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DE-NOISING OF AUDIO SIGNAL USING DISTRIBUTED APPROXIMATE MESSAGE PASSING (DAMP) ALGORITHM

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Abstract: The modern world makes the heavy use of multimedia. This field factually uses the Digital Signal processing of sound. Adaptive filtering constitutes one of the core technologies in DSP and has various applications in science and industry including echo cancellation, adaptive equalization, adaptive noise cancellation, audio denoising, etc. In any communication system, noise always plays a major area of concern. Various de-noising techniques are used for removing these noises. In the proposed research work, we have implemented Adaptive Noise Canceller on audio signal followed by the application of modified PSO. The optimization is achieved by the application of DAMP algorithm which uses the weight control factor. The results achieved have faster convergence but at the cost of complexity.

Keywords: *Adaptive Filter, Adaptive Noise Canceller, ECG, Audio Signal, PSO, MPSO, DAMP, LDI, NLI, SNR, MSE, PRE.*

I INTRODUCTION

Make India Programmed is driven by the digital revolution at grass root level. There are a dramatic development and upgradation in the World Wide Web applications throughout the world. The internet-based applications are inevitable for the human progress. The education from primary to research level directly depends on the multimedia resources throughout the digital system [1]. It is seen that audio is corrupted by different types of noises during its acquisition. Audio Denoising aims at attenuating noise without changing the original signal. The major applications are audio coding, digital generation and synthesis of audio signals. The recent advances in the quality of hearing aids, a cochlear implant. The better perceptual measurement methods are based on digital coding. These techniques are standardized at the global level. Motion Picture Experts Group (MPEG) has emerged as a standard in the field of high-quality digital audio perceptual coding. Acoustic technology development has been accelerated due to the smart handling of the architectural acoustic problem of the building. The reverberation present in the sound can be filtered using reverberation algorithms. The application of effective sound reduction systems like Dolby makes the heavy use of the digitally processed data. Digital Audio Signal Processing (DASP) is used in recording and restoring the music and speech signals for mixing and the digital program production used by the broadcasting station and the receiver. The methods to control noise present in the signal have attracted many researchers overs the last few years [2].

Adaptive Noise Cancellation is one of the approach which is used to reduce the noise present in the signal. The adaptive filter is considered as a noise canceller as it is capable of adjusting its filter coefficient in order to minimize the error. Figure 1 shows the block diagram of adaptive noise canceller. In figure s(n) and q(n) are primary inputs, $q_o(n)$ is the reference input, d(n) is the desired response which is a combination of the original signal s(n) and noisy signal q(n). Adaptive noise canceller has two inputs i.e. primary and reference. The primary input receives a signal s(n) that is corrupted by a noise q(n) uncorrelated with the signal. The reference input receives noise signal $q_o(n)$ uncorrelated additive with noise and correlated with q(n). The error signal e(n) is the difference between y(n) and d(n). The reference input $q_o(n)$ is passed through an adaptive filter to produce an output y(n) which is a close estimate of primary input noise which is then subtracted from the corrupted signal at the primary input to produce an estimate of a signal i.e. $s_o(n)$ which is the Adaptive Noise Cancellation output. Here the task of the designer is to reduce noise q(n) from the original signal. The audio signal corrupted with noise is taken as primary input and the noise signal is used as a reference input [3].

Vivek Joshi and et.al have proposed adaptive noise canceller for removing noise in ECG signal using modified particle swarm optimization technique (MPSO).

