

# A Variation of LMS Algorithm for Noise Cancellation

C Mohan Rao<sup>1</sup>, Dr. B Stephen Charles<sup>2</sup>, Dr. M N Giri Prasad<sup>3</sup>

Associate Professor, Department of ECE, NBKRIST, Vidyanagar, India<sup>1</sup>

Principal, SSCET, Kurnool, India<sup>2</sup>

Professor & Head, Department of ECE, JNTUACE, Anantapuram, India<sup>3</sup>

**Abstract:** This paper presents a new adaptive filter whose coefficients are dynamically changing with an evolutionary computation algorithm and hence reducing the noise. This algorithm gives a relationship between the update rate and the minimum error which automatically adjusts the update rate. When the environment is varying, the rate is increased while it would be decreased when the environment is stable and the computation complexity of adaptive filter can be significantly reduced. In the simulation, additive white Gaussian noise is added to the randomly generated information signal and efficiently reduced this noise with minimum or no error by using evolutionary computation with Least Mean Square (LMS) algorithms.

**Keywords:** Noise cancellation, LMS, MSE, Adaptive filter.

## I. INTRODUCTION

In numerous application areas, including biomedical engineering, radar, sonar and digital communications, the goal is to extract a useful signal corrupted by interferences and noises. Noise/interference removal is facilitated when multiple sensors on different locations record the biomedical phenomenon simultaneously. The usual method of estimating a signal corrupted by additive noise' is to pass it through a filter that tends to suppress the noise while leaving the signal relatively unchanged. Filters used for the above purpose can be fixed or adaptive.

The design of fixed filters is based on prior knowledge of both the signal and the noise. Adaptive filters, on the other hand, have the ability to adjust their own parameters automatically, and their design requires little or no a priori knowledge of signal or noise characteristics. Noise cancelling is a variation of optimal filtering that is highly advantageous in many applications. It makes use of a reference input derived from one or more sensors located S at points in the noise field where the signal is weak or undetectable. This input is filtered and subtracted from a primary input containing both signal and noise. As a result the primary noise is attenuated or eliminated by cancellation. Acoustic noise problems becomes more pronounce as increase in number of industrial equipment such as engines, transformers, compressors and blowers are in use. The traditional approach to acoustic noise cancellation uses passive techniques such as enclosures, barriers and silencers to remove the unwanted noise signal [1][2].

Silencers are important for noise cancellation over broad frequency range but ineffective and costly at low

frequencies. Mechanical vibration is a type of noise that creates problems in all areas of communication and electronic appliances. Signals are carriers of information, both useful and unwanted. Extracting or enhancing the useful information from a mix of conflicting information is a simplest form of signal processing. Signal processing is an operation designed for extracting, enhancing, storing, and transmitting useful information. Hence signal processing tends to be application dependent.

In contrast to the conventional filter design techniques, adaptive filters do not have constant filter coefficients and no priori information is known. Such a filter with adjustable parameters is called an adaptive filter. Adaptive filter adjust their coefficients to minimize an error signal and can be realized as finite impulse response (FIR), infinite impulse response (IIR), lattice and transform domain filter [3]. The rest of the paper is organized as follows. Section II gives a survey of literature. Section III presents an overview of adaptive noise cancellation. Section IV describes the conventional LMS algorithm. Section V presents the simulation results and section VI concludes the paper.

## II. RELATED WORK

In [4], Ali A. Milani, et. al, proposed a new UDFTM-based adaptive subband filtering method that alleviates the degrading effects of the delay and side-lobe distortion introduced by the prototype filter on the system performance. The delay in filter bank is reduced by prototype filter design and the side-lobe distortion is compensated for by oversampling and appropriate stacking



of subband weights. Experimental results show the improvement of performance and computational complexity of the proposed method in comparison to two commonly used subband and block adaptive filtering algorithms.

