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A Review on Beamforming Techniques in Wireless Communication

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ABSTRACT - ***Various innovation adaptive algorithms are presented for the beamforming of smart antennas in wireless communication system. These leading techniques show the improvement in capacity, quality and coverage. A consolidated study of some of adaptive beamforming algorithms are presented in this research work. In the beginning time domain and frequency domain processing of signals is described, then beamforming techniques like Side Lobe Cancellers, Linearly Constrained Minimum Variance (LCMV), Null Steering Beamforming, Sample Matrix Inversion (SMI) Algorithm, Least Mean Squares (LMS), Frost Beamforming, and MVDR DOA estimation are discussed and compared.***

INTRODUCTION

Beamformingisverywell-knownsignalprocessingtechniquefortransmissionandreceivingofthesignals.Beamformingtechniqueusedinsensorarrayfordirectionalsignals.Thistechniquebasicallyallowsthesignalreceivingfromaparticulardirectionandrejectorsimplyattenuatedthesignalwhichiscomingfromotherdirections.Inthistechniquethearrayofantennasisexploitedinaparticulardirection,byvaryingtheweightsofeachsensorantennas.Itisestimatedthatsignaliscomingfromthisparticulardirection.Optimizationofweightadaptionofsensorarrayisdonebycomplexalgorithms.Becauseofweightadaptationthistechniqueisalsocalledadaptivebeamformingtechnique[1]. Adaptivebeamformingtechniqueisinitiallydevelopedinearly1960'sinsonarandradarinmilitaryapplications[2,3].Howeverwiththeadvancementinalgorithms,itextendtoseveralbiomedicalultrasonicimagingandseismicapplications[4].Variousbeamformingtechniquesareproposedsincethen.Widelythesebeamformingtechniquesareclassifiedastimedomainsignalprocessinginbeamformingandfrequencydomainsignalprocessinginbeamforming.

TIME DOMAIN SIGNAL PROCESSING IN BEAMFORMING

Aspace-timeprocessorassociatesspatialfilteringwithtemporalfiltering,asshowninFig.1.Withregardtospatialfiltering,thesignals comingtoeachantennaelementaremultipliedbyweights.For timeprocessing,atapped-delay-line(TDL)isusedoneachbranchofthearray,whichallowseachelementtohaveaphaseresponsethatvarieswithfrequency,compensatingforthefactthatlowerfrequencysignalcomponentshavelessphaseshiftthanhigherfrequencysignalcomponentsforagivenpropagationdistance.Thisconfigurationcanbeconsideredtobeanequalizer,whichmakestheresponseofthearraythesameacrossdifferentfrequencies[5,6,7].

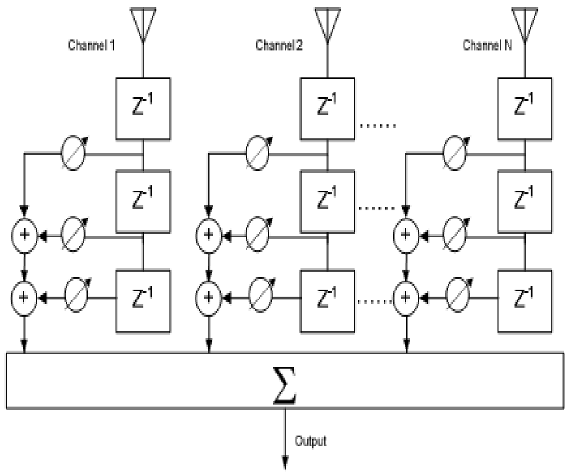

Fig-1:Timedomainprocessing[8]

FREQUENCY DOMAIN SIGNAL PROCESSING IN BEAMFORMING

Inthisconfiguration,thewidebandsignalisconvertedtoanintermediatefrequencyanddecomposedintonon-overlappingnarrowbandsignalsusingband-passfiltersasshowninFig.2.Thedecomposedsignalsareweightedwithaconventionalnarrowbandweightingscheme,andthensummedtoformtheoutput.Thisapproachprovidesaneasedealingwithawidebandsignalduetotheuseofconventionalnarrowbandweightingscheme.However,therequirementofalargenumberoffiltersincreasethecostofthesystem,andalso,filtersimperfectionmightintroduceotherproblems,thereforethisapproachisnotverysuitableforpracticalapplications[5,6].

