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A Comprehensive Survey on Antenna Array Signal Processing*

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ABSTRACT

In recent years, power saving in transmitter or/and receiver, achieving higher capacity and reducing interference, are the main attractive research subjects in the field of wireless radio communications. The essential goal of these systems is to increase the power of the receiving signal by appropriate forming the antenna radiation pattern in the transmitter, receiver, or both of them. Antenna beamforming techniques, in addition to increase the overall system capacity and quality of the system, decrease the energy consumption. In this study, besides a short review on the advances on antenna and associated applications, by reviewing the current methods for antenna beamforming and their positive effects on reduction of energy consumption, some newest techniques and research areas are proposed. In the rest of study, we focus on antenna array digital processing. Two types of antenna beamforming proposed in antenna array digital processing, fixed-beam as well as adaptive-beam and these two major categories are illustrated with more details. Besides, Simulation results of three fixed-beam methods (Max-SIR, MMSE and LCMV) and two adaptive weighting algorithms (LMS and CM) are described and their performances are evaluated based on different metrics, normalized mean square error, bit error rate, maximum gain of array factor and signal to noise plus interference ratio. Finally, the advantages and disadvantages of each category and related techniques are extracted and they are compared based on computational complexity and convergence time.

Key words: Antenna array, radiation pattern, beamforming, fixed-beam, adaptive processing

INTRODUCTION

Nowadays, wireless communications have been very popular and diverse applications of them can be seen in various aspects of human life. Cellular wireless communications, satellite communications, wireless radio of Police, radio taxies, Bluetooth, Wireless Local Loop (WLL), point-to-point microwave links, Wireless Local Area Network (WLAN) and wireless wideband networks such as internet are some examples of wireless communications. Growth in wireless technologies and user's demands, lead us to extend these systems in rural and urban areas, indoor and outdoor environments, short-range as well as long-range applications and then optimizing them for long

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term scheduling. In this regard, wireless cellular communications, wireless networks, wireless wideband communications and digital radio transmitters takes precedence over other technologies due to their diversities, flexibilities and number of users (Ahmadi, 2009; Alexiou and Haardt, 2004).

In one hand, by optimum using of available frequency bandwidth and reusing of radio spectrum and on the other hand, by decreasing the number of fixed stations (to reduce costs), the required energy consumption will be decreased. In noisy systems, by reducing internal noises, Signal to Noise Ratio (SNR) will be increased and then the system can produce better Quality of Services (QoS). In systems with interference, the main goal is to reduce interferences and increase Carrier to Interference Ratio (CIR) in the way that consuming energy doesn't increase. Time-space techniques, such as, space-time coding, low noise filters, channel equalizers and high performance modulations, can decrease the effects of interferences and noises and then reduce the power consumption. Furthermore, due to frequency-reuse, co-channel interference will be increased and then the quality of system will be decreased (Rappaport, 1999; Zhang and Hsiao-Hwa, 2008).

Four methods are proposed to manage radio resources and decrease power consumption as follow:

- Increasing the performance of energy convertor devices, such as, high performance radio amplifiers, mixers and modulators
- Using low power electronic and communication devices, such as, CMOS-based technologies and Radio Frequency Integrated Circuits (RFIC)
- Reducing electrical energy consumption in such way that radio systems transmit or receive in lower power. For example, some power control techniques can reduce power consumption in each element of wireless systems
- Applying antenna features to produce strong signals in transmitters or receivers

During these two decades, appropriate beamforming and concentrating radiated power in specific directions are been so attractive. As so, in this research, we focus on antenna beamforming. It is obvious that considering passive elements as directional antennas or active antenna structures, such as, fixed-beam and adaptive arrays, radio resources (power, time, frequency and space) can be used for different communication systems as well as broadcasting wireless systems (Kaiser *et al*., 2005).

NUMBER OF MOBILE SUBSCRIBERS AT A GLANCE

Currently, there are more than 5 billion mobile users in the world and this number will reach to 5.5 billion users at the end of 2010. Figure 1 (extracted from www.computerweekly.com) shows the number of mobile subscribers in the years between 2000 and 2010. As shown, in 2000, there were 750 million users in the world and it is predicted that this number growth to 4.6 billion in 2010. Figure 1 also shows a 61% rise in the number of mobile users in time interval 2000 to 2010. It is the highest growth between different communication technologies.

Figure 2 (extracted from www.itu.int) shows the penetration rate of mobile technology between years 2000 and 2010. It is predictable that the penetration rate in 2010 will be more than 80%. According to Fig. 1 and 2 and the importance of wireless communication systems in the human life, it is very obvious that power consumption of these systems should be optimized, interference should be decreased and radio resources should be managed.

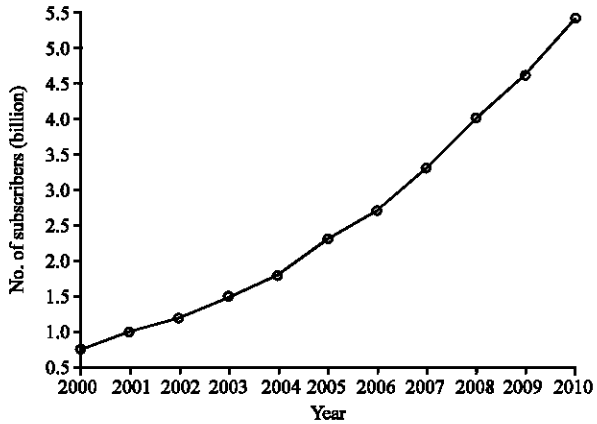

Fig. 1: Number of mobile subscribers

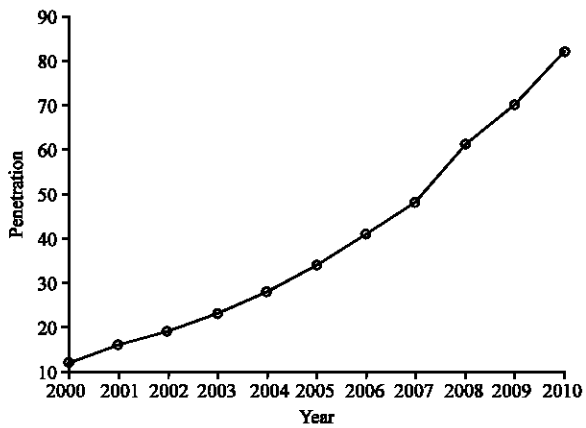

Fig. 2: Worldwide penetration of mobile subscribers

ANTENNA DEVELOPMENTS IN WIRELSS COMMUNICATIONS

In the past, antenna had viewed as a single element, but, nowadays, antenna arrays have been one of the most important parts of current wireless communication systems. The evolution of antenna in wireless systems is as follow.

Omni-directional antennas: Omni-directional antennas are used for broadcasting and local applications. For covering large zones the height and power of the antenna should be increased (Kraus and Marhefka, 2006).

Directional antennas: In these antennas, signals are transmitted in a specific direction. These antennas can be used instead of high power omni-directional antennas and we gain higher coverage and lower interference (Kraus and Marhefka, 2006).

Cellular structure: In cellular mobile and multi-beam satellite communications, the coverage area is divided to several zones (cells) that each zone will be covered by a base-station containing one omni-directional or several directional antennas. In this regard, by reusing radio resources (time, frequency and/or code), both capacity and quality of service can be increased (Bellofiore *et al.*, 2002).

Cellular sectorization: In cellular systems that are co-channel interference limited, directional antennas are very useful to decrease the received power of interferers from side-lobes of antenna instead of increasing the power. This means, each base-station equipped with three 120-degree or six 60-degree directional antennas (Bellofiore *et al.,* 2002; Etemad, 2008).

Space diversity: In order to improve the quality of received signals in radio receivers and also overcoming multipath fading, space diversity is used. In this technique, multiple antennas are located in such way that they are too distant (about 5-10 wavelengths). Signals which received from multipath are combined in a decision making box. Four methods are considered to combining and finding the better signal, selection method that select the signal belongs to higher quality path, scanning method that search for a new path if signal reaches below a defined threshold, Equal Gain Combining (EGC) that considers all paths with similar weights and Maximal Ratio Combining (MRC) that considers paths with related SNR-based weights. Output of scanning and selection methods just belongs to a path whereas output of two other methods is a combination of the signals of all paths (Bhobe and Perini, 2001).

MIMO systems: In Multi-Input Multi-Output (MIMO) systems that use multiple antennas at both transmitter and receiver, have demonstrated the potential for increased capacity and diversity gain in rich multipath environments same as cellular mobile and wireless broadband communication systems. It is remarkable that the maximum achievable diversity gain of a MIMO system with N_T antenna elements at the transmitter and N_R antenna elements at the receiver is $N_T \times N_R$. Moreover, it has been proved that when the fades connecting pairs of transmit and receive antenna elements are independently and identically distributed (i.i.d.), the capacity of a Rayleigh distributed flat fading channel increases almost linearly with the min $\{N_T, N_R\}$ (Godara, 2004, Nooralizadeh and Moghaddam, 2010; Moghaddam and Saremi, 2008).

