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Research Papers

BEAM STEERING IN ANTENNAS USING NOVEL LOW COMPLEX ADAPTIVE ALGORITHMS

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Abstract

An adaptive antenna system consists of a combination of multiple antenna elements with a signal-processing capability to optimize its radiation and/or reception pattern automatically in response to the signal environment. In a telecommunication system, adaptive antenna system is the port through which radio frequency (RF) energy is coupled from the transmitter to the environment and, in reverse, to the receiver from the environment.In this paper ,an efficient and simple adaptive beam steering technique is presented. The proposed method is based on Least Mean Square(LMS) algorithm, provides a comprehensive and detailed treatment of the signal model used for beam forming. In order to improve the convergence rate of LMS algorithm in smart antenna system, this paper proposes the Block Based Normalized LMS (BBNLMS) algorithm. The performance of the BBNLMS algorithm in the presence of Multi path effects and multiple users is analyzed using MATLAB simulations. Simulation results confirm that the convergence rate and error reduction of BBNLMS is superor than conventional LMS algorithm.

KEYWORDS:
smart antenna,LMS,BBNLMS,DOA, convergence rate

REVIEW OF LITERATURE

Antenna is a transducer which converts high frequency time varying voltage signal/ current signal to electromagnetic(EM) wave of the same frequency, which can propagate in free space over large distances. Smart antenna is the critical technique of the third mobile communication, while the core antennas can be used to achieve different benefits. Among those the most important is higher network capacity[4],[5] by precise control of signal nulls quality and mitigation of interference combine reuse reduction distance improving capacity. The term adaptive antenna is used for a phased array when the weight of each element is applied in a dynamic fashion. The amount of weighting on each channel is not fixed at the time of the array design, but rather decided by the system at the time of processing the signals to meet required objectives. In other words, the array pattern adapts to the situation and the adaptive process is under control of the system. For example, consider the situation of a communication system operating in the presence of a directional interference operating at the carrier frequency used by the desired signal, and the performance measure is to maximize the output SNR, in such systems the desirable is output SNR should be maximized by cancelling the directional interference using optimal antennas. The antenna pattern in this case has a main beam pointed in the desired signal direction, and has a null in the direction of the interference. Assume that the interference is not stationary but moving slowly. If optimal performance is to be maintained, the antenna pattern needs to adjust so that the null position remains in the moving interference direction.

A system using adaptive antennas adjusts the weighting on each channel with an aim to achieve such a pattern[6]. For adaptive antennas, the conventional antenna pattern concepts of beam width, side lobes, and main beams are not used, as the antenna weights are designed to achieve a set performance criterion such as maximization of the output SNR. On the other hand, in conventional phase-array design these characteristics are specified at the time of design.

In this paper we propose a novel adaptive algorithm for steering the antenna beam electronically. Generally LMS algorithm is widely used in adaptive filter due to its relatively good robustness against implementational errors. However, the least mean square (LMS) algorithm has poor convergence rate, which reduces the system performance. In order to increase the convergence rate, LMS algorithm is modified by normalization, which is known as normalized LMS (NLMS) [8]. Normalization of step size in LMS algorithm improves the convergence rate and decreases excess mean square error, by exploiting this we have implemented beam forming using NLMS algorithms. In this paper, we adapt BBNLMS algorithm to increase the convergence rate [9]. In literature several smart antenna processing techniques were presented [10]-[17], to the best of author's knowledge such an approach is not addressed in the array processing. Finally in our simulations we considered two received signals and three directions of arrivals (DOAs). Simulation results confirm that the proposed BBNLM based beam steering is superior to conventional LMS algorithm in terms less error level and convergence rate.

