Volume 5, Issue 6, June 2015 ISSN: 2277 128X
International Journal of Advanced Research in Computer Science and Software Engineering
Research Paper
Available online at: www.ijarcsse.com

Speech Enhancement Using Signal-To-Noise Ratio

Farzana Kosser[1], Anil Garg[2]
[1] (M.Tech(ECE), MMEC/MMU, India
[2] Assoc. Professor(ECE),MMEC/MMU, India

Abstract: In this paper, a significant improved Signal-to-Noise ratio (SNR) based speech enhancement method is presented. Three different modules have been designed to enhance the speech signal. In this paper, a meta- heuristic approach for the speech is implemented. Different weights are generated using Particle Swarm Optimization (PSO) algorithm and then these weights are multiplied with the noisy signal to improve the Signal-to-Noise ratio by significant amount.

Keywords: Meta-Heuristic approach, Particle Swarm Optimization (PSO), Signal-to-Noise ratio (SNR).

I. INTRODUCTION

Background acoustic noise is generally a reoccurring problem in applications encompassing the recording and processing of real world speech signals, e.g., speech recognition and radio communications [1]. These types of applications are depend on a reasonable signal quality and their performance/execution is frequent appreciably trade-off by low signal-to-Noise ratios (SNRs). As a result, the speech enhancement in interference conditions has gained a lot of research interest, particularly in applications viz. mobile voice communications, automatic speech recognition, and hearing aids [2]. In many such cases only a single-channel speech signal is available [1]. The problem of enhancing the speech becomes much harder for single channel speech enhancement where there is no reference input signal available to assess the noise. In this case, the noise is assessed by utilizing the properties of speech and noise signals such as stationary and frequency content, or during silence/noise periods using a voice activity detector [3]. The goal of speech enhancement is to suppress additive background noise components while maintaining the quality and intelligibility of speech [2]. This task is normally completed by protecting the attributes of speech utilizing the short-term spectral amplitude (STSA), for which the reliable assessment of the signal-to-noise ratio (SNR) is crucial in noisy environments [2]. A numerous methods have been taken into account to cope with background noise namely spectral subtraction [2], Wiener filtering [4], and statistical approaches [5]. Out of these categories, statistical techniques are perhaps the most advanced. Where the Wiener filtering category is restricted by linearity, and the spectral subtraction category involves largely simplified mathematical expressions, statistical approaches are strictly optimal given a set of initial assumptions and optimality criteria [1]. In addition to this statistical strategies have also been assessed to be among those with the best performance [6].

From last several years, the problem/issue of noise cancellation has gained a lot of attention in divers speech applications, namely speech bandwidth compression, speech recognition, speaker verification, for instance, in automatic speech recognition from contaminated speech, the reduction of noise strategy yields an enhanced quality of speech signal that assist in procuring an excellence recognition performance [7]. The most common problem in speech processing is the effect of interference noise in the signals. This noise masks the speech signal and diminishes its intelligibility. Therefore, reduction of noise and enhancement of the speech become necessary for many practical applications. Noise reduction or speech enhancement algorithms are used to suppress background noise and improves the quality and intelligibility of speech [8]**.** Conventional linear filtering is the most common way to do single trial analysis of speech signal, by which contaminations due to on-going background noise can be attenuated from the speech signal. A major difficulty in conventional linear filtering is very low SNR, since then, the concept of adaptive filtering was introduced [8].]. The intent of optimization is to ascertain the best-suited solutions to an issue under a given set of hindrances [9]. Now-a-days, the issue of optimization is depicted as an intelligent search problem, where one or more agents are implemented to determine the optima on a search landscape, representing the constrained surface for the optimization issue [9]. In mid 1990s Eberhart and Kennedy asserted an solution to the complex non-linear optimization obstacle by imitating the aggregate demeanour of bird flocks, particles, the boids method of Craig Reynolds and socio-cognition are called their brainchild the particle swarm optimization (PSO) [9]. Stochastic and heuristic today's are becoming are more potent for resolving the noise diminution issue. These optimization models are freelance of system structure and they do not immediately impact the parameter update [9]. In the class of optimization methods particle swarm optimization is one of the recent models and it is influenced by the demeanour of swarms of insects, schools of fish, flocks of birds, etc [9].

The organization of the paper is as follows. Section II briefs about particle swarm optimization (PSO) model. In section III methodology of the presenting/suggesting approach is discussed. Section IV presents the results obtained and section V conclude and presents the future scope of the suggesting approach.

