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OPTIMIZATION OF BLIND SPOOFING USING DISCRETE MODEL

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ABSTRACT: In order to improve the optimizing efficiency, one dimensional blind-walking optimization method is proposed, which can be realized by halving step or doubling step for the applicability test condition of the sensing point. The optimum point, then, can be reached at high rate by doubling step and converged by halving step. Current point should be updated in whole design space. The flow chart of this algorithm with operating process is put forward. And then, two optimization problems with uni-modal and multimodal objective functions are solved respectively. The simulation results show that the proposed method is better than the ordinary method, which has the advantages of fast convergence speed, less calculating amounts, and wide application scope, etc. Taking the method as innovative kernel, random research method, feasible direction method and other complex methods are improved. Its characteristics are suitable for vivid teaching like interpreting. The linear subspace-based blind and group-blind multiuser detectors recently developed represent a robust and efficient adaptive multiuser detection technique for code-division multiple-access (CDMA) systems. In this paper, we consider adaptive transmitter optimization strategies for CDMA systems operating in fading multipath environments in which these detectors are employed. We make use of more recent results on the analytical performance of these blind and group-blind receivers in the design and analysis of the transmitter optimization techniques. In particular, we develop a maximum-eigenvector-based method of optimizing spreading codes for given channel conditions and a utility-based power control algorithm for CDMA systems with blind or group-blind multiuser detection.

Keywords: Adaptive multiuser detection, power control, spreading sequences, utility, wireless communications.

I. INTRODUCTION

Typical physical-layer work in adaptive multiuser detection for CDMA considers the transmitter parameters (rate, power, spreading codes, error-correction codes, and spreading gain) to be fixed. Optimization is usually attempted at the receiver only. In recent years, more researchers have investigated transmitter optimization but usually in the context of rate optimization or power control. This paper discusses how optimization of Blind Spoofing (BS) is achieved using the Linear Subspace-based Blind (LSB) and Group-blind Multiuser Detectors (GMD) method. A system has developed to consider adaptive transmitter optimization strategies for Code Division Multiple Access (CDMA) systems operating in fading multipath environments in which these detectors are employed. It makes use of more recent results on the analytical performance of these blind and group-blind receivers in the design and analysis of the transmitter optimization techniques.

In particular, a system has developed a maximum eigenvector based method of optimizing spreading codes for given channel conditions and a utility-based power control algorithm for CDMA systems with blind or group-blind multiuser detection. A system has designed a receiver incorporating joint optimization of spreading codes and transmitter power by combining these algorithms in an iterative configuration. These methods reduce the power control and spreading code and increase the throughput.

A. LINEAR SUBSPACE-BASED BLIND

One of the CDMA transmitter parameters that are largely ignored in adaptive systems is the spreading code. It is well known that CDMA systems are interference limited where multi-user detectors must be estimated, are also estimation-error limited, i.e., performance is limited by the difference between the (unavailable) exact detector and the (available) estimated detector. Multi-user detection performance in estimation/interference-limited environments

International Journal of Advanced Research in Computer and Communication Engineering
Vol. 1, Issue 2, April 2012

improves when the correlation of the spreading codes decreases.

With multiple-access interference reduction in mind, researchers have considered optimal (binary) spreading sequences for synchronous CDMA over Additive White Gaussian Noise (AWGN) channels when the number of users is larger than the spreading gain. They have also identified good spreading sequences in the context of spread-spectrum systems with conventional matched filter receivers and equal received power for all users. The system addressed the problem of code sequence design in an information-theoretic setting for which the sum of the rates of all users is maximized.

B. GROUP-BLIND MULTIUSER DETECTORS

Typical physical-layer works in adaptive multiuser detection for CDMA considers the transmitter parameters (rate, power, spreading codes, error-correction codes, and spreading gain) to be fixed. Optimization is usually attempted at the receiver only. In recent years, more researchers have investigated transmitter optimization but usually in the context of rate optimization or power control.

The power is the transmitter parameter is most often exploited to improve performance in CDMA systems. This is due to the near-far problem, in which correlation among user's spreading codes (or composite signature waveforms) can cause severe performance discrepancies between transmitters that are close to the base station and those that are distant from the base station when transmitter power is unregulated. Initially, the goal of power control was simply to regulate transmitter power to maintain minimum system wide performance criteria, which is typically measured in signal-to-carrier power ratio or Signal-to-Interference-plus-Noise Ratio (SINR).

