IJARCCE
ISSN (Online) 2278-1021
ISSN (Print) 2319 5940

International Journal of Advanced Research in Computer and Communication Engineering
Vol. 5, Issue 4, April 2016

Rapidity and authenticity augmentation using adaptive beamforming procedure for smart antenna systems

Mr.A.Suban[1], Mr.V.Karthick[2], D.Nagasuganthi[3], N.R.Sakila[4]

Assistant Professor, ECE, VCET, Madurai[1]

Lecturer, ECE, VCET, Madurai[2]

UG Final year, ECE, VCET, Madurai[3,4]

Abstract: In this paper, a modular adaptive beamforming algorithm has been proposed which is used for smart antenna users tracking purpose in a wide angle environment. It can be used for adaptation of subjective variations in eigen vectors. It can also be used for the autocorrelation matrix which consists of eigen values of the signal vector which is received is mostly useful for the case of moving subscriber situation. Furthermore, it uses one adaptive module which is better than previous works where two adaptive modules have been used and will lead to a high speed twice more than the previous works.

Keywords: adaptive beamforming,smart antenna, non blind algorithms,optimal weight vector.

I.INTRODUCTION

In general, a channel vector model for the uplink mobile communication assumes a narrow angle spread, which is the case for base stations with tall antenna heights. Therefore, most beamforming algorithms have been developed for the case of a narrow angle spread. Some of these beamforming algorithms have been proposed in [1,2], in which one eigenvector of autocorrelation matrix of received signal is computed to form the optimal weight vector. The performance of the beamforming algorithms developed for narrow angle spread degrades considerably as the angle spread increases. Studies have shown that in the case of a wide angle spread, two eigenvectors with the largest eigenvalues of the autocorrelation matrix should be computed to form the optimal weight vector [6,7]. Although Siriteanu and Blostein [6] and Zekavat et al. [7] present the main idea of using two eigenvectors of the autocorrelation matrix of the received signal, but do not contain answer to the question that how the eigenvalues and eigenvectors of the autocorrelation matrix can be calculated. Lee and Choi [4] try to present a computational procedure to compute eigenvalues and eigenvectors of the autocorrelation matrix of the received signal. On the other hand, for mobile communication when the subscribers are moving during their communication with the smart antenna, the autocorrelation matrix and its eigenvalues and eigenvectors vary without a rule that can be understood conveniently. For special scenarios of these variations the beamforming procedure of Lee and Choi [4] cannot provide a desirable response. This means the reliability of this beamforming procedure is not showable in a firm way for use in a smart antenna, because the presented scenario can be possible to occur. In this paper, an improved adaptive beamforming algorithm has been proposed which can be used for tracking the subscribers in a smart antenna with a wide angle spread environment when there are arbitrary variations in both eigenvalues and eigenvectors of the autocorrelation matrix of the received signal. Moreover, the number of adaptive modules in the proposed algorithm is less than the previous work [4] which is a reason for achieving a high speed.

II.PREVIOUS WEAKER WORKS

So far, smart antennas are studied for the purposes of enhancing the base station performance in multipath fading conditions and increasing SNR of the receiver [2,5,8]. In these works the main purpose is to compute an optimal weight vector to use in a smart antenna array for phase and amplitude shifting. Siriteanu and Blostein [6] and Zekavat et al. [7] show importance of using two eigenvectors in computation of weight vector and to apply them in a smart antenna system in order to improve BER (Bit Error Rate) performance in a wide angle spread environment. Siriteanu and Blostein [6] analyze maximal ratio eigen-combining as an alternative to conventional maximum average SNR beamforming as well as maximal ratio combining in scenarios with practically correlated channel gains. Zekavat et al. [7] present a novel merger of an adaptive smart antenna maximum noise fraction beamforming, which maximizes the SNR and leads to a generalized singular value decomposition, and MC-CDMA systems. But, Siriteanu and Blostein [6] and Zekavat et al. [7] do not present how to calculate the eigenvalues and eigenvectors to improve the BER performance, which is the main purpose of a smart antenna's digital environment. In this section, we represent previous works that are done in order to calculate the suitable eigenvalues and eigenvectors of the

IJARCCE

ISSN (Online) 2278-1021
ISSN (Print) 2319 5940

International Journal of Advanced Research in Computer and Communication Engineering
Vol. 5, Issue 4, April 2016

autocorrelation matrix of received signals of a smart antenna that should finally form the optimal weight vector for a wide angle spread environment. These works have some weakpoints, and their performance compared to the performance of the solution presented in this paper is discussed in the subsequent sections.