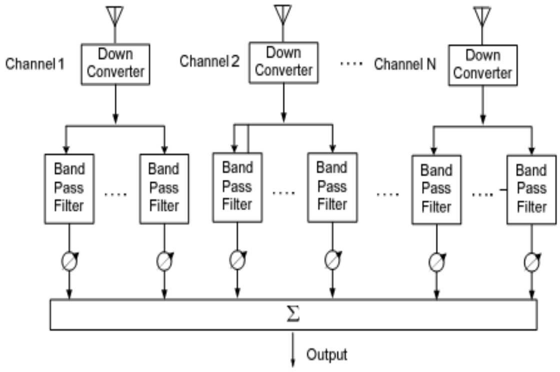

Fig-2:Frequencydomainprocessing[8]

BEAMFORMING TECHNIQUES

Review of beamforming was studied in terms of the Physical components needed to perform such a task. While at this point that topic is well understood, it is still not known how to determine the weights necessary for beamforming. In the following discussion, it is desired to study means in which specific characteristics of the received signal incident upon the array (in addition to the spatial separation among users in the environment) can be exploited to steer beams in directions of desired users and nulls in directions of interferers. In particular, the Mean Square Error (MSE) criterion of a particular weight vector will be minimized through the use of statistical expectations, time averages and instantaneous estimates. As well, the distorted constant modulus of the array output envelope due to noise in the environment will be restored.

SIDE LOBE CANCELLERS

This simple beamformer shown below consists of a main antenna and one or more auxiliary antennas. The main antenna is highly directional and is pointed in the desired signal direction. It is assumed that the main antenna receives both the desired signal and the interfering signals through its side lobes. The auxiliary antenna primarily receives the interfering signals since it has very low gain in the direction of the desired signal. The auxiliary array weights are chosen such that they cancel the interfering signals that are present in the side lobes of the main array response.

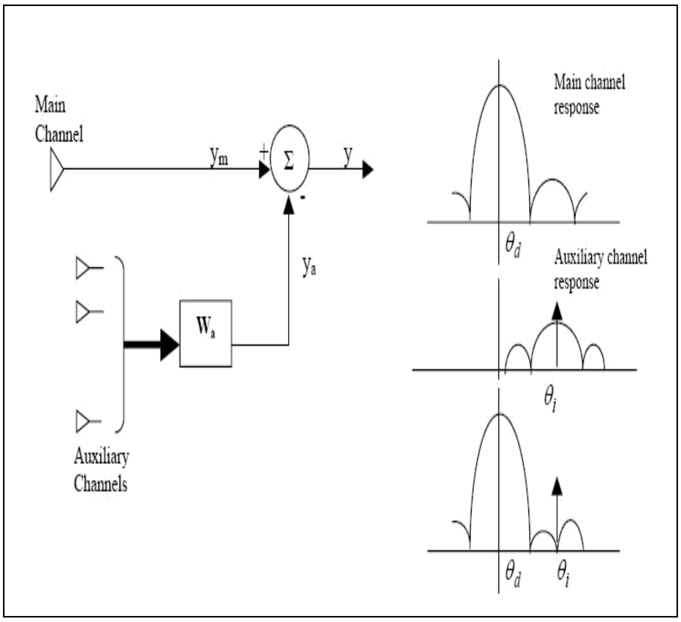

Fig-3: Side lobe canceller beamforming

If the responses to the interferers of both the channels are similar then the overall response of the system will be zero, which can result in white noise. Therefore the weights are chosen to trade off interference suppression for white noise gain by minimizing the expected value of the total output power. Therefore the criteria can be expressed mathematically as follows;

$$\min_{w_a} E\{\left|y_m - w_a^H x_a\right|^2$$

The optimum weights which correspond to the sidelobe canceller's adaptive component were found to be

$$w_a = R_a^{-1} r_{ma}$$

$R_a = E\{x_a x_a^H\}$ is the auxiliary array correlation matrix and the vector is the cross correlation between auxiliary array elements and the main array. This technique is simple in operation but it is mainly effective when the desired signal is weaker compared to the interfering signals since the stronger the desired signal gets (relatively), its contribution to the total output power increases and in turn increases the cancellation percentage. It can even cause the cancellation of the desired signal [9].