The satisfaction that the user received in such a system, i.e., the utility, was a binary function that was zero when the SINR dropped below a threshold and unity when the SINR achieved or surpassed the threshold. This is appropriate for voice communications in which SINR above a threshold do not provide additional benefit and SINR below that threshold lead to unintelligible speech, which has zero benefit (utility) for the user. However, this kind of utility function is not appropriate for data because data services must meet different requirements to satisfy the user. In particular, data applications are typically delay tolerant but require very low bit-error rates.

C. IMPLEMENTATION DETAILS OF GROUP-BLIND MULTIUSER DETECTORS

The implementation of adaptive optimization of spreading codes and transmitter powers both separately and jointly to maximize utility with the lowest possible transmit power in a heterogeneous traffic environment where adaptive blind or group-blind linear multiuser detection is employed. A system has considered that are able to adapt to changes in the channel, traffic, number of users, etc., in practical channel environments. In light of the recent work, a system will consider the effects of both multiple-access interference and estimation error on the receiver. The contributions of these works include the following,

- A blind or group-blind adaptive algorithm for adapting spreading codes to maximize SINR in fading multipath environments.
- A utility-based power control algorithm for CDMA systems using adaptive blind or group-blind multiuser detectors.
- A practical receiver design including joint adaptive power control and spreading code optimization that improves the performance of adaptive CDMA systems servicing heterogeneous traffic in dispersive channel environments.

The system model including a description of the general discrete-time signal and channel models that will be used throughout. A system will summarize and cite references for brevity.

C1. DISCRETE TIME SIGNAL MODEL

The following model is general in that it takes asynchronism and multipath fading into account. A system has considered a K user sliding-window, discrete-time linear model of the form,

$$r[i] = HAb[i] + v[i] \qquad (1)$$

Where the bits that the system wish to demodulate from the equation (1) are $[b[i]]_{kt=1}$ through $[b[i]]_{k(t=1)}$, where t denotes the maximum total delay (path delay plus transmit delay) in symbol intervals and where v[i] is composed, complex Gaussian random variables with variance σ^2. The bits we wish to demodulate are henceforth denoted by $\{b_k[i]\}^K k=1$. The smoothing factor, which is necessary to ensure that H is "tall" for blind channel identification, is given by m. If the system define r = K, then the sizes of r[i], v[i],H, b[i], and A are given by N_{m*1}, N_{m*1}, N_{m*r}, N_{r*1}, and N_{r*r}, respectively, where N is the system processing gain. Note that A contains the user's transmit powers and is a block diagonal matrix of the form,

$$A = \begin{pmatrix} P & & 0 \\ & \ddots & \\ 0 & & P \end{pmatrix} \qquad (2)$$

Where $P = \mathrm{diag}(p_1, p_2 \ldots p_k)$. Denote by D the matrix with the same structure as A with $p_1, p_2 \ldots p_k$ replaced with the corresponding distances $d_1, d_2 \ldots d_k$ between each user and the base station.

The columns of H that correspond to the bits in $\{b_k[i]\}^K k=1$ are the composite signature waveforms and are given by $h_k = he_{kt+k}$ for $k = 1 \ldots K$, where e_{kt+k} is the vector whose entries are all zero except the (K_{t+k})th entry, which is one. The system assume that the complex path gains for each user are normalized such that the composite signature waveforms satisfy,

$$\| hk \|^2 = C_0/dk^4 \qquad (3)$$

Here the value of k=1,….., K, where d_k is the distance from the base station to the mobile of User k, and C_0 is a constant that depends on antenna gains, signal wavelengths, etc. For convenience, C_0 is set such that a single user at 1000 m from the base station transmitting at 10 W over a non-fading Additive White Gaussian Noise (AWGN) channel will achieve an SNR of 15 dB. Note that the columns of H (the composite signature waveforms) contain information about both the timings and the complex path gains of the multipath channel of each user. Hence, an estimate of these waveforms eliminates the need for separate estimates of the timing information.

