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Joint ICA-Based Blind Detection and Parameter Assessment in DS-CDMA Systems

Mohammad Eslami, Javad Afshar Jahanshahi and Seyed Ali Ghorashi
Cognitive Telecommunications Research Group, Department of Electrical Engineering,
Faculty of Electrical and Computer Engineering, Shahid Beheshti University G.C.,
Evin, 1983963113, Tehran, Iran

Abstract: In this study, blind code extraction of Direct Sequence Code Division Multiple Access (DS-CDMA) signals is considered, based on Independent Component Analysis (ICA) method. In order to distinguish between correct and incorrect extracted codes, to estimate the number of active users and also to determine the quality of detection along with the ICA based blind detection procedure, some propositions are defined. These propositions are used to improve the performance of the ICA blind detection based method. Then, in order to analyze the proposed criteria, Principle Component Analysis (PCA) and Gaussian Mixture Model (GMM) are employed. Experimental results illustrate that the achieved performance of the defined criteria.

Key words: Active user enumeration, blind detection, code division multiple access, gaussian mixture model, independent component analysis, principle component analysis

INTRODUCTION

The main objective of communication is reliable transfer of information between two parties, in the sense that the information reaches the intended party with as few errors as possible. Code Division Multiple Access (CDMA) is emerging as the popular multiple access scheme, mainly due to its soft multiple access characteristics, robustness against fading and anti-interference capability. In this approach, each user transmits the symbols asynchronously with a different spreading code and the identification of a particular user is done by this unique code.

In a Direct Sequence CDMA (DS-CDMA) system, users share the same frequency bands and the same time slots, but they are separated in codes. Conventional multiuser detection algorithms are designed based on some priori information of active users (John, 2001). In blind user detection algorithms, however, the receiver does not have sufficient information about the number of active users or codes, in order to detect their signals efficiently (Wu *et al*., 1998). Most of the active users enumeration algorithms proposed in literature use some information theory criteria (Valaee, 2004, Khoyari-RostamAbad, 2007) and Eigen Value Decomposition (EVD) (Anderson, 1963). ICA is a statistical technique based on higher order statistics, whose goal is to represent a set of random variables as a linear transformation of statistically independent components (Hyvarinen *et al*., 2001). ICA based techniques assume that sources are Non-Gaussian and independent. Fast-ICA algorithm is applied for detection of DS-CDMA in (Ristaniemi, 1999), but the convergence is not guaranteed. The RAKE-ICA proposed by (Ristaniemi, 2000), needs the information of multi-path delay time of the desired user, which is difficult to be estimated. Two types of receivers, RAKE-ICA and MMSE-ICA, are proposed in (Ristaniemi, 2002), in which a Rayleigh fading channel is assumed. The MMSE-ICA normally requires training sequences, but (Leong, 2006) proposed a new blind multiuser detector that requires no training data sequences. In (Leong, 2004), ICA has been applied using SAND algorithm and in addition JADE and RADICAL ICA algorithms are applied for DS-CDMA detection in (Raja, 2008). This method is very useful in a multi user CDMA environment where prior information about the user's code is generally available with the receiver. In general, the mentioned methods in literature have not considered estimation of the number of active users, which can be useful for modifying the ICA algorithm. The working states of the detection in respect with the number of users, number of observed signals and signal to noise ratio have not been considered as well. In this study, it has been shown that how these states which are labeled as excellent, good and bad, can improve the performance of ICA algorithm. In the present research, some propositions are defined in

Corresponding Author: Mohammad Eslami, Cognitive Telecommunications Research Group, Department of Electrical Engineering, Faculty of Electrical and Computer Engineering, Shahid Beheshti University G.C., Evin, 1983963113, Tehran, Iran

order to estimate the number of active users. By taking advantages of the propositions, the proposed algorithm is capable to distinguish between correct and incorrect extracted codes. In addition, these propositions are used to determine the quality of detection along with the ICA based blind detection procedure.

BACKGROUND AND SYSTEM MODEL

Independent component analysis (ICA): The Independent Component Analysis (ICA) is a statistical technique in order to represent a set of random variables as a linear transformation of statistically independent component variables (Hyvarinen *et al*., 2001). The main application of ICA is in the Blind Source Separation (BSS) problem. In other words, Independent Component Analysis involves the task of computing the matrix projection of a set of components onto another set of so called independent component.

Suppose X=AS where S is an n -dimensional random vector whose components are mutually independent, A is the constant mixing matrix by size m×n and X is an m -dimensional product vector. Independent component analysis goal is to estimate matrice A and vector S from vector X that is called one observed vector. The result of the separation process is the demixing matrix W which can be used to obtain the estimated statistical independent sources, $\hat{S}$, from the mixtures: $\hat{S} = WX$. This process is described by (1) and a schematic illustration of the mathematical model is shown in Fig. 1.

$$X = AS \rightarrow \hat{S} = WX \tag{1}$$

With the matrix w, the components s and $\hat{S}i$ of any $\hat{s}_j$ are observed as uncorrelated. The fundamental restriction of ICA is that independent components must be non-Gaussian for ICA to be possible. In real applications, observed matrix commonly contains several observed vectors, and so estimated matrix $\hat{S}$ will contains vectors.

