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Smart antenna array processing techniques and implementation of Spatio-temporal sampling and Equality check algorithm

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***Abstract*—Research and development in smart or adaptive antenna array is always in progress to estimate direction of arrival (DOA) accurately and to form the beam in the direction of DOA. This paper presents different temporal and spatial array processing techniques used for DOA estimation. Temporal class contains all algorithms which use temporal properties of the desired signal during the adaptation process. This can be a training sequence as well as the constant envelope property of the signal to be received. The antenna weight vectors are directly determined from the received signals at the antenna elements and the temporal signal properties, where no channel estimation is performed. Temporal processing algorithms include LMS, RLS, SQRLS, DMI, SMI, CMA algorithms. Spatial algorithms use knowledge about the properties of the array manifold to determine the DOAs of the incident signals. Afterwards the antenna weight vectors are determined and the signals are separated and further processed by any detector. Spatial processing algorithms include MUSIC, ESPRIT, UNITARY ESPRIT, SAGE algorithms.**

In this paper by studying the above method one different method i.e. 'spatio-temporal sampling and equality check' method is developed and implemented using MATLAB SIMULINK and the performance is checked for different combination of input signal and noise signal.

Keywords—LMS, RLS, SQRLS, DMI, SMI, CMA, MUSIC, ESPRIT, UNITARY ESPRIT, SAGE.

I. INTRODUCTION

Today, several terms are used to refer to the various aspects of smart-antenna system technology, including intelligent antennas, phased arrays, SDMA, spatial processing, digital beamforming, adaptive antenna systems, and others. Smart-antenna systems, however, are usually categorized as either switched-beam or adaptive-array systems. Although each system commits to increase gain within the direction of the user, solely the adaptive-array system offers optimum gain, at the same time distinguishing, tracking, and minimizing interfering signals. It's the adaptive system's active interference capability that gives substantial performance benefits and adaptability over the more-passive switched-beam approach.

Smart antennas communicate in the required direction by forming specific beam patterns in that direction. They direct their main lobe, with increased gain, in the direction of the user, and they direct nulls in directions away from the main lobe. Different switched-beam and adaptive smart antennas control the lobes and the nulls with varying degrees of accuracy and flexibility [1].

A. Beam Steering and Switching

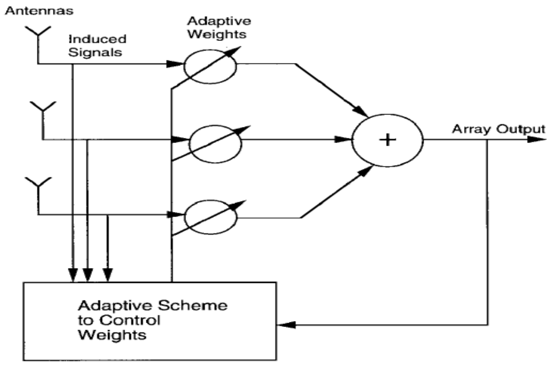

Fig. 1. Adaptive antenna array system

Thus, this can be the direction wherever the array has the maximum gain. For a linear array, once signals are combined with no gain and phase change, this is broadside to the array, that is, perpendicular to the line joining all elements of the array.

The array pattern drops to a low value on either side of the beam pointing direction. The place of the low value is generally mentioned as a null. In strict words, a null may be a position wherever the array response is zero. [2].

For beamforming concerns, the reference signal is typically obtained by a periodic transmission of a training sequence, which is a priori known at the receiver and is referred to as temporal reference. Note that information about the direction of the signal of interest is usually referred to as spatial reference. The temporal reference is of vital importance in a fading environment due to lack of direction of arrival information.

The adaptive array reference signal needn't essentially be a precise reproduction of the desired signal, even though this is often what happens in most of the cases[3].

In fig. 2 classification of linear algorithms is shown [4]. Temporal and Spatial are the two main types of algorithms. In Temporal type seven algorithms exist. In this paper LMS (Least Mean Square), RLS (Recursive Least Square), CMA (Constant Modulus Algorithm) are the three algorithms discussed. In Spatial type four algorithms exist. In this paper MUSIC (MUltiple SIgnal Classification), ESPRIT (Estimation of Signal Parameters via Rotational Invariant Techniques) algorithms are discussed [5].

