A Setup for the Evaluation of MUSIC and LMS Algorithms for a Smart Antenna System

Raed M. Shubair, Mahmoud A. Al-Qutayri, and Jassim M. Samhan
Etisalat University College
P.O.Box 573, Sharjah, UAE
Telephone: +971 6 5611333, Fax: + 971 6 5611789
Email: rshubair@ece.ac.ae; maq@ece.ac.ae

Abstract— **This paper presents practical design of a smart antenna system based on direction-of-arrival estimation and adaptive beamforming. Direction-of-arrival (DOA) estimation is based on the MUSIC algorithm for identifying the directions of the source signals incident on the sensor array comprising the smart antenna system. Adaptive beamforming is achieved using the LMS algorithm for directing the main beam towards the desired source signals and generating deep nulls in the directions of interfering signals. The smart antenna system designed involves a hardware part which provides real data measurements of the incident signals received by the sensor array. Results obtained verify the improved performance of the smart antenna system when the practical measurements of the signal environment surrounding the sensor array are used. This takes the form of sharper peaks in the MUSIC angular spectrum and deep nulls in the LMS array beampattern.**

Keywords — **Smart antennas, DOA estimation, adaptive beamforming, least mean squares.**

I. Introduction

Wireless networks face ever-changing demands on their spectrum and infrastructure resources. Increased minutes of use, capacity-intensive data applications, and the steady growth of worldwide wireless subscribers mean carriers will have to find effective ways to accommodate increased wireless traffic in their networks. However, deploying new cell sites is not the most economical or efficient means of increasing capacity. Wireless carriers have begun to explore new ways to maximize the spectral efficiency of their networks and improve their return on investment [1]. Smart antennas have emerged as one of the leading innovations for achieving highly efficient networks that maximize capacity and improve quality and coverage. Smart antennas provide greater capacity and performance benefits than standard antennas because they can be used to customize and fine-tune antenna coverage patterns to the changing traffic or radio frequency (RF) conditions in a wireless network [1].

A smart antenna is a digital wireless communications antenna system that takes advantage of diversity effect at the source (transmitter), the destination (receiver), or both. Diversity effect involves the transmission and/or reception of multiple RF-waves to increase data speed and reduce the error rate. In conventional wireless communications, a single antenna is used at the source, and another single antenna is used at the destination. Such systems are vulnerable to problems caused by multipath effects.

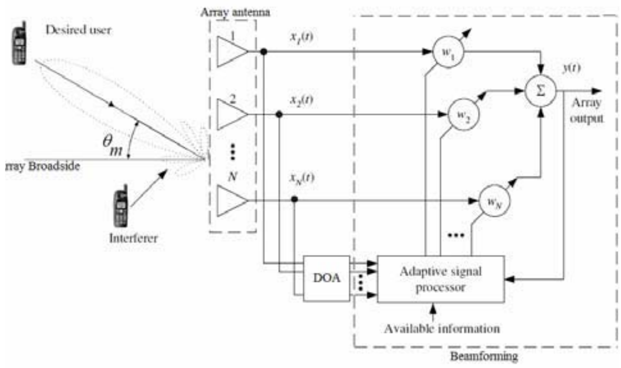

Fig. 1. A functional block diagram of a smart antenna system.

When an electromagnetic field (EM field) is met with obstructions such as buildings the wavefronts are scattered, and thus they take many paths to reach the destination. The late arrival of scattered portions of the signal causes problems such as fading. In a digital communications system it can cause a reduction in data speed and an increase in the number of errors. Multi-path fading and delay spread lead to inter-symbol interference (ISI) and co-channel interference. The use of smart antennas can reduce or eliminate these problems resulting in wider coverage and greater capacity.

A smart antenna system at the base station of a cellular mobile system is depicted in Fig. 1. It consists of a uniform linear antenna array for which the current amplitudes are adjusted by a set of complex weights using an adaptive beamforming algorithm. The adaptive beamforming algorithm optimizes the array output beam pattern such that maximum radiated power is produced in the directions of desired mobile users and deep nulls are generated in the directions of undesired signals representing co-channel interference from mobile users in adjacent cells. Prior to adaptive beamforming, the directions of users and interferes must be obtained using a direction-of-arrival (DOA) estimation algorithm [2] .

