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Electronic Information System Signal Noise for Noise Reduction using Variational Bayesian based Robust Adaptive Filter

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Abstract: - The most significant issues for a thousand users is the unwanted or loud signals in sound files, it is impossible to eliminate or minimize these noise signals without knowledge their types and ranges. To overcome this issue, present an Electronic Information System Signal Noise for Noise Reduction using Variational Bayesian based Robust Adaptive Filter (EIS-SNR-VBRAF) is proposed. Initially, the data is collected from Adaptive Myriad Filter using Time-Varying Noise and Signal-Dependent Parameters dataset. Then, the data is given for Pre-processing section, Variational Bayesian based Robust Adaptive Filter (VBRAF) is used to reduce the signal noise from Gaussian Noise, Traffic noise and Audio signal back ground noise. The proposed technique is implemented and efficacy of EIS-SNR-VBRAF technique is assessed by support of numerous performances such as BER, Signal-to-Noise-Ratio (SNR), Mean Squared Error, Peak Signal-to-Noise Ratio (PSNR), Root Mean Square Error, Structural Similarity Index, Cross-Correlation and Computational Complexity is analyzed. The proposed EIS-SNR-VBRAF method attains 21.18%, 23.52% and 23.65% lower RMSE, 21.52%, 21.76% and 23.24% higher PSNR, 21.19%, 21.73% and 20.48% higher Structural Similarity Index are compared with existing methods like early detection of mechanical malfunctions in vehicles utilizing sound signal processing (ED-MMV-SSP),noise reduction in infrasound signals based on mask coefficient binary weighting generalized cross correlation non-negative matrix factorization algorithm (NRID-MCWG-NMFA) and Click-event sound detection in automotive industry using machine/deep learning (CE-SDSI-DL) respectively.

Keywords: Audio signal background noise, Gaussian noise, Noise Reduction, Signal-to-Noise-Ratio, Traffic noise, Variational Bayesian based Robust Adaptive Filter.

I. INTRODUCTION

The unwanted signal that obstructs the measurement or transmission of other signal is referred to as noise. A variety of sources can produce noise like, audio frequency acoustic noise from moving or vibrating objects, or radio-frequency electromagnetic noise that impedes the transmission and data reception, speech and image over radio-frequency spectrum [1-3]. For a thousand users, undesired signals in sound files are biggest problems as well as obstacles. As a result, some businesses and scholars have attempted to offer an alternative approach. Nevertheless, none of these researches have suggested a low-cost adaptive solution. Several filters are employed to enhance speech [4]. The type of Gaussian noise is taken into account in this actual noisy environment. The authors came to the conclusion that audio signals with varying ripple factors and frequencies might have their noise levels successfully reduced by using the Butterworth filter [5-7]. The order of varying frequencies yields distinct outcomes. The best digital filters have been developed through extensive academic work on signal reconstruction from noisy observations using a range of numerical techniques [8]. The Audio Noise Reduction System is used to eliminate noise from the audio transmission. In this system, filters are used to adjust a signal's amplitude or phase response based on its frequency. When stop band and pass band frequencies are tuneable, filters are referred to as tuneable filters in contracts [9]. The requirements of the applications determine these frequencies are changed. Noise appears as grains in an data and is a random change in data intensity [10]. The data show effects from simple physics like the light photon nature or the thermal energy of heat in the data sensors. It could show up when transferring or capturing pictures. Noise is the result of variable intensity values appearing in place of actual pixel values in an data [11-13]. The technique of eliminating or lowering the noise in an data is called a noise removal technique. The whole data is smoothed out by the noise reduction algorithms, leaving regions around contrast limits, which lessens or completely removes the visibility of noise. Nevertheless, these methods could obscure delicate, low contrast features. [14].In obtained data, the noise with a Gaussian distribution is frequently found. Traditional linear filters blur edges but effectively smooth noise, such as the Gaussian and arithmetic mean filters [15]. The objective of the filtering operation eliminates noise while maintaining the edge accuracy as well as detail data, nonlinear methods typically yield better results than linear ones [16]. Every five years, the European member states' action plans and noise maps are to be addressed under the Environmental Noise Directive (END) of 2002.

