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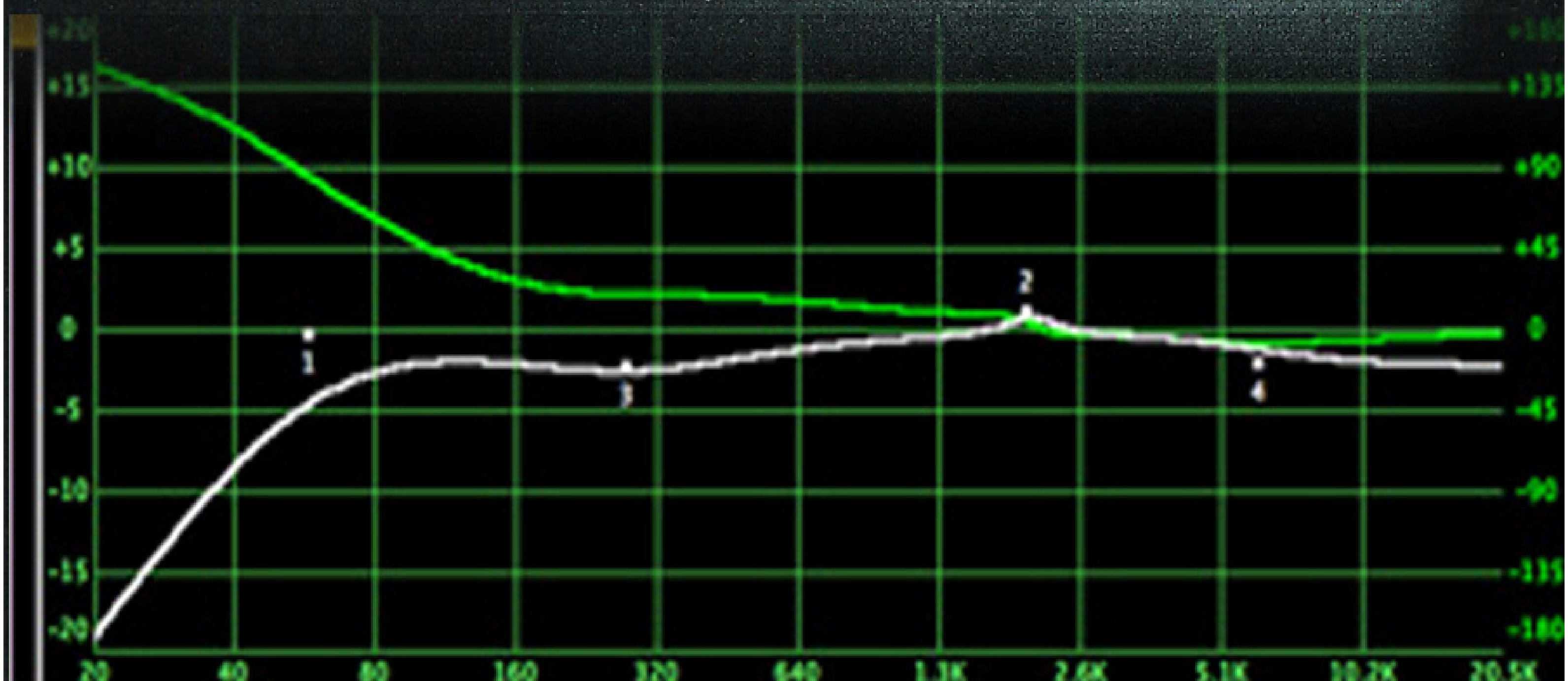

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Editorial Preface

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The Convergence Speed of Single- And Multi-Objective Immune Algorithm Based Optimization Problems

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Abstract

Despite the considerable amount of research related to immune algorithms and it applications in numerical optimization, digital filters design, and data mining, there is still little work related to issues as important as sensitivity analysis, [1]-[4]. Other aspects, such as convergence speed and parameters adaptation, have been practically disregarded in the current specialized literature [7]-[8]. The convergence speed of the immune algorithm heavily depends on its main control parameters: population size, replication rate, mutation rate, clonal rate and hyper-mutation rate. In this paper we investigate the effect of control parameters variation on the convergence speed for single- and multi-objective optimization problems. Three examples are devoted for this purpose; namely the design of 2-D recursive digital filter, minimization of simple function, and banana function. The effect of each parameter on the convergence speed of the IA is studied considering the other parameters with fixed values and taking the average of 100 times independent runs. Then, the concluded rules are applied on some examples introduced in [2] and [3]. Computational results show how to select the immune algorithm parameters to speedup the algorithm convergence and to obtain the optimal solution.

Keywords: Immune Algorithm, Convergence, Mutation, Hypermutation, Population Size, Clonal Selection.

1. INTRODUCTION

The parameters of the immune algorithm have a large effect on the convergence speed. These parameters are the population size (p_s) which estimates the number of individuals (antibodies) for each generation, the mutation rate (p_m) which increases the diversity in population, and the replication rate (p_r) which estimates the number of antibodies chosen from the antibody population pool to join the algorithm operations. Other parameters such as the clonal rate (p_c) which estimates the number of individuals chosen from the antibody population pool to join the clonal proliferation (selection), as well as the hypermutation rate (p_h) which improves the capabilities of exploration and exploitation in population, have also great effect on the speed of convergence. In spite of the research carried out up to date, there are no general rules on how these parameters can be selected. In literature [1]-[2] and [13], the immune parameters are selected by certain values (e.g. p_s =200, p_r =0.8, p_m =0.1, p_c =0.06, p_h =0.8) without stating the reason for this selection.

In this paper we investigate the effect of parameters variation on the convergence speed of the immune algorithms developed for three different illustrative examples: 2-D recursive digital filter design (multi-objective problem), minimization of simple function (single-objective problem), and finding the global minimum of banana function. The obtained results can be used for selecting the values of these parameters for other problems to speed up the convergence. The paper is organized as follows. Section 2 describes the immune algorithm behavior. In Section 3 three illustrative examples are given to investigate the effect of parameters variation on the convergence speed of the immune algorithm. Section 4 discusses the selection criteria of these parameters to guarantee the convergence speed. In section 5, some examples introduced in [3] and [12] are considered to demonstrate the effectiveness of the selection of immune algorithm control parameters. And finally, Section 6 offers some conclusions.

2. IMMUNE ALGORITHMS BEHAVIOR

Immune algorithms are randomized algorithms inspired by immune functions and principles observed in nature [10]. Such algorithms begin by generating population pool (chromosome) using real coding representation and evaluating the objective values. Then, the population pool undergoes the algorithm operations which will be described in this section. The operations are repeated at each generation (gen) until the termination condition is satisfied [1]-[2]. Table (1) illustrates the main steps of the immune algorithm [16].

2.1 Generation of Antibody Population

The antibody population is generated either by using binary coding representation or real coding representation. In the binary coding representation, each variable is encoded as a binary string and the resulting strings are concatenated to form single chromosome (antibody) [11]. However, in the real coding representation, each antibody is encoded as a vector of floating point numbers, with the same length as the vector of decision variables. This representation is accurate and efficient because it is closest to the real design space, and the string length represents the number of design variables.

2.2 Selection for Reproduction

The roulette wheel selection is employed in immune bases algorithms for chromosomes reproduction. Its basic idea is to determine the selection probability for each solution in proportion with the fitness value. For solution j with fitness f_j, its probability p_j is defined as:

$$p_j = \frac{f_j}{\sum_{j=1}^{\rho_s} f_j} \qquad , j = 1, 2, ..., \rho_s \tag{1}$$

And the cumulative probability q_j for each solution is calculated as:

$$q_j = \sum_{i=1}^{j} p_i \qquad , j = 1, 2, ..., \rho_s \tag{2}$$

Where, the fitness f_j is relation to the objective function value of the j[th] chromosome.

```
Gen=1;                                              % The first generation
Chrom=Initial_pop();                                % Construct the initial population pool
While (termination_condition)
      Evaluuate (Chrom);                            % Objective function evaluation
      Chrom_sel=RWS_Selection(Chrom);               % Roulette wheel selection
      Chrom_rep=replication(Chrom_sel);                    % Selection of better antibodies using
Replication
      Chrom_clon=Cloning(Chrom_rep);                % Clonal operation
      Chrom_hyper=Hypermutation(Chrom_clon);        % Hypermutation operation
      Chrom_tot=[ Chrom_rep, Chrom_hyper];
      Chrom_child=Mutation(Chrom_tot);              % Mutation Operation
      Evaluuate (Chrom_child);                      % Objective function evaluation
      Chrom=Better_selection(Chrom, Chrom_child);        % Selection of better antibodies for next
generation
      gen=gen+1;                                    % Increment the number of generations
end
```

TABLE (1): The Immune Algorithm

2.3 Replication Operation

The replication operation is used to select better antibodies, which have low objective values to undergo algorithm operations. This is termed by clonal proliferation within hypermutation and mutation operations.

2.4 Clonal Proliferation within Hypermutation

Based on the biological immune principles, the selection of a certain antibody from the antibody population pool to join the clonal proliferation depends on the clonal selection rate (p_c). Each gene, in a single antibody, depending on the hypermutation rate (p_h), executes the hypermutation of convex combination. The hypermutation rate (p_h) has an extremely high rate than the mutation rate to increase the antibody diversity. For a given antibody $X = (X_1, X_2, ..., X_i, X_j, X_k, ..., X_\rho)$, if the gene X_i is determined to execute the hypermutation and another gene X_k is randomly selected to join in, the resulting offspring antibody becomes $X' = (X_1, X_2, ..., X_i', X_j, X_k, ..., X_\rho)$, where the new gene X_i' is $X_i' = (1-\beta)X_i + \beta X_k$, and β ∈ [0, 1] is a random value.

2.5 Mutation Operation

Similar to the hypermutation mechanism, the mutation operation is also derived from the convex set theory [9], where each gene, in a single antibody, depending on the mutation rate (p_m), executes the mutation of convex combination. Two genes in a single solution are randomly chosen to execute the mutation of convex combination [15]. For a given antibody $X = (X_1, X_2, ..., X_i, X_j, X_k, ..., X_\rho)$, if the genes X_i and X_k are randomly selected for mutation depend on the mutation rate (p_m), the resulting offspring is $X^{'} = \left(X_1,\ X_2,...,X_i^{'},X_j,X_k^{'},...,X_\rho\right)$. The resulting two genes $X_i^{'}$ and $X_k^{'}$ are calculated as:

$$X_i^{'} = (1-\beta)X_i + \beta X_k \text{ and } X_k^{'} = \beta X_i + (1-\beta)X_k \quad (3)$$

where, β is selected randomly in the range [0, 1].

2.6 Selection Operation

The selection operation is generally used to select the better p_s antibodies which have low objective values as the new antibody population of the next generation.

3. ILLUSTRATIVE EXAMPLES

In this section three different examples are considered to investigate the effect of parameters variation on the convergence speed of the immune algorithm. The first example simulates the multi-objective function problem that has an infinite set of possible solutions difficult to find [7]. The second example is a single-objective function problem and it is less difficult and the third example represents the family of problems with slow convergence to the global minimum [6].

Example 1:

This example considers the design of a second order 2-D narrow-band recursive LPF with magnitude and group delay specifications. The specified magnitude $M_d(\omega_1,\omega_2)$ is shown in Figure (1) [1], [5]. Namely, it is given by Equation (4) with the additional constant group delay $\tau_{d_1}=\tau_{d_2}=5$ over the passband $\sqrt{\omega_1^2+\omega_2^2} \le 0.1\pi$ and the design space is [-3 3]. To solve this problem, the frequency samples are taken at $|\omega_i/\pi| = 0,\ 0.02, 0.04, \ldots, 0.2,\ 0.4, \ldots, 1$ in the ranges $-\pi \le \omega_1 \le \pi$, and $-\pi \le \omega_2 \le \pi$.

$$M_d(\omega_1,\omega_2) = \begin{cases} 1.0, & for \sqrt{\omega_1^2+\omega_2^2} \le 0.08\pi \\ 0.5, & for\ 0.08\pi < \sqrt{\omega_1^2+\omega_2^2} \le 0.12\pi \\ 0.0, & for \sqrt{\omega_1^2+\omega_2^2} > 0.12\pi \end{cases} \quad (4)$$

Example 2:

This example considers the optimization of the exponential function shown in Figure (2) and described by the following equation:

$$y(x) = \sum_{i=0}^{9} a_i x^i \quad (5)$$

With the following desired specified values $Y_d(x)$ at x= [0, 1, 2, 3, ………., 20].

$$\begin{aligned} Y_d(x) = [&0.01\quad -0.01\quad -3.83\quad -4.79\quad 758.33\quad 9.0021\times10^3\quad 5.7237\times10^4\quad 5.7237\times10^4 \\ &9.2998\times10^5\ 2.8368\times10^6\ 7.6281\times10^6\ 1.8563\times10^7\ 4.165\times10^7\ 8.7358\times10^7 \\ &1.7309\times10^8\ 3.2667\times10^8\ 5.9104\times10^8\ 1.0306\times10^9\ 1.7397\times10^9\ 2.8528\times10^9 \\ &4.5587\times10^9] \end{aligned}$$

Example 3:

This example considers a Rosenbrock banana function that described by the following equation [6]. This function is often used to test the performance of most optimization algorithms [6]. The global minimum is inside a long, narrow, parabolic shaped flat valley as shown in Figure (3). In fact find the valley is trivial, however the convergence to the global minimum is difficult.

$$f(x,y) = (1-x)^2 + 100\left(y-x^2\right)^2 \tag{6}$$

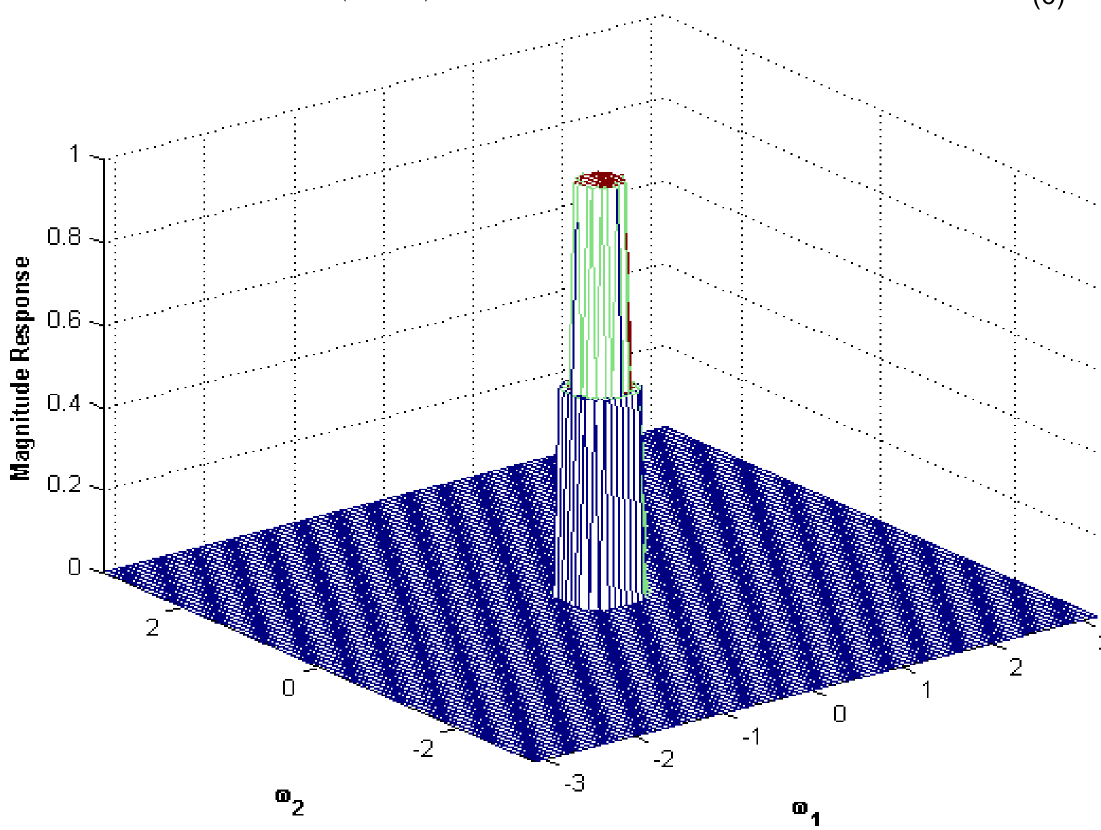

FIGURE 1: Desired Amplitude Response $\left|M_d(\omega_1,\omega_2)\right|$ Of The 2-D Narrow-Band LPF (Example 1)

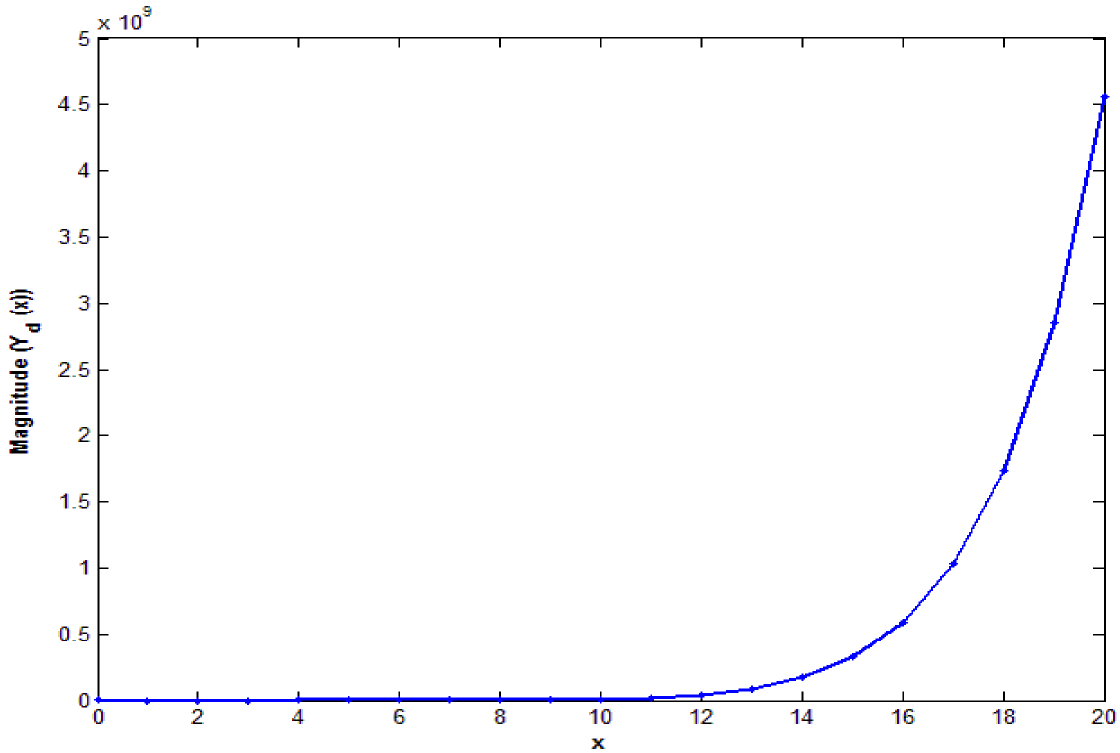

FIGURE 2: Desired Specifications of the Function $y(x)$ (Example 2)

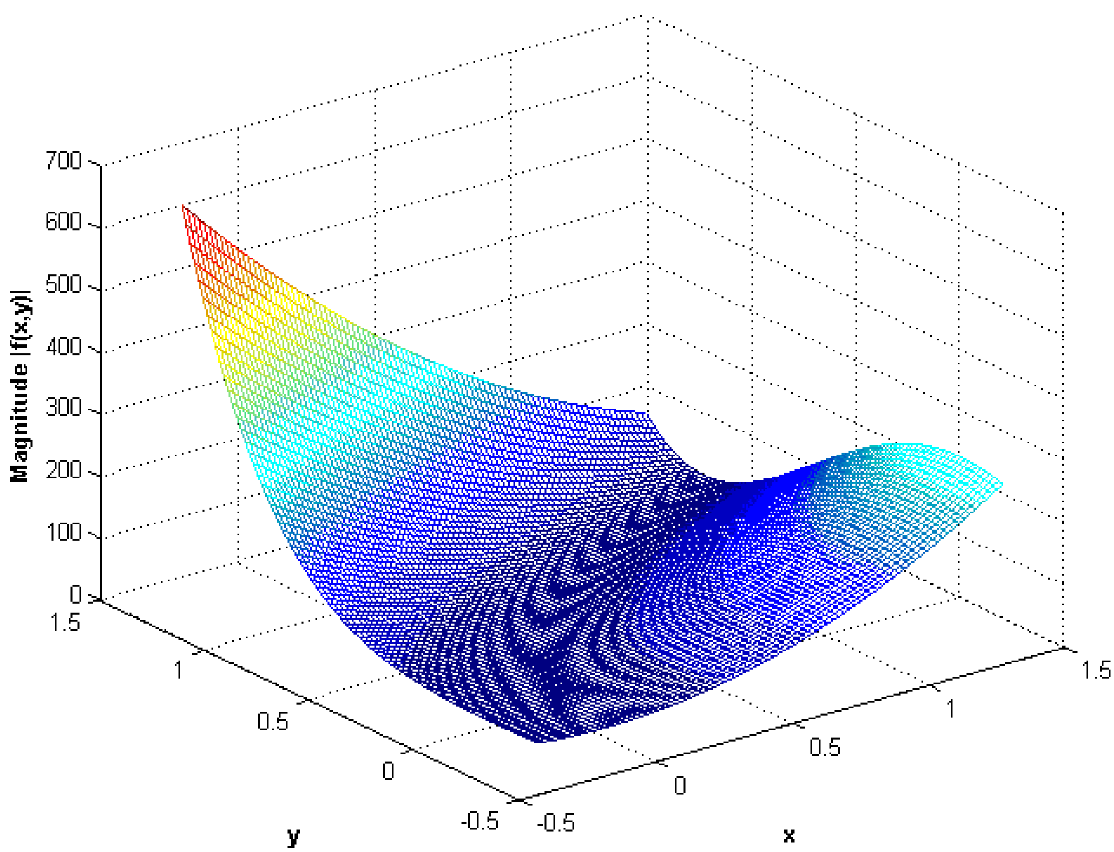

FIGURE 3: Rosenbrock Banana Function (Example 3)

4. SENSITIVITY ANALYSIS

In this section, we examine the effect of parameters variations on the convergence speed of the immune algorithm for the three examples described in section 3. The number of genes (the encoding length L) for each example is defined by the number of unknown coefficients. For the filter design problem, the filter transfer function is expressed by:

$$H(z_1,z_2)=H_0\frac{a_{00}+a_{01}z_2+a_{02}z_2^2+a_{10}z_1+a_{11}z_1z_2+a_{12}z_1z_2^2+a_{20}z_1^2+a_{21}z_1^2z_2+a_{22}z_1^2z_2^2}{(1+b_1z_1+c_1z_2+d_1z_1z_2)(1+b_2z_1+c_2z_2+d_2z_1z_2)},\ a_{00}=1 \tag{7}$$

So, 15 genes can be adjusted to approximate the specified magnitude and group delay. For the simple function and banana function problems, the number of genes considered are 10 and 2 respectively.

4.1 Effect of the population size (p_s)

The population size (p_s) is defined as the number of antibodies used in each generation. The variations in p_s can have substantial effect on the convergence speed of immune algorithm. If the p_s is too small, the IA cannot reach to optimal solution. However, if it is too large, the IA wastes computational time effort on extra objective values evaluations. Here, the effect of p_s on the convergence speed of the algorithm is studied by taking the average of 100 times independent runs at each p_s value. The value of p_s was varied from 10 to 400 with the other parameters fixed at p_r =0.8, p_h =0.8, p_m =0.1, and p_c =0.06. The effect of population size variations on number of generations required to get the solution for filter design problem, simple function and banana function are shown in Figures (4-6), respectively.

The results illustrated in Figures (4-6) show that, the speed of convergence can be measured by the number of generations required to reach to the optimal chromosome (global solution). Moreover, it can be noticed that the speed of convergence depends not only on the p_s but also on the number of genes. Here, the p_s after which optimal chromosome is obtained is denoted by p_s*. Increasing the p_s above p_s* has insignificant effect on speeding up the convergence.

4.2 Effect of the Replication Rate (p_r)

The replication rate (p_r) estimates the number of antibodies chosen from the antibody population pool to join the algorithm operations. The effect of p_r on the speed of convergence of the IA is studied by taking the average of 100 times independent runs at each p_r value. The value of p_r was varied from 0.1 to 1 with the other parameters fixed at p_s =100 p_h =0.8, p_m =0.1, and p_c =0.06. The effect of p_r variation on the number of generations required to produce the solution for filter design problem, simple function and banana function are shown in Figures (7-9), respectively.

These figures show that, the high values of replication rate have a significant effect on speeding up the convergence, but the computational time increases as the p_r increases. It is also noticed that the values of p_r greater than p_r* have no further effect on speeding up the convergence.

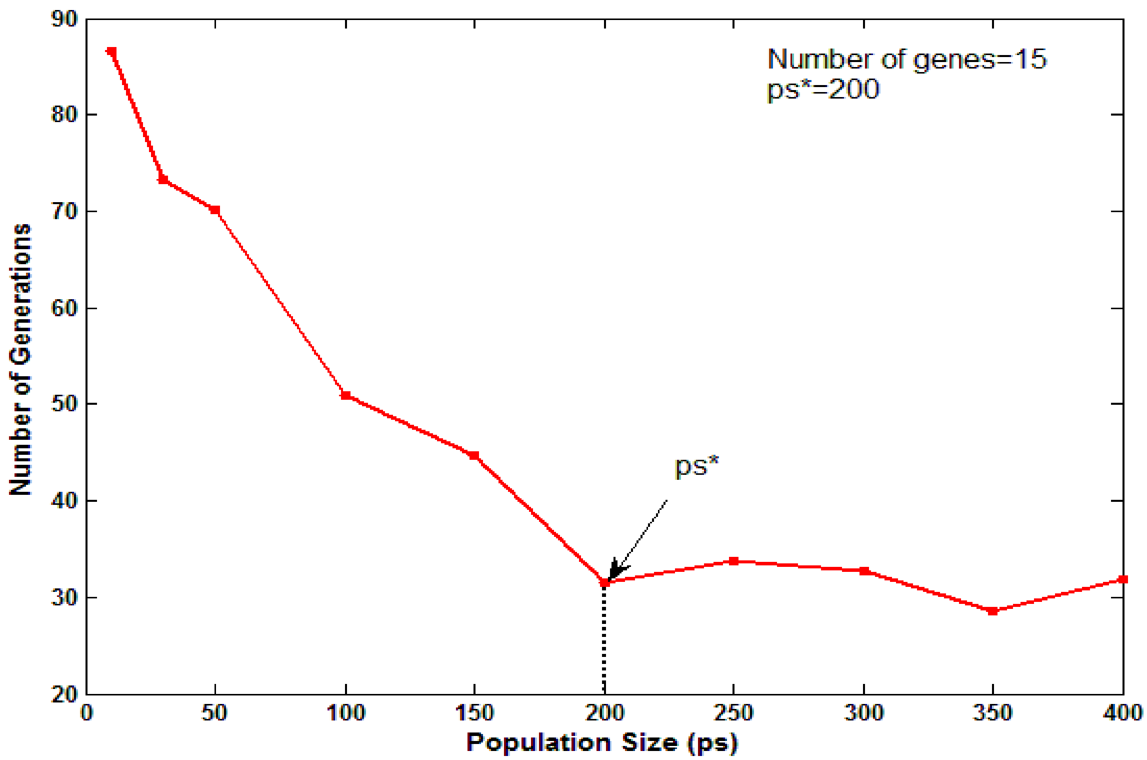

FIGURE 4: The Effect of Population Size on the Speed of Convergence of the Filter Design Problem.

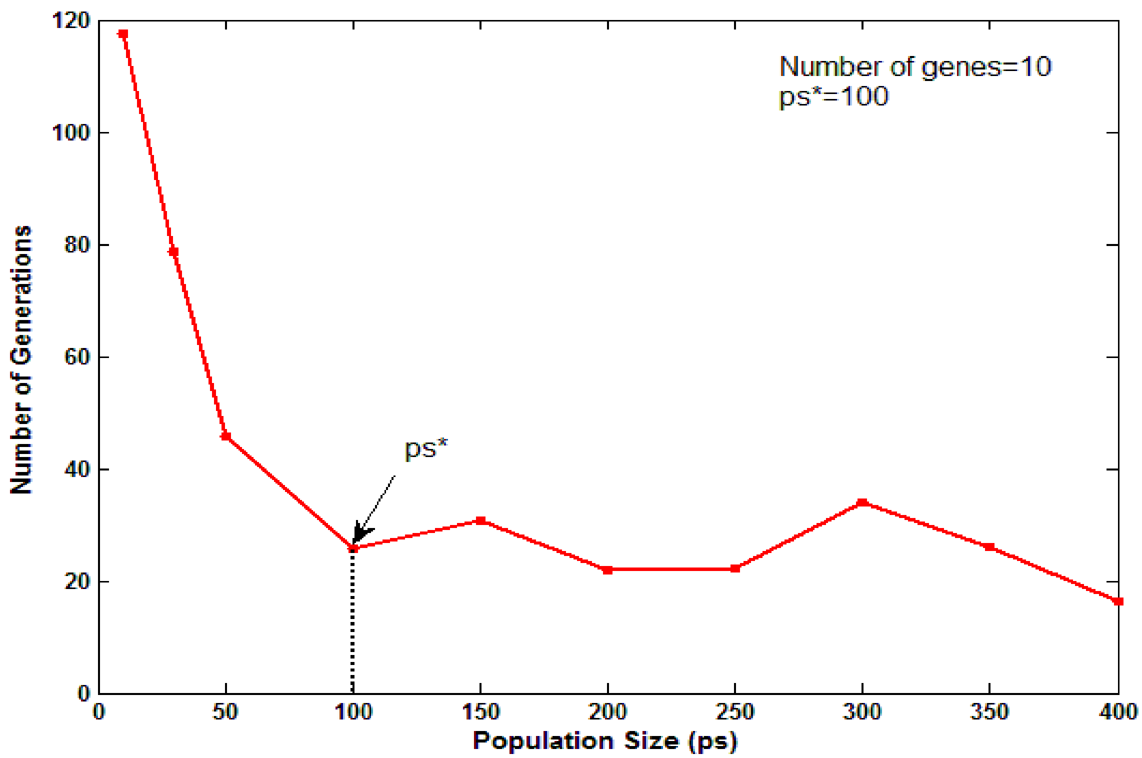

FIGURE 5: The Effect of Population Size on the Speed of Convergence for Simple Function Minimization

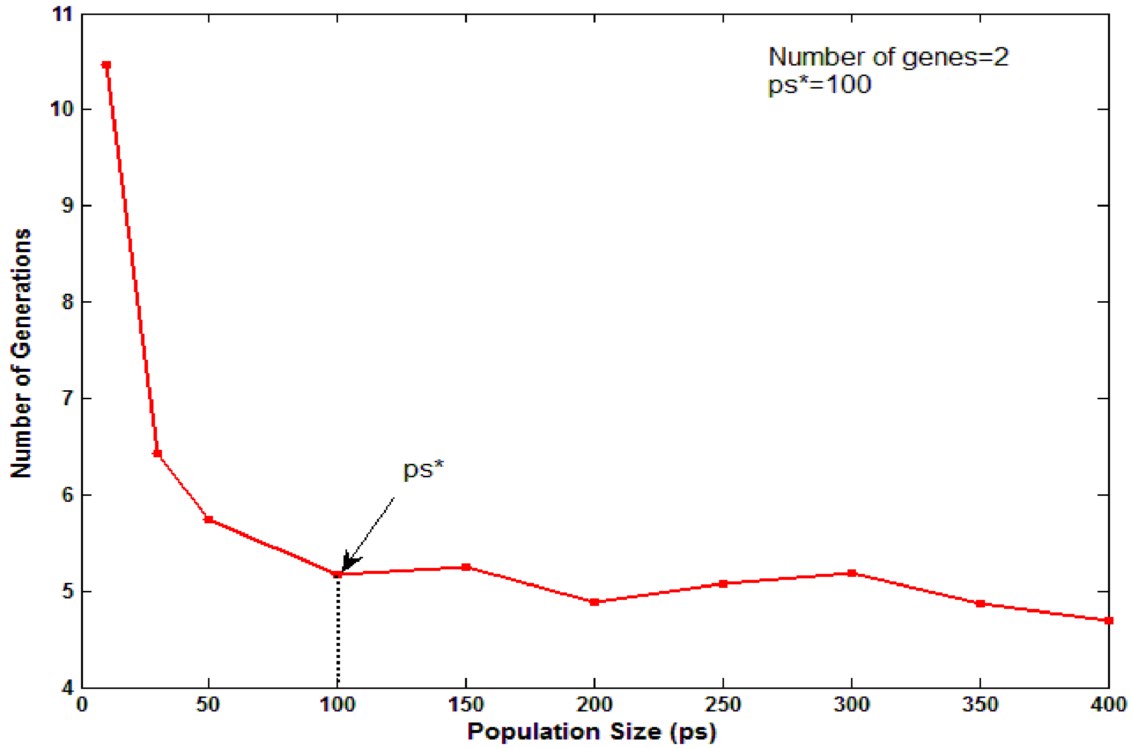

Figure 6: The Effect Of Population Size On The Speed Of Convergence For Finding The Global Minimum Of Banana Function.