Some preprocessing is useful before attempting to estimate W. The observed signals should be centered by subtracting their mean values E{X}. Then they are whitened, which means they are linearly transformed so that the components become uncorrelated with unit variance. Whitening can be performed via using Eigen values.

Fast ICA is a practical ICA algorithm that is a fixed-point iteration scheme for finding the maximum of the non-Gaussianity which is purposed in (Hyvarinen, 1997). The algorithm estimates just one of the independent components (ICA) once. To estimate several independent components, the Fast ICA needs to run several times. The MATLAB toolbox for Fast ICA is available on the web (http://www.cis.hut.fi/projects/ica/fastica/).

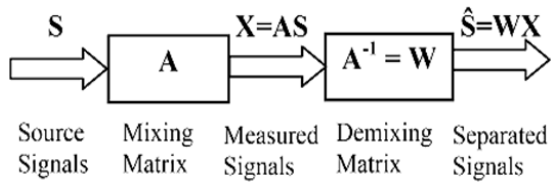


Fig. 1: Schematic illustration of the mathematical model used to perform ICA decomposition

System model: The continuous DS-CDMA received signal in multipath fading channel can be modeled as:

$$y(t) = \sum_{m=1}^{M} \sum_{k=1}^{k} d_{km} \sum_{l=1}^{L} a_{lm} c_k (t - mT - d_l) + n(t) \tag{2}$$

where d_{km} is the mth symbol of the kth user, A_{lm} is fading factor of the lth path corresponding to the mth symbol, which may vary from symbol to symbol, M is the number of observation symbols, L is the number of independent transmission paths for each of the K simultaneous users, T is the symbol duration, the d_l denotes the delay of the lth path, which is assumed to be constant during the observation interval of M symbol bits, and the last term n(t) denotes the additive white Gaussian noise with zero mean and unit variance. The chip sequence length (i.e., processing gain) is Gs = T/T_c , where T_c is chip duration, and it is assumed that T_c = 1 for the sake of simplicity (Hyvarinen *et al*., 2001).

The continuous received signal is sampled at chip rate. Here, it is assumed that both code timing and channel estimation are already done. According to (2), the discrete data samples are described as:

$$Y = \begin{bmatrix} y(1) & y(G_s+1) & \dots & y((M-1).G_s+1) \\ y(2) & \dots & & \\ \vdots & & & \\ y(G_s) & y(2G_s) & & y(M.G_s) \end{bmatrix} \tag{3}$$

The observed matrix R with the size of G_s x N is then consists of N vectors of y_m, where $R = [ym, ym+1, \dots, ym']$, and:

$$R = \begin{bmatrix} y(m.Gs+1) & y((m+1)Gs+1) & \dots & y(m'.G_s+1) \\ y(m.Gs+2) & \dots & & y(m'.G_s+2) \\ \vdots & & & \\ y((m+1).G_s) & y((m+2).G_s) & & y((m'+1).G_s) \end{bmatrix} \tag{4}$$

where m′>m, N = m′ - m and m′, m ∈ {0, 1, ..., M-1}. Each column of matrix R is an observed vector or signal

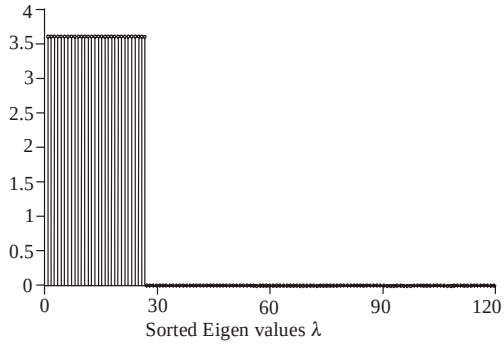
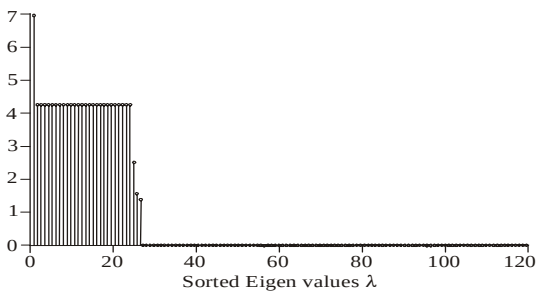
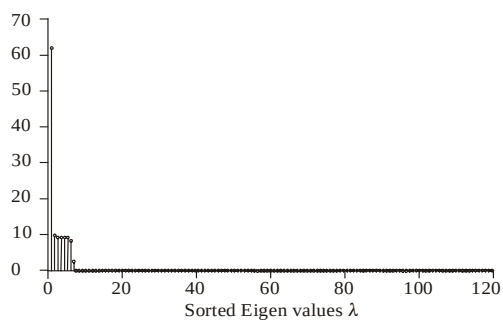


Fig. 2: Sorted Eigen Values for Hadamard codes with the length of 64 and L = 4, K = 30



(a)



(b)

Fig. 3a: The possible sets of sorted Eigen Values for Gold codes with the length of 63 and l = 4, k = 30

for training the ICA algorithm. In typical ICA, N should be much greater than G_s. After code timing and channel estimation, the observed matrix can be modeled as:

$$R = G.B + N_\circ \tag{5}$$

where R is the $G_s \times N$ observed matrix, $G = [c_1\ c_2 \ldots c_k]$is the mixing matrix by the size of $G_s \times K$, and its vectors are c_i, for i = 1,….,K, (c_i is the related code for the ith user), $B = [d_m, d_{m+1}, \ldots, d_{m'}]$ is the symbol matrix with the size of K x N and contains N separate vectors of d_m, where, $d_m = [d_{1m}a_{1m},\ldots,d_{km}a_{km}]^T$ andfinally $N_o = [N_m, N_{m+1}, \ldots, N_{m'}]^T$ is the corresponding noise matrix by the size of Gs × N.