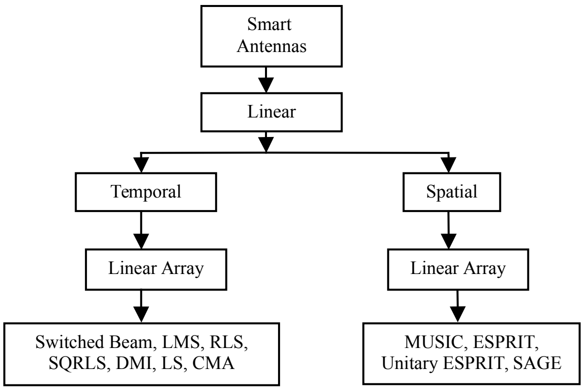

Fig. 2. Classification of Algorithms

Section II and Section III present different linear adaptation schemes: Temporal and Spatial. Section IV presents a new technique named 'Spatio-temporal sampling and Equality check algorithm'. Section V discusses the whole MATLAB simulation setup. In Section 4 we describe the different adaptation strategies. Section 5 gives the simulation results for 'Spatio-temporal sampling and Equality check algorithm'in MATLAB-SIMULINK.

II. TEMPORAL ALGORITHMS:

A. LMS Algorithm

The application of the LMS algorithm to estimate the optimal weights of an array is widespread, and its study has been of considerable interest for some time now. The algorithm is named as the constrained LMS algorithm when the weights are considered as constraints at each iteration. It is called as an unconstrained LMS algorithm when the weights are not constrained at every iteration. The latter is mostly applicable when weights are updated using a reference signal and no knowledge of the direction of the signal is utilized, as is the case for the constrained case. The algorithm updates the weights at each iteration by estimating the gradient of the quadratic surface and then moving the weights in the negative direction of the gradient by a small quantity. The constant that determines this quantity is generally called as the step size. If this step size is small enough, the process leads these calculated weights to the optimal weights. The convergence and therefore the transient behavior of these weights, along with their covariance, characterize the LMS algorithm, and therefore the manner that the step size and therefore the method of gradient estimation have an effect on these parameters is of nice sensible importance.

The LMS algorithm is perhaps the most widely used adaptive filtering algorithm, being used in many communication systems. It is famous because of its low computational complexity and proven robustness .It incorporates new observations and iteratively minimizes linearly the mean-square error. The LMS algorithm changes the weight vector **w** along the direction of the calculated gradient based on the negative steepest descent technique. As the quadratic characteristics of the mean square-error function $E|e(k)|^2$ has only one minimum, the convergence of the steepest descent is guaranteed[5]. At adaptation index k, given a mean-square-error (MSE) function

$$E\{|e\,(k)|^2\} = E\{|d(k) - \mathbf{w}H\mathbf{x}(k)|^2\},$$

The weight vectors of the LMS algorithm are updated as per the following equation.

$$w(k+1) = w(k) - \frac{\mu}{2}\frac{\partial J_{w,w*}}{\delta w*}$$

$$= \mathrm{w(k)} + \mu \mathrm{e} * \mathrm{(k)x(k)} \qquad (1)$$

B. RLS Algorithm

The convergence of the LMS algorithm depends upon the eigenvalues. In an environment yielding with a large eigenvalue spread, the algorithm converges with slow speed. This problem is solved in an RLS algorithm by replacing the gradient step size with a gain matrix at the k^{th} iteration, producing the weight update equation where, a real scalar smaller than but close to one, is used for exponential weighting of the past data and is referred to as the forgetting factor, as the update equation tends to deemphasize the old samples. The quantity is normally referred to as the memory of the algorithm. Thus, the memory of the algorithm is close to 100 samples. The RLS algorithm updates the required inverse using the previous inverse and the present sample.

The RLS algorithm minimizes the cumulative square error and its convergence is independent of the eigenvalue distribution of the correlation matrix.

Unlike the LMS algorithm which uses the method of steepest descent to update the weight vector, the RLS adaptive algorithm approximates the Wiener solution directly using the method of least squares for adjustment of the weight vector, without putting extra load for approximation of optimizing the procedure. The least square method includes, the weight vector **w**(k), so chosen for minimizing a cost function consisting of the sum of error squares over a time period, i.e., the least-square (LS) solution is recursively minimized.