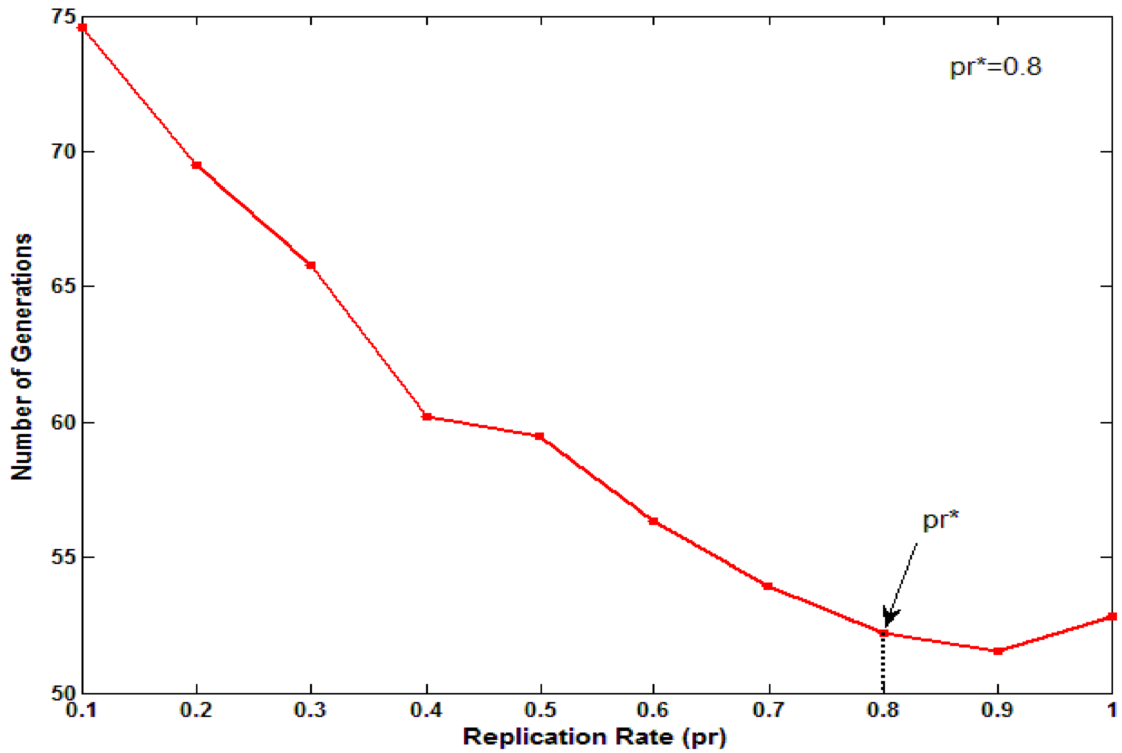

FIGURE 7: The Effect of Replication Rate on the Speed of Convergence for Filter Design Problem.

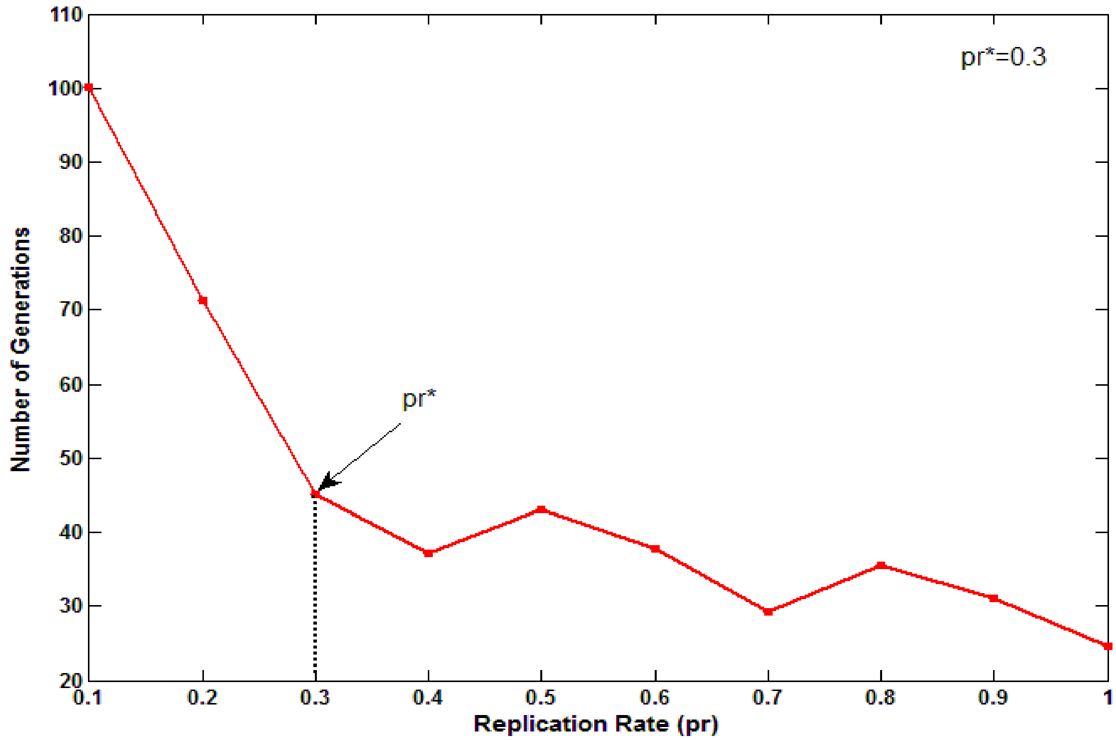

FIGURE 8: The Effect of Pr on the Speed of Convergence for Simple Function Minimization.

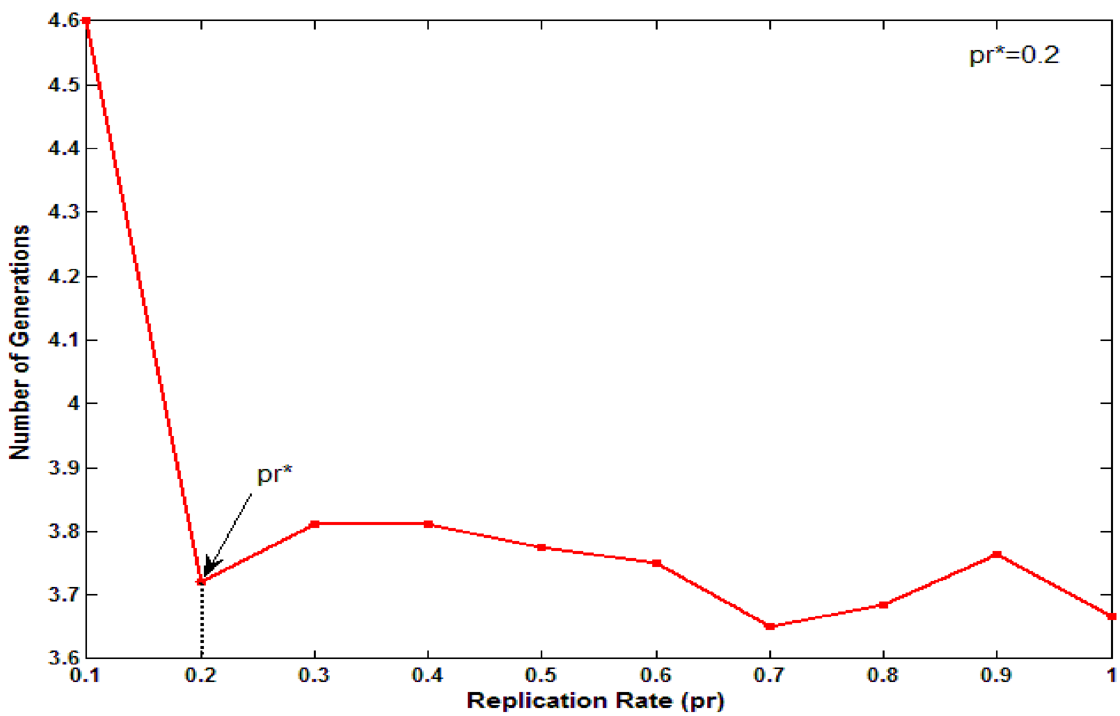

FIGURE 9: The Effect of Pr on the Speed of Convergence for Finding the Global Minimum of Banana Function**.**

4.3 Effect of the Clonal Selection Rate (p_c)

The clonal selection rate (p_c) estimates the number of antibodies that can be chosen from the antibody population pool to join the clonal proliferation. The effect of p_c on the speed of convergence of the IA is studied by taking the average of 100 times independent runs at each p_c value. The value of p_c was varied from 0.01 to 1 with the other parameters fixed at p_s =100, p_r =0.8, p_h =0.8, and p_m =0.1. The effect of p_c variation on the number of generations required to produce the optimal solution for filter design problem, simple function and banana function are shown in Figures (10-12), respectively.

From these figures, we can conclude that low values of p_c ($0.05 \leq p_c < 0.1$) have significant effect on speeding up the convergence. It is also noticed that the use of high values of p_c ($p_c \geq p_c^*$) have an effect of slowing down the convergence. This is mainly due to the infeasible selected individuals which joined to the clonal proliferation.

4.4 Effect of the Hypermutation Rate (p_h)

The hypermutation rate (p_h) is used to improve the capabilities of exploration and exploitation in population. The effect of p_h on the convergence speed of the IA is evaluated by taking the average of 100 times independent runs at each p_h value. The value of p_h was varied from 0.01 to 1 with the other parameters fixed at p_s =100, p_r =0.8, p_c =0.06, and p_m =0.1. The effect of hypermutation variation on the number of generations required to produce the solution for filter design problem, simple function and banana function are shown in Figures (13-15), respectively.

The results given in Figures (13-15) show that, the value of p_h depends on the problem domain. The values of p_h for the three illustrative examples are 0.5, 0.5, and 0.7, respectively. The p_h should be in the range ($0.5 \leq p_h < 1$) to speed up the convergence of small number of genes problems (example 3) and it is about 0.5 for other ones.

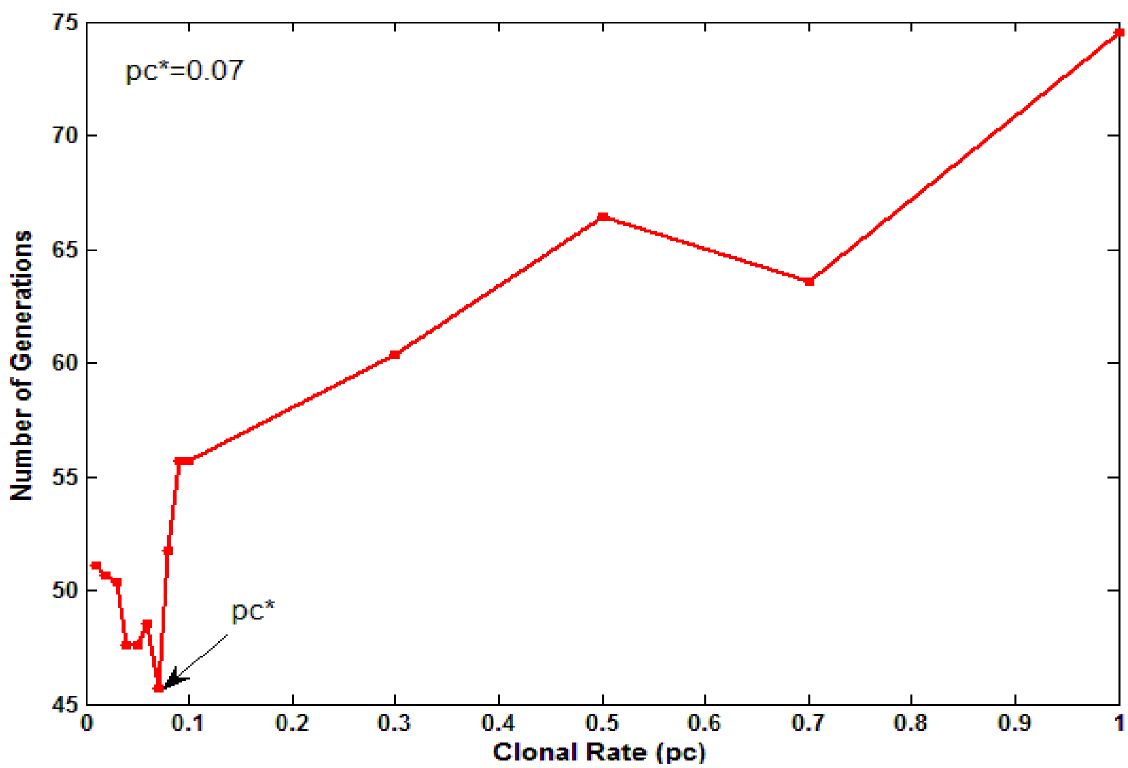

FIGURE 10: The Effect of Clonal Rate on the Speed of Convergence for Filter Design Problem.

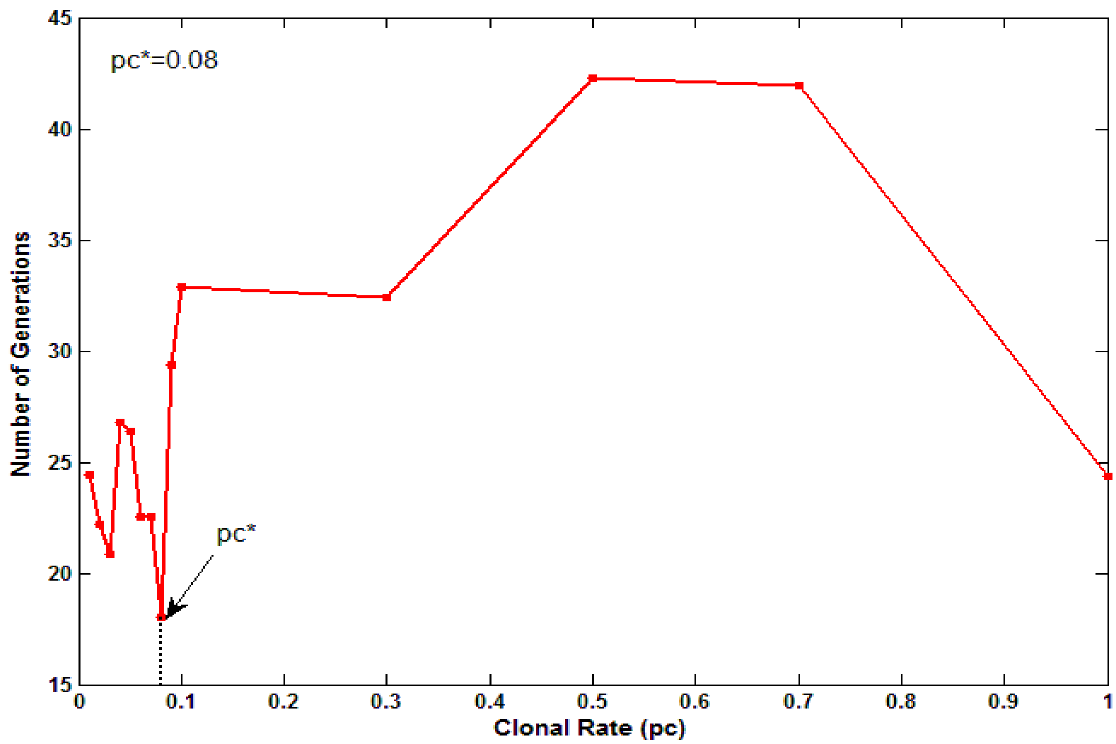

FIGURE 11: The Effect of Clonal Rate on the Speed of Convergence for Simple Function Minimization.

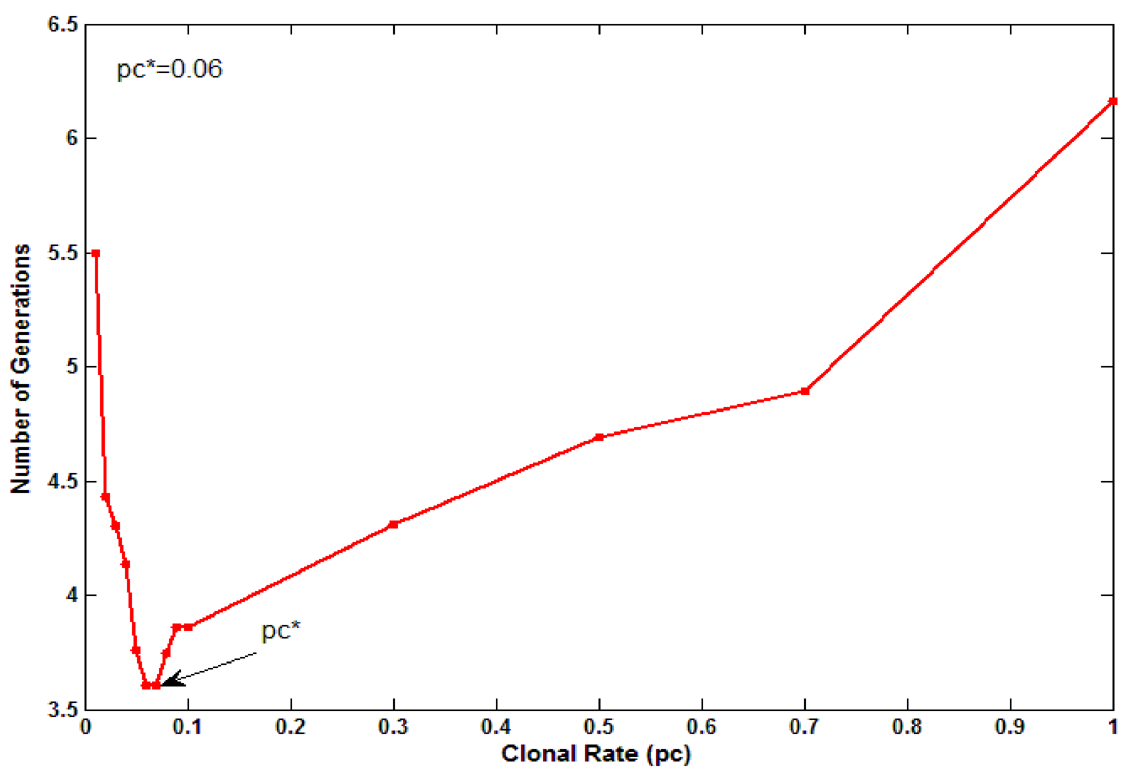

FIGURE 12: The Effect of Clonal Rate on the Speed of Convergence for Finding the Global Minimum of Banana Function.

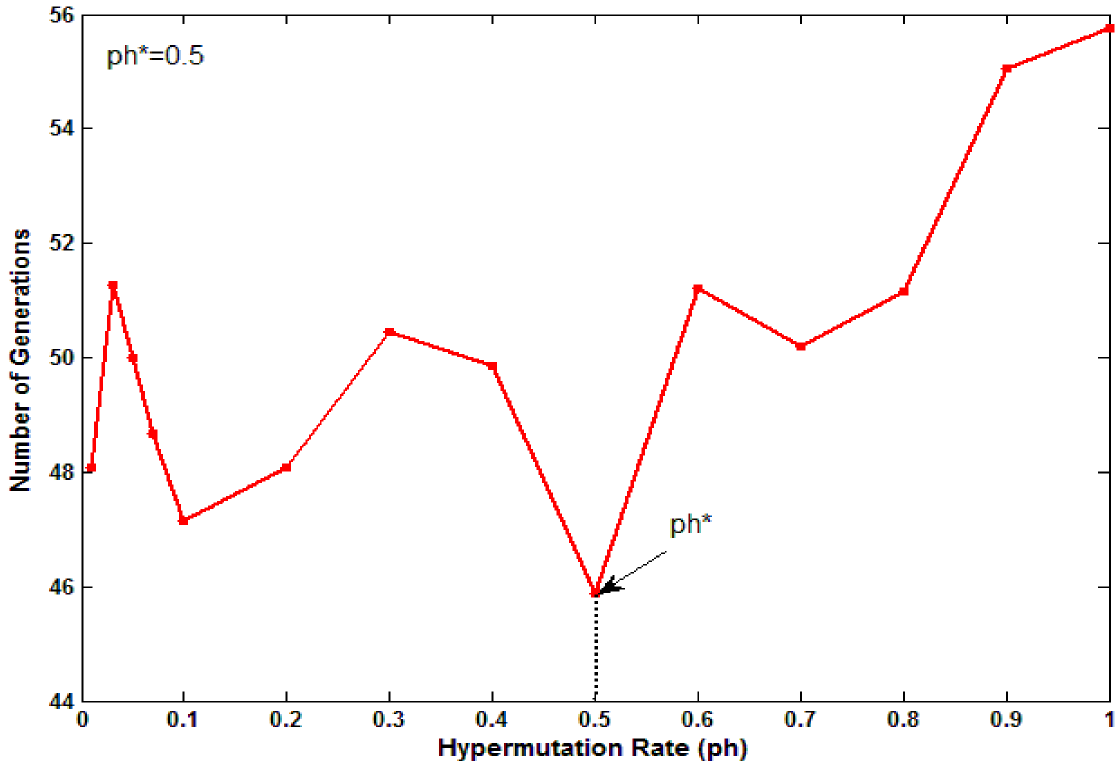

FIGURE 13: The Effect of Hypermutation Rate on the Speed of Convergence for Filter Design Problem.

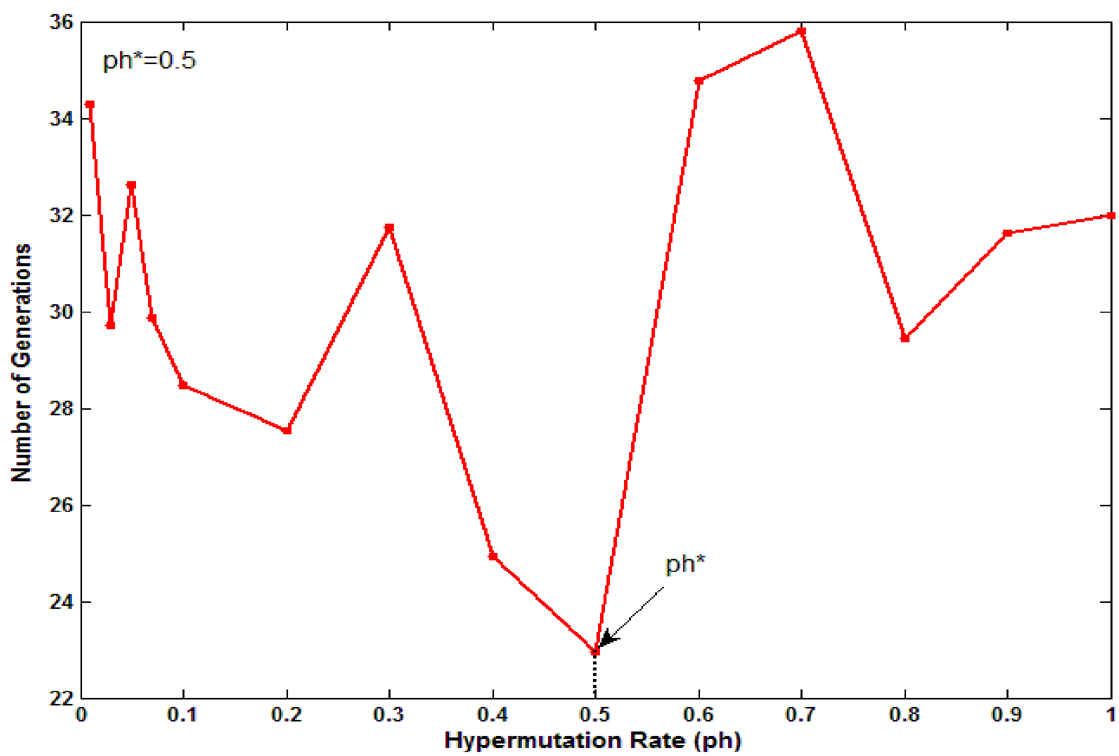

FIGURE 14: The Effect of Hypermutation Rate on the Speed of Convergence for Simple Function Minimization.

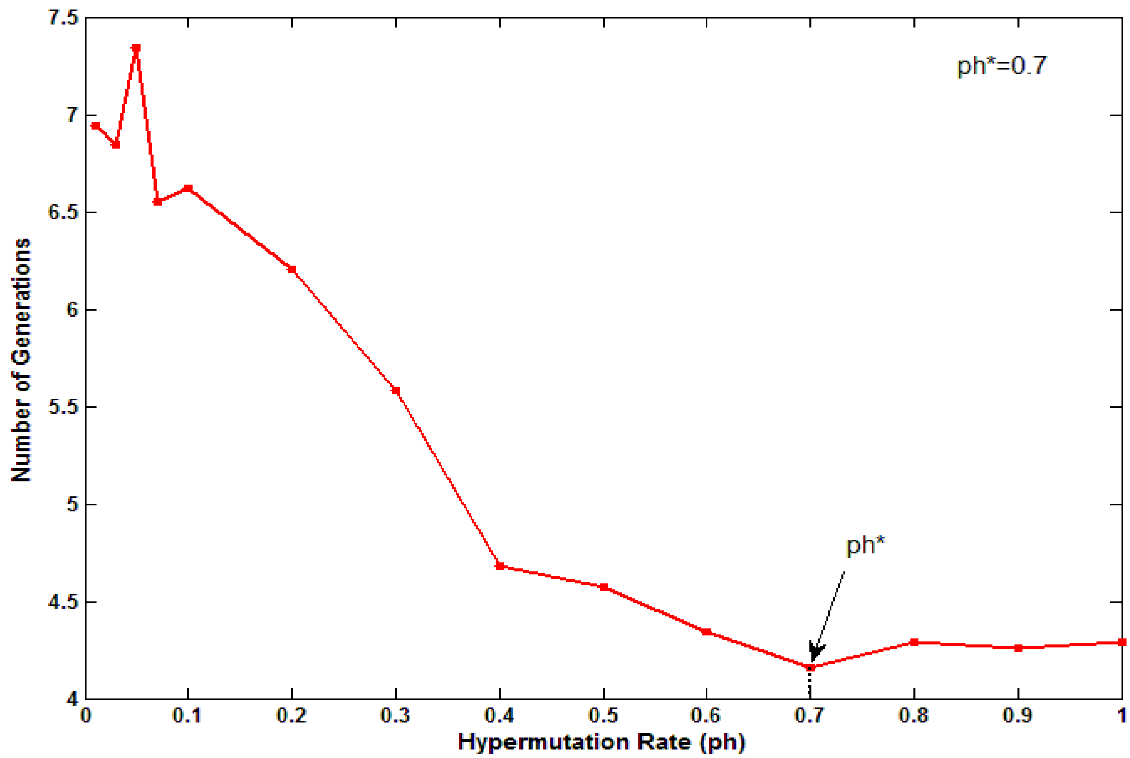

FIGURE 15: The Effect of Hypermutation Rate on the Speed of Convergence for Finding the Global Minimum of Banana Function.

4.5 Effect of the Mutation Rate (p_m)

The mutation rate (p_m) is one of the most sensitive immune algorithm parameters, since it increases the diversity in population. The choice of mutation rate is essentially a tradeoff between conservatism and exploration [14]. The effect of p_m on the convergence speed of IA is studied by taking the average of 100 times independent runs at each p_m value. The value of p_m was varied from 0.01 to 1 with the other parameters fixed at p_s =100, p_r =0.8, p_c =0.06, and p_h =0.8. The effect of mutation rate variation on the number of generations required to produce the solution for filter design problem, simple function and banana function are shown in Figures (16-18), respectively.

From these figures, we can conclude that the low values of mutation rate ($p_m \leq p_m$*) have significant effect on speeding up the convergence. Also, it is noticed that to guarantee the convergence speed, the p_m should be between 1/ p_s and 1/L, where p_s is the population size and L is the encoding string length.

From above studying, we can conclude that the general heuristics on IA parameters to guarantee the convergence speed are: 1) the population size should be greater than 100; 2) the replication rate should be higher than 0.2; 3) the clonal rate should be small in the range (0.05≤ p_c <0.1); 4) the hypermutation rate should be high in the range (0.5≤ p_h <1); and 5) the mutation rate should be between 1/ p_s and 1/L.

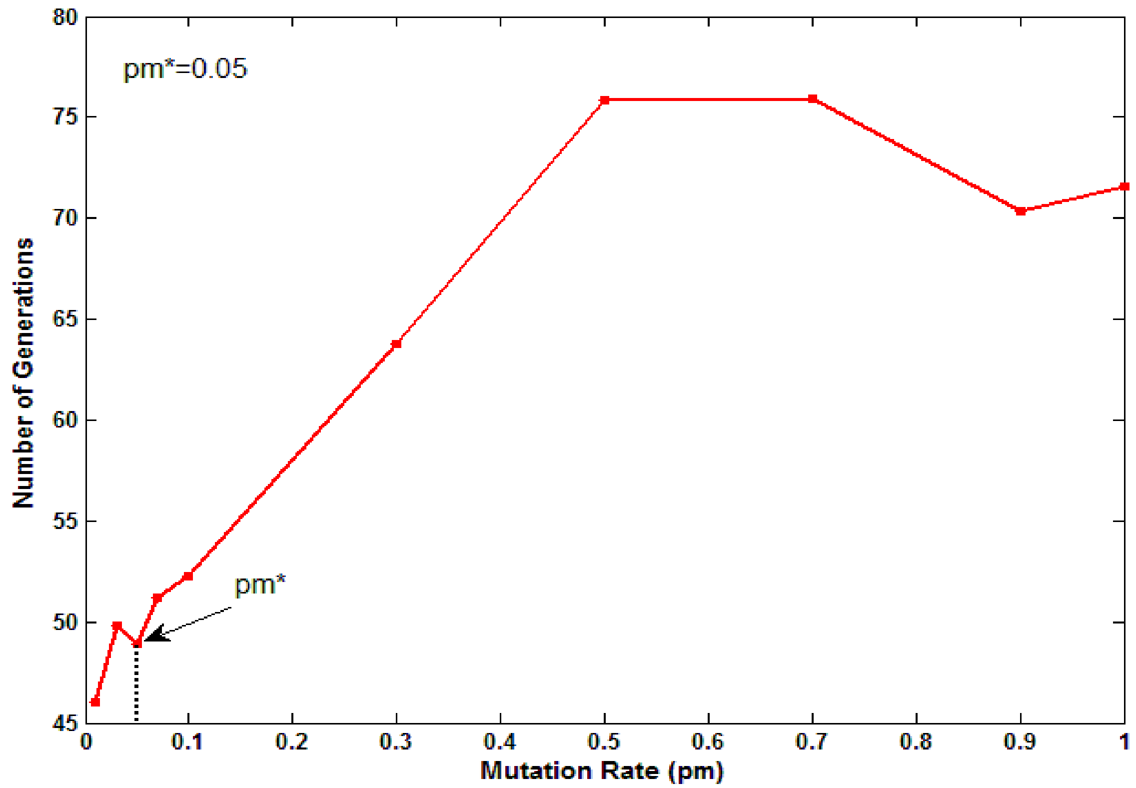

FIGURE 16: The Effect of Mutation Rate on the Speed of Convergence for Filter Design Problem (Ps=100 and L=15).