III.NEW PROPOSED ALGORITHM

Combining in scenarios with practically correlated channel gains. Zekavat et al. [7] present a novel merger of an adaptive smart antenna maximum noise fraction beamforming, which maximizes the SNR and leads to a generalized singular value decomposition, and mc-cdma systems. But, siriteanu and blostein [6] and zekavat et al. [7] do not present how to calculate the eigenvalues and eigenvectors to improve the BER performance, which is the main purpose of a smart antenna's digital environment. In this section, we represent previous works that are done in order to calculate the suitable eigenvalues and eigenvectors of the autocorrelation matrix of received signals of a From [4], in a smart antenna consider y is the received signal vector. The weight vector maximizing the snr can be obtained from the eigenvector corresponding to the largest eigenvalue of the following eigen-equation:

$$Ryyw = \lambda w \qquad \ldots\ldots\ldots\ldots\ldots(1)$$

Where **Ryy** is the autocorrelation matrix of the received signal vector obtained at the output of the despreader. In order to obtain a more appropriate weight vector in the signal environment of a wide angle spread, the weight vector is to be found in eigen-space. Considering more than two eigenvectors is not very helpful and does not conspicuously improve the performance. It particularly means that the weight vector is computed as a combination of the primary and secondary eigenvectors. Consequently, the weight vector is computed as a linear combination of the two primary eigenvectors as follows:

$$W^* = \alpha e_1 + \beta e_2 \qquad \ldots\ldots\ldots\ldots\ldots(2)$$

Where $\mathbf{e_1}$ and $\mathbf{e_2}$ denote the primary and secondary eigenvector respectively. $\boldsymbol{\alpha}$ and $\boldsymbol{\beta}$ are the constants representing the channel coefficients, which are obtained from the inner product of the eigenvector and received signal vector, and can be determined by:

$$\alpha = e^H{}_1\, y, \beta = e^H{}_2\, y \qquad \ldots\ldots\ldots\ldots\ldots(3)$$

In [4], an adaptive beamforming algorithm based on eigen-space method is proposed that utilizes two eigenvectors. In the presented technique in [4], the primary eigenvector is computed from the lagrange algorithm [2] and the secondary eigenvector is also computed from combination of the deflation method [3] and the lagrange algorithm. Basically, the entire procedure consists of a repetition of the lagrange's formula twice. First, the primary eigenvector is computed and then the secondary eigenvector is obtained by invoking the deflation method for **Ryy** before the lagrange's formula is used repeatedly. By applying the deflation method to **Ryy** based on [3], the autocorrelation matrix for the second eigenvector can be written As:

$$R'_{y\,y} = R_{y\,y} - \lambda_1 w_1 w^H{}_1 \qquad \ldots\ldots\ldots\ldots\ldots(4)$$

Where $\boldsymbol{\lambda_1}$ is the first largest eigenvalue and $\mathbf{w_1}$ is a normalized primary eigenvector which corresponds to the first largest eigenvalue $\boldsymbol{\lambda_1}$.

similar to section 2, in a smart antenna consider **y** is the received signal vector. Also, the weight vector maximizing the SNR can be obtained from the eigenvector corresponding to the largest eigenvalue of the following eigen-equation:

$$R_{y\,y}\, w = \lambda w \qquad \ldots\ldots\ldots\ldots\ldots(5)$$

Where $\mathbf{R_{yy}}$ is the autocorrelation matrix of the received signal vector. For computing the eigenvector with the largest eigenvalue the lagrange algorithm can be proposed [2]. The formulation of this algorithm is as follows:

$$W_{k+1}=[1-\mu_1\gamma_1]w_k+\mu_1 R_{yy} \qquad \ldots\ldots\ldots\ldots\ldots(6)$$

The coefficient $\boldsymbol{\gamma_1}$ is determined so that the equation

$$w^H{}_k\, w_k = 1 \qquad \ldots\ldots\ldots\ldots\ldots(7)$$

Would be satisfied in all iterations and also initial guesses in which the operation $^{\mathbf{H}}$ represents conjugate transpose. The weight vector w will be converged to the eigenvector of the autocorrelation matrix $\mathbf{R_{yy}}$ with the largest eigenvalue. In order To work in a wide angle spread environment, a similar adaptive algorithm is used in this paper parallel to (2) represented by:

$$v_{k+1}=[1-\mu_2\gamma_2]v_k+\mu_2 R_{yy} v_k \qquad \ldots\ldots\ldots\ldots\ldots(8)$$