Space-time Coding: In multiple antenna systems by using space-time coding, such as, Alamouti coding, we can add high gain to the system instead of increasing the power level of the transmitter (Badic *et al.,* 2003).

Antenna arrays with fixed weights: There are several antenna arrays (windows) with fixed weight, such as, Bartlett, Chebychev, Blackman, Hanning, Hamming, Tukey, Natal, Gaussian and Kaiser. The main goal of these predefined weighting windows is to obtain an appropriate gain for improving the transmitting and/or receiving power (El-Zooghby, 2005).

Phased array antennas: These antenna arrays have very huge applications in recent years. In these antennas, for improving the transmitted or received signal, processing is held in Intermediate Frequency (IF) or Radio Frequency (RF) and the phase of each antenna element will be changed (Fakharzadeh Jahromi, 2008).

Digital Beam Forming: In digital beamforming, instead of hardware changes, major part of processing is done by digital processors in IF or baseband. This type of processing, increase the flexibility, reduce the size of the system and by using high speed processors and doing processes with software operations, the energy consumption will be decreased. By appropriate bemforming at the transmitter, receiver or both, we can reach to higher receiving power, better Signal to Noise Plus Interference Ratio (SNIR) and lower power consumption. In the following section, two major techniques for forming the radiation pattern of antenna arrays, fixed beam and adaptive processing, are discussed with more details (Balanis and Ioannides, 2007; Bellofiore *et al.,* 2002; Litva and Lo, 1996; Sarkar *et al.,* 2003; Sun *et al.,* 2009).

ANTENNA ARRAY SIGNAL PROCESSING

With the direction of the incoming signals known or estimated via Direction of Arrival (DOA) estimation methods, the next step is to use spatial processing techniques to improve the reception performance of the receiving antenna array based on this information. Some of these spatial processing techniques are referred to as beamforming because they can form the array radiation pattern to meet the requirements dictated by the wireless system. Given a one dimensional (1D) Uniform Linear Array (ULA) of elements (Fig. 3) and an impinging wave-front from an arbitrary point source, the directional power pattern P(θ) can be expressed as:

$$P(\theta)=\int a(x).e^{-j.\beta.d(x,\theta)}\,dx \qquad (1)$$

where, α (x) is the amplitude distribution along the array, β is the phase constant and d (x, θ) is the relative distance of the impinging wave-front, with an angle of arrival θ, has to travel between points uniformly spaced a distance x apart along the length of the array.

The exponential term is the one that primarily scans the beam of the array in a given angular direction. The integral of Eq. 1 can be generalized for two- and three-dimensional configurations. Equation 1 is basically the Fourier transform of α (x) along the length of the array and is the basis for beamforming methods. The amplitude distribution α (x), necessary for a desired P(θ), is usually difficult to implement practically. Therefore, most of the times, realization of (1) is accomplished using discrete sources, represented by a summation over a finite number of elements. Thus, by controlling the relative phase between the elements, the beam can be scanned electronically with some possible changes in the overall shape of the array pattern.

This is the basic principle of array phasing and beam shaping. The main objective of this spatial signal pattern shaping is to simultaneously place a beam maximum toward the Signal of Interest

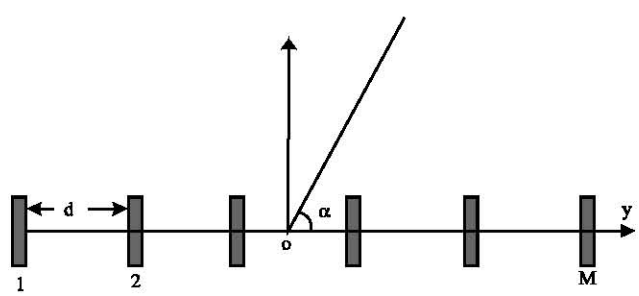

Fig. 3: 1-D uniform linear array

(SOI) and ideally nulls toward directions of interfering signal(s) or Signal Not of Interest (SNOI). This process continuously changes to accommodate the incoming SOIs and SNOIs. The signal processor of the array must automatically adjust the weight vector $W = [W_1, W_2 \ldots W_M]^T$ which corresponds to the complex amplitude excitation along each antenna element.

It is usually convenient to represent the signal envelopes and the applied weights in their complex envelope form. This relationship is represented by Eq. 2:

$$r(t)=\mathrm{Re}[x(t).e^{j\omega_c.t})] \tag{2}$$

where, ω_c is the angular frequency of operation and x (t) is the complex envelope of the received real signal r (t). The incoming signal is weighted by the array pattern and the output is represented by:

$$y(t)=\mathrm{Re}\left[\sum_{n=1}^{M} W_n^*(t).x_n(t).e^{j\omega_c.t}\right]=\mathrm{Re}[W^H(t).x(t).e^{j\omega_c.t}] \tag{3}$$

where, n indicates each of the array elements and $W^H(t).x(t)$ is the complex envelope representation of y (t). Since, for any modern electronic system, signal processing is performed in discrete-time, the weight vector W combines linearly the collected discrete samples to form a single signal output expressed as:

$$y(k)=\sum_{n=1}^{M} W_n^*.x_n(k)=W^H x(k) \tag{4}$$

where, k denotes discrete time index of the received signal sample being considered. The concept of beamforming is applicable in both continuous-time and discrete-time signals. Therefore, each element of the receiving antenna array possesses the necessary electronics to down-convert the received signal to baseband and for Analog-to-Digital (AD) conversion for digital beamforming.

To simplify the analysis, only baseband equivalent complex signal envelopes along with discrete-time processing will be considered herein. Various adaptive algorithms have already been developed to calculate the optimal weight coefficients that satisfy several criteria or constraints. Once the beamforming weight vector W is calculated, the response of this spatial filter is represented by the antenna radiation pattern (beampattern) for all directions, which is expressed as:

$$P(\theta)=\left|W^H(\theta).a(\theta)\right|^2 \tag{5}$$

where, 5, P (θ) represents the average power of the spatial filter output when a single, unity-power signal arrives from angle θ. With proper control of the magnitude and phase of W, the pattern will exhibit a main beam in the direction of the desired signal and, ideally, nulls toward the direction of the interfering signals (Balanis and Ioannides, 2007; Bellofiore *et al.,* 2002). In following subsections three classes of beamformers, classical, fixed-beam and adaptive algorithms are described.

(1) Classical beamformers: In classical beamforming, the beamforming weights are set to be equal to the array response vector of the desired signal. For each particular direction θ_0, the antenna pattern formed using the weight vector W_b has the maximum gain in this direction compared to any other possible weight vector of the same magnitude. This is accomplished because W_b adjusts the phases of the incoming signals arriving at each antenna element from a given direction θ_0 so that they add in-phase (or constructively). Because all the elements of the beamforming weight vector are basically phase shifts with unity magnitude, the system is commonly referred to as phased array. Mathematically, the desired response of the method can be justified by the Cauchy-Schwartz inequality:

$$\left|W^H(\theta).a(\theta_0)\right|^2 \leq \left\|W\right\|^2.\left\|a(\theta_0)\right\|^2 \tag{6}$$

for all vectors W, with equality holding if and only if W is proportional to α (θ_0). In the absence of array ambiguity, the effective pattern in Eq. 5 possesses a global maximum at θ_0. Even though the classical beamformer is the ideal choice to direct the maximum of the beampattern toward the direction of a SOI, since the complex weight vector W can be easily derived in closed form, it lacks the additional ability to place nulls toward any present SNOIs, often required in pragmatic scenarios. This is obvious when observing the expression in Eq. 5 where, besides the look direction θ_0, control of the beampattern cannot be achieved in the rest of the angular region of interest. Thus, to accommodate all the requirements, a more advanced spatial processing technique is necessary to be applied. As expected, the classical beamformer directs its maximum toward the direction of the SOI but fails to form nulls toward the directions of the SNOIs, since it does not have control of the beampattern, whereas the adaptive beamforming algorithms achieve simultaneously to form a maximum toward the direction of the SOI and place nulls in the directions of the SNOIs (Balanis and Ioannides, 2007; Bhobe and Perini, 2001).

(2)Fixed-beam methods: Depending on how the beamforming weights are chosen, beamformers can be classified as data independent or statistically optimum. The weights in a data independent beamformer do not depend on the received array data and are chosen to present a specified response for all signal and interference scenarios. In practice, propagating waves are perturbed by the propagating medium or the receive mechanism. In this case, the plane wave assumption may no longer hold and weight vectors based on plane-wave delays between adjacent elements will not combine coherently the waves of the desired signal (El-Zooghby, 2005).

Matching of a randomly perturbed signal with arbitrary characteristics can be realized only in a statistical sense by using a matrix weighting of input data which adapts to the received signal characteristics. This is referred to as statistically optimum beamforming. In this case, the weight vectors are chosen based on the statistics of the received data. The weights are selected to optimize the beamformer response so that the array output contains minimal contributions due to noise and signals arriving from directions other than that of the desired signal (Godara, 2004).