C2. DISCRETE TIME CHANNEL MODEL

The continuous-time channel model for User that is implicit in equation (1) is given by,

$$gk(t) = \sum_{l=1}^{L} (\propto kt\, \delta)\, (t - Tkt) \qquad (4)$$

$$gk(t) = \sum_{l=1}^{L} (\propto kt\delta)(t - Tkt)$$

Where α_{kl} is the complex path gain associated with the l^{th} path for the k^{th} user, and T_{kl}, $T_{k1} < T_{k2} < \ldots < T_{kL}$ is the sum of the associated path and initial transmission delays of User *k*. The system assumes a quasistatic channel. Define the sequence f[.] as,

$$f[N] = \sum_{l=1}^{L} (\propto kt \int \Psi(t)\ \Psi(t - Tkl + nTc)\, dt \qquad (5)$$

Where T_c is the chip interval, and $\psi(t)$ is a normalized chip waveform of duration T_c. The system can see that f[n] is zero whenever $n < 0$ or $n > tN$. The system denote the discrete-time channel response for User *k* by,

$$fk = [fk[0] \ldots\ldots fk[lN]]^T \qquad (6)$$

If the system also define,

$$C_k = \begin{pmatrix} c_k & & 0 \\ & \ddots & \\ 0 & & c_k \end{pmatrix}$$

$$F_k = \begin{pmatrix} f_k & & 0 \\ & \ddots & \\ (3)\,0 & & f_k \end{pmatrix} \qquad (7)$$

Where $c_k = [c_k[1]\ \ c_k[2] \ldots\ldots C_k[N]]^T$ is the normalized spreading code of User k, then the system may write the composite signature waveforms in equation (3),

$$h_k = c_k f_k = F_k c_k \qquad (8)$$

Where k = 1,2, …… K.

D. REVIEW OF BLIND AND GROUP BLIND MULTIUSER DETECTION

The transmitter optimization for blind and group-blind multiuser detection, the system briefly reviews these detectors in this section. Note that E{.} will denote ensemble averaging. Since the ambient noise is white, i.e., $E\{v[i]v[i]^H\} = \sigma^2 I_{Nm}$, where I_{Nm} is the $N_m * N_m$ identity matrix and since the transmitted bits are assumed uncorrelated, the autocorrelation matrix of the received signal in (1) is,

$$C_r = E\{r[i]r[i]^H\} = HA^2H^H + \sigma^2 I_{Nm} \qquad (9)$$
$$= U_s A_s U_s^H = \sigma^2 U_n U_n^H \qquad (10)$$

ISSN 2278 – 1021
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Vol. 1, Issue 2, April 2012

Where the equation (10) is the eigen decomposition of C_r. U_s have size N_m * t and U_n has size N_m * (N_{m-r}). The multiuser detector and corresponding bit estimate for $b_k[i]$ are given by,

$$\omega_k[i] = \arg_{\omega} \min E\{|b_k[i] - \omega^H r[i]^2\} \qquad (11)$$

$$b_k i = \text{sign}\,[\text{Re}\{\omega_k[i]^H r[i]\}],\ k = 1,2,\ldots\ldots, K \quad (12)$$

The solution to equation (11) can be written in terms of the signal subspace components as,

$$\omega_k[i] = U_s \phi_s^{-1} U_s^H h_k \qquad (13)$$

This detector can be implemented in a blind fashion, where the receiver has knowledge only of the signature waveform of the user of interest, by estimating the signal subspace components U_s, from the received signal. This can be accomplished using the sample autocorrelation matrix of the received signal or via subspace tracking. The system has developed also need to use some form of blind channel estimation.

There are some situations in which the receiver may have knowledge of K, 1 < k < K signature waveforms, e.g., uplink CDMA when inter cell interference is present. With this additional information, the system can develop detectors that outperform the blind implementations of equation (13). A set of these "group blind" detectors was developed. Define the matrix A similarly. Then, the group-blind linear hybrid detector for User k (1 < k < K) is given by the solution to the following constrained optimization problem,

$$\omega_k = \arg_{\omega \varepsilon \text{range}(H)} \min E\{(b_k[i]-\omega^H r[i])^2\} \quad (14)$$

Heuristically speaking, this detector zeros forces the interference caused by the known users and suppresses the interference from unknown users according to the Minimum Mean Square Error (MMSE) criterion. The solution and the corresponding bit estimate for User k.

$$\omega_k = U_s \wedge_s^{-1} U_s^H HA[A^T H^H U_s \wedge_s^{-1} U_s^H HA]^{-1} e_{ki+k}\ (15)$$

$$\omega_k = U_s \wedge_s^{-1} U_s^H HA[A^T H^H U_s \wedge_s^{-1} U_s^H HA]^{-1} e_{ki+k}\ (15)$$

$$b_k[i] = \text{sign}[\text{Re}\{\omega_k^H r[i]\}],\ k = 1,2,\ldots\ldots, K \quad (16)$$

II. DESIGN

In the Blind Spoofing, the algorithm can be implemented in blind or group-blind fashion and, therefore, is appropriate for both uplink and downlink transmissions. Choosing optimal sequences for synchronous CDMA over a non-fading AWGN channel when K <= N is a trivial problem, use orthogonal sequences. The problem has been investigated for situations in which K > N. Therefore, the system has restricted our attention to adapting codes for the fading multipath channel model. This problem is relevant since spreading code sets with good correlation properties can, after convolution with the channel, lead to composite signature waveform sets with poor correlation properties.