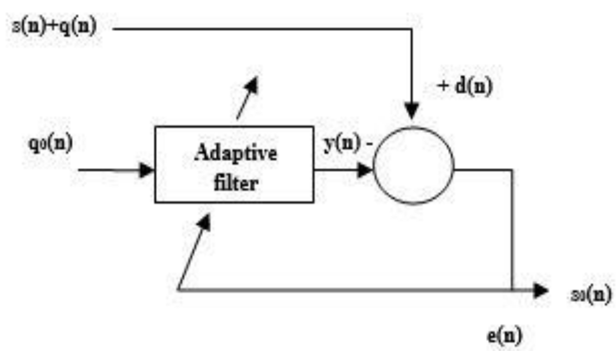

Figure 1: Adaptive Noise Cancellation

MPSO technique provides better performance than any other optimization technique. Various parameters like SNR, Peak reconstruction error and Mean square error have been evaluated. There are several complexes as well as nonlinear problems which can be solved by using special optimization techniques i.e. conventional PSO algorithms, here velocity and position of a particle are updated. The conventional PSO faces the problem for large signal length, so the PSO is modified by giving inertia weight parameters. In MPSO the position of each particle in the swarm is updated. Adaptive Noise Canceller (ANC) is basically implemented using RLS & LMS algorithms but PSO provides faster convergence rate, here, at each iteration MSE (mean square error) is calculated. Performance parameters of ANC using MPSO technique has been evaluated which shows that MPSO performance is better than PSO. The simulation results also show 19 % improvement in SNR, 91% decrease in Peak Reconstruction Error (PRE) and 99% reduction in Mean Square Error (MSE) using MPSO technique [4].

Yang Liu and et.al have proposed LMS adaptive filtering algorithm for the reduction of noise from audio signal or speech signal. Here the signal is filtered in the time domain and the filter coefficients are calculated adaptively by LMS algorithm further NLMS algorithm is also used. In this proposed work the noise is reduced from the audio signal by using LMS adaptive filter algorithm. Simulation results show that by using NLMS algorithm performance quality of the noisy audio signal is improved. Therefore, the proposed method is quite effective in reducing the noise from audio signal especially when white Gaussian noise is in use [5].

Ali T. Al-Awami and et.al [6] in this paper have presented a new modified PSO technique and illustrated its superiority over PSO technique with its applications in Adaptive channel equalization. Results show that PSO not only improves the convergence time of the equalizer but also improves its BER performance. Results obtained here provide us with ample encouragement to further explore the use of PSO technique in other adaptive filtering application such as echo cancellation in telephony and ANC in industrial settings.

Nitika Gulbadhar and et.al [7] have presented various adaptive algorithms for acoustic echo cancellation. To remove noise and enhance the quality of signal the technique which is used is called Acoustic robustness have been evaluated 2.9 seconds and higher stability.

Mitul Kumar Ahirwal, Anil Kumar, and Girish Kumar Singh have proposed an improved method for filtering EEG/ERP signals. Adaptive Noise Canceller (ANC) has been implemented through five versions of PSO i.e. particle swarm optimization technique. Also, the comparative study of the performance of PSO and its various version has been done. Parameters like SNR (in dB), the correlation between resultant and template ERP and mean square error are also observed. Results show that performance is dependent on parameter selection and PSO variants. It is seen that the NLI and LDI variants of PSO have more score in fidelity parameter evolution and in shape measure as compared to another variant. Therefore, it is concluded that the ANC based on NLI and LDI variants of PSO technique can be very effectively used in ERP filtering from the EEG signal [9].

II PROPOSED ALGORITHM

2.1 Modified Particle Swarm Optimization (MPSO)

There are several complexes as well as nonlinear problems which can be solved using a special type of optimization techniques. Some of which are inspired by natural phenomenon like Fish Schooling, Swarm behavior, Ant colony etc. Among these, the PSO is a simple but powerful search technique which gives better results. The PSO algorithm maintains a population of particle where each particle represents a potential solution to an optimization problem, each potential solution in PSO is also associated with a randomized velocity and then the potential solution called particles are flown through the problem space. Let S be the size of swarm where each particle i can be represented as an object with several characteristics. A population of the particle is initialized with random position X_i and velocities V_i objective function F_i is evaluated using the particles positional coordinates as input values. Each particle keeps the track of its coordinate in problem space which is associated with the best solution i.e. fitness achieved by it. This best value is called p_{best}. Another best value that is tracked by a global version of the swarm is the overall best value, and its location obtained so far by any particle in the population is called gbest. The disadvantage of conventional PSO is its large signal length. Therefore PSO can be modified by giving inertia weight (w) parameter. Here the position of each particle (p) in the swarm is updated as follows:

$$V_{id}^{(t+1)} = w\, V_{id}^{(t)} + c_1\, rand_1 \left(p_{best\ id}^{(t)} - X_{id}^{(t)} \right) + c_2\, rand_2 \left(g_{best\ d}^{(t)} - X_{id}^{(t)} \right) \quad \text{"(Eq.1)"}$$

$$X_{id}^{(t+1)} = X_{id}^{(t)} + V_{id}^{(t+1)} \quad \text{"(Eq.2)"}$$

Where $V_{id}^{(t)}$ and $X_{id}^{(t)}$ are the velocity and position of particle i, in d dimensional space respectively. $p_{best\ id}^{(t)}$ is best position of individual i in d dimensional space until generation t; $g_{best\ d}^{(t)}$ is best position of the group in d dimensional space until generation t; w is the inertia weight factor controlling dynamics of flying; c_1 and c_2 are accelerating constants; $rand_1$ and $rand_2$ are random variables in the range [0,1]. The update position is updated only if current position $X_{id}^{(t+1)}$ has better results compared to the previous position $X_{id}^{(t)}$ otherwise, the position of the particle remains unchanged as the new position of a particle depends on previous position, p_{best} and g_{best}. Therefore p_{best} and g_{best} play an important role in optimization technique [4,8].

2.1.1. PSO Variants

The two main feature of optimization algorithms is exploitation and exploration. Exploration is an ability of the algorithm to explore a different region of search space in a manner to locate good optimum while exploitation is the ability to concentrate the search around the promising area in order to refine a candidate solution. Also, exploration deals with global optimal and exploitation provide local optimization and to handle these feature inertia weight parameter (w) is used in modified PSO. A Higher value of 'w' gives better exploration and lower value of 'w' gives better exploitation [4,9].

2.1.2 Constant Weighted Inertia PSO (CWI - PSO)

CWI –PSO provides a constant rate for Exploitation and Exploration. Here inertia weight remains constant in all iteration. This algorithm is problem specific and it is difficult to find out the constant value for a particular problem. To find constant inertia weight many simulations are carried out with different inertia weights. It is defined as

$$w_t = c \quad \text{"(Eq.3)"}$$

Where w_t denotes inertia at any time t for a constant value c.

2.1.3 Linear Decay Inertia PSO (LDI - PSO)

It is a good example for a trade-off between exploration and exploitation. In LDI-PSO there is a reduction in exploration area after each iteration. In LDI-PSO maximum and minimum inertia values must be defined before the process is started, these are the initial and final values of inertia. Below equation shows the resultant inertia after each iteration

$$w_t = w_{max} - \frac{(w_{max} - w_{min}) * t}{t_{max}} \quad \text{"(Eq.4)"}$$

Where w_t is the inertia value at time t, w_{max} and w_{min} are initial and final values of inertia respectively. Maximum iteration or end time is denoted by t_{max}.

2.1.4. Non-Linear Inertia PSO (NLI – PSO)

In NLI- PSO, the inertia weight changes non linearly. It is a modification of LDI –PSO and the inertia weight equation in each step is modified as

$$w_t = w_{max} - \frac{(w_{max} - w_{min}) * (t_{max} - t)^n}{(t_{max})^n} \quad \text{"(Eq.5)"}$$

Where n denotes the nonlinear modulation index.