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But according to the most recent END revision, noise pollution is still a significant health concern in Europe [17]. Recent changes have been made to the Common Noise Assessment Methods in Europe (CNOSSOS-EU) to specify the measurement guidelines required to enable comparable noise assessment evaluations [18-20].

The main problem is to design an effective noise reduction system that can improve the quality of signals in this electronic environment. The Electronic Information System (EIS) that is being considered is affected by unwanted noise, which compromises the integrity and utility of the transmitted or recorded signals. Improving the electronic information system's correctness, dependability, and user experience will lead to increased overall performance and utility. Tackle the problems associated with noise reduction in the EIS. Increased SNR and important signal characteristics preservation lead to a more accurate depiction of the recorded or transmitted data;

This study focuses on identifying noisy signals using the VBRAF method. Using a comparison between the original signal's properties and noise signals, this approach first analyses the entire file before specifying undesired signals.

The main contribution of this paper includes,

- In this research work, Electronic Information System Signal Noise for Noise Reduction using Variational Bayesian based Robust Adaptive Filter (EIS-SNR-VBRAF) is proposed.
- Initially, the data is collected from Adaptive Myriad Filter using Time-Varying Noise and Signal-Dependent Parameters dataset [28]
- Then, Variational Bayesian based Robust Adaptive Filter (VBRAF) [29] is used to decrease the noise from the signals.
- The simulation outcomes executed, proposed method improves Bit Error Rate, SNR, Mean Squared Error, PSNR, Root Mean Square Error, Structural Similarity Index, Cross-Correlation and Computational Complexity are analyzed with existing techniques such ED-MMV-SSP, NRID-MCWG-NMFA and CE-SDSI-DL.

Rest of the manuscript is arranged as below: part 2 examines literature review, proposed technique is defined in part 3, results are established in part 4, conclusion is presented in part 5.

II. LITERATURE REVIEW

Several investigation works were presented in literature linked to DL depend Noise reduction in electronic information system, some current works are reviewed here,

Suman et al. [21] have presented the use of acoustic signal processing to detect mechanical issues in vehicles early. The presented article emphasizes the use of acoustic signal processing in the early identification of mechanical problems in vehicles. The paper concentrated on engine noises. When there was damage or malfunction, the engine makes a different noise. This research suggests an algorithm that uses auditory signals to identify mechanical breakdown. The study also suggests a smart gadget for tracking a car's health that has a microprocessor and several sensors. It was possible to put the gadget inside the car. To identify the mode of the acoustic signal, a technique based on the MFCC and adaptive Kalman filter was suggested. It provides low RMSE and it attains high BER.

Dai et al. [22] have presented a non-negative matrix factorization method for mask coefficient binary weighting generalized cross correlation that reduces noise in infrasound signals. To introduce MCWGCC-NMF, a method designed to reduce noise in multiple sensor infrasound signal recordings. The technique leverages geographical information assessed via generalized cross correlation and mask coefficient binary weighting in conjunction with non-negative matrix factorization (NMF) as its foundation. The GCC-NMF performs source dictionary masking, which reduces frequency overlap by using threshold selection and frequency weighting by using the spatial information of every NMF atoms. It attains high Structural Similarity Index and it provides low SNR.

Espinosa et al. [23] have presented Click-event sound identification in automotive industry using machine/deep learning. In the presented study, present a machine/deep learning based sound detection scheme to recognise click sounds generated during the electrical harness connection process. This system's goals are to provide feedback to the staff and count the connections that were correctly created. To gather and make available to the public a dataset of 25,000 click sounds, each lasting 25ms at a frequency of 22kHz, generated during the course of three months of assembly work on a Mexican car factory. It provides high cross correlation and it attains high MSE.

Zhang and Wang [24] have presented an active noise control method using deep learning. The presented research presents a deep learning method called as deep ANC and formulates ANC as a supervised learning issue. The primary concept involves utilizing deep learning techniques to represent the ideal control settings that correlate to various noise levels and surroundings. Convolutional recurrent networks (CRNs) were trained by an ANC system to forecast the real and imaginary spectrograms of the cancelling signal from the reference signal. The presented study allows the related anti-noise to reduce or eradicate the primary noise. To provide resilience against a wide variety of sounds and strong generalization, large-scale multi-condition training was applied. It attains low MSE and it attains high computation complexity.