Various experimental models have been developed in the literature for the purpose of investigating the performance

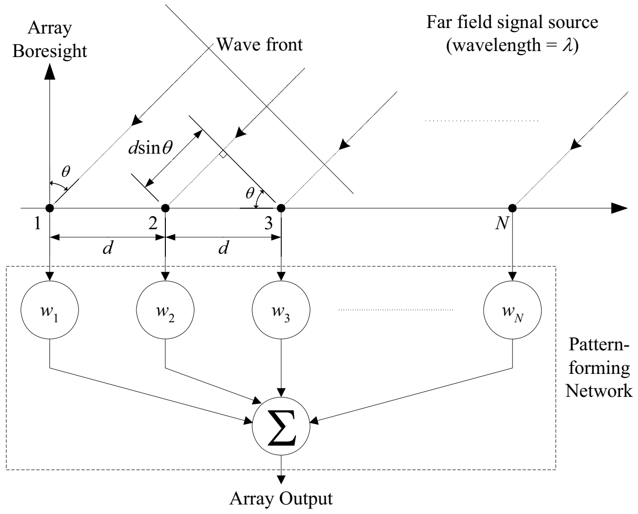

Fig. 2. Geometry of a uniform linear array.

of smart antenna systems [3], [4] with emphasis on DOA estimation [5]; adaptive beamforming [6]; hardware implementations [7], [8]; spread spectrum systems [9]; OFDM [10], [11]; CDMA [12], [13]; WCDMA [14]-[16]; and mobile adhoc networks (MANETs) [17]-[19].

Previous research work also focused on developing computer models and simulations of smart antenna systems including DOA estimation [20]-[25]. as well as adaptive beamforming [26]-[28]. These models and simulations were based on pre-defined input data signals that simulate the signal environment surrounding the sensor array. This paper investigates the performance of smart antenna algorithms using an experimental setup that involves a hardware part used to collect real data measurements of the received signals impinging on the smart antenna sensor array. In this way, a more realistic and accurate description of the signal environment surrounding the sensor array is used to provide the input for the MUSIC and LMS algorithms being investigated.

The paper is organized as follows: Section II develops the theory of smart antenna systems. Section III describes the hardware part which was setup to provide real data measurements at the input of the smart antenna system. Section IV presents performance results for the designed smart antenna system. Finally, conclusions are given in Section IV.

II. Theory of Smart Antenna Systems

A. Signal Model

Let a uniform linear array be composed of N sensors, and let it receive M narrowband source signals $s_m(t)$ from desired users arriving at directions $\theta_1, \theta_2, ...\theta_M$, as shown in Figure 2. The array also receives I narrowband source signals $s_i(t)$ from undesired (or interference) users arriving at directions $\theta_1, \theta_2, ...\theta_I$. At a particular instant of time $t = 1, 2, ..., K$,where K is the total number of snapshots taken. The desired users signal vector $\mathbf{x}_S(t)$ can be defined as

$$\mathbf{x}_M(t) = \sum_{m=1}^{M} \mathbf{a}(\theta_m) s_m(t) \quad (1)$$

where $\mathbf{a}(\theta_m)$ is the $N \times 1$ array steering vector which represents the array response at direction θ_m and is given by

$$\mathbf{a}(\theta_m) = [\exp[j(n-1)\psi_m]^T; \qquad 1 \leq n \leq N \quad (2)$$

where$[(.)]^T$ is the transposition operator, and ψ_m represents the electrical phaseshift from element to element along the array. This can be defined by

$$\psi_m = 2\pi(\frac{d}{\lambda}) \sin(\theta_m) \quad (3)$$

where d is the inter-element spacing and λ is the wavelength of the received signal.

The desired users signal vector $\mathbf{x}_M(t)$ of (1) can be written as

$$\mathbf{x}_M(t) = \mathbf{A}_M \mathbf{s}(t) \quad (4)$$

where $\mathbf{A}_M$ is the $N \times M$ matrix of the desired users signal direction vectors and is given by

$$\mathbf{A}_M = [\mathbf{a}(\theta_1), .\mathbf{a}(\theta_2), ..., \mathbf{a}(\theta_M)] \quad (5)$$

and $\mathbf{s}(t)$ is the $M \times 1$ desired users source waveform vector defined as

$$\mathbf{s}(t) = \left[\begin{array}{ccccc} s_1(t) & s_2(t) & .. & .. & s_M(t) \end{array} \right]^T . \quad (6)$$

We also define the undesired (or interference) users signal vector $\mathbf{x}_I(t)$ as

$$\mathbf{x}_I(t) = \mathbf{A}_I \mathbf{i}(t) \quad (7)$$

where $\mathbf{A}_I$ is the $N \times I$ matrix of the undesired users signal direction vectors and is given by

$$\mathbf{A}_I = [\mathbf{a}(\theta_1), .\mathbf{a}(\theta_2), ..., \mathbf{a}(\theta_I)] \quad (8)$$

and $\mathbf{i}(t)$ is the $I \times 1$ undesired (or interference) users source waveform vector defined as

$$\mathbf{i}(t) = \left[\begin{array}{ccccc} i_1(t) & i_2(t) & .. & .. & i_I(t) \end{array} \right]^T . \quad (9)$$