Any possible performance degradation may occur due to a deviation of the actual operating conditions from the assumed ideal and can be minimized by the use of complementary methods that introduce constraints. Due to the interest in applying array signal processing techniques in cellular communications, where mobile units can be located anywhere in the cell, statistically optimum beamformers provide the ability to adapt to the statistics of different subscribers. There exist different criteria for determining statistically-optimum beamformer weights (Gross, 2005). Three of them are reviewed in this section.

The essential goal of the fixed beam methods is to locate the main lobe of the radiation pattern in the direction of the signal and set to zero the radiation pattern in the direction of interference signals. There exist three different criteria for determining statistically-optimum beamformer weights, that are Maximum Signal to Noise Plus Interference Ratio (MaxSNIR), Minimum Mean Square Error (MMSE) and Linearly Constrained Minimum Variance (LCMV).

(a) Maximum Signal to Noise Plus Interference Ratio (MaxSNIR): In the case of more than one user in the communication system, it is often desired to suppress the interfering signals, in addition to noise, using appropriate signal processing techniques. There are some intuitive methods to accomplish this, for example, the Multiple Side lobe Canceller (MSC). The basic idea of the MSC is that the conventional beamforming weight vectors for each of the signal sources are first calculated and the final beamforming vector is a linear combination of them in a way that the desired signal is preserved whereas all the interference components are eliminated. MSC has some limitations, however. For instance, for a large number of interfering signals it cannot cancel all of them adequately and can result in significant gain for the noise component. The solution to these limitations is the maximum SNIR beamformer that maximizes the output signal to noise and interference power ratio (Balanis and Ioannides, 2007; Godara, 2004).

As depicted in Fig. 4, the output of the beamformer is given by:

$$y = W^H.X = W^H(s+n+i) = y_s + y_{NI} \tag{7}$$

where, all the components collected by the array at a single observation instant are N×1 complex vectors and are classified as s is the desired signal component arriving from DOA θ_0, $i = \sum_{i=1}^{I} s_i$ the interference component (assuming I such sources to be present) and n is the noise component. In (7), we also separate the desired signal array response weighted output, $y_s = W^H.S$ and the interference-plus-noise total array response, $y_{NI} = W^H.(n+i)$.

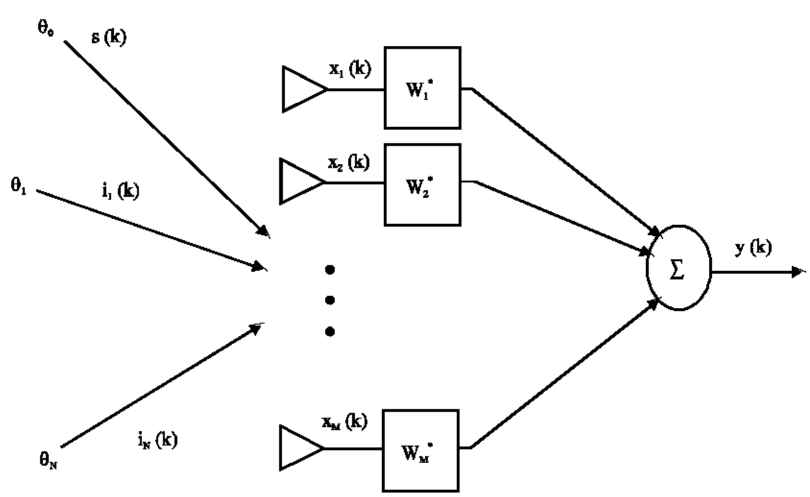

Fig. 4: Antenna array structure with MaxSNIR weighting

Consequently, the weighted array signal output power is

$$E\{|y_s|^2\} = W^H.E\{s.s^H\}.W = W^H.R_{ss}.W \tag{8}$$

where, R_{ss} is the auto-covariance matrix of the signal vectors S and the weighted noise plus interference output power is

$$E\{|y_{NI}|^2\} = W^H.E\{|i+n|^2\}.W = W^H.R_{NI}.W \tag{9}$$

where, R_{NI} is the auto-covariance matrix of the vectors i+n. Therefore, the weighted output SNIR can be expressed as:

$$\frac{E\{|y_s|^2\}}{E\{|y_{NI}|^2\}} = \frac{W^H.R_{ss}.W}{W^H.R_{NI}.W} \tag{10}$$

By appropriate factorization of R_{NI} and manipulation of the SNIR expression, the maximization problem can be recognized as an eigen-decomposition problem. The expression for W that maximizes the SNIR is found to be:

$$W_{MaxSNIR} = R_{NI}^{-1}.a(\theta_0) \tag{11}$$

This is the statistical optimum solution in maximizing the output SNIR in a noise plus interference environment, but it requires a computationally intensive inversion of R_{NI}, which may be problematic when the number of elements in the antenna array is large.

(b) Minimum Mean Square Error (MMSE): If sufficient knowledge of the desired signal is available, a reference signal d can be generated. A block diagram of an antenna array system using reference signals is shown in Fig. 5. These reference signals are used to determine the optimal

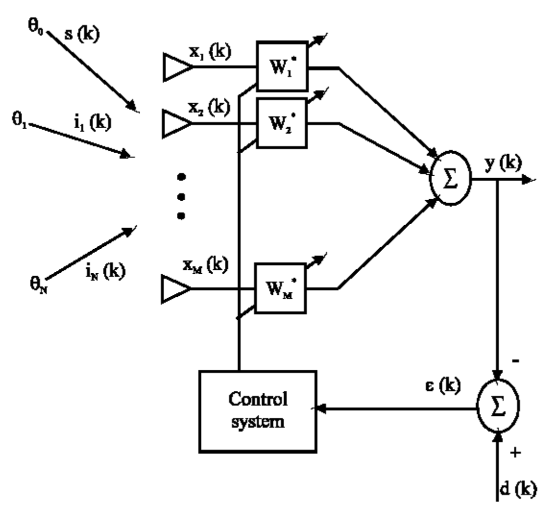

Fig. 5: Antenna array structure with MMSE or LCMV techniques

weight vector. This is done by minimizing the mean square error of the reference signals and the outputs of the M-element antenna array. The concept of reference signal use in antenna array system was first introduced by Widrow in where he described several pilot-signal generation techniques (Balanis and Ioannides, 2007; Moghaddam and Saremi, 2010).

For beamforming considerations, the reference signal is usually 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 desired signal is usually referred to spatial reference. The temporal reference is of vital importance in a fading environment due to lack of angle of arrival information. The array reference signal need not necessarily be an exact replica of the desired signal, even though this is what occurs in most of the cases. In general, it can be unknown but needs to be correlated with the desired signal and uncorrelated with any possible interference.

As depicted in Fig. 5, at each observation instance k, the error e (k) between the reference signal d (k) and the weighted array output y (k) is given by:

$$e(k) = d(k) - y(k) = d(k) - W^H.x(k) \quad (12)$$

Mathematically, the MMSE criterion can be expressed as:

$$\min_W \left\{ E\left[|e(k)|^2 \right] \right\} \quad (13)$$

In order to get a meaningful result, the objective function needs to have explicit dependency on the conjugate of the weight vector. This simply usually translates into changing transposition to conjugate transposition (or Hermitian). Therefore, we have

$$\frac{\partial |e\,(k)|^2}{\partial W^*} = -2e^*\,(k).x\,(k) \quad (14)$$

To minimize the objective function, we set Eq. 14 to zero. Considering additionally the expectation value of the minimum of $|e\,(k)|^2$, it yields

$$2R_{xx}.W - 2r_{xd} = 0 \quad (15)$$

where, $R_{xx} = E\{X.X^H\}$ is the signal auto-covariance matrix and $r_{xd} = E\{X.d^*\}$ is the reference signal covariance vector. Thus, the optimal MMSE weight solution is given by Eq. 16.

$$W_{MSE} = R_{XX}^{-1}.r_{xd} \quad (16)$$

and is usually referred to as the Wiener-Hopf solution. One disadvantage using this method is the generation of an accurate reference signal based on limited knowledge at the receiver.

(c) Linearly Constrained Minimum Variance (LCMV): In the MMSE criterion, the Wiener filter minimizes the MSE with no constraints imposed on the solution (i.e., the weights). However, it may be desirable, or even mandatory, to design a filter that minimizes a mean square criterion subject to a specific constraint. The LCMV constrains the response of the beamformer so that signals from the direction of interest are passed through the array with a specific gain and phase. However it requires knowledge, or prior estimation, of the desired signal array response $\alpha\,(\theta_0)$ with DOA θ_0. Its weights are chosen to minimize the expected value of the output power/variance subject to the response constraints (Balanis and Ioannides, 2007, Godara, 2004). That is

$$\min_W\{W^H.R_{XX}.W\}\ \text{subject to}\ C^H.W=g^* \tag{17}$$

$C\epsilon\ C^{NxK}$ has K linearly independent constraints and $g\epsilon C^{K\times 1}$ is the constraint response vector.