In [5], Akash Kashyap, et. al, designed a least mean square (LMS) adaptive filter to remove the unwanted noise which might occur during music recordings, echo in telephone networks, etc. Generally all LMS algorithm starts with an assumption of weight vector as zero initially and iteration continues till the error is minimized till its optimum level. This takes much more time to compute the optimized coefficients. In our work we designed the Wiener Filter using Wiener-Hopf equation. Then the LMS algorithm is used to optimize the coefficients. In this method it is observed that less number of iterations is sufficient. Since Wiener-Hopf equation is basically considered for the problem of designing the filter that would produce the minimum mean square error of the desired signal, this will produce the optimized estimate.

In [6], J. M. Górriz, et. al, propose a novel least-mean-square (LMS) algorithm for filtering speech sounds in the adaptive noise cancellation (ANC) problem. It is based on the minimization of the squared Euclidean norm of the difference weight vector under a stability constraint defined over the *a posteriori* estimation error. To this purpose, the Lagrangian methodology has been used in order to propose a nonlinear adaptation rule defined in terms of the product of differential inputs and errors which means a generalization of the normalized (N)LMS algorithm. They provide an extensive performance evaluation along with an exhaustive comparison to standard LMS algorithms with almost the same computational load, including the NLMS and other recently reported LMS algorithms such as the modified (M)-NLMS, the error nonlinearity (EN)-LMS, or the normalized data nonlinearity (NDN)-LMS adaptation.

[7] describes the concept of adaptive noise cancelling, an alternative method of estimating signals corrupted by additive noise or interference. The method uses a “primary” input containing the corrupted Signal and a “reference” input containing noise correlated in some unknown way with the primary noise. The reference input is adaptively filtered and subtracted from the primary input to obtain the signal estimate. A desired signal corrupted by additive noise can often be recovered by an adaptive noise canceller using the least mean squares (LMS) algorithm. Computer simulations with uncorrelated Gaussian noise and signals confirm the results of the analysis and demonstrate the effectiveness of the least mean squares (LMS) algorithms. This Adaptive Noise Canceller is then useful for enhancing the S/N ratio of data collected from sensors (or sensor arrays) working in noisy environment, or dealing with potentially weak signals.

### III. ADAPTIVE NOISE CANCELLATION

Adaptive noise Cancellation is an alternative technique of estimating signals corrupted by additive noise or interference. Its advantage lies in that, with no apriori estimates of signal or noise, levels of noise rejection are attainable that would be difficult or impossible to achieve by other signal processing methods of removing noise. Its cost, inevitably, is that it needs two inputs - a primary input containing the corrupted signal and a reference input containing noise correlated in some unknown way with the primary noise. The reference input is adaptively filtered and subtracted from the primary input to obtain the signal estimate. Adaptive filtering before subtraction allows the treatment of inputs that are deterministic or stochastic, stationary or time-variable.

The effect of uncorrelated noises in primary and reference inputs, and presence of signal components in the reference input on the ANC performance is investigated. It is shown that in the absence of uncorrelated noises and when the reference is free of signal; noise in the primary input can be essentially eliminated without signal distortion. A configuration of the adaptive noise canceller that does not require a reference input and is very useful many applications is also presented. The usual method of estimating a signal corrupted by additive noise is to pass it through a filter that tends to suppress the noise while leaving the signal relatively unchanged i.e. direct filtering.

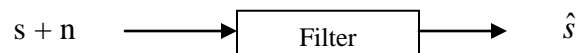


Fig. 1. Filter representation with input and output

The design of such filters is the domain of optimal filtering, which originated with the pioneering work of Wiener and was extended and enhanced by Kalman, Bucy and others. Filters used for direct filtering can be either Fixed or Adaptive.

1. Fixed filters - The design of fixed filters requires a priori knowledge of both signal and noise, i.e. if the signal and noise are known beforehand, a filter that passes frequencies contained in the signal and rejects the frequency band occupied by the noise can be designed.
2. Adaptive filters - Adaptive filters, on the other hand, have the ability to adjust their impulse response to filter out the correlated signal in the input. They require little or no a priori knowledge of the signal and noise characteristics. (If the signal is narrowband and noise broadband, which is usually the case, or vice versa, no a priori information is needed; otherwise they require a signal (desired response) that is correlated in some sense to the signal to be estimated.) Moreover adaptive filters have the capability of adaptively tracking the signal under non-stationary conditions.