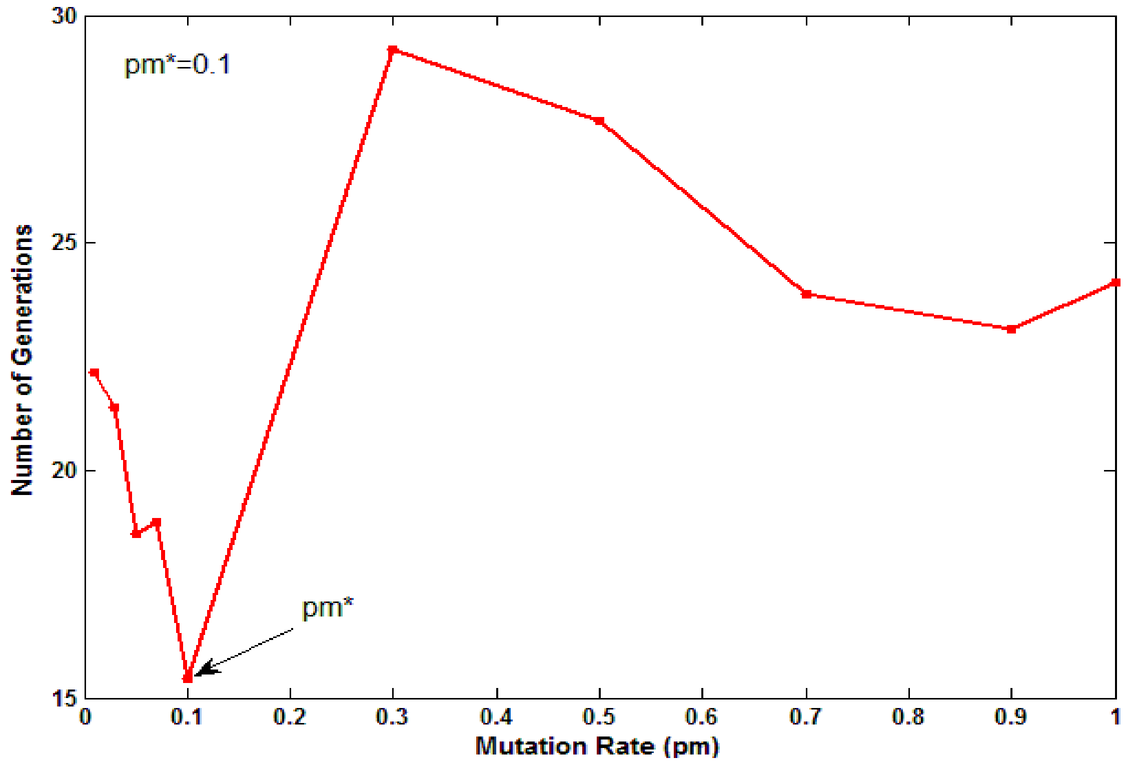

FIGURE 17: The Effect of Mutation Rate on Speed of Convergence for Simple Function Minimization (Ps=100 and L=10).

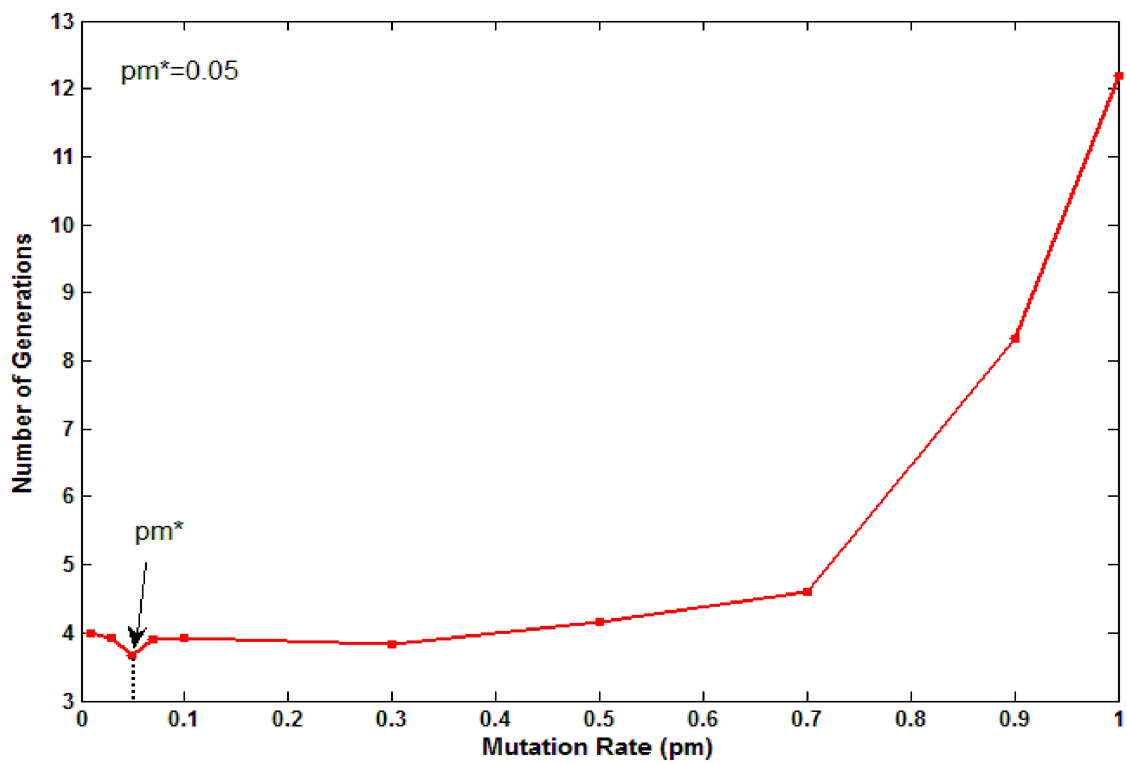

FIGURE 18: The Effect Of Mutation Rate On Speed Of Convergence For Finding The Global Minimum Of Banana Function (Ps=100 And L=2).

5 RESULTS AND DISCUSSION

In this section, some examples introduced in [3] and [12] are considered to illustrate the effect of immune algorithm parameters on the convergence speed.

Example 4:

This example is considered in [3] for solving system identification problem. It is repeated here to demonstrate the effectiveness of the selection of immune algorithm control parameters. In this example, it is required to approximate second-order system by first-order IIR filter. The second-order system and the filter are described respectively by the following transfer functions [3]:

$$H_p\left(z^{-1}\right)=\frac{0.05-0.4z^{-1}}{1-1.1314z^{-1}+0.25z^{-2}} \quad \text{and} \quad H_f\left(z^{-1}\right)=\frac{a_0}{1-b_1z^{-1}} \tag{8}$$

In Table (2), the control parameters selected based on the study described in previous section and that used in [3] are given. Table (3) illustrates the transfer function, the number of function evolution and NMSE of the resulting IIR filter and that is described in [3]. The NMSE is calculated using the following equation:

$$NMSE=\sqrt{\sum_{k=1}^{N}\left(\left|M(k)\right|-M_d(k)\right)^2}\Bigg/\sqrt{\sum_{k=1}^{N}\left(M_d(k)\right)^2} \tag{9}$$

Where, $M_d(k)$ and $M(k)$ are the magnitude responses of the 2nd order system and that of the designed filter respectively calculated at N=2000 sampling points.

IA Parameters	The selected parameters based on the above study	The selected parameters in [3]
Population size	100	50
Replication rate	0.85	0.80
Mutation rate	0.2	0.015
Clone rate	0.05	Not used in this method
Hypermutation rate	0.8	Not used in this method

TABLE 2: The IA Control Parameters Of Examples 1 And 2

	IIR filter obtained using proposed parameters values	IIR filter obtained using parameters values stated in [3]
Transfer Function	$H_f\left(z^{-1}\right)=\frac{-0.4153}{1-0.8645z^{-1}}$	$H_f\left(z^{-1}\right)=\frac{-0.311}{1-0.906z^{-1}}$
NMSE	0.0796	0.2277
Number of function evaluations to find the global optimal solution	1056	1230

TABLE 3: The Transfer Function, Number Of Function Evolutions And NMSE Of Both Resulting IIR Filter And IIR Filter Described In [3].

Figure (19) shows the magnitude responses of the second-order system, the resulting IIR filter and IIR filter described in [3]. From Figure (19) and Table (3), noticed that the resulting IIR filter converge to the second-order system after smaller number of objective function evaluations with smaller NMSE compared to that given in [3]. So, the good selection of the IA control parameters speeds up the algorithm convergence.

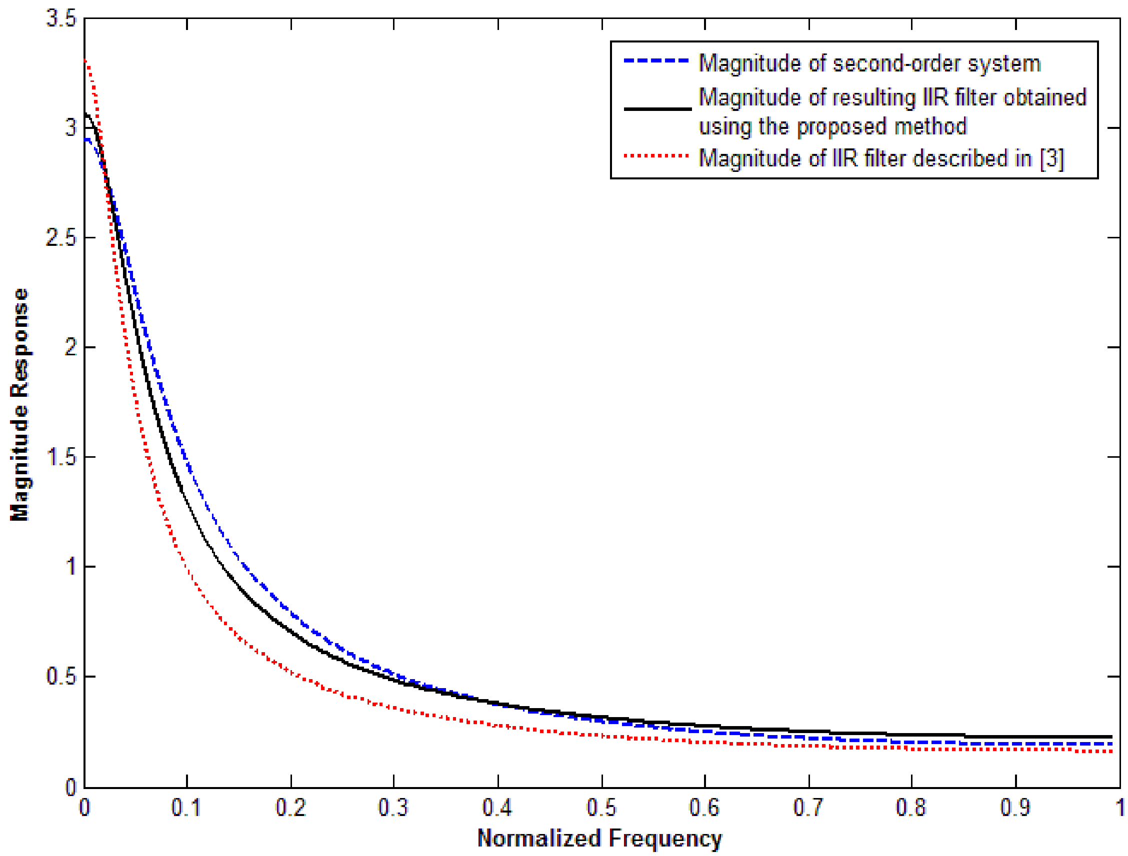

FIGURE 19: The magnitude responses of second-order system and IIR filter

Example 5:

This example is also considered in [3] for solving system identification problem. It is required to approximate a second order system by IIR filter with the same order. The system and the filter are described respectively by the following transfer functions [3]:

$$H_p\left(z^{-1}\right)=\frac{1}{1-1.2z^{-1}+0.6z^{-2}} \quad \text{and} \quad H_f\left(z^{-1}\right)=\frac{1}{1-b_1z^{-1}-b_2z^{-2}} \tag{10}$$

Using the same control parameters of example 1, the optimal solution (b_1= -1.1966, b_2= -0.59522) is obtained after 1503 objective function evaluations with MSE=0.393x10-3. However, the solution in [3] is obtained after 3000 objective function evaluations with MSE=0.5x10-3.

Example 6:

This example is considered in [12], for finding the global solution of the following test function:

$$f_4=\frac{1}{4000}\sum_{i=1}^{N}x_i^2-\prod_{i=1}^{N}\cos\left(\frac{x_i}{\sqrt{i}}\right)+1 \tag{11}$$

The proposed IA is used to solve this function with 30 dimensions (i.e. N=30) in solution space [-600, 600]. In Table (4), the control parameters selected based on the study described in previous section and that used in [12] are given.

IA Parameters	The selected parameters based on the above study	The selected parameters in [12]
Population size	200	200
Replication rate	0.2	0.1
Mutation rate	0.02	0.02
Clone rate	0.06	0.01
Hypermutation rate	0.8	0.01

Table 4: The IA Control Parameters Of Example 3

Using the proposed IA, the solution is obtained after 13120 function evaluations; however in [12] is reached after 15743 function evaluations. So, the IA control parameters are having significant effect on the convergence speed.

6 CONCLUSIONS

In this paper, general rules on speeding up the convergence of the IA are discussed. The convergence speed of the IA is important issues and heavily depends on its main control parameters. In spite of the research carried out up to date, there are no general rules on how the control parameters of the IA can be selected. In literature [12]-[13], the choice of these parameters is still left to the user to be determined statically prior to the execution of the IA. Here, we investigate the effect of the parameters variation on the convergence speed by adopting three different objective optimization examples (2-D recursive filter design, minimization of simple function, and banana function). From the studied examples, the following general heuristics on immune algorithm parameters that guarantee the convergence speed are concluded: 1) the population size should be greater than 100; 2) the replication rate should be higher than 0.2; 3) the clonal rate should be small in the range ($0.05\leq p_c <0.1$); 4) the hypermutation rate should be high in the range ($0.5\leq p_h <1$); and 5) the mutation rate should be between $1/p_s$ and 1/L. These heuristics are applied to study cases solved in [3] and [12] to show effect of control parameter selection on the IA performance. Numerical results show that the good selection of the control parameters of the IA have significant effect on the convergence speed of the algorithm.

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Performance Study of Various Adaptive Filter Algorithms for Noise Cancellation in Respiratory Signals

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Abstract

Removal of noises from respiratory signal is a classicl problem. In recent years, adaptive filtering has become one of the effective and popular approaches for the processing and analysis of the respiratory and other biomedical signals. Adaptive filters permit to detect time varying potentials and to track the dynamic variations of the signals. Besides, they modify their behavior according to the input signal. Therefore, they can detect shape variations in the ensemble and thus they can obtain a better signal estimation. This paper focuses on (i) Model Respiratory signal with second order Auto Regressive process. Then synthetic noises have been corrupted with respiratory signal and nullify these noises using various adaptive filter algorithms (ii) to remove motion artifacts and 50Hz Power line interference from sinusoidal 0.18Hz respiratory signal using various adaptive filter algorithms. At the end of this paper, a performance study has been done between these algorithms based on various step sizes. It has been found that there will be always tradeoff between step sizes and Mean square error.

Keywords: Adaptive filter, Least Mean Square (LMS), Normalized LMS (NLMS), Block LMS (BLMS), Sign LMS (SLMS), Sign-Sign LMS (SSLMS), Signed Regressor LMS (SRLMS), Motion artifact, Power line interference

1. INTRODUCTION

Various biomedical signals are present in human body. To check the health condition of a human being it is essential to monitor these signals. While monitoring these signals, various noises interrupt the process. These noises may occur due to the surrounding factors, devices connected and physical factors. In this paper, noises associated with the respiratory signals are taken into account. The monitoring of the respiratory signal is essential since various sleep related disorders like sleep apnea (breathing is interrupted during sleep), insomnia (inability to fall asleep), narcolepsy can be detected earlier and treated. Also breathing disorders like snoring, hypoxia (shortage of O_2), hypercapnia (excess amount of CO_2) hyperventilation (over breathing) can be treated. The respiratory rate for new born is 44 breathes/min for adults it is 10-20 breathes/min. Various noises affecting the respiratory signal are motion artifact due to instruments, muscle contraction, electrode contact noise, powerline interference, 50HZ interference, noise generated by electronic devices, baseline wandering, electrosurgical noise.

One way to remove the noise is to filter the signal with a notch filter at 50 Hz. However, due to slight variations in the power supply to the hospital, the exact frequency of the power supply might (hypothetically) wander between 47 Hz and 53 Hz. A static filter would need to remove all the frequencies between 47 and 53 Hz, which could excessively degrade the quality of the ECG since the heart beat would also likely have frequency components in the rejected range. To circumvent this potential loss of information, an adaptive filter has been used. The adaptive filter would take input both from the patient and from the power supply directly and would thus be able to track the actual frequency of the noise as it fluctuates.

Several papers have been presented in the area of biomedical signal processing where an adaptive solution based on the various algorithms is suggested. Performance study and comparison of LMS and RLS algorithms for noise cancellation in ECG signal is carried out in [1]. Block LMS being the solution of the steepest descent strategy for minimizing the mean square error is presented in [2]. Removal of 50Hz power line interference from ECG signal and comparative study of LMS and NLMS is given in [3]. Classification of respiratory signal and representation using second order AR model is discussed in [4]. Application of LMS and its member algorithms to remove various artifacts in ECG signal is carried out in [5]-[7]. Mean square error behavior, convergence and steady state analysis of different adaptive algorithms are analyzed in [8]-[10]. The results of [11] show the performance analysis of adaptive filtering for heart rate signals. Basic concepts of adaptive filter algorithms and mathematical support for all the algorithms are taken from [12].

In [13] the authors present a real-time algorithm for estimation and removal of baseline wander noise and obtaining the ECG-derived respiration signal for estimation of a patient's respiratory rate. In [14], a simple and efficient normalized signed LMS algorithm is proposed for the removal of different kinds of noises from the ECG signal. The proposed implementation is suitable for applications requiring large signal to noise ratios with less computational complexity. The design of an unbiased linear filter with normalized weight coefficients in an adaptive artifact cancellation system is presented in [15]. They developed a new weight coefficient adaptation algorithm that normalizes the filter coefficients, and utilize the steepest-descent algorithm to effectively cancel the artifacts present in ECG signals. The paper [16] describes the concept of adaptive noise cancelling, a method of estimating signals corrupted by additive noise. In [17], an adaptive filtering method is proposed to remove the artifacts signals from EEG signals. Proposed method uses horizontal EOG, vertical EOG, and EMG signals as three reference digital filter inputs. The real-time artifact removal is implemented by multi-channel Least Mean Square algorithm. The resulting EEG signals display an accurate and artifact free feature.

The results in [18] show that the performance of the signed regressor LMS algorithm is superior than conventional LMS algorithm, the performance of signed LMS and sign-sign LMS based realizations are comparable to that of the LMS based filtering techniques in terms of signal to noise ratio and computational complexity. An interference-normalized least mean square algorithm for robust adaptive filtering is proposed in [19].The INLMS algorithm extends the gradient-adaptive learning rate approach to the case where the signals are nonstationary. It is shown that the INLMS algorithm can work even for highly nonstationary interference signals, where previous gradient-adaptive learning rate algorithms fail. The use of two simple and robust variable step-size approaches in the adaptation process of the Normalized Least Mean Square algorithm in the adaptive channel equalization is investigated in [20].In the proposed algorithm in [21], the input power and error signals are used to design the step size parameter at each iteration. Simulation results demonstrate that in the scenario of channel equalization, the proposed algorithm accomplishes faster start-up and gives better precision than the conventional algorithms. A novel power-line interference (PLI) detection and suppression algorithm is presented in [22] to preprocess the electrocardiogram (ECG) signals. A distinct feature of this proposed algorithm is its ability to detect the presence of PLI in the ECG signal before applying the PLI suppression algorithm. An efficient recursive least-squares (RLS) adaptive notch filter is also developed to serve the purpose of PLI suppression. In [23] two types of adaptive filters are considered to reduce the ECG signal noises like PLI and Base Line Interference. Various methods of removing noises from ECG signal and its implementation using the Lab view tool was referred in [24]. Results in [25] indicate that respiratory signals alone are sufficient and perform even better than the combined respiratory and ECG signals.

2. MATHEMATICAL MODEL OF RESPIRATION SIGNALS

The respiratory systems' function is to allow gas exchange to all part of the body. In addition to supplying oxygen, the respiratory system aids in removing of carbon dioxide. It prevents the lethal buildup of this waste product in body tissues. The respiratory system carries out its life-sustaining activities through the process of respiration. Respiration is the process by which the atmospheric oxygen is inhaled in to the body and the unwanted carbon dioxide is exhaled out through the nostrils and mouth.

Respiratory signals are not a constant signal with common amplitude and regular variations from time to time. Hence to estimate the signal it is necessary to frame an algorithm which can analyze even the small variations in the input signal. Respiratory signal is modeled in to a second order AR equation so that the parameters can be utilized for determining the fundamental features of the respiratory signal. The autoregressive (AR) model is one of the linear prediction formulas that attempt to predict an output Y(n) of a system based on the previous inputs {x(n), x(n-1), x(n-2)...}. It is also known in the filter design industry as an infinite impulse response filter (IIR) or an all pole filter, and is sometimes known as a maximum entropy model in physics applications.

The respiration signal can be modeled as a second order autoregressive model [4] as the following,

$X(n)=a_1X(n-1)+a_2X(n-2) + e(n)$ (1)

Where e (n) is the prediction error and $\{a_1,a_2\}$ are AR model coefficients to be determined through burgs method.

3. NOISES IN RESPIRATORY SIGNALS

Methods of respiration monitoring fall into two categories. Devices such as spirometers and nasal thermocouples measure air flow into and out of the lungs directly. Respiration can also be monitored indirectly, by measuring body volume changes; transthoracic inductance and impedance plethysmographs, strain gauge measurement of thoracic circumference, pneumatic respiration transducers, and whole-body plethysmographs are examples of indirect techniques. When the doctors are examining the patient on-line and want to review the respiratory signal waveform in real-time, there is a good chance that the signal has been contaminated by baseline wander (BW), power line interference (PLI), muscle artifacts (MA) and electrode motion artifacts (EM) etc., mainly caused by patient breathing, movement, power line noise, bad electrodes and improper electrode site preparation. All these noises mask the tiny features of the signal and leads to false diagnosis. To allow doctors to view the best signal that can be obtained, we need to develop an adaptive filter to remove the artifacts in order to better obtain and interpret the respiratory signal data.

3.1 Motion Artifact

Motion artifact cause false alarms during patient monitoring, which can reduce clinician confidence in monitoring equipment alarms and, consequently, slow response time. When motion artifact is introduced to the system, the information is skewed. Motion artifact causes irregularities in the data. Motion artifact can be reduced by proper design of the electronic circuitry and set-up. The shape of the baseline disturbance caused by motion artifacts can be assumed to be a biphasic signal resembling one cycle of a sine wave. The peak amplitude and duration of the artifact are variables since the respiratory unit is a sensitive device, it can pickup unwanted electrical signals which may modify the actual respiratory signal.

3.2 Power line interference

Power line interference consists of 50Hz pickup and harmonics which can be modelled as sinusoids and combination of sinusoids***.*** Characteristics which might need to be varied in a model of power line noise include the amplitude and frequency content of the signal. These characteristics are generally consistent for a given measurement situation and, once set, will not change during a detector evaluation. Power line interference is often a nuisance in bio potential measurements, mostly because of the long wires between the subject and the amplifier, the separation between the measurement points (electrodes), capacitive coupling between the subject (a volume conductor) and power lines, and the low amplitude of the desired signals. High-resolution measurements searching for potentials as small as 1 V further exacerbate the problem. It is a common interference source with low frequency and weak amplitude in signal detection and transmission.

3.3 Electrode Contact Noise

Electrode contact noise occurs due to the loss of contact between electrode and skin. The measurement of bioelectric events is exposed to various sources of noise. The reactions that take place at the electrode make the electrode itself a source of noise. Electrode contact noise can be modeled as a randomly occurring rapid baseline transition (step) which decays exponentially to the baseline value and has a superimposed 50 Hz component. This transition may occur only once or may rapidly occur several times in succession. Characteristics of this noise signal include the amplitude of the initial transition, the amplitude of the 50 Hz component and the time constant of the decay.

3.4 Baseline Drift

The wandering of baseline results from the gross movements of the patients or from mechanical strain on the electrode wires. If there is no proper application of jelly between the electrode and the skin, during that time also baseline wandering occurs. Respiration, muscle contraction, and electrode impedance changes due to perspiration or movement of the body are the important sources of baseline drift. The drift of the baseline with respiration can be represented as a sinusoidal component at the frequency of respiration. The amplitude and frequency of the sinusoidal component should be variables. The amplitude of the respiratory signal also varies by about 15 percent with the original signal. The variation could be reproduced by amplitude modulation of the respiratory by the sinusoidal component which is added to the baseline.

4. ADAPTIVE FILTER ALGORITHMS

A system is said to be adaptive when it tries to adjust its parameters with the aid of meeting some well-defined goal or target that depends upon the state of the system and its surroundings. So the system adjusts itself so as to respond to some phenomenon that is taking place in its surroundings. An event related signal could be considered as a process, which can be decomposed into an invariant deterministic signal time locked to a stimulus and an additive noise uncorrelated with the signal. The most common signal processing of this type of bioelectric signal separates the deterministic signal from the noise. Several techniques can be considered of which we are considering the adaptive signal processing technique. Adaptive filters are self-designing filters based on an algorithm which allows the filter to “learn” the initial input statistics and to track them if they are time varying. These filters estimate the deterministic signal and remove the noise uncorrelated with the deterministic signal. The principle of adaptive filter is as shown in Figure 1.

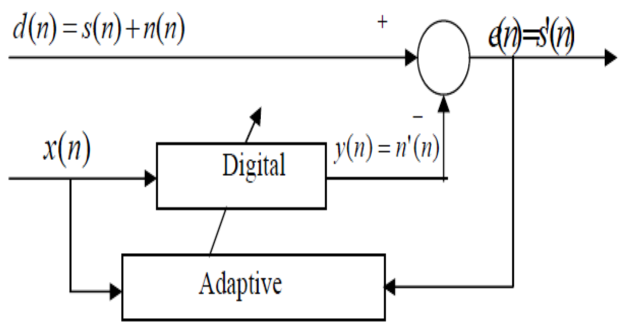


FIGURE 1: Principle of Adaptive Filter

Obtained signal d (n) from sensor contains not only desired signal s (n) but also undesired noise signal n (n). Therefore measured signal from sensor is distorted by noise n (n). At that time, if undesired noise signal n(n) is known, desired signal s(n) can be obtained by subtracting noise signal n(n) from corrupted signal d(n). However entire noise source is difficult to obtain, estimated noise signal n' (n) is used. The estimate noise signal n' (n) is calculated through some filters and measurable noise source X(n) which is linearly related with noise signal n(n). After that, using estimated signal n' (n) and obtained signal d (n), estimated desired signal s' (n) can be obtained. If estimated noise signal n' (n) is more close to real noise signal n(n), then more desired signal is obtained. In the active noise cancellation theory, adaptive filter is used. Adaptive filter is classified into two parts, adaptive algorithm and digital filter. Function of adaptive algorithm is making proper filter coefficient. General digital filters use fixed coefficients, but adaptive filter change filter coefficients in consideration of input signal, environment, and output signal characteristics. Using this continuously changed filter coefficient, estimated noise signal n' (n) is made by filtering X (n). The different types of adaptive filter algorithms can be explained as follows.

4.1 LMS Algorithm

The LMS algorithm is a method to estimate gradient vector with instantaneous value. It changes the filter tap weights so that e (n) is minimized in the mean-square sense. The conventional LMS algorithm is a stochastic implementation of the steepest descent algorithm. It simply replaces the cost function $\xi(n) = E[e^2(n)]$ by its instantaneous coarse estimate.

The error estimation e(n) is

$$e(n) = \mathbf{d}(n) - w(n)\,X(n) \qquad (2)$$

Coefficient updating equation is

$$\mathbf{w}(n+1) = \mathbf{w}(n) + \mu\, x(n)\, e(n), \qquad (3)$$

Where μ is an appropriate step size to be chosen as $0 < \mu < 0.2$ for the convergence of the algorithm. The larger step sizes make the coefficients to fluctuate wildly and eventually become unstable. The most important members of simplified LMS algorithms are:

4.2 Signed-Regressor Algorithm (SRLMS)

The signed regressor algorithm is obtained from the conventional LMS recursion by replacing the tap-input vector x (n) with the vector sgn{x(n)}.Consider a signed regressor LMS based adaptive filter that processes an input signal x(n) and generates the output y(n) as per the following:

$$y(n) = \mathbf{w}^t(n)x(n) \qquad (4)$$

where, $\mathbf{w}(n) = [\, w0(n), w1(n), \ldots, wL\text{-}1(n)\,]^t$ is a L-th order adaptive filter. The adaptive filter coefficients are updated by the Signed-regressor LMS algorithm as,

$$\mathbf{w}(n+1) = \mathbf{w}(n) + \mu\, \mathrm{sgn}\{x(n)\}e(n) \qquad (5)$$

Because of the replacement of x(n) by its sign, implementation of this recursion may be cheaper than the conventional LMS recursion, especially in high speed applications such as biotelemetry these types of recursions may be necessary.

4.3 Sign Algorithm (SLMS)

This algorithm is obtained from conventional LMS recursion by replacing e(n) by its sign. This leads to the following recursion:

$$\mathbf{w}(n+1) = \mathbf{w}(n) + \mu\, x(n)\, \mathrm{sgn}\{e(n)\} \qquad (6)$$

4.4 Sign – Sign Algorithm (SSLMS)

This can be obtained by combining signed-regressor and sign recursions, resulting in the following recursion:

$$\mathbf{w}(n+1) = \mathbf{w}(n) + \mu\, \mathrm{sgn}\{x(n)\}\, \mathrm{sgn}\{e(n)\}, \qquad (7)$$

Where sgn{ . } is well known signum function, e(n) = d(n) – y(n) is the error signal. The sequence d (n) is the so-called desired response available during initial training period. However the sign and sign – sign algorithms are both slower than the LMS algorithm. Their convergence behavior is also rather peculiar. They converge very slowly at the beginning, but speed up as the MSE level drops.

4.5 Block LMS (BLMS) Algorithm

To reduce the computational requirements of LMS algorithm, block LMS is introduced. Here the filter coefficients are held constant over each block of L samples, and the filter output y(n) and the error e(n) for each value of n within the block are calculated using the filter coefficients for that block. Then at the end of each block, the coefficients are updated using an average for the L gradients estimates over the block.

4.6 Normalized LMS (NLMS) Algorithm

In NLMS, the step size takes the form of,

$$\mu(n) = \frac{\beta}{\left\| x(n) \right\|^2} \qquad (8)$$

Where β is a normalized step size with 0< β<2. When x(n) is large, the LMS experiences a problem with gradient noise amplification. With the normalization of the LMS step size by $||x(n)||^2$ in the NLMS, noise amplification problem is diminished.

5. SCOPE OF THE PROPOSED WORK

The work carried out in [1]-[7], [13]-[18], [24] analyzes the removal of noises in ECG and EMG signal using adaptive filter algorithm. An ECG recording requires more number of electrodes on the skin and people may wear it continuously for effective monitoring. EEG measurements are always random in nature. For the complete detection, we need more number of samples for analysis. Also, the mathematical modeling of EMG signals is very complex. Removal of motion artifacts and power line interference from ECG or EMG is complex since it requires more number of electrodes for measurement. From the results in [25], the respiratory signals alone are sufficient and perform even better than ECG, EEG and EMG. In our paper, we consider only the respiratory signal for noise removal since it is more convenient and do not require more number of electrodes on the skin. We studied the performance of various adaptive filter algorithms for the removal of noises in respiratory signal. Autoregressive **(AR)** spectral estimation techniques are known to provide better resolution than classical periodogram methods when short segments of data are selected for analysis. In our study, we adopted the Burg's method to compute AR coefficients. The major advantage of Burg method for estimating the parameters of the AR model are high frequency resolution, stable AR model and it is computationally efficient.