The overall received signal vector $\mathbf{x}_M(t)$ is given by the superposition of the desired users signal vector $\mathbf{x}_M(t)$, undesired (or interference) users signal vector $\mathbf{x}_I(t)$, and an $N \times 1$ vector $\mathbf{n}(t)$ which represents white sensor noise. Hence, $\mathbf{x}(t)$ can be written as

$$\mathbf{x}(t) = \mathbf{x}_M(t) + \mathbf{n}(t) + \mathbf{x}_I(t) \quad (10)$$

where $\mathbf{n}(t)$ represents white Gaussian noise. The conventional (forward-only) estimate of the covariance matrix defined as

$$\mathbf{R} = E\{\mathbf{x}(t)\mathbf{x}^H(t)\} \quad (11)$$

where $E\{.\}$ represents the ensemble average; and $(.)^H$ is the Hermitian transposition operator. Equation (11) can be approximated by applying temporal averaging over K snapshots (or samples) taken from the signals incident on the sensor array. This averaging process leads to forming a spatial correlation (or covariance) matrix $\mathbf{R}$ given by [29]:

$$\mathbf{R} = \frac{1}{K}\sum_{k=1}^{K} \mathbf{x}(k)\mathbf{x}^H(k) \tag{12}$$

Substituting for $\mathbf{x}(t)$ from (10) in (12) yields

$$\mathbf{R} = \mathbf{A}_M \mathbf{R}_{ss} \mathbf{A}_M^H + \mathbf{n}(k)\ \mathbf{n}(k)^H + \mathbf{A}_I \mathbf{R}_{ii} \mathbf{A}_I^H \tag{13}$$

where $\mathbf{R}_{ss} = E\{\mathbf{s}(t)\mathbf{s}^H(t)\}$ is an $M \times M$ desired users source waveform covariance matrix; $\mathbf{R}_{ii} = E\{\mathbf{i}(t)\mathbf{i}^H(t)\}$ is an $I \times I$ undesired users source waveform covariance matrix. Finally, equation (13) can be rewritten as

$$\begin{aligned}\mathbf{R} \ &= \ \frac{1}{K}\sum_{t=1}^{K} \mathbf{A}_M \left[\mathbf{s}(k)\mathbf{s}(k)^H\right] \mathbf{A}_M^H + \boldsymbol{\sigma}_n^2 \mathbf{I} \\ &\quad + \frac{1}{K}\sum_{t=1}^{K} \mathbf{A}_I \left[\mathbf{i}(k)\mathbf{i}(k)^H\right] \mathbf{A}_I^H \end{aligned}\tag{14}$$

where $\boldsymbol{\sigma}_n^2$ is the noise variance, and $\mathbf{I}$ is an identity matrix of size $N \times N$.

B. DOA Estimation Using MUSIC Algorithm

A common a subspace-based DOA estimation algorithm is MUSIC (MUltiple SIgnal Classification) [2]. It starts by expressing the covariance matrix $\mathbf{R}$ obtained in (14) as

$$\mathbf{R} = \mathbf{J}\mathbf{R}^*\mathbf{J} \tag{15}$$

where $\mathbf{J}$ is the exchange matrix with ones on its anti-diagonal and zeros elsewhere; and $(.)^*$ stands for complex conjugate. The covariance matrix $\mathbf{R}$ in (15) is known to be centro-Hermitian if and only if $\mathbf{S}$ is a diagonal matrix, i.e., when the signal sources are uncorrected.

It can be shown ([24], [25]) that the covariance matrix $\mathbf{R}$ obtained in (14) has M signal eigenvalues with corresponding eigenvectors $\mathbf{v}_1,\ \mathbf{v}_2\ , \ldots\ldots, .\mathbf{v}_M$, i.e.,

$$\mathbf{V}s = [\mathbf{v}_1, \mathbf{v}_2, ..., \mathbf{v}_M] \tag{16}$$

The remaining $N - M$ eigenvalues of the covariance matrix $\mathbf{R}$ represent noise eigenvalues with corresponding eigenvectors $\mathbf{v}_{M+1},\ \mathbf{v}_{M+2}\ , \ldots\ldots, .\mathbf{v}_N$, i.e.,

$$\mathbf{V}_n = [\mathbf{v}_{M+1}, \mathbf{v}_{M+2}, ..., \mathbf{v}_N] \tag{17}$$

Hence, the eigen-decomposition of the covariance matrix in (14) be defined in a standard way as [29]:

$$\mathbf{R} = \mathbf{V}\mathbf{\Pi}\mathbf{V} = \mathbf{V}_s\mathbf{\Pi}_s\mathbf{V}_s + \sigma^2\mathbf{V}_n\mathbf{V}_n^H \tag{18}$$

where the subscripts s and n stand for signal- and noise-subspace, respectively. In (18) $\mathbf{\Pi}_s$ is defined as

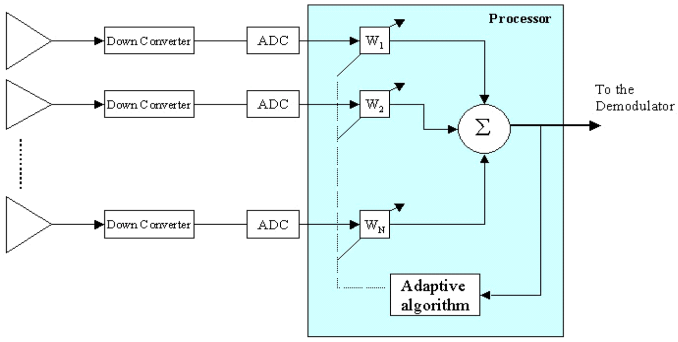

Fig. 3. Block diagram of an adaptive beamformer.

