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+ADAPTIVE IMPLEMENTATION OF OPTIMUM MTI PROCESSOR

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I INTRODUCTION

The optimization of moving target indicator(MTI) filter for unknown target doppler is accomplished based upon two optimization criteria; maximizing the improvement factor(IF)[1] or minimizing the residual clutter power at filter output[2]. The first approach leads to an eigenvector(EV) problem while the latter leads to a linear prediction(LP) problem. An iterative technique for computing the minimum eigenvector is the inverse power method(IPM)[3]. The IPM has a considerably fast convergence property[4]. Neverthless, requirement of the inversion of the covariance matrix is a main drawback of the algorithm. To avoid instability due to inversion of the covariance matrix, a method of implementing the IPM using an adaptive lattice predictor was proposed[4] for the application of spectral estimation. However, the transform matrix of the lattice predictor must be computed to estimate the inverse covariance matrix, which requires extra computations to obtain the corresponding values of PEF coefficients.

In this paper, the adaptive EV filter which recursively estimates the minimum eigenvector using an adaptive Gram-Schmidt(GS) predictor and two nonadaptive GS processors based on the IPM is proposed for implementing optimum MTI processor. Using a GS predictor, in contrast to a lattice predictor, adaptive estimation of the minimum eigenvector can be performed in a simple structure without extra computations.

II ADAPTIVE SCHEMES OF ESTIMATING THE MINIMUM EIGENVECTOR

It is a well known fact that the backward prediction errors of successive stages of the lattice predictor are uncorrelated to each other[7]. Accordingly, the covariance matrix of backward prediction errors is diagonal. The inverse covariance matrix is $M^{-1}(n) = L_b^T D_b^{-1}(n) L_b^*$, where L_b is unit lower triangular(ULT) transform matrix of increasing orders of prediction coefficients which can be computed from a given set of reflection coefficients using Levinson recursion[7]. Combining the inverse covariance matrix with the IPM iteration[4], we get

$$\underline{w}(n) = \frac{1}{z(n)} M^{-1}(n)\, \underline{w}(n-1) = \frac{1}{z(n)} L_b^T D_b^{-1}(n) L_b^* \underline{w}(n-1) \qquad (1)$$

$$z(n) = \| L_b^T D_b^{-1}(n) L_b^* \underline{w}(n-1) \|$$

Now, an adaptive EV filter for implementing optimum MTI filter can be obtained using the decomposition property of $M^{-1}(n)$. Fig. 1 illustrates an adaptive EV filter implementing the IPM using a adaptive lattice predictor. However, as shown in Fig. 1, we need an external transform matrix estimation unit, in which the ULT transform matrix L_b is computed from the estimated reflection coefficients using Levinson recursion at every iteration. This may increase computational cost and be the main drawback for hardware implementation of lattice based method. To overcome such difficulties, the adaptive implementation of the EV filter using a adaptive GS predictor based on the IPM is proposed in this paper. The transform matrix of the GS predictor and its transposition can be easily obtained due to its modular structure.

The filter having an alternative structure for implementing the PEF is the GS filter. Escalator realization of the GS filter was proposed[5], where a modular structure, referred to as the escalator, for implementing the GS orthogonalization procedure was exploited. The GS predictor produces different sets of mutually uncorrelated prediction errors in a sequential manner, and the errors in each set is obtained using the ones preceding it. A

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GS predictor of order 4 is illustrated in Fig. 2. Coefficients of the GS predictor of order N α_{ij}, $i=1,2,\ldots N-1$, $j=1,2,\ldots,N-i$ is determined to perform decorrelation operation based on the Wiener filter theory[5]. Now the inverse covariance matrix is $M^{-1}(n) = L_d^T D_d^{-1}(n) L_d^*$,where L_d is (NxN) ULT transform matrix which can be expressed as a product of N-1 elementary ULT matrices as follows[5]:

$$L_d = L_{d,N-1} \ \ldots \ L_{d2} \ L_{d1} \tag{2}$$

where $L_{d1} = \begin{vmatrix} 1 & 0 & \ldots & 0 \\ -\alpha_{11} & 1 & \ldots & 0 \\ -\alpha_{12} & 0 & \ldots & 0 \\ \ldots & & & . \\ -\alpha_{1,N-1} & 0 & & 1 \end{vmatrix}$ $L_{d2} = \begin{vmatrix} 1 & 0 & \ldots & 0 \\ 0 & 1 & \ldots & 0 \\ 0 & -\alpha_{21} & \ldots & 0 \\ & \ldots & & . \\ 0 & -\alpha_{2,N-2} & \ldots & 1 \end{vmatrix}$ $L_{d,N-1} = \begin{vmatrix} 1 & 0 & \ldots & 0 & 0 \\ 0 & 1 & \ldots & 0 & 0 \\ & & \ldots & & \\ 0 & 0 & \ldots & 1 & 0 \\ 0 & 0 & \ldots & -\alpha_{N-1,1} & 1 \end{vmatrix}$

Using Eq. (2), the IPM iteration can be expressed in a form similiar to Eq. (1).

From Eq. (2), it should be noted that the transposition of the transform matrix can be expressed as a product of the transposition of elementary ULT transform matrices in reverse order. That is

$$L_d^T = L_{d1}^T \ L_{d2}^T \ \ldots \ L_{d,N-1}^T \tag{3}$$

Therefore, the transposition procedure of the transform matrix in Eq. (3) can be modelled as a processor, referred to as the transpose GS processor, in which the same coefficients estimated by an adaptive GS predictor are rearranged in reverse order and applied to the same node in the reverse direction. The transpose GS processor for N=4 is illustrated in Fig. 3.

Now, the adaptive EV filter in Fig. 1 can be reconstructed in a simple structure using the GS and transpose GS processors as illustrated in Fig. 4. The adaptive EV filter in Fig. 4 includes one adaptive GS predictor which makes input samples orthogonal to each other and nonadaptive GS and transpose GS processors having the same coefficients as the adaptive GS predictor which recursively estimate the minimum eigenvector.

III ADAPTIVE ALGORITHMS

The least-mean-squares(LMS) algorithm is the most widely used adaptation method due to its effectiveness as well as its simplicity. The adaptive lattice filter[6] and adaptive GS filter [5] whose coefficients are updated using the LMS algorithm are extensively studied for various applications. In addition to the estimation of the reflection coefficients, mean-squared backward prediction errors should be recursively estimated to implement the EV method adaptively. For this purpose, a simple low pass filter can be considered to produce the following recursion:

$$P^b_p(n) = (1-\mu) \ P^b_p(n-1) + \mu \ |b_p(n)|^2 \tag{4}$$

where $p=0,1,\ldots,N-1$, and μ is a step-size paramater of the LMS algorithm.

To implement Burg's harmonic-mean algorithm in a recursive way, Haykin introduced an exponential weighting factor λ to control the adaptive speed of the lattice filter[7], referred to as the standard gradient(SG) method. The coefficient at the i-th stage of the GS filter can be determined in a locally optimum sense. Accordingly, optimum coefficients can be determined by direct inversion(DI) of the reference signal variance based on the least squares criterion. The exponential weighting factor can be introduced again to estimate locally optimum coefficient. Now, the recursion is

$$\alpha_{i,j}(n) = \frac{M_{i,j}(n)}{C_i(n)} \tag{5}$$

where $M_{i,j}(n) = \lambda \ M_{i,j}(n-1) - e_{i-1,1}(n) \ e^*_{i-1,j+1}(n)$

$C_i(n) = \lambda \ C_i(n-1) + |e_{i-1,1}|^2$.

In this case, mean-squared backward prediction errors can be estimated using the same exponential weighting factor.

$$P^d_p(n) = \lambda \ P^d_p(n-1) + |d_p(n)|^2 \tag{6}$$

IV SIMULATION RESULTS AND DISCUSSION

The performances of the adaptive EV filter which implement the IPM by using adaptive GS predictor will be evaluated and compared with those of the PEF[7] via computer simulations for artificially generated radar signals. For comparison purposes, the following schemes are considered in simulations.

(1) Lattice PEF using LMS algorithm(LMS_LAT).
(2) Lattice PEF using SD algorithm(SD_LAT).
(3) Adaptive EV filter using LMS-GS(EV_LMS_GS).
(4) Adaptive EV filter using DI-GS(EV_DI_GS).

