International Journal of Advanced Information Science and Technology (IJAIST) ISSN: 2319:2682
Vol.3, No.6, June 2014 DOI:10.15693/ijaist/2014.v3i6.14-19

Bit Error Rate Comparison of ICA Algorithms to DS-CDMA Detection

PROF A.JANARDHAN
ECE Department, JITS
Warangal-AP, India

PROF.K.KISHEN RAO
Director, VCE
Warangal-AP , India

***Abstract*---In CDMA system multiple users share the same channel bandwidth and transmit signals simultaneously. Users can distinguish their own signals by the spread codes. However, owing to multipath fading , the signals at receiving end are no longer orthogonal and therefore, using ICA can help improve the SNR at the receiving side. This paper evaluates the Bit Error Rate performance of some major ICA algorithms like Hyvarinen's fastICA algorithm, Molgedey and Schuster's ICA-MS and Optimized Generalized Weighted Estimator (OGWE) algorithms to solve symbol estimation problem of multi users in a DS-CDMA communication system. The main aim is on blind separation of convolved CDMA mixture and improvement of downlink BER estimation. The results of experiment are compared with Single User Detection SUD receiver, ICA detector and combined SUD_ICA detector.**

***Keywords*--SUD, ICA, FastICA, OGWE, ICA-MS**

1. INTRODUCTION

Wireless communication networks and systems such as those used in mobile phones pose challenge in division of the common transmission medium among several users. The primary goal of communication system is to provide reliable communication to each user of the system despite the fact that the other users share resources possibly simultaneously. As day by day users in the system are growing, it becomes necessary to improve the efficiency of these common communication resources. This paper evaluates the major ICA algorithms on blind separation of convolved CDMA mixture and improvement of the downlink symbol estimation.

Code Division Multiple Access (CDMA) technique efficiently provides high quality voice services and high-speed packet data access and became very popular as it offers advantages over more traditional and TDMA schemes FDMA based on the use of non-overlapping frequency or time slots assigned to each user. The capacity of CDMA based communication system is larger and it degrades gradually with increasing number of simultaneous asynchronous users. Correct reception of CDMA signals is more difficult because of several disturbing phenomena such as multipath propagation, fading of channels, interferences of different types, time delays and different power settings of users[2],[3].

In Direct Sequence CDMA users share the same band of frequencies and same time slots, but they are separated by unique spreading codes. The main sources of errors at the receiver are due to the Multiple Access Interface (MAI),the Inter-Symbol Interference (ISI), the asynchronous users and near-far problem. In downlink signal processing, each mobile station knows only its own code while the codes of the others stations are unknown. There is also less processing power in mobile station than in the base station. These features of downlink processing calls for new, efficient, simple reliable solutions.

In DS-CDMA system, information sequences of different users remains statistically independent and the pseudo noise sequences of different users are uncorrelated, so the DS-CDMA signals satisfy the theory model of Blind source Separation (BSS) very well. Independent Component Analysis (ICA) and BSS techniques provide a promising approach to the downlink signal processing of DS-CDMA systems using short spreading codes[1],[4].

In the past two decades, a particular method of finding underlying components from multivariate data, called ICA has attracted lot of interest both in statistical signal processing and neural network communities. Since then many different approaches have been attempted researchers using higher order statistics, mutual information, artificial learning, beam forming, each claiming various degrees of success. In this paper the DS-CDMA downlink signal Bit Error Rate (BER) is estimated by means of Molgedey and Schuster's (MS) ICA-MS [5] ,OGWE[6], and Hyvarinen's FastICA [7] based methods. The results of numerical experiment are compared with those obtained by the conventional match filter of Single User Detection (SUD) receiver.

This paper is organized as follows. In section 2,the System Model and ICA Methods are established, in Section 3,the Numerical Experiment is discussed, in section 4 some important simulation experiment results are given to testify the BER performance of the proposed methods.

2. MODEL AND METHODS

We consider the linear ICA model with instantaneous mixing. Assume that we observe m linear mixtures $x_1,..., x_m$ of n independent components (sources) $s_1,.....,s_n$. Then we can define the ICA model

$$x=As \quad \text{.........} 2.1$$

Where the sources $s=[s_1,s_2,....s_n]$ are mutually independent random variables and A is an m x n unknown invertible mixing matrix. The goal is to find only from observations x, a matrix W such that the output

$$y= Wx \quad \text{.........} 2.2$$

is an estimate of the possible scaled and permutated source vector s.