ADAPTIVE BEAM FORMING

In certain applications the gain of a single antenna may not sufficient, array antennas plays a vital role in such situations. In array antennas the beam forming can be steered in two ways i.e; mechanical steering and electronic steering. Adaptive beam forming can be performed in many ways using adaptive algorithms. Several adaptive algorithms are presented in literature. Most of the algorithms are concerned with the minimization of the SNR. A functional diagram of an adaptive array system is shown in figure 1. Adaptive array systems can locate and track signals (users and interferers) and dynamically adjust pattern to enhance reception while minimizing interference using signal processing algorithms. After the system down converts the received signals to baseband and digitizes them, it locates the SOI using the direction-of-arrival (DOA) algorithm, and it continuously tracks the SOI and SNOIs by dynamically changing the complex weights (amplitudes and phases of the antenna elements). Basically, the DOA computes the direction-of-arrival of all the signals by computing the time delays between the antenna elements, and afterward, the adaptive algorithm, using a cost function, computes the appropriate weights that result in an optimum radiation pattern. Because adaptive arrays are generally more digital processing intensive and require a complete RF portion of the transceiver behind each antenna element, they tend to be more expensive than switched-beam systems. Adaptive arrays utilize sophisticated signal-processing algorithms to continuously distinguish between desired signals, multipath, and interfering signals, as well as calculate their Directions of Arrival (DOA). This approach updates its transmit strategy continuously based on changes in both the desired and interfering signal locations.

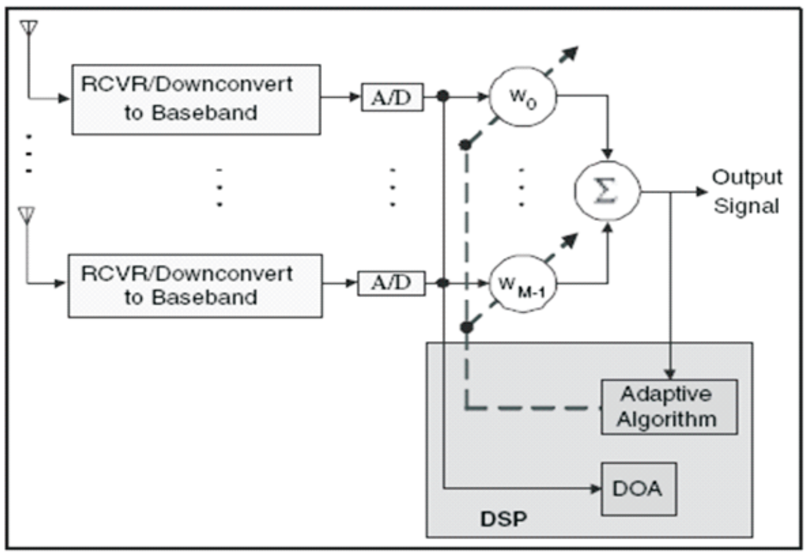

Figure1 Functional block diagram of an adaptive array system

In adaptive beam forming techniques, two main strategies are distinguished. The first one is based on the assumption that the part of the desired signal is already known through the use of a training sequence. This known signal is then compared with what is received, and the weights are then adjusted to minimize the Mean Square Error (MSE) between the known and the received signals. In this way, the beam pattern can adjusted to null the interferers. This approach optimizes the signal-to-interference ratio (SIR), and is applicable to non-line-of-sight (NLOS) environments. Since the weights are updated according to the incoming signals, not only the interference is reduced but the multipath fading is also mitigated. In the second one, the direction of arrivals from all sources transmitting signals to the array antenna are first identified. The complex weights are then adjusted to produce a maximum toward the desired angle and null toward interfering signals. This strategy may turn out to be deficient in practical scenarios where there are too many DOAs due to multi paths, and the algorithms are more likely to fail in properly detecting them. This is more likely to occur in NLOS environments where there are many local scatterers close to the users and the base station, thus resulting in a wider spread of the angle of arrival. Another significant advantage of the adaptive antenna systems is the ability to share spectrum. Because of the accurate tracking and robust interference rejection capabilities, multiple users can share the same conventional channel with in the same cell. System capacity increase through lower inter-cell frequency reuse patterns as well as intra-cell frequency reuse.