Noise Cancellation is a variation of optimal filtering that involves producing an estimate of the noise by filtering the reference input and then subtracting this noise estimate from the primary input containing both signal and noise.

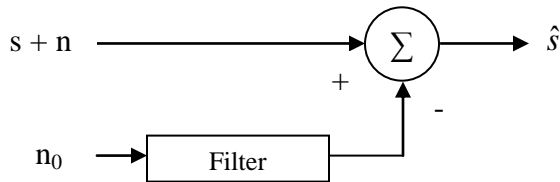


Fig. 2 Noise phenomenon in Channel

It makes use of an auxiliary or reference input which contains a correlated estimate of the noise to be cancelled. The reference can be obtained by placing one or more sensors in the noise field where the signal is absent or its strength is weak enough. Subtracting noise from a received signal involves the risk of distorting the signal and if done improperly, it may lead to an increase in the noise level. This requires that the noise estimate  $\hat{n}$  should be an exact replica of  $n$ . If it were possible to know the relationship between  $n$  and  $\hat{n}$ , or the characteristics of the channels transmitting noise from the noise source to the primary and reference inputs are known, it would be possible to make  $\hat{n}$  a close estimate of  $n$  by designing a fixed filter.

However, since the characteristics of the transmission paths are not known and are unpredictable, filtering and subtraction are controlled by an adaptive process. Hence an adaptive filter is used that is capable of adjusting its impulse response to minimize an error signal, which is dependent on the filter output. The adjustment of the filter weights, and hence the impulse response, is governed by an adaptive algorithm. With adaptive control, noise reduction can be accomplished with little risk of distorting the signal. In fact, Adaptive Noise Cancelling makes possible attainment of noise rejection levels that are difficult or impossible to achieve by direct filtering. The error signal to be used depends on the application. The criteria to be used may be the minimization of the mean square error, the temporal average of the least squares error etc. Different algorithms are used for each of the minimization criteria e.g. the Least Mean Squares (LMS) algorithm, the Recursive Least Squares (RLS) algorithm etc.

#### IV. LMS ALGORITHM

If it were possible to make exact measurements of the gradient vector in all iterations and if the step-size parameter  $\mu$  is suitably chosen, then the tap-weight vector computed by using the method of steepest-descent would indeed converge to the optimum Wiener solution. In reality, however, exact measurements of the gradient vector are not possible, and it must be estimated from the available data. In

other words, the tap-weight vector is updated in accordance with an algorithm that adapts to the incoming data. One such algorithm is the least mean square (LMS) algorithm. A significant feature of LMS is its simplicity; it does not require measurements of the pertinent correlation functions, nor does it require matrix inversion.

The LMS algorithm is a search algorithm in which a simplification of the gradient vector computation is made possible by appropriately modifying the objective function [3][1]. The LMS algorithm, as well as others related to it, is widely used in various applications of adaptive filtering due to its computational simplicity [8]-[12]. The convergence speed of the LMS is shown to be dependent on the eigenvalue spread of the input signal correlation matrix [1],[8]-[11]. The LMS algorithm is by far the most widely used algorithm in adaptive filtering for several reasons. The main features that attracted the use of the LMS algorithm are low computational complexity, proof of convergence in stationary environment, unbiased convergence in the mean to the Wiener solution, and stable behaviour when implemented with finite-precision arithmetic.