The AWGN noise, N_o , can be treated as one of the independent components of matrix R, then (5) can be rewritten as R = G.B. Therefore, comparing this recent equation with ICA model in (1) we can calculate $\hat{G}$ and $\hat{B}$ as the decomposition results of matrix R by using ICA algorithm. Extracted codes then would be the columns of extracted matrix $\hat{G}$, and corresponding symbols would be the rows of matrix $\hat{B}$.

Proposed method: Shape pattern of eigen-values: In the present research work, at first some shape patterns of Eigen-values in CDMA codes should be considered in order to explain the proposed method procedure. Then, Principal Component Analysis (PCA) (Hyvarinen *et al*., 2001) is used as a tool to compute Eigen-values (λ_n) of codes. Suppose that matrix $\hat{G}$ is defined as follows:

$$\overline{\overline{G}} = [G_{r1}, G_{r2} \ldots . G_{rL}] \tag{6}$$

Each G_{rj}, j = 1,….,L is a matrix similar to G, in which users' codes c_i, i = 1,…,K are randomly located in columns (e.g., Grj = [c_{k-1} c_3 … c_s]). By taking advantageous of the PCA algorithm, Eigen-values (λ_n ,n = 1,2,…,$G_s \times L$)) of matrix $\overline{\overline{G}}$ are obtained. In Fig. 2, a typical sorted set of Eigen-values for Hadamard Code by length 64 is shown, where L = 4 and K = 30. Fig. 3 shows two examples of possible patterns for the sorted Eigen-values of Gold codes by the length of 63. By comparison Fig. 2 and 3, two different behaviors can be inferred.

In regular behavior (Fig. 2 and 3a) the number of nonzero Eigen-values is close to the number of users' codes, K = 30, while in irregular behavior (Fig. 3b) this is not true. Since in this study, the proposed method for joint blind detection and active user enumeration is based on Eigen-values, the regular and irregular behavior should be distinguished. It is necessary to recognize the irregular and regular behaviors, then for this purpose, it is required to define a new criterion. The criterion is based on the significant amplitudes than others. For example, as it can be seen in Fig. 3b, the maximum amount of Eigen-values is about 6 times larger than the second level. Based on the pattern of the magnitudes of sorted Eigen-values. In the irregular behavior, some of Eigen-values have much more empirical results, the criterion can be defined as follows. Assume that λ_{max} and λ_{ave} are the maximum and the average of nonzero Eigen-values, respectively.

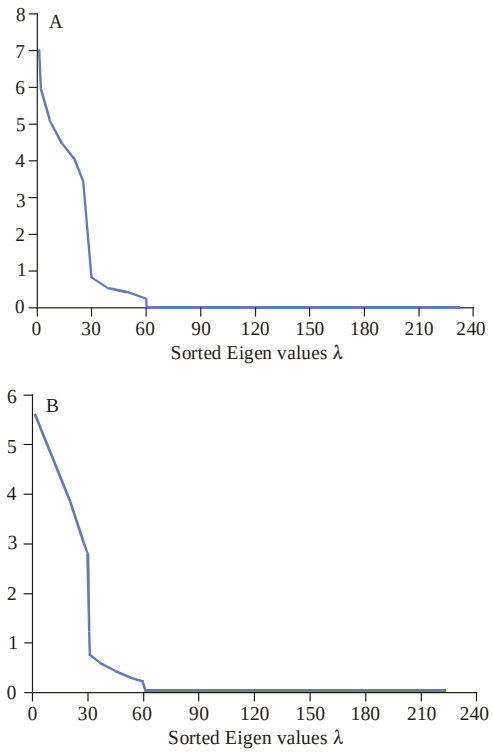


Fig. 4: Achieved sorted Eigen values for;)a) Gold sequence withGs=63 (b) Hadamard Code with Gs = 64

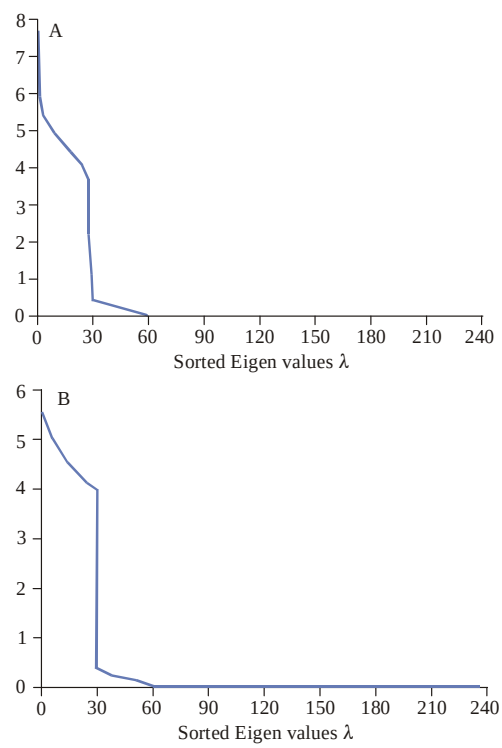


Fig.. 5: Achieved sorted Eigen values for, a) Gold sequence with G_s = 63, b) Hadamard Code with G_s = 64