Gaussian clutter signals are generated using the discrete Fourier transform(DFT) method[8]. For simplicity, it is assumed that the same PRF is used for every scan. On all simulations presented here, PRF=3000 Hz and number of hits per beamwidth is 20. Two clutter sources having the parameters listed in Table 1 are assumed. To compare initial convergence behavior of the algorithms, we computed the instantaneous IF values. Initial convergence behavior of the 4 methods are compared in Fig. 5, where convergence parameter $\mu=0.05$, forgetting parameter $\lambda=0.95$ and $N=4$. The corresponding plots of IF values are obtained by ensemble averaging over 10 independent trials of the simulation. In Fig. 5, we can see that EV filter using DI_GS converges to about 26 dB in a single scan. On the other hand, PEF filter using SG_LAT algorithms needs 4 scans to reach 26 dB. If the LMS algorithm is used, EV filter converges to 25.5 dB in just 3 scans while PEF filter requires 30 or more scans. Steady state frequency responses of the four algorithms are illusrated in Fig. 6. Responses are evaluated after the 200-th scan. Steady state IF values of the methods are summarized in Table 2 for varying CNR2. IF values in Table 2 are obtained by averaging the instantaneous IF values from the 150-th to 200-th scan. The IF values of optimum MTI processors are the inverse of the minimum eigenvalue of the clutter covariance matrix. Each covariance matrix was estimated from 4000 clutter samples. On all occasions, we can see that the steady state IF values approach near optimum.

V CONCLUSION

The adaptive EV filter where the minimum eigenvector is recursively estimated using the adaptive GS predictor based on the IPM was proposed. Using a lattice filter to implement the adaptive EV filter, the corresponding values of the PEF coefficients must be computed using the Levinson recursion formula. Using a GS predictor, however, the EV filter can be implemented in a simple structure due to the modular structure of the transform matrix. Simulation results showed that the convergence speed of the adaptive EV filter was faster than that of the adaptive PEF and IF values of the adaptive EV shemes always approached near optimum.

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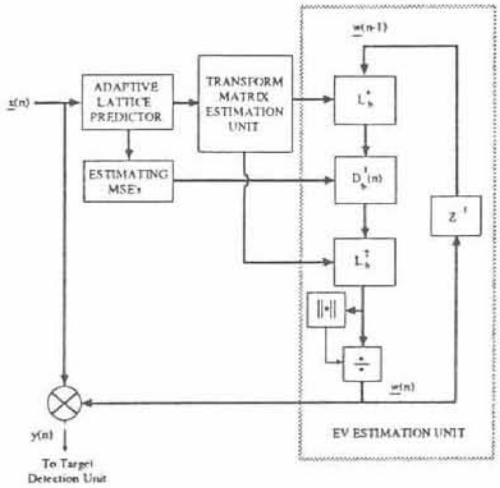
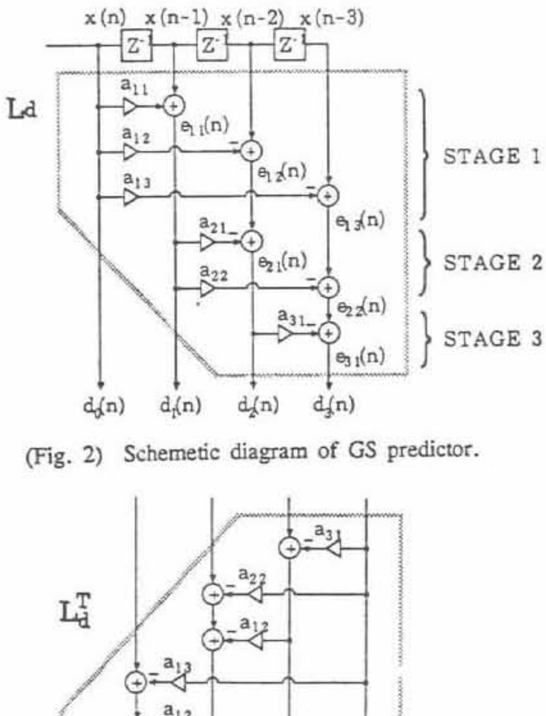
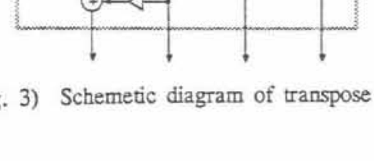


(Fig. 1) Schemetic diagram of adaptive EV filter implementing IPM using lattice predictor.