Let  $x(n)$  and  $d(n)$  represent the reference input and the desired output signal, respectively, to the adaptive filter. Let  $L$  denote the total number of filter coefficients. Define the  $L \times 1$  coefficient vector  $H(n)$  and the input vector  $X(n)$  as

$$H(n) = [h_0(n), h_1(n), \dots, h_{L-1}(n)]^T \quad (1)$$

$$X(n) = [x(n), x(n-1), \dots, x(n-L+1)]^T \quad (2)$$

The LMS is described as

$$e(n) = d(n) - H^T(n)X(n) \quad (3)$$

$$H(n+1) = H(n) + \mu_s X(n)e(n) \quad (4)$$

In practice, (4) may be replaced with

$$H(n+1) = H(n) + \frac{\mu}{X^T(n)X(n) + \sigma} X(n)e(n) \quad (5)$$

or

$$H(n+1) = H(n) + \frac{\mu}{Lr(0)} X(n)e(n) \quad (6)$$

where the positive step-size  $\mu$  is bounded by 2,  $\sigma$  is a small positive number and  $r(0)$  is the estimated autocorrelation function value of  $x(n)$  for lag 0.

Digital filter is the basic building block of Digital Signal Processing systems. Finite Impulse Response (FIR) is preferred when compared to Infinite Impulse Response (IIR), because of its properties like guaranteed stability, linear phase and low response, but with expense of large number of arithmetic operations are involved. In communication systems channel noise and Inter Symbol Interference (ISI) degrades the performance of communication system. To reduce this problem adaptive equalizers are used to shape the signals at the receivers. Least Mean Square technique is the one of the adaptive techniques.

It is easy to realize, the computational complexity causes a long output delay, which is not tolerable. This computational



complexity can be reduced using frequency domain adaptive filtering, but nonlinear systems performance degrades drastically. To overcome this, problem of derivative base and derivative free learning algorithm, we use natural selection or derivative free algorithms. A new evolutionary computation algorithm based on natural learning to update the weights of adaptive filter was used. In this method Genetic Algorithm (GA) is used to update weights of filter coefficients.

**V. SIMULATION RESULTS**

In this section, the simulation results of the noise cancellation with LMS as well as the proposed technique are presented. First of all 500 random samples are generated. The generated sequence was considered as the input. The fig. 3 shows the input signal. The only two possible values that input signal take are +1 and -1. The channel was considered as a system which imposes noise on the original input signal. Because of the noise effect of channel the original signal was corrupted. The signal from the channel was plotted in fig. 4. The signal from the channel is taking almost all the values between -2 to 2, as compared to the original signal taking only -1 and 1. After the equalization using the conventional LMS algorithm the noise was well corrected. The signal from the equalizer with conventional LMS was shown in the fig. 5.

The noise in the signal from channel was almost removed. Still the signal is continuous. After using thresholding, the reconstructed signal is ready. The recovered signal is shown in the fig. 6. The mean square error (MSE) was plotted in the fig. 7. The MSE is in the range of -40dB to -60dB. The performance of the proposed LMS variation is presented in the figures 8, 9 and 10. The fig. 8 shows signal from the equalizer, 9 recovered signal after thresholding and 10 the MSE.