6. SIMULATION RESULTS

This section presents the results of simulation using MATLAB to investigate the performance behaviors of various adaptive filter algorithms in non stationary environment with two step sizes of 0.02 and 0.004. The principle means of comparison is the error cancellation capability of the algorithms which depends on the parameters such as step size, filter length and number of iterations. A synthetically generated motion artifacts and power line interference are added with respiratory signals. It is then removed using adaptive filter algorithms such as LMS, Sign LMS, Sign-Sign LMS, Signed Regressor, BLMS and NLMS. All Simulations presented are averages over 1000 independent runs.

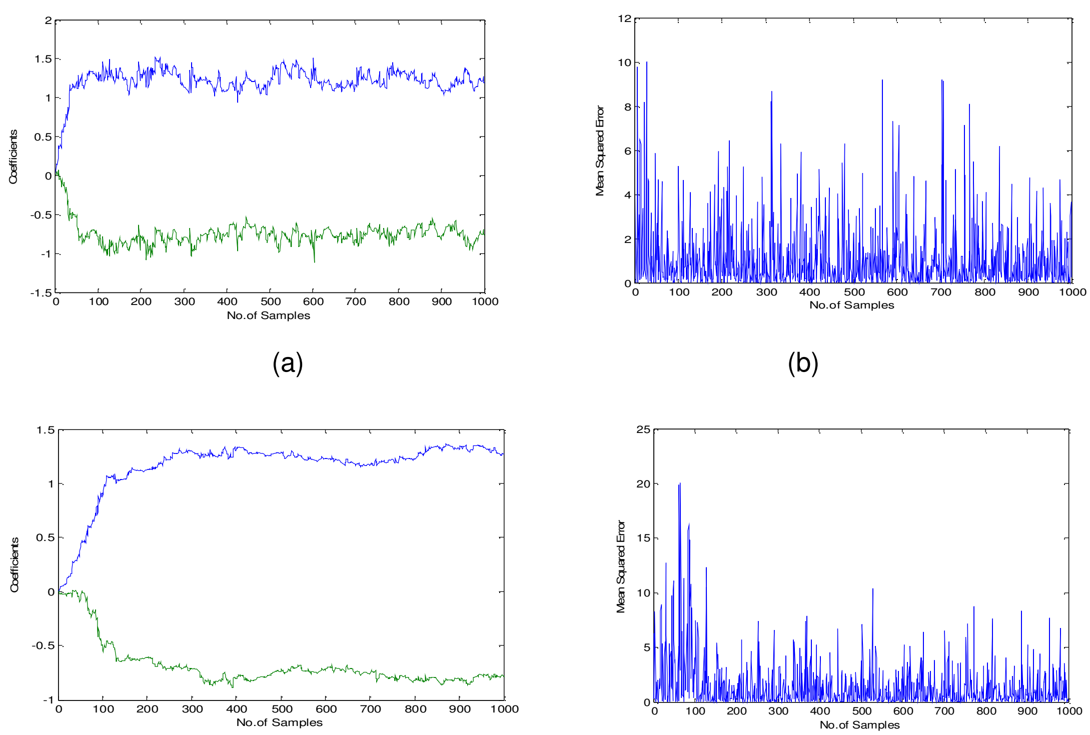
6.1 Removal of Motion Artifacts

Respiratory signal is represented by second-order autoregressive process that is generated according to the difference equation,

$$x(n)=1.2728x(n-1) - 0.81x(n-2) + v(n) \qquad (9)$$

Where v (n) is randomly generated noise.

Figure 2 and Figure 3 shows the convergence of filter coefficients and Mean squared error using LMS and NLMS algorithms. An FIR filter order of 32 and adaptive step size parameter (μ) of 0.02 and 0.004 are used for LMS and modified step sizes (β) of 0.01 and 0.05 for NLMS. It is inferred that the MSE performance is better for NLMS when compared to LMS. The merits of LMS algorithm is less consumption of memory and amount of calculation.



(a) (b)

(c) (d)

FIGURE 2: Performance of LMS adaptive filter. (a),(b) Plot of trajectories of filter coefficients and Squared error for μ=0.02 (c),(d) Plot for μ=0.004

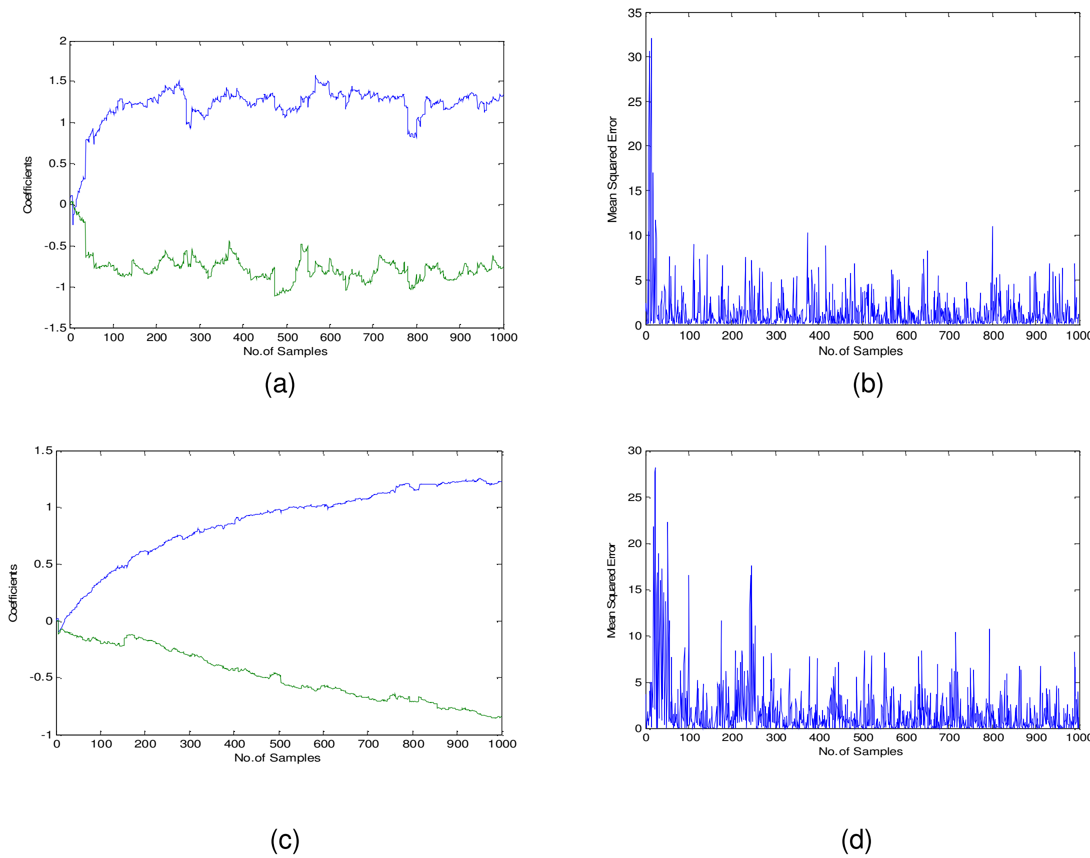


FIGURE 3: Performance of NLMS adaptive filter. (a),(b) Plot of trajectories of filter coefficients and Squared error for μ=0.02 (c),(d) Plot for μ=0.004

6.2 Removal of Power line Interference

A synthetic power line interference of 50 Hz with 1mv amplitude is simulated for PLI cancellation. Power line interference consists of 50Hz pickup and harmonics which can be modeled as sinusoids and combination of sinusoids. Figure 4 shows the generated power line interference.

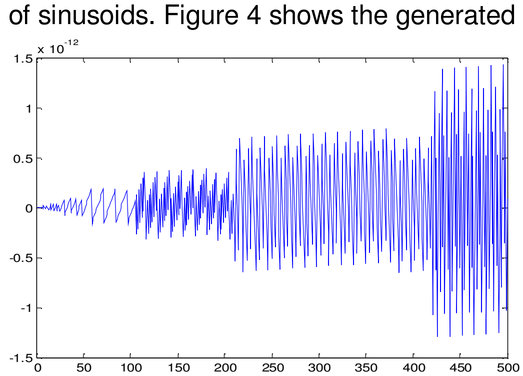


FIGURE 4: Power line interference

The mean square learning curves for various algorithms are depicted as shown in Figure 5. The input x(n) is 0.18Hz sinusoidal respiratory signal. It is observed that minimization of error is better with BLMS compared with other algorithms.

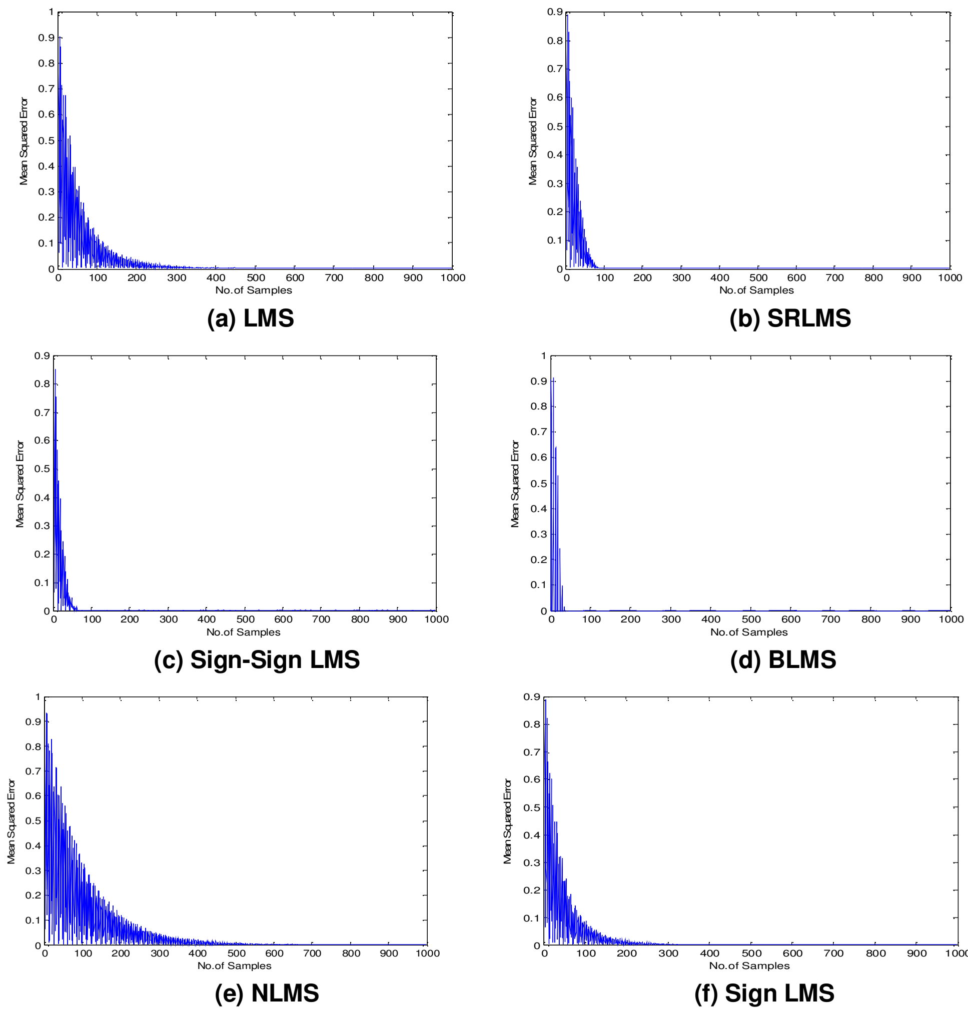


FIGURE 5: Mean Squared Error Curves for various Adaptive filter algorithms

7. COMPARITIVE EVALUATION AND DISCUSSION

Table 1 provides the comparison of mean squared error (MSE) and Convergence rate (C in terms of number of iterations that the filter coefficients converge) of different algorithms. It is observed from Figure 2 and Figure 3, the convergence speed for μ =0.02 is faster than μ=0.004. But MSE performance is comparatively better for μ=0.004 than μ=0.02. Convergence rate of LMS algorithm is better when μ=0.02 and low MSE value when μ=0.004. It is also inferred that the MSE performance of Sign Regressor LMS (SRLMS) at the step size of 0.02 is better when compared to other algorithms. But there is always tradeoff between convergence rate and mean squared error. Hence choosing an algorithm depends on the parameter on which the system has more concern.

Algorithm	μ=0.02		μ=0.004	
	MSE	C	MSE	C
LMS	2.3873e-004	100	5.4907e-005	250
SRLMS	8.5993e-006	100	5.3036e-004	550
SIGN LMS	1.3406e-004	100	4.9436e-005	550
SIGN-SIGN LMS	4.9514e-004	200	8.7072e-004	500
NLMS	β=0.05, 6.8306e-004	100	β=0.01, 0.0012	700

TABLE 1: Comparison of MSE and Convergence Rate

Table 2 shows the comparison of resulting mean square error while eliminating power line interference from respiratory signals using various adaptive filter algorithms with different step sizes. The observed MSE for LMS as shown in Figure 5 (a) is very low for μ =0.02 compared with μ =0.004. The performance of BLMS depends on block length L and NLMS depends on the normalized step size β. Observing all cases, we can infer that choosing μ =0.02 for the removal of power line interference is better when compared to μ =0.004. The step size μ =0.004 can be used unless the convergence speed is a matter of great concern. It is found that the value of MSE also depends on the number of samples taken for analysis. The filter order is 32.

Algorithm	Motion Artifacts		Power line interference	
	μ=0.02	μ=0.004	μ=0.02	μ=0.004
	MSE	MSE	MSE	MSE
LMS	1.5973e-007	2.6776e-005	8.7683e-009	8.8808e-005
BLMS	3.1966e-004	0.0160	3.2675e-004	0.0160
SR LMS	5.3616e-007	2.1528e-007	3.8242e-010	4.8876e-005
SIGN LMS	1.9924e-007	1.2130e-005	2.1145e-007	5.7397e-010
SIGN-SIGN LMS	3.7528e-006	5.5596e-007	1.9290e-007	4.2355e-008
NLMS	β=0.05, 2.1528e-007	β=0.01, 1.0570e-008	β=0.05, 4.7339e-012	β=0.01, 3.6219e-005

TABLE 2: Comparison of MSE in removing motion artifacts and power line interference

From the simulation results, the proposed adaptive filter can support the task of eliminating PLI and motion artifacts with fast numerical convergence. Compared to the results in [23], the mean square value obtained in this work is found to be very low by varying the step sizes and increasing the number of iterations. An FIR filter order of 32 and adaptive step size parameter (μ) of 0.02 and 0.004 are used for LMS and modified step sizes (β) of 0.01 and 0.05 for NLMS. It is inferred that the MSE performance is better for NLMS when compared to LMS. The merits of LMS algorithm is less consumption of memory and amount of calculation. It has been found that there will be always tradeoff between step sizes and Mean square error. It is also observed that the performance depends on the number of samples taken for consideration.

7. CONCLUSION & FUTURE WORK

This study has revealed useful properties of various adaptive filter algorithms. The objective is to optimize different adaptive filter algorithms so that we can reduce the MSE so as to improve the quality of eliminating interference. It is inferred that the MSE performance is better for NLMS when compared to LMS. The merits of LMS algorithm is less consumption of memory and amount of calculation. It has been found that there will be always tradeoff between step sizes and Mean square error. It is also observed that the performance depends on the number of samples taken for consideration. Choosing an algorithm depends on the parameter on which the system has much concern. The future work includes the optimization of algorithms for all kinds of noises and to use the optimized one in the implementation of DSP Microcontroller that estimates the respiratory signal.

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Single-Channel Speech Enhancement by NWNS and EMD

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Abstract

This paper presents the problem of noise reduction from observed speech by means of improving quality and/or intelligibility of the speech using single-channel speech enhancement method. In this study, we propose two approaches for speech enhancement. One is based on traditional Fourier transform using the strategy of Noise Subtraction (NS) that is equivalent to Spectral Subtraction (SS) and the other is based on the Empirical Mode Decomposition (EMD) using the strategy of adaptive thresholding. First of all, the two different methods are implemented individually and observe that, both the methods are noise dependent and capable to enhance speech signal to a certain limit. Moreover, traditional NS generates unwanted residual noise as well. We implement nonlinear weight to eliminate this effect and propose Nonlinear Weighted Noise Subtraction (NWNS) method. In first stage, we estimate the noise and then calculate the Degree Of Noise (DON1) from the ratio of the estimated noise power to the observed speech power in frame basis for different input Signal-to-Noise-Ratio (SNR) of the given speech signal. The noise is not accurately estimated using Minima Value Sequence (MVS). So the noise estimation accuracy is improved by adopting DON1 into MVS. The first stage performs well for wideband stationary noises and performed well over wide range of SNRs. Most of the real world noise is narrowband non-stationary and EMD is a powerful tool for analyzing non-linear and non-stationary signals like speech. EMD decomposes any signals into a finite number of band limited signals called intrinsic mode function (IMFs). Since the IMFs having different noise and speech energy distribution, hence each IMF has a different noise and speech variance.

These variances change for different IMFs. Therefore an adaptive threshold function is used, which is changed with newly computed variances for each IMF. In the adaptive threshold function, adaptation factor is the ratio of the square root of added noise variance to the square root of estimated noise variance. It is experimentally observed that the better speech enhancement performance is achieved for optimum adaptation factor. We tested the speech enhancement performance using only EMD based adaptive thresholding method and obtained the outcome only up to a certain limit. Therefore, further enhancement from the individual one, we propose two-stage processing technique, NWNS+EMD. The first stage is used as a pre-process for noise removal to a certain level resulting first enhanced speech and placed this into second stage for further removal of remaining noise as well as musical noise to obtain final enhancement of the speech. But traditional NS in the first stage produces better output SNR up to 10 dB input SNR. Furthermore, there are musical noise and distortion presented in the enhanced speech based on spectrograms and waveforms analysis and also from informal listening test. We use white, pink and high frequency channel noises in order to show the performance of the proposed NWNS+EMD algorithm.

Keywords: speech enhancement, non linear weighted noise subtraction, degree of noise, empirical mode decomposition, adaptive thresholding.

1. INTRODUCTION

In many speech related systems like mobile communication in an adverse environment, the desired signal is not available directly; rather it is mostly contaminated with some interference sources of noise. These background noise signals degrade the quality and intelligibility of the original speech, resulting in a severe drop in the performance of the applications. The degradation of the speech signal due to the background noise is a severe problem in speech related systems and therefore should be eliminated through speech enhancement algorithms. In our previous study, we have proposed a two stage noise reduction algorithm by noise subtraction and blind source separation [1]. In that report, we recommended further research to improve the algorithm over wide ranges of SNRs as well as noise reduction performance for narrow-band noises.

Research on speech enhancement techniques started more than 40 years ago at AT&T Bell Laboratories by Schroeder as mentioned in [2]. Schroeder proposed an analog implementation of the spectral magnitude subtraction method. Then, the method was modified by Schroeder's colleagues in a published work [3]. However, more than 15 years later, the spectral subtraction method as proposed by Boll [4] is a popular speech enhancement techniques through noise reduction due to its simple underlying concept and its effectiveness in enhancing speech degraded by additive noise. The technique is based on the direct estimation of the short-term spectral magnitude. Recent studies have focused on a non-linear approach to the subtraction procedure [5-7]. In Martin [5] algorithm modifies the short time spectral magnitude of the corrupted speech signal such that the synthesized signal is perceptually as close as possible to the clean speech signal. The estimating noise is obtained as the minima values of a smoothed power estimate of the noisy signal, multiplied by a factor that compensates the bias. The algorithm eliminates the need of speech activity detector by exploiting the short time characteristics of speech signal. Martin's study compared the result with Malah [6], and found an improved SNR. However, this noise estimation is sensitive to outliers, and its variance is about twice as large as the variance of a conventional noise estimator. These approaches have been justified due to the variation of signal-to-noise ratio across the speech spectrum. Unlike white

Gaussian noise, which has a flat spectrum, the spectrum of real-world noise is not flat. Thus, the noise signal does not affect the speech signal uniformly over the whole spectrum. Some frequencies are affected more adversely than others. In high frequency channel noise (HF channel), for instance, in the low frequencies, where most of the speech energy resides, are affected more than the high frequencies. Hence it becomes imperative to estimate a suitable factor that will subtract just the necessary amount of the noise spectrum from each frequency bin (ideally), to prevent destructive subtraction of the speech while removing most of the residual noise. Then it is usually difficult to design a standard algorithm that is able to perform homogeneously across all types of noise. For that, a speech enhancement system is based on certain assumptions and constraints that are typically dependent on the application and the environment.

There are some crucial restrictions of the Fourier spectral analysis [8]: the system must be linear; and the data must be strictly periodic or stationary; otherwise the resulting spectrum will make little physical sense. From this point of view, Fourier filter methods will fail when the processes are nonlinear. The empirical mode decomposition (EMD), proposed by Huang *et.al* [9] as a new and powerful data analysis method for nonlinear and non-stationary signals, has made a new path for speech enhancement research. EMD is a data-adaptive decomposition method, which decompose data into zero mean oscillating components, named as intrinsic mode functions (IMFs). It is mentioned in [10] that most of the noise components of a noisy speech signal are centered on the first three IMFs due to their frequency characteristics. Therefore EMD can be used for effectively identifying and removing these noise components. Xiaojie et. al. [11] proposed EMD that effectively identify and remove noise components. Recently there are many speech enhancement methods [12-14] have been developed in dual-channel and single-channel modes using EMD. In [12] EMD based speech enhancement is achieved by removing those IMFs whose energies exceeded a predefined threshold value. The IMFs, which represent empirically, observed applying EMD in observed speech contaminated with white Gaussian noise generates noise model. In [13] speech enhancement based on EMD-MMSE is performed by filtering the IMFs generated from the decomposition of speech contaminated with white Gaussian noise. In [14], an optimum gain function is estimated for each IMF to suppress residual noise that may be retained after single-channel speech enhancement algorithms.

In our previous study, Hamid [1] proposed noise subtraction (NS) technique where noise is estimated using minimum value sequence (MVS) and the noise floor is updated with the help of estimated degree of noise (DON). The main drawback of this method is that we estimate DON on the basis of pitch period over the frame and the pitch period of unvoiced sections is not accurately estimated. To solve this problem, in this paper, we estimate EDON on the basis of estimated SNRs of clean and noisy speech spectrums. Then, the EDON is estimated in two stages from a function, which is previously prepared as the function of the parameter of the degree of noise [1]. We consider the valleys of the observed smoothed power spectrum of a noisy speech signal to estimate noise power. This spectrum is tuned by EDON to adjust the noise level for a particular SNR. We also perform suitable steps to minimize the residual noise problem. Now the estimated noise spectrum with a controlled non-linear factor is subtracted from the observed spectrum in time domain to obtain noise reduced speech. This paper presents a parametric formulation to estimate noise weight on the basis of EDON. The weighting factor increases with increasing SNRs, and results non-linear weighting factor with speech activity. Although Fourier transform and wavelet analysis make great contributions, they suffer from many shortcomings in case of nonlinear and nonstationary signals. For this reason, for further enhancement, EMD technique has been used for robust noisy speech analysis in this work.

Since the IMFs in EMD having different noise and speech energy distribution, hence each IMF has a different noise and speech variance. These variances change for different IMFs. Therefore an adaptive threshold function is used, which is changed with newly computed variances for each IMF. Moreover, since IMFs are generated from EMD and therefore, we call the proposed method as EMD based adaptive thresholding technique. To enhance the speech, EMD based adaptive thresholding algorithm applied into each IMFs for removing the noise embedded in the underlying

IMFs. In the adaptive threshold function, adaptation factor is the ratio of the square root of added noise variance to the square root of estimated noise variance. It is experimentally observed that the better speech enhancement performance is achieved for optimum adaptation factor. We tested the speech enhancement performance using only EMD based adaptive thresholding method and obtained the outcome only up to a certain limit. Moreover, each individual method has some performance limitations.

Therefore, further enhancement from the individual one, we propose two-stage processing technique, namely, a time domain NS or NWNS followed by an EMD based adaptive thresholding. The first stage is used as a pre-process for noise removal to a certain level resulting first enhanced speech and placed this into second stage for further removal of remaining noise as well as musical noise to obtain final enhancement of the speech. But traditional NS in the first stage produces better output SNR up to 10 dB input SNR. Furthermore, there are musical noise and distortion presented in the enhanced speech based on spectrograms and waveforms analysis and also from informal listening test. EMD based adaptive thresholding does not work well on distorted speech and not be able to recover the speech from the distorting speech when it cascaded with NS. As a result, the overall performance of enhanced speech obtained from NS+EMD based adaptive thresholding is not so good based on the objective and subjective measures. In the first stage, the performance of speech enhancement improves by introducing nonlinear weight in NS, namely NWNS, to control the noise level and improves its overall performance for wide range of input SNRs provide first enhanced speech without distortion and with minimum effect of musical noise. Moreover, the overall performance is further improved by cascading NWNS in the first stage and EMD based adaptive thresholding in the second stage. In this two-stage processing, NWNS is influenced to increase the performance of EMD based adaptive thresholding. The advantage of the method is the effective removal of noise and produces better output SNR for wide range of input SNR and also improves the speech quality with reducing residual noise.

2. NOISE ESTIMATION AND SUBTRACTION

The main component of speech noise reduction is noise estimation that is a most difficult task for a single-channel enhancement system. The noise estimate can have a major impact on the quality of the enhanced speech. That is, with a better noise estimation, a more correct SNR is obtained, resulting in the enhanced speech with low distortion. We have assumed that speech and noise are uncorrelated to each other. We further assume that signal and noise are statistically independent.

2.1 Estimating Minimum Value Sequence (MVS)

The sections of consecutive samples are used as a single frame l(320 samples) and spaced l'(100 samples) achieving an almost 62.75% overlap. The short-term representation of a signal $y(n)$ is obtained by Hamming windowing and analyzed using N=512 point Discrete-Fourier transform (DFT) at sampling frequency 16KHz. Initially, noise spectrum is estimated from the valleys of the amplitude spectrum [1]. The algorithm for noise estimation is as follows:

Compute the RMS value Y_{rms} of the amplitude spectrum $Y(k)$. We detect the minima of $Y(k)$ by obtaining the vector k_{min} such that $Y(k_{min})$ are the minima in $Y(k)$. Then the interpolation is performed between adjoining minima positions to obtain $Y_{min}(k)$ representing the minimum value sequences (MVS). We smooth the sequences by taking partial average called smoothed minimum value sequences (SMVS). An estimation of noise from the SMVS is survived by an overestimation and underestimation of the SNR which is controlled by proposed EDON. The block diagram of the noise estimation process is shown in Figure 1.

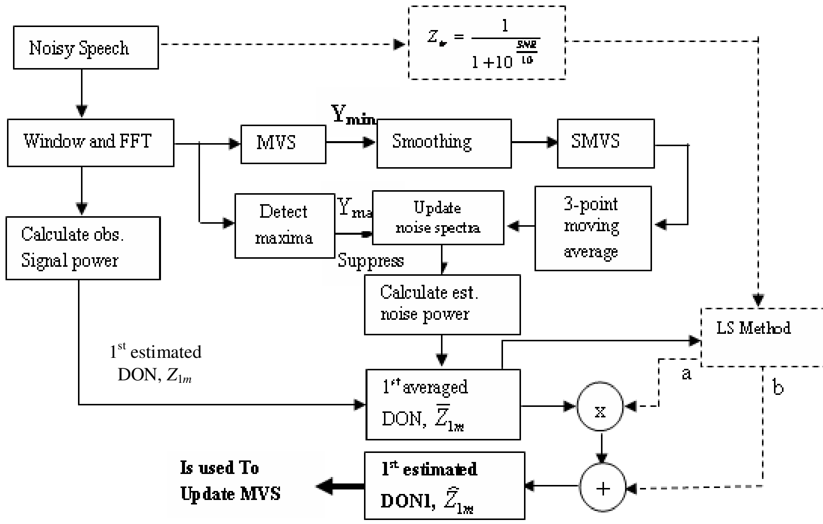

FIGURE 1: Block diagram of the 1st estimated DON, Z_{1m}.

2.2 Estimation of the Degree Of Noise (EDON)

In a single-channel method, we only know the power of the observed signal. To obtain EDON, we estimate noise of the observed signal in every analysis frame *m*. First white noise of various SNR is added to voiced vowel sounds. Now for each SNR, DON of each phoneme is estimated and averaged which corresponds the input SNR. Then each of these estimated 1st averaged DONs of each frame *m* for corresponding input SNR expressed as $\overline{Z}_{1m}$. The estimated $\overline{Z}_{1m}$ is aligned with the true DON (Z_{tr}) using the least-square (LS) method results the 1st estimated DON $Z_{1m}$of that frame. The true DON (Z_{tr}) is given by

$$Z_{tr} = \frac{P_d}{P_s + P_d} = \frac{1}{1 + 10^{\frac{dB}{10}}} \qquad (1)$$

where *dB* is input SNR. The 1st averaged DON is

$$\overline{Z}_{1m} = \frac{1}{M} \sum_{m=1}^{M} \frac{P_\eta(m)}{P_{obs}(m)} \qquad (2)$$

where, *M* are the noise added frames; $P_\eta(m)$and $P_{obs}(m)$ are the powers of noise and observed signals, respectively. Here it obvious that we consider only the voiced phonemes in our experiment. So the value of $\overline{Z}_{1m}$should be limited to voiced portion of a speech sentence. We used the same experiment with unvoiced speech. Practically the unvoiced portion contaminated with higher degree of noise. Hence the estimated noise is higher for unvoiced frame than from voiced frame. Consequently higher DON value is obtained from unvoiced frame than from voiced frame that is logically resemblance. The degree of noise estimated from a function using least square method is given as

$$Z_{tr} = a \times \overline{Z}_{1m} + b$$

here *a* and *b* are unknown. We estimate *a* and *b* via LS method, yielding $\overline{a}$ and $\overline{b}$and the estimated degree of noise is given by

$$Z_{1m} = \overline{a} \times \overline{Z}_{1m} + \overline{b} \qquad (3)$$

where Z_{1m} is the 1st estimated DON of frame *m*. The value os Z_{1m} is applied to update the MVS. Next, the noise level is re-estimated and updated with the help of Z_{1m}. Finally, from the estimated noise, we again estimate 2nd averaged DON ($\bar{Z}_{2m}$) and similarly the 2nd estimated DON (Z_{2m}) which is used to estimate the noise weight for non linear weighted noise subtraction.

2.3 Noise Spectrum Estimation

We detect the minima $Y_{\min}(k_{\min}) \leftarrow \min(Y(k))$ values of amplitude spectrum Y(*k*) when the following condition (Y(*k*)<Y(*k*-1) and Y(*k*)<Y(*k*+1) and Y(*k*)<Y_{rms}) is satisfied. The $k_{\min}$ expresses the positions of the frequency bin index of minima values. Then interpolate between adjoining minima positions $(k_{\min} \leftarrow k)$ to obtain the minima value sequence (MVS) $Y_{\min}(k)$. Now we smooth the sequences by taking partial average called smoothed minima value sequence (SMVS). This process continuously updates the estimation of noise among every analysis frames. Now the noise spectrum is estimated from the SMVS and 1st estimated DON according to the condition

$$D_m(k) = Y_{\min}(k) + \left(\sqrt{Z_{1m}} \times Y_{rms}\right) \tag{4}$$

where Y_{rms} is the rms value of the amplitude spectrum. Then we made some updates of $D_m(k)$, the updated spectrum is again smoothed by three point moving average, and lastly the main maximum of the spectrum is identified and are suppressed [1]. Figure 2 shows the spectrums.

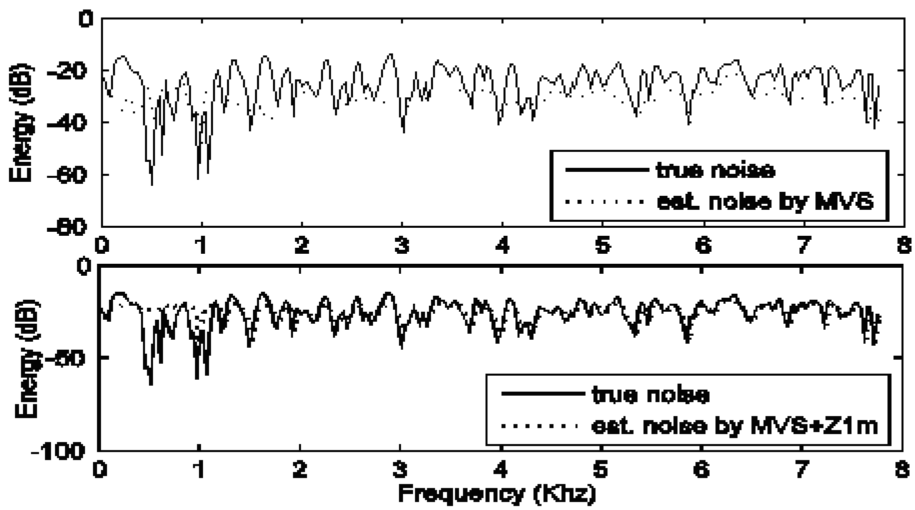

FIGURE 2: Noise spectrums (true and estimated).

