Proceedings of APMC2001, Taipei, Taiwan, R.O.C.

ADAPTIVE BEAMFORMING OF ESPAR ANTENNA BASED ON STOCHASTIC APPROXIMATION THEORY

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A novel approach based on stochastic approximation theory is devoted to adaptive beamforming of electronically steerable passive array radiator (ESPAR) antennas. Because of the low cost the ESPAR antenna has only a single-port output. The proposed algorithm by non-conventional way performs adaptive control of loaded reactances on the passive radiators and thus forming both beam and nulls. Our study and simulation results show that ESPAR antenna can effectively suppress interference and noise background and is attractive in modern wireless communications systems.

1 Introduction

Electronically Steerable Passive Array Radiator (ESPAR) antennas have been proposed for low cost analog adaptive beamforming and have shown strong potential for application to wireless communications systems, and especially to mobile user terminals [1]. The essence of beamforming functionality of the ESPAR antenna is complex weighting in each branch of the array and adaptive optimization of weights via adjustable reactances [2]. Although several adaptive algorithms for single-port antennas have been proposed [3],[4], they are still not sufficient for application to mobile communications systems. Our objective is to develop an adaptive algorithm that makes the ESPAR antenna steer its beam and nulls automatically, thus making it self-adaptive. The control must be implemented in complex signal environment consisting of signals of interest, interferences, additive Gaussian noise , gradient noise etc.

2 Antenna ESPAR Formulation

The basic formulation of the ESPAR antenna was given in [2]. An (M+1) – element ESPAR antenna with M=6 is depicted in Fig.1. The 0-th element is an active radiator located at the center of a circular ground plane. It is a $\lambda/4$ monopole (where λ is the wavelength) and is connected to the RF receiver in a coaxial fashion. The remaining M elements of $\lambda/4$ monopoles are passive radiators surrounding the active radiator symmetrically with radius $R=\lambda/4$ of the circle. Each of these M elements is terminated by a variable reactance. Thus adjusting the values $x_m(m=1,2,\dots,M)$ of the reactances can change the pattern of the antenna. In practical applications, the reactance x_m may be constrained in certain ranges, e.g., from -300Ω to $+300\Omega$. The vector denoted by $\mathbf{x}=[x_1,x_2,\dots,x_M]$ is called the reactance vector.

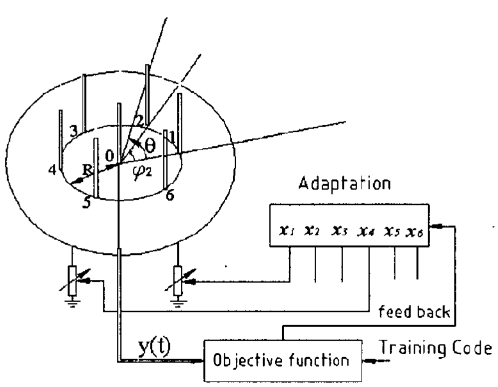

Fig.1 A 7-element ESPAR antenna

The output of the antenna is generally expressed as the model (discrete time)

$$y(n)=\mathbf{w}_{nc}^H \sum_{k=1}^{K} \mathrm{a}(\theta_k)\, s_k(n)+v(n), \quad n=1,2,\dots,N \tag{1}$$

where $s_k(n)$, $k=1,2,\dots,K$ are signal of interest (SOI) plus interferences; $v(n)$ is complex valued additive Gaussian noise (AGN); $\mathbf{a}(\theta_k)$ is the steering vector and θ are the directions of arrivals (DOA's). A key role is played by the RF current weight vector $\mathbf{i}$ [2],[5] which does not have independent components but is a non-conventional one - $\mathbf{w}_{nc}$

$$\mathbf{i} = \mathbf{w}_{nc} = (\mathbf{I} + \mathbf{YX})^{-1}\mathbf{y}_0 = \left\{ \mathbf{I} - [\mathbf{YX}] + [\mathbf{YX}]^2 - [\mathbf{YX}]^3 + \cdots \right\} \mathbf{y}_0, \text{ if} |\lambda_{\max}(\mathbf{B})| \langle\ 1, \mathbf{B} = \mathbf{YX} \tag{2}$$

Here $\mathbf{Y}$ and $\mathbf{y}_0$ are the admittance matrix and vector (mutual admittances between the elements of the antenna); $\mathbf{X} = diag[50, jx_1, ..., jx_M]$ is the reactance matrix and $\mathbf{I}$ is the identity matrix. In our formulation $b, \mathbf{b}$ and $\mathbf{B}$ stand for scalar, vector and matrix in that order. Similarly $\mathbf{B}^*, \mathbf{B}^T, \mathbf{B}^H$ and $\|\mathbf{B}\|$ represent the complex conjugate, transpose, complex conjugate transpose and norm of $\mathbf{B}$ respectively. $E(\cdot)$ denotes the expectation operator. Unlike conventional beamforming techniques, the only one observable output is a highly nonlinear function of adjustable reactances in ESPAR antenna, as shown see in Eqs. (1) and (2). Conventional techniques of determining $\mathbf{w}$ are useless and adaptive implementation of ESPAR antenna must be considered as a nonlinear spatial filter that has variable parameters.