Using the condition,

$$v^H{}_k\, v_k = 1 \qquad \ldots\ldots\ldots\ldots\ldots(9)$$

With initial guesses similar to vector **w**. The weight vector **v** would be also converged to the eigenvector with the largest eigenvalue of $\mathbf{R_{yy}}$. Therefore, the weight vectors would fall on each other after convergence. In order to prevent them to be equal to each other, we change the algorithm. We keep the angle between **w** and **v** in a non-zero value and keep **w** and **v** orthogonal to each other during the execution of the algorithm. Assume that when the algorithm executes, $\mathbf{v_k}$ then $\mathbf{w_k}$ and then $\mathbf{v_{k+1}}$ are computed. By this assumption, we can do our change by applying these conditions in the algorithm convergence procedure:

$$w^H{}_k\, v_k = 0 \qquad \ldots\ldots\ldots\ldots..(10)$$

and

DOI 10.17148/IJARCCE.2016.54164

IJARCCE

ISSN (Online) 2278-1021
ISSN (Print) 2319 5940

International Journal of Advanced Research in Computer and Communication Engineering
Vol. 5, Issue 4, April 2016

$$w^H_k\, v_{k+1} = 0 \quad \text{..............(11)}$$

Which is also satisfied by the initial guesses. Obviously, w and v cannot be equal because of (7) and (9). Now, consider the situation in which the $\mathbf{v_{k+1}}$ and wk have been computed.

Now $\mathbf{w_{k+1}}$ should be computed. If (6) is used, $\mathbf{w_{k+1}}$ may not be Orthogonal to $\mathbf{v_{k+1}}$ according to (10). Thus a factor of $\mathbf{v_{k+1}}$ can be added to the resulted $\mathbf{w_{k+1}}$ in order to remove the mirror of $\mathbf{w_{k+1}}$ on $\mathbf{v_{k+1}}$:

$$w_{k+1} = [1-\mu_1\gamma_1]w_k + \mu_1 R_{yy}\, w_k + \alpha_1 v_{k+1} \quad \text{.............(12)}$$

For determination $\boldsymbol{\alpha_1}$ of multiply $\mathbf{v^H_{k+1}}$ to (12) from the left and use (9)–(11). It results in:

$$\alpha_1 = -\,\mu_1\, v^H_{k+1}\, R_{yy}\, w_k \quad \text{..............(13)}$$

Similar changes are done on (6). We obtain

$$v_{k+1} = [1-\mu_2\gamma_2]v_k + \mu_2 R_{yy}\, v_k + \alpha_2\, w_k \quad \text{..............(14)}$$

By multiplying $\mathbf{w^H_k}$ to (14) from the left and using (7), (10) and (11) we obtain:

$$\alpha_2 = -\,\mu_2\, w^H_k\, R_{yy}\, v_k \quad \text{..............(15)}$$

After finding these formulations for $\boldsymbol{\alpha_1}$ and $\boldsymbol{\alpha_2}$ we can find the formulas to compute $\boldsymbol{\gamma_1}$ and $\boldsymbol{\gamma_2}$. Completely similar to the lagrange algorithms [2], multiply (12) after an operation ^{H} to (12), then substitute (7), (9), (10) and (4.3.6.11) in it. Then, a second order equation will be produced that can be solved by $\boldsymbol{\gamma_1}$. This procedure will result in:

$$\gamma_1 = \frac{b-\sqrt{b^2-ac}}{a} \quad \text{.............(16)}$$

By these assumptions:

$$a = \mu^2_1 \quad \text{.............(17)}$$

$$b = \mu_1 + \mu^2_1\, w^H_k\, R_{yy}\, w_k \quad \text{.............(18)}$$

$$c = \mu^2_1\, w^H_k\, R^2_{yy}\, w_k + \alpha^2_1 + 2\,\mu_1\, w^H_k\, R_{yy}\, w_k + \mu_1\alpha_1(v^H_{k+1}R_{yy}w_k + w^H_k R_{yy} v_{k+1}) \quad \text{............(19)}$$