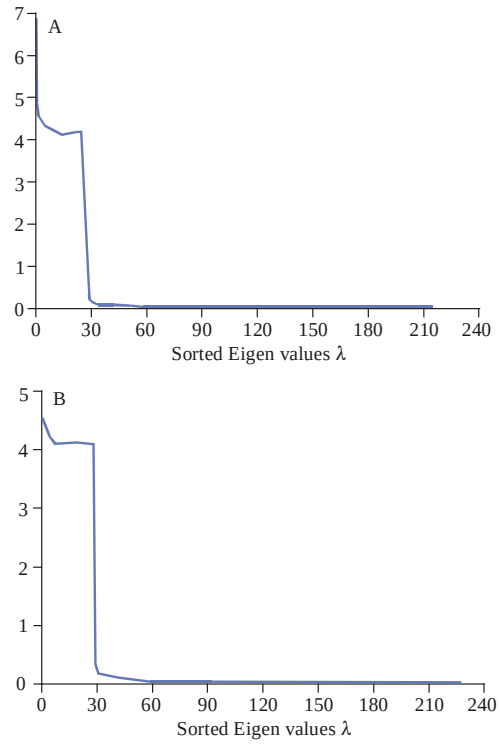


Fig. 6: Achieved sorted Eigen values for L = 4, N = 7000, K = 30, (a) Gold sequence with G_s = 63, (b) Hadamard Code with G_s = 64

Proposition 1: Irregular behaviors occur when the maximum of Eigen-values λ_{max} is larger than the twice of λ_{ave} i.e., $\lambda_{max} > \lambda_{ave.}$. Therefore, the regular behavior occurs when $\lambda_{max} < 2\ \lambda_{ave}$, obviously.

Active user enumeration and blind detection's situations: Based on the described model above, the parameters, the number of active users K, Signal to Noise Ratio (SNR) of received signals and the number of observed signal vectors N in matrix R, do have a great influence over the blind multi-user detection procedure. With respect to the relations between these parameters, three detection quality states are possible (called as Blind Detection's Situations):

Situation 1: ICA cannot merge to any users' codes correctly. Then, extracted matrix $\hat{G}$ contains incorrect codes and therefore wrong extracted symbols would be in $\hat{B}$.

Situation 2: ICA can converge to part of users' codes.

Situation 3: ICA converges completely and all users' codes are extracted correctly.

Note that in all of the situations (1-3), the number of extracted codes may be larger than the real number of

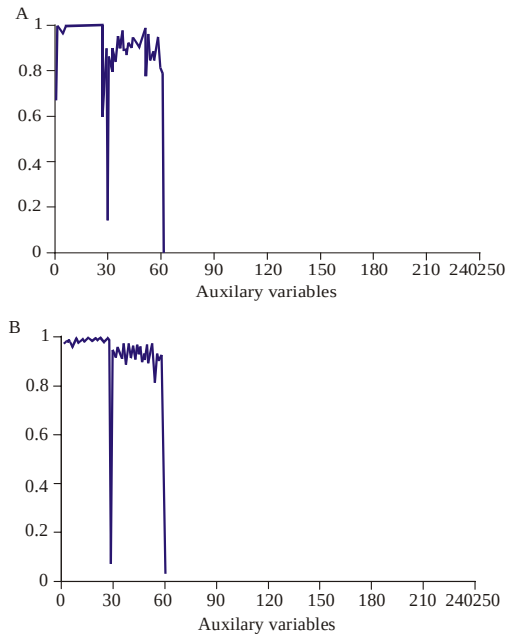


Fig.. 7: Achieved auxiliary variables γ_i, L = 4, N1000, K = 30, (a) Gold sequence with G_s = 63 (b) Hadamard Code with G_s = 64

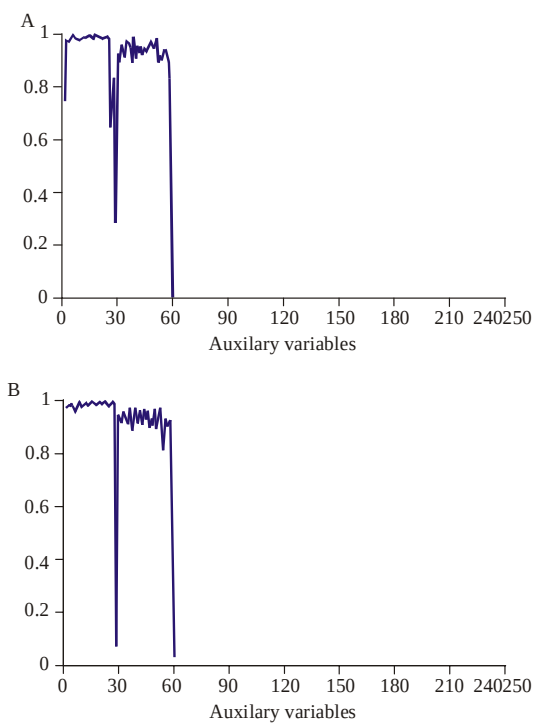


Fig. 8: Achieved auxiliary variables γ_i, L = 4,N = 4000, K = 30, (a) Gold sequence with G_s = 63 b) Hadamard Code with G_s = 64

