FAST ADAPTIVE BLIND BEAMFORMING TECHNIQUE FOR CYCLOSTATIONARY SIGNALS

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Abstract

Castedo et al. have present a blind beamforming criterion based on the property of cyclostationary signals. A stochastic gradient-based algorithm, which needs to choose the step size suitably, was derived to compute the optimum weight vector. In this paper a fast adaptive algorithm is proposed. We show that the recursive least square techniques can be applied to solve this problem successfully by making an appropriate approximation. Simulation results demonstrate the effect of the theoretic analysis.

I. INTRODUCTION

In recently years, array signal processing techniques have been proposed for application in radio communication system [1][2]. Conventional beamformer must have some *prior* knowledge, such as direction of arrive (DOA) or steering vector [3]. Nevertheless, the *prior* knowledge often can not be achieved. Motived by the limitations of conventional beamformer, other approaches have been recently proposed exclusively relying on temporal features of the signal of interest (SOI) but without appealing to a reference signal[4,5,6]. Cyclostationary signal property is one of these temporal features. For most man-made random signal encountered in communication, some parameters do fluctuate periodically with time and can be modeled as cyclostationary. The fluctuation frequencies are usually known by the receivers since they are related to the frequency of periodic phenomena involved in the construction of the signal. The fact that linear digital modulated signals will generate spectral lines when they are passed through the zero-memory nonlinearity, is exploited to develop a blind beamforming algorithm [7] by Castedo *et al.*. A stochastic gradient-based algorithm (SGA) was proposed to compute the optimum weight of the array.

II. DATA MODEL

Let x(n) be an $M\times 1$ complex vector representing the digitized data received by an array of M sensors. The real and imaginary parts of the sample from the in-phase and quadrature parts of the data received by the mth sensor. The vector $x(n)$ can then be modeled as

$$\boldsymbol{x}(n) = \boldsymbol{d}(\theta)s(n) + \boldsymbol{i}(n) + \boldsymbol{v}(n) \qquad (1)$$

where $s(n)$ is the signal of interest, $\boldsymbol{d}(\theta)$ is the steering vector at the direction of arrival θ, $i(n)$ is a combination of interference, and $v(n)$ is an $M \times 1$ vector of the white noise.

The objective of an adaptive beamforming is to find the weighting vector w according to a chosen criterion to extract the desired signal such that

$$y(n) = \boldsymbol{w}^H \boldsymbol{x}(n) \qquad n = 1, \ldots, N \qquad (2)$$

Communication signals are often modeled as cyclostationary random processes. The most typical example are digital modulated signals where two periodic phenomena inevitably appear: the presence of a sinusoidal carrier and the repetition of a pulse waveform each time a new symbol is transmitted. Hence, the self-coherence frequency(or conjugate self-coherence frequency) of communication signals can be easily determined[5,6].

The cyclic correlation matrix and the cyclic conjugate correlation matrix are respectively defined as

$$\boldsymbol{R}_{xx}^{\alpha}(\tau) = \left\langle \boldsymbol{x}(n)\boldsymbol{x}^H(n+\tau)e^{-j2\pi\alpha n} \right\rangle_\infty \qquad (3)$$

$$\boldsymbol{R}_{xx^*}^{\alpha}(\tau) = \left\langle \boldsymbol{x}(n)\boldsymbol{x}^T(n+\tau)e^{-j2\pi\alpha n} \right\rangle_\infty \qquad (4)$$

where $\langle\cdot\rangle_\infty$ denotes the time average over an infinite observation period, and 'H' 'T' denote the conjugate transpose and conjugate respectively. An M-element vector $x(n)$ is said to be cyclostationary if the cyclic correlation matrix or cyclic conjugate correlation matrix has rank $L_\alpha(L_\alpha \le M)$ at some time shift τ and some frequency shift α. It's assumed that the receiver knows that the signals of interest has nonzero cyclostationary content at a known cyclic frequency α.

III. BLIND BEAMFORMING ALGORITHMS

The blind beamforming algorithm proposed by Castedo is based on an optimization problem that minimizes the following cost function [7]:

$$J = \left\langle \left| e^{j2\pi\alpha n} - (y(n))^p \right|^2 \right\rangle \qquad (5)$$

where <·> denotes the time average operation. The values of p and α are selected according to the order and the frequency of the spectral line generated by the signal to be extracted. Since the $(\cdot)^p$ nonlinearity is being used, the spectral lines will be centered around the frequency $\alpha=pf$.