METHOD

ADAPTIVE ALGORITHMS:

An adaptive filter is a transversal filter trained by an Adaptive algorithm. The algorithm updates the weights at each iteration by estimating the gradient of the quadratic MSE surface and then moving the weights in the negative direction of the gradient $\mu(n)$ by a minute amount. The constant that determines this amount is referred to as the step size (μ). When this step size is small enough, the process leads these estimated weights to the optimal weights. The convergence and transient behavior of those weights along with their covariance characterize the LMS algorithm and the way the step size and process of gradient estimation affect these parameters are of great practical importance.

A.The Least Mean Square (LMS) Algorithm:

Consider a L length LMS based adaptive filter in which 'W' is the weight vector updated in accordance with the statistical nature of the input signal x(n) arriving from the antenna array. An adaptive processor will minimize the error e(n) between a desired signal d(n) and the array output y(n). LMS is the simplest algorithms for adaptive processing. This algorithm is based on the knowledge of the arriving signal. The knowledge of the received signal eliminates the need for beamforming, but the reference can also be a vector which is some what correlated with the received signal. As shown in Figure 1, an adaptive beam former 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 signal of not interest, while enhancing the signal of interest. Hence, beam forming is some time referred to as special directions are filtered out, while others are amplified. The output response of the uniform linear array is given by

$$y(n) = w(n) * u(n) \qquad (1)$$

We consider the adaptive filter where the input signal u(n) is convolved by an unknown w(n) filter (to produce y(n)) which has an additive interference signal v(n) before observed as d(n). The value of error signal estimation is e(n)=d(n)-y(n). The estimated convolved signal y(n) is subtracted from d(n), giving an output signal e(n) containing both the interference v(n) and a residual signal r(n)=y(n)-y(n). In many scenarios, such as echo cancellation, the interference v(n) is actually the signal of interest in the system. We arrive at the recursion for the LMS adaptive algorithm for updating the step as

$$w(n+1) = w(n) + \mu x(n)e^*(n) \quad (2)$$

Where μ is constant step and the filter can be adaptively updated by using above recursive relation.

B.Normalized Least Mean Square(NLMS) Algorithm:

One of the primary disadvantage of LMS algorithm is having a fixed step size parameter for every iteration. This requires an understanding of the statistics of the input signal prior to commencing the adaptive filtering operation. In practice this is rarely achievable. Even if assume the only signal to be input to the adaptive echo cancellation system in speech, there are still many factors such as input power and amplitude which will affect its performance. The normalized least mean square algorithm (NLMS) is an ex fixedtention of the LMS algorithm which bypasses this issue by selecting a different step size value μ(n), for each iteration of the algorithm. This step size is proportional to the inverse of the total expected energy of the instantaneous values of the coefficients of the input vector x(n).

The standard normalized least mean square (NLMS) algorithm is given by

$$e\,(n) = d\,(n) - \hat{\boldsymbol{w}}^H(n)\,\mathbf{u}\,(n) \quad (3)$$

$$\hat{\boldsymbol{W}}(n+1) = \hat{\boldsymbol{W}}\,(n) + \frac{\tilde{\mu}}{||\boldsymbol{u}(n)||^2}\mathbf{u}\,(n)e^*(n) \quad (4)$$

Comparing (2) and (4), it is observed that update is a scaled version of regression vector u(n), namely μx(n). This increases the convergence rate. In (4) a small constant δ must be added to the denominator to avoid denominator being zero when the data at any instant is zero.

$$\hat{\boldsymbol{w}}\,(n+1) = \hat{\boldsymbol{w}}\,(n) + \frac{\tilde{\mu}}{\delta + ||\boldsymbol{u}(n)||^2}\mathbf{u}\,(n)e^*(n) \quad (5)$$

Where $\mu(n) = \frac{\tilde{\mu}}{\delta + ||\boldsymbol{u}(n)||^2}$ is the variable step size. The advantage of the algorithm is that the step size can be chosen independent of the input signal power and the number of tap weights. Hence the NLMS algorithm has a convergence rate and a steady state error better than LMS algorithm. On the other hand some additional computations are required to compute the variable step size.