A. DESIGN APPROACHES

Maximum Eigenvector Method – There are a number of optimization problems that the system has formulated with the stated goal of improving performance. The system has developed for the example, form optimal codes by minimizing composite signature waveform correlations via,

$$\text{Arg}_{c1\ldots ck} \min \|[h_1\ldots h_k]^H[h_1\ldots h_k]\|_1 \qquad (17)$$

$$= \arg_{c1\ldots ck} \min \sum_{j=1}^{K} \sum_{k=1}^{K}$$

$$\sum_{j=1}^{K} \quad \sum_{k=1}^{K} \quad C_j^T F_j^H F_k C_k$$

Where $\|\ .\ \|_1$ is the l_1 matrix norm defined as the sum of the absolute value of each of the matrix elements. The system has chosen a different, more direct, approach by note from the equation (1) that the SINR for User k (1 < k < K), when H is perfectly known and an MMSE multiuser detector is employed, is given by equation (18), where H_j denotes the j^{th} column of H, and $[A]_{j,j}$ denotes the element in the j^{th} column and j^{th} row of the matrix . Equation (18) suggests a strategy, in which each user independently chooses the new spreading sequence C_k^{new} to satisfy,

$$C_k^{new} = \arg_{C\varepsilon\{-1,+1\}^N} \max C^T,{}_k C \quad (18)$$

The solution to a related problem,

$$\max_{C\varepsilon CN} C^H ,{}_k C \qquad (19)$$

Whenever m+i > 0, there is some weak dependence in that 1 out of every K columns of H has some dependence on c_k. Despite this weak dependence, this algorithm provides substantial increases in achievable SINR.

ISSN 2278 – 1021

International Journal of Advanced Research in Computer and Communication Engineering
Vol. 1, Issue 2, April 2012

B. COMPLEXITY OF DESIGN

The design complexities that subspace tracking and channel estimation are necessary for the detection process. Furthermore, the maximum eigenvector computation can be computed with $O(N^2)$ floating-point operations per user per iteration. Therefore, the additional computational complexity incurred by spreading code optimization per user per iteration is dominated by the 6(m+i) vector outer products and matrix-vector product, each of which has complexity $O(N^2)$.

Assuming the channel is relatively constant over a block of data, the system need only perform code optimization once per block. If the block length is M, then the computational complexity per user per iteration per symbol is then $O([m+i]N^2/M)$. The total complexity per symbol is then $O(QK[m+i]N^2/M)$. Note that m and i are generally O(1), and M can be $O(10^3)$ for high data rate systems.

C. EXTENSIONS OF NON BINARY CODES

The extensions of Non Binary Codes (NBC) is natural to expect that the system should be able to improve on algorithm by taking advantage of the degrees of freedom that are eliminated by the sign{.} and Re{.} functions used to obtain C_k^{new}. The use of Quadrature Phase-Shift Keying (QPSK) modulation instead of Binary Phase-Shift Keying (BPSK), for example, results in baseband complex spreading non binary codes of the form $2Nc_k \varepsilon \{1+j,1-j,-1+j,-1-j\}^N$.

If the system also replace the typical binary shift-adder sequence generator with a layer of chip-level modulation, the system can generate complex codes that vary (almost) continuously, that is $c_k \varepsilon C^N$, $||c_k|| = 1$. In light of the (baseband) complex and continuously varying channel model, the system would expect that these additional degrees of freedom would enable us to generate superior composite signature waveform sets.

III. SIMULATIONS AND PERFORMANCE EVALUATION

To evaluate the optimization of Efficient Blind Spoofing (EBS) the MATLAB that is developed by Microsoft computer science department. This tool is utilized to compare the performance of the EBS against the Basic Blind Spoofing (BBS). MATLAB provides interactive tools and command line functions for data analysis operations including,

- Extracting sections of data, scaling and averaging
- Threshold and smoothing
- Correlation, Fourier analysis and filtering
- 1-D peak, valley and zero finding
- Basic statistics and curve fitting
- Matrix analysis

A. SIMULATION RESULTS

Optimization is measured based on parameters like binary codes, complex codes, blind case and fixed channel. The average optimization of networks on the various parameters against SINR is computed for varying numbers of users.