Kumar et al. [25] have presented a stationary wavelet transform-based approach for denoising ECG signals. In addition to the presented stationary wavelet transform denoising methodology; this study investigates several other denoising techniques: discrete wavelet transform, Fourier decomposition technique, low pass and high pass filtering, and empirical mode decomposition. The aim of the presented method was Denoising an ECG signal that has been distorted by noise. The SNR, root mean square error, and percentage root mean square difference were used to compare the ECG signaldenoising performance. The suggested stationary wavelet transform-based ECG denoising method preserves more ECG signal components than alternative denoising techniques. It provides high RMSE and it attains low cross correlation.

El Helou and Süsstrunk [26] have developed Blind universal Bayesian data denoising using Gaussian noise level learning. To provide a universal deep learning picture denoise for additive Gaussian noise removal was theoretically supported and blind. Fusion denoising, an ideal denoising method, is the foundation of our network. It was theoretically generated under the previous assumption of a Gaussian picture. The generalisation strength of our network to unknown additive noise levels was demonstrated by synthetic tests. Furthermore, the fusion denoising network structure for practical image denoise was utilized. For real-world grayscale additive picture denoising PSNR outcomes, our technique improves both training and non-training noise levels. It attains high PSNR and it provides low structural similarity index.

Cai et al. [27] have presented utilizing an adaptive filtering approach to reduce noise on an interferometry fibre optic hydrophone. Based on the Least Mean Square method, the given work proposes an adaptive filtering strategy that improves hydrophone detection sensitivity. An identical reference interferometer to the signal interferometer was added to the optical structure to remove the noise interference. The noise signal and the sensor signal are then separated by two couplers that are placed in that order. The adaptive filtering approach was ultimately successful in eliminating the noise. The experiment's results show that both the noise and harmonic distortion signals was reduced by using the suggested method. It provides high SNR and it provides high BER.

III. PROPOSED METHOD

In this section, Electronic Information System Signal Noise for Noise Reduction using Variational Bayesian based Robust Adaptive Filter (EIS-SNR-VBRAF) is proposed. The proposed EIS-SNR-VBRAF is represented in figure 1. This process contains two steps: data collection and pre-processing. The preprocessing is utilized to decrease the noise from three noise signals. Accordingly, detailed description of all step given as below,