$$\mathbf{\Pi}_s = diag\{\pi_1, \pi_2, ..., \pi_M\} \tag{19}$$

The normalized MUSIC angular spectrum is defined as [29], [30]:

$$P(\theta) = \frac{\mathbf{A}^H\mathbf{A}}{\mathbf{A}^H\mathbf{V}_n\mathbf{V}_n^H\mathbf{A}} \tag{20}$$

By examining the denominator in (20) it is evident that peaks in the MUSIC angular spectrum occur at angles θ for which the array manifold matrix $\mathbf{A}$ is orthogonal to the noise subspace matrix $\mathbf{E}_n$. Those angles θ define the desired directions-of-arrival of the of the signals impinging on the sensor array.

The number of signals that can be detected is restricted by the number of elements in the sensor array. In [24] and [25] it was verified that an N element sensor array can detect up to $N-1$ uncorrelated signals. This number reduces to $N/2$ signals if they are correlated. A comprehensive performance evaluation of the MUSIC algorithm for DOA estimation can be found in [20]-[25].

C. Adaptive Beamforming Using LMS Algorithm

An adaptive beamformer, which is shown in Fig. 3, consists of multiple antennas; complex weights, the function of which is to amplify (or attenuate) and delay the signals from each antenna element; and a summer to add all of the processed signals, in order to tune out the signals not of interest, while enhancing the signal of interest. Hence, beamforming is sometimes referred to as spatial filtering, since some incoming signals from certain spatial directions are filtered out, while others are amplified. The output response of the uniform linear array is given by:

$$y(n) = \mathbf{w}^H\mathbf{x}(n), \tag{21}$$

where $\mathbf{w}$ is the complex weights vector and $\mathbf{x}$ is the received signal vector given in (10).

The complex weights vector $\mathbf{w}$ in (21) is obtained using an adaptive beamforming algorithm. Adaptive beamforming algorithms are classified as either DOA-based, temporal-reference-based, or signal-structure-based. In DOA-based beamforming, the direction-of-arrival algorithm passes the DOA information to the beamformer, as illustrated in Fig. 3. The beamforming algorithm is used to design a radiation pattern with the main beam directed towards the signal of interest, and with nulls in the directions of the interferers.

On the other hand, temporal-reference beamformers use a known training sequence to adjust the weights, and to form a radiation pattern with a maximum towards the signal of interest and nulls towards the signals not of interest. Specifically, if $d(n)$ denotes the sequence of reference or training symbols known a priori at the receiver at time n, an error, $\epsilon(n)$ is formed as:

$$\epsilon(n) = d(n) - \mathbf{w}^H x(n) \tag{22}$$

This error signal ϵ is used by the beamformer to adaptively adjust the complex weights vector $\mathbf{w}$ so that the mean-squared error (MSE) is minimized. The choice of weights that minimize the MSE is such that the radiation pattern has a beam in the direction of the source that is transmitting the reference signal, and that there are nulls in the radiation pattern in the directions of the interferers. Once the beamformer has locked onto the reference signal, then the complex weights are maintained as fixed, and transmission of the data packet begins.

The LMS algorithm is based on the steepest-descent method which recursively computes and updates the sensor array weights vector $\mathbf{w}$. It is intuitively reasonable that successive corrections to the weights vector in the direction of the negative of the gradient vector should eventually lead to minimum mean square error, at which point the weights vector assumes its optimum value. In a standard LMS algorithm, the array weights vector $\mathbf{w}$ is initialized arbitrarily, and is then updated using the LMS equation [30]:

$$\mathbf{w}(n+1) = \mathbf{w}(n) + \mu \mathbf{x}(n)\epsilon^*(n) \tag{23}$$

where $\mathbf{w}(n+1)$ denotes the weights vector to be computed at iteration $n+1$ and μ is the LMS step size which is related to the rate of convergence: in other words, how fast the LMS algorithm reaches steady state. The smaller the step size the longer it takes the LMS algorithm to converge. This means that a longer reference or training sequence is needed, which would reduce the payload and, hence, the bandwidth available for transmitting data. In order to ensure the stability and convergence of the algorithm, the adaptive step size should be chosen within the range specified as:

$$0 < \mu < \frac{1}{\lambda_{\max}} \tag{24}$$

where$\lambda_{\max}$ is the maximum eigenvalue of the input covariance matrix $\mathbf{R}$ obtained in (14). As noted from (22) and (23), the LMS algorithm requires knowledge of the desired signal, $d(n)$. This can be done in a digital system by periodically transmitting a training sequence that is known to the receiver, or by using the spreading code in the case of a direct-sequence CDMA system.