Also do this operation identically on (14). You will obtain:

$$\gamma_2 = \frac{b'-\sqrt{b'^2-a'c'}}{a'} \quad \text{..............(20)}$$

By these assumptions:

$$a' = \mu^2_2 \quad \text{..............(21)}$$

$$b' = \mu_2 + \mu^2_2\, v^H_k\, R_{yy}\, v_k \quad \text{..............(22)}$$

$$c' = \mu^2_2\, v^H_k\, R^2_{yy}\, v_k + \alpha^2_2 + 2\,\mu_2\, v^H_k\, R_{yy}\, v_k + \mu_2\alpha_2(w^H_k R_{yy} v_k + v^H_k R_{yy} w_k) \quad \text{...........(23)}$$

IV.STEADY STATE EQUATIONS

The algorithm steady state equations are produced by these substitutions in (12) and (14):

$$w = w_{k+1} = w_k \quad \text{..............(24)}$$

$$v = v_{k+1} = v_k \quad \text{..............(25)}$$

That results in:

$$\mu_1\, \gamma_1\, w = \mu_1\, R_{yy}\, w + \alpha_1 \quad \text{..............(26)}$$

And

$$\mu_2\, \gamma_2\, v = \mu_2\, R_{yy}\, v + \alpha_2\, w \quad \text{..............(27)}$$

The vectors **w** and **v** can be written as:

$$w = k_1e_1 + k_2e_2 + \dots + k_n e \quad \text{..............(28)}$$

$$v = k'_1e_1 + k'_2e_2 + \dots + k'_n e_n \quad \text{..............(29)}$$

Where e1,e2,. . . Are the eigenvectors of matrix $\mathbf{R_{yy}}$. These equations can be substituted in (18) and (19). Then in n passes if $\mathbf{e^H_1}$, $\mathbf{e^H_2}$ . . Are multiplied to the resulted equations from the left, we have:

$$(\mu_1\gamma_1 - \mu_1\lambda_i)\backslash k_1 - \alpha_1 k'_i = 0 \quad \text{.............(30)}$$

$$\alpha_2\, k_i + (\mu_2\lambda_i - \mu_2\,\gamma_2)\, k'_i = 0. \quad \text{...........(31)}$$

For i = 1,2, . . . ,n, where $\boldsymbol{\lambda_i}$ represents the eigen values. Now if $\mathbf{k_i}$, $\mathbf{k'_i} = \mathbf{0}$,we should have:

$$\mathrm{Det}\begin{vmatrix} \mu1\,\gamma1 - \mu1\lambda i & -\alpha 1 \\ \alpha 2 & \mu2\lambda i - \mu2\,\gamma2 \end{vmatrix} \quad \text{........(32)}$$

This equation provides only two values for λ_i, as λ_1 and λ_2. Therefore, for i > 2 we have $\mathbf{k_i} = \mathbf{k'_i} = 0$.Thus the weight vectors w and v are linear combinations of the two eigenvectors whose corresponding eigen values can be found from (27). Then k_1, k_2, and k'_1, k'_2 can be obtained from (26) and orthogonality of w and v. Thus the eigenvectors e_1 and e_2 can be obtained. The vector w in the algorithm with the formulation of (12) in the steady state is placed on the surface of v and the eigenvector with the largest possible eigen value of Ryy based on [2].

This is also true for v in (14). This means that w and v are placed on the surface of the two eigenvectors with the largest eigen values. Thus in the discussion above the $\boldsymbol{\lambda_1}$ and $\boldsymbol{\lambda_2}$ are the largest Eigen values. Finally, according to lee and choi [7], the optimal weight vector **w*** can be found from the two eigenvectors with the largest eigenvalues as:

$$w^* = \alpha e_1 + \beta e_2 \quad \text{..............(33)}$$

In which:

$$\alpha = e^H_1 y \quad \text{.............(34)}$$

$$\beta = e^H_2 y \quad \text{.............(35)}$$

Copyright to IJARCCE
DOI 10.17148/IJARCCE.2016.54164

IJARCCE

ISSN (Online) 2278-1021
ISSN (Print) 2319 5940

International Journal of Advanced Research in Computer and Communication Engineering
Vol. 5, Issue 4, April 2016

V.PERFORMANCE OF THE PROPOSED ALGORITHM

A simulation by MATLAB will help to show the performance of our proposed algorithm. Consider the autocorrelation matrix has the largest eigenvalues of $\boldsymbol{\lambda}_1$ and $\boldsymbol{\lambda}_2$ with eigenvectors of $\mathbf{q}_1$ and $\mathbf{q}_2$ respectively. Parameters

$a_{11} = e^{H}_{1}\, q_1$ …………..(36)

$a_{22} = e^{H}_{2}\, q_2$ …………..(37)

$a_{12} = e^{H}_{1}\, q_2$ …………..(38)

$a_{21} = e^{H}_{2}\, q_1$ ………….(39)

are defined. It is expected that two of these coefficients should be equal to 1 and two of them are equal to 0 after convergence. These results have been obtained by simulation results , in the case that the eigenvalues are varying with a scenario. The convergence is done with a high accuracy in the proposed algorithm.