The constraints have an effect of preserving the desired signal while minimizing contributions to the array output due to interfering signals and noise arriving from undesired directions. The solution to this constrained optimization problem requires the use of the Lagrange multiplier vector $b\epsilon C^K$. Letting F (W) = $W^H.R_{xx}.W$ be the cost function and G (W) = C^H. W-g* = 0 be the constraint function, the following expression is formed:

$$H(W)=\frac{1}{2}F(W)+b^H.G(W)=\frac{1}{2}W^H.R_{XX}.W+b^H.(C^H.W-g^*) \tag{18}$$

F (W) has its minimum value at a point W subject to the constraint G (W) = C^H W-g* = 0, i.e., when H (W) is minimum. Therefore, to find the minimum point in Eq. 18, we differentiate with respect to W and set it equal to zero, which yields:

$$W_{opt}=-R_{XX}^{-1}.C.b \tag{19}$$

$$b=-[C^H.R_{XX}^{-1}.C]^{-1}.g^* \tag{20}$$

where, the existence of $[C^H.R_{xx}^{-1}.C]$ follows from the fact that R_{xx} is positive definite and C is full-rank. Therefore, the LCMV estimate of the weight vector is

$$W_{opt}=-R_{XX}^{-1}.[C^H.R_{XX}^{-1}.C]^{-1}.g^* \tag{21}$$

As a special case, a requirement would be to force the beam pattern to be constant in the bore-sight direction; concisely, this can be stated mathematically as:

$$\min_w\{W^H.R_{XX}.W\}\ \text{subject to}\ W^H.\alpha(\theta_0)=g^* \tag{22}$$

where, g is a complex scalar which constrains the output response to $\alpha\,(\theta_0)$. In this case, the LCMV weight estimate is

$$W_{opt}=g^*.\frac{R_{XX}^{-1}\,\alpha(\theta_0)}{\alpha^H(\theta_0).R_{XX}^{-1}.\alpha(\theta_0)} \tag{23}$$

For the special case when g = 1 (i.e., the gain constant is unity), the optimum solution of Eq. 23 is termed as the Minimum Variance Distortionless Response (MVDR) or Minimum Variance (MV) beamformer. The advantage of using LCMV criteria is general constraint approach that permits extensive control over the adapted response of the beamformer. It is a flexible technique that does not require knowledge of the desired signal auto-covariance matrix R_{xx}, the noise plus interference auto-covariance matrix R_{NI}, or any reference signal d (k). A certain level of beamforming performance can be attained through the design of the beamformer, allowed by the constraint matrix. However, the LCMV is computationally complex.

(d) Simulation results of fixed-beam methods: By comparing three well-known methods for fixed-beam forming the antenna array pattern, considering 8-element uniform linear antenna array, the following simulation results are obtained. These results can be extended to different element numbers or other array geometries.

As depicted in Fig. 6, when the angle of interference signal is close to the angle of the main one, the amplitude of the main signal (maximum gain of Array Factor (AF) that pointed to the source signal) will be decreased. The performance of MaxSIR and MMSE methods are similar and they have higher gain than MVDR method.

Figure 7 shows that the SNIR in MMSE algorithm is higher than other methods. After that, MVDR has high SNIR. In MaxSIR, because the angle of the main signal is not considered in calculations, it has lower SNIR than others.

As illustrated in Fig. 8, Bit Error Rate (BER) for MMSE method is lower than other methods. After that, before the angle of 5 degrees, MaxSIR has lower BER. In other words, in low angular differences, MMSE has the best performance among all other methods. Despite the MaxSIR algorithm, BER of other methods tend to zero for high angular differences, i.e., the accuracy of weighting algorithm for MMSE and MVDR methods are increased in high angular differences.

Figure 9 shows the variations of Normalized Mean Square Error (NMSE) in terms of different signal to noise ratios. As depicted in this figure, NMSE in MMSE method is lower than others. MaxSIR is the second one. It means that, in low SNRs, the best algorithm in terms of NMSE, is MMSE. In high SNRs, the performance of all methods is similar.

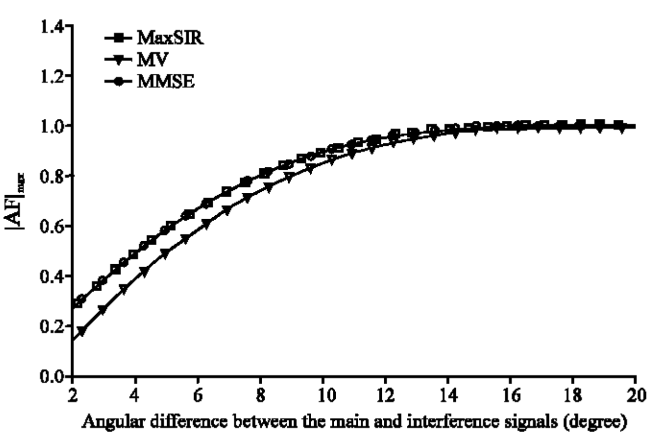

Fig. 6: Maximum array factor gain vs. angular difference

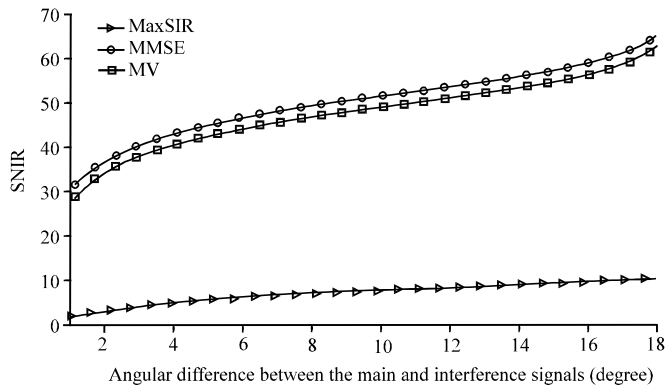

Fig. 7: Signal to noise plus interference ratio vs. angular difference

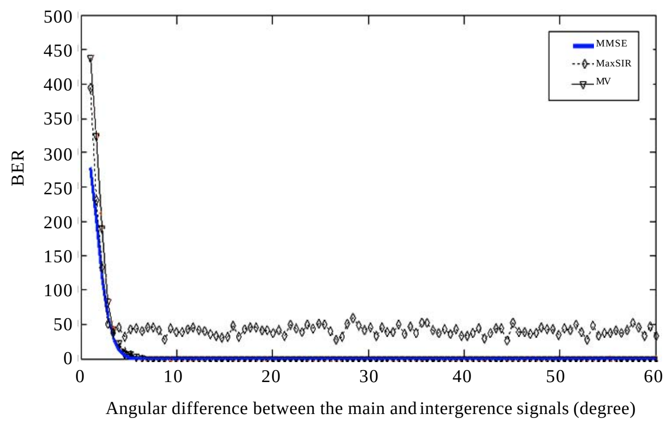

Fig. 8: Bit error rate vs. angular difference

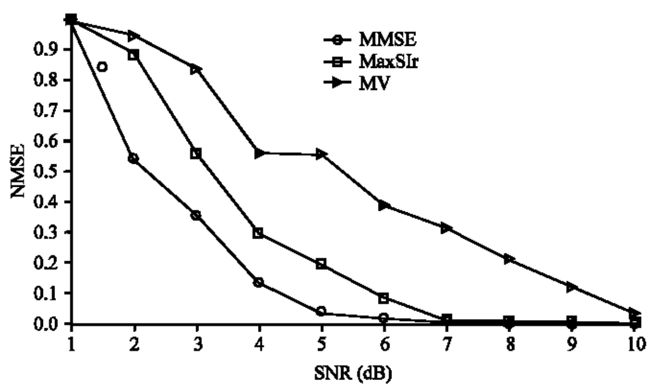

Fig. 9: Normalized MSE in different SNRs

(3) Adaptive processing: As previously shown in fixed-beam methods, statistically optimum weight vectors for beamforming can be calculated by the Wiener solution. However, knowledge of the asymptotic Second Order Statistics (SOS) of the signal and the interference-plus-noise was assumed. These statistics are usually not known but with the assumption of ergodicity, where the time average equals the ensemble average, they can be estimated from the available data. For

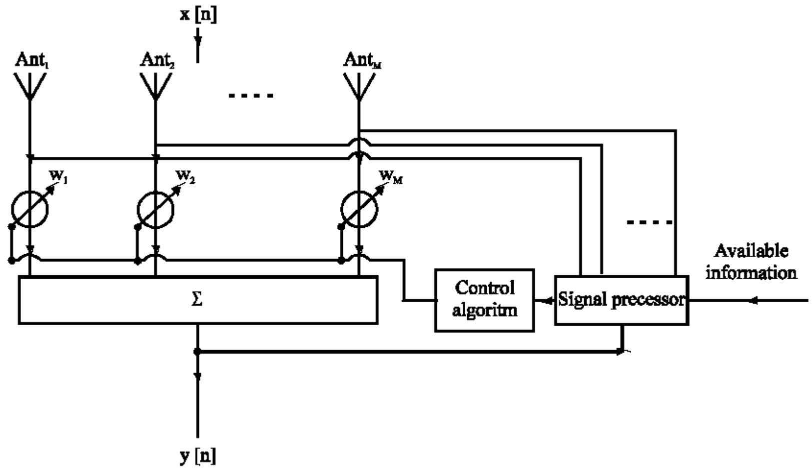

Fig. 10: Adaptive antenna array structure

time-varying signal environments, such as wireless cellular communication systems, statistics change with time as the source and interferers move around the cell. For the time-varying signal propagation environment, a recursive update of the weight vector is needed to track a moving mobile so that the spatial filtering beam will adaptively steer to the target mobile's time-varying DOA, thus resulting in optimal transmission/reception of the desired signal. To solve the problem of time-varying statistics, weight vectors are typically determined by adaptive algorithms which adapt to the changing environment (Fuhl and Bonek, 1998, Haykin, 1996).

