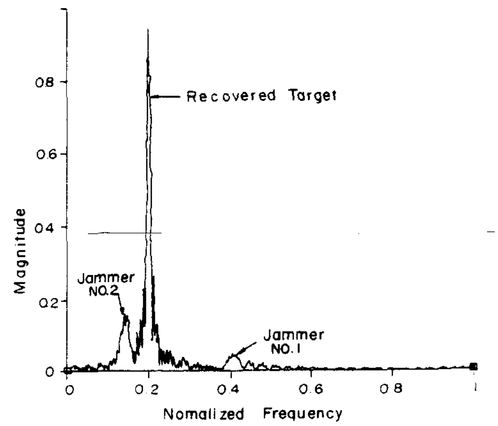

Fig.11. Array output spectrum for 79-tap ZMS array.

VII. Conclusion

An adaptive nulling algorithm with a residual noise constraint is presented to synthetically overcome some drawbacks associated with the conventional LMS algorithm. The proposed method is to remove the target signal from the array input signal by means of prefiltering and to eliminate the reference signal prior to optimization

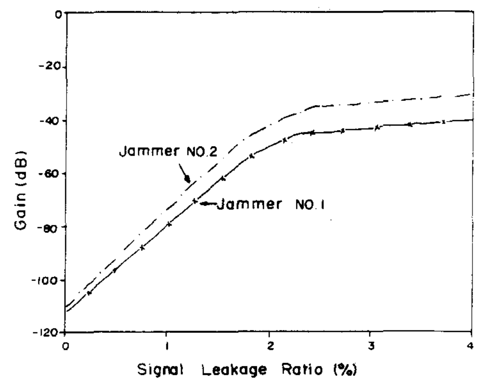

Fig.12. Sensitivity of directional gain due to signal leakage effect in the ZMS array.

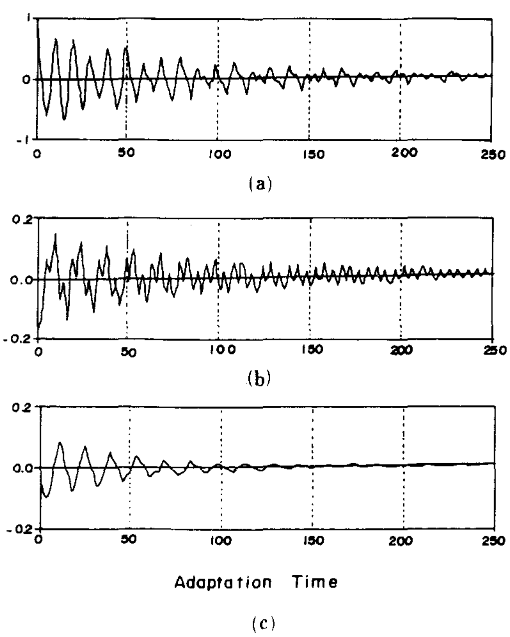

Fig.10. Output errors: (a) LMS, (b) FIR-ZMS, (c) SP-ZMS.

processing. A new algorithm is constrained to the residual noise level of the adaptive processor. Instead, it does not require the reference signal generation. The analysis and simulation results show the effectiveness of the proposed algorithm (ZMS) for coherent and/or incoherent interference rejection, wide dynamic range of convergence factor, rapid adaptation rate, and small mean-square error in comparison with the conventional LMS algorithm. Two types of ZMS arrays can be realized depending on the types of input notch filter, i.e., spatially notch filtered ZMS array and the frequency domain notch filtered ZMS array. Analysis and simulation results show that reducing the input signal power results in the rapid adaptation rate, the wide convergence range and more stable system, and small mean-square error. However, these arrays can be sensitive to both the array imperfection and beam steering error.

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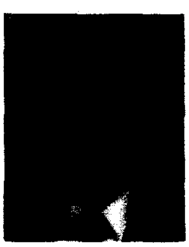

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