Several algorithms exist for Blind Source Separation. We evaluate the performance of ICA-MS, OGWE and Fast ICA algorithms to DS-CDMA detection.

A. ICA-MS Algorithm

Molgedey and Schuster [5] proposed an approach based on dynamic de-correlation which can be used if the independent source signals have different autocorrelation functions. The main advantage of this approach is that the solution is simple and constructive, and can be implemented in a fashion that requires the minimal user intervention (parameter tuning).

Let $\mathbf{X}_\tau$ be the time shifted version of the mixed vector **X**. The delayed correlation approach is based on solving the simultaneous eigenvalue problem for the correlation matrices $\mathbf{X}_\tau \mathbf{X}^T$ and $\mathbf{XX}^T$. This is implemented by solving the eigenvalue problem for the quotient matrix $\mathbf{Q} \equiv \mathbf{X}_t\mathbf{X}^T(\mathbf{XX}^T)^{-1}$. From 2.1, $\mathbf{XX}^T = \mathbf{ASS}^T\mathbf{A}^T$ and $\mathbf{X}_t\mathbf{X}^T= \mathbf{ASS}^T\mathbf{A}^T$ are obtained.

If the sources furthermore are independent, the diagonal source cross-correlation matrix is obtained at lag zero in the $\lim_{N\to\infty} N^{-1}\mathbf{SS}^T = \mathbf{C(0)}$. Similarly, $\lim_{N\to\infty} N^{-1}\mathbf{S}_\tau\mathbf{S}^T = \mathbf{C(\tau)}$ produces the diagonal cross-correlation matrix at lag τ .Hence, to zero[th] order in 1/N ,

$$\mathbf{X}_\tau \mathbf{X}^T(\mathbf{XX}^T)^{-1} \approx \mathbf{AC(\tau)A}^T(\mathbf{A}^T)^{-1}\mathbf{C(0)}^{-1}\mathbf{A}^{-1} \quad \text{..........} 2.3$$

with $\mathbf{C(\tau)C(0)}^{-1}$ being a diagonal matrix. If the eigenvalue problem is solved for the quotient matrix.

$$\mathbf{Q} \equiv \mathbf{XX}^T(\mathbf{XX}^T)^{-1} \approx \mathbf{AC(\tau)C(0)}^{-1}\mathbf{A}^{-1} \quad \text{....................} 2.4$$

then the direct scheme is obtained to estimate **A**, **S**. Let $\mathbf{Q\Phi} = \mathbf{\Phi\Lambda}$ and $\mathbf{\Phi} = \mathbf{A}$ and $\mathbf{\Lambda} = \mathbf{C(\tau)C(0)}^{-1}$ up to scaling factors are identified.

Then the de-mixing matrix **W** is the inverse of the mixing matrix **A**. The sources can be estimated as $\hat{\mathbf{S}}=\mathbf{WX}$.

B. OGWE Algorithm

In OGWE (Optimized Generalized Weighted Estimator) [6], the marginal entropy contrast function (Φ^{ME}) is written in terms of second-order and fourth-order cumulants, and then it is minimized for all possible distributions for the sources S , it follows that

$$\varphi^{ME}(\mathbf{Y}) \approx \frac{1}{48}\varphi^{ME}_{24}(\mathbf{Y}) = -\frac{1}{48}\sum_i (C^{\mathbf{Y}}_{iiii})^2 \quad \text{...............} 2.5$$

where for the zero mean signals $C^{Y}_{iiii} = E[Y_i^4] - 3E[Y_i^2]$ are the marginal cumulants. In the two dimensional case, the pair of normalized sources $s_l = [\bar{s}_p(t)\bar{s}_q(t)]^T$ in polar coordinators may be written as (r(t),α(t)) so that the outputs yield

$$\begin{pmatrix} Y_p(t) \\ Y_q(t) \end{pmatrix} = \mathbf{R}(\theta)\begin{pmatrix} r(t)\cos(\beta(t)) \\ r(t)\sin(\beta(t)) \end{pmatrix} = \mathbf{R}(\theta)Z_t \quad \text{.........} 2.6$$

where $\mathbf{Z_t} = \mathbf{[Zp(t)\ Zq(t)]}^T$ are whitened mixtures and matrix **V** performs a rotation of θ so that ρ(t)=θ + β(t) is the angle of vector y. Note that ideally, at separation θ + β(t)=α(t).

i)The whitening matrix **P** is computed to whiten the vector **X** and the vector **Y=PX** is formed.