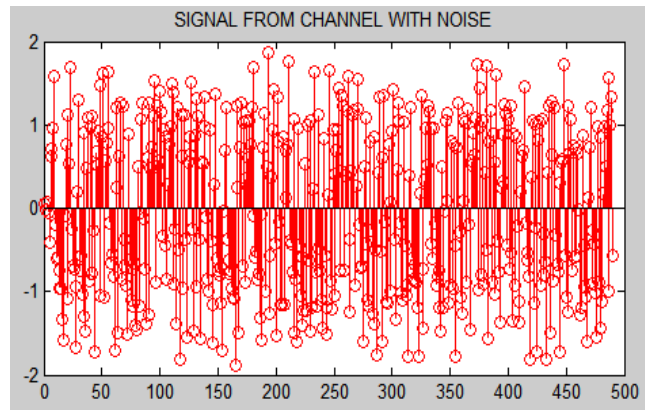


Fig. 4. Signal from channel with Noise

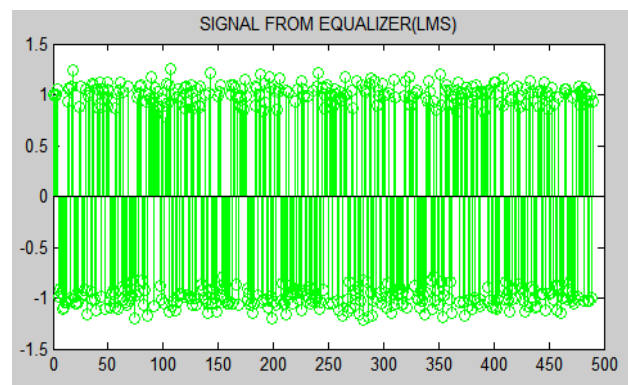


Fig. 5. Signal from Equalizer using Conventional LMS

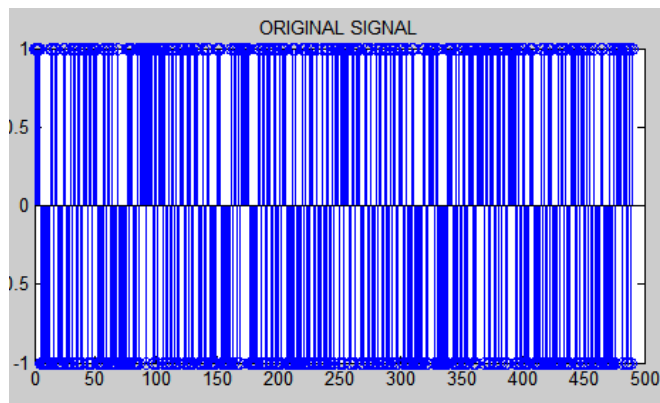


Fig. 3. Input Signal

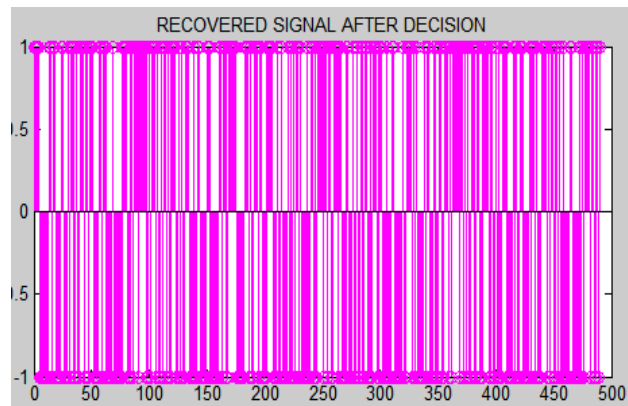


Fig. 6. Recovered signal after decision using LMS

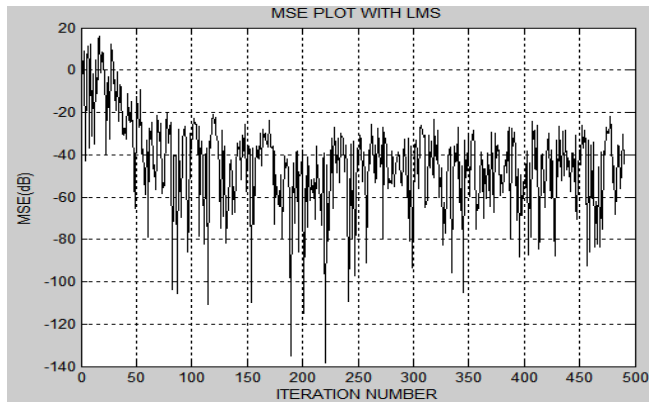


Fig. 7. MSE using conventional LMS

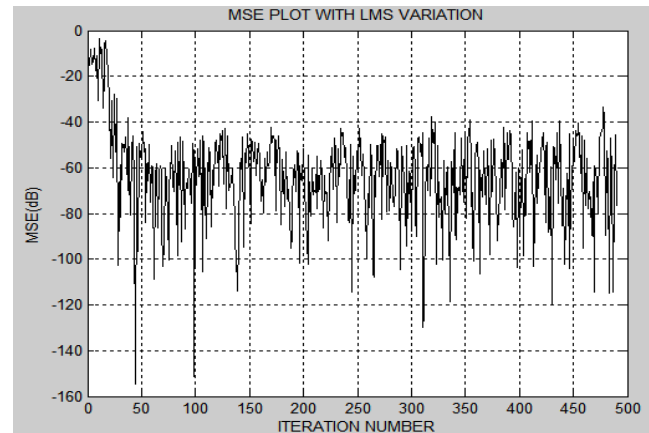


Fig. 10. MSE with LMS variation

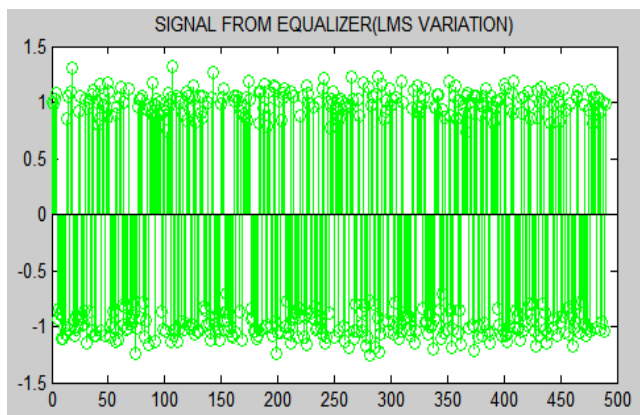


Fig. 8. Signal from Equalizer using LMS variation

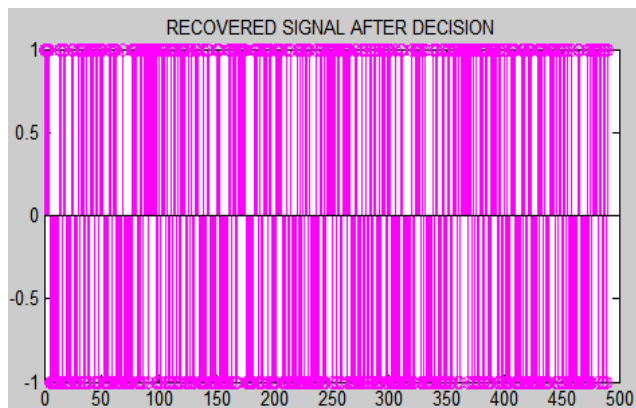


Fig. 9. Recovered signal after decision using LMS variation

From the fig. 10, one can observe that the MSE is in the range of -50dB to -80dB. The improvement in the MSE or the precise reconstruction costs the execution speed. The time required to run the LMS variation is very high when compared to that of conventional LMS. New methods are required, so that the execution speed can be increased.

## VI. CONCLUSIONS

Adaptive Noise Cancellation is an alternative way of cancelling noise present in a corrupted signal. The principal advantage of the method is in its adaptive capability, its low output noise, and its low signal distortion. The adaptive capability allows the processing of inputs whose properties are unknown and in some cases non-stationary. Output noise and signal