3 Objective Function

Let the error $e = d(n) - y(n)$ be defined as the difference between the desired response $d(n)$ (an externally supplied input sometimes called the "training signal") and the actual response of ESPAR antenna $y(n)$. The mean squared error is used as a performance measure to evaluate waveform estimators such as spatial filters

$$J(n) = MSE(d, y) = E\left[e(n)e(n)^*\right] = E\left[(d(n) - y(n))(d(n)^* - y(n)^*)\right] \tag{3}$$

This objective function is real valued scalar function of reactance vector $\mathbf{x}, \mathbf{x} \in R^M$ and is denoted by $J(\mathbf{x})$. The functional $J(\mathbf{x})$ has to be minimized with respect to $\mathbf{x}$ .However for the ESPAR antenna the surface of optimization $J(\mathbf{x})$ in $M+1$ dimensional space is so complicated, gradient and Hessian matrix are not analytically available and we have to search for optimum solution by using nonlinear models and no derivatives methods. It is convenient to normalize the expression in Eq. (3) in such way that the minimum value of the mean-squared error always lies between zero and one. Let's have the vectors $\mathbf{d}(n)$ and $\mathbf{y}(n)$ that are discrete time samples of the desired signal $d(t)$ and the output signal $y(t)$. Then the following objective function has to be minimized .

$$J(n) = NMSE(d, y) = 1 - \frac{\mathbf{d}(n)^H \mathbf{y}(n)\mathbf{y}(n)^H \mathbf{d}(n)}{\|\mathbf{d}(n)\|_2^2 \|\mathbf{y}(n)\|_2^2} \tag{4}$$

4 Adaptive Beamforming

To minimize $J(\cdot)$ let's turn to the basic Newton procedure $\mathbf{x}_{n+1} = \mathbf{x}_n - J_{xx}^{-1}(\mathbf{x}_n)J_x(\mathbf{x}_n)$ where $J_x(\cdot)$ is the gradient vector and $J_{xx}(\cdot)$ is the Hessian matrix. Our objective function is not analytically tractable with respect to $\mathbf{x}$ but can be observed and "noise" corrupted observations can be taken, then the solution is searched into framework of stochastic approximation method [6] which is based on a "noisy" finite difference forms of gradient. Let $\{c_n\}$ denote a sequence of positive finite difference intervals of reactances $\{x_i, i = 1, ..., M\}$, tending to zero as number of iterations $n \to \infty$ and let $\mathbf{e}_i$ denote the unit vector in the i^{th} coordinate direction. Also, let $\mathbf{x}_n = n^{th}$ estimate of the optimal (minimizing) value of the parameter and $J_n(\cdot) = n^{th}$ actual noise corrupted observation of the performance. Since $\mathbf{x} \in R^M$, M observations will be used to estimate the derivative $J_x(\mathbf{x}_n)$. Define the finite difference vectors $\mathbf{dif}J(\mathbf{x}_n, c_n)$, $\mathbf{dif}J_n(\mathbf{x}_n, c_n)$, and vector observation noise $\mathbf{n}_n$ (please don't confuse by the AGN $v(n)$ in Eq. (1)). i^{th} component of $\mathbf{dif}J(\mathbf{x}_n, c_n), \mathbf{dif}J_n(\mathbf{x}_n, c_n)$, is

$$\mathbf{dif}J^i(\mathbf{x}_n, c_n) = [J(\mathbf{x}_n + c_n\mathbf{e}_i) - J(\mathbf{x}_n)]/c_n \tag{5}$$

$$\mathbf{dif}J_n^i(\mathbf{x}_n, c_n) = [J_{Mn+i-1} - J_{Mn+i}]/c_n \tag{6}$$

$$\mathbf{n}_n = \mathbf{dif}J_n(\mathbf{x}_n, c_n) - \mathbf{dif}J(\mathbf{x}_n, c_n) \tag{7}$$

A Kiefer-Wolfowitz stochastic approximation procedure is given by the algorithm [6]

$$\mathbf{x}_{n+1} = \mathbf{x}_n - \mu_n \mathbf{dif}J_n(\mathbf{x}_n, c_n) = \mathbf{x}_n - \mu_n[\mathbf{dif}J(\mathbf{x}_n, c_n) + \mathbf{n}_n] \tag{8}$$

The significance of control step parameter μ_n is of paramount importance for the adaptive beamforming and will be discussed further in simulation results. The sequence $\{\mu_n\}$ must be of positive numbers, tending to zero and such that $\sum \mu_n = \infty$. Note that effectivc noise $\mathbf{n}_n$ is inversely proportional to c_n. The finite difference iteration (8) makes sense even if the gradient $J_x(\mathbf{x}_n)$ does not exist at all. In stochastic approximation literature they use $\mu_n = \mu_0/n$, where μ_0 is a constant. In such way the influence of gradient noise is greatly reduced. However, when this constant is large, there is a danger of parameter blowup for small $\boldsymbol{n}$. As an alternative, the modified control step parameter is used [7] : $\mu_n = \mu_0[1 + (n/\tau)]^{-1}$, where μ_0 and τ are user-selected constants.