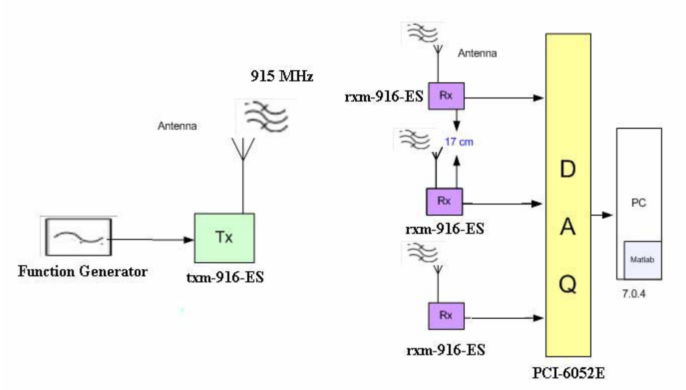

Fig. 4. The developed smart antenna hardware system.

A significant feature of the LMS algorithm is its simplicity; it does not require measurements of the pertinent correlation functions, nor does it require matrix inversion. A comprehensive performance evaluation of the LMS algorithm for adaptive beamforming can be found in [26]-[28].

III. Experimental Setup

A hardware part of the smart antenna system was implemented so that it can provide real-data measurements of the received signals. In this way, a more accurate description of the signal environment surrounding the sensor array is used to provide the input for the DOA estimation and adaptive algorithms being investigated.

The general block diagram of the hardware system is depicted in Fig. 4. It consists of three parts: the transmitter, wireless channel, and receiver. At the transmitter side, a sinusoidal signal was generated and sent wirelessly through a transmitter chip operating at 900 MHz, which is in line with [4].

At the receiver side, three receivers, spaced apart by half-wavelength, were situated horizontally in order to receive the incoming signal and perform down conversion. The spacing between the three receiver elements was chsosen to be half-wavelength in order to reduce the effects of inter-element mutual coupling [20], [21].

The information signal is then captured using a data acquisition (DAQ) board and subsequently uploaded to a PC for post processing using Matlab. The DAQ board uses 8-bit analog-to-digital converters (ADCs). Following some signal conditioning the acquired physical data is used to evaluate and compare the performance of the algorithms described in Section II. A 50-Ω antenna was set on each of the array elements in order to radiate and receive the modulated FM signal which in turn was illustrated on a spectrum analyzer. The hardware components were mounted on a PCB in order to ease the movement of the system.

The above setup enabled capturing and subsequent processing of both modulated and de-modulated signals. This added flexibility enabled verification of the physical data.

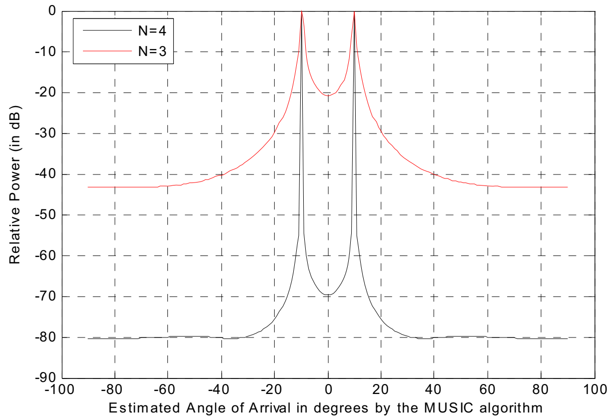

Fig. 5. MUSIC angular spectrum for different values of number of elements.

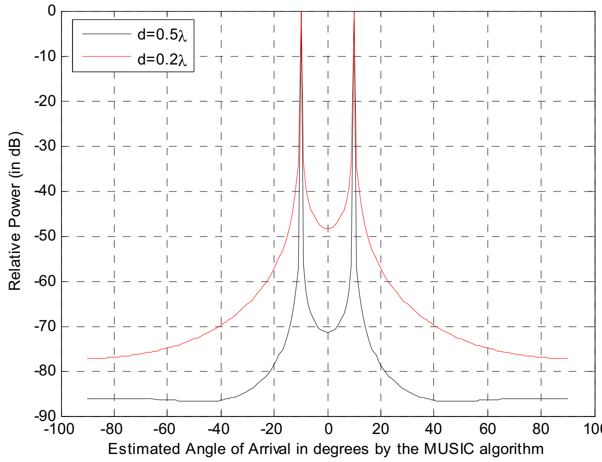

Fig. 6. MUSIC angular spectrum for different values of inter-element spacing.

IV. Simulation and Performance Evaluation

Fig. 5 shows that when the number of elements in the sensor array is increased from $N = 3$ to $N = 4$, the performance of the system improves. This takes the form of sharper peaks and lower noise floor in the MUSIC angular spectrum. Fig. 6 shows that the performance of the smart antenna system improves also when the spacing between the elements in the sensor array changes from $d = \lambda/5$ to $d = \lambda/2$. Again, this takes the form sharper peaks and lower noise floor in Fig. 6 for the MUSIC angular spectrum. This verifies that $d = \lambda/2$ represents the optimum value of the element spacing in the sensor array since the effects of inter-element mutual couplings are minimized.