In adaptive beamforming, according to the system condition, antenna array and its radiation pattern adjusted dynamically. Thus, in this system, there is a processing unit. Types of antennas (sensors) and forwarding information to the processor depend on the application. For example, communication system that uses information of different signals to process the main signal and separating it from others is one of these applications.

Figure 10 shows a generic adaptive antenna array system consisting of an M-element antenna array with a real time adaptive array signal processor containing an update control algorithm. The data samples collected by the antenna array are fed into the signal processing unit which computes the weight vector according to a specific control algorithm. Steady-state and transient-state are the two classifications of the requirement of an adaptive antenna array. These two classifications depend on whether the array weights have reached their steady-state values in a stationary environment or are being adjusted in response to alterations in the signal environment. If we consider that the reference signal for the adaptive algorithm is obtained by temporal reference, a priori known at the receiver during the actual data transmission, we can either continue to update the weights adaptively via a decision directed feedback or use those obtained at the end of the training period.

Several adaptive algorithms can be used such that the weight vector adapts to the time-varying environment at each sample. As depicted in Fig. 11, there are two major types of adaptive weighting algorithms, i.e., training-based methods and blind methods. In training-based methods, such as, Least Mean Squares (LMS) and Recursive Least Squares (RLS), one reference signal is required. In contrast, in blind methods, such as, Constant Modulus (CM), Least Squares (LS), Decision Directed (DD) and Conjugate Gradient (CG), the only thing that is required is the DOA

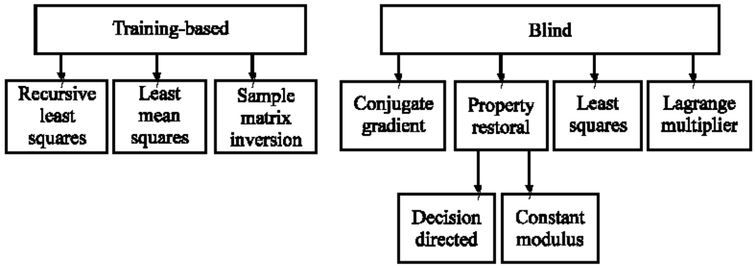

Fig. 11: Adaptive array processing algorithms

of the main signal (source) and other information should be obtained from received signal. In the following, Sample Matrix Inversion (SMI), LMS and RLS algorithms of training-based category and CM, LS and DD algorithms of blind category is reviewed with more details. In addition, some simulation results of LMS and CM algorithms are illustrated (Godara, 2004; Gross, 2005).

Sample Matrix Inversion (SMI) algorithm: If the desired and interference signals are known a priori, (16) provides the most direct and fastest solution to compute the optimal weights. However, the signals are not known exactly since the signal environment undergoes frequent changes. Thus, the signal processing unit must continually update the weight vector to meet the new requirements imposed by the varying conditions. This need to update the weight vector, without a priori information, leads to estimating the covariance matrix, R_{xx} and the cross-correlation vector, r_{xd}, in a finite observation interval. Note that this is a block-adaptive approach where the statistics are estimated using temporal blocks of the array data. The adaptivity is achieved via a sliding window, say of length L symbols. The estimates R_{xxest} and r_{xdest} can be evaluated as:

$$R_{xxest} = \frac{1}{L}\sum_{i=N_1}^{N_2} X(i).X^H(i) \tag{24a}$$

$$R_{xdest} = \frac{1}{L}\sum_{i=N_1}^{N_2} X(i).d^{*}(i) \tag{24b}$$

where, N_1 and N_2 are, respectively, the lower and upper limits of the observation interval such that $N_2 = N_1 + L - 1$. Thus, the estimate for the weight vector is given by

$$W_{MSEest} = R_{xxest}^{-1}.r_{xdest}^{-1} \tag{25}$$

The advantage of the method is that it converges faster than any adaptive method and the rate of convergence does not depend on the power level of the signals. However, two major problems are associated with the matrix inversion. First, the increased computational complexity cannot be easily solved through the use of integrated circuits and second, the use of finite-precision arithmetic and the necessity of inverting a large matrix may result in numerical instability (Li and Stoica, 2006).

Least Mean Square (LMS) algorithm: The LMS algorithm is probably the most widely used adaptive processing algorithm, being employed in several communication systems. It has gained popularity due to 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 estimated gradient based on the negative steepest descent method. By the quadratic characteristics of the mean square-error function $E\{|e(k)|^2\}$ that has only one minimum, the steepest descent is guaranteed to converge. At adaptation index K, given a MSE function $E\{|e(k)|^2\} = E\{|d(k)-W^H.x(k)|^2\}$ the LMS algorithm updates the weight vector according to

$$W(k+1) = W(k) - \frac{\mu}{2}.\frac{\partial|e(k)|^2}{\partial W^*} = W(k) + \mu.e^*(k).x(k) \quad (26)$$

where, the rate of change of the objective function $|e(k)|^2$ has been derived earlier in (14) and μ is a scalar constant which controls the rate of convergence and stability of the algorithm. In order to guarantee stability in the mean-squared sense, the step size μ should be restricted in the interval

$$0 < \mu < \frac{2}{\lambda_{max}} \quad (27)$$

where, λ_{max} is the maximum eigenvalue of R_{xx} Alternatively, in terms of the total power of the x

$$\lambda_{max} \le trace\{R_{xx}\} \quad (28)$$

where

$$trace\{R_{xx}\} = \sum_{i=1}^{M} E\{x_i^2\}$$

is the total input power. Therefore, a condition for satisfactory Wiener solution convergence of the mean of the LMS weight vector is

$$0 < \mu < \frac{2}{\sum_{i=1}^{M} E\{x_i^2\}} \quad (29)$$

where, M is the number of elements in the array. A significant drawback from the use of the LMS algorithm is its slow convergence for colored noise input signals. The LMS algorithm is a member of a family of stochastic gradient algorithms since the instantaneous estimate of the gradient vector is a random vector that depends on the input data vector x (k). It requires about 2 M complex multiplications per iteration, where M is the number of weights (elements) used in the adaptive array. The convergence characteristics of the LMS depend directly on the Eigen-structure of R_{xx}. Its convergence can be slow if the Eigen-values are widely spread. When the covariance matrix Eigen-values differ substantially, the algorithm convergence time can be exceedingly long and highly data dependent. Therefore, depending on the Eigen-value spread, the LMS algorithm may not have sufficient iteration time for the weight vector to converge to the statistically optimum solution and adaptation in real time to the time-varying environment will not be able to be performed. In addition, employing the LMS algorithm, it is assumed that sufficient knowledge of the desired signal is known (Enosawa *et al.*, 2006; Moghaddam *et al.*, 2010a, b).

Recursive Least Squares (RLS) algorithm: 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 LS to adjust the weight vector, without imposing the additional burden of approximating an optimization procedure. In the method of least squares, the weight vector W (k) is chosen so as to minimize a cost function that consists of the sum of error squares over a time window, i.e., the LS solution is minimized recursively. In the method of steepest-descent, on the other hand, the weight vector is chosen to minimize the ensemble average of the error squares. The recursions for the most common version of the RLS algorithm are a result of the Weighted Least Squares (WLS) objective function

$$|e(k)|^2 = \sum_{i=1}^{k} \lambda^{k-1}.|e(i)|^2 \quad (30)$$

where, the error signal e (i) has been defined earlier and $0<\lambda\leq 1$ is an exponential scaling factor which determines how quickly the previous data are de-emphasized and is referred to as the forgetting factor. Usually, λ is chosen close to, but less than, unity. However, in a stationary environment λ should be equal to 1, since all data past and present should have equal weight. Differentiating the objective function $|e(k)|^2$ with respect to W* and solving for the minimum yields

$$\left[\sum_{i=1}^{k} \lambda^{k-1}.x(i).x^H(i)\right].W(k) = \sum_{i=1}^{k} \lambda^{k-1}.x(i).d^*(i) \quad (31)$$

Furthermore, defining the quantities

$$R(k) = \sum_{i=1}^{k} \lambda^{k-1}.x(i).x^H(i) \quad (32)$$

and

$$p(k) = \sum_{i=1}^{k} \lambda^{k-1}.x(i).d^*(i) \quad (33)$$

the solution is obtained as:

$$W(k) = R^{-1}(k).p(k) \quad (34)$$

The recursive implementations are a result of the formulations

$$R(k) = \lambda.R(k-1) + x(k)x^H(k) \quad (35)$$

and

$$p(k)=\lambda.p(k-1)+x(k)d^{*}(k) \tag{36}$$

The R^{-1} (k) can be obtained recursively in terms of R^{-1} (k-1), thus avoiding direct inversion of R (k) at each time instant k.