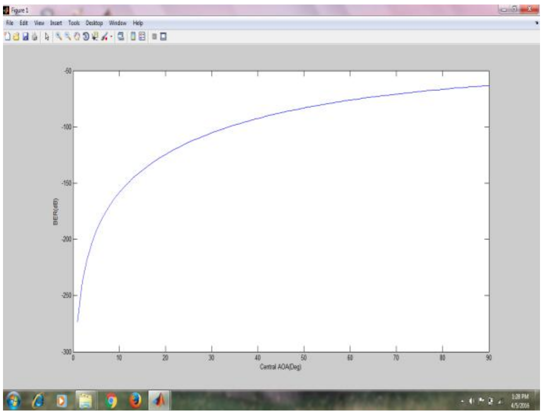

Fig.1 BER vs central AOA

VI.CONVERGENCE SPEED COMPARISON

In steady state it is not needed for the weight vectors w and v to converge to eigenvectors. It is sufficient for w and v to be placed on the surface of eigenvectors. Besides it, the number of adaptive modules in the proposed algorithm is less compared to that of Lee and Choi [7] (one module against two serial modules). Thus, it is expected that the proposed algorithm will converge faster than that of Lee and Choi [7]. Comparison between simulation results of the proposed algorithm and the algorithm in [7] that are done in the same conditions, verifies this phenomenon.

VII.TRACKING RELIABILITY

The eigenvector with the largest eigenvalue changes suddenly in the iteration 25. The beamforming procedure in [4] uses two serial adaptive modules. The first module computes the eigenvector with the largest eigenvalue for using in the second module. Thus, in the mentioned scenario, the beamforming procedure in [4] will start to converge again and will miss the lock on the target.