- The average binary codes represent the binary codes of the whole system in different iterations.
- The average complex codes represent the complex codes of the whole system in different iterations.
- The average fixed channels represent the fixed channel of the whole system in different iterations.

B. BINARY CODES ANALYSIS

The performance comparison of EBS with BBS for binary codes varies with the different known users in Table 3.1. Through the implementation of the EBS an increase of SINR is achieved for various number of users with respect to SNR for is fixed at 9 dB for each initial code set.

SINR (dB)									
Number of nodes	Known user = 1		% Of savings	Known user = 2		% Of savings	Known user = 3		% Of savings
	BBS	EBS		BBS	EBS		BBS	EBS	
4	5.5	7.5	13.6	5.5	7.5	13.6	5.5	7.5	13.6
8	9.5	13.5	15.2	9.8	13.9	15.3	10	14.1	15.1
12	11.5	14	18.1	11	15.5	18.2	12	16.5	18.1

Table 3.1 Performance comparison of EBS with BBS for SINR with various numbers of nodes in binary code analysis

The comparison with 4 numbers of nodes, which is the average SINR for increasing known user, is given in Table 3.1. The Figure 5.1 shows the comparison with 4 numbers of nodes while increasing known user. The SINR for the EBS is increased by 13.6 % when compared with BBS.

ISSN 2278 – 1021

International Journal of Advanced Research in Computer and Communication Engineering
Vol. 1, Issue 2, April 2012

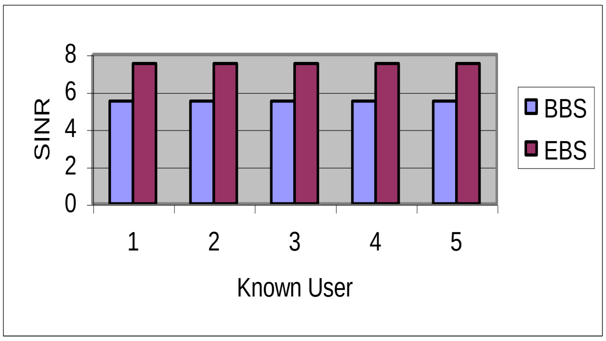

Figure 3.1 Average SINR comparisons with 4 nodes in Binary code

The comparison with 8 numbers of nodes, which is the average SINR for increasing known user, is given in Table 3.1. The Figure 3.2 shows the comparison with 8 numbers of nodes while increasing known user. The SINR for the EBS is increased by 14 % when compared with BBS.

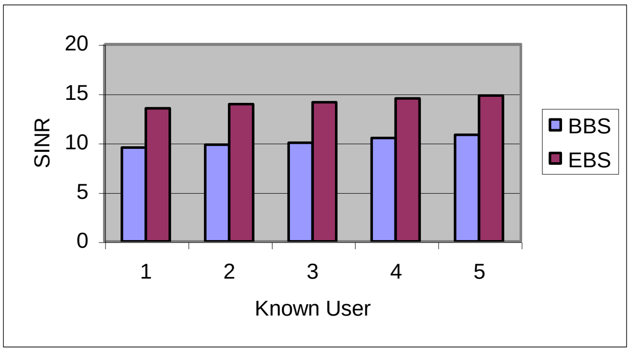

Figure 3.2 Average SINR comparisons with 8 nodes in Binary code

The comparison with 12 numbers of nodes, which is the average SINR for increasing known user, is given in Table 3.1. The Figure 3.3 shows the comparison with 12 numbers of nodes while increasing known user. The SINR for the EBS is increased by 18.1 % when compared with BBS.

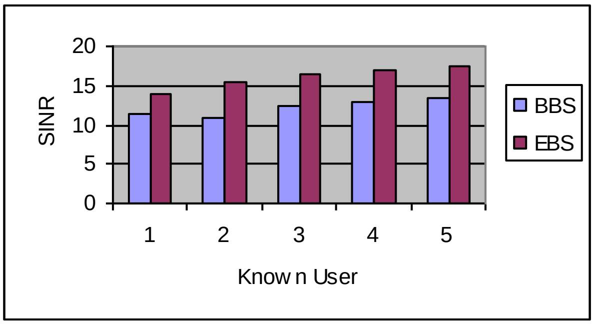

Figure 3.3 Average SINR comparisons with 12 nodes in Binary code

C. COMPLEX CODES ANALYSIS

The performance comparison of EBS with BBS for complex codes varies with the different known users in Table 3.2. Through the implementation of the EBS an increase of SINR is achieved for various numbers of users with respect to SNR for is fixed at 9 dB for each initial code set.