$$R^{-1}(0) = \delta^{-1}I, \quad \delta small\ positive\ constant\ and$$
$$I\ the\ N \times N\ identity\ matrix$$
$$for\ each\ k$$
$$\{$$
$$k(k) = R^{-1}(k-1)x(k)$$
$$k(k) = \frac{k(k)}{\lambda + x^H(k)k(k)}$$
$$R^{-1}(k) = \frac{1}{\lambda}\left[R^{-1}(k-1) - \frac{k(k)k^H(k)}{\lambda + x^H(k)k(k)}\right]$$
$$\mathrm{e}(\mathrm{k}) = \mathrm{d}(\mathrm{k}) - w^H(k)x(k)$$
$$\mathrm{w}(\mathrm{k}+1) = \mathrm{w}(\mathrm{k}) + \mathrm{e} * (\mathrm{k})\mathrm{x}(\mathrm{k})$$
$$\} \tag{2}$$

On the other hand, the steepest descent method chooses the weight vector to minimize the average of the error squares. The weighted least-squares (WLS) objective function results in the recursions of the RLS algorithm in its most common version.

$$J_{w,w^*} = \sum_{i=1}^{k} \lambda^{k-1} |e(i)|^2 \tag{3}$$

C. CMA

CMA is a gradient-based algorithm that works on the premise that the existence of an interference causes fluctuation in the amplitude of the array output, which otherwise has a constant modulus. It updates the weights by minimizing the cost function.

Many communication signals, frequency or phase modulated, such as FM,CPFSK modulation, and square pulse-shaped complex pulse amplitude modulation (PAM) have a constant complex envelope. This property is usually referred to as the constant modulus (CM) signal property.

For these types of communication signals, one can take advantage of the prior knowledge of this characteristic and specify the adaptation algorithm to achieve a desired steady state response from the array. The constant-modulus algorithm is the most well-known algorithm of this kind. It is suitable for the transmission of a modulated signal over the wireless channel, since noise and interference corrupt the CM property of the desired signal. A signal traveling through a frequency selective channel is almost sure to also lose its constant modulus property.

Thus, the CM provides an indirect measure of the quality of the filtered signal. It adjusts the weight vector of the adaptive array so as to minimize the variation of the desired signal at the array. After the algorithm converges, a beam is steered in the direction of the signal of interests, where as nulls are placed in the direction of interference.

The objective of CM beamforming is to restore the array output $y(k)$ to a constant envelope signal. Using the method of steepest descent, the weight vector is updated using the following recursive equation,

$$for\ each\ k$$
$$\{$$
$$y(k) = w^H(k)x(k)$$
$$e(k) = \frac{y(k)}{|y(k)|} - y(k)$$
$$w(k+1) = w(k) + \mu e * (k)x(k)$$
$$\} \tag{4}$$

CMA is useful for eliminating correlated arrivals and is effective for constant modulated envelope signals such as GMSK and QPSK, which are used in digital communications.

The algorithm, however, is not appropriate for the CDMA system because of the required power control.

III. SPATIAL ALGORITHMS:

A. MUSIC Algorithm

Within the class of the so-called *signal-subspace* algorithms, MUSIC (MUltiple SIgnal Classification) has been the most widely examined. In a detailed performance evaluation based on hundreds of simulations, among the high-resolution algorithms then available, MUSIC was the most promising and a leading candidate for further study and actual hardware implementation. MUSIC algorithm is more popular owing to its generality. For example, it can be applied to antenna array of any but known configuration and performance, and can help to estimate multiple parameters of source signals (e.g. elevation, azimuth, range, polarization etc.). However, this generality is accompanied with the expense that the array response must be known for all possible combinations of source parameters; i.e., the response must be either measured (calibrated) and stored, or one must be able to characterize it analytically. In addition, MUSIC requires a priori knowledge of the second-order spatial statistics of the background noise and interference field. These assumptions are never satisfied in reality as explained earlier [4].

The MUSIC algorithm was developed by Schmidt by noting that the desired signal array response is orthogonal to the noise subspace. From the received signal covariance matrix by Eigen decomposition, signal and noise subspaces are identified. Next, the MUSIC spatial spectrum is computed, which helps in the estimation of DOAs.

B. ESPRIT Algorithm

Although the performance advantages of MUSIC are substantial, they are achieved at a considerable cost in computation (searching over parameter space) and storage (of array calibration data). Moreover, even for the one-dimensional MUSIC estimation (DOA in the particular case), there exist several drawbacks although being conceptually easy. Primarily, problems in the finite measurement case arise from the fact that since K signals are known to be present, the search for their DOAs, (θ_1, θ_2, . . . , θ_K), should be sought simultaneously by maximizing an appropriate function rather than obtaining estimates one at a time as is done in the search for spectral peaks over $P_{MUSIC(\theta)}$. However, multidimensional searches are accompanied with an intense expense compared to one-dimensional searches. The reduction in computational load achieved with an one-dimensional search for *K* parameters comes with the trade-off of the method being finite-sample-based in a multisource environment. Furthermore, in either low SNR scenarios or closely spaced sources (i.e., multiple peaks observed in the measurements) MUSIC's performance reduces dramatically. Nevertheless, despite its drawbacks, it should be emphasized that MUSIC has proven to outperform techniques existed prior to its development.