ii) One sweep. For all g = m (m-1)/2 pairs i.e.,for l<=p<=q<= m, the following steps have to be done:

a) The given angle $\theta_{pq} = \theta_{GWE}$ is computed, with $[ZpZq]^T=[YpYq]^T$ as follows:

$$\hat{\theta}_{GWE}(\omega_r, \omega_\xi) = \frac{1}{4}\angle(\omega_\xi\omega_r\xi_r + (1-\omega_\xi)\xi_\eta) \quad 0 < \omega_\xi < 1, \omega_r \pm 1, \gamma \quad \text{.........} 2.7$$

$$\hat{\theta}_{SICA} = \hat{\theta}_{GWE}(\gamma, \frac{3}{7}) \quad \text{.........} 2.8$$

where ∠(.) supplies the principal value of the argument.

$$\xi_r = E[r^4(t)e^{j4\beta(t)}]$$
$$\xi_\eta = E^2[r^4(t)e^{j2\beta(t)}]$$
$$\gamma = E[r^4(t)] - 8 \quad \text{.........} 2.9$$

b) If $\theta_{pq} > \theta$ min the pair (Zp Zq) is rotated by θpq according to equation 2.5 and also rotation matrix R is updated.The value of θmin is selected in such a way that rotations by a smaller angle are not statistically significant.Typically, θ min=$10^{-2}/\sqrt{N}$ where N is number of samples.

iii) End if the number of iterations n_{it} satisfies nit>=1+√M or no angle θpq has been updated, stop otherwise go to step(ii) for another sweep.

(iv) Then the mixing matrix **W=RP** and the independent sources are estimated as $\hat{\mathbf{S}}$ =WX.

C. FastICA Algorithm

FastICA algorithm [7] is a fixed-point iteration scheme for finding a maximum of the non-Gaussanity. It uses kurtosis and computations can be performed either in batch mode or in a semi-adaptive manner. It uses deflation approach to update the columns of separating matrix W and to find the independent components one at a time. More recent versions are using hyperbolic tangent, exponential or cubic functions as contrast function. The update rule for the deflation method is given by [7]

$$w^*(k)=C^{-1}E\{x\, g(w(k-1)^T x)\}-E\{g'(w(k-1))^T x\}w(k-1) \quad \text{.....................(2.10)}$$

$$w(k) = w^*(k)w^*(k)^T C\, w^*(k)... \quad \text{............................(2.11)}$$

where g can be any suitable non-quadratic contrast function, with derivative g'; and C is the covariance matrix of the mixtures, x. $w^*(k)^T$ x(t); t = 1, 2,…equals one of the sources.

D. System Model

The DS-CDMA signal model in mobile receiver over an Additive White Gaussian Noise (AWGN) channel is mathematically represented as in equation 2.1.

R= GB + N.... ....(2.12)

Where, matrices G, B and N denotes the unknown mixed matrix, symbols and noise.

R = [rm, ..., rm']
B = [bm, ..., bm']
N = [nm, ..., nm']

where R, N is C x M' matrix, G is C x 2KL matrix and B is 2KL x M' matrix.

Comparing with the model of linear ICA in Eq. 2.1, B is the source signal **s** need to be estimated, R is the observed mixed signal **x**, and **G** is the unknown mixing matrix A. the noise matrix N in Eq. 2.12 can be treated as an independent component to be added into x . In this paper, the code timing and channel estimation are assumed the prerequisite tasks. In other words, the received signal for ICA detector is assumed the sampled and synchronized data. Thus the path is down to 1; the propagation delay is equal to 0. In view of ICA algorithm, the AWGN can be treated as one of the independent components. Then the Eq. 2.12 is changed to

R=GB... (2.13)

where the dimension of matrices R, B and G are C x M', C x K and K x M', respectively.

3. NUMERICAL EXPERIMENT

The algorithms were tested using simulated DS-CDMA downlink data in the presence of AWGN . The short Gold code to make the length of chips to be C = 31, was used. Thus the maximum number of users is K = 30 as the 31st user is AWGN Noise. Monte Carlo simulation that has incorporated the ICA-MS, OGWE and FastICA algorithm were run to verify the validity of the system model. A combined scheme of the ICA-SUD detector proposed [4] was devised and implemented. This combined scheme is illustrated in Fig 1. One independent ICA detectors are incorporated in parallel with a SUD detector. The majority of the one ICA and one SUD detectors make final decisions on the outcomes. The results of numerical experiment are shown in Fig. 2 to 10. The performance shown as of average Bit-Error-Rate (BER).