An important feature of the RLS algorithm is that it utilizes information contained in the input data, extending back to the time instance the algorithm was initiated. The resulting rate of convergence is therefore typically an order of magnitude faster than the simple LMS algorithm. This improvement in performance, however, is achieved at the expense of a large increase in computational complexity. Other drawbacks associated with its implementation are potential divergence behavior in a finite-precision environment and stability problems that usually result in loss of symmetry and positive definiteness of the matrix R^{-1} (k) (Balanis and Ioannides, 2007; Chen *et al.,* 2004; Santi Rani *et al.,* 2009; Skolnik, 2002).

Constant Modulus (CM) algorithm: This algorithm is first proposed by Godard and it uses the constant envelope feature that is existed in some techniques that modulate information in phase or frequency of the signal such as, M-ary Frequency Shift Keying (MFSK) and M-ary Phase Shift Keying (MPSK) modulations. By calculating this envelope, adaptive beamforming algorithm can be managed. CM algorithm uses a cost function, named as diffraction function of order p and after minimization, the optimum weights can be obtained. The Godard's cost function is shown in Eq. 36.

$$J(k)=E\left\{\left(|y(k)|^{p}-R_{p}\right)^{2q}\right\} \tag{37}$$

where, p and q are equal to 1 or 2. Godard showed that if R_p is defined as in Eq. 38, the slope of the cost function will be zero.

$$R_{p}=\frac{E\left\{|s(k)|^{2p}\right\}}{E\left\{|s(k)|^{p}\right\}} \tag{38}$$

where s (k) is the memoryless estimation of y (k) and then the estimation error is:

$$e(k)=y(k)|y(k)|^{p-2}\left(R_{p}-|y(k)|^{p}\right) \tag{39}$$

If we assume that p = 1, the cost function has the form as in Eq. 40.

$$J(k)=E\{(|y(k)|-R_{1})^{2}\} \tag{40}$$

$$R_{1}=\frac{E\left\{|s(k)|^{2}\right\}}{E\left\{|s(k)|\right\}} \tag{41}$$

By rewriting the error signal in Eq. 38 and 41 can be derived.

$$e(k) = y(k) - \frac{y(k)}{|y(k)|} \tag{42}$$

Updating equation of weights is:

$$W(k+1) = W(k) + \mu\left(1 - \frac{1}{|y(k)|}\right)y^*(k)x(k) \tag{43}$$

It has been shown that the fastest convergence is obtained by using p = 1.

This method has some problems. One of them is that the algorithm simply locks on the strongest signal with constant envelope, even if this signal is interference. In multiuser environments, by changing the initial condition of array, i.e., array weighting before the starting time, we can lock on different signals, if signals have the same power. Another problem of this algorithm is higher convergence time in comparison with other algorithms that use MMSE criteria directly (Ghadian and Moghaddam, 2010; Yuvapoositanon and Chambers, 2002).

Decision Directed (DD) algorithm: In this algorithm, a reference signal is generated based on the outputs of a threshold decision device. The beamformer output y (k) is demodulated to obtain the signal q (k). The decision device then compares q (k) to the known alphabet of the transmitted data sequence and makes a decision in favor of the closest value to q (k) denoted by r (k). The reference signal is obtained by modulating r (k) then the cost function for the beamformer is established. The DD algorithm convergence depends on the ability of the receiver to lock onto the desired signal. Since, it may not always be able to do that, the convergence is not guaranteed (Moghaddam and Saremi, 2010; Moghaddam and Saremi, 2008).

Least Squares (LS) algorithm: Using the standard array model, we can write the received signal at the array output as:

$$X(k) = A.S(k) + N(k) \tag{44}$$

where, $X(k) = [x_1(k), x_2(k), ..., x_M(k)]^T$, $S(k) = [s_1(k), s_2(k), ..., s_M(k)]^T$ is the signal vector and $N(k) = [n_1(k), n_2(k), ..., n_M(k)]^T$ is the noise vector.

The LS algorithm minimizes the Maximum Likelihood (ML) criterion as Eq. 45 to find proper A that equals to weighting vector (Balanis and Ioannides, 2007, Shirvani Moghaddam and Saremi, 2010).

$$\min_{S \in \Omega} \|X - A.S\| \tag{45}$$

Simulation results of least mean squares algorithm: This section shows some simulation results of an antenna array considering LMS algorithm in different environmental conditions such as noise, interference and number of array elements.

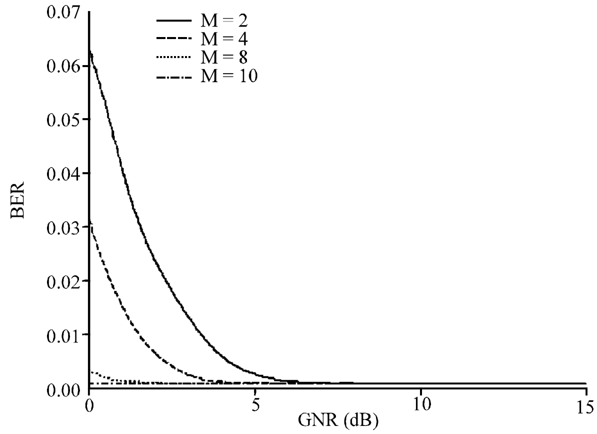

Fig. 12: BER vs. SNR for different number of ULA elements in a noisy channel

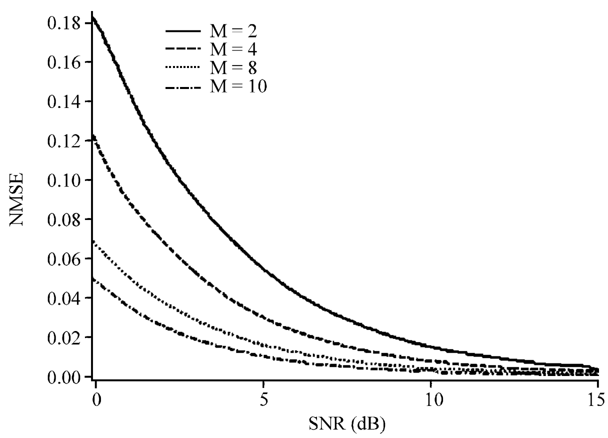

Fig. 13: Normalized MSE vs. SNR for different number of ULA elements in a noisy channel

As depicted in Fig. 12 and 13, increasing the signal to noise ratio and also the number of array elements are the reason for decreasing BER and NMSE. Higher number of array elements introduces more computational complexity but it offers lower performance criteria (BER and NMSE) rather than lower number of array elements. As it shows, in a noisy channel, BER will be equal to zero in SNR = 8 dB and SNR = 0 dB for M = 2 and M = 16, respectively. On the other hand, NMSE will be equal to zero in SNR = 15 dB and SNR = 10 dB for M = 2 and M = 16, respectively.

Figure 14 and 15 show the simulation results of a receiver equipped with a uniform linear array in the case of noisy channel with one interference signal that its power equals to source signal. It means Signal to Interference Ratio (SIR) equals to 0 dB. Due to adding an interference, BER and NMSE in the Fig. 14 and 15 are higher than those belong to Fig. 12 and 13.

To illustrate the effect of the power of interference signal, simulations are repeated for an 8-element ULA in SIR = 0, 1, 3 and 10 dB. In SIR = 0 dB the power of source and interference signals are the same and in SIR = 10 dB, source signal is 10 times stronger than interference signal. Figure 16 and 17 show BER and NMSE of a LMS-based 8-element ULA adaptive antenna array system for different SIRs.

These simulation results show that the antenna array equipped with LMS algorithm introduces good performance under different conditions. In noise dominant environment, increasing the

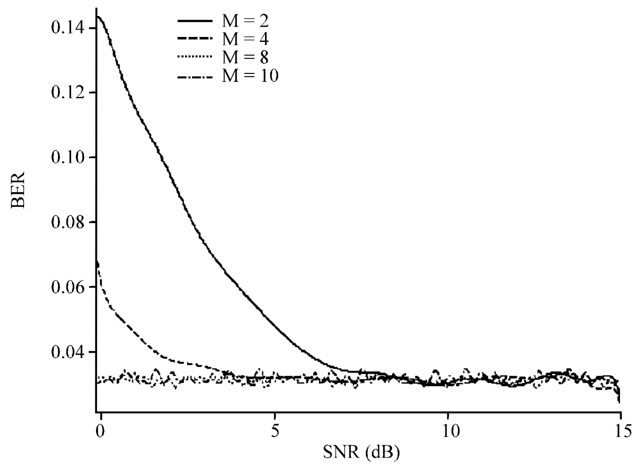

Fig. 14: BER vs. SNR for different number of ULA elements in a noisy channel with one interferer (SIR = 0dB)