Results for LMS adaptive beamforming are demonstrated in Fig. 7 and 8. Fig. 7 shows that a better beampattern with deeper nulls is obtained when dealing with only a single interference signal $I = 1$ rather than two interference signals $I = 2$. Fig. 8 shows that according to the condition stated in (24) using a larger value for the LMS adaptive step size $\mu = 0.001$ yields better results when compared to a smaller step size $\mu = 0.0001$.

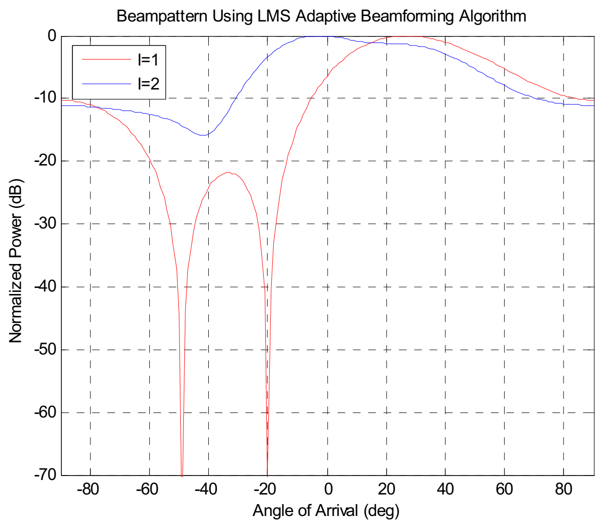

Fig. 7. Array beampattern for different values of the number of interference signals.

V. Conclusions

This paper presented a practical setup of a smart antenna system for the performance evaluation of the the MUSIC DOA estimation and LMS adaptive beamforming algorithms. The performance evaluation process is based on two steps. Fist, a hardware part is implemented used to collect real data measurements of the signals incident on the smart antenna sensor array. Second, the measured data is processed in Matlab which is used to predict the performance of the smart antenna algorithms being investigated. Results obtained verify the improved performance of the smart antenna system when the real data measurements of the signal environment surrounding the sensor array are used. This takes the form of sharper peaks in the MUSIC angular spectrum indicating locations of desired users, and deep nulls in the LMS array beampattern indicating the location of the undesired interference signals.

References

[1] L.C. Godara, "Applications of Antenna Arrays to Mobile Communications. I. Performance Improvement, Feasibility, and System Considerations," *Proceedings of IEEE*, Volume 85, Issue 7, July 1997, Pages 1031-1060.

[2] L.C. Godara, "Application of Antenna Arrays to Mobile Communications. II. Beamforming and Direction-of-Arrival Considerations," *Proceedings of IEEE*, Volume 85, Issue 8, August 1997, Pages1195-1245.

[3] S. Jeng; G.T. Okamoto, G. Xu, H. Lin, and W.J. Vogel, "Experimental Evaluation of Smart Antenna System Performance for Wireless Communications," *IEEE Transactions on Antennas and Propagation*, Volume 46, Issue 6, June 1998, Pages 749-757.

[4] S. Jeng; G. Xu, H. Lin, and W.J. Vogel, "Experimental Studies of Spatial Signature Variation at 900 MHz for Smart Antenna Systems," *IEEE Transactions on Antennas and Propagation*, Volume 46, Issue 7, July 1998, Pages 953-962.

[5] A. Kuchar, M. Tangemann, and E. Bonek, "A Real-Time DOA-Based

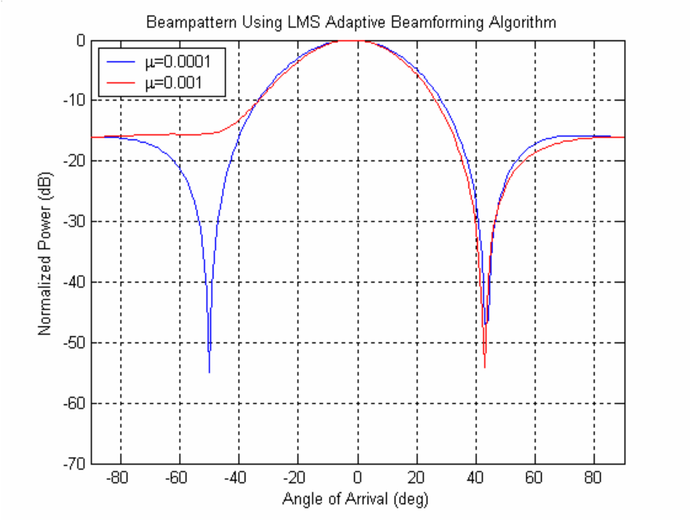

Fig. 8. Array beampattern for different values of LMS adaptive step size μ.