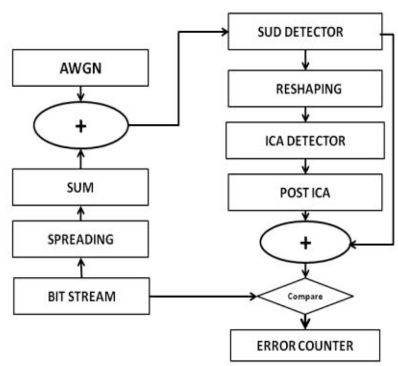

Fig. 1 SUD-ICA Detector

For AWGN Parameters were set as follows: In order to test the performance of the ICA detector, the values of Number of symbol M were varied for M = 2000, 5000 and 10000; Number of users K = 30; Number of paths L = 1. Signal-to-Noise Ratio (SNR) was varied with respect to the individual user from -10dB to 0dB. All the signals for each of users are sent in same power. The AWGN is treated as an independent component (IC). One of the typical simulation results of the ICA detector is shown in Fig. 8,9 and 10 along with the results of the SUD receiver, ICA receiver and combined SUD and ICA, SUDICA receiver.
We can easily observe that the ICA detector is functionally working. It can semi-blindly estimate DS-CDMA downlink

signal. However, when the decoding is blind, it requires training sequences to match the decoded bit stream to the user who should receive it. ICA receiver alone cannot work well for presence of AWGN Gaussian noise. A combined scheme of the ICA detector, SUD detector and SUDICA detector was devised and implemented. The results of numerical experiment of the SUD,ICA, and SUDICA detectors are shown in Fig. 8,9 and 10. The performance appears to be of average BER. However, the SUDICA detector outperforms the ICA detector giving the lowest BER to the SUDICA detector as shown in Fig. 8,9 and 10. Fig. 2 ,3,4,5,6,and 7. Show comparison of ICA detectors and SUDICA detectors for ICA-MS, OGWE and FastICA algorithms. FastICA and OGWE algorithms performed well compared to ICA-MS.

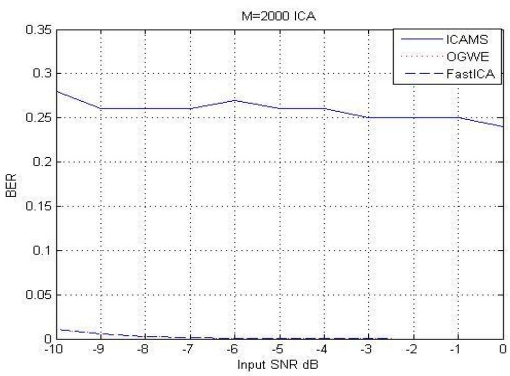

Fig. 2 Comparison of ICA detector in presence of noise using ICA algorithms for M=2000.

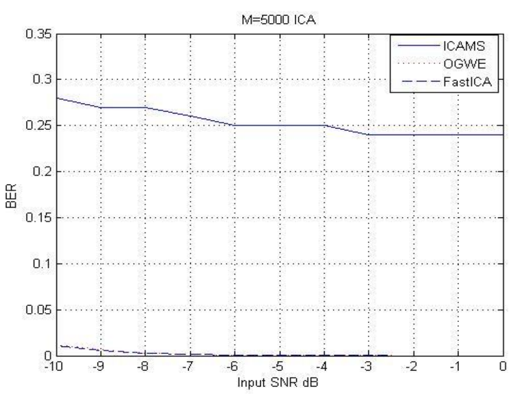

Fig. 3 Comparison of ICA detector in presence of noise using ICA algorithms for M=5000.

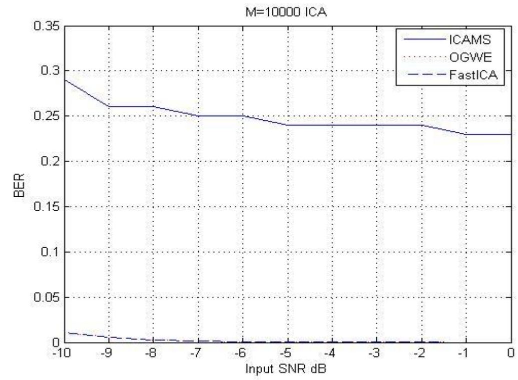

Fig. 4 Comparison of ICA detector in presence of noise using ICA algorithms for M=10000.