2.4 Non-linear Weighted Noise Subtraction (NWNS)

Noise reduction in the front-end is based on implementation of the traditional spectral subtraction (SS) require an available estimation of the embedded noise, here, in time domain we named noise subtraction (NS). The goal of this section is to modify the noise subtraction process by adopting a non linear weight for minimizing the effect of residual noise in the processed speech and then to improve the performance by using EMD.

For subtraction in time domain, the estimated noise in the previous section is recombined with the phase of the noisy speech and inverse transformed one. Then we obtain $\hat{d}_{ss}(n)$ by withdrawing the effect of the window. The NWNS is given by:

$$s_1(n) = y(n) - \sqrt{\alpha \times Z_{tr}} \times \hat{d}_{ss}(n) \tag{5}$$

where $\alpha = 0.3019 + 6.4021 \times Z_{2m} - 14.109 \times Z_{2m}^2 + 9.8273 \times Z_{2m}^3$ is nonlinear weighting factor. We use least-square method for the estimation process. We find that for each input SNR, certain weight is required for best noise reduction results over wide ranges of SNR. In this experiment, we used 7 male and 7 female speakers of 10 different sentences at different SNR levels, randomly selected from the TIMIT database. We use 3rd degree polynomials to derive the above formulation. It is observed from Eq. (1) that it needs the input SNR. The input SNR can be estimated using variance is given by

$$SNR_{input} = 10 \log_{10} \left(\frac{\sigma_s^2}{\sigma_\eta^2} \right) \tag{6}$$

where, σ_s^2 and σ_η^2 are the variances of speech and noise respectively. We assume that due to the independency of noise and speech, the variance of the noisy speech is equal to the sum of the speech variance and noise variance. It is found that by adopting nonlinear weighted in NS, a good noise reduction is obtained. Although with the NWNS, we find the good performance with less musical noise by informal listening test but for further enhancement we cascade another method EMD and get better results.

3. CASCADE OF NWNS AND EMD

The general block diagram of the proposed system is shown in Figure 3. In the block diagram, first stage is incorporated a Noise Subtraction (NS) method with weight and second stage a Empirical Mode Decomposition (EMD) based adaptive thresholding method.

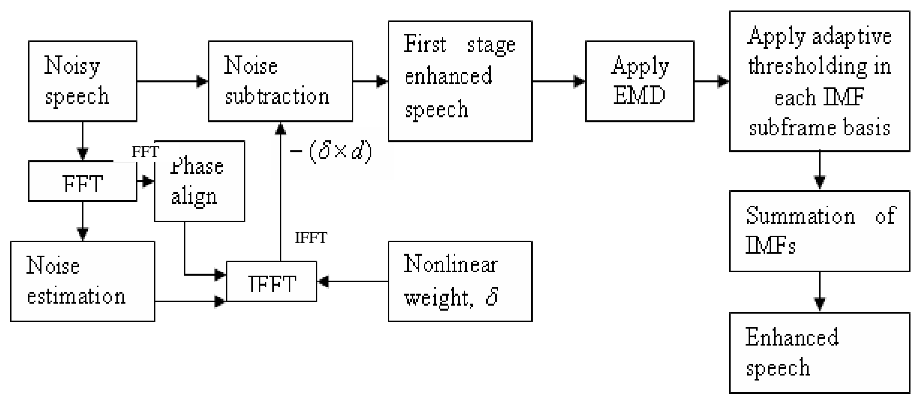

FIGURE 3: The block diagram of the two-stage NWNS+EMD method.

3.1 Empirical Mode Decomposition (EMD)

The principle of EMD technique is to decompose any signal $y(n)$ into a set of band-limited functions, which are the zero mean oscillating components, called simply the intrinsic mode functions (IMFs) [9]. Although a mathematical model has not been developed yet, different methods for computing EMD have been proposed after its introduction [15]. The very first algorithm, called as the sifting process, is adopted here to find the IMF's include the following steps;

1. Identify the extrema of y(n)
2. Generate the upper and lower envelopes ($u(n)$ and $l(n)$) by connecting the maxima and minima points by interpolation
3. Calculate the local mean $\mu_1(n)=[u(n)+l(n)]/2$
4. Since IMF should have zero local mean, subtract out $\mu_1(n)$ from $y(t)$ to obtain $h_1(t)$
5. Check whether $h_1(t)$ is an IMF or not
6. If not, use $h_1(t)$ as the new data and repeat steps 1 to 6 until ending up with an IMF.

Once the first IMF is derived, we should continue with finding the remaining IMFs. For this purpose, we should subtract the first IMF $c_1(n)$ from the original data to get the residue signal $r_1(t)$. The residue now contains the information about the components of longer periods. We should treat this as the new data and repeat the steps 1 to 6 until we find the second IMF.

3.2 Soft-thresholding

The soft thresholding strategy proposed in [16] for a frame, *m* of length *L* in transform-domain as

$$\widehat{Y}_q = \begin{cases} Y_q, & if \quad \phi \geq \sigma_n^2 \\ sign(Y_q)\left[\max\{0, (|Y_q| - j\gamma)\}\right], & otherwwise \end{cases} \tag{7}$$

where $\phi = \frac{1}{L}\sum_{q=1}^{L}|Y_q|^2$ denotes the average power of the frame, and σ_n^2 is the global noise variance of the speech, Y_q is *q*th coefficient of the frame obtained by the required transformation and $\widehat{Y}_q$ denotes to the thresholded samples of the frame. The multiplication factor $j\gamma$ is the linear threshold function while *j* being the sorted index-number of $|Y_q|$. An estimated value of γ can be obtained as:

$$\gamma = \frac{\lambda\sigma_n}{\sqrt{\frac{1}{Q}\sum_{q=1}^{Q} q^2}} \tag{8}$$

where λ is an adaptation factor and its value is determined experimentally such that $0<\lambda<1$. It is observed that the first part of Eq. (7) is for signal dominant frame when the condition satisfies, and second part is for noise dominant frame where soft thresholding will have to apply. So the classification of frames either to be signal dominant or noise dominant depends on average power of a frame and global noise variance of the given noisy speech. In this paper, we apply this soft thresholding strategy adaptively in each IMF, as discuss in the next section.

3.3 Adaptive thresholding

Soft thresholding strategy performs better on wide range of input SNR due to thresholded noise dominant frames only and kept remain the same in case of signal dominant frames but the misclassification of frames is a major drawback that causes musical noise [9]. Therefore this method is mainly appropriate for white noise. All the drawbacks can be significantly reduced with the proposed EMD based adaptive thresholding strategy with some modification of frame classification criteria. Since the IMFs will have different noise and speech energy distribution, so it suggests that each IMF will have a different noise and speech variance. After applying EMD, the soft thresholding technique is applied on each sub-frame of each IMF based on the computed variances. It is obvious that the variances will be changed for different sub-frames as well as with the individual IMF. The threshold will also be changed with newly computed variances and hence this technique is termed as adaptive thresholding. The proposed EMD based adaptive thresholding strategy for r^{th} subframe of $(i')^{th}$ IMF as:

$$\hat{Y}_{q,i'}^{(r)} = \begin{cases} Y_{q,i'}^{(r)}, & if\, \varphi_{i'}^{(r)} \geq 2\sigma_{n,i'}^2 \\ sign(Y_{q,i'}^{(r)})\left[\max\{0, (|Y_{q,i'}^{(r)}| - j'\hat{\gamma})\}\right], & otherwise \end{cases} \tag{9}$$

Here, $\hat{Y}_{q,i'}^{(r)}$ denotes to the thresholded samples of r^{th} subframe of the $(i')^{th}$ IMF, $Y_{q,i'}^{(r)}$ is q^{th} coefficient of r^{th} subframe of $(i')^{th}$ IMF and the multiplication $j'\hat{\gamma}$ is the adaptive threshold function while j' being the sorted index-number of $|Y_{q,i'}^{(r)}|$. The threshold factor $\hat{\gamma}$ is varied adaptively for individual IMF according to its variance. An estimated value of $\hat{\gamma}$ can be obtained as:

$$\hat{\gamma} = \frac{\sigma_{-n,i'}}{\sqrt{\frac{1}{Q}\sum_{q=1}^{Q} q^2}} \quad \text{or,} \quad \hat{\gamma} = \frac{\lambda\sigma_{n,i'}}{\sqrt{\frac{1}{Q}\sum_{q=1}^{Q} q^2}}$$

where, $Q = 64$, $\sigma_{-n,i'} = \lambda\sigma_{n,i'}$, $\lambda =$ adaptation factor and $\sigma^2_{n,i'} =$ noise variance of the $(i')^{th}$ IMF. Since global noise variance is estimated from silent frames, therefore, it assumes each frame as well as subframe belong that variance. That is why; the boundary for the classification of subframes should be set to two times of the globally estimated noise variance when noise variance and speech variance of that subframe are same. The enhanced speech signal of the EMD based adaptive thresholding is given by

$$s_2(n) = \sum_{i'=1}^{I}\left[\sum_{r=1}^{R}\left(\sum_{q=1}^{Q}\hat{Y}^{(r)}_{q,i'}\right)\right] \tag{10}$$

where, I=total number of IMFs,
R=total number of subframe and
Q=length of a subframe.

4. EXPERIMENTAL RESULTS AND DISCUSSION

We study the effectiveness of the proposed NWNS+EMD based adaptive thresholding algorithm are tested on the speech data corrupted by three different types of additive noise like white, pink and HF channel noise are taken from NOISEX database. N=56320 samples of the clean speech /she had your dark suit in greasy wash water all year/ from TIMIT database were used for all simulations. The noises are added to the clean speeches at different SNRs from –10dB to 30dB of step 5 to obtain noisy speech signals.

For evaluating the performance of the method, we are used the overall output and average segmental SNRs that are graphically represented as for measuring objective speech quality. The results of the average output SNR obtained from for white noise, pink noise and HF channel noise at various SNR levels are given in Table 1 for pre-processed speech in the first stage and final enhanced speech in the second stage respectively. Since in the real world environments, the noise power is sometimes equal to or greater than the signal power or the noise spectral characteristics sometimes change rapidly with time, NS or NWNS is not so effective in such situations. Because, there have to introduced large errors in the noise estimation process. EMD based adaptive thresholding method plays a vital role for the above case as found in Table 1. Table 2 presents a comparison the overall average output SNR among our previous method WNS and WNS+BSS with proposed method NWNS+EMD.

Input SNR	White noise		HF channel noise		Pink noise	
	NWNS	EMD	NWNS	EMD	NWNS	EMD
-10dB	-1.57	2.06	-7.47	-0.58	-7.06	-6.69
-5dB	2.39	5.69	-2.66	3.03	-2.32	-1.92
0dB	5.26	8.85	1.91	6.29	2.14	2.82
5dB	8.66	11.94	6.42	9.74	6.33	7.22
10dB	11.64	15.15	10.77	13.46	10.73	11.71
15dB	15.77	18.72	15.42	17.42	15.40	16.26
20dB	20.37	22.62	20.22	21.64	20.22	20.91
25dB	25.17	26.85	25.11	26.12	25.11	25.64
30dB	30.05	31.27	30.02	30.77	30.02	30.44

TABLE 1: The average output SNR for various types of noises at different input SNR by NWNS and NWNS+EMD (indicated as EMD).

Input SNR	White noise			HF channel noise			Pink noise		
	WNS	WNS+BSS	EMD	WNS	WNS+BSS	EMD	WNS	WNS+BSS	EMD
0dB	0.66	8.1	8.9	0.4	4.3	6.3	0.4	2.1	2.8
5dB	6.0	10.2	11.9	5.5	7.8	9.7	5.5	6.8	7.2
10dB	11.1	11.2	15.2	10.5	10.9	13.5	10.4	10.2	11.7
15dB	15.7	13.8	18.7	15.1	13.1	17.4	15.0	13.2	16.3
20dB	19.2	15.2	22.6	18.6	14.9	21.6	18.8	15.1	10.1
25dB	21.3	15.7	26.9	20.8	15.7	26.1	21.4	15.8	25.6
30dB	22.3	16.0	31.3	21.8	15.8	30.8	22.7	16.1	30.5

TABLE 2: The average output SNR for various types of noises at different input SNR by WNS, WNS+BSS (previous methods) and NWNS+EMD (indicated as EMD).

In terms of speech quality and intelligibility, the proposed two-stage (NWNS+EMD based adaptive thresholding method has to given a better tradeoff between noise reduction and speech distortion. We investigate this effect from the enhanced speech waveforms obtained from various methods as shown in Figure 4. It is observed from the waveforms that the enhanced speech is distorted in low voiced parts due to remove the noise in NS method whereas NWNS does not. A little amount of noise is removed from the corrupted speech by NWNS method. So in NS method there is a loss of speech intelligibility while NWNS maintains it. Although the EMD based adaptive thresholding can be able to successfully remove the noise from voiced parts but there is some noise remaining in the silent parts because of misclassification of subframes as signal-dominant. This remedy can be avoided using the proposed method. We also observed that by NS+EMD based adaptive thresholding method, there is loss of information in lower voiced parts and as a result speech intelligibility reduced. Moreover, the wavefrom obtained by NWNS+EMD based adaptive thresholding, it can be seen that there is no loss of information in lower voiced parts and maintains the speech intelligibility. We use two perceptually motivated objective speech quality assessments, namely the average segmental SNR (ASEGSNR) and the Perceptual Evaluation of Speech Quality (PESQ) to study the effectiveness of the proposed method. In Figures 5 and 6, it is observed that our proposed NWNS+EMD based adaptive thresholding approach achieve comparable improvements of speech quality. The PESQ scores of the speech at –10dB and –5dB (pink and HF channel noise) are almost equal to input PESQ scores. This is due to the presence of musical noise in first stage

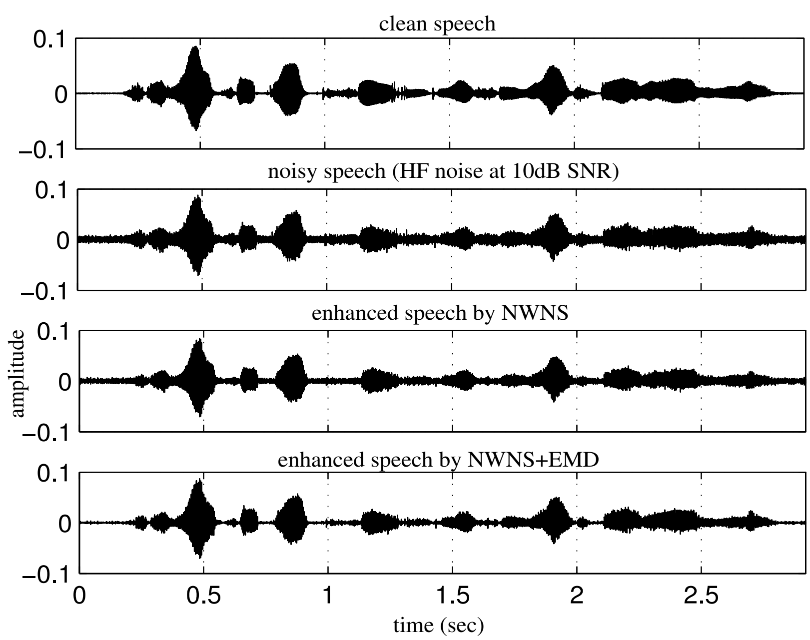

FIGURE 4: Speech waveforms of (from top) clean, noisy (HF noise at 10dB), enhanced by NWNS and NWNS+EMD.

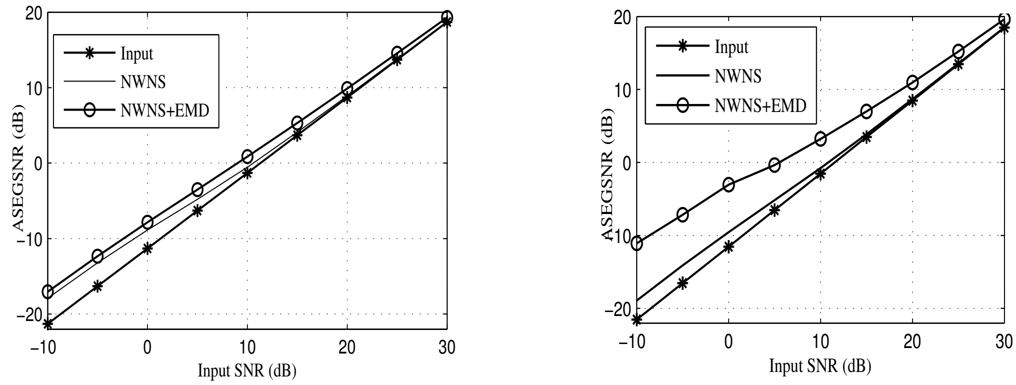

FIGURE 5: Comparisons of the average output segmental SNR (ASEGSNR) by NWNS and NWNS+EMD methods for pink noise (left) and HF channel noise (right).

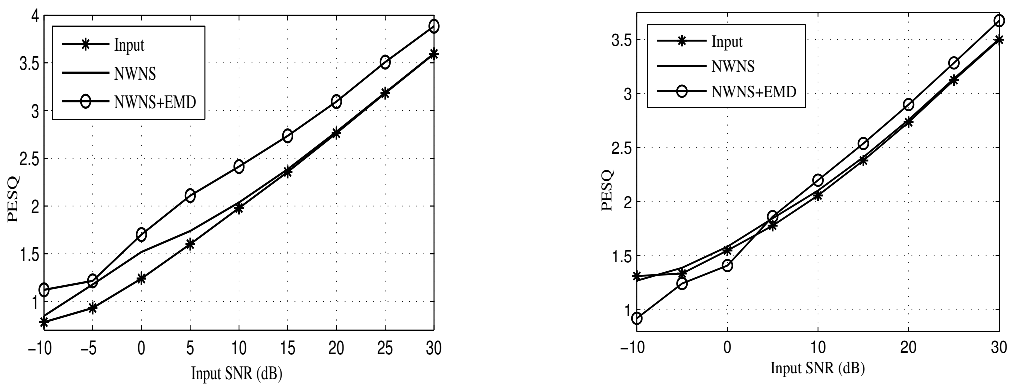

FIGURE 6: Comparison of PESQ scores by NWNS and NWNS+EMD methods for pink noise (left) and HF channel noise (right).

5. CONCLUSION & FUTURE WORK

In this paper, we presented a new algorithm to effectively remove the noise components in all frequency levels of a noisy speech signal. Our aimed to improve SNR of noise contaminated speech by removing and/or reducing noise using a two-stage processing technique; namely, a time domain nonlinear weighted noise subtraction (NWNS) followed by an Empirical Mode Decomposition (EMD) based adaptive thresholding. The first enhanced speech became as input of the second stage for further enhancement and obtained final enhanced speech after second stage processing. We introduced the degree of noise (DON1 and DON2) estimation process. DON1 was used to improve noise estimation accuracy and DON2 to calculate nonlinear weighting factor for NWNS in order to reduce musical noise. The parameters of DON1 and DON2 were estimated for white noise and we used the same parameters for all color/real world noises. Since the empirical mode decomposition (EMD) was fully data adaptive and highly effective for nonlinear and nonstationary data, it overcame inadequacy effect of the first stage for assumption as stationary of nonstationary speech segment. We combined NWNS+EMD based adaptive thresholding enhancement algorithm which worked most efficiently for wide range of input SNR. It was found that the amount of this improvement decreased when the interfering source power was minimal. This was because the algorithm was dependent upon the interfering noise signal estimation in the first stage and also dependent upon the adaptation factor and adaptive threshold factor in the second stage. When the interfering noise power was increased (up to 0dB), the proposed methods were able to perform better noise estimation. However, as the interfering noise power became much larger, as was true for extremely small SNR’s (<0dB), the algorithm did not perform well in the case of color noises due to the inability of the method to obtain an adequate estimate of the original signal. The performance of the proposed method over speech contaminating with white noise or color noise was good based on objective measures and spectrograms and waveforms analysis.

Since in single channel speech enhancement method, there was difficulty removing all the noise components from speech without introducing musical noises or distortions, hence in this regard further research can be conducted to increase the accuracy of noise estimation (DON1) and also the more adjustment needed of the nonlinear weight (DON2) for voiced/unvoiced sections for underlying noisy speech to reduce musical noise and to improve speech quality. All EMD based algorithm suffers from computational complexity and the empirical process takes long time and is not applicable for real time processing. Therefore, it is suggested that more research can be conducted on insight the EMD making it less empirical and more mathematical.

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Consistent Nonparametric Spectrum Estimation Via Cepstrum Thresholding

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Abstract

For stationary signals, there are number of power spectral density estimation techniques. The main problem of power spectral density (PSD) estimation methods is high variance. Consistent estimates may be obtained by suitable processing of the empirical spectrum estimates (periodogram). This may be done using window functions. These methods all require the choice of a certain resolution parameters called bandwidth. Various techniques produce estimates that have a good overall bias Vs variance tradeoff. In contrast, smooth components of this spectral required a wide bandwidth in order to achieve a significant noise reduction. In this paper, we explore the concept of cepstrum for non parametric spectral estimation. The method developed here is based on cepstrum thresholding for smoothed non parametric spectral estimation. The algorithm for Consistent Minimum Variance Unbiased Spectral estimator is developed and implemented, which produces good results for Broadband and Narrowband signals.

Keywords: Cepstrum, Consistency, Cramer Rao Lower Bound, Unbiasedness.

1. INTRODUCTION

The main objective of spectrum estimation is the determination of the Power Spectral density (PSD) of a random process. The estimated PSD provides information about the structure of the random process, which can be used for modeling, prediction, or filtering of the deserved process. Digital Signal Processing (DSP) Techniques have been widely used in estimation of power spectrum. Many of the phenomena that occur in nature are best characterized statistically in terms of averages [20].

Power spectrum estimation methods are classified as parametric and non-parametric. Former one a model for the signal generation may be constructed with a number of parameters that can be estimated from the observed data. From the model and the estimated parameters, we can compute the power density spectrum implied by the model. On the other hand, do not assume any specific parametric model of the PSD. They are based on the estimate of autocorrelation sequence of random process from the observed data. The PSD estimation is based on the assumption that the observed samples are wide sense stationary with zero mean. Traditionally four techniques are used to estimate non parametric spectrum such as Periodogram, Bartlett method (Averaging periodogram), Welch method (Averaging modified periodogram) and Blackman-Tukey method (smoothing periodogram) [18] and [19].

2. CEPSTRUM ANALYSIS

The cepstrum of a signal is defined as the Inverse Fourier Transform of the logarithm of the Periodogram. The cepstrum of $\{y(t)_{t=0}^{t=N-1}\}$ can be defined as [7],[8] and [13]

$$c_k = \frac{1}{N}\sum_{p=0}^{N-1}\ln(\phi_p)e^{j\omega_k p}\ ; k = 0,......N-1 \tag{1}$$

Consider a stationary, discrete-time, real valued signal $\{y(t)_{t=0}^{t=N-1}\}$, the Periodogram estimate is given by

$$\hat{\phi}_p = \frac{1}{N}\left|\sum_{t=0}^{N-1} y(t)e^{-j2\pi ft}\right|^2 \tag{2}$$

A commonly used cepstrum estimate is obtained by replacing ϕ_p with the periodogram $\hat{\phi}_p$.

$$\hat{c}_k = \frac{1}{N}\sum_{p=0}^{N-1}\ln(\hat{\phi}_p)e^{j\omega_k p}\ ; \quad k = 0,......, N-1 \tag{3}$$

to make unbiased estimate the cepstrum coefficients only at origin is modified, remaining are unchanged.

$$\begin{cases} \bar{c}_0 = \hat{c}_0 + 0.577126 \\ \bar{c}_k = \hat{c}_k \qquad k = 1,......N/2 \end{cases} \tag{4}$$

In this approach, we smooth $\left\{\ln \hat{\phi}_p\right\}$ by thresholding the estimated cepstrum $\{\bar{c}_k\}$, not by direct averaging of the values of $\left\{\ln \hat{\phi}_p\right\}$. The following test can be used to infer whether c_k is likely to be equal or close to zero and, there fore, whether $\overline{c_k}$ should be truncated to zero [9]-[12].

$$\tilde{c}_k = \begin{cases} 0 & if\left|\bar{c}_k\right| \le \dfrac{\mu\pi}{(d_k N)^{1/2}} \\ \bar{c}_k & else \end{cases} \tag{5}$$

The spectral estimate corresponding to $\{\tilde{c}_k\}$ is given by

$$\tilde{\phi}_p = \exp\left[\sum_{k=0}^{N-1}\tilde{c}_k e^{-j\omega_p k}\right]; \quad p = 0,........N-1 \tag{6}$$

The proposed non parametric spectral estimate is obtained from $\tilde{\phi}_p$ by a simple scaling

$$\hat{\hat{\phi}}_p = \hat{\alpha}\tilde{\phi}_p,\ p = 0,.....N-1 \tag{7}$$

where $\hat{\alpha} = \dfrac{\sum_{p=0}^{N-1} \hat{\phi}_p \tilde{\phi}_p}{\sum_{p=0}^{N-1} \tilde{\phi}_p^{\,2}}$; $\hat{\alpha}$ *isa scalingfactor*

Statistics of log periodogram

The mean and variance of the kth component of the log periodogram of the signal, $\log\left|\overline{Y}_k\right|^2$, assuming that the spectral component $\overline{Y}_k$ is Gaussian, are, respectively, given by [1]-[6],

$$E\{\log\left|\overline{Y}_k\right|^2\} = \begin{cases} \log(\lambda_{Y_k}) - \gamma - \log 2 & k = 0, K/2 \\ \log(\lambda_{Y_k}) - \gamma & k = 1, \ldots\ldots\ldots K/2-1 \end{cases} \tag{8}$$

where $\gamma = 0.57721566490$ is the Euler constant, and

$$\operatorname{var}(\log\left|\overline{Y}_k\right|^2) = \begin{cases} \sum_{n=1}^{\infty} \dfrac{n!}{(0.5)_n} \dfrac{1}{n^2} & k = 0, K/2 \\ \sum_{n=1}^{\infty} \dfrac{1}{n^2} & k = 1, \ldots. K/2-1 \end{cases} \tag{9}$$

where $(a)_n \cong 1.a.(a+1).(a+2)\ldots\ldots..(a+n-1)$. Furthermore,

$$\sum_{n=1}^{\infty} \frac{n!}{(0.5)_n} \frac{1}{n^2} = \frac{\pi^2}{2}; \ \sum_{n=1}^{\infty} \frac{1}{n^2} = \frac{\pi^2}{6};$$

Note from (8) that the expected value of the kth component of the log-periodogram equals the logarithm of the expected value of the periodogram plus some constant. This surprising linear property of the expected value operator is of course a result of the Gaussian model assumed here. From (9) the variance of the kth log-periodogram component of the signal is given by the constant.

Statistics of Cepstrum

The mean of the cepstral component of the signal is obtained from (8) and is given by [1], [2] and [7]

$$E\{c_y(n)\} = \frac{1}{K} \sum_{k=0}^{K-1} \log(\lambda_{Y\,k}) \exp\{ j \frac{2\pi}{K} kn\} - \frac{1}{K} \xi_n \tag{10}$$

where $\xi_n = \begin{cases} 2\log 2, \ \mathit{if}\ n = 0 \ \mathit{or}\, n \ \mathit{even} \\ 0, \ \mathit{if}\ \ n \ \mathit{odd} \end{cases}$

the variance of the cepstral components is obtained from (9) and given by for $n = 0, \ldots\ldots\ldots..K/2$

$$\begin{aligned} \operatorname{var}(c_y(n)) &= \operatorname{cov}(c_y(n), c_y(n)) \\ &= \begin{cases} \dfrac{2}{K} k_1 + \dfrac{2}{K^2}(k_0 - 2k_1), \ \mathit{if}\ n = 0, \dfrac{K}{2} \\ \dfrac{1}{K} k_1 + \dfrac{2}{K^2}(k_0 - 2k_1), \ \mathit{if}\ 0 < n < \dfrac{K}{2} \end{cases} \end{aligned} \tag{11}$$

and for $n, m = 0, 1, \ldots\ldots\ldots.., K/2, n \neq m$

$$\operatorname{cov}(c_y(n), c_y(m)) = \begin{cases} \frac{2}{K^2}(k_0 - 2k_1) & if\ n-m = \pm 2, \pm 4, \ldots\ldots\ldots \pm \frac{K}{2} \\ 0, & otherwise \end{cases} \tag{12}$$

where $k_0 = \frac{\pi^2}{2}$; $k_1 = \frac{\pi^2}{6}$

The covariance matrix of cepstral components of the signal, assuming the spectral components of the signal are statistically independent complex Gaussian random variables. The covariance matrix of cepstral components given by (11) and (12) is independent of the underlying power spectral density which characterizes the signal under the Gaussian assumption. The covariance of cepstral components under the Gaussian assumption is a fixed signal independent matrix that approaches, for large K a diagonal matrix given by

$$\operatorname{cov}(c_y(n), c_y(m)) = \begin{cases} \frac{1}{K}\frac{\pi^2}{3}, & if\ n = m = 0, \frac{K}{2} \\ \frac{1}{K}\frac{\pi^2}{6}, & if\ 0 < n = m < \frac{K}{2} \\ 0, & otherwise \end{cases} \tag{13}$$

Cepstrum algorithm

1. Let a stationary, discrete-time, real valued signal $\{ y(t)_{t=0}^{t=N-1} \}$
2. Compute the periodogram estimate of ϕ_p using FFT.

$$\hat{\phi}_p(\omega) = \frac{1}{N} \left| \sum_{t=0}^{N-1} y(t) e^{-j\omega t} \right|^2$$

3. First apply natural logarithm and take IFFT to compute the cepstrum estimate.

$$\hat{c}_k = \frac{1}{N} \sum_{p=0}^{N-1} \ln(\hat{\phi}_p) e^{j\omega_k p}; \quad k = 0, \ldots\ldots, N-1$$

4. Compute the threshold by choosing the appropriate value of μ depending on the type of signal and determine the cepstral coefficients

$$\tilde{c}_k = \begin{cases} 0 & if |\bar{c}_k| \le \frac{\mu\pi}{(d_k N)^{1/2}} \\ \bar{c}_k & else \end{cases}$$

5. Compute the spectral estimate corresponding to $\{\tilde{c}_k\}$ is given by

$$\tilde{\phi}_p = \exp\left[\sum_{k=0}^{N-1} \tilde{c}_k e^{-j\omega_p k} \right]; \quad p = 0, \ldots\ldots\ldots N-1$$

6. Obtain the proposed non parametric spectral estimate by a simple scaling

$$\hat{\hat{\phi}}_p = \hat{\alpha}\tilde{\phi}_p, \ p = 0, \ldots\ldots N-1$$

Simulation Results

In this section, we present experimental results on the proposed algorithm for simulated data to estimate the power spectrum. The performance of proposed method is verified for simulated data, generated by applying Gaussian random input to a system, which is either broad band or narrow band.The MA broad band signal is generated by using the difference equation [18]

$$\begin{aligned} &y(t)-1.3817y(t-1)+1.5632y(t-2)-0.8843y(t-3)+\\ &0.4096y(t-4)=e(t)+0.3544e(t-1)+0.3508e(t-2)+\\ &0.1736e(t-3)+0.2401e(t-4),\\ &\quad t=0,1,\ldots N-1 \end{aligned} \tag{14}$$

where $e(t)$ is a normal white noise with mean zero and unit variance. The ARMA narrow band signal is generated by using the difference equation

$$\begin{aligned} &y(t)-0.2y(t-1)+1.61y(t-2)-0.19y(t-3)+\\ &0.8556y(t-4)=e(t)-0.21e(t-1)+0.25e(t-2),\\ &\quad t=0,1,\ldots N-1 \end{aligned} \tag{15}$$

The number of samples in each realization is assumes as N=256.