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While handling one dimensional constellations, such as BPSK, FSK, ASK, spectral lines are obtain at $\alpha=2f_c$ and $\alpha=2f_c\pm kf_s$, k=1,2,... While the symbol constellation is symmetric with respect to the origin, the $(\cdot)^4$ should be used. Then $\alpha=4f_c$ and $\alpha=4f_c\pm kf_s$, k=1,2,...

It has been proved [7] that for the three most commonly found sources of perturbation in communication: Gaussian noise, statistically independent interference, and multipath propagation. The minima of eqn.5 corresponds the points where output noise power is minimized, interferences are canceled and intersymbol interference is removed.

The simplest method to minimized the cost function is straightforward to apply the stochastic gradient-based algorithm

$$w(n+1) = w(n) + \mu e^*(n) y^{p-1}(n) x(n) \quad (6)$$

where $e(n) = e^{j2\pi\alpha n} - y^{p-1}(n)$ is the error signal whose variance we are minimizing. Similarly to other stochastic gradient-based algorithms, the main features of eqn.6 are their simplicity. The step size $\mu > 0$ should be suitably chosen for the well-known trade-off between tracking capability and accuracy. Obviously, small step size will lead to slow convergence speed while large step size will results in the adapted parameters' oscillating around the fixed pointed without ever actually converging to it.

The simulation examples in [7] indicated, dependent on experimental condictions, the gradient-based algorithm requires 1000 to 5000 iterations to converge. With so slowly convergence speed, the algorithm can not track the moving target.

If rewriting eqn.5

$$J(w(t)) = \left\langle \left| e^{j2\pi\alpha n} - \left(w^H(t)x(n)\right)^{p-1} w^H(t)x(n)\right|^2 \right\rangle \quad (7)$$

and approximate $w^H(t)x(n)$ by $y_a(n) = w^H(n-1)x(n)$, which can be calculated for $1 \le n \le t$ at the time instant t.

This will result in a modified cost function

$$J'(w(t)) = \left\langle \left| e^{j2\pi\alpha n} - (y_a(n))^{p-1} w^H(t)x(n)\right|^2 \right\rangle \quad (8)$$

For stationary or slowly varying signals, the difference between $w^H(n-1)x(n)$ and $w^H(n-1)x(n)$ is small. We therefore expect $J'(w(t))$ to be a good approximation of $J(w(t))$.

Let $z(n) = (y_a(n))^{p-1} x(n)$, then

$$J'(w(t)) = \left\langle \left| e^{j2\pi\alpha n} - w^H(t)z(n)\right|^2 \right\rangle \quad (9)$$

Eqn.9 can be concluded to be a least squares problem, which is well studied in adaptive signal processing and has many fast implementation algorithms [8]. We choose the most common Recursive Least-Square(RLS) as an example without derivations. Table I summarizes the new algorithm in MATLAB® format.

Table I The new algorithm for blind beamforming

```
Choose P(0) and w(0) suitably
for  n = 1,2,...
z(n) = (y_a(n))^(p-1) x(n)
h(n) = P(n-1) z(n)
g(n) = h(n)/[1 + z^H(n) h(n)]
P(n) = P(n-1) - g(n) h^H(n)
e(n) = e^(j2παn) - w^H(n) z(n)
w(n) = w(n-1) + e^H(n) g(n)
end
```

We note that the similar technique has been used in PAST[9] by Yang for tracking the signal subspace successful.

IV. SIMULATIONS

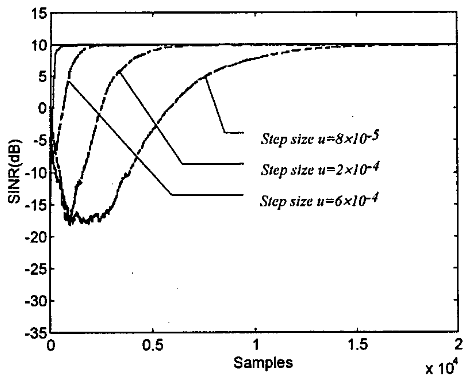
In our study, a uniform linear array is employed, and the distance of adjacent sensors is half a wavelength of the carrier of the desired signal.

The performance measure used to judge the quality of the processor output is the output SINR

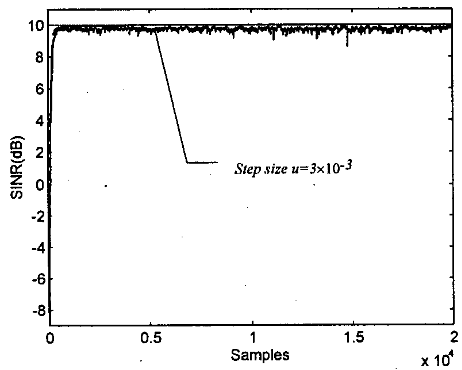
$$SINR = \frac{w^H d R_{ss} d^H w}{w^H R_I w} \quad (10)$$

where d, R_{ss} are, respectively, the true direction vector and the true power of the desired signal, R_I is the true autocorrelation matrix of the interference (noise and other signal) in the environment..