SINR (dB)									
Number of nodes	Known user = 1		% Of savings	Known user = 2		% Of savings	Known user = 3		% Of savings
	BBS	EBS		BBS	EBS		BBS	EBS	
4	5.6	10.2	23	5.6	10.1	22.5	5.6	10.4	23.5
8	6.8	11.5	21	6.8	11.8	21.6	6.8	12.2	22.6
12	9.7	16.5	19.5	9.7	16.8	9.9	9.7	16.6	9.7

Table 3.2 Performance comparison of EBS with BBS for SINR with various numbers of nodes in complex code analysis

The comparison with 4 numbers of nodes, which is the average SINR for increasing known user, is given in Table 3.2. The Figure 3.4 shows the comparison with 4 numbers of nodes while increasing known user. The SINR for the EBS is increased by 23 % when compared with BBS.

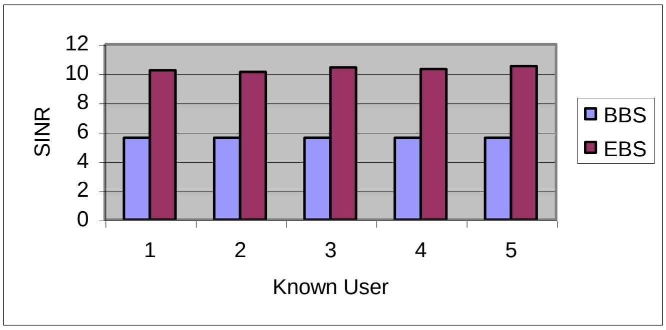

Figure 3.4 Average SINR comparisons with 4 nodes in complex code

The comparison with 8 numbers of nodes, which is the average SINR for increasing known user, is given in Table 3.2. The Figure 3.5 shows the comparison with 8 numbers of nodes while increasing known user. The SINR for the EBS is increased by 21.5 % when compared with BBS.

ISSN 2278 – 1021

International Journal of Advanced Research in Computer and Communication Engineering
Vol. 1, Issue 2, April 2012

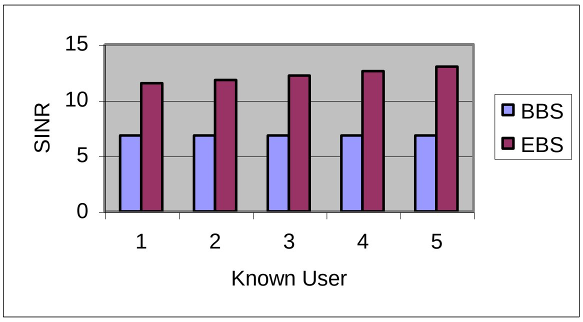

Figure 3.5 Average SINR comparisons with 8 nodes in complex code

The comparison with 12 numbers of nodes, which is the average SINR for increasing known user, is given in Table 3.2. The Figure 3.6 shows the comparison with 12 numbers of nodes while increasing known user. The SINR for the EBS is increased by 9.7 % when compared with BBS.

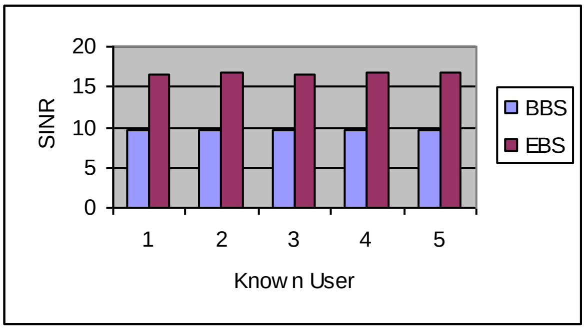

Figure 3.6 Average SINR comparisons with 12 nodes in complex code

D. FIXED CHANNEL ANALYSIS

The performance comparison of EBS with BBS for fixed channel varies with the different known users in Table 3.3. Through the implementation of the EBS an increase of SINR is achieved for various numbers of users with respect to SNR for is fixed at 9 dB for each initial code set.