2.2 Damp Methodology

The proposed distributed algorithm is based on AMP i.e. Approximate Message Passing Algorithm. It does not require any information about the sparse signal. It follows linearity in convergence. It is not required for the distributed nodes to understand the global matrix. A simple matrix is solved at the local level and for the purpose of global computation, some modification is made to reduce data transmission load. The AMP (Approximate Message Passing) task is to recover sparse signal $s_o \in R^N$ and it is measured as $y = As_o + n$, where $A \in R^{M*N}$ is the sensing matrix, s_o is the input signal and n is an additive noise. So the solution is

$$\min_x \frac{1}{2} \| y - A_x \|_2^2 + \lambda \| x \|_1 \quad \text{"(Eq.6)"}$$

Where $\lambda > 0$ is the regularization parameter. For practical purposes, λ is ignored. The AMP can solve effectively the problem of signal recovery where it is not important to know the value of K and λ beforehand [10]. From $x_0 = 0$ and $z_0 = y$ after the iterations input signal s_0 can be estimated as

$$x_{t+1} = \eta_t (x_t + A^t Z_t\, ;\, \tau\, \sigma_t) \quad \text{"(Eq.7)"}$$

$$z_{t+1} = y - Ax_{t+1} + \frac{\|x_{t+1}\|_0}{M} z_t \quad \text{"(Eq.8)"}$$

Where $[.]^T$ denotes transpose operation, $\| \cdot \|_0$ is the l_0 norm of a vector $\sigma_t^2 = \frac{\| x_t \|^2}{M}$ [11],

$$\eta_t\,(x; \beta) = \begin{cases} (|x| - \beta)\,\mathrm{sgn}(x), & |x| > \beta \\ 0, & |x| \le \beta \end{cases} \quad \text{"(Eq.9)"}$$

Required to find unknown K from which the value of τ can be obtained which is very close to the optimum [12].

2.2.1. Framework of DAMP

Suppose the network consists of P distributed nodes. Each node p is set of (p=1,……, P) therefore signal s_0 can

$$\begin{bmatrix} y^1 \\ \cdot \\ \cdot \\ y^P \end{bmatrix} = \begin{bmatrix} A^1 \\ \cdot \\ \cdot \\ A^P \end{bmatrix} s_0 + \begin{bmatrix} n^1 \\ \cdot \\ \cdot \\ n^P \end{bmatrix} \quad \text{"(Eq.10)"}$$

Now equations (7) and (8) can be modified as

$$x_{t+1} = \eta_t \left(x_t + \textstyle\sum_{p=1}^{P} A^{pT} z_t^p \,;\, \tau\sigma_t \right) \quad \text{"(Eq.11)"}$$

$$z_{t+1}^p = y^p - Ax_{t+1}^p + \frac{\|x_{t+1}\|_0}{M} z_t^p \quad ; \forall_p = 1, \ldots, P \quad \text{"(Eq.12)"}$$

One intimate matrix can be included with each column computed by the corresponding nodes as:

$$w_t^p = \begin{cases} x_t + A^{pT} z_t^p, & p = 1 \\ A^{pT} z_t^p, & \text{otherwise} \end{cases} \quad \text{"(Eq.13)"}$$

Which is same as equations (9) and (11)?

$$x_{t+1} = \eta_t \left(\textstyle\sum_{p=1}^{P} w_t^p ;\, \tau\sigma_t \right) \quad \text{"(Eq.14)"}$$

Damp can be divided into two groups local parts (w_t^p, z_t^p) and global part x_{t+1} and σ_{t+1} which needs transmission of data between different nodes. This leads to high communication cost when N is large. Thus, the cost can be reduced by introducing local computation and at the same time getting better recovery like centralized AMP [12].