2. LINEARLY CONSTRAINED MINIMUM VARIANCE (LCMV)

Most of the beamforming techniques discussed require

some knowledge of the desired signal strength and also the reference signal. These limitations can be overcome through the application of linear constraints to the weight vector. LCMV spatial filters are beamformers that choose their weights so as to minimize the filter's output variance or power subject to constraints. This criterion together with other constraints ensures signal preservation at the location of interest while minimizing the variance effects of signals originating from other locations.
In LCMV beamforming the expected value of the array output power is minimized, i.e.

$E\{|y|^2\} = w^H R_x w$ is minimized subject to $C^H w = f$;

where Rx denotes the covariance matrix of x(t), C is the constraint matrix which contains K column vectors and is the response vector which contains Kscalar constraint values.
The solution to the above equation using Lagrange multipliers gives the optimum weights as

$$w_{opt} = R_x^{-1} C (C^H R_x^{-1} C)^{-1} f$$

This beam forming method is flexible and does not require reference signals to compute optimum weights but it requires computation of a constrained weight vector. C [9].

3. NULL STEERING BEAMFORMING

Unlike other algorithms null steering algorithms do not look for the signal presence and then enhance it, instead they examine where nulls are located or the desired signal is not present and minimize the output signal power. One technique based on this approach is to minimize the mean squared value of the array output while constraining the norm of the weight vector to be unity.

$$\min_{w} w^H R w \quad \text{subject to } w^H A w = 1$$

The matrix A, a positive-definite symmetric matrix, serves to balance the relative importance of portions of the weight vectors over others [9].

4. SAMPLE MATRIX INVERSION (SMI) ALGORITHM

In practice, the mobile channel environment is constantly changing making estimation of the desired signal quite difficult. These frequent changes will require a continuous update of the weight vector, which would be difficult to produce for reasons already stated. However, Reed, Mallet, and Brennan [31] proposed an estimate to the Weiner solution through the use of time averages called Sample Matrix Inversion (SMI). Suppose we takeK time samples of the received signal to form an input data matrix, X, defined by

$$X = [\tilde{x}(1), \tilde{x}(2), \dots\dots, \tilde{x}(k)]$$

Where; $\tilde{x}(1) = s(1)\bar{a}(\theta) + \bar{n}(1)$ and so on for the input data model.
An estimate of N*N covariance matrix $\hat{k}_{xx,}$ can then formed by total average over K samples, and given by:

$$\hat{k}_x = \frac{1}{k} \sum_{k=1}^{k} \tilde{X}(k) * \tilde{X}^t(k)$$

For the rapidly changing environment, it is possible to estimate blocks of data that can repeat the process periodically. We can alter the input data matrix X, to reflect the dynamic block size of K samples.

$X(l) = [\tilde{x}(1 + lk), \tilde{x}(2 + lk), \dots\dots, \tilde{x}(k + lk)]$ For; l=1,2,3,.....,L

The desired signal vector can be altered to reflect 0.this dynamic block size as well.