C.The Block Based Normalized Least Mean Square (BBLMS) Algorithm:

The additional computations required to compute μ(n) in equation (5) can be further reduced by using BBNLMS in which the input data is portioned into blocks and maximum magnitude within each block is used to compute μ(n). With this the weight update relation in (5) for u(n)max=0 and p=0 takes the following form

$$\hat{\boldsymbol{w}}(n+1) = \hat{\boldsymbol{w}}(n) + \frac{\tilde{\mu}}{p + u(n)_{max} X\ u(n)_{max u(n)}}\mathbf{u}(n)e^*(n) \quad (6)$$

Where u(n)max is the maximum of u(n) in the block. Using such an approach the number of multiplications reduces in the computation on μ(n). In addition to this, BBBNLMS enjoys fast convergence rate as the normalization factor is maximum data sample of block, where as in normalization factor varies from sample to sample.

RESULTS

TO prove the the ability of BBNLMS algorithm in adaptive beam forming we consider two transmitting training signals, each with three multipath components. The second and third multipath of both signals is set to arrive at the base station. This is the case with two white signals and three DOAs. The transmission of two different signals with one DOA each is in effect the same as sending one signal with two multi path separated by at least one sample period. This is because in both situations the two signals are uncorrelated with each other. The first signal is exposed to gain with amplitude 0.5 and the second signal 1.0. These results vary to a certain degree, when compared to the BBNLMS algorithm shown in fig 9. The third multi path of signal 1, is made weak in order to limit the interference caused by the first and second multipath of signal 2. The result of which is the increased signal power in direction of 30. Similarly the reason for the third multipath of signal 2 being weak is due to presence of near by DOAs.

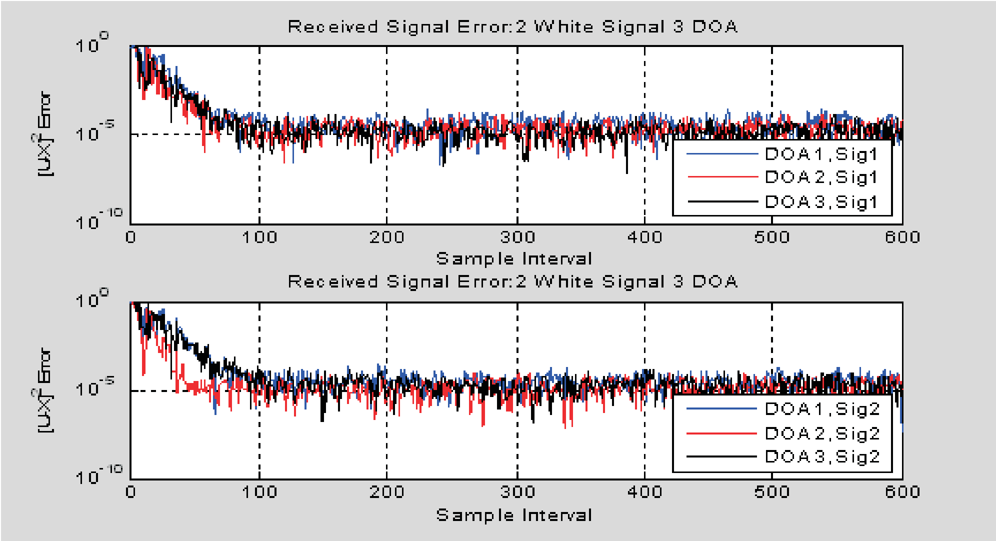

Fig.4:Received signal error with Two white signals with three DOAs each for LMS algorithm.