III RESULT AND DISCUSSION

In the proposed work, we have implemented an Adaptive Noise Canceller (ANC) for audio signals with the help of Modified Particle Swarm Optimization (MPSO) by enabling the damping as weight control factor. The performance of proposed work is computed by determining various fidelity parameters such as Signal to Noise Ratio (SNR), Mean Square Error (MSE) and Peak Reconstruction Error (PRE) given by the following equations:

$$SNR_{dB} = 10\log_{10} \frac{(Audio_{pure})^2}{(Audio_{filtered} - Audio_{pure})^2} \quad \text{"(Eq.15)"}$$

$$MSE = \frac{1}{N} \sum_{i=1}^{n} (Audio_{filtered} - Audio_{pure})^2 \quad \text{"(Eq.16)"}$$

$$PRE = \frac{Audio_{pure} - Audio_{filtered}}{Audio_{pure}} \quad \text{"(Eq.17)"}$$

Where $Audio_{pure}$ is the pure audio signal and $Audio_{noisy}$ is the noisy audio signal combined to get $Audio_{filtered}$ as the filtered audio signal at the output terminal. In this work, various variants of PSO and damp technique is compared on the basis of SNR, PRE, and MSE. All the simulation work is carried out in MATLAB R2013a. Figure 2 and Figure 3 show pure Audio signal and Audio signal with noise. Figure 4, Figure 5, Figure 6 and Figure 7shows the performance of various variants of PSO and proposed Damp technique. Also Figure 8, Figure 9 and Figure 10 show fidelity parameters performance for CWI, LDI, NLI and Damp technique. Table 1, Table 2 and Table 3 shows SNR, PRE and MSE results obtained from different techniques.

Therefore, we have concluded that proposed technique gives an improvement in all fidelity parameters over the conventional technique.

Proposed Algorithm (SNR = 20dB)

TABLE 1: SNR values for Audio signal (proposed)

Constant		**Linear**	
Min.	**Max.**	**Min.**	**Max.**
$4.017e^{+05}$	$3.436e^{+06}$	$1.791e^{+05}$	$3.436e^{+06}$
mean	$7.935e^{+05}$	mean	$3.66e^{+05}$
median	$7.746e^{+05}$	median	$3.184e^{+025}$
Non linear		**Proposed**	
Min.	Max.	Min.	Max.
$2.343e^{+05}$	$3.436e^{+05}$	$3.551e^{+05}$	$3.43e^{+05}$
mean	$4.054e^{+05}$	mean	$5.104e^{+05}$
median	$3.64e^{+05}$	median	$4.843e^{+05}$

The SNR values for the proposed and the constant out performs the linear and nonlinear. The linear and nonlinear technique doesn't perform better for the audio signal.

TABLE 2: PRE values for Audio signals (proposed)

Constant		**Linear**	
Min.	**Max.**	**Min.**	**Max.**
21.06	37.66	21.06	45.03
mean	32.6	mean	39.56
median	32.65	median	39.7
Non linear		Proposed	
Min.	Max.	Min.	Max.
21.06	42.55	21.06	40.34
mean	38.17	mean	36.78
median	38.55	median	36.96

The PRE follows the order constant <proposed<nonlinear<linear. The constant technique gives the less error compared to remaining techniques whereas the proposed technique outperforms the linear and non linear.

TABLE 3: MSE values for audio signal (proposed)

Constant		**Linear**	
Min.	**Max.**	**Min.**	**Max.**
0.0001714	0.00783	$3.142e^{-05}$	0.00783
mean	0.0006408	mean	0.0002055
median	0.0005428	median	0.0001072
Non linear		Proposed	
Min.	Max.	Min.	Max.
$5.554e^{-05}$	0.00783	$9.238e^{-05}$	0.00783
mean	0.0002424	mean	0.0002886
median	0.0001398	median	0.0002012

The MSE values follow the order constant>proposed>nonlinear>linear. The linear technique gives the less error compared to remaining techniques whereas the proposed technique outperforms the linear and non linear.