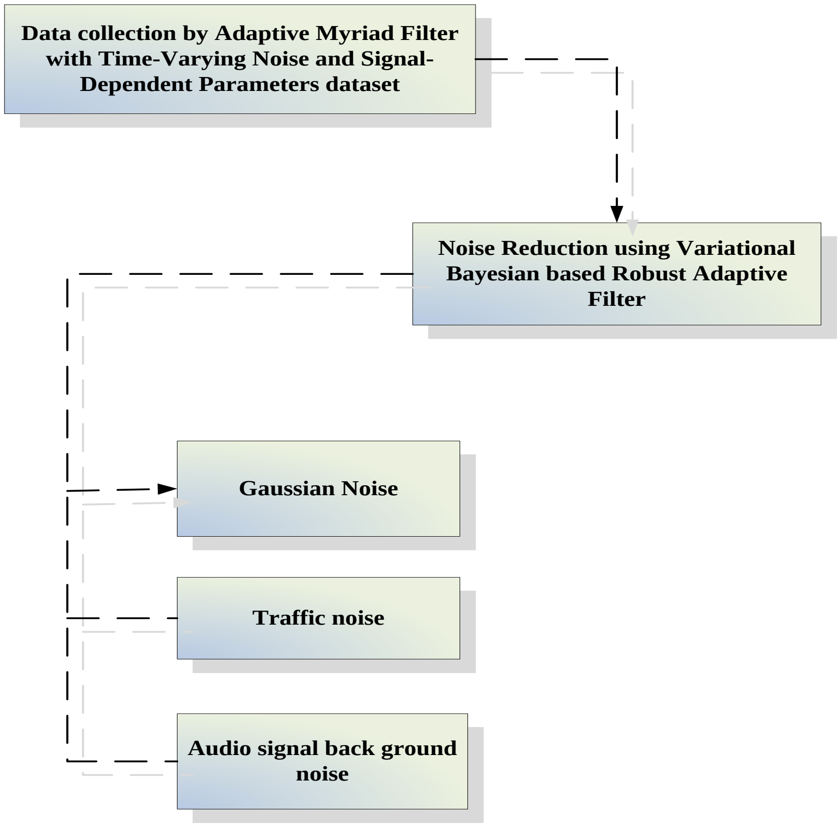

Figure1: Block Diagram for proposed EIS-SNR-VBRAF method

A. Data Collection

Initially, data is collected from Adaptive Myriad Filter using Time-Varying Noise and Signal-Dependent Parameters dataset [28]. The techniques for locally adaptive filtering non-stationary signals are the article's research topic. The objective is to provide a locally-adaptive algorithm with limited a previous knowledge about a signal modeas well as noise variance for suppression of non-stationary noise in signals with distinct informative component behaviour. The tasks that need to be completed are as follows: calculate numerical statistical processing quality estimates for a complex model of a one-dimensional process that contains various elementary signals in an extensive variety of additive Gaussian noise variance variation to assess the efficacy of the proposed local-adaptive myriad filter; and explore the efficacy of non-stationary noise suppression for real and model signals.

B. Pre-Processing using Variational Bayesian-based Robust Adaptive Filtering

In this section, VBRAF [29] technique is utilized to reduce the signal noise from Gaussian Noise, Traffic noise and Audio signal back ground noise. The standardized residual of every observation is basis on which the robust Adaptive filter builds a robust equivalent weight function. This is not a major matter. The distinct categories standardized residual distributions of observations differ, but the distribution form of same type of observation that is, the normal distribution filter is universal. This is expressed in equation (1).

$$T_i^{-1} = \begin{cases} 1 & S_i^k \le s_0(b_0, \tau) \\ \dfrac{s_0}{S_i^k}\left(\dfrac{s_1 - S_i^k}{s_1 - s_0}\right)^2 & s_0(b_0, \tau) < S_i^k \le s_1(b_1, \tau) \\ 0 & S_i^k > s_1(b_1, \tau) \end{cases} \quad (1)$$

Where, T_i^{-1} represents the variance inflation factor of the k^{th} type observation's i^{th} measurements; S_i^k *and* s_0 indicates the process noise vector's in the variance matrix; b_0 *and* b_1 and τ is the matrix of filtering gains. The first kind is created when all harmful signals have nearly identical characteristics, which happens infrequently. In contrast, the second type is created when the audio file has a variety of unwanted signal types. Then, it is given as equation (2).

$$S_i^L = \frac{\left| w_i^{-1} - \frac{1}{m^g} \sum_{L=1}^{m^k} w_L^{-1} \right|}{\sqrt{\frac{1}{m^k} \sum_{l=1}^{m^k} \left(w_i^{-1} - \frac{1}{m^k} \sum_{l=1}^{m^k} w_i^{-k} \right)^2}} \tag{2}$$

Where, S_i^L represented as the measurement of noise from the collected data; m^k is the quantity of k^{th} type observation measurements; w_i^{-1} denoted the noise driven filter and m^g denoted as the identity matrix of filter. In order to reduce unwanted signals, for instance, if the sound file has three noise or unwanted signals, two of which are identical, then three filters of two types will be used, and the Gaussian noise is decreased by determining the equation (3)

$$\overline{P_l} = P_l / \overline{R_l} \tag{3}$$

Where, $\overline{P_l}$ denoted as the diagonal weight matrix and each component noise data and $P_l / \overline{R_l}$ denoted as the divergence approaches in filtering process, which is considered as the smallest noise value in data. Then, the traffic noise is removed by calculating in equation (4).