Smart Antenna Processor," *IEEE Transactions on Vehicular Technology*, Volume 51, Issue 6, November 2002, Pages 1279-1293

[6] H. Li and T. Liu, "Comparison of Beamforming Techniques for W-CDMA Communication Systems," *IEEE Transactions on Vehicular Technology*, Volume 52, Issue 4, July 2003, Pages 752-760

[7] S. Jeon; Y. Wang; Y. Qian, and T. Itoh, "A Novel Smart Antenna System Implementation for Broadband Wireless Communications," *IEEE Transactions on Antennas and Propagation*, Volume 50, Issue 5, May 2002, Pages 600-606.

[8] N. Celik, W. Kim, M.F. Demirkol, M.F. Iskander, and R. Emrick, "Implementation and Experimental Verification of Hybrid Smart-Antenna Beamforming Algorithm," *IEEE Antennas and Wireless Propagation Letters*, Volume 5, Issue 1, December 2006 Pages 280-283

[9] X. Wang and Z. Wang, "The Estimation of the Directions of Arrival of the Spread-Spectrum Signals with Three Orthogonal Sensors," *IEEE Transactions on Vehicular Technology*, Volume 51, Issue 5, September 2002, Pages 817-822

[10] K. Wong, R.S. Cheng, K.B. Letaief, and R.D. Murch, "Adaptive Antennas at the Mobile and Base Stations in an OFDM/TDMA System," *IEEE Transactions on Communications*, Volume 49, Issue 1, January 2001, Pages 195-206

[11] A.T. Alastalo and M. Kahola, "Smart-Antenna Operation for Indoor Wireless Local-Area Networks Using OFDM," *IEEE Transactions on Wireless Communications*,Volume 2, Issue 2, March 2003, Pages 392-399

[12] S. Choi and D. Shim, "A Novel Adaptive Beamforming Algorithm for a Smart Antenna System in a CDMA Mobile Communication Environment," *IEEE Transactions on Vehicular Technology*, Volume 49, Issue 5, September 2000, Pages 1793-1806

[13] J. Choi and S. Choi; "Diversity Gain for CDMA Systems Equipped with Antenna Arrays," *IEEE Transactions on Vehicular Technology*, Volume 52, Issue 3, May 2003, Pages 720-724

[14] A. Osseiran and A. Logothetis, "Smart Antennas in a WCDMA Radio Network System: Modeling and Evaluations," *IEEE Transactions on Antennas and Propagation*, Volume 54, Issue 11, Part 1, November 2006, Pages 3302-3316.

[15] C. Li, H. Li, and P. Wang, "Beamforming Degradation of a W-CDMA Smart Antenna Under FDD and MAI Channel Estimation Errors," *IEEE Antennas and Wireless Propagation Letters*, Volume 6, 2007, Pages 137-140

[16] B. Allen and M. Beach, "On the analysis of switched-beam antennas for the W-CDMA downlink," *IEEE Transactions on Vehicular Technology*, Volume 53, Issue 3, May 2004, Pages 569-578

[17] S. Bellofiore, J. Foutz, R. Govindarajula, J. Bahceci, C.A. Balanis, A.S. Spanias, J.M. Capone, and T.M. Duman, "Smart Antenna System Analysis, Integration and Performance for Mobile Ad-Hoc Networks (MANETs)," *IEEE Transactions on Antennas and Propagation*, Volume 50, Issue 5, May 2002, Pages 571-581.

[18] J.H. Winters, "Smart Antenna Techniques and Their Application to Wireless Ad-hoc Networks," *IEEE Transactions on Wireless Communications*, Volume 13, Issue 4, August 2006, Pages 77-83

[19] J. Frigon, A.M. Eltawil, E. Grayver, A. Tarighat, and H Zou, "Design and Implementation of a Baseband WCDMA Dual-Antenna Mobile Terminal," *IEEE Transactions on Circuits and Systems I: Regular Papers*, Volume 54, Issue 3, March 2007, Pages 518-529

[20] E.M. Al Ardi, R.M. Shubair, and M.E. Al Mualla, "Investigation of High-Resolution DOA Estimation Algorithms for Optimal Performance of Smart Antenna Systems," *Proceedings of IEE International Conference on Third Generation Mobile Communications* (3G'03), London, UK, June 25–27, 2003, Pages 460–464.

[21] E.M. Al Ardi, R.M. Shubair, and M.E. Al Mualla, "Performance Evaluation of Direction Finding Algorithms for Adaptive Antenna Arrays," *Proceedings of IEEE International Conference on Electronics, Circuits, and Systems* (ICECS'03), Sharjah, UAE, December 14-17, 2003, Volume 2, Pages 735–738.

[22] R.M. Shubair and A. Al Merri, "Robust Algorithms for Direction Finding and Adaptive Beamforming: Performance and Optimization," *Proceedings of IEEE International Midwest Symposium on Circuits and Systems* (MWSCAS'04), Hiroshima, Japan, July 25-28, 2004, Pages 589–592.

[23] E.M. Al Ardi, R.M. Shubair, and M.E. Al Mualla, "Computationally Efficient DOA Estimation in a Multipath Environment Using Covariance Differencing and Iterative Spatial Smoothing," *Proceedings of IEEE International Symposium on Circuits and Systems* (ISCAS'05), Kobe, Japan, May 23-26, 2005, Pages 3805–3808.