3.1 Simulation Results

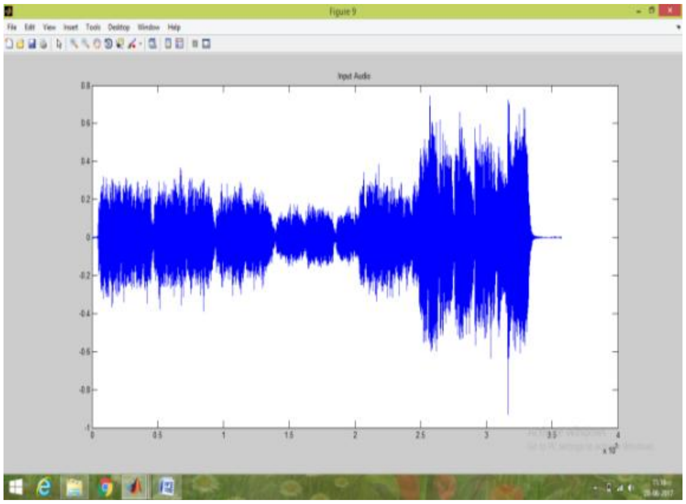

Figure 2: Audio signal at Input (20 to 20 KHz) heard by human ear

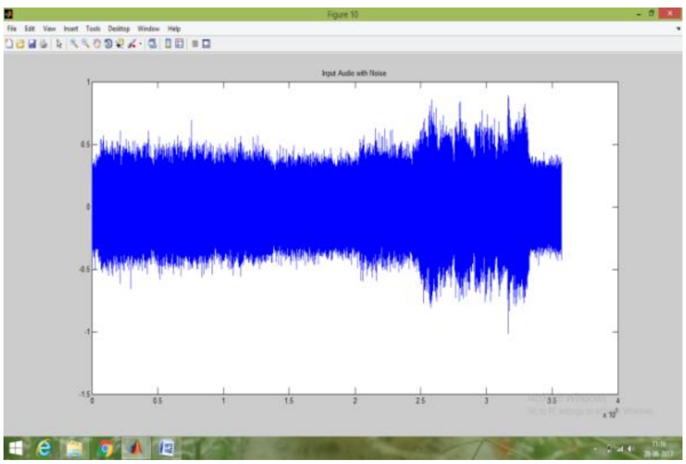

Figure 3: Audio signal mixed with White Gaussian Noise

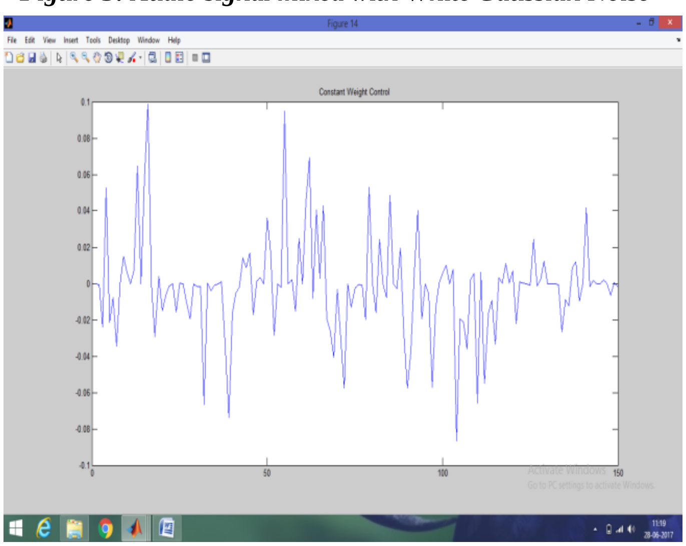

Figure 4: Constant Weight Control (Audio signal filtered using technique CWI)