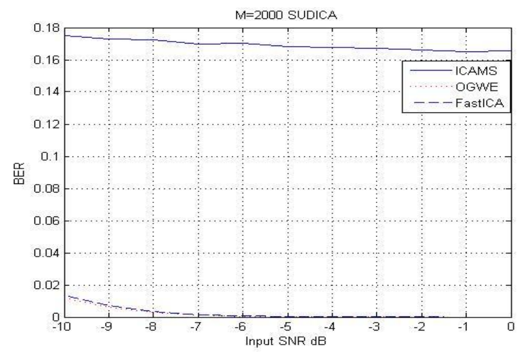

Fig 5.Comparison of SUDICA detector in presence of noise using ICA algorithms for M=2000.

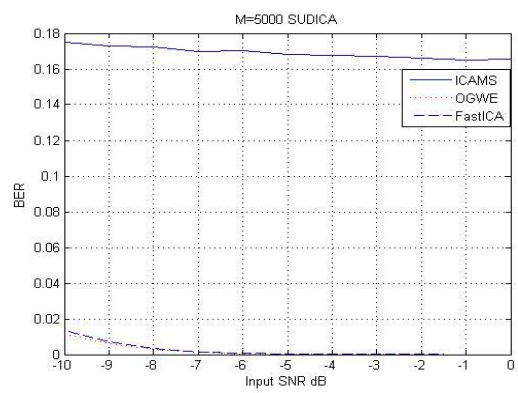

Fig. 6.Comparison of SUDICA detector in presence of noise using ICA algorithms for M=5000.

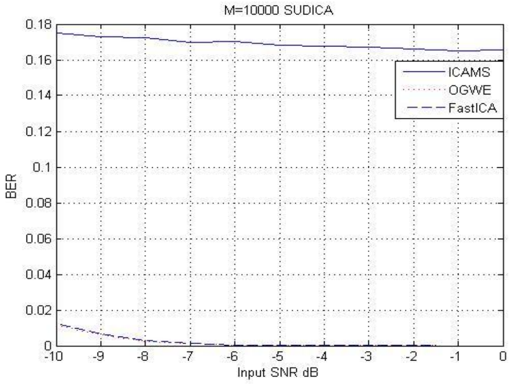

Fig. 7.Comparison of SUDICA detector in presence of noise using ICA algorithms for M=10000.

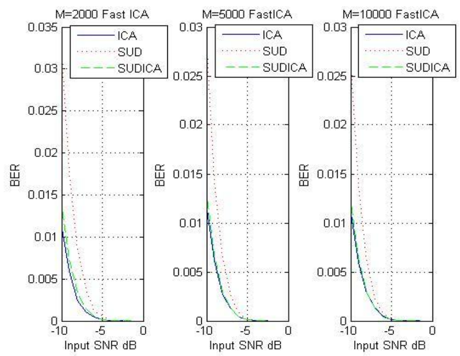

Fig.8 .BER in presence of noise using FastICA algorithm for M=2000,5000 and 10,000.

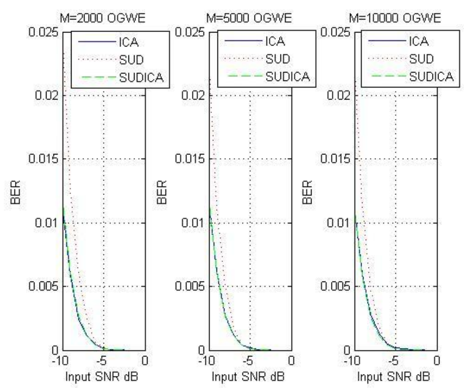

Fig. 9.BER in presence of noise using OGWE algorithm for M=2000.5000 and 10,000.

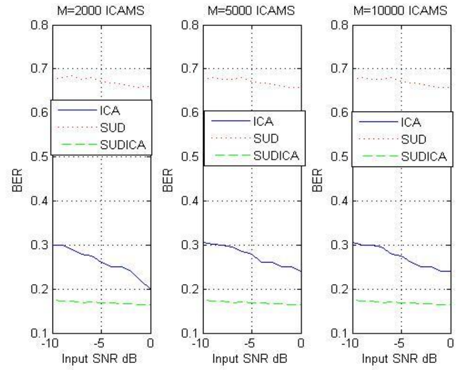

Fig. 10.BER in presence of noise using ICA-MS algorithm for M=2000.5000 and 10,000.