[24] E.M. Al Ardi, R.M. Shubair, and M.E. Al Mualla, "Computationally Efficient DOA Estimation in a Multipath Environment," *IEE Electronics Letters*, Volume 40, Issue 14, July 2004, Pages 908-909.

[25] E.M. Al Ardi, R.M. Shubair, and M.E. Al Mualla, "Direction of Arrival Estimation in a Multipath Environment: An Overview and a New Contribution," *Applied Computational Electromagnetics Society Journal*: *Special Issue on Phased and Adaptive Array Antennas*, Volume 21, Issue 3, November 2006, Pages 226-239.

[26] R.M. Shubair and A. Al Merri, "Convergence Study of Adaptive Beamforming Algorithms for Spatial Interference Rejection," *Proceedings of International Symposium on Antenna Technology and Applied Electromagnetics* (ANTEM'05), Saint-Malo, France, June 15-17, 2005.

[27] R.M. Shubair and W. Al Jessmi, "Performance Analysis of SMI Adaptive Beamforming Arrays for Smart Antenna Systems," *Proceedings of IEEE International Symposium on Antennas and Propagation* (AP-S'05), Washington, D.C., USA, July 3-8, 2005, Pages 311–314.

[28] R.M. Shubair, A. Al Merri, and W. Al Jessmi, "Improved Adaptive Beamforming Using a Hybrid LMS/SMI Approach," *Proceedings of IEEE International Conference on Wireless and Optical Communications Networks* (WOCN'05), Dubai, UAE, March 6-8, 2005, Pages 603–606.

[29] S. Haykin, *Adaptive Filter Theory*. Prentice-Hall, 4th Ed., 2002.

[30] H.L. Van Trees, *Detection, Estimation, and Modulation Theory, Part IV: Optimum Array Processing*. John Wiley & Sons, 2002.

R aed M. Shubair received his B.Sc. degree with Distiction and Class Honors from Kuwait University, Kuwait, in June 1989 and his Ph.D. degree with Distinction from the University of Waterloo, Canada, in February 1993, both in Electrical Engineering. From March 1993 to August 1993 he was a Postdoctoral Fellow at the Department of Electrical and Computer Engineering, University of Waterloo, Canada. In September 1993 he joined Etisalat University College, UAE, where he is currently an Associate Professor at the Communication Engineering Department and Leader of the Communication & Information Systems Research Group. His current research interests include adaptive array processing, smart antennas and MIMO systems, as well as applied and computational electromagnetic modeling of RF and microwave circuits for wireless communications. He has published widely in in refereed technical journals and international conferences. He has been a member of the technical program, organizing, and steering committees of numerous international conferences and workshops. He organized and chaired a number of technical sessions in international conferences including IEEE Symposium on Antenna and Propagation (AP-S), IEEE Symposium on Electronics, Circuits and Systems (ICECS), Progress in Electromagnetics Research Symposium (PIERS), and Applied Computational Electromagnetics Symposium (ACES). Dr. Shubair is a Senior Member of the IEEE. He was also elected to the MIT Electromagnetics Academy in 2001. While at the University of Waterloo he received several scholarships and grants from Canada National Science and Engineering Research Council (NSERC), Canada National Research Council (NRC), and Ontario Graduate Scholarship (OGS). Dr. Shubair supervised a large number of research projects including *Adaptive Beamforming for Next-Generation Wireless Communications*, recipient of the 2004 IEE Award, as well as *Design of Optimum SMI Beamformers for Spatial Interference Rejection*, recipient of the 2005 IEE Award. Dr. Shubair is a founding member of the IEEE UAE Signal Processing and Communications Joint Societies Chapter. He is listed in Who's Who in Electromagnetics and in several editions of Who's Who in Science and Engineering.

M ahmoud A. Al-Qutayri received the B.Eng degree from Concordia University, Canada, the M.Sc. degree from University of Manchester, UK, and the Ph.D. degree from the University of Bath, UK, all in electrical and electronic engineering in 1984, 1987 and 1992 respectively. From 1992 to 1996 he was a Senior Lecturer at DeMontfort University, Leicester, UK. He subsequently joined Etisalat University College, Sharjah, UAE, where he is currently an Associate Professor in the Department of Electronic Engineering. He published numerous technical papers in international journals and conferences in his fields of research, which include application of reconfigurable computing to signal processing systems and test and design for testability of mixed-signal integrated circuits. Dr. Al-Qutayri is a senior member of the IEEE, member of the IEE, UK and holds CEng. status from the UK Engineering Society.

J assim M. Samhan received his B.Eng. (Honours) degree in Communication Engineering from Etisalat University College, UAE in June 2006. Since then, he has been with the Emirates Telecommunications Corporation (Etisalat), UAE where he is currently an Engineer at the Mobile Systems Section. His current responsibilities include quality control of the nationwide GSM, GPRS and UMTS networks.