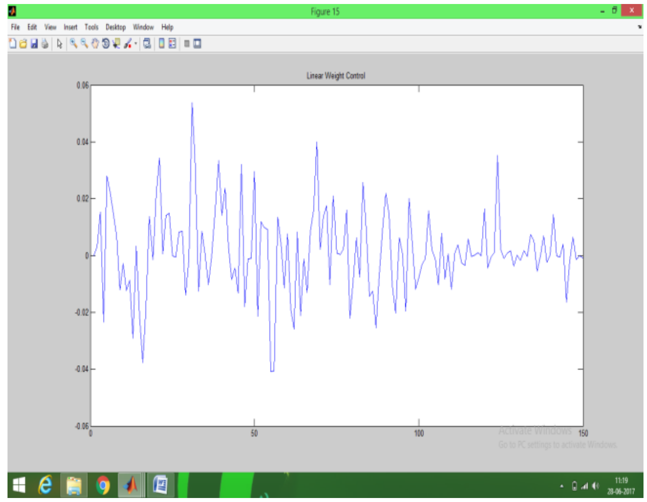

Figure 5: Linear Weight Control (Audio signal filtered using technique LDI)

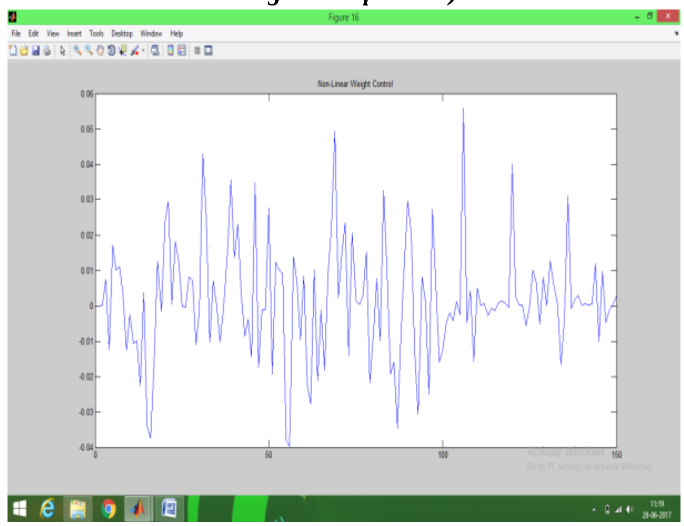

Figure 6: Non-Linear Weight Control (Audio signal filtered using technique NLI)

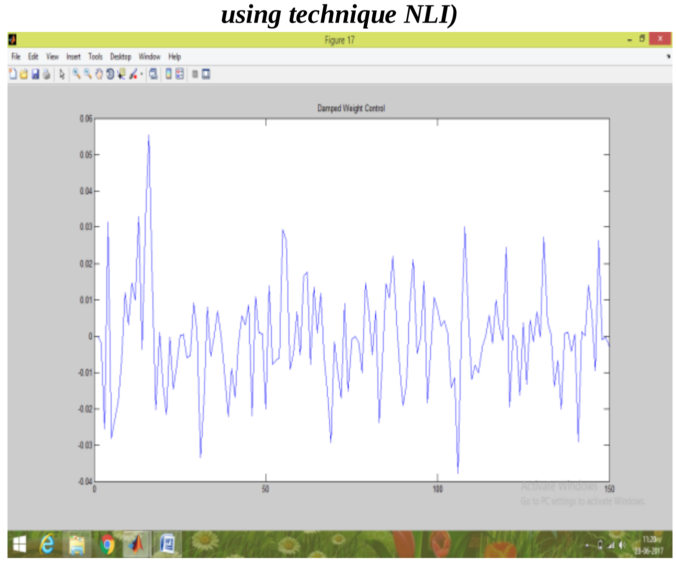

Figure 7: DAMP Weight Control (Audio signal filtered using Damp weight control)