$$R\left(R_{l|l-1} \middle| K_{1:L-1}\right) = IV\left(R_{l|l-1}; \hat{o}_{l|l-1}, \hat{O}_{l|l-1}\right) \tag{4}$$

Where, $R\left(R_{l|l-1} \middle| K_{1:L-1}\right)$ denoted as the expected noise covariance matrix's prior distribution is represented by the inverse VBRAF probability integral function from the collected data; IV symbolizes the VBRAF probability integral function in reverse; $\hat{o}_{l|l-1}$ *and* $\hat{O}_{l|l-1}$ denotes the inverse proportional matrix and the degrees of freedom, in turn and $R_{l|l-1}$ indicates by multiplying two Gaussian distributions and an inverse VBRAF distribution. Thus, VBRAF to remove Audio signal back ground noise using equation (5).

$$\begin{cases} \hat{o}_{l|l-1} = m + \tau + 1 \\ \hat{O}_{l|l-1} = \tau R_{l|l-1} \end{cases} \tag{5}$$

Where, $\hat{o}_{l|l-1}$ *and* $\hat{O}_{l|l-1}$ denotes the inverse proportional matrix and the degrees of freedom, in turn m represented as the state vector's number of rows; τ represented as a adjustment parameter in VBRAF and $R_{l|l-1}$ indicates by multiplying two Gaussian distributions and an inverse VBRAF distribution. Obtain a noise-free sound file by first eliminating the undesired frequencies from the original signal and then performing convolution among the remaining frequencies. Finally, VBRAF in all noise signals are removed from three noises such as Gaussian Noise, Traffic noise and Audio signal back ground noise.

IV. RESULT AND DISCUSSION

The investigational outcome of proposed technique is discussed. The proposed EIS-SNR-VBRAF method is implemented in Matlab. The performance of EIS-SNR-VBRAF technique is evaluated under some metrics. The obtained results of EIS-SNR-VBRAF technique are analyzed with existing techniques like ED-MMV-SSP [21], NRID-MCWG-NMFA [22] and CE-SDSI-DL [23]respectively.

A. Performance measures

This is an important task for optimal classifier selection. The performance metrics like Bit Error Rate, SNR, Mean Squared Error, PSNR, Root Mean Square Error, Structural Similarity Index, Cross Correlation and Computational Complexity are examined to calculate the performance of the proposed technique.

1) Signal noise ratio

Ratio of SNR level is expressed in equation (6)

$$SNR = \frac{K_s}{K_n} \tag{6}$$

Where, K_s signifies power signal, K_n means power noise.

2) Root mean square error (RMSE)

The RMSE is a metric to compare values that the approach predicted with actual values obtained in the modeled environment. This is calculated using equation (7)

$$RMSE = \sqrt{\frac{\sum (x_i - \hat{x}_i)^2}{M - Y}} \tag{7}$$

Here, x_i signifies i^{th} observation actual value, $\hat{x}_i$ implies predicted value for i^{th} observation, Y indicates number of parameter estimated, including the constant and M is the number of observation.

3) Peak Signal-to-Noise Ratio

A typical metric for measuring the quality of a compressed or reconstructed signal by contrasting it with the original is the PSNR. The PSNR is given in equation (8)

$$PSNR = 10.\log_{10} \frac{Max^2}{MSE} \tag{8}$$

Where, $PSNR$ represents Peak signal to Noise ratio, Max denotes the maximal possible pixel value of data, MSE represents the Mean squared Error between the original data.

4) Structural Similarity Index

Structural Similarity Index (SSI) is the another metric that is frequently used to evaluate the quality of a reconstructed or compressed signal. Then, the SSI is given in equation (9)

$$SSI\,(q,r) = \frac{(2\mu_q \mu_r + b_1)(2\sigma_{qr} + b_2)}{(\mu_q^2 + \mu_r^2 + b_1)(\sigma_q^2 + \sigma_r^2 + b_2)} \tag{9}$$

Here, $q\, and\, r$ represents the signals, μ_q *and* μ_r denotes the means of $q\, and\, r$, σ_q^2 *and* σ_r^2 represents the variance of $q\, and\, r$, σ_{qr} indicates the covariance between $q\, and\, r$, b_1 *and* b_2 denotes the constants to avoid instability.