After performing 1000 Monte Carlo Simulations, the comparison of the mean Power Spectrum, Variance and Mean Square Error for the broad band signal and narrow band signals, obtained using periodogram and cepstrum approach along with the true power spectrum are shown in Figure 1 (a) , (b) and (c) and Figure 2 (a), (b) and (c) respectively.

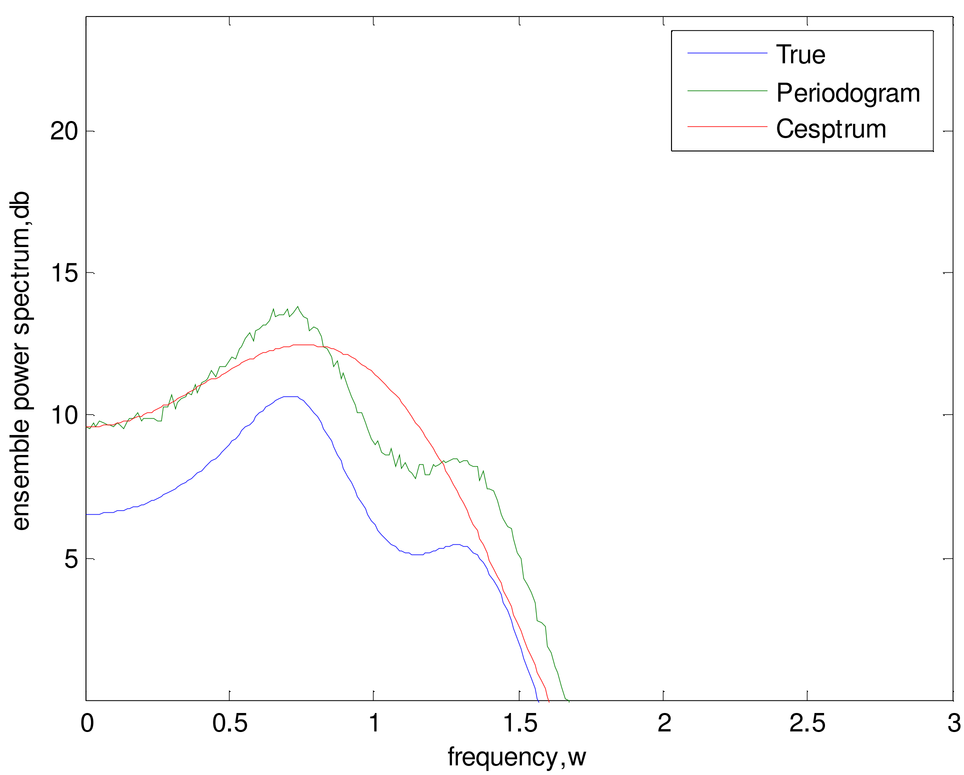

FIGURE 1: (a) PSD vs frequency for broadband signal

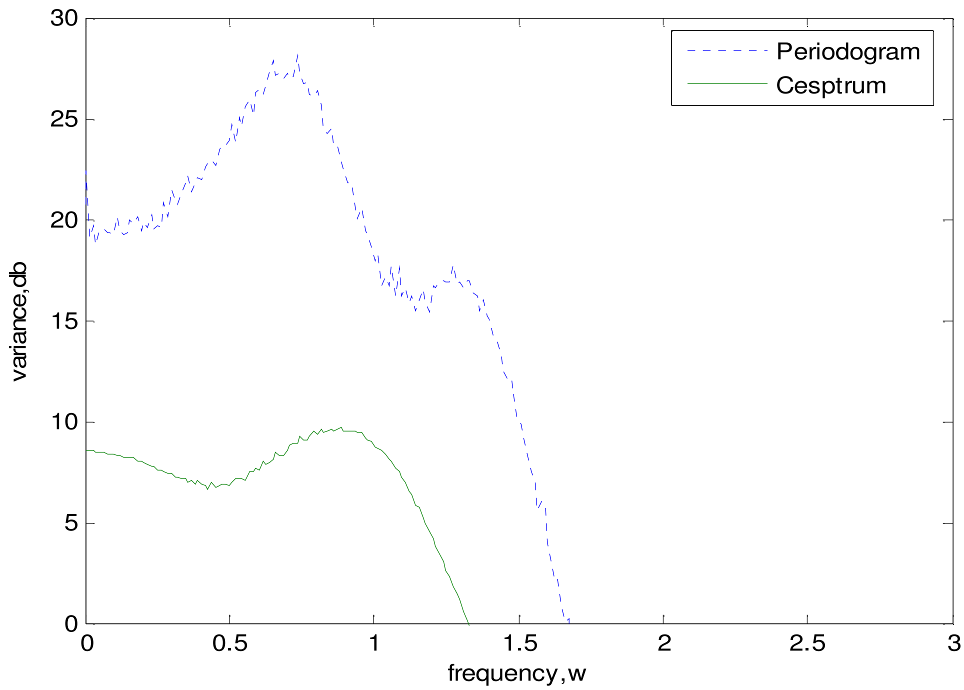

FIGURE 1: (b) Variance vs frequency for broadband signal

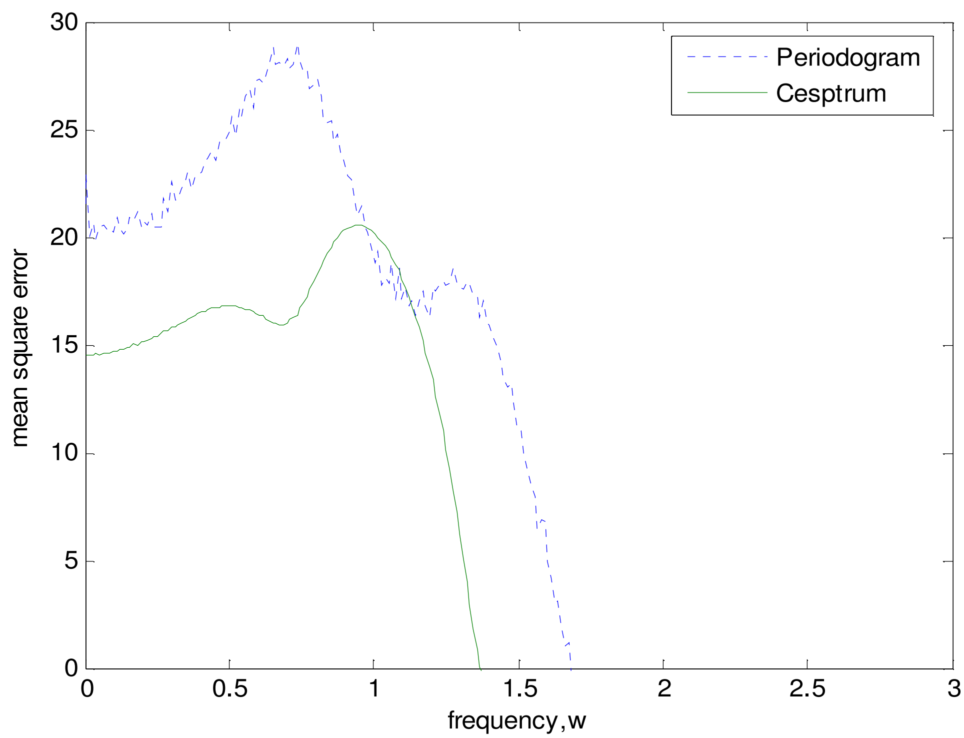

FIGURE 1: (c) Mean Square Error vs frequency for broadband signal

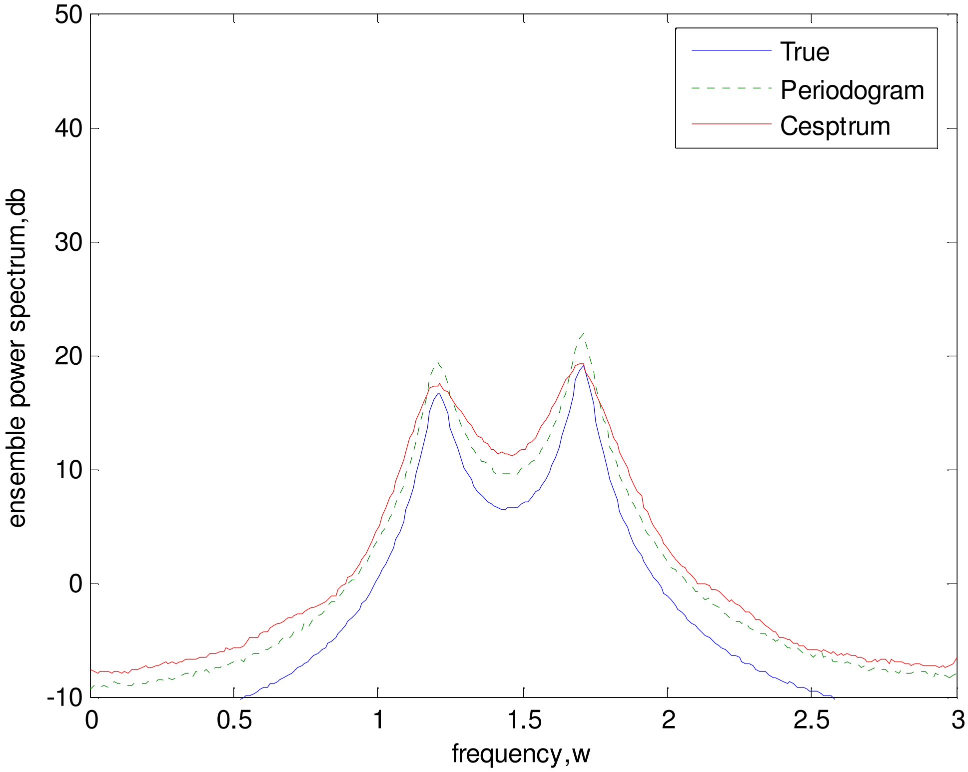

FIGURE 2: (a) PSD vs frequency for narrowband signal

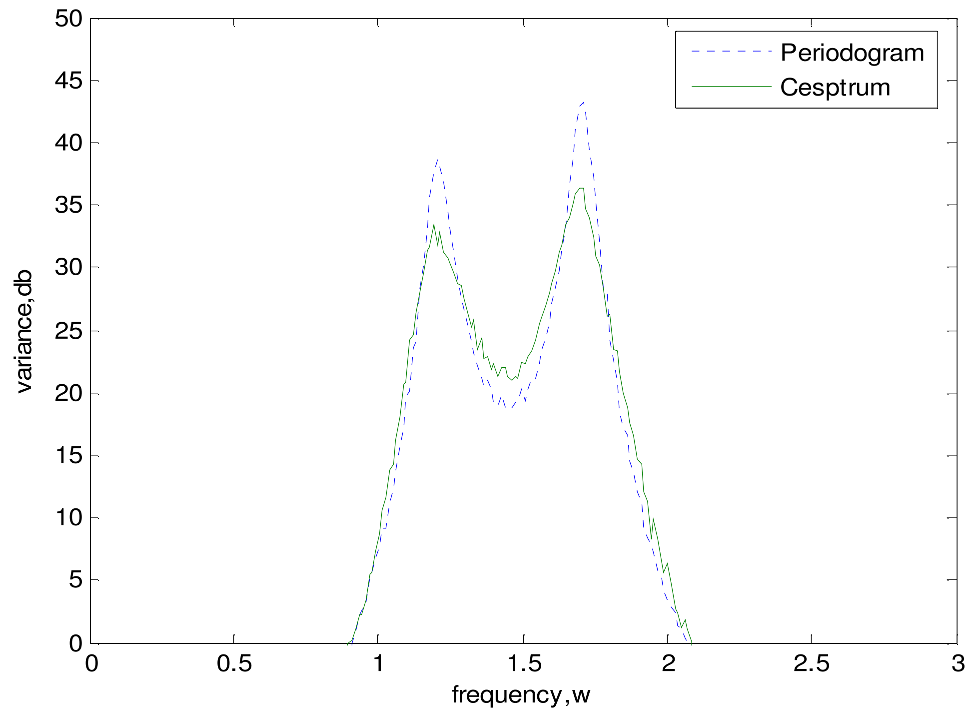

FIGURE 2: (b) Variance vs frequency for narrowband signal

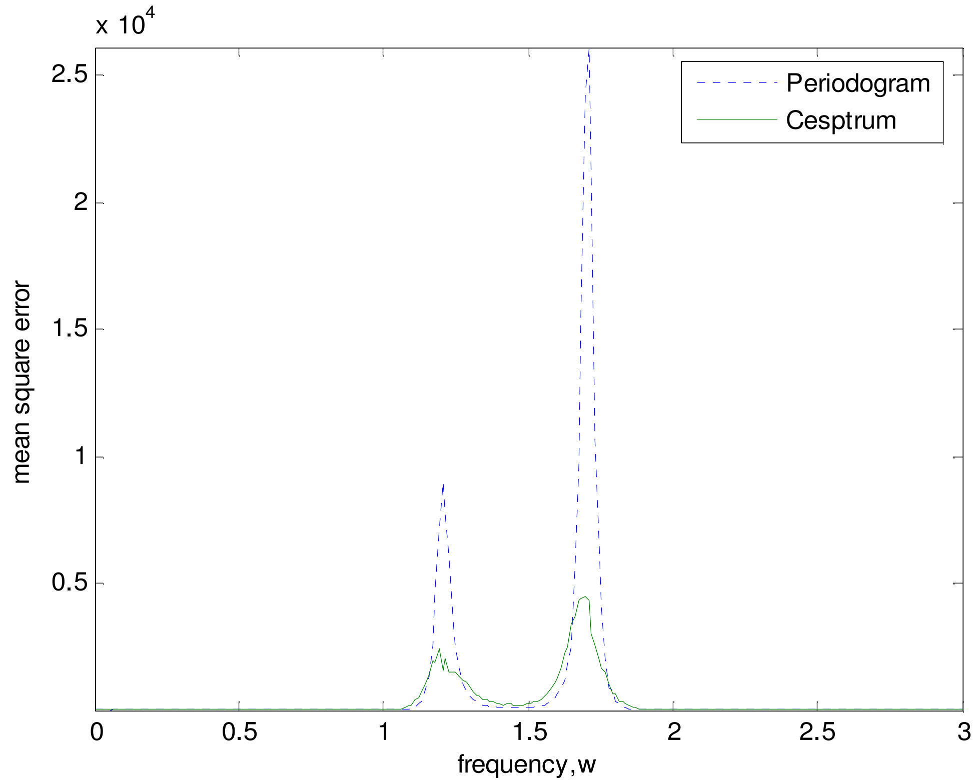

FIGURE 2: (c) Mean Square Error vs frequency for narrowband signal

From the above results we can say that

1. In the case of broad band signal the spectral estimates through cepstrum approach has very smooth response compared to the periodogram approach. However it can be observed that the mean square error is more in the case of periodogram and least with cepstrum thresholding approach.
2. In the case of broad band signals, variance obtained through cepstrum thresholding approach is very small as compared to the periodogram approach.
3. It is also observed that the mean square error estimated through cepstrum approach for narrowband signals is less compared to broadband signals.

Comparison among the traditional methods and the cepstrum method

In order to evaluate the performance of the cepstrum technique, which is compared with the traditional methods such basic Peridogram, Bartlett method, Welch method and Blackman and Tukey [21] for simulated ARMA narrow band signal, which is generated by using equation (15).

The various PSD techniques	Mean	Variance
Cepstrum	0.0090	2.4023e-004
Periodogram	0.0092	4.8587e-004
Black-man and Tukey	0.0521	0.0047
Welch	0.0138	8.9491e-004
Bartlett	0.2474	0.0637

TABLE 1: Comparison table for the parameters mean and variance (Record length N=128).

From the comparison table 1, for short record length, with respect to mean and variance, the cepstrum technique produces better results in comparison with the traditional methods. For longer record length, with reduced computational complexity, the cepstrum method produces the values of mean and variance as same as that of the Welch method, but these methods are better than the remaining techniques. For 1000 Monte carlo simulations, the ensemble power spectrum for various techniques is shown in figure 3.

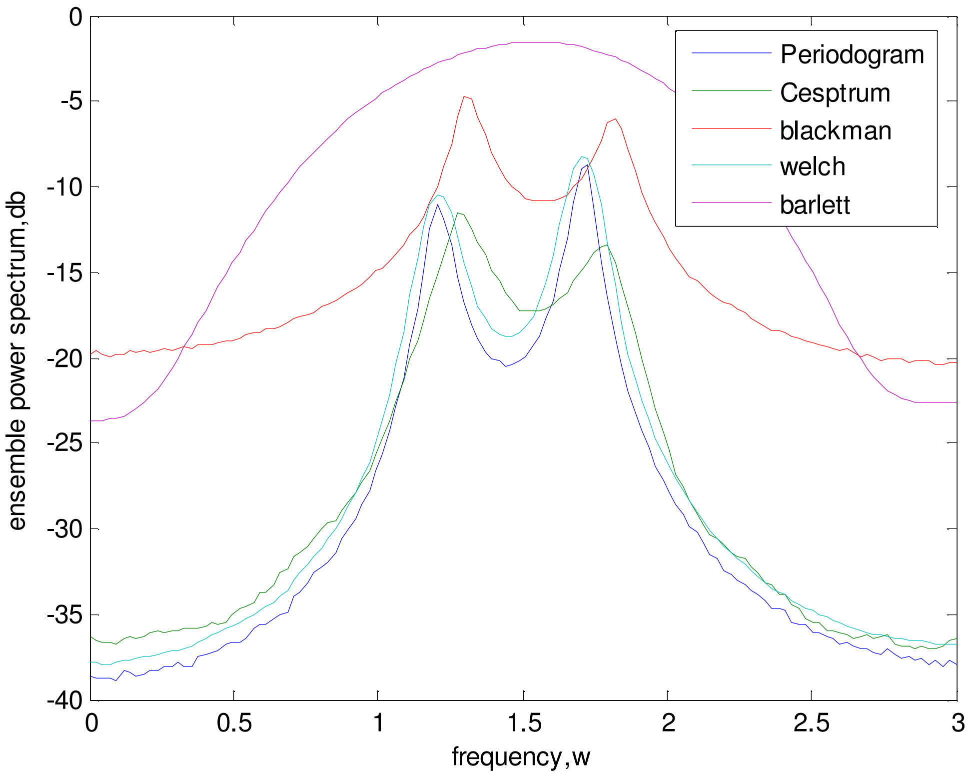

FIGURE 3: an ensemble power spectrum of an ARMA narrowband signal by using the traditional methods and the cepstrum method

Results for MST Radar data

The concept of cepstrum is applied to atmospheric data collected from the MST Radar on 10th August 2008 at Gadhanki, Tirupati, India. 150 sample functions, each having 256 samples are used to know the performance of cepstrum in comparison with the standard periodogram. The better results are obtained through the cepstrum than the periodogram. The comparison of the mean Power Spectrum, Variance for Radar data, obtained using periodogram and cepstrum approach are shown in Figure 4 (a) and (b) respectively. It is observed that the smooth power spectra and less variance in cepstrum than that of the periodogram.

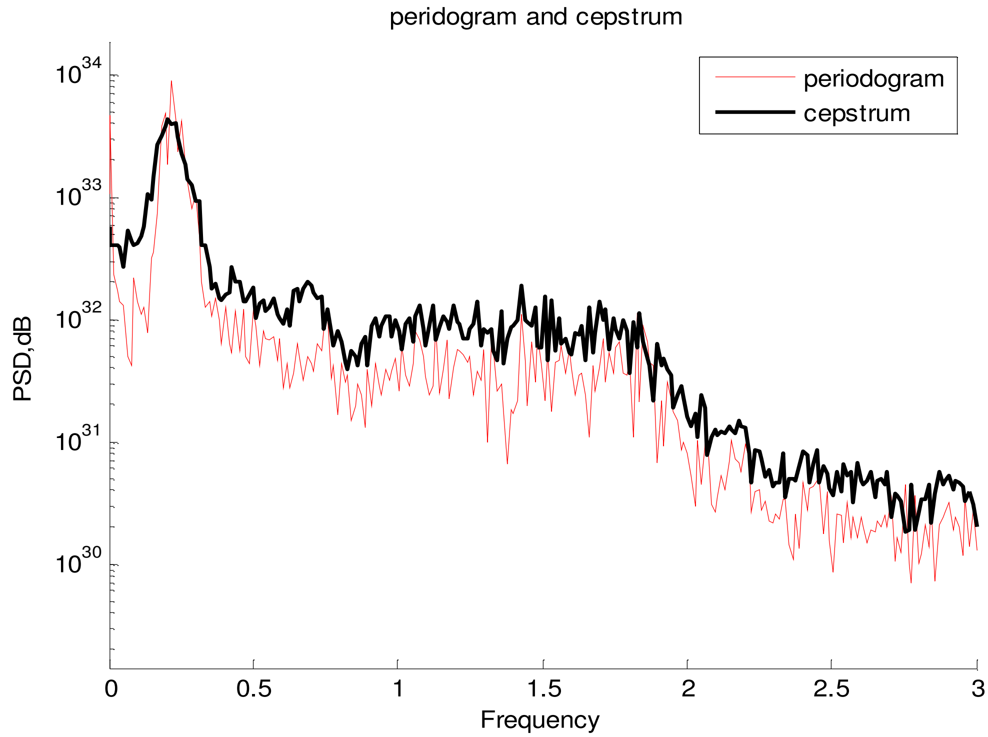

FIGURE 4: (a) Mean Power Spectra Vs Frequency for MST Radar data

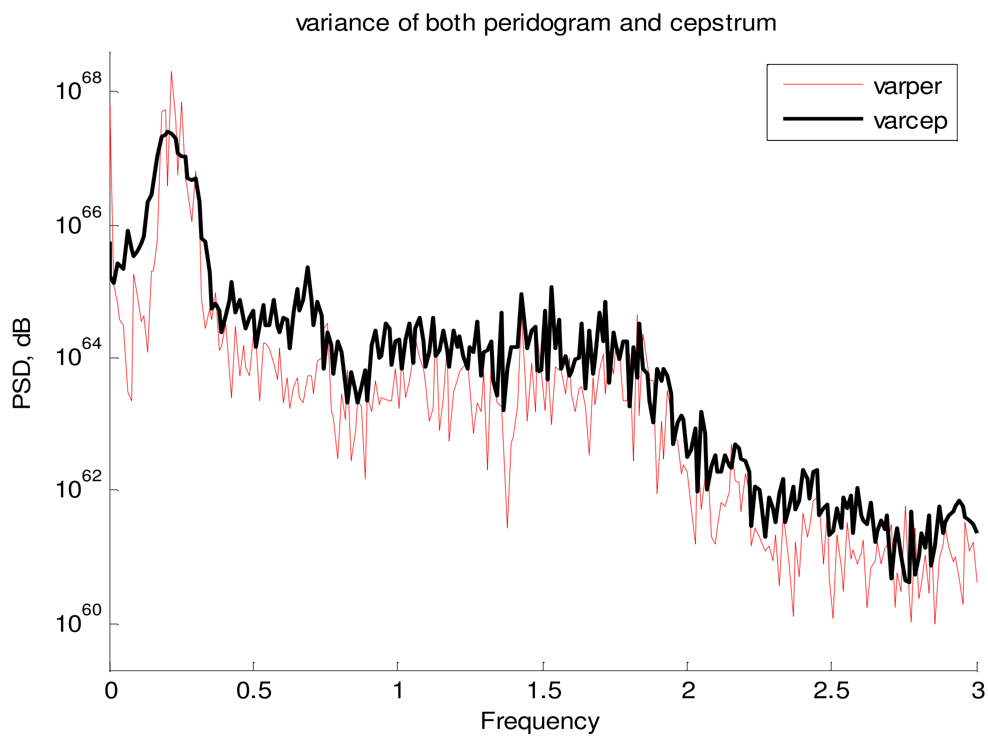

FIGURE 4: (b) Variance Vs Frequency for MST Radar data

3. CONSLUSION & FUTURE WORK

The problem in traditional methods is that the variance becomes proportional to square of power spectrum instead of converging into zero, thus the estimated spectrum is an inconsistent. In this paper the new technique has been proposed, called cepstrum, which gives reduce variance while evaluating the smoothed nonparametric power spectrum estimation. The expression for mean and variance of the cepstrum has been presented. The total variance reduction is more through broadband signals when compared to narrowband signals. All results are verified by using MAT lab 7.0.1. The concept of Cepstrum can be also extended for higher order spectral estimations.

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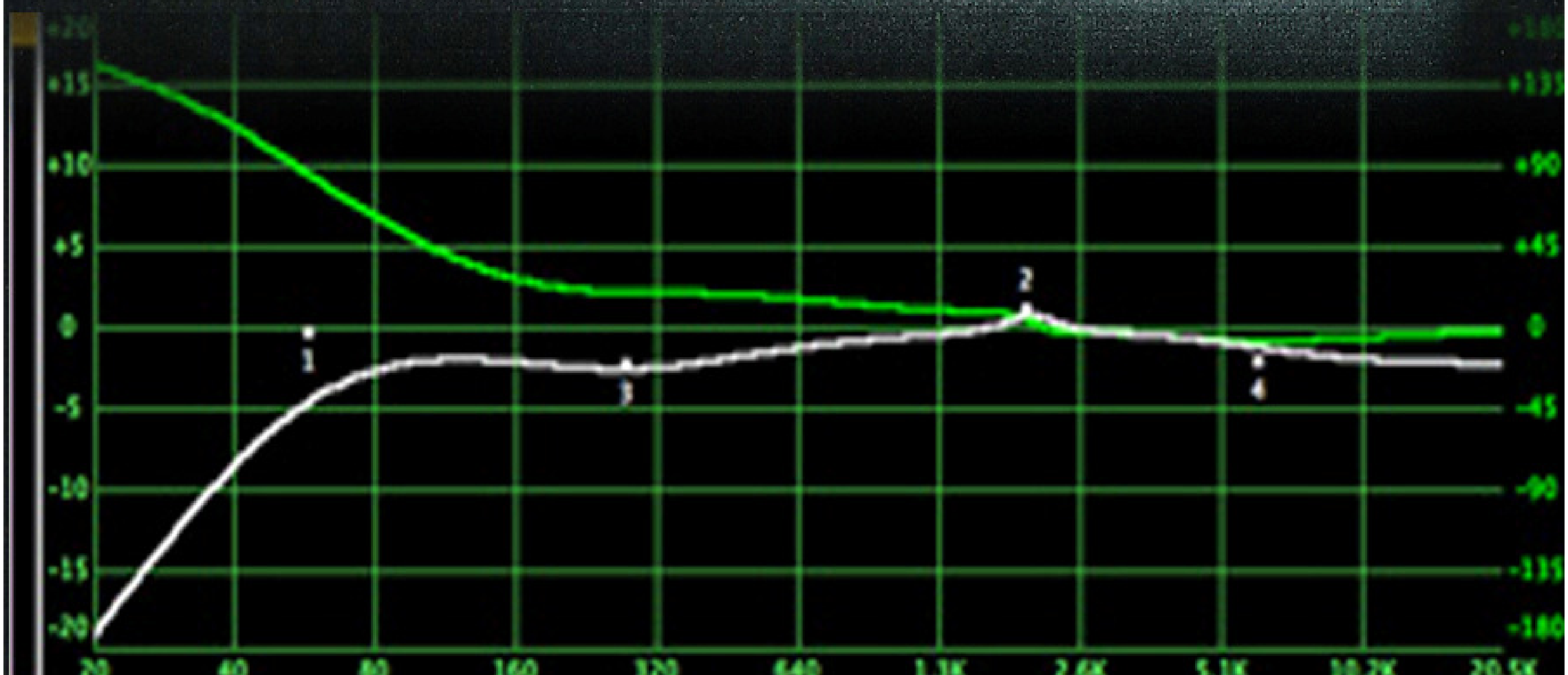

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The Convergence Speed of Single- And Multi-Objective Immune Algorithm Based Optimization Problems

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Abstract

Despite the considerable amount of research related to immune algorithms and it applications in numerical optimization, digital filters design, and data mining, there is still little work related to issues as important as sensitivity analysis, [1]-[4]. Other aspects, such as convergence speed and parameters adaptation, have been practically disregarded in the current specialized literature [7]-[8]. The convergence speed of the immune algorithm heavily depends on its main control parameters: population size, replication rate, mutation rate, clonal rate and hyper-mutation rate. In this paper we investigate the effect of control parameters variation on the convergence speed for single- and multi-objective optimization problems. Three examples are devoted for this purpose; namely the design of 2-D recursive digital filter, minimization of simple function, and banana function. The effect of each parameter on the convergence speed of the IA is studied considering the other parameters with fixed values and taking the average of 100 times independent runs. Then, the concluded rules are applied on some examples introduced in [2] and [3]. Computational results show how to select the immune algorithm parameters to speedup the algorithm convergence and to obtain the optimal solution.

Keywords: Immune Algorithm, Convergence, Mutation, Hypermutation, Population Size, Clonal Selection.

1. INTRODUCTION

The parameters of the immune algorithm have a large effect on the convergence speed. These parameters are the population size (p_s) which estimates the number of individuals (antibodies) for each generation, the mutation rate (p_m) which increases the diversity in population, and the replication rate (p_r) which estimates the number of antibodies chosen from the antibody population pool to join the algorithm operations. Other parameters such as the clonal rate (p_c) which estimates the number of individuals chosen from the antibody population pool to join the clonal proliferation (selection), as well as the hypermutation rate (p_h) which improves the capabilities of exploration and exploitation in population, have also great effect on the speed of convergence. In spite of the research carried out up to date, there are no general rules on how these parameters can be selected. In literature [1]-[2] and [13], the immune parameters are selected by certain values (e.g. p_s =200, p_r =0.8, p_m =0.1, p_c =0.06, p_h =0.8) without stating the reason for this selection.

In this paper we investigate the effect of parameters variation on the convergence speed of the immune algorithms developed for three different illustrative examples: 2-D recursive digital filter design (multi-objective problem), minimization of simple function (single-objective problem), and finding the global minimum of banana function. The obtained results can be used for selecting the values of these parameters for other problems to speed up the convergence. The paper is organized as follows. Section 2 describes the immune algorithm behavior. In Section 3 three illustrative examples are given to investigate the effect of parameters variation on the convergence speed of the immune algorithm. Section 4 discusses the selection criteria of these parameters to guarantee the convergence speed. In section 5, some examples introduced in [3] and [12] are considered to demonstrate the effectiveness of the selection of immune algorithm control parameters. And finally, Section 6 offers some conclusions.

2. IMMUNE ALGORITHMS BEHAVIOR

Immune algorithms are randomized algorithms inspired by immune functions and principles observed in nature [10]. Such algorithms begin by generating population pool (chromosome) using real coding representation and evaluating the objective values. Then, the population pool undergoes the algorithm operations which will be described in this section. The operations are repeated at each generation (gen) until the termination condition is satisfied [1]-[2]. Table (1) illustrates the main steps of the immune algorithm [16].

2.1 Generation of Antibody Population

The antibody population is generated either by using binary coding representation or real coding representation. In the binary coding representation, each variable is encoded as a binary string and the resulting strings are concatenated to form single chromosome (antibody) [11]. However, in the real coding representation, each antibody is encoded as a vector of floating point numbers, with the same length as the vector of decision variables. This representation is accurate and efficient because it is closest to the real design space, and the string length represents the number of design variables.

2.2 Selection for Reproduction

The roulette wheel selection is employed in immune bases algorithms for chromosomes reproduction. Its basic idea is to determine the selection probability for each solution in proportion with the fitness value. For solution j with fitness f_j, its probability p_j is defined as:

$$p_j = \frac{f_j}{\sum_{j=1}^{\rho_s} f_j} \qquad , j = 1, 2, ..., \rho_s \tag{1}$$

And the cumulative probability q_j for each solution is calculated as:

$$q_j = \sum_{i=1}^{j} p_i \qquad , j = 1, 2, ..., \rho_s \tag{2}$$

Where, the fitness f_j is relation to the objective function value of the jth chromosome.

```
Gen=1;                                          % The first generation
Chrom=Initial_pop();                            % Construct the initial population pool
While (termination_condition)
        Evaluuate (Chrom);                      % Objective function evaluation
        Chrom_sel=RWS_Selection(Chrom);         % Roulette wheel selection
        Chrom_rep=replication(Chrom_sel);              % Selection of better antibodies using
Replication
        Chrom_clon=Cloning(Chrom_rep);          % Clonal operation
        Chrom_hyper=Hypermutation(Chrom_clon);  % Hypermutation operation
        Chrom_tot=[ Chrom_rep, Chrom_hyper];
        Chrom_child=Mutation(Chrom_tot);        % Mutation Operation
        Evaluuate (Chrom_child);                % Objective function evaluation
        Chrom=Better_selection(Chrom,  Chrom_child);     % Selection of better antibodies for next
generation
        gen=gen+1;                              % Increment the number of generations
end
```

TABLE (1): The Immune Algorithm

2.3 Replication Operation

The replication operation is used to select better antibodies, which have low objective values to undergo algorithm operations. This is termed by clonal proliferation within hypermutation and mutation operations.