ESPRIT (Estimation of Signal Parameters via Rotational Invariant Techniques) is similar to MUSIC in that it correctly exploits the underlying data model. Beyond retaining most of the essential features of the arbitrary array of sensors, ESPRIT achieves a significant reduction in the aforementioned computation and storage costs. This is done by imposing a constraint on the structure of the sensor array to possess a displacement invariance, i.e., sensors occur in matched pairs with identical displacement vectors. Such conditions are or can be satisfied in many practical problems. In addition to obtaining signal parameters efficiently, ESPRIT is also less sensitive to array imperfections than other techniques including MUSIC .The method simultaneously estimates the number of sources and DOAs.

IV. SPATIO-TEMPORAL SAMPLING AND EQUALITY CHECK ALGORITHM

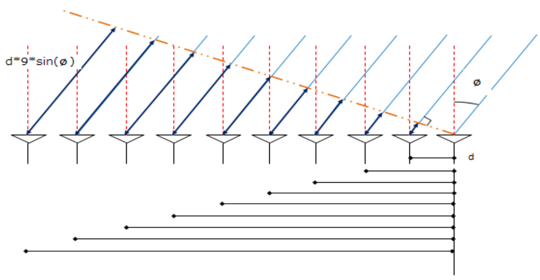

Fig. 3. Ten element Antenna Array

Fig.3 shows ten element antenna array separated by distance d. The signal arriving from direction ϕ is shown.

Spatial Sampling details:

- Perform digitization of all signal samples arriving at ten antenna elements.
- One digitizer for each Antenna element.
- Master - Slave configuration. The digitizer with Reference Antenna element is called as a Master and all other digitizers are Slaves.
- The output of all digitizers stored in the respective dataset. Ten datasets are now ready for processing. This is must for spatial sampling.
- Reference Dataset represents the reference antenna element or Master Dataset. Each Slave Dataset has the data with some delay as compared to master. The duration of delay depends upon azimuth angle requirement and the position of antenna element in relation with reference antenna.

Temporal Sampling details:

- Each Digitizer(Master/Slave) takes snapshots of input signal with fixed sampling frequency. This frequency is selected as per the Nyquist Criteria.
- The 200 snapshots for each input signal are captured by both Master as well as Slave Digitizers.
- The slave Digitizer shares these snapshots with Master for further processing.

DOA Estimation:

- DOA estimation is done based on Equality concept. A set of snapshots from all Slave Digitizers are processed at Master Digitizers. The Master Digitizer uses its own set as a reference set for processing of Slave sets. The processing steps are as given below.
- Master compares its own set with the sets received from all the slaves, one at a time. This is for equality check. If equality check is true, Master records azimuth angle otherwise ignores it.
- Master checks for next azimuth angle and continues the task until it reaches last azimuth angle i.e. 90^0.
- Master displays all identified azimuth angles to user.

V. MATLAB SIMULINK IMPLEMENTATION AND RESULTS

Here in fig.4 we see a MATLAB-Simulink implementation of the concerned model considering single user. Same can be repeated for (n-1) number of users. But as the simulink diagram for two or more signals will not fit in a legible manner in a page, only single user case is shown.

Block diagram has two important parts. First is signal separation and second is the digitization block where datasets for signal1 at each antenna element are created. Thus, there will be ten datasets.

Algorithm Test Results:

Fig.4 shows block diagram for MATLAB simulink implementation, considering one signal arriving from different directions.