II. PARTICLE SWARM OPTIMIZATION MODEL

Particle swarm optimization (PSO) is an evolutionary computation model was coined by Eberhart and Kennedy in 1995 based on the demeanour of bird flock and fish school where each individual is allowed to learn from the experience of its own and from its neighbours [10]. In this model, every member of the population is named a ‘‘particle’’, and the population is called a swarm [11]. Entire particle have fitness values which are assessed by the fitness function to be optimized, and have velocities which direct the flying of the particles [12]. Each particle ‘‘flies’’ everywhere in the multidimensional search space along a velocity, that is continuously upgraded by the particle’s own knowledge and the knowledge of the entire swarm [11]. The PSO technique assumes the social demeanour of particles manoeuvre in a multidimensional search space, as long as every particle has its position and velocity. Every particle is tackle as a possible resolution to the optimization issues [13].

Commonly, the position is presented as a vector $X_i = x_{i1}, x_{i1}, \ldots, x_{iD}$ while the velocity is presented as another vector $V_i = v_{i1}, v_{i2}, \ldots\ldots v_{iD}$ where *i* present the index of the particle, and *D* is the dimensionality of the search space.

In standard/basic/original PSO, the velocity and position is given by Kennedy and Eberhart as:

$$v_{id}^{t+1} = v_{id} + c_1 r_1 (pbest_{id}^{\ t} - x_{id}^{\ t}) + c_2 r_2 (gbest_d^{\ t} - x_{id}^{\ t}) \quad (1)$$

$$x_{id}^{\ t+1} = x_{id}^{\ t} + v_{id}^{\ t+1}, i = 1,2,\ldots\ldots\ldots m \quad (2)$$

Where c_1 and c_2 are constants and are known as accelerating factor, r_1 and r_2 are uniformly distributed random variable in the range [0, 1]. $V_i \in [-V_{\max}, V_{\max}]$, Where V_{max} is a problem-dependent constant describe for clamp the excessive roaming of particles, $pbest_{id}^{\ t}$ presents the best position particle along the d^{th} dimension of particle *i* in iteration *t*, $gbest_d^{\ t}$ presents the best position particle in the entire swarm or among all the particles along d^{th} dimension of particle *i* in iteration *t.*

In the PSO the course of every particle in the search space is adapted by dynamically altering the velocity of every particle. Soon after, the particles very quickly quest the resolution space utilizing the manoeuvre velocity of every particle. The position of these particles is scored to procure a fitness value found on how to describe the resolution of the obstacle. Chih-Chia Yao and Ming-Hsun Tsai the suggested the improved PSO by modifying the original equation (1) to

$$v_{id}^{\ t+1} = wv_{id}^{\ t} + c_1 r_1 (pbest_{id}^{\ t} - x_{id}^{\ t}) + c_2 r_2 (gbest_d^{\ t} - x_{id}^{\ t}) \quad (3)$$

Where $w \geq 0$ is defined as inertia weight factor, experimental analysis of PSO along inertia weight have displayed that a comparatively large *w* have more global quest capability while comparatively small *w* results in a faster convergence [13].

III. METHODOLOGY OF PARTICLE SWARM OPTIMIZATION

The working methodology of the particle swarm optimization model is discussed in a flow chart and the steps of this module are discussed below.