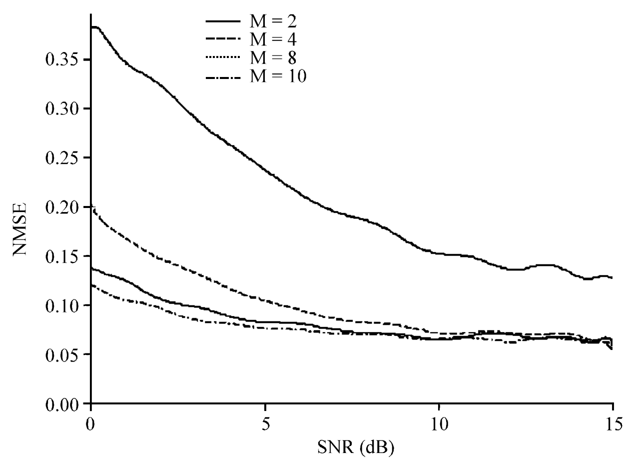

Fig. 15: Normalized MSE vs. SNR for different number of ULA elements in a noisy channel with one interferer (SIR = 0dB)

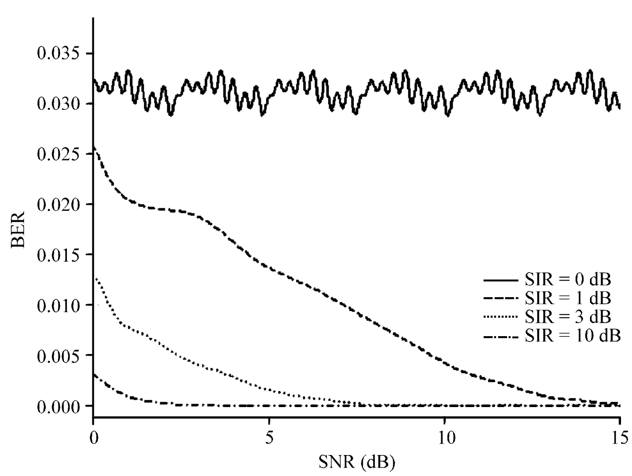

Fig. 16: BER vs. SNR for different SIRs in a noisy channel with one interferer and 8-element ULA

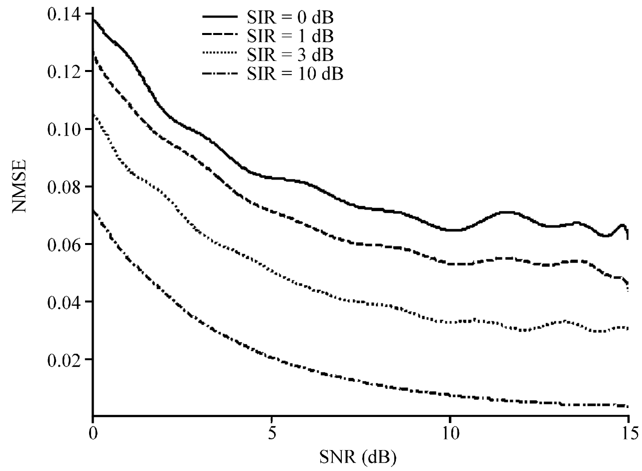

Fig. 17: Normalized MSE vs. SNR for different SIRs in a noisy channel with one interferer and 8-element ULA

number of array elements has a sensible impact on system performance. Also in channel with interference signals, system is able to reject the interference signals. Besides, simulations show that the performance of the system will be changed in terms of different SIRs.

Simulation results of constant modulus algorithm: In this section, performance of constant modulus algorithm, in 8-element uniform linear array, different SNRs, two channels (pure noisy and noisy channel with one interferer) are evaluated based on BER, NMSE and polar radiation pattern. Simulations are carried out under stationary scenarios. To get each result, simulations are repeated 1000 times. In all simulations, the SOI-DOA (source signal) is 40°. Also, Binary Phase Shift Keying (BPSK) modulation is employed.

As depicted in Fig. 18, after 1000 snapshots, main lobe of antenna array pattern is adjusted to 40°C.

Figure 19 and 20 show BER and normalized MSE of a receiver equipped with digital beamforming system based on CMA. This beamforming system includes 8-element ULA. As depicted in these figures, BER and NMSE are increased whereas the number of iterations (snapshots) is increased. It is obvious that after 1000 iterations, BER converge to 0.015 and NMSE converge to 0.01. In this interference-free simulation, the step size was set equal to 0.001.

After 1000 snapshots, BER and NMSE will be constant. In this situation, for different signal to noise ratios, antenna array beamforming considering CM algorithm is repeated and output BER and NMSE are plotted in Fig. 21 and 22. As expected, increasing SNR force BER and NMSE to be decreased.

Figure 23 shows antenna array radiation pattern of a receiver equipped with 8-element ULA applying CM algorithm after 1000 snapshots. As shown, the main lobe is pointed to SOI-DOA (40°) and the first null is in the direction of interferer (20°). As depicted in Fig. 24 and 25, in the case of noisy channel with one interference, also increasing the SNR is the reason for decreasing BER and NMSE.

In this research, the effect of adaptive step size on the results is also investigated. One can deduce from simulation results that increasing the power and number of interference signals is the

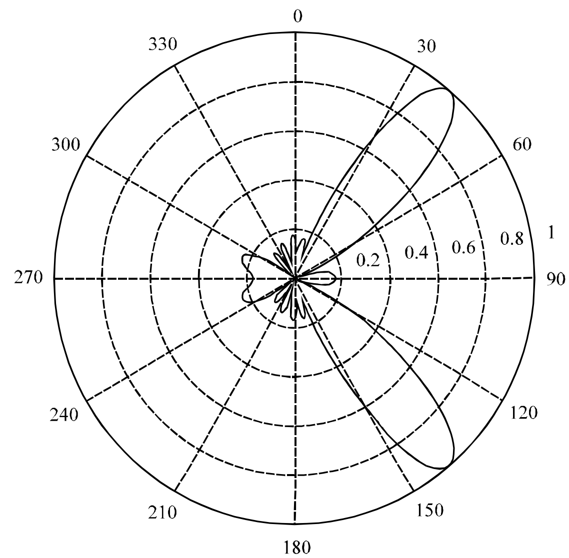

Fig. 18: Polar radiation pattern of 8-element ULA in a noisy channel (SNR = 10dB, SOI-DOA=40°)

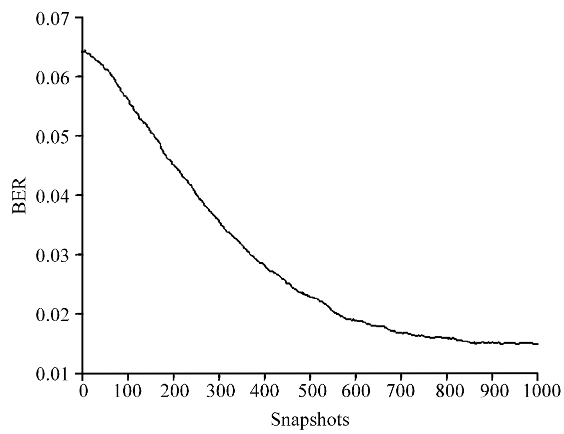

Fig. 19: BER vs. snapshots for 8-element ULA in a noisy channel (SNR = 10dB, SOI-DOA = 40°)

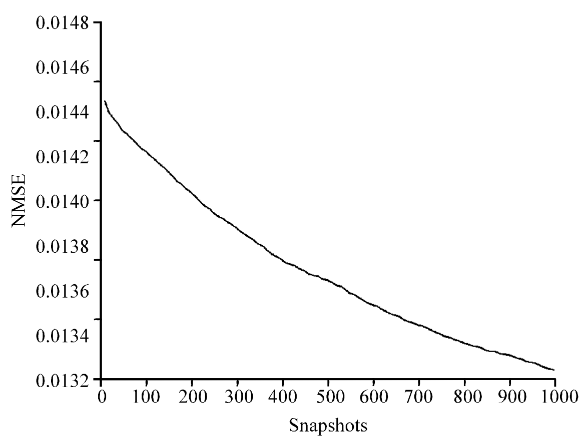

Fig. 20: NMSE vs. snapshots for 8-element ULA in a noisy channel (SNR = 10dB, SOI-DOA= 40°)

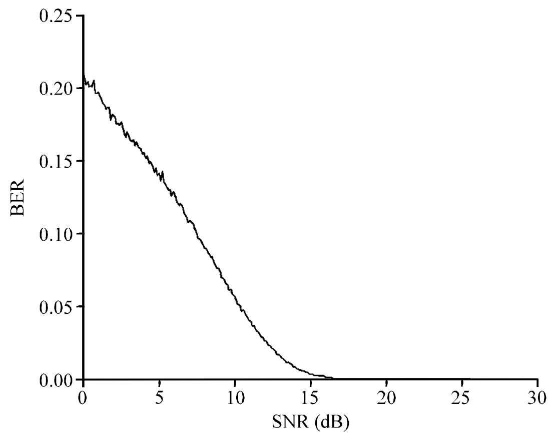

Fig. 21: BER vs. SNR for 8-element ULA in a noisy channel (SOI-DOA=40°)