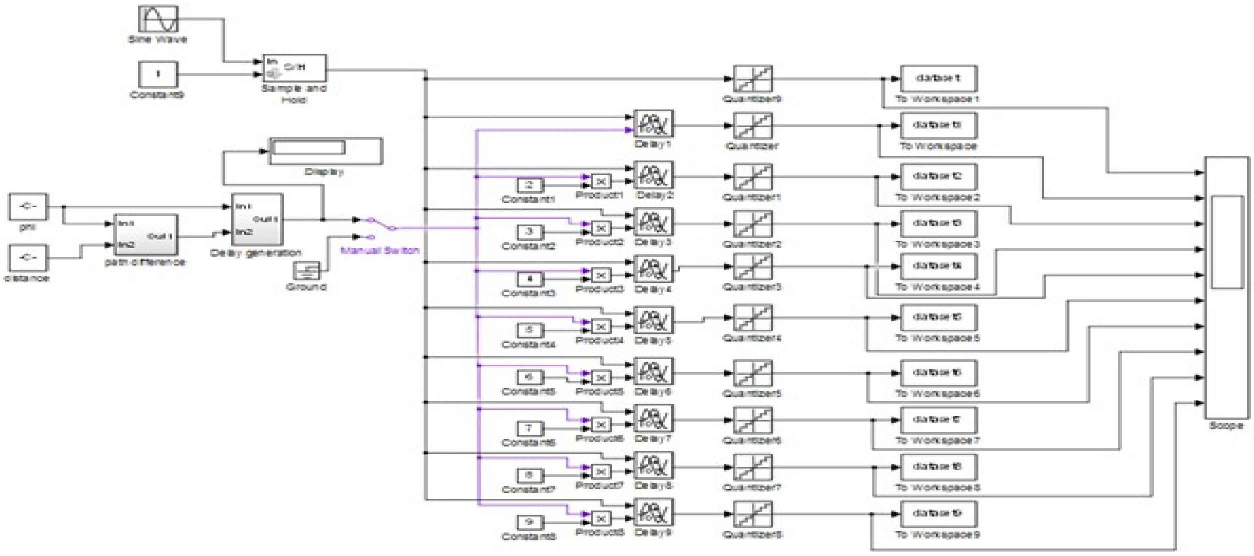

Fig. 4. block diagram for MATLAB simulink implementation, considering two signals arriving from different directions.

First the spatio-temporal equality check algorithm was tested for 10^0 steps from 0^0 to 90^0. The test results are shown in table1.

TABLE1. DOA RESULTS FOR SIGNAL1

Signal1 I/P $\phi 1$	Signal1 O/P $\phi 1$
10	10
19	20
30	30
54	60
74	80

Next the spatio-temporal equality check algorithm was tested for 10^0 steps from 0^0 to 90^0 considering two signals arriving from different directions and the test results are shown in table2.

TABLE2. DOA RESULTS FOR SIGNAL1 AND SIGNAL2

Signal1 I/P $\phi 1$	Signal2 I/P $\phi 2$	Signal1 O/P $\phi 1$	Signal2 O/P $\phi 2$
10	20	10	20
19	15	20	20
30	60	30	60
54	40	60	40
74	89	80	90

VI. CONCLUSION

Smart antennas have a great promise for DOA estimation and beamforming. Both the Spatial (SR) and Temporal(TR) algorithms have their advantages and their disadvantages. Some systems do not provide a training sequence, so SR algorithms are to be preferred for them.SR algorithms are only applicable to scenarios where the concept of nominal DOAs associated with a limited angular spread exists.

Due to the use of finite length training sequences only a limited number of array elements makes sense for TR approaches and synchronization is much more critical than for SR approaches.

A new technique of ‘Spatio-temporal sampling and Equality check algorithm’ provides better results. The main advantages of this technique are low complexity and less number of computations which results in faster speed enhancing the performance.

References

[1] *Minghui Li,"* ADVANCED ARRAY PROCESSING TECHNIQUES AND SYSTEMS", International Journal of Computer Research ISSN: 1535-6698, Volume 17, Issue 4, pp. 1–33 © 2009 Nova Science Publishers, Inc.

[2] LAL C. GODARA, "Application of Antenna Arrays to Mobile Communications, Part II: Beam-Forming and Direction-of-Arrival Considerations", PROCEEDINGS OF THE IEEE, VOL. 85, NO. 8, AUGUST 1997.

[3] Constantine A. Balanis, Panayiotis I. Ioannides, a book on "Introduction to Smart Antennas".

[4] Suraya Mubeen, Dr.A.m.Prasad, Dr.A.Jhansi Rani, " Smart Antenna its Algorithms and Implementation", Volume 2, Issue 4, April 2012 ISSN: 2277 128X International Journal of Advanced Research in Computer Science and Software Engineering.

[5] JOSEF FUHL and ERNST BONEK," Temporal Reference Algorithms versus Spatial Reference Algorithms for Smart Antennas", *Wireless Personal Communications* **9:** 271–293, 1998.