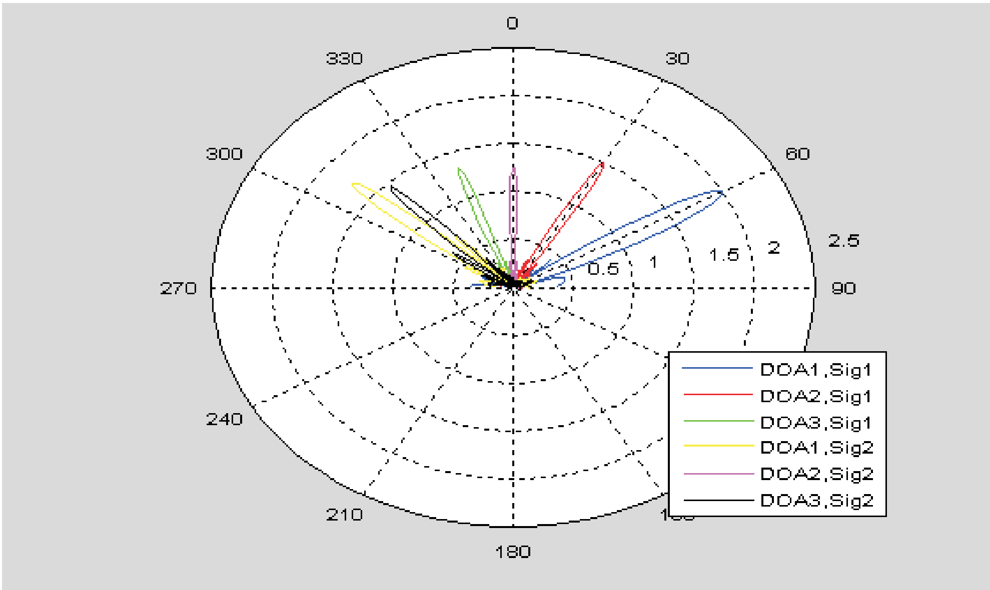

Fig.5:LMS:polar plot for Two white signals with three DOAs

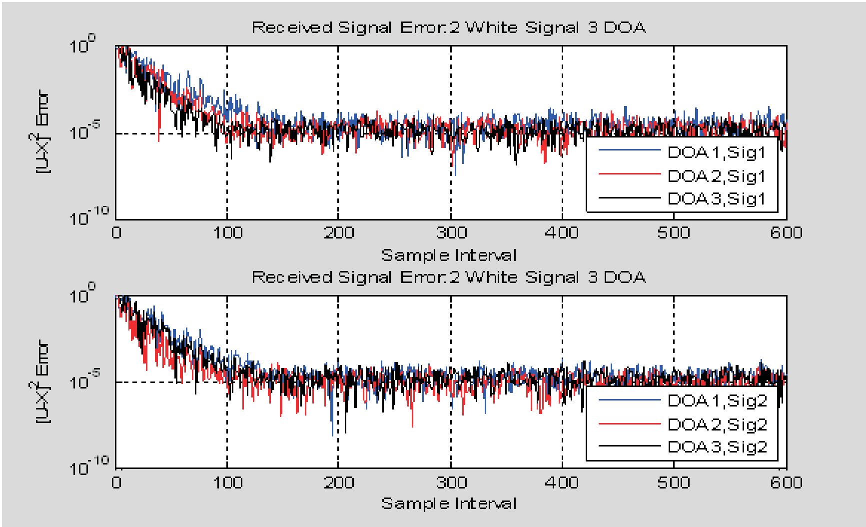

Fig.6: Received signal error with Two white signals with three DOAs each for NLMS algorithm