2.4 Clonal Proliferation within Hypermutation

Based on the biological immune principles, the selection of a certain antibody from the antibody population pool to join the clonal proliferation depends on the clonal selection rate (p_c). Each gene, in a single antibody, depending on the hypermutation rate (p_h), executes the hypermutation of convex combination. The hypermutation rate (p_h) has an extremely high rate than the mutation rate to increase the antibody diversity. For a given antibody $X = (X_1, X_2, ..., X_i, X_j, X_k, ..., X_\rho)$, if the gene X_i is determined to execute the hypermutation and another gene X_k is randomly selected to join in, the resulting offspring antibody becomes $X' = (X_1, X_2, ..., X_i', X_j, X_k, ..., X_\rho)$, where the new gene X_i' is $X_i' = (1-\beta)X_i + \beta X_k$, and $\beta \in [0, 1]$ is a random value.

2.5 Mutation Operation

Similar to the hypermutation mechanism, the mutation operation is also derived from the convex set theory [9], where each gene, in a single antibody, depending on the mutation rate (p_m), executes the mutation of convex combination. Two genes in a single solution are randomly chosen to execute the mutation of convex combination [15]. For a given antibody $X = (X_1, X_2, ..., X_i, X_j, X_k, ..., X_\rho)$, if the genes X_i and X_k are randomly selected for mutation depend on the mutation rate (p_m), the resulting offspring is $X' = \left(X_1,\ X_2,...,X_i',X_j,X_k',...,X_\rho\right)$. The resulting two genes X_i' and X_k' are calculated as:

$$X_i' = (1-\beta)X_i + \beta X_k \text{ and } X_k' = \beta X_i + (1-\beta)X_k \tag{3}$$

where, β is selected randomly in the range [0, 1].

2.6 Selection Operation

The selection operation is generally used to select the better p_s antibodies which have low objective values as the new antibody population of the next generation.

3. ILLUSTRATIVE EXAMPLES

In this section three different examples are considered to investigate the effect of parameters variation on the convergence speed of the immune algorithm. The first example simulates the multi-objective function problem that has an infinite set of possible solutions difficult to find [7]. The second example is a single-objective function problem and it is less difficult and the third example represents the family of problems with slow convergence to the global minimum [6].

Example 1:

This example considers the design of a second order 2-D narrow-band recursive LPF with magnitude and group delay specifications. The specified magnitude $M_d(\omega_1,\omega_2)$ is shown in Figure (1) [1], [5]. Namely, it is given by Equation (4) with the additional constant group delay $\tau_{d_1}=\tau_{d_2}=5$ over the passband $\sqrt{\omega_1^2+\omega_2^2} \le 0.1\pi$ and the design space is [-3 3]. To solve this problem, the frequency samples are taken at $|\omega_i/\pi| = 0,\ 0.02, 0.04, \ldots, 0.2,\ 0.4, \ldots, 1$ in the ranges $-\pi \le \omega_1 \le \pi$, and $-\pi \le \omega_2 \le \pi$.

$$M_d(\omega_1,\omega_2) = \begin{cases} 1.0, & for \sqrt{\omega_1^2+\omega_2^2} \le 0.08\pi \\ 0.5, & for\ 0.08\pi < \sqrt{\omega_1^2+\omega_2^2} \le 0.12\pi \\ 0.0, & for \sqrt{\omega_1^2+\omega_2^2} > 0.12\pi \end{cases} \tag{4}$$

Example 2:

This example considers the optimization of the exponential function shown in Figure (2) and described by the following equation:

$$y(x) = \sum_{i=0}^{9} a_i x^i \tag{5}$$

With the following desired specified values $Y_d(x)$ at x= [0, 1, 2, 3, ………., 20].

$$\begin{aligned} Y_d(x) = [&0.01\ \ -0.01\ \ -3.83\ \ -4.79\ \ 758.33\ \ 9.0021\times10^3\ \ 5.7237\times10^4\ \ 5.7237\times10^4 \\ &9.2998\times10^5\ \ 2.8368\times10^6\ \ 7.6281\times10^6\ \ 1.8563\times10^7\ \ 4.165\times10^7\ \ 8.7358\times10^7 \\ &1.7309\times10^8\ \ 3.2667\times10^8\ \ 5.9104\times10^8\ \ 1.0306\times10^9\ \ 1.7397\times10^9\ \ 2.8528\times10^9 \\ &4.5587\times10^9] \end{aligned}$$

Example 3:

This example considers a Rosenbrock banana function that described by the following equation [6]. This function is often used to test the performance of most optimization algorithms [6]. The global minimum is inside a long, narrow, parabolic shaped flat valley as shown in Figure (3). In fact find the valley is trivial, however the convergence to the global minimum is difficult.

$$f(x, y) = (1 - x)^2 + 100(y - x^2)^2 \qquad (6)$$

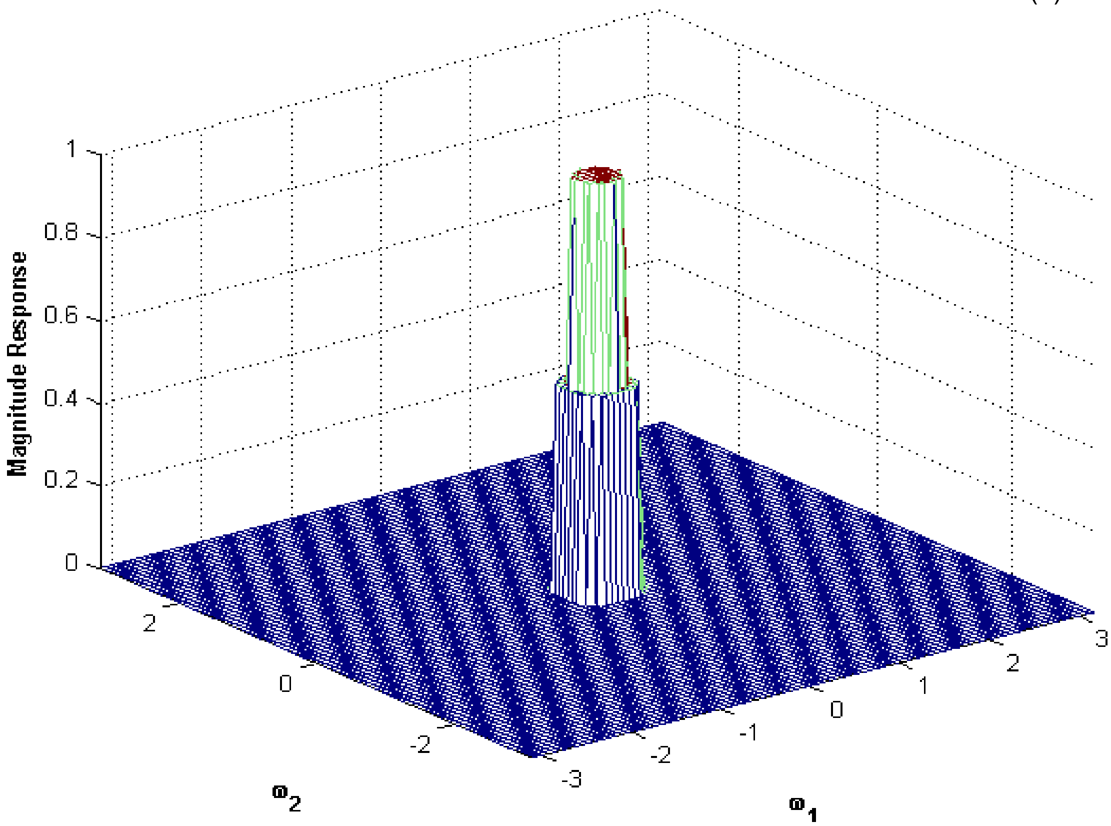

FIGURE 1: Desired Amplitude Response $|M_d(\omega_1, \omega_2)|$ Of The 2-D Narrow-Band LPF (Example 1)

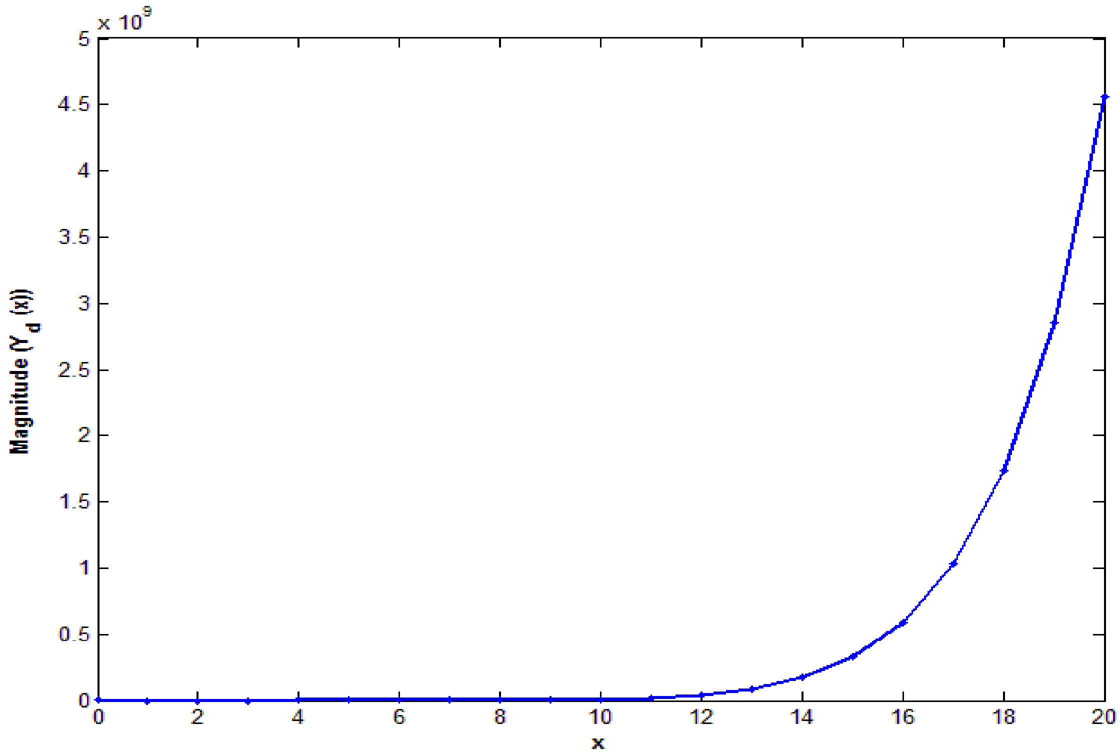

FIGURE 2: Desired Specifications of the Function $y(x)$ (Example 2)

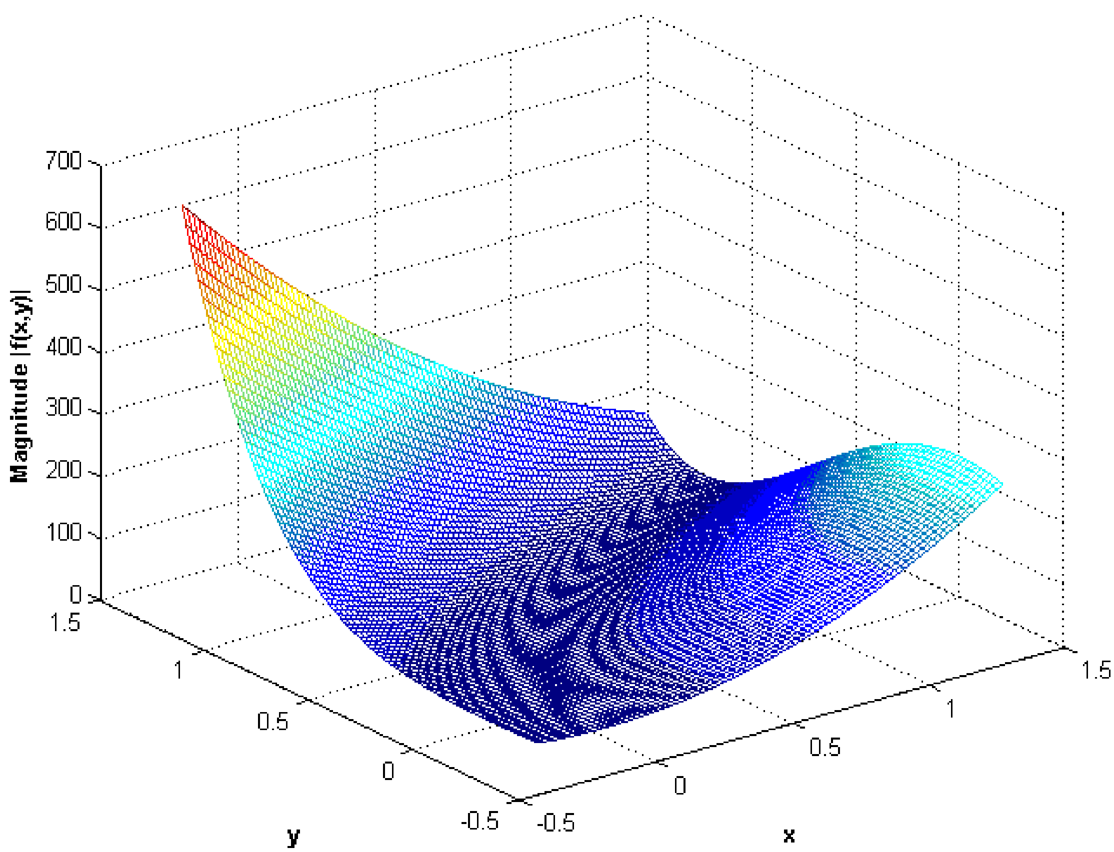

FIGURE 3: Rosenbrock Banana Function (Example 3)

4. SENSITIVITY ANALYSIS

In this section, we examine the effect of parameters variations on the convergence speed of the immune algorithm for the three examples described in section 3. The number of genes (the encoding length L) for each example is defined by the number of unknown coefficients. For the filter design problem, the filter transfer function is expressed by:

$$H(z_1, z_2) = H_0 \frac{a_{00} + a_{01}z_2 + a_{02}z_2^2 + a_{10}z_1 + a_{11}z_1z_2 + a_{12}z_1z_2^2 + a_{20}z_1^2 + a_{21}z_1^2z_2 + a_{22}z_1^2z_2^2}{(1 + b_1z_1 + c_1z_2 + d_1z_1z_2)(1 + b_2z_1 + c_2z_2 + d_2z_1z_2)}, \ a_{00} = 1 \tag{7}$$

So, 15 genes can be adjusted to approximate the specified magnitude and group delay. For the simple function and banana function problems, the number of genes considered are 10 and 2 respectively.

4.1 Effect of the population size (p_s)

The population size (p_s) is defined as the number of antibodies used in each generation. The variations in p_s can have substantial effect on the convergence speed of immune algorithm. If the p_s is too small, the IA cannot reach to optimal solution. However, if it is too large, the IA wastes computational time effort on extra objective values evaluations. Here, the effect of p_s on the convergence speed of the algorithm is studied by taking the average of 100 times independent runs at each p_s value. The value of p_s was varied from 10 to 400 with the other parameters fixed at p_r =0.8, p_h =0.8, p_m =0.1, and p_c =0.06. The effect of population size variations on number of generations required to get the solution for filter design problem, simple function and banana function are shown in Figures (4-6), respectively.

The results illustrated in Figures (4-6) show that, the speed of convergence can be measured by the number of generations required to reach to the optimal chromosome (global solution). Moreover, it can be noticed that the speed of convergence depends not only on the p_s but also on the number of genes. Here, the p_s after which optimal chromosome is obtained is denoted by p_s*. Increasing the p_s above p_s* has insignificant effect on speeding up the convergence.

4.2 Effect of the Replication Rate (p_r)

The replication rate (p_r) estimates the number of antibodies chosen from the antibody population pool to join the algorithm operations. The effect of p_r on the speed of convergence of the IA is studied by taking the average of 100 times independent runs at each p_r value. The value of p_r was varied from 0.1 to 1 with the other parameters fixed at p_s =100 p_h =0.8, p_m =0.1, and p_c =0.06. The effect of p_r variation on the number of generations required to produce the solution for filter design problem, simple function and banana function are shown in Figures (7-9), respectively.

These figures show that, the high values of replication rate have a significant effect on speeding up the convergence, but the computational time increases as the p_r increases. It is also noticed that the values of p_r greater than p_r* have no further effect on speeding up the convergence.

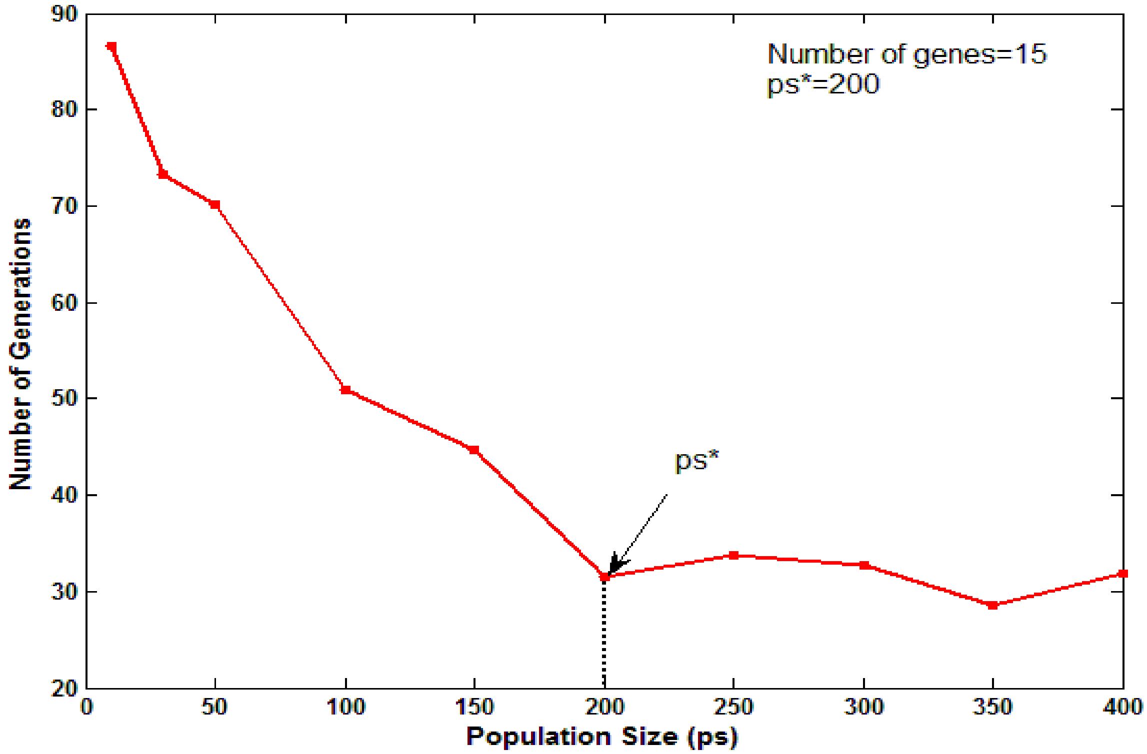

FIGURE 4: The Effect of Population Size on the Speed of Convergence of the Filter Design Problem.

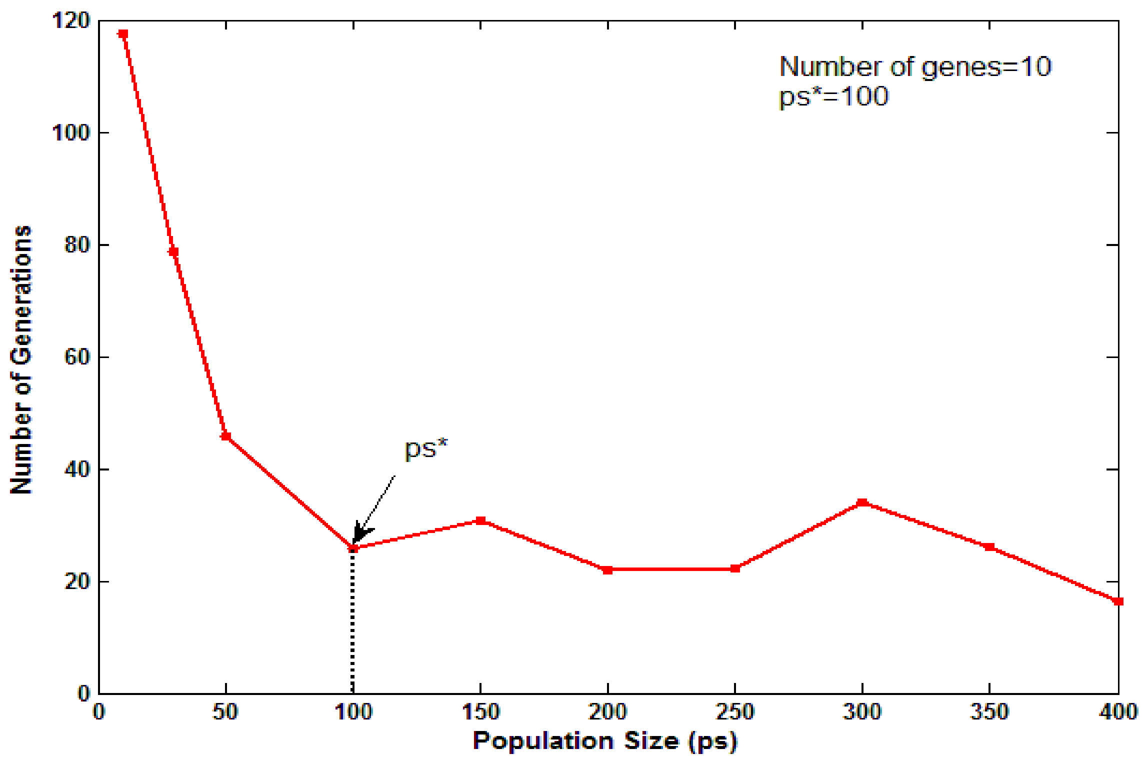

FIGURE 5: The Effect of Population Size on the Speed of Convergence for Simple Function Minimization

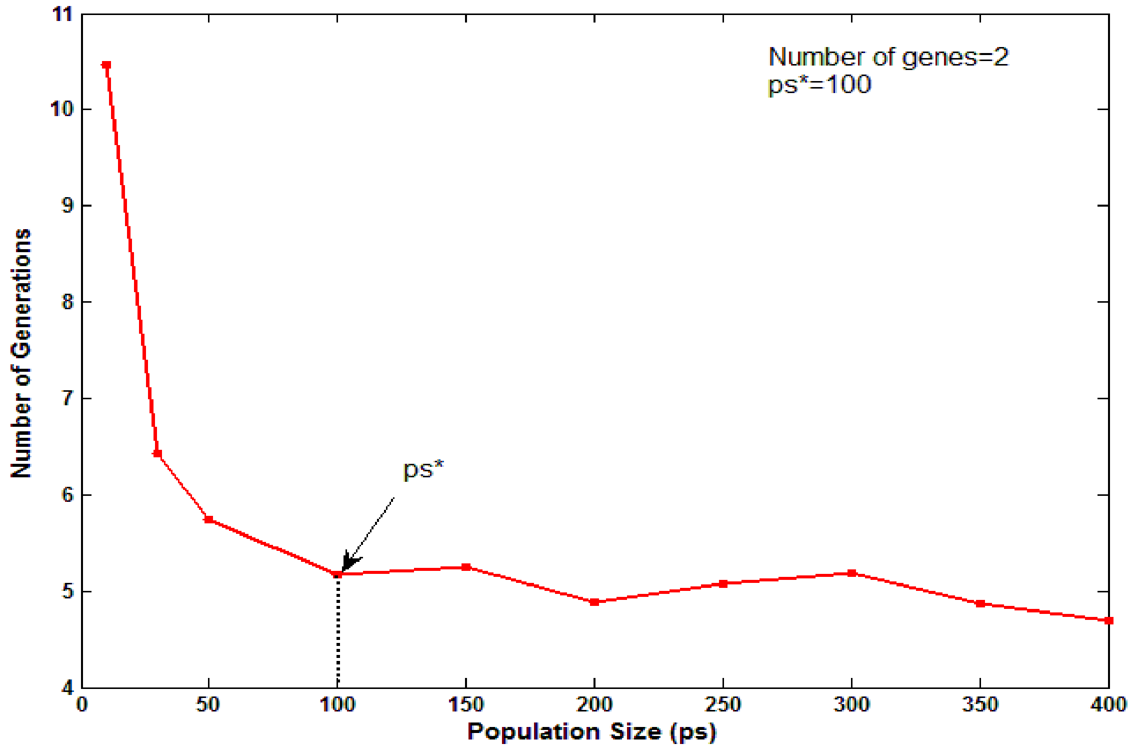

Figure 6: The Effect Of Population Size On The Speed Of Convergence For Finding The Global Minimum Of Banana Function.

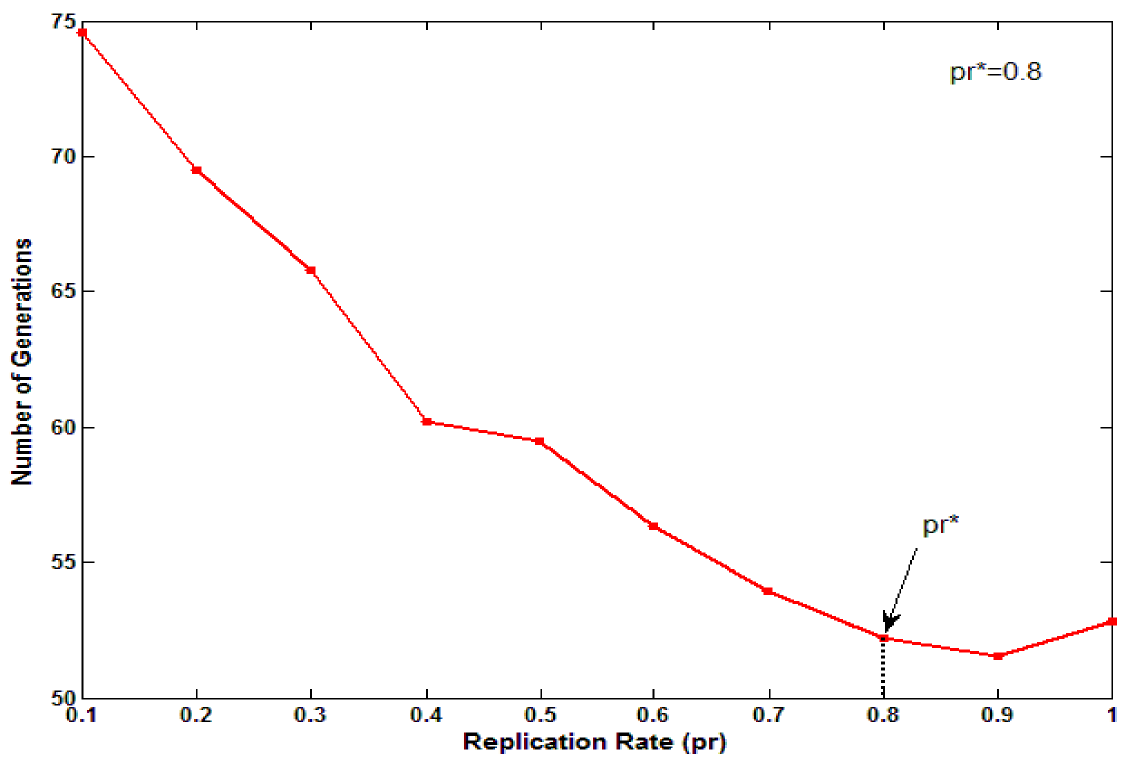

FIGURE 7: The Effect of Replication Rate on the Speed of Convergence for Filter Design Problem.

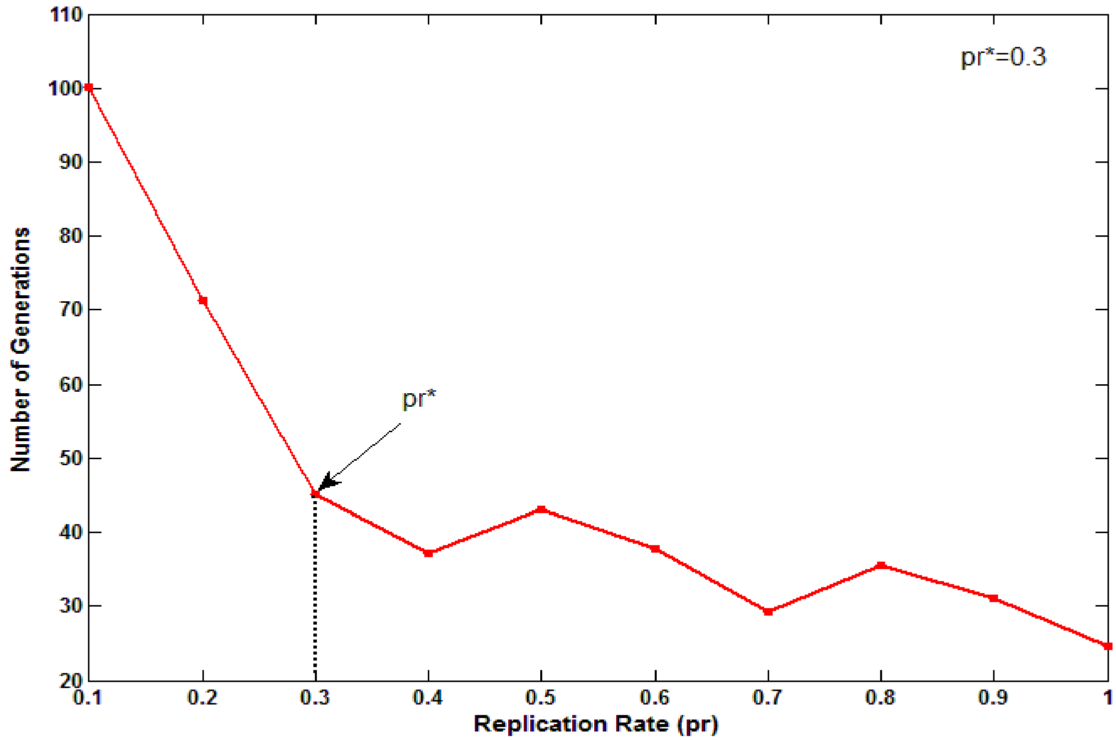

FIGURE 8: The Effect of Pr on the Speed of Convergence for Simple Function Minimization.