distortion are generally lower than can be achieved with conventional optimal filter configurations. The adaptive cancellation of the noise has many applications, because interferences are common for many environments. The conventional LMS and a variation of LMS are considered in this paper. It is proved that the proposed LMS gives better MSE performance. The average difference between the MSEs produced in the conventional LMS and LMS variation is 20dB. But it is observed that the time required to run the LMS variation is very high compared to that of conventional LMS. By using Genetic Algorithm or Particle Swarm Optimization, one may find better solution to the problem of noise cancellation.

## REFERENCES

- [1] Simen Haykin, "Adaptive Filter Theory", 3rd Edition, Pearson Education Asia.LPE.
- [2] John G Proakis, "Adaptive Signal Processing", 3rd Edition, Perntice Hall of India.
- [3] Bernard Widrow and Samuel D.Stearns, "Adaptive Signal Processing", Pearson Education Asia, LPE.
- [4] Ali A. Milani, Et.Al, "A New Delayless Subband Adaptive Filtering Algorithm For Active Noise Control Systems", IEEE Transactions on Audio, Speech and Language Processing, Vol. 17, No. 5, July 2009.
- [5] Akash Kashyap And Mayank Prasad, "Audio Noise Cancellation Using Wiener Filter Based LMS Algorithm Using Labview", International



Journal Of Emerging Technology And Advanced Engineering, Volume 3, Issue 3, March 2013.