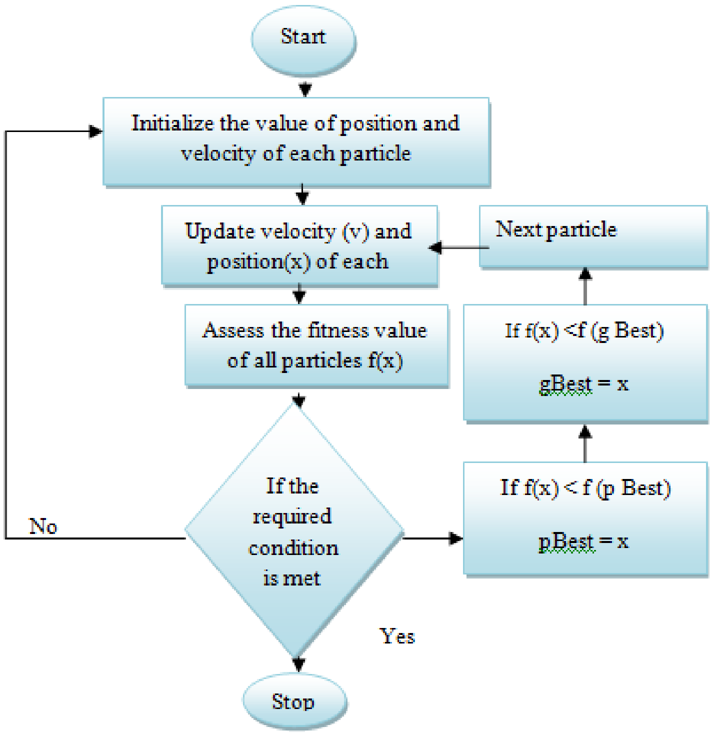

Fig 1. Proposed Flowchart of PSO

IV. RESULTS AND DISCUSSION

In this section, evolutionary algorithm is implemented based on the proposed denoising scheme is used for speech signals. Performance of the proposed model is assessed by determining different Signal-to-Noise (SNR). Fig 2, fig3,fig 4 shows the spectrogram of clean, noisy and enhanced speech signal. Table 1 shows the result procured by running the model for an input SNR of 0dB, 5dB, 10dB and 15 dB for distinct noises.

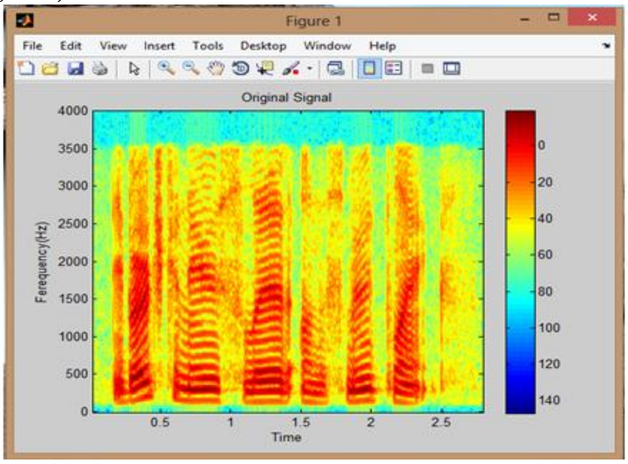

Fig 2. Spectrogram of clean signal

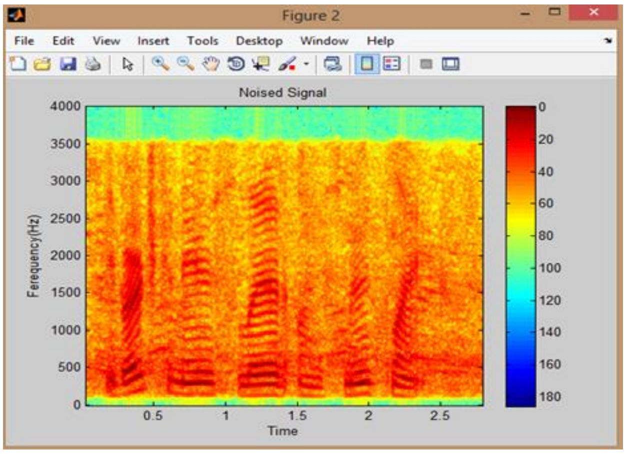

Fig 3. Spectrogram of noisy signal

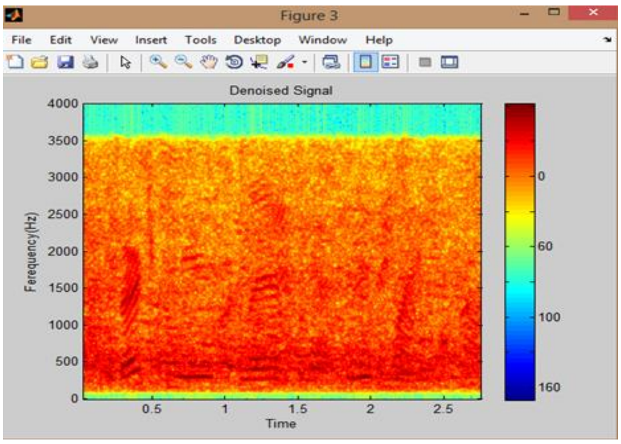

Fig 4. Spectrogram of denoised signal

Table 1- Several Proposed noises

Amount of noise added	Proposed babble noise	Proposed car noise	Proposed exhibition noise	Proposed restaurant noise	Proposed street noise	Proposed train noise
0 dB	2.17	1.337	1.64	1.86	1.699	1.699
5 dB	6.99	7.221	8.846	7.508	7.906	7.906
10 dB	9.92	9.584	9.662	9.765	9.989	9.989
15dB	23.88	23.42	23.88	20.67	23.95	23.95