5) Cross Correlation

Cross-correlation is a technique used to quantify the similarity between two signals as a function of the time lag applied to one of them. This is calculated using equation (10)

$$(k * h)[y] = \sum_{n=-\infty}^{\infty} k^*[n]h[n+y] \tag{10}$$

Here, k^* represents the complex conjugate of k, h denotes the time lag, n indicates the valid values, ∞ represents the infinity value.

B. Performance analysis

Figure 2 to 9 portrays simulation results of EIS-SNR-VBRAF technique. The proposed EIS-SNR-VBRAF technique is analyzed with existing ED-MMV-SSP, NRID-MCWG-NMFA and CE-SDSI-DL method.

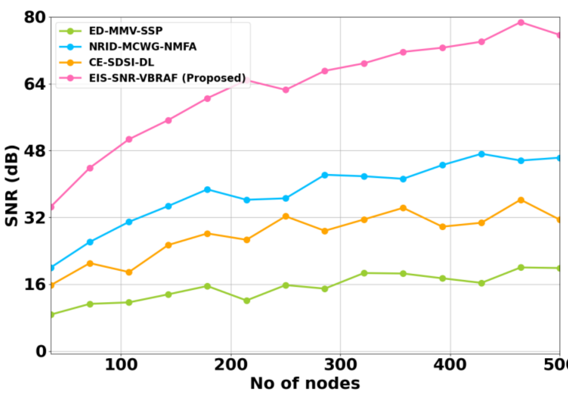

Figure2: Performance Analysis of SNR

Figure 2 depicts SNR analysis. Here, EIS-SNR-VBRAF method attains 21.65%, 20.32% and 21.19% higher SNR at No of nodes 100; 23.16%, 22.87% and 20.19% higher SNR at No of nodes 300; 20.54%, 21.67% and

21.43% higher SNR at No of nodes 500; when analyzed with existing ED-MMV-SSP, NRID-MCWG-NMFA and CE-SDSI-DL method respectively.

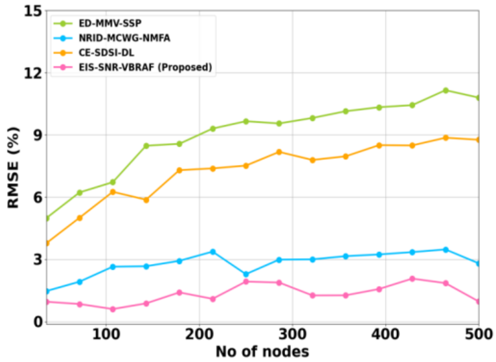

Figure3: Performance Analysis of RMSE

Figure 3 depicts RMSE analysis. Here, EIS-SNR-VBRAF method attains 21.18%, 23.52% and 23.65% lower RMSE at No of nodes 100; 23.54%, 21.65% and 23.47% lower RMSE at No of nodes 400; 24.68%, 25.62% and 23.68% lower RMSE at No of nodes 500; when analyzed with existing ED-MMV-SSP, NRID-MCWG-NMFA and CE-SDSI-DL method respectively.

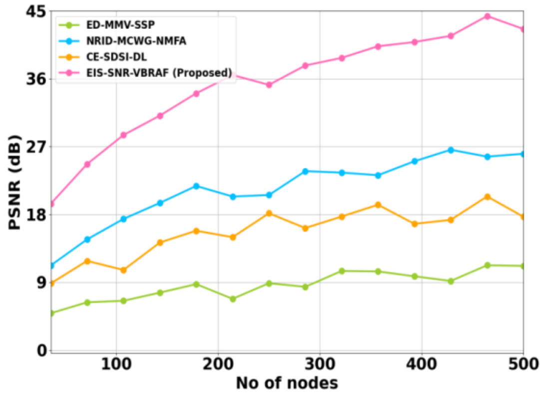

Figure4: Performance Analysis of PSNR

Figure 4 depicts Peak Signal-to-Noise Ratio (PSNR) analysis. Here, EIS-SNR-VBRAF method attains 21.52%, 21.76% and 23.24% higher PSNR at No of nodes 100; 22.54%, 21.17% and 21.87% higher PSNR at No of nodes 400; 24.54%, 24.43% and 23.46% higher PSNR at No of nodes 500; when analyzed with existing ED-MMV-SSP, NRID-MCWG-NMFA and CE-SDSI-DL method respectively.