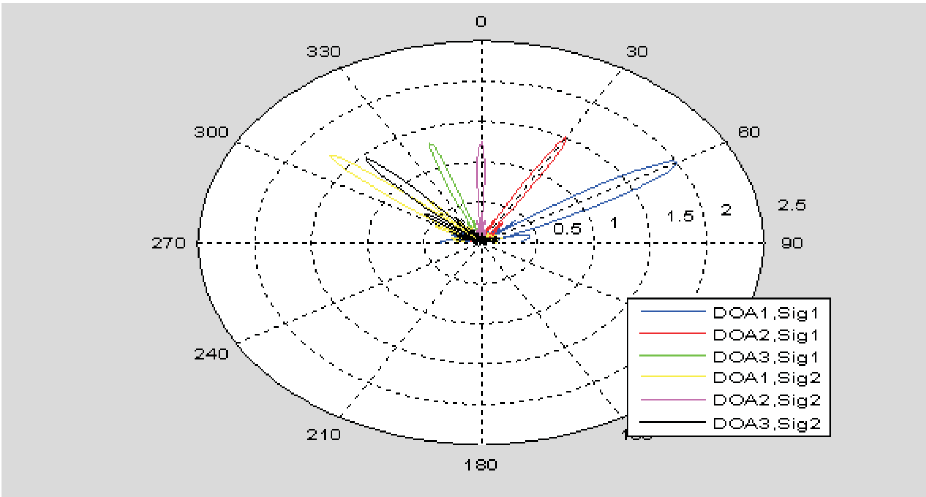

Fig.5:NLMS:polar plot for Two white signals with three DOAs

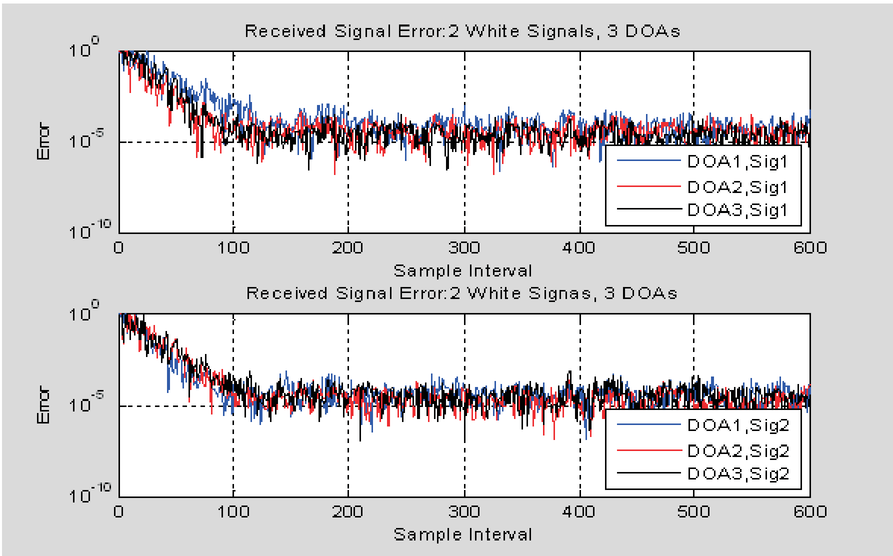

Fig.4:Received signal error with Two white signals with three DOAs each for BBNLMS algorithm

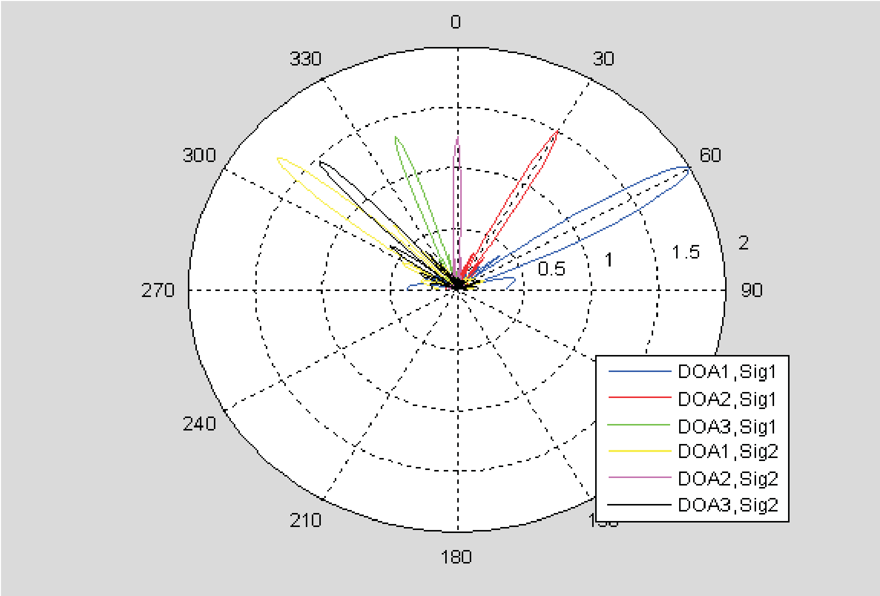

Fig.5:BBNLMS:polar plot for Two white signals with three DOAs

CONCLUSION

In this paper several beam forming algorithms are presented with some simulation and results Using NLMS and BBNLMS algorithms, compared to LMS algorithm, a 100% and 145% increase in overall convergence rate is achieved in a multi user multipath environment. With regards to beam patterns, NLMS and BBNLMS algorithms are able to steer beams in the direction of the desired signal and place nulls elsewhere.