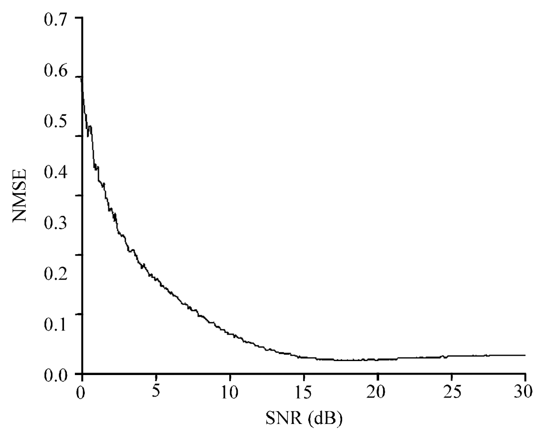

Fig. 22: NMSE vs. SNR for 8-element ULA in a noisy channel (SOI-DOA=40°)

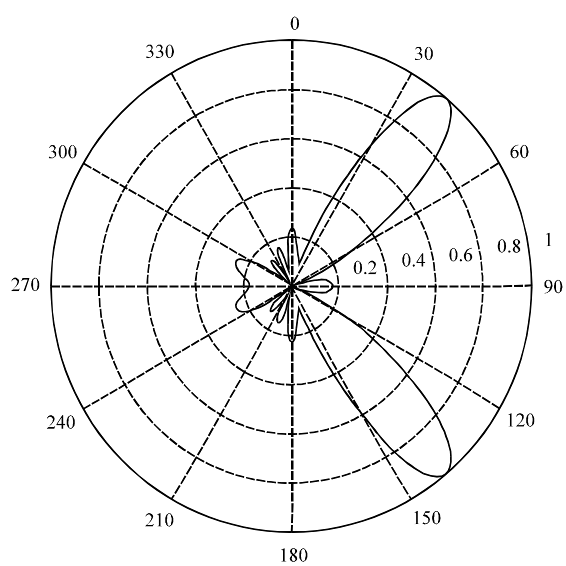

Fig. 23: Polar radiation pattern of 8-element ULA in a noisy channel with one interferer (SNR = 10dB, SIR = 0dB, SOI-DOA = 40°, SNOI-DOA = 20°)

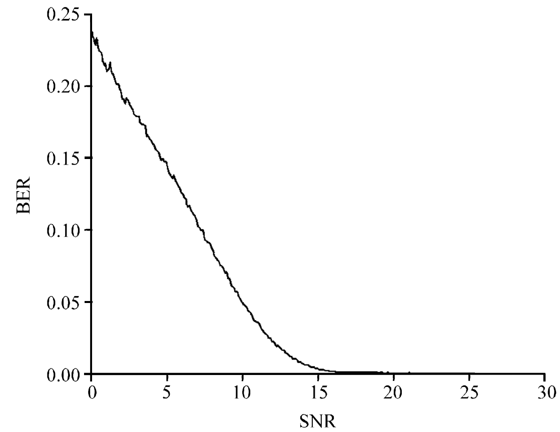

Fig. 24: BER vs. SNR for 8-element ULA in a noisy channel with one interferer (SIR = 0dB, SOI-DOA = 40°, SNOI-DOA=20°)

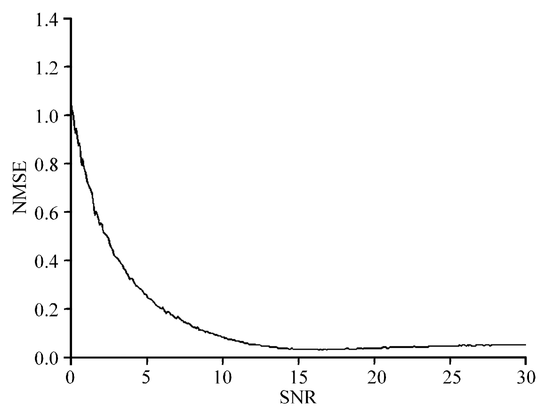

Fig. 25: NMSE vs. SNR for 8-element ULA in a noisy channel with one interferer (SIR = 0dB, SOI-DOA=40°, SNOI-DOA=20°)

reason to decrease the CMA step size and to increase the number of array elements. In addition, some new modified versions of CMA are introduced in Ghadian and Moghaddam (2010).

Comparing adaptive processing algorithms: Table 1 compares three training-based and two blind methods and show advantages as well as disadvantages. As we know, training-based methods have a real convergence point but they require a training sequence or reference signal. In contrast, blind methods may be diverged and their performance depends on channel conditions, however, they don't have a large amount of information as training-based methods (Li and Stoica, 2006, Liberti and Rappaport, 1999).

Table 1: Comparison of adaptive beamforming techniques

Algorithm	Advantages	Disadvantages
LMS	Always converges	Requires training sequence
SMI	Always converges, Faster than LMS	Requires training sequence, Computationally complex
RLS	Always converges, 10 times faster than LMS	Requires training sequence and R_{xx}^{-1}
CM	Does not require training sequence	Theoretically may not converge
DD	Does not require training sequence	High dependency on quality of the received signal

CONCLUSIONS

Today, wireless communication systems have progressed in the way that their effects on various aspects of human life are very obvious. Smart Antenna systems have received much attention in the last few years because they can increase system capacity (very important in urban and densely populated areas) by dynamically tuning out interference while focusing on the intended user along with impressive advances in the field of digital signal processing.

In this study, antennas are divided into 5 categories, i.e., omni-directional, directional, different windows, phased array and digital beamforming (DBF) methods. The Fixed beamforming approaches, mentioned in which included MMSE, MaxSNIR and LCMV methods were assumed to apply to fixed arrival angle emitters. If the arrival angles don't change with time, the optimum array weights won't need to be adjusted. However, if the desired arrival angles change with time, it is necessary to devise an optimization scheme that operates on-the-fly so as to keep recalculating the optimum array weights. The receiver signal processing algorithm then must allow for the continuous adaptation to an ever-changing electromagnetic environment. The adaptive algorithm takes the Fixed beam forming process one step further and allows for the calculation of continuously updated weights. The adaptation process must satisfy a specified optimization criterion. Several examples of popular adaptive algorithms include training-based, LMS, SMI and RLS and blind ones such as CM and DD algorithms. We discussed and explained each of these techniques. According to simulation results of fixed-beam as well as adaptive processing, it is obvious that by appropriate beamforming methods in transmission or reception, better radio signals with lower energy consumption, higher SNIR and lower BER and NMSE will be achieved.

In recent years, researchers focused on DBF in wireless cellular systems, satellite networks and wideband systems such as WiMAX (Etemad, 2008, Hoymann and Wolz, 2006) and according to capabilities of these techniques and baseband processing, it will be a great technology in the future. As a summery, some research subjects on digital antenna array signal processing are as follow:

- Applications and performance evaluation of adaptive array beamforming in wireless communications and broadcasting networks (Hoymann and Wolz, 2006; Pattan, 2000; Shaukat, *et al.,* 2009)
- New array geometries 1-D as well as 2-D and 3-D same as L-shape, 2L-shape, Z-shape, Displaced Sensor Array (DSA),. .. (Azevedo, 2009; Huang *et al.,* 2010; Shubair and Al Nuaimi, 2008; Liu *et l.,* 2007)
- Low complexity and fast weighting algorithms (Moghaddam *et al.,* 2010a, b; Wang *et al.,* 2009, Yang *et al.,* 2006)
- New ideas to avoid divergence (Miranda, 2008)
- Coupling effects of array elements on array processing (Tuncer and Friedlander, 2009; Yuan *et al.,* 2006)
- New aspects on DOA estimation (Chandra, 2005; Foutz *et al.,* 2008; Gershman *et al.*, 2010; Jalali *et al.,* 2007; Tuncer and Friedlander, 2009)
- Wide-band adaptive array signal processing and beamforming such as, Tapped Delay Lines (TDL) and Sensor Delay Lines (SDL) and frequency independent DOA estimation (Tuncer and Friedlander, 2009; Liu *et l.,* 2007; Zhang *et al.,* 2010a)
- Considering the effect of multipath fading on adaptive array processing (Yu *et al.,* 2010; Zhang *et al.,* 2010b)
- Antenna array signal processing based on Higher Order Statistics (HOS) (Karfoul *et al.,* 2008)

- New LMS-based algorithms such as, Variable Step Size LMS (VSS-LMS) and Normalized LMS (NLMS) (Wang *et al.,* 2003)
- New versions of constant modulus algorithm such as, Constrained Constant Modulus (CCM), Time Averaging Step Size (TASS) and Modified Adaptive Step Size (MASS) (Bouacha *et al.,* 2008; Ghadian and Moghaddam, 2010; Wang *et al.,* 2009; Zarzoso and Comon, 2008)
- Combined algorithms such as, RLS-CMA, LMS-RLS, LS-RLS, SMI-CMA, SMI-LMS, LS-CMA, Bartlett-CMA (Bouacha *et al.,* 2008; Djigan, 2007; Nooralizadeh and Shirvani Moghaddam, 2009; Nooralizadeh *et al.,* 2009; Moghaddam and Saremi, 2008, 2010)
- LMS and CM algorithms based on direction and relative velocity of source signal (Moghaddam *et al.,* 2010a, b)

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