- [6] J. M. Górriz, et. al, "A Novel LMS Algorithm Applied To Adaptive Noise Cancellation", IEEE Signal Processing Letters, Vol. 16, No. 1, January 2009.
- [7] Mamta M. Mahajan et al., "Design Of Least Mean Square Algorithm For Adaptive Noise Canceller", International Journal Of Advanced Engineering Sciences And Technologies Vol No. 5, Issue No. 2, 172 – 176.
- [8] John R. Glover, Jr., "Adaptive Noise Cancelling Applied to Sinusoidal Interferences", IEEE Trans. ASSP, Vol. ASSP-25, No. 6, Pp. 484-491, Dec. 1977.
- [9] J.R. Zeidler et al., "Adaptive Enhancement Of Multiple Sinusoids In Uncorrelated Noise", IEEE Trans. ASSP, Vol. ASSP-26, No. 3, Pp. 240-254, June 1978.
- [10] D. W. Tufts, "Adaptive Line Enhancement And Spectrum Analysis", Proc. IEEE (Letts.), Vol. 65, Pp.169-170, Jan. 1977
- [11] L. Griffiths, Proc. IEEE (Letts.), Vol. 65, Pp.170-171, Jan. 1977.
- [12] B. Widrow et al., Proc. IEEE (Letts.), Vol. 65, Pp.171-173, Jan. 1977

### BIOGRAPHY



**C. Mohan Rao** (India) born on 21st April 1975, is pursuing Ph.D in Jawaharlal Nehru Technological University Anantapur. He received Master of Technology from Pondicherry Central University in the Year 1999, Bachelor of

Technology form S.V University, Tirupati in the year 1997. He started his carrier as hardware Engineer in Hi-com technologies, during 1999 to 2001, after he worked as Assistant Professor in G. P. R. E. C during 2001 to 2007 and as Associate Professor in N. B. K. R. I. S. T. from 2007 to till date. He is a member of IETE and ISTE.



**Dr. B. Stephen Charles** (India) born on the 9th of August 1965. He received Ph.d degree in Electronics & Communication Engineering from Jawaharlal Nehru Technological University, Hyderabad in 2001. His area of interest is Digital signal Processing. He received his B.Tech

degree in Electronics and Communication Engineering from Nagarjuna University, India in 1986. He started his carrier as Assistant professor in Karunya institute of technology during 1989 to 1993, later joined as Associate Professor in K. S. R. M. College of Engg. During 1993 to 2001 after that he worked as Principal of St. John's College of Engineering & Technology during 2001 to 2007 and now he is the Secretary, Correspondent and Principal in Stanley Stephen College of Engineering & Technology, Kurnool. He has 24 years of teaching and research experience. He published more than 40 research papers in national and international journals and more than 30 research papers in national and international conferences. He is a member of Institute of Engineers and ISTE.



**Dr. M.N. Giri Prasad** (India) received his B.Tech degree from J.N.T University College of Engineering, Anantapuram, Andhrapradesh, India in 1982. M.Tech degree from Sri Venkateshwara University, Tirupati, Andhra Pradesh, India in 1994 and Ph.D degree from J.N.T. University,

Hyderabad, Andhra Pradesh, Indian in 2003. Presently he is working as a Professor in the Department of Electronics and Communication at J.N.T University College of Engineering Anantapuram, Andhrapradesh, India. He has more than 25 years of teaching and research experience. He has published more than 50 papers in national and international journals and more than 30 research papers in national and international conferences. His research areas are Wireless Communications and Biomedical instrumentation, digital signal processing, VHDL coding and evolutionary computing. He is a member of ISTE, IE & NAFEN.