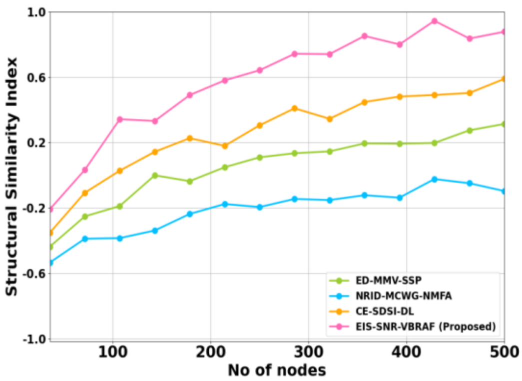

Figure5: Performance Analysis of Structural Similarity Index

Figure 5 depicts Structural Similarity Index analysis. Here, EIS-SNR-VBRAF method attains 21.19%, 21.73% and 20.48% higher Structural Similarity Index at No of nodes 200; 20.43%, 23.65% and 21.39% higher Structural Similarity Index at No of nodes 300; 21.87%, 21.98% and 20.43% higher Structural Similarity Index at No of nodes 400; when analyzed with existing ED-MMV-SSP, NRID-MCWG-NMFA and CE-SDSI-DL method respectively.

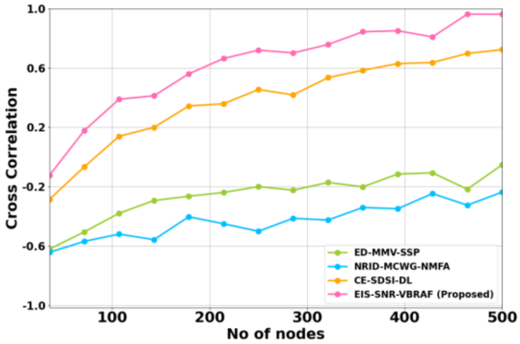

Figure6: Performance Analysis of Cross Correlation

Figure 6 depicts Cross Correlation analysis. Here, EIS-SNR-VBRAF method attains 23.42%, 23.51% and 21.72% higher Cross Correlation at No of nodes 100; 21.23%, 21.38% and 20.75% higher Cross Correlation at No of nodes 300; 24.33%, 24.87% and 22.54% higher Cross Correlation at No of nodes 500; when analyzed with existing ED-MMV-SSP, NRID-MCWG-NMFA and CE-SDSI-DL method respectively.

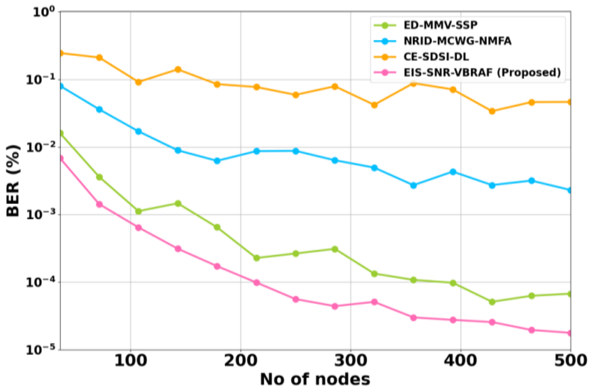

Figure7: Performance Analysis of Bit Error Rate

Figure 7 depicts Bit Error Rate (BER) analysis. Here, EIS-SNR-VBRAF method attains 20.54%, 21.54 and 20.34% lower BER at No of nodes 100; 21.34%, 22.65% and 21.93% lower BER at No of nodes 300; 21.19%, 20.31% and 20.38% lower BER at No of nodes 500; when analyzed with existing ED-MMV-SSP, NRID-MCWG-NMFA and CE-SDSI-DL method respectively.