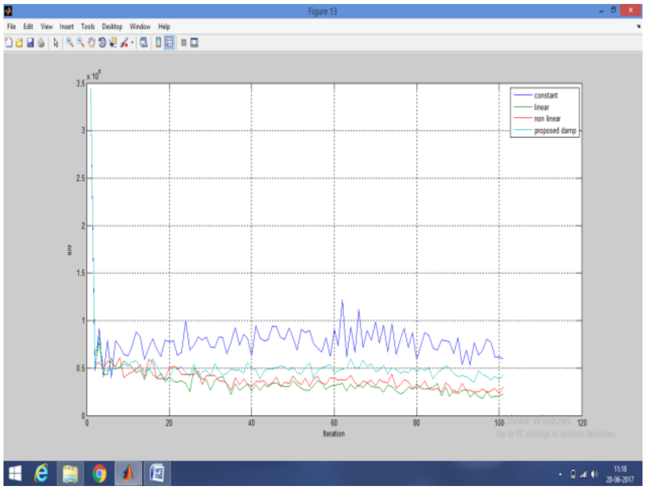

Figure 8: Graph showing SNR performance of CWI, LDI, NLI and proposed technique which have higher SNR among all four techniques.

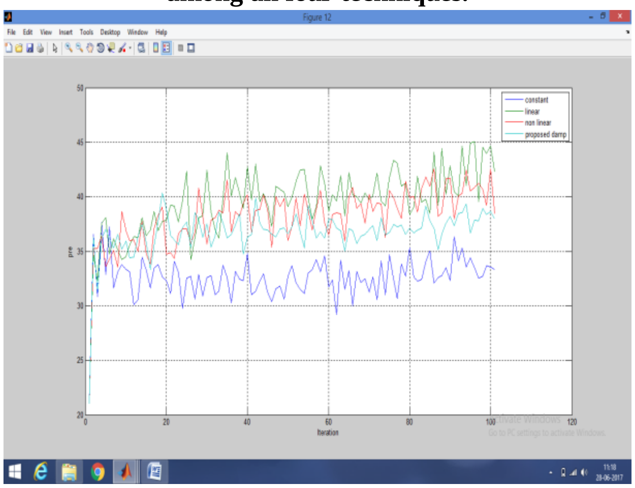

Figure 9: Graph showing PRE performance of CWI, LDI, NLI and proposed technique which have lowe error among all four techniques.

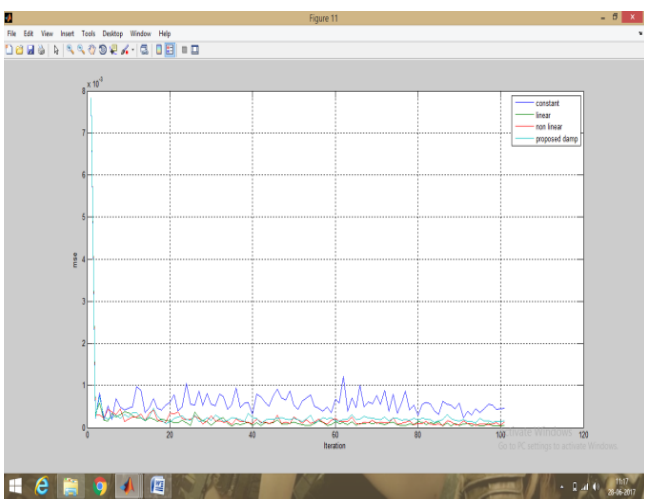

Figure 10: Graph showing MSE performance of CWI, LDI, NLI and proposed technique which have lower Mean Square Error among all four techniques.

IV CONCLUSION

In the proposed simulation we have implemented Adaptive Noise Canceller (ANC) for audio signals further the Modified Particle Swarm Optimization by enabling damping as weight control factor. This methodology improves the audio signal. The fidelity parameters like Signal to Noise Ratio (SNR), Peak Reconstruction Error (PRE), Mean Square Error (MSE) results are evaluated. From the experimental results, it can be concluded that the proposed DAMP method outperforms the remaining methods in most of the cases. In order to further improve the performance, iterative approach can be applied to select the optimal parameters.

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