SINR (dB)									
Number of nodes	Known user = 1		% Of savings	Known user = 2		% Of savings	Known user = 3		% Of savings
	BBS	EBS		BBS	EBS		BBS	EBS	
4	5.5	10.8	21	5.5	8	14	5.5	6.4	6
8	6.5	11.5	22	6.5	11.8	15	6.5	11.6	15
12	7.5	12.2	21	7.5	12.3	15.5	7.5	12.5	16

Table 3.3 Performance comparison of EBS with BBS for SINR with various numbers of nodes in fixed channel analysis

The comparison with 4 numbers of nodes, which is the average SINR for increasing known user is given in Table 3.3. The Figure 3.7 shows the comparison with 4 numbers of nodes while increasing known user. The SINR for the EBS is increased by 15 % when compared with BBS.

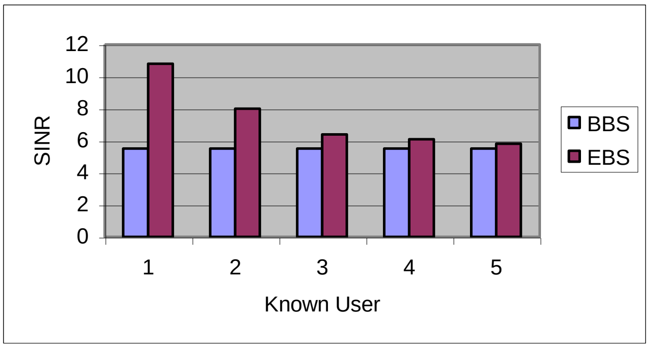

Figure 3.7 Average SINR comparisons with 4 nodes in fixed channel

The comparison with 8 numbers of nodes, which is the average SINR for increasing known user, is given in Table 3.3. The Figure 3.8 shows the comparison with 8 numbers of nodes while increasing known user. The SINR for the EBS is increased by 16 % when compared with BBS.

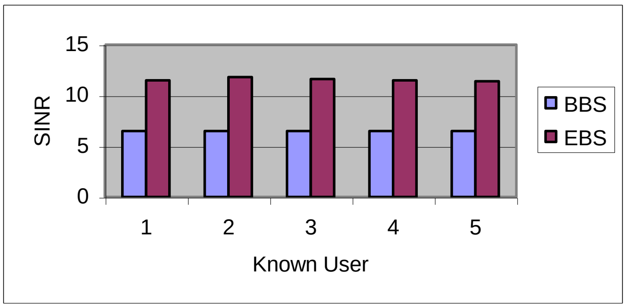

Figure 3.8 Average SINR comparisons with 8 nodes in fixed channel

The comparison with 12 numbers of nodes, which is the average SINR for increasing known user, is given in Table 3.3. The Figure 3.9 shows the comparison with 12

ISSN 2278 – 1021

International Journal of Advanced Research in Computer and Communication Engineering
Vol. 1, Issue 2, April 2012

numbers of nodes while increasing known user. The SINR for the EBS is increased by 18 % when compared with BBS.

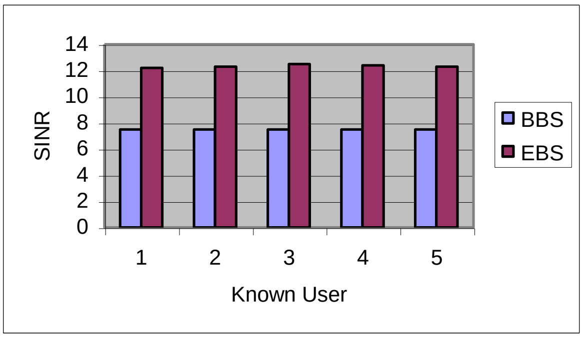

Figure 3.9 Average SINR comparisons with 12 nodes in fixed channel

IV. CONCLUSION

The process of establishing an optimization of blind spoofing, an EBS is developed to find the SINR during the various known user. The EBS developed here considers the binary codes, complex codes and fixed channels duration for known user selection criteria. The EBS shows increase in the SINR compared to the BBS. The EBS has increased 18.1% of SINR in binary codes, increased 9.7 % of SINR in complex codes and increased 18 % of SINR in fixed channels.

REFERENCES

[1]. Bell T, and Orglmeister R (2007), 'Blind source separation of real world signals', Proceeding of International Conference on Neural Networks, Vol. 4, pp. 2129-2134.