5 Simulations and Discussions

Our simulations were implemented for the signal model – Eq. (1). The five signals (SOI plus four interferences) were generated in binary phase shift keying (BPSK) mode and with specified DOA's $[0^\circ, 40^\circ, 60^\circ, 220^\circ, 300^\circ]$. The binary symbols are uniformly random and the power of all signals was chosen to be unity. Thus the input SIR was adjusted at -6 dB and complex AGN was added (the input SNR was varying from 80 dB to 40 dB). The gain patterns are depicted in Fig.2 and Fig.3 for the SINR = 25 dB and 17.8 dB. They are obtained using 20 samples ($N_s = 20$) in the segments and after 45 iterations ($N_i = 45$). $N_s(M+1)N_i = 20(6+1)45 = 6300$ is the total number of symbols in the training sequence. The total output SINR was computed as a slight modification of our objective function – Eq.(4). Reactance values are presented in Table 1:

Reactance	x_1	x_2	x_3	x_4	x_5	x_6
Initial value (Ω)	30	30	30	30	30	30
After convergence (Ω) SINR 25.0 dB	62.44	45.67	38.89	4.68	38.86	45.61
After convergence (Ω) SINR 17.8 dB	76.62	37.75	40.77	-17.38	27.56	38.01

Table 1: The values of reactances

Further the total output SINR was studied when the additive noise was gradually augmented and under different angle of separation of sources. The results are presented in Table 2 :

Input SNR [dB]	80	70	60	50	42
Output SINR [dB]	25	21	17.80	13.76	10.1

Table 2: Total output SINR

The other observation was made: if the angle of separation between SOI and interferences is less than $60^\circ - 70^\circ$ the suppression of interferences is not so good. By using temporal (spectral) correlations between output of ESPAR antenna and training signal the SINR can be further improved [5]. A special attention was paid on influence of control step parameter μ_n and reactance step parameter c_n over the stability and rate of convergence of algorithm, see Fig.4 and Fig.5. The last was reduced considerably in comparison of this showed in [2]. The optimal range of μ_0 was found (6–9). If μ_0>9 the stability of algorithm decreases. If 3<μ_0<6 the rate of convergence is slower and if μ_0<3 there is no control.

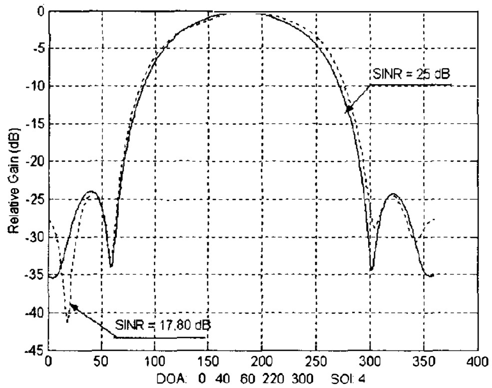

Fig.2

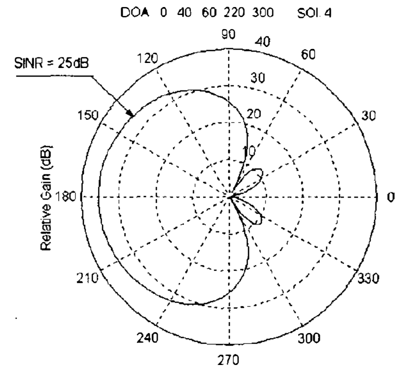

Fig.3

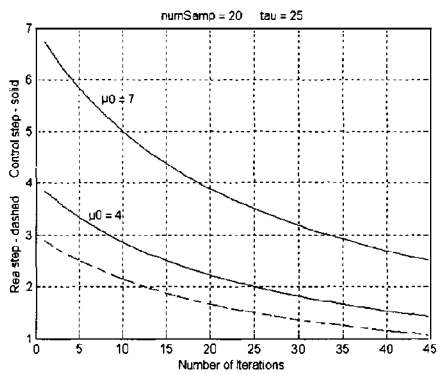

Fig.4

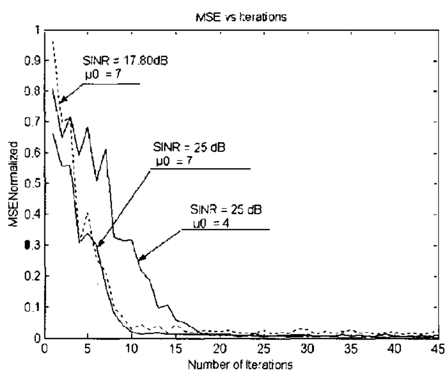

Fig.5

5 Conclusion

The stochastic gradient algorithm for adaptive beamforming of ESPAR antenna is proposed and analyzed. The proposed algorithm makes the antenna steer its beam and nulls automatically and can effectively suppress interference and noise background even though the ESPAR has only one RF port. ESPAR antenna has strong potential to be used in mobile terminals and seems to be very perspective.

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