4 CONCLUSIONS

In this paper we have evaluated the BER of some major ICA algorithms such as FastICA, OGWE, and ICA-MS algorithm to solve the symbol estimation problem of the multi-users in a DS-CDMA communication system. We observe that the performances of the algorithms are affected by AWGN. The performance of the FastICA and OGWE algorithm are slightly better compared to the ICA-MS. ICA based DS-CDMA downlink detector demonstrated that ICA detector can solve the symbol estimation problem with no spreading code required, though the spreading code should be utilized to identify each user. Thus an ICA, SUDICA detector have been used and their symbol error rate is lower than the conventional SUD detector concluded from this numerical experiments. Even if the powers of the signals are the same, additional multiple access interference can be mitigated by ICA, thus improving the performance of SUD. With the increase in the number of symbols from 2000 to 5000 and 10,000, the symbol error rate is not much affected.

REFERENCES

[1] Yue Fang and Kunio Takaya,"An Application of ICA to Ds-CDMA Detection,0840-7789/07/2007 IEEE

[2] T. Ristaniemi, K. Raju, and J. Karhunen,“ Jammer mitigation in DSCDMA array system using independent component analysis”.In Proc. of the 2002 IEEE Int. Conference on Communications (ICC 2002), New York, USA, April 28 - May 02, 2002, 2002.

[3] T. Ristaniemi, K. Raju, J. Karhunen, and E. Oja,“ Jammer cancellation in DS-CDMA array systems: Pre and post switching of ICA and RAKE” In Proc. of the 2002 IEEE Int. Symposium on Neural Networks for Signal Processing (NNSP 2002),

pages 495-504, Martingy, Switzerland, September 04 - 06, 2002

[4] S.D.Parmar and Unhelkar, B. 14th - 16th March 2009. Separation performance of ica algorithms in communication systems, International Conference on Multimedia, Signal Processing and Communication Technologies (IMPACT-2009),Aligarh, UP -India pp. 143–146.

[5] L. Molgedey and H. Schuster, "Separation of independent signals using time-delayed correlations," Physical Review Letters, vol. 72, no. 23, pp. 3634–3637, 1994.

[6] Juan J. Murillo-Fuentes and Rafael Boloix-Tortosa, Francisco J. Gonz´alez-Serrano, "Initialized Jacobi Optimization in Independent Component Analysis".

[7] A. Hyvarinen, "A family of fixed-point algorithms for independent component analysis," IEEE Conference on Acoustics, Speech and Signal Processing, pp. 3917-3920, 1997.

[8] T. Ristaniemi and R. Wu, "Mitigation of continuous-wave jamming in DS-CDMA systems using source separation techniques", Proc. Third International Workshop on Independent component Analysis and Signal Separation, (ICA2001), San Diego, CA, USA, December 2001, pp. 55-58.

[9] T. Ristaniemi and J. Joutsensalo, On the performance of Blind Source Separation in CDMA Downlink, Proc. International Work shop on Independent Component Analysis and Signal Separation, (ICA99), Aussois, France, January 1999.

[10] Miao Yu Jianzhong Chen,Lei Shen and Shiju Li,"Blind Separation of DS-CDMA Signals with ICA Method",JOURNAL OF NETWORKS VOL 6,No2 Feb 2011

[11] V.Matic,WDeburchgraeve, S.Van Huffer "Comparison of ICA Algorithms for ECG Artifact Removal From EEG Signals

Authors Profile

PROF A. Janardhan received M Tech degree in Advanced electronics from Jawaharlal Nehru Technological University, Hyderabad, India . Currently doing Ph D in electronics and communication engineering (Digital Signal Processing) in , Jawaharlal Nehru Technological University ,Hyderabad , India. His research interest includes Machine Learning, Source separation Algorithms ,Signal processing in Geophysics and Communication networks.

PROF Kishen Rao obtained B.E., & M.E., Degrees from Osmania University ,Hyderabad, India in 1965 and 1967 respectively. Obtained Ph.D from IIT Kanpur in 1973. Joined REC(NIT) Warangal on 1st September , 1972 as Lecturer in ECE Department. Promoted as Assistant Professor in May ,1974 and as Professor in March.1979. Held Positions of Head of Department, Chief Warden, Dean (Academic Affairs) and retired as PRINCIPAL on 22nd March,2002.Worked on 5 Research Projects of MHRD., DOE & DST. Conducted 8 FDP programs. Delivered more than 60 Expert Lectures. Published 51 Research papers in National Journals and 40 Research Papers in International Journals. Guided 3 candidates for their Ph.D. Degree . At present 8 candidates are working for their Ph.D. Degree under my Guidance in fields of Wireless Communications and Digital Signal Processing.