active users. Therefore, it would be helpful to estimate the number of active users before multi-user detection process. So in order to do active user enumeration, and to estimate the correct codes and recognize the blind detection's situations, three propositions are proposed in the following. It should be noted that the current discussion is validated for the regular behaviors which are defined in the proposition 1.

Suppose that the received signal is split into L segments, and each segment contains N x Gs samples in a noisy condition and $\hat{G}j$ is the extracted code matrix by ICA algorithm from the Jth segment. Now consider matrix $\underline{\hat{G}}$ as follows:

$$\underline{\hat{G}} = [\hat{G}_1 \hat{G}_2 ... \hat{G}_L] \tag{7}$$

The Eigen-values of matrix $\hat{G}$ are computed by PCA algorithm (Hyvarinen *et al.*, 2001). In Fig. 4, 5 and 6 three examples of sorted Eigen-values of extracted matrix are shown for Gold and Hadamard codes by the length of 63 and 64, respectively. SNR is set to 5 dB, L = 4 UOTE and K = 30 for three different choices of the observed signal numbers: N = 1000, 4000 and 7000, respectively.

The average number of extracted codes in matrix $\underline{\hat{G}}$ is 59. From Fig. 4 to 6, it can be found that by setting the number of observed signals N=7000 all of the users' codes $\hat{G}j$ are extracted, and the number of observed signals equals to N=4000, just 28 and 8 users' codes are discovered correctly in Gold and Hadamard codes, respectively. By setting the number of observed signals to N=1000, all of the extracted codes in matrix $\hat{G}j$ are incorrect and none of the users' codes are discovered. Therefore N = 7000, 4000 and 1000 are related to situation 3, 2 and 1, respectively. By focusing our attention on Fig. 4, 5 and 6, three features can be observed. The first important observed feature is that there is a severe drop between the kth and the K+1th Eigen-values. The amount of drop is comparable to the value of significant Eigen-values. Another observed feature is that there are two significant clusters around the drop. In each cluster there is a uniform slope among sorted Eigen-values. Finally it can be observed that the amount of drop between clusters depends on N. On the other hand, If the drops amount are labeled as d, then we have $d_{N=7000} > d_{N=4000} > d_{N1000}$ or we may say: $d_{situation\ 3} > d_{situation\ 2} > d_{situation\ 1}$.

The observed features are verified for plenty of different codes' length and number of observed signals N. In order to summarize the features, a simple formula is defined by using an auxiliary variable γ_i as follows:

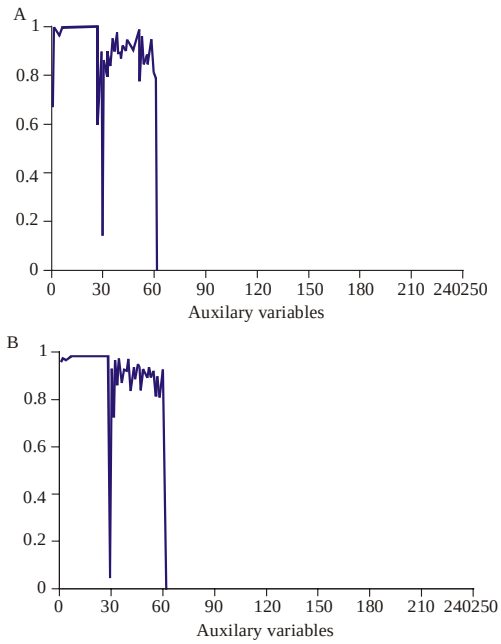


Fig. 9: Achieved auxiliary variables ,L = 4, N = 7000, K = 30, (a) Gold sequence by G_s = 63, (b) Hadamard Code by G_s = 64

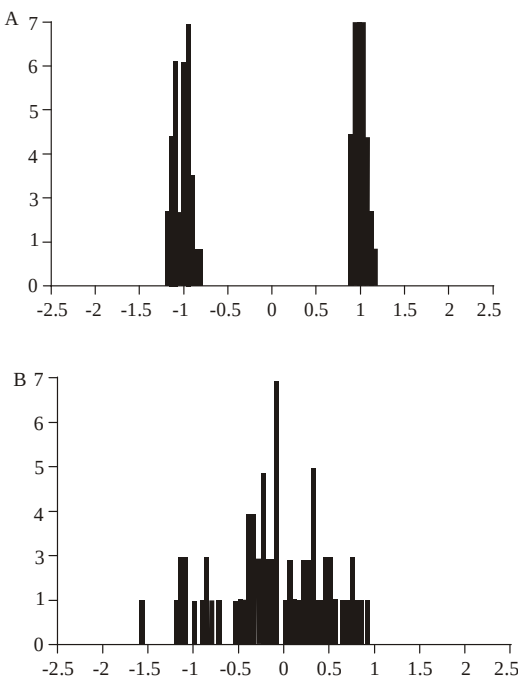


Fig. 10: Histogram of an extracted code, (a) correct code, (b) incorrect code

$$\gamma i = \frac{\lambda_i + 1}{\lambda_i}, i = 1,2,\ldots,(G_s \times L - 1) \quad (8)$$