REFERENCES

[1] L.Gargouri, R.Ghayoula, N.Fadlallah, A.Gharsallah, M.Rammal; "Steering an adaptive antenna array by LMS algorithm" IEEE transactions on digital signal processing, pp 459-462, oct 2009.
[2]Optus Administration Ptv Ltd Website, Nodate, [Online]. Available at http://www.optus.com.au[Accessed30/09/02].
[3] J. Y.-L. Chou, "An investigation on the impact of antenna array geometry on beam forming user capacity," Master's thesis, Queen's University, Kingston 2002.
[4] International Telecommunications Union (ITU). [Online]. Available: http://www.itu.int/home
[5] "Air Interface Fundamentals: UMTS and W-CDMA," Award Solutions. [Online].Available: http://www.awardsolutions.com/training/elearning pdfs
[6] R.D.Murch and K. B. Letaief, "Antenna systems for broadband wireless access," IEEECommun. Mag., Apr. 2002.
[7] L. C. Godara, "Applications of antenna arrays to mobile communications. Part I: Performance improvement, feasibility, and system considerations," in Proc. IEEE, vol. 85,pp. 1031–1060, July 1997. doi:10.1109/5.611108
[8]Rappaport, T.S.1996Wireless Communications:Principles&Practice, Prentice Hall Communications Engineering and Emerging Technology Series.
[9]Rosol,G. 1995. Base Station Antennas: Part1, Part2, Part3. Microwaves&RF, August, pp.117-123,September, pp.127-131,October, pp.116-124.
[10] J. H. Winters, "Smart antennas for wireless systems," IEEE Personal Commun. Mag.,vol. 5, no. 1, pp. 23–27, Feb. 1998. doi:10.1109/98.656155
[11] I. Stevanovi´c, A. Skrivervik, and J. R. Mosig, "Smart antenna systems for mobilecommunications," Ecole Polytechnique F´ed´erale de Lausanne, Lausanne, Suisse, Tech.Rep., Jan. 2003. [Online]. Available: http://lemawww.epfl.ch
[12] S. Bellofiore, "Smart antenna systems formobile platforms," Ph.D. dissertation, ArizonaState

University, Dec. 2002..
[13] P. H. Lehne and M. Pettersen, "An overview of smart antenna technology for mobile communications systems," IEEE Communications Surveys, vol. 2, no. 4, pp. 2–13, FallQuarter1999. [Online]. Available:
www.comsoc.org/livepubs/surveys/public/4q99issue/pdf/Lehne.pdf
[14] A. R. Lopez, "Performance predictions for cellular switched beam intelligent antenna systems, "IEEE Commun. Mag., vol.34 ,no.10, pp.152154, Oct. 1996 .doi: 10.1109/35.544336
[15] T. Thrassyvoulou, "Adaptive beamforming: Using a complex bounding ellipsoid algorithmwith gradient projections," Master's thesis, Arizona State University, Aug.2003.
[16] N. C. T. Desmond, "Smart antennas for wireless applications and switched beamforming,"The University of Queensland, Brisbane, Australia, Tech. Rep., 2001.
[17] T. Do-Hong and P. Russer, "Signal processing for wideband array applications," IEEEMicrow., vol. 5, no. 1, pp. 57–67, Mar. 2004. doi:10.1109/MMW.2004.1284944
[18] L. C. Godara, "Applications of antenna arrays to mobile communications. Part I: Performance improvement, feasibility, and system considerations," in Proc. IEEE, vol. 85, pp. 1031–1060, July 1997.