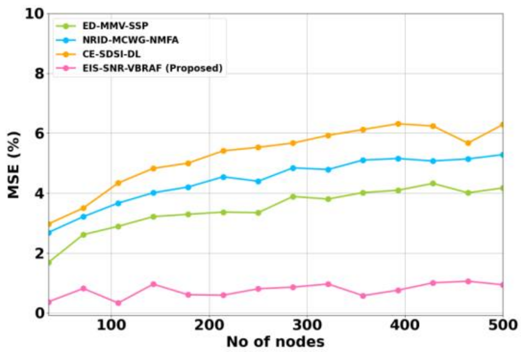

Figure8: Performance Analysis of Mean Square Error

Figure 8 depicts Mean Square Error (MSE) analysis. Here, EIS-SNR-VBRAF method attains 20.19%, 21.25% and 21.31% lower MSE at No of nodes 100; 22.56%, 21.65% and 21.78% lower MSE at No of nodes 300; 23.52%, 21.87% and 23.87% lower MSE at No of nodes 500; when analyzed with existing ED-MMV-SSP, NRID-MCWG-NMFA and CE-SDSI-DL method respectively.

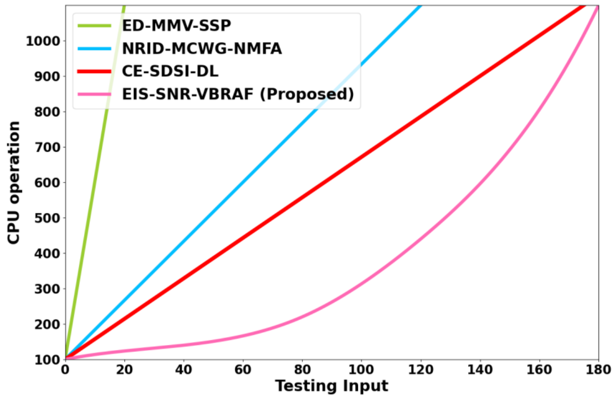

Figure9: Computation Complexity analysis

Figure 9 depicts computational complexity analysis. Here, time complexity of proposed EIS-SNR-VBRAF method shows lower than the existing ED-MMV-SSP, NRID-MCWG-NMFA and CE-SDSI-DL methods respectively.

C. Discussion

The proposed work in this article focuses on the main problems with either digital or analogue communication, noisy or unwanted signals. Noise signals in sound files are regarded by a thousand users as one of the worst issues. The proposed method depend on building many digital filters, was implemented using Matlab code. This document provides a thorough illustration of the VBRAF algorithm. Each stage's output was plotted and thoroughly described. Plotting the frequency response for every and final filter allowed us to provide a broad overview of the work is completed on this work. The proposed algorithm was effectively implemented, as evidenced by the results, which also show that there were no adverse effects on the Noise signals. The PSNR values of EIS-SNR-VBRAF are 31.56%, 30.27% and 31.54% higher than existing methods such as ED-MMV-SSP, NRID-MCWG-NMFA and CE-SDSI-DL respectively. Similar to this, the Cross correlation of proposed method is 96.94% analyzed with average Cross correlation of comparison techniques of 82.54%. The proposed method EIS-SNR-VBRAF has high PSNR and Cross correlation evaluation metrics than existing methods. Therefore, the comparative methods are expensive than the proposed technique. As a result, the proposed technique reduces the noise from the signals more effectively and efficiently.

V. CONCLUSION

In this manuscript, Electronic Information System Signal Noise for Noise Reduction using Variational Bayesian based Robust Adaptive Filter (EIS-SNR-VBRAF) is successfully implemented. The proposed EIS-SNR-VBRAF method implemented in MATLAB; Performance of proposed EIS-SNR-VBRAF approach attains23.42%, 23.51% and 21.72% higher Cross Correlation, 20.54%, 21.54 and 20.34% lower BER, 20.19%, 21.25% and 21.31% lower MSE, is analyzed with existing methods like ED-MMV-SSP, NRID-MCWG-NMFA and CE-SDSI-DL method respectively.

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