The γ_i vector of the Eigen-values of the Fig. 4, 5 and 6 is illustrated graphically in Fig. 7, 8 and 9, respectively. larger than that of situation 2 (Fig. 8) and the same has happened between situation2 and situation1 (Fig. 7).

Proposition 2 - active user enumeration: Suppose that:

$$\gamma_i = \frac{\lambda_{i+1}}{\lambda_i}, \ i = 1,2,\ldots,(Gs \times L - 1)$$

is an auxiliary vector where λ_i, i = 1, 2, …, Gs×L are the sorted Eigen-values of matrix $\hat{G}$. If $\hat{K}$ is the location of the first notch in λ_i vector, the number of active users K is one of these values $\{\hat{K}, \hat{K}+1, \hat{K}+2\}$.

Estimation of correct codes and recognition of the blind detection's situation: In order to verify and check out the correctness of the extracted codes, a novel criterion based on the extracted codes distribution is proposed in this subsection. Therefore, in addition to ICA based blind detection procedure, the reliable symbols can be selected in the rows of matrix $\hat{B}$ only based on the correct codes and the redundant symbols are ignored. Finally, based on the proposed criterion, a method for recognizing of the situation in a $\hat{G}_j$ will be described.

In common CDMA codes such as Gold and Hadamard ones, code samples have only -1 & +1 values and also the probability of their usage is close to 0.5. On the other hand, if the histogram of samples of a code sequence with the length of U is found, there will be just two impulses in +1 and -1 with magnitudes of U/2. This means that correct extracted codes in noise free conditions should satisfy the mentioned simple facts, as well. Since samples in extracted codes by ICA algorithm are not integers, it can be proposed that the distribution of samples in each correct extracted code should have two Gaussian distribution around +1 and -1 with equal variances. In Fig. 10a and b, a typical histogram of a correct extracted code and incorrect ones is presented, respectively (where SNR is set to 5dB and code length is 64). From the Fig. 10, it can be found that an extracted code is incorrect if it does not satisfy the criterion. The proposed criterion for determining the correctness of the extracted codes is based on Gaussian Mixture Model (GMM) (Marques, 2001). GMM algorithm tries to model an unknown distribution by superposition of some Gaussian distributions and fit their parameters such as means and variances. In the present work, GMM has been used as a tool to model the distribution of symbols in extracted codes.

Proposition 3- check out the correctness of extracted codes: For a selected $\hat{G}j$, the distribution of the correct

extracted code samples should be a combination of two Gaussians distributions with equal variances around +1 and -1. In order to check the distribution of extracted codes, GMM clustering is used:

Proposition 4 – recognize the situation of the detection system: Suppose that p is the number of extracted codes that satisfy the proposition 3 and therefore they are correct. The type of the quality state of detection system can be recognized as follows:

$$if \quad P \geq \hat{K} \quad \overset{yields}{\rightarrow} \; Situation\,3$$

$$if \quad \hat{K} > P > 0 \quad \overset{yields}{\rightarrow} \; Situation\,2$$

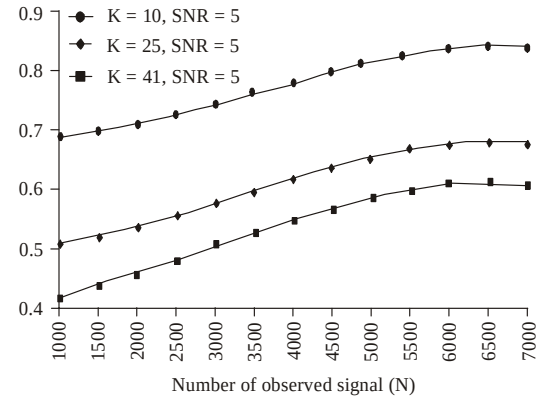
$$if \quad P = 0 \quad \overset{yields}{\rightarrow} \; Situation\,1$$

Overall algorithm: According to the defined propositions 1-4, the joint blind detection and active user enumeration algorithm follows the procedure summarized as follows:

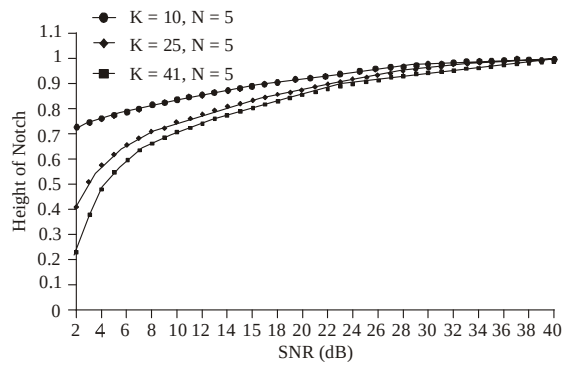
- Choose L x N G_s samples of the received signal, split it in
- Lsegments and reshape each segment to obtain observed matrix R_j, j = 1,…L.
- Apply ICA algorithm and compute extracted matrixes $\hat{G}j$ and $\hat{B}j$ for each R_j, j = 1,…L.
- Generate matrix $\overline{\hat{G}} = [\hat{G}_1 \hat{G}_2 ... \hat{G}_L]$
- Apply PCA algorithm on matrix $\overline{\hat{G}}$ to find Eigen-values.
- Sort the Eigen-values in respect with their values λ_i, i={1,2,…,L xG_s}.
- Compute $\gamma_i = \frac{\lambda_{i+1}}{\lambda_i}, i = 1,2,...,(Gs \times L - 1)$
- Determine the number of active users based on proposition 2.
- Select one of $\hat{G}j, \; j = 1,2,...,L.$
- Check each extracted code by using proposition 3 and find P and index of correct codes.
- Determine the state of blind detection based on proposition 4.
- If this situation is desired, just use correct extracted codes and their corresponding detected symbols. Otherwise, go to step 1 with larger number of observed signals N .

SIMULATION RESULTS

In this section, in order to show the reliability of the proposed algorithm and clarify the mentioned facts, some of the experimental results are presented. In all simulation results, three different kinds of Gold sequence codes with the length of 63 is used to consider the proposed algorithm and these codes behave like the regular behavior (proposition 1). It is necessary to mention that, since ICA algorithm is a statistical method, the reported results are the average of ten times simulations for each kind of code and then, the results



(a)



(b)

Fig. 11: a, b:Height of Notch (HoN) in K location in respect with the variations of a)N b)SNER

Table 1: Some of the experimentally achieved user enumeration results $\hat{K}$, with different user numbers (K = 10, 25 and 41), signal to noise ratios (SNR = 2.5 and 10) and number of observed signals (N = 500, 2000 and 7000)

	N = 500		N = 2000		N = 7000	
	K	$\hat{K}$	K	$\hat{K}$	K	$\hat{K}$
SNR = 2	10	9	10	9	10	9
	25	25	25	24	25	24
	60	58	60	58	60	58
SNR = 5	10	9	10	9	10	9
	25	24	25	24	25	24
	60	58	60	58	60	59
SNR = 10	10	9	10	9	10	9
	25	24	25	24	25	24
	60	58	58	58	60	59

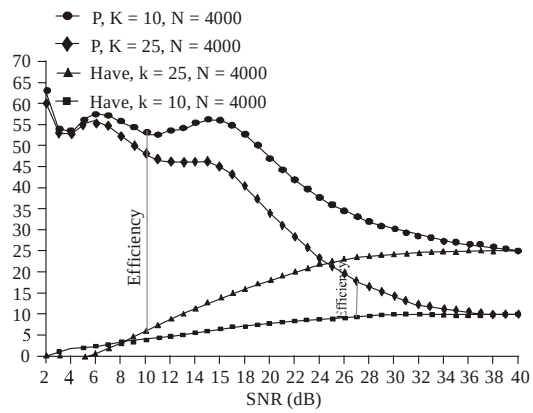


Fig.. 12: P and Havecurves versus SNR variations and efficiency plot for two different number of users K = 10 and25 in the fixed number of observed signals N = 4000

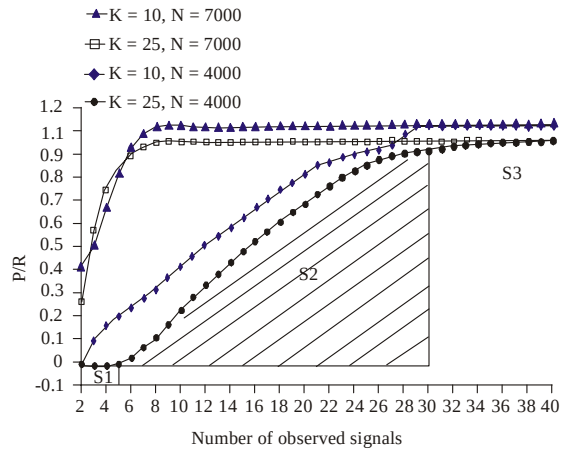
themselves are averaged on codes in order to achieve the final reported values.

Some of the experimentally achieved user enumeration results $\hat{K}$, with different user numbers (K = 10, 25 and 41), signal to noise ratios (SNR = 2, 5 and 10) and number of observed signals (N=500,5000 and 7000) are categorized and reported in Table 1.