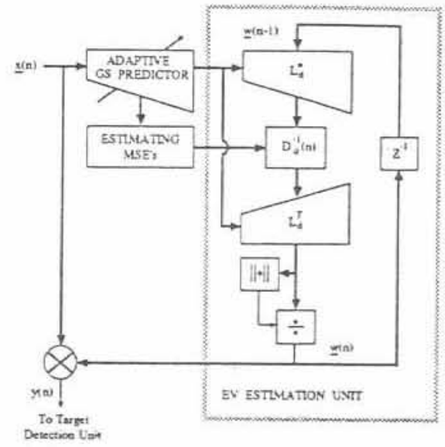
(Fig. 2) Schemetic diagram of GS predictor.



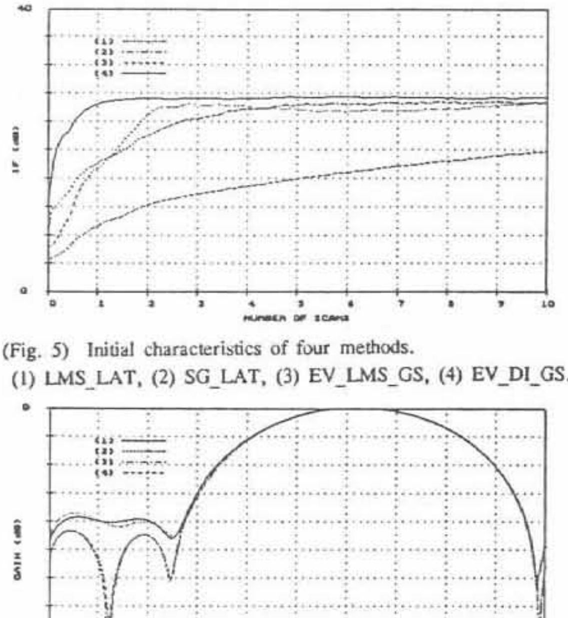
(Fig. 3) Schemetic diagram of transpose GS predictor.

(Table 1) Clutter source parameters

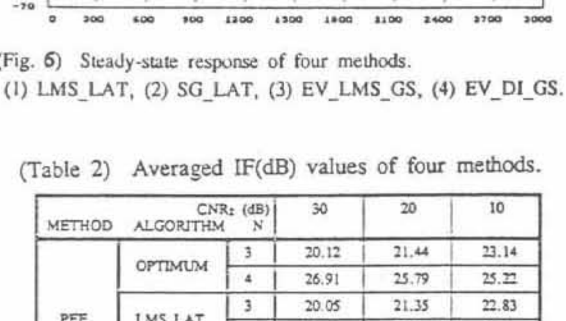
	Clutter 1	Clutter 2
Center Frequency (Hz/PRF)	0	0.2
3 dB bandwidth (Hz)	157	360
Correlation Coefficient (ρ)	0.99	0.95
CNR (dB)	40	40



(Fig. 4) Schemetic diagram of adaptive EV filter implementing IPM using GS predictor.



(Fig. 5) Initial characteristics of four methods.
(1) LMS_LAT, (2) SG_LAT, (3) EV_LMS_GS, (4) EV_DI_GS.



(Fig. 6) Steady-state response of four methods.
(1) LMS_LAT, (2) SG_LAT, (3) EV_LMS_GS, (4) EV_DI_GS.

(Table 2) Averaged IF(dB) values of four methods.

METHOD	ALGORITHM	CNR: (dB) N	30	20	10
PEF	OPTIMUM	3	20.12	21.44	23.14
		4	26.91	25.79	25.22
	LMS_LAT	3	20.05	21.35	22.83
		4	26.73	25.34	25.04
	SG_LAT	3	19.98	21.33	22.85
		4	26.68	25.49	24.96
EV Filter	OPTIMUM	3	20.40	21.88	23.94
		4	27.64	27.02	27.04
	EV_LMS_GS	3	20.32	21.70	23.68
		4	27.50	26.92	26.96
	EV_DI_GS	3	20.28	21.71	23.72
		4	27.40	26.96	26.93