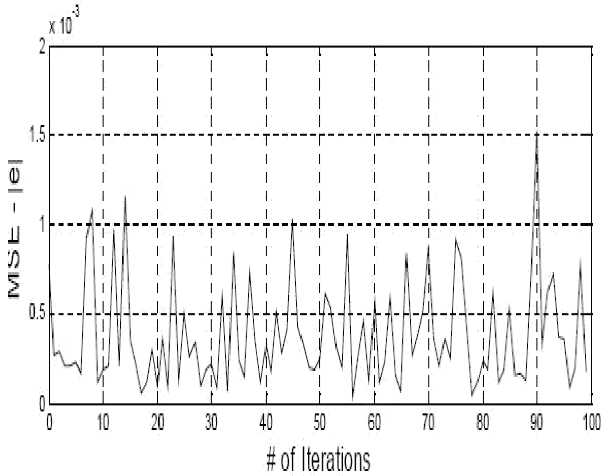

Fig-4: MSE of Dynamic SMI Method w/block size of 10

From the above results, we can see that the error for each iteration is very small. The stability of the SMI method depends on the ability to invert the NxN estimate of the covariance matrix given in equation 4.11. Typically, noise is added to the system to offset the diagonal elements of the input data vector in order to avoid singularities when inverting the covariance matrix. These singularities are caused by the number of received signals to be resolved being less than the number of elements in the array. The SMI method is a particularly desirable algorithm to determine the complex weight vector due to the fact that the convergence rate is usually greater than a typical LMS adaptive array and is independent of signal powers, AOA's and other parameters. The number of multiplications needed to form the estimated covariance matrix is proportional to N 3. Also, the number of linear equations needed to solve equation 4.16 increases as N 3.

Therefore, the SMI method operates at its best when the number of elements in the adaptive ray is small. Figure 4.4 below depicts the beampattern for an 8-element ULA where the weights ere determined using the SMI method. We assume a multipath scenario where the received signal is a polar NRZ waveform whose values appear with equal probability. The desired user's amplitude was five times greater than that of the multipath component. The desired user's AOA was -45o and the interferer's AOA were 30 [9].

5. LEAST MEAN SQUARES [LMS]

This algorithm was first developed by Widrow and Hoff in 1960.The design of this algorithm was stimulated by the Wiener-Hopf equation. By modifying the set of Wiener-Hopf equations with the stochastic gradient approach, a simple daptive algorithm that can be updated recursively was developed. This algorithm was later on known as the least-mean-square (LMS) algorithm. The algorithm contains threestepsineachrecursion:thecomputation ofthe processed signal with the current set of weights, the generation of the error between the processed signal and the desired signal, and the adjustment of the weights with the new error information [10, 11].The following equations summarize the above three steps.

$$\mathcal{E}(k) = d(k) - y(k)$$

$$Y(k) = WMX(k)$$

$$W(k+1) = W(k) + \mu X(k)[d(k) - XM(k).W(k)]$$

The w in the above equations is a vector which contains the whole set of weights.The H represents the Hermitian transpose of a vector. Here, we have taken eight elements, so there are eight for each symbol received at time n. All eight weights are updated according in each recursion.At time zero, all weights are initialized to have a value of zero. The symbol μ is called the step size parameter. The value of this parameter affects the settling time and the steady state error of the LMS algorithm. A large step-size allows fast settling but causes poor steady state performance [12].

6. FROST BEAMFORMING

Frost's beamformer Fig. 5 (a) consists of an array with K sensors, where each sensor is followed by a transversal filter with J weights. The number of weights is equal for all transversal filters. The sum of the filter outputs is the beam former output. Weights are updated by Frost's constrained least mean square (CLMS) algorithm which minimizes the mean square error of the output signal while satisfying a constraint. In order the input signal s(t) to be passed without any distortion, the impulse response of the whole system must be equal to the unit impulse. This impulse response represents the constraint for the weights of all filters. The whole system can be replaced by one transversal FIR filter for the signals s(t).
The replacement is shown in Fig.4 (b), where f1, f2, . . . , f_j is the impulse response for the signal. Constraint equations can be written also in matrix form as:

$$W\begin{bmatrix}1\\ \vdots \\ 1\end{bmatrix}=\begin{bmatrix}f1\\ \vdots \\ fj\end{bmatrix}, \qquad (1)$$

Where W stands for weight matrix with actual elements

$$\begin{bmatrix} w\,1 & \cdots & w\,k \\ \vdots & \ddots & \vdots \\ w\,jk-k+1 & \cdots & w\,jk \end{bmatrix} \qquad (2)$$