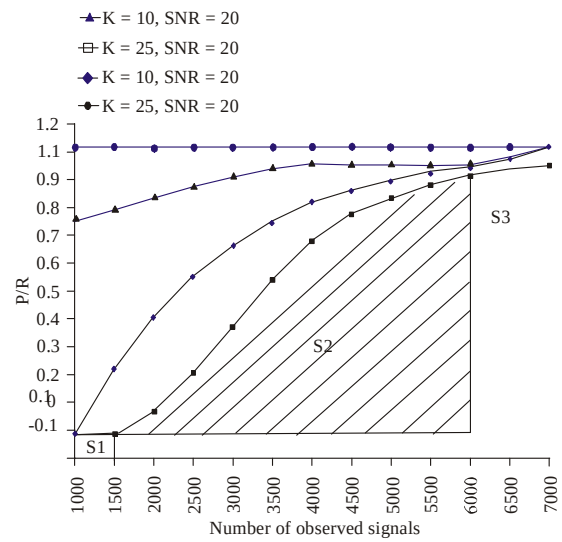
It can be seen from Table 1 that the Proposition2 is always happened regardless of the observed signal's number and SNR values. It is shown in the following simulations that the state of the situation is determined by the relations between K,SNR and N in the rest of paper. Moreover, Table 1 includes all of the defined situations and implies that the Proposition 2 is acceptable in all situations.

Fig. 11 shows that the Height of Notch (HoN) in $\hat{K}$ location in respect with the variations of SNR and the number of observed signals, N. The curves of Fig. 11a show the HONs versus N for three different number of Users, K=10,25 and 4 in a fixed SNR=5dB It can be seen that the height on notch decreases for a greater number of users and also by increasing the number of observed signals, the height of notch increases.

As mentioned earlier, increases in the height of notches make the performance of ICA algorithm better. Therefore, two facts can be implied from Fig. 11a. Firstly, in a fixed number of users, K, the performance of ICA improves by increasing the number of observed signals. Secondly, larger number of users, K, needs more number of observed signals, N, for a desirable performance. Similar facts are also seen in Fig. 11b between SNR and the number of users for a fixed number of signals, N = 4000. In addition, it can be inferred that the number of observed signals N = 4000 is suitable for SNR≥32 dB, SNR≥26dB, SNR≥30dB and when K = 41,255 and 10,



(a)



(b)

Fig. 13: $P/\hat{K}$ versus; (a) SNR (b) N

respectively, and also it yields to the situation 3 (typical results show that complete convergence of ICA occur when HON≥0.96). These estimated SNR values for situation 3 has been mentioned and verified again in the following experimental results.

Figure 12 shows the P and H_{ave} (the average number of extracted codes in matrix ($\hat{G}_j$) curves versus SNR variations for two different number of users K = 10 and 25 in the fixed number of observed signals N = 4000.

The following properties can be inferred from Fig. 12:

- The efficiency of the defined criterion in proposition 3 with the GMM method, is shown by the gap between p curve and Have curve. For instance, the

efficiency diagram in K = 25 and SNR = 12 is depicted in Fig. 12, where the number of acceptable codes via proposition 3 is just 8 and the average number of extracted codes is 53. It means that, there are 45 redundant and incorrect extracted codes and the proposed criterion in proposition 3 causes to remove these wrong codes.

- In high SNRs, such as SNR>38, the number of observed signals N = 4000 is sufficient for complete convergence of ICA algorithm, so that there is no redundant extracted code. On the other hand, all of the extracted codes satisfy the GMM criterion and these codes are exactly users' ones.
- While in lower SNRs, there is no distinct behavior for H_{ave}, and by increasing SNRs, the H_{ave}, and P curves merge to each other.

As mentioned before, blind detection system for K = 10 and N = 4000 works in situation 3 for SNR>26. Fig. 12 clarifies that while the system withSNR=26 works in situation 3 and all of the users' codes are extracted correctly, there are still some incorrect and redundant codes which will be ignored by applying proposition 3.

$P/\hat{K}$ versus SNR and N are shown in Fig. 13a and b, respectively. P denotes the number of extracted codes which satisfies GMM criteria in proposition 3 and therefore are labeled as the correct extracted codes. $\hat{K}$ is the estimated number of active users based on proposition 2. According to the proposition 4, the situation 3 occurs when $P/\hat{K} \geq 1$.

As expected in Fig. 13a, the blind detection system with N = 7000 enters to the situation 3 in lower SNRs than N = 4000 for both K = 10 and K = 25 cases. For example, the curves of {K = 10, N = 7000} and {K = 10, N = 4000} intersect the line N in SNR = 6 and 26, respectively. The condition {K = 10, N = 4000} have also great performance in SNR≥26 in Fig. 11b. The same can be distinguished in Fig. 13b in respect with the number of observed signals. For example, {K = 25, SNR = 40} meets the situation 3 in N = 3000 while {K = 25, SNR = 20} merged to the situation 3 in larger number of observed signals N such as N = 6000 and it is caused by SNR considerations. According to the proposition 4, situations 1, 2 and 3 are sketched in Fig. 13 by stripping regions for K = 25 in respect with two following conditions:

- SNR variations, while the number of observed signals is fixed, N = 4000 (Fig. 13a).
- N variations, while SNR is fixed, SNR = 20 (Fig. 13b).

CONCLUSION

Enumeration of active users is very helpful in blind detection methods such as ICA based multi-user detection algorithms. In this study, some propositions are defined to estimate the number of active users. By taking advantages of the propositions, the proposed algorithm is capable to distinguish between correct and incorrect extracted codes. In addition, these propositions are used to determine the quality of detection along with the ICA based blind detection procedure. Several simulation results show that these propositions improve the performance of the ICA blind detection based method.

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