In the first example, the number of array sensors is four. One BPSK signal with *100%* cosine rolloff is impinging on the array at 40° to its normal. It has a normalized carrier frequency of f_c=0.1 and a baud rate of 1/5, relative to the sampling rate, *i.e.* five samples per symbol. The background noise is white. The SNR is placed at *0dB*. The cyclic conjugate correlation is employed, and α is chosen to be $2f_c$=0.2. The SINR of the outputs at various time instants for the method by Castedo and the proposed approach are shown in Fig.1. It is apparent that the proposed algorithm converges to the optimal weight much faster than the algorithm in [7]. As we have seen in Fig.1(b), when the step size is too large, the case fluctuates around the optimal point.



(a)



(b)

Fig.1 Time evolution of the SINR in an environment containing a single signal and Guassian noise. The input SNR is *0dB*. (a) The step size of curve A, B, C are 8×10^{-5}, 2×10^{-4}, 6×10^{-4}, respectively. (b)The step size of the stochastic gradient-based method is 3×10^{-3}

- - - - Gradient-descent method
—— The proposed algorithm
········ Optimum value

In the second example, the SOI is perturbed by the presence of external interference. The interference is also a BPSK signal with *100%* cosine rolloff. And it has the same baud rate, but its carrier has *0.05* offset, compared with that of the desired signal. The desired signal and the interference arrive at incident angles of 40° and -30° respectively. The array is the same as that in the last example. The cyclic conjugate correlation is employed, and α is chosen to be $2f_c$=0.2 too. Fig.2 shows the performance of the various algorithms at different input SNR conditions. Two step size u=8×10^{-5}, 4×10^{-4} are chosen. If larger step size is used, the SGA algorithm will not converge to the optimum value.

We note in both cases, the convergence speed of our algorithm is faster than that of the algorithm in [7].

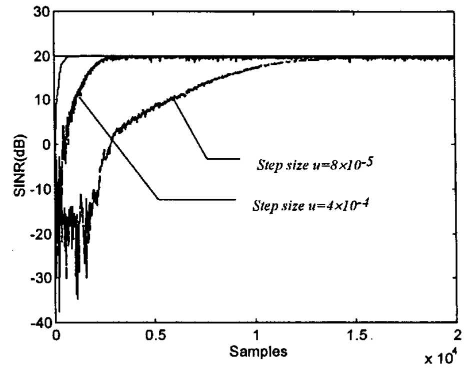


Fig.2 Time evolution of the SINR in an environment containing a signal, an interference and Guassian noise. The signal SNR is *10dB*, the interference SNR is *5dB*.

The third example shows an experiment of using the new algorithm to track a moving signal source. A linear uniform array of 10 sensors is used. The source is from a vehicle moving in a direction parallel to the array axis at a speed of 100km/h. The distance between the vehicle and the array axis is 100m. The sampling rate is 150K samples/s, and the relative baud rate of the signal is 1/5. The beamforming weight vector is calculated and updated every 0.2s using 900 of the fresh samples (or 180 symbols). The interference has the same baud rate but the carrier frequency has the 0.05 offset. The DOA of the interferemce is 50°. The SNR for the desired signal is 10dB and that for the interference is 5dB. The tracking starts when the target is at -50°. Ten updates of the beam pattern using the new algorithm are shown. We observe that due to the fast convergence rate, it is suitable for tracking a quickly moving source.

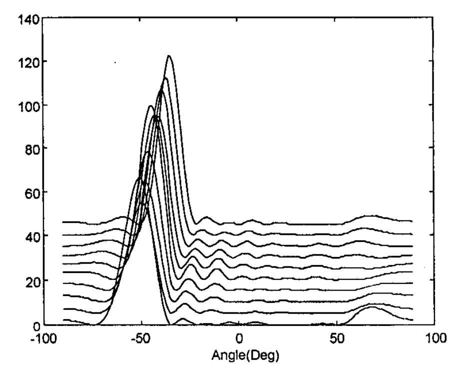


Fig.3 Beam patterns of the new algorithm for tracking the moving target

V. CONCLUSIONS

We have presented a new fast adaptive blind beamforming algorithm in this paper. The minimization task simplifies to the well-known least squares problem by using appropriate approximation. Simulation results show that the tracking capability of the new algorithm is better than that of the stochastic gradient-based method. Hence, it can be a good candidate to the next generation digital mobile communications.

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