To discuss the Frost's beam former behavior in details, let us define some terms needed. The digitized input noisy signals $x_i[n]$, i = 1,2, . . . , JK are formed by components of both clean signals(t) and noise n(t). The vector ˜x[n] represents noisy signals on taps, the vector w consists of weights value, and the vector F represents the constrained impulse response and the matrix C will be used in constraint formulation

$\tilde{x}^T[n] = [x_1[n]\ x_2[n] \ldots x_{jk}[n]]$,

$w^T = [w_1\ w_2 \ldots w_{jk}]$,

$FT = [f_1\ f_2 \ldots f_j]$,

$C = [c_1\ c_2 \ldots c_j]$. (3)

Elements C_i represent the column vectors of length jk with (i−1) K zeroes followed by K ones and (J−i) K zeroes

c^T_i= [0 0 .... 0 1 1 .... 1 0 0 .... 0] (4)

(i−1)K zeroes k ones (j-i)k zeroes

Now the problem of finding the optimum weight vector for a stationary signal w_{opt} (Wiener solution) can be formulated. The weight vector minimizing E [y_2 [n]] = w_{te}[˜x [n]˜x [n]^T] w = $w^T R_{xx}$ w and satisfying the constraint C^T w=F have to be found. R_{xx} stands for the autocorrelation matrix. In [13] the method of Lagrange multipliers was used to obtain the Wiener solution.

$$w_{opt}=R^{-1}_{xx}C(C^T R^{-1}_{xx}C)^{-1}F \quad (5)$$

and the adaptive CLMS algorithm

w [0] = f,

$$w[n+1] = P(w[n] - \mu y[n]\tilde{x}[n]) + f. \quad (6)$$

The vector f and the projection matrix Pare defined as

$$f = C\,(C^T C)^{-1}F,$$

$$P = E - C\,(C^T C)^{-1}C^T. \quad (7)$$

Positive scalar μ is a step-size parameter. The choice of μ is the trade of between theconvergence time and the miss adjustment of weights from Wiener solution. An easily computable upper bound for μ is given by $\mu < 2/(3E[\tilde{x}^T\tilde{x}])$.

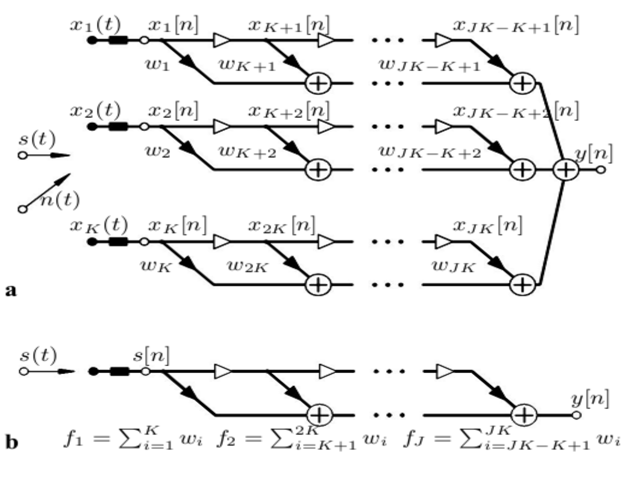

Fig-5: (a) Frost's beam former structure,

(b) Frost's beam former from s(t) view - constraint formulation

The convergence performance and the choice of μ is deeply discussed in [14].

The alternative form of equation (6) for the implementation is

$$W_i[n+1] = w_i[n] - \mu\, y[n]x_i[n] - \frac{1}{k} \sum_{\lfloor \frac{i}{k} \rfloor k-1}^{(\lfloor \frac{i}{k} \rfloor+1)k} w_i[n] - \mu y[n] x_i[n] + [(f \left\lfloor \frac{i}{k} \right\rfloor + 1)/k]$$

7. MVDR DOA ESTIMATION

There are two types of MVDR DOA estimation techniques. First, the MVDR DOA spectrum and polar plot for estimated directions.