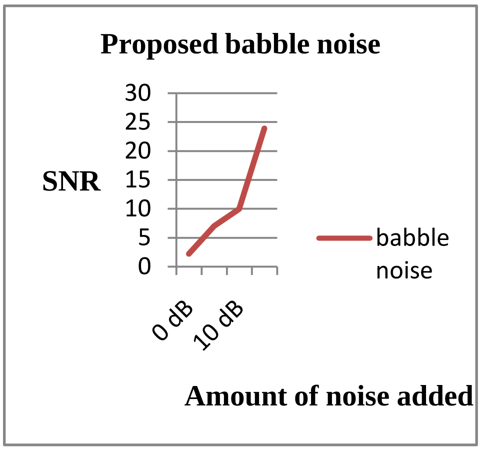

Fig 5. Proposed babble noise

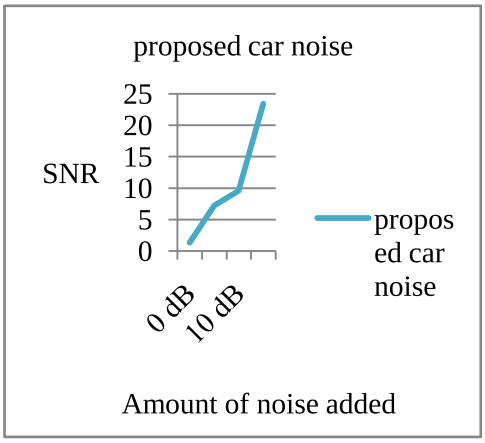

Fig 6.Proposed Car Noise

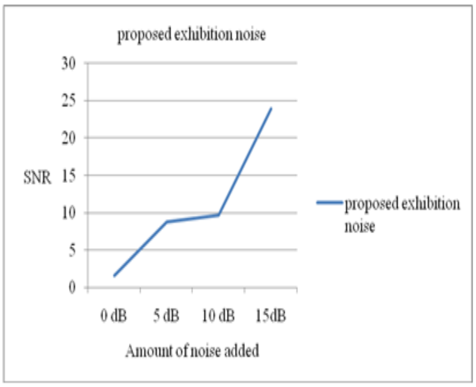

Fig 7. Proposed exhibition noise

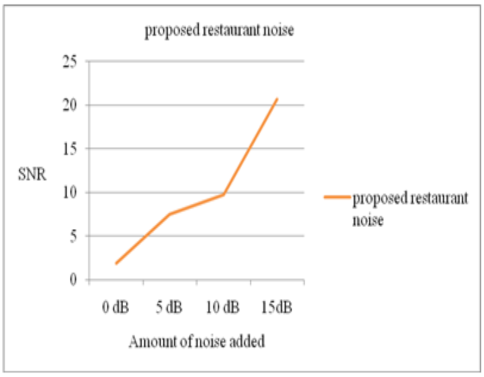

Fig 8.Proposed restaurant noise

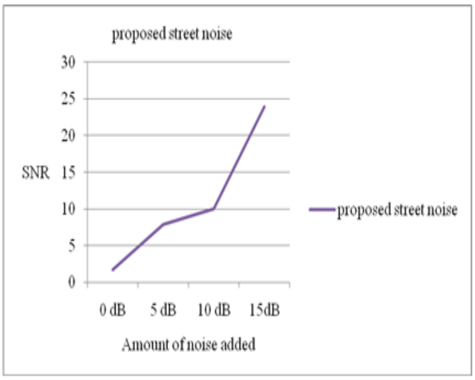

Fig 9 Proposed Street noise

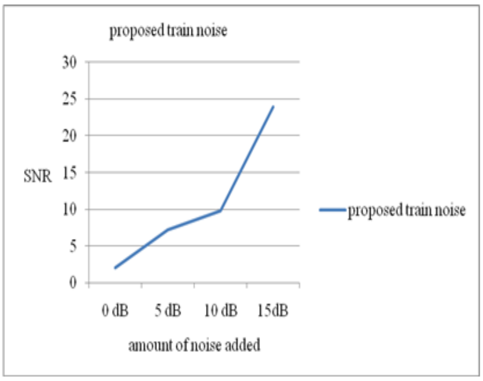

Fig 10.Proposed train noise

Figure (5) –figure (10) shows the graphical representation of the proposed noise. From these figure it is deduced/sequel that as the of the level/range of the noises varies from lower to upper level then the signal-to-noise ratio of various noise goes on increasing