[2]. Belouchrani A, and Abed-Meraim K (1997), 'A blind source separation technique using second-order statistics', IEEE Journal on Transaction Signal Process, Vol. 45, No. 2, pp. 434-443.

[3]. Bensley S, and Aazhang B (2006), 'Subspace based channel estimation for code-division multiple access communication systems', IEEE Journal on Transaction Communication, Vol. 44, pp. 1009-1020.

[4]. Bettahar, Arar, and Bouabdallah (2004), 'An efficient QoS Server selection protocol for duplicated layered multicast servers', IEEE Journal on Communication Society 2004, pp.675-676.

[5]. Bettstetter C, Hartenstrein H, and Perez-Costa X (2004), 'Stochastic Properties of the Random-Way Point Mobility Model', Proceedings of International Conference on wireless networks, Vol. 10, No. 5, pp. 555-567.

[6]. Beverly R, and Bauer S (2005), 'Inferring the extent of Internet source address filtering on the Internet', Proceedings of International Workshop on Information Technologies, pp. 345-356.

[7]. Blazevic, Giordano, and Le Boudec (2002), 'Anchored Path Discovery in Terminode Routing', Proceedings of 2nd International Conference on TC6 Networking, Vol. 17, No. 8, pp. 1395-1414.

[8]. Bolot (1993), 'End to End packet delay and loss behavior in the Internet', ACM Journal on Signal Communication 1993, pp. 289-298.

[9]. Boris Rankov, and Armin Wittneben (2007), 'Spectral Efficient Protocols for Half-Duplex Fading Relay Channels', IEEE Journal on selected areas in Communications, Vol. 25, No. 2, pp.379-389.

[10]. Boukerche A (2004), 'Performance evaluation of routing protocols for ad hoc wireless networks', Proceedings of International Conference on Mobile Networks and Applications, Vol. 9, Issue 4, pp. 435-445.

[11]. Boushbia-Salah H, Belouchrani A, and Abed-Meraim K (2001), 'Blind separation of convolutive mixtures using joint block diagonalization', Proceedings of 6th International Symposium Signal Process and its application, Vol. 1, pp. 13-16.

[12]. Breslau, Estrin, McCanne, and Varadhan (2000), 'Advances in Network Simulation', IEEE Journal on Computer Society 2000, Vol. 33, No. 5, pp. 59-67.

[13]. Buch V, Von elicken, Basu, and Vogels (1995), 'U-net: A user level network interface for parallel and distributed computing', ACM Journal on Symposium operating systems, pp.40-53.

[14]. Capkun S, Buttyan L, and Hubaux J (2003), 'Self organized public key management for mobile ad hoc networks', IEEE Journal on Transaction Mobile Computing, Vol. 2, No. 1, pp. 52-64.

[15]. Cardoso J, and Laheld B (1996), 'Equi-variant adaptive source separation', Proceedings of International Conference on Communication Transaction Signal Process, Vol. 44, No. 12, pp. 3017-3030.

[16]. Cardoso J, and Souloumiac A (2003), 'Blind beam-forming for non Gaussian signals', Proceedings of International Conference on Institute of Electrical Engineering Radar Signal Process, Vol. 140, No. 6, pp. 362-370.

[17]. Chang E, and Roberts R (1999), 'An improved algorithm for decentralized extrema finding in circular configurations of processors', Proceedings of International Conference on Communication Systems, Vol. 22, No. 5, pp. 281-283.

[18]. Chang-Jung Kao, De-Nian Yang, and Wanjiun Liao (2001), 'Source Filtering in IP Multicast Routing', IEEE Journal on Communication Society 2001, pp. 82-90.

[19]. Chatree Sangpachatanaruk, and Taieb Znati (2004), 'A P2P overlay architecture for personalized resource discover, access, and sharing over the internet', IEEE Journal on Communication Society 2004, pp.24-29.

[20]. Chen W, Hsu H, and Shen H (2005), 'Application of SVM and ANN for intrusion detection', Proceedings of International Conference on Elsevier Computers and Operations Research, pp. 2617-2634.

[21]. Cheng, Garay, Herzberg, and Krawczyk (1998), 'A security architecture for the Internet Protocol', Proceedings of International Conference on IBM systems, Vol. 37, No. 1, pp. 42-60.

[22]. Chuang Yu (2010), 'Blind detection algorithm based on adaptive chaotic particle swarm optimization', Proceedings of 3rd International Conference on Image and Signal Processing, pp. 376-379.