Let DOAs of incoming signals, Angle of Incidence of the desired source signal {60°}, and the angle of incidence of the undesired interference source signal {45°, 30°, 75°}. SNR is assumed to be 10 db for all incoming sources as shown in fig. 6.

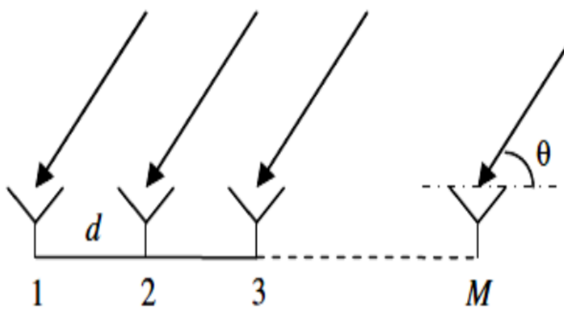

Fig-6: Linear array

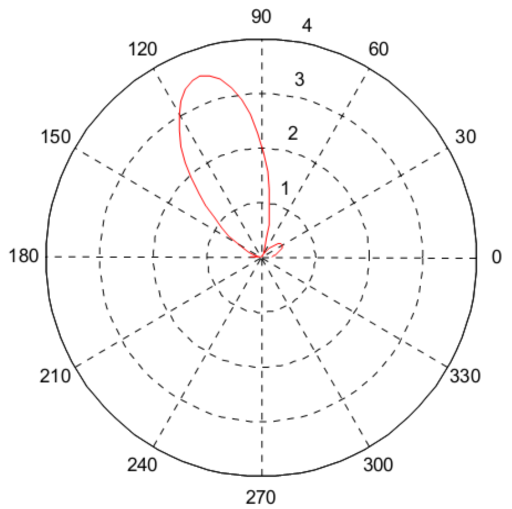

Fig-7: Polar Plot of MVDR Beamforming

Second, Null steering beamforming for the single desired user a single desired source is considered in direction φ = 40°. Weights are calculated using Eq (A) to produce a beam in the direction of desired user (φ = 40°) and null in the direction of interferences (30°, 60°, 100°) [15]. The Fig.8 shows the power spectrum and polar plot for null steering beamforming respectively.

$$Y(n)=WH(n)*(n) \quad (A)$$

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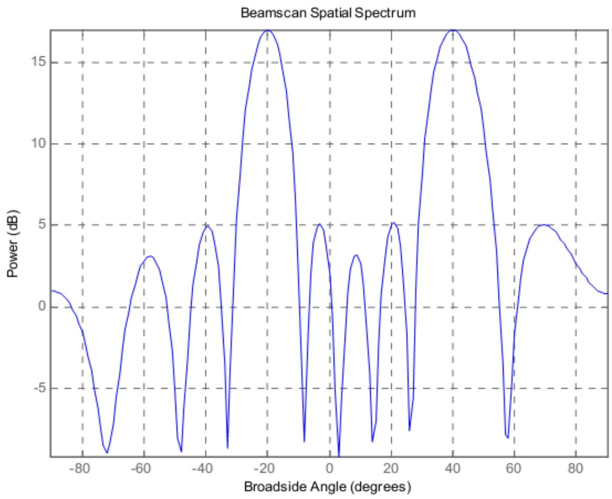

Fig-8: Power spectrum of MVDR Beamforming

CONCLUSION

It was shown that beamformers could be expected to operate on signals in a wide frequency range, and it is therefore important to consider the nature of the signals to be processed. Low pass sampling is sufficient for low-frequency signals, however for high frequency band-pass and narrowband signals,band pass sampling techniques must be adopted. It was also shown that interpolation could be used to increase the effective sampling frequency.

Beamforming was introduced using the simple time do main beamformer and later extended using interpolation and quadrature sampling. Beamforming in the frequency domain was also discussed, and in some cases may be more efficient method of forming simultaneous beams. MATLAB simulations were given for each beamformer to supplement the understanding of the operations required in the beamformer. The simulations also give an insight into design considerations and specifications of areal implementation.

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