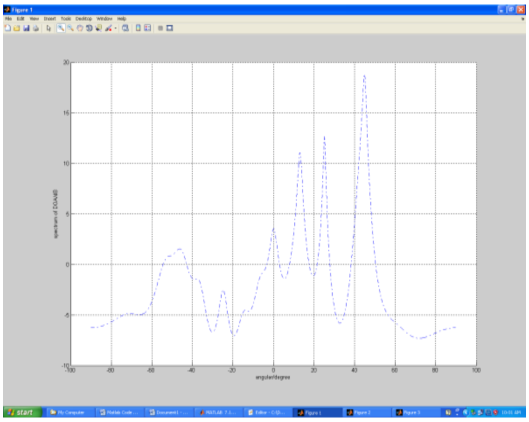

Fig.2 spectrum of DOA vs angular degree

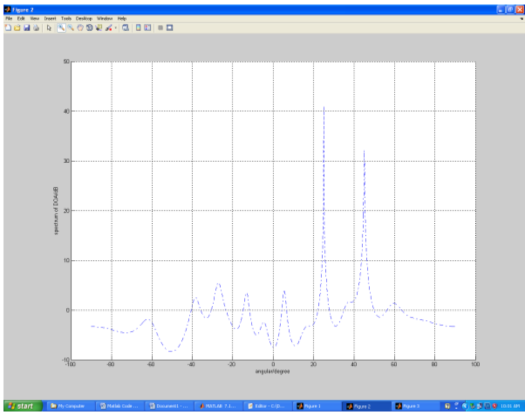

Fig.3 spectrum of DOA vs angular degree

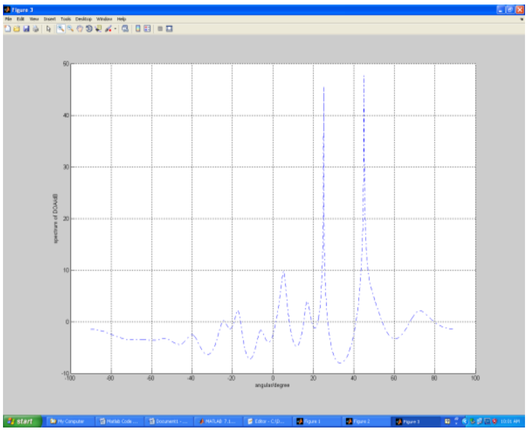

Fig.4 spectrum of DOA vs angular degree

This phenomenon can be found after the iteration 25. The algorithm in [4] supposes that its memory about the eigenvectors that are computed so far has been invalidated. Though this is the new proposed algorithm, it encounters no problem in its operation. No change is observed in the response of the proposed algorithm even in the iteration 25 in which the eigenvector with the largest eigenvalue changes suddenly. It is because of the special architecture and the one modular adaptive procedure used in the proposed algorithm. The adaptive module of the proposed algorithm is free from change of operating conditions during the execution of scenario, because the two eigenvectors with the largest eigenvalues are produced together and not distinctly during the execution of the

IJARCCE

ISSN (Online) 2278-1021
ISSN (Print) 2319 5940

International Journal of Advanced Research in Computer and Communication Engineering
Vol. 5, Issue 4, April 2016

proposed algorithm. None of the eigenvectors in the proposed algorithm are forced to have the first largest eigenvalue (or the second largest eigenvalue). Thus the proposed algorithm is compatible with more scenarios than the work in [7].

VIII.CONCLUSION

In this project, an adaptive beamforming algorithm was proposed that performs the tracking duties of a smart antenna when it works in a wide angle spread environment. Confidence on a smart antenna performance for arbitrary variations of eigen values and eigenvectors produced by variations of input signal is very important for reliability of the tracking procedure. If this is not done, there is a need for some firm predictions about the relations between positions of subscribers and the eigen values and eigenvectors of the autocorrelation matrix. Without these predictions, there will be still this probability that the smart antenna performance will degrade in practice. Previous works in this field start from [6,7] in which the initial idea of importance of using two eigenvectors for computation of weight vectors of a smart antenna in a wide angle spread environment is proposed.

Lee and Choi [7] try to compute these two eigenvectors and neglect some important points. In this paper, we showed that Lee and Choi [7] are not so successful in such a computation. Although in static conditions, Lee and Choi [7] may provide a good response, but for dynamic conditions they [7] have not provided an appropriate beamforming technique. Against Lee and Choi [7], in this paper a faster and more reliable algorithm as a continuation for [6,7] has been proposed. It is fast because it uses one modular adaptive procedure. Also its architecture causes that it would be adaptable to more diverse scenarios of variations of the eigen values and eigenvectors of the autocorrelation matrix.

REFERENCES

[1] Amara Prakasa Rao and N.V.S.N. S,' Adaptive Beamforming Algorithms For Smart Antenna Systems', Wseas Transactions On Communications
[2] Constantin Siriteanu and Steven D. Blostein,'Maximal-Ratio Eigen-Combining for Smarter Antenna Arrays', IEEE Transactions On Wireless Communications, Vol. 6, No. 3, March 2007.
[3] Ifeagwu E.N. and Edeko F.O., Emagbetere J.O.,' Analysis of Least Mean Square Adaptive Beam forming Algorithm of the Adaptive Antenna for Improving the Performance of the CDMA20001X BaseMobile Radio Network, International Journal on Recent and Innovation Trends in Computing and Communication Volume: 3.
[4] Neelapu G R Reddy, K.Rama Devi,' Smart Antennas Adaptive Beamforming through Statistical Signal Processing Techniques', International Journal of Research in Computer and Communication Technology, Vol 2, Issue 8, August -2013
[5] Seungwon Choi and Donghee Shim,' A Novel Adaptive Beamforming Algorithm for a Smart Antenna System in a CDMA Mobile Communication Environment', IEEE Transactions On Vehicular Technology, Vol. 49, No. 5, September 2000.
[6] Wei Wang,' Eigen analysis of autocorrelation Matrices in the Presence of Non central and Signal-Dependent Noise', IEEE SIGNAL PROCESSING LETTERS, VOL. 12, NO. 2, FEBRUARY 2005.
[7] Weon-Cheol Lee and Seungwon Choi, Member, IEEE,' 'Adaptive Beamforming Algorithm Based on Eigen-space Method for Smart Antennas'ieee Communications Letters, Vol. 9, No. 10, October 2005.
[8] Zhonghai Wang and Seyed A. (Reza) Zekavat,' Omnidirectional Mobile NLOS Identification and Localization via Multiple Cooperative Nodes', IEEE Transactions On Mobile Computing, Vol. 11, No. 12, December 2012.