V. CONCLUSION

Novel speech enhancement strategies are suggested and assessed in which it is sequel that the enhancement/augmentation of the signal can be procured by processing the several parameters. But, the quality of the speech signal remains distorted. To overcome this limitation an optimization strategy is suggested. The experimental result shows that this optimization strategy yields a better signal-to-noise ratio in comparison of the existing techniques. As the signal-to-noise ratio (SNR) is more, the accuracy of the speech quality will be more. By improving speech quality of the speech, the hearing impaired person will percept/recognize the word more easily

REFRENCES

[1] M. Mccallum, B. Guillemin, "Stochastic-Deterministic Mmse Stft Speech Enhancement With General *A Priori* Information" *IEEE Transactions On Audio, Speech, And Language Processing, 21(7),2013, pp.1445-1457*

[2] S. Man Kim, H. K. Kim, "Direction-Of-Arrival Based Snr Estimation For Dual-Microphone Speech Enhancement" *IEEE/Acm Transactions On Audio, Speech, And Language Processing, 22(12) ,2014, pp. 2207-2217*

[3] J. H. L. Hansen, V. Radhakrishnan , K. H. Arehart, "Speech Enhancement Based On Generalized Minimum Mean Square Error Estimators Andmasking Properties Of The Auditory System" *IEEE Transactions On Audio, Speech, And Language Processing, 14(6) 2006, pp.2049-2063* .

[4] J. Limand, A. Oppenheim, "Enhancement And Bandwidth Compression Of Noisy Speech," *Proc. IEEE, 67(12),1979, pp.1586–1604*

[5] Y. Ephraim And D. Malah, "Speech Enhancement Using A Minimum- Mean Square Error Short-Time Spectral Amplitude Estimator*" IEEE Transactions On Acoustics, Speech, And Signal Processing, 32(6), 1984, pp.1109-1121*

[6] Y. Hu And P. C. Loizou, "Subjective Comparison And Evaluation Of Speech Enhancement Algorithms," *Speech Commun. 49(7), 2007, pp.588–601*

[7] Y. Ephraim And D. Malah, "Speech Enhancement Using A Minimum Mean-Square Error Log-Spectral Amplitude Estimator*," IEEE Trans. Acoust., Speech, Signal Process, 33(2), 1985, pp. 443–445*

[8] R. Thakur1, P. Dutta2, Dr. G.C. Manna, " Analysis And Comparison Of Evolutionary Algorithms Applied To Adaptive Noise Cancellation For Speech Signal" *International Journal Of Recent Development In Engineering And Technology, 3(1), 2014, pp.172-178,*

[9] S. Das, A. Abraham, A. Konar," Particle Swarm Optimization And Differential Evolution Algorithms" *Technical Analysis, Applications And Hybridization Perspectives, Studies In Computational Intelligence (Sci) 116, 2008, pp.1-38*

[10] Anil Kumar_,Arun Khoslay,Jasbir Singh Sainiz, Satvir Singh, "Meta-Heuristic Range Based Node Localization Algorithm For Wireless Sensor Networks" *978-1-4673-2343-7/12/$31.00 ©2012 IEEE*

[11] X. Yang, J. Yuan, J. Yuan , H. Mao, "A Modified Particle Swarm Optimizer With Dynamic Adaptation" *Elsevier Applied Mathematics And Computation 189, 2007, pp.1205-1213*

[12] Y. Zhou, X. Wei, "A Novel Numerical Computation Method Based On Particle Swarm Optimization Algorithm" *Journal Of Computers, 5(2), 2010, pp.226-233*

[13] C.C. Yao, M.H. Tsai, "Adaptive Fuzzy Filter For Speech Enhancement" *Department Of Computer Science And Information Engineering, Chaoyang University Of Technology, Wufong, Taichung 41349, Taiwan*.