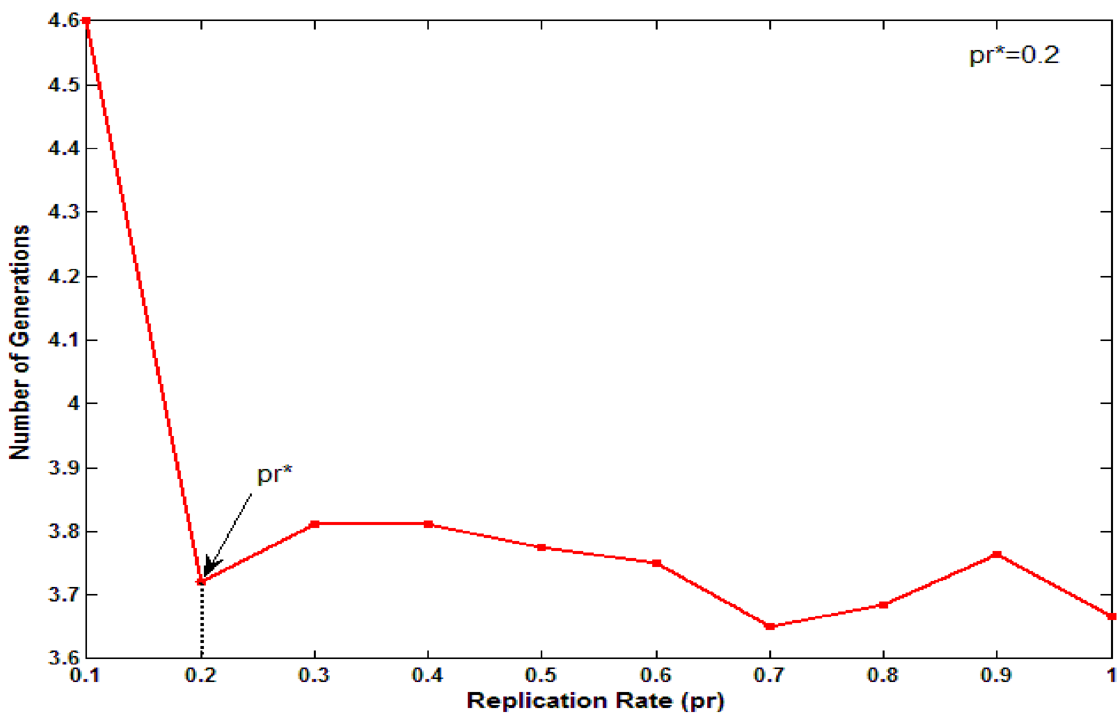

FIGURE 9: The Effect of Pr on the Speed of Convergence for Finding the Global Minimum of Banana Function**.**

4.3 Effect of the Clonal Selection Rate (p_c)

The clonal selection rate (p_c) estimates the number of antibodies that can be chosen from the antibody population pool to join the clonal proliferation. The effect of p_c on the speed of convergence of the IA is studied by taking the average of 100 times independent runs at each p_c value. The value of p_c was varied from 0.01 to 1 with the other parameters fixed at p_s =100, p_r =0.8, p_h =0.8, and p_m =0.1. The effect of p_c variation on the number of generations required to produce the optimal solution for filter design problem, simple function and banana function are shown in Figures (10-12), respectively.

From these figures, we can conclude that low values of p_c ($0.05 \le p_c < 0.1$) have significant effect on speeding up the convergence. It is also noticed that the use of high values of p_c ($p_c \ge p_c$*) have an effect of slowing down the convergence. This is mainly due to the infeasible selected individuals which joined to the clonal proliferation.

4.4 Effect of the Hypermutation Rate (p_h)

The hypermutation rate (p_h) is used to improve the capabilities of exploration and exploitation in population. The effect of p_h on the convergence speed of the IA is evaluated by taking the average of 100 times independent runs at each p_h value. The value of p_h was varied from 0.01 to 1 with the other parameters fixed at p_s =100, p_r =0.8, p_c =0.06, and p_m =0.1. The effect of hypermutation variation on the number of generations required to produce the solution for filter design problem, simple function and banana function are shown in Figures (13-15), respectively.

The results given in Figures (13-15) show that, the value of p_h depends on the problem domain. The values of p_h for the three illustrative examples are 0.5, 0.5, and 0.7, respectively. The p_h should be in the range ($0.5 \le p_h < 1$) to speed up the convergence of small number of genes problems (example 3) and it is about 0.5 for other ones.

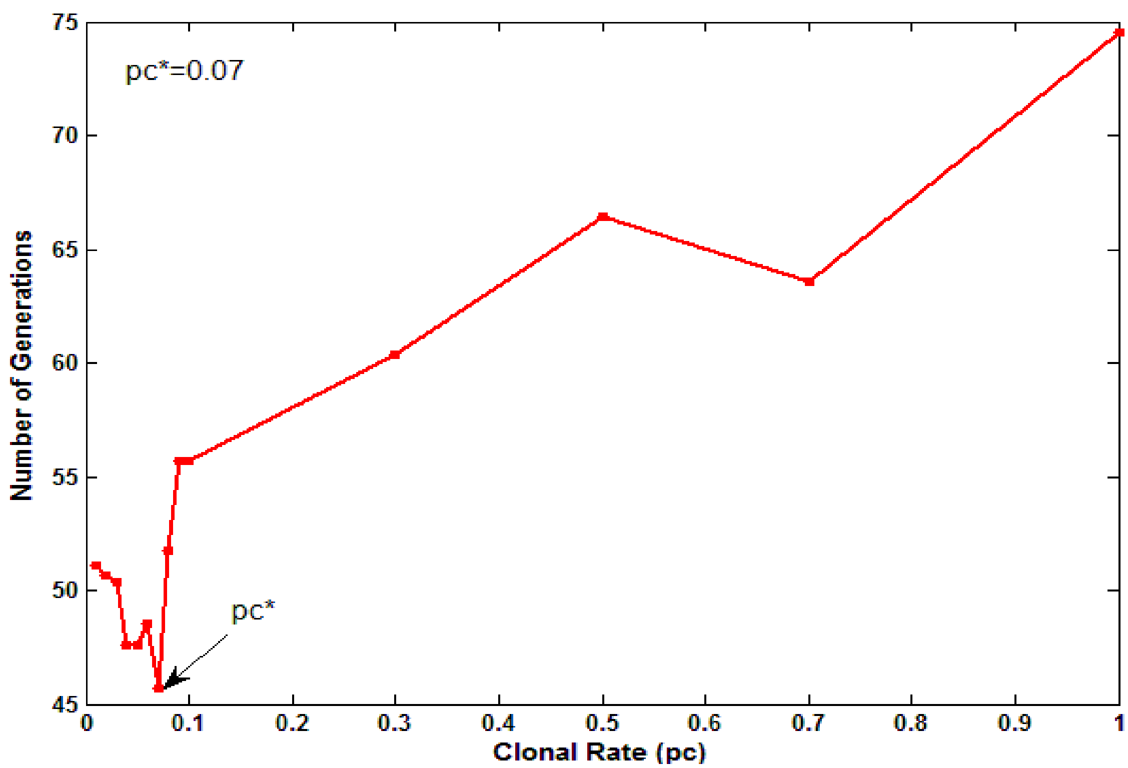

FIGURE 10: The Effect of Clonal Rate on the Speed of Convergence for Filter Design Problem.

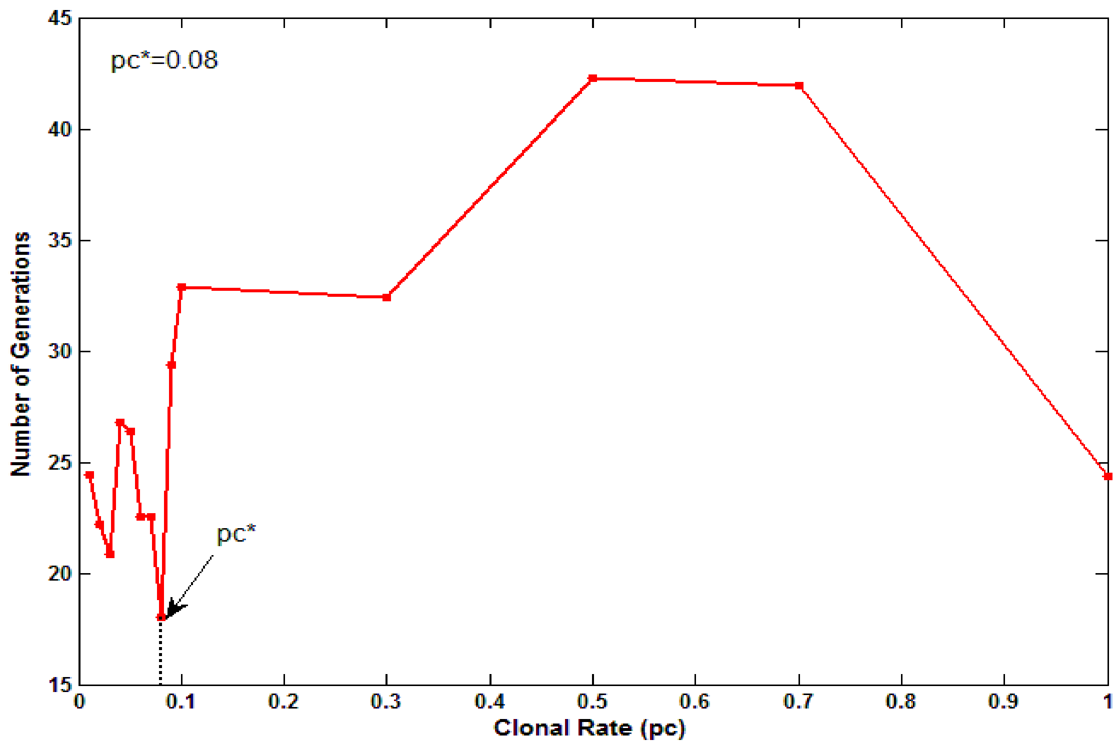

FIGURE 11: The Effect of Clonal Rate on the Speed of Convergence for Simple Function Minimization.

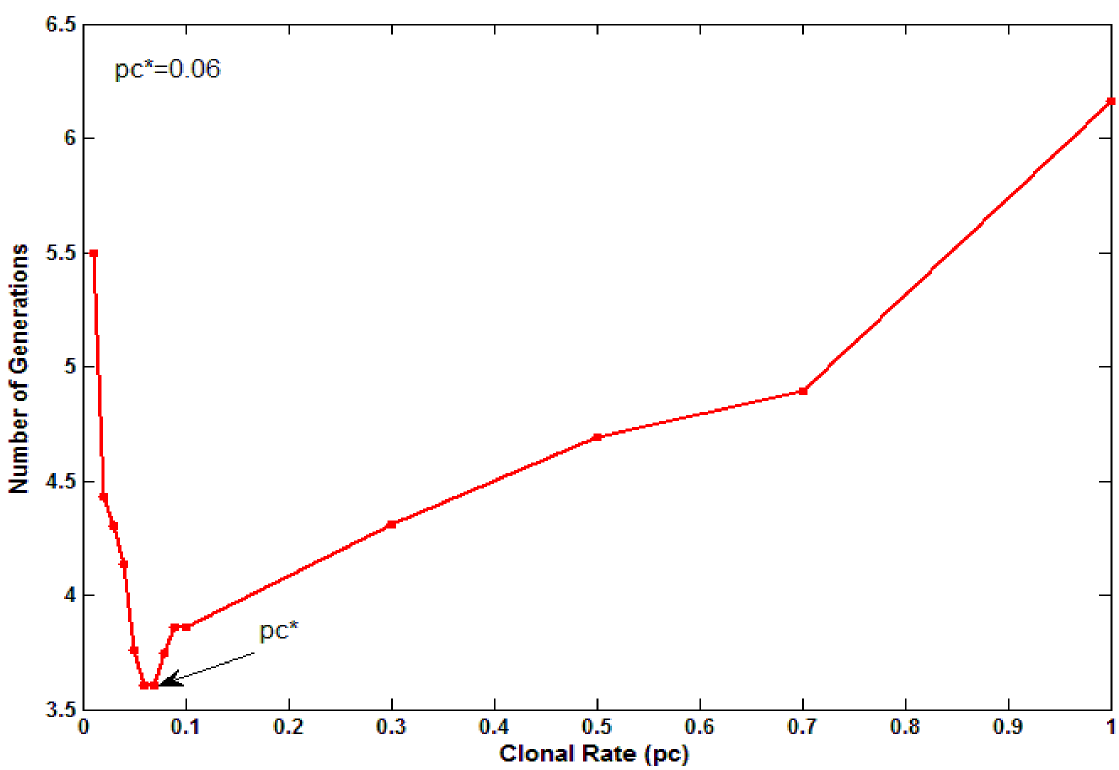

FIGURE 12: The Effect of Clonal Rate on the Speed of Convergence for Finding the Global Minimum of Banana Function.

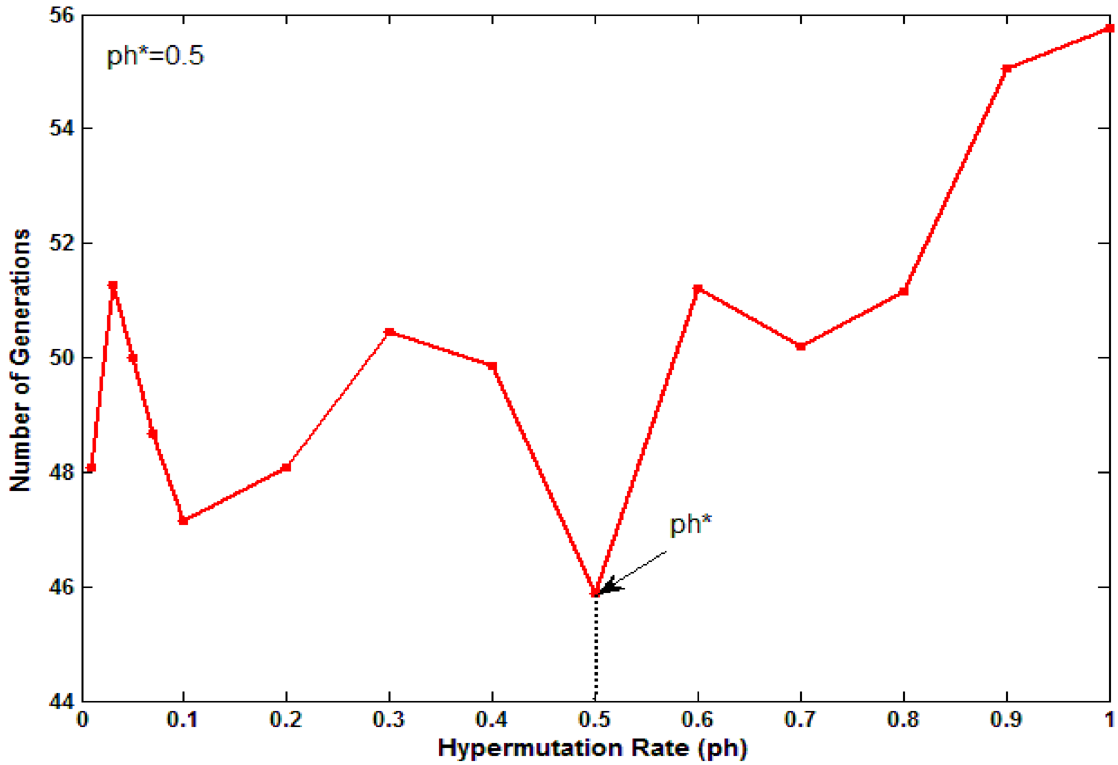

FIGURE 13: The Effect of Hypermutation Rate on the Speed of Convergence for Filter Design Problem.

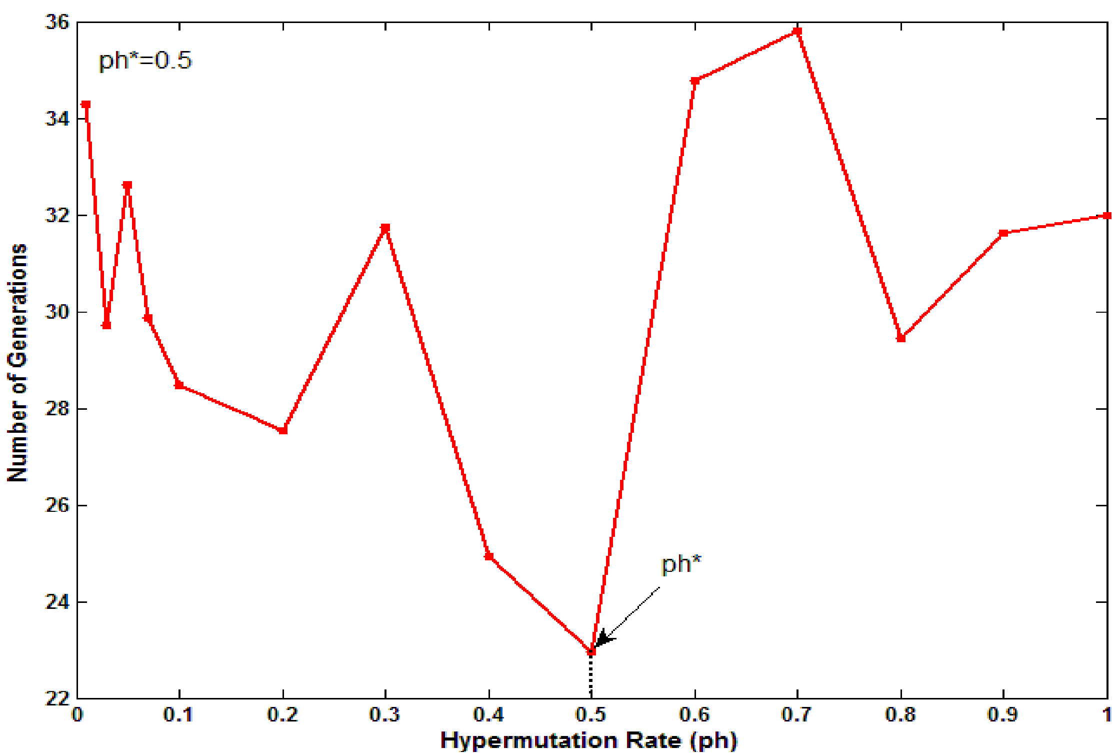

FIGURE 14: The Effect of Hypermutation Rate on the Speed of Convergence for Simple Function Minimization.

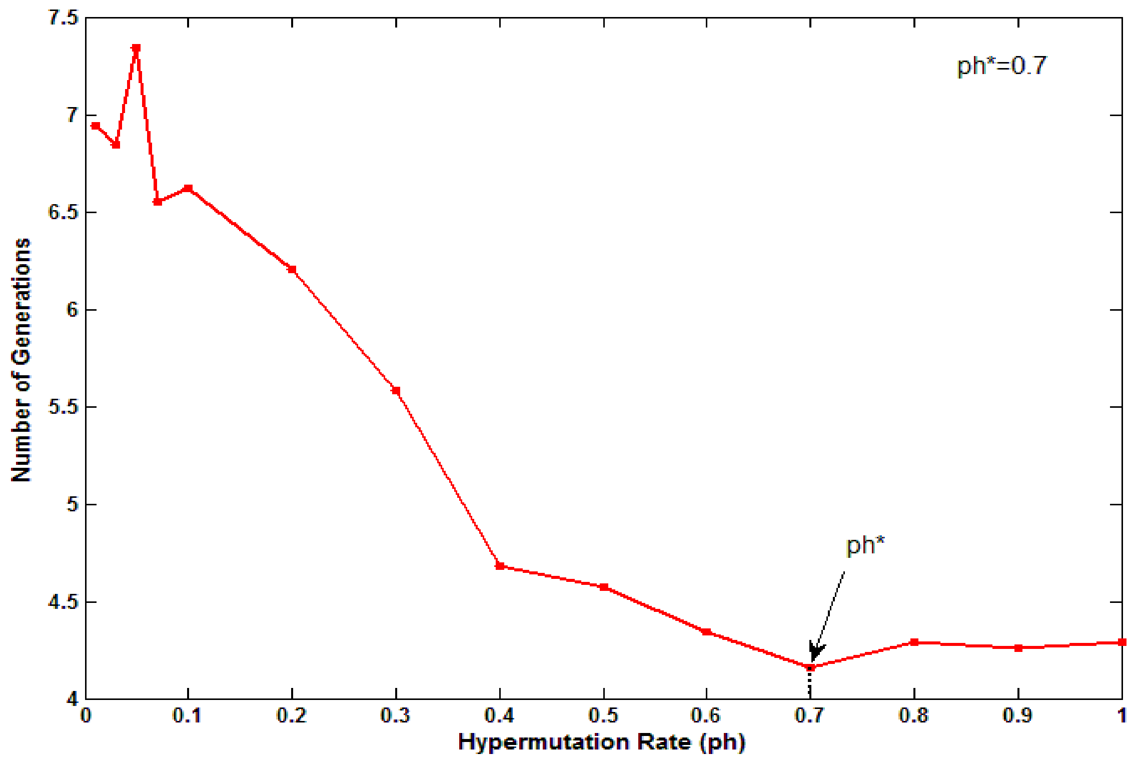

FIGURE 15: The Effect of Hypermutation Rate on the Speed of Convergence for Finding the Global Minimum of Banana Function.

4.5 Effect of the Mutation Rate (p_m)

The mutation rate (p_m) is one of the most sensitive immune algorithm parameters, since it increases the diversity in population. The choice of mutation rate is essentially a tradeoff between conservatism and exploration [14]. The effect of p_m on the convergence speed of IA is studied by taking the average of 100 times independent runs at each p_m value. The value of p_m was varied from 0.01 to 1 with the other parameters fixed at p_s =100, p_r =0.8, p_c =0.06, and p_h =0.8. The effect of mutation rate variation on the number of generations required to produce the solution for filter design problem, simple function and banana function are shown in Figures (16-18), respectively.

From these figures, we can conclude that the low values of mutation rate ($p_m \leq p_m$*) have significant effect on speeding up the convergence. Also, it is noticed that to guarantee the convergence speed, the p_m should be between 1/ p_s and 1/L, where p_s is the population size and L is the encoding string length.

From above studying, we can conclude that the general heuristics on IA parameters to guarantee the convergence speed are: 1) the population size should be greater than 100; 2) the replication rate should be higher than 0.2; 3) the clonal rate should be small in the range (0.05≤ p_c <0.1); 4) the hypermutation rate should be high in the range (0.5≤ p_h <1); and 5) the mutation rate should be between 1/ p_s and 1/L.

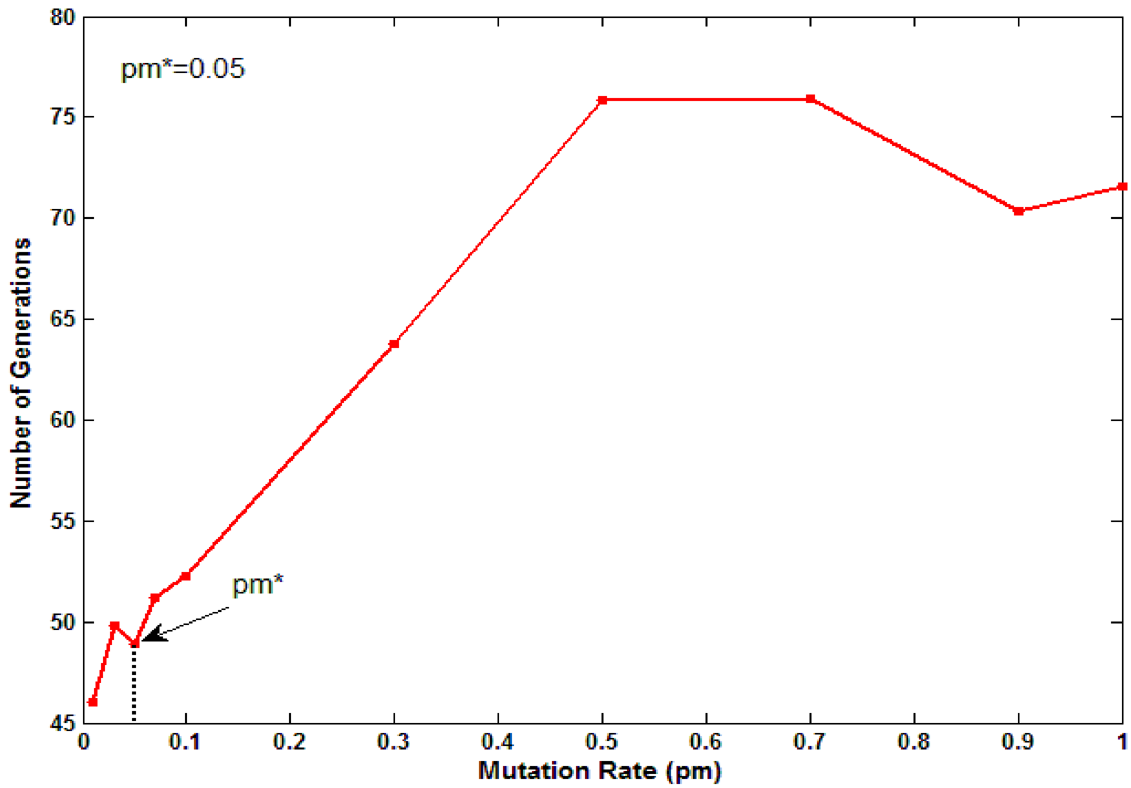

FIGURE 16: The Effect of Mutation Rate on the Speed of Convergence for Filter Design Problem (Ps=100 and L=15).

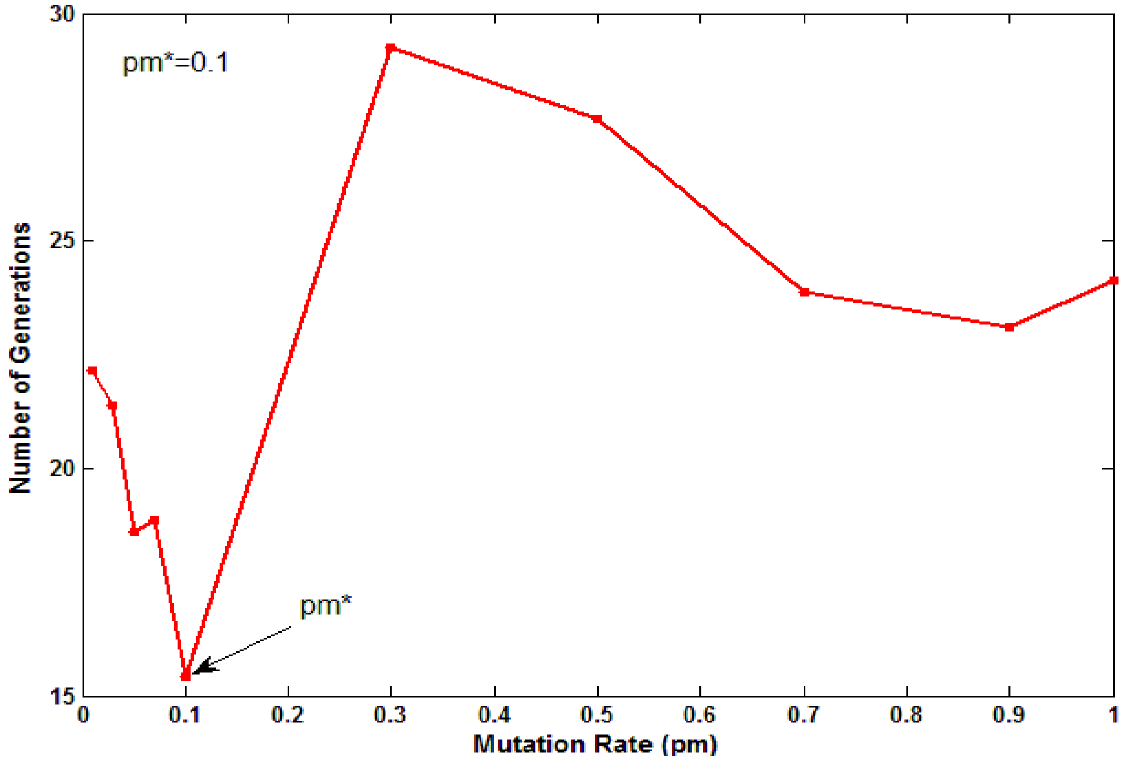

FIGURE 17: The Effect of Mutation Rate on Speed of Convergence for Simple Function Minimization (Ps=100 and L=10).

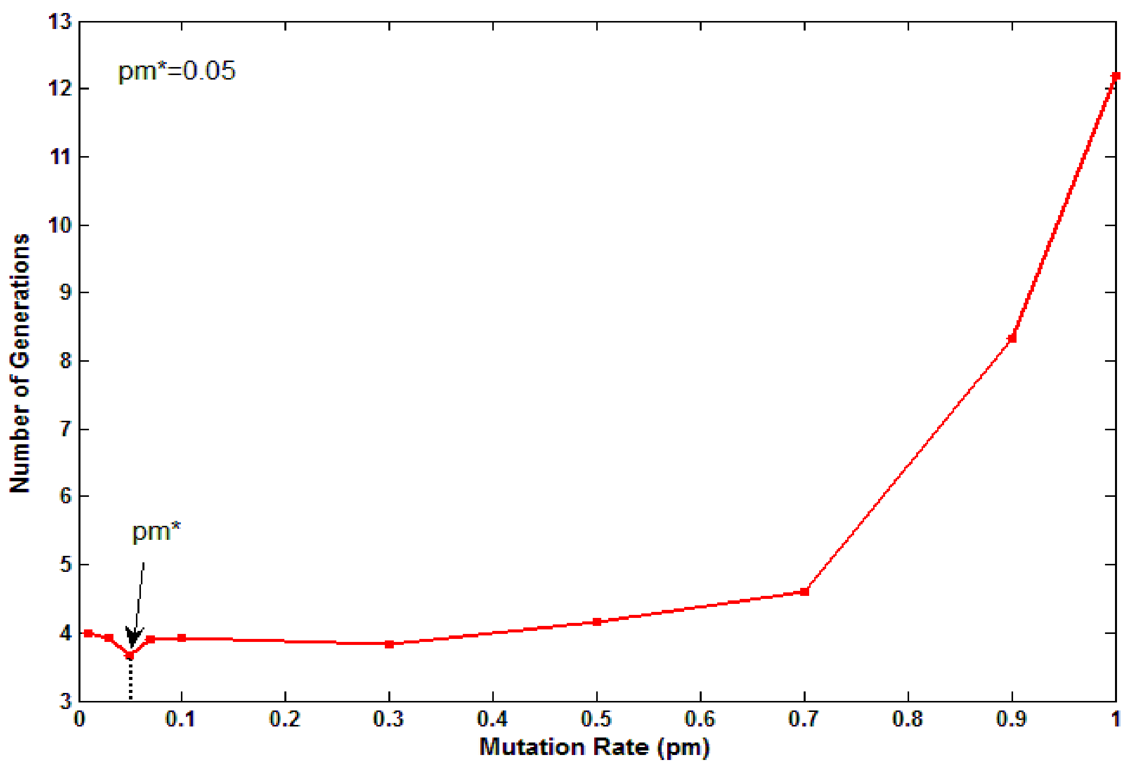

FIGURE 18: The Effect Of Mutation Rate On Speed Of Convergence For Finding The Global Minimum Of Banana Function (Ps=100 And L=2).

5 RESULTS AND DISCUSSION

In this section, some examples introduced in [3] and [12] are considered to illustrate the effect of immune algorithm parameters on the convergence speed.

Example 4:

This example is considered in [3] for solving system identification problem. It is repeated here to demonstrate the effectiveness of the selection of immune algorithm control parameters. In this example, it is required to approximate second-order system by first-order IIR filter. The second-order system and the filter are described respectively by the following transfer functions [3]:

$$H_p\left(z^{-1}\right)=\frac{0.05-0.4z^{-1}}{1-1.1314z^{-1}+0.25z^{-2}} \quad \text{and} \quad H_f\left(z^{-1}\right)=\frac{a_0}{1-b_1 z^{-1}} \tag{8}$$

In Table (2), the control parameters selected based on the study described in previous section and that used in [3] are given. Table (3) illustrates the transfer function, the number of function evolution and NMSE of the resulting IIR filter and that is described in [3]. The NMSE is calculated using the following equation:

$$NMSE=\sqrt{\sum_{k=1}^{N}\left(\left|M(k)\right|-M_d(k)\right)^2}\Bigg/\sqrt{\sum_{k=1}^{N}\left(M_d(k)\right)^2} \tag{9}$$

Where, $M_d(k)$ and $M(k)$ are the magnitude responses of the 2nd order system and that of the designed filter respectively calculated at N=2000 sampling points.

IA Parameters	The selected parameters based on the above study	The selected parameters in [3]
Population size	100	50
Replication rate	0.85	0.80
Mutation rate	0.2	0.015
Clone rate	0.05	Not used in this method
Hypermutation rate	0.8	Not used in this method

TABLE 2: The IA Control Parameters Of Examples 1 And 2

	IIR filter obtained using proposed parameters values	IIR filter obtained using parameters values stated in [3]
Transfer Function	$H_f\left(z^{-1}\right)=\frac{-0.4153}{1-0.8645z^{-1}}$	$H_f\left(z^{-1}\right)=\frac{-0.311}{1-0.906z^{-1}}$
NMSE	0.0796	0.2277
Number of function evaluations to find the global optimal solution	1056	1230

TABLE 3: The Transfer Function, Number Of Function Evolutions And NMSE Of Both Resulting IIR Filter And IIR Filter Described In [3].

Figure (19) shows the magnitude responses of the second-order system, the resulting IIR filter and IIR filter described in [3]. From Figure (19) and Table (3), noticed that the resulting IIR filter converge to the second-order system after smaller number of objective function evaluations with smaller NMSE compared to that given in [3]. So, the good selection of the IA control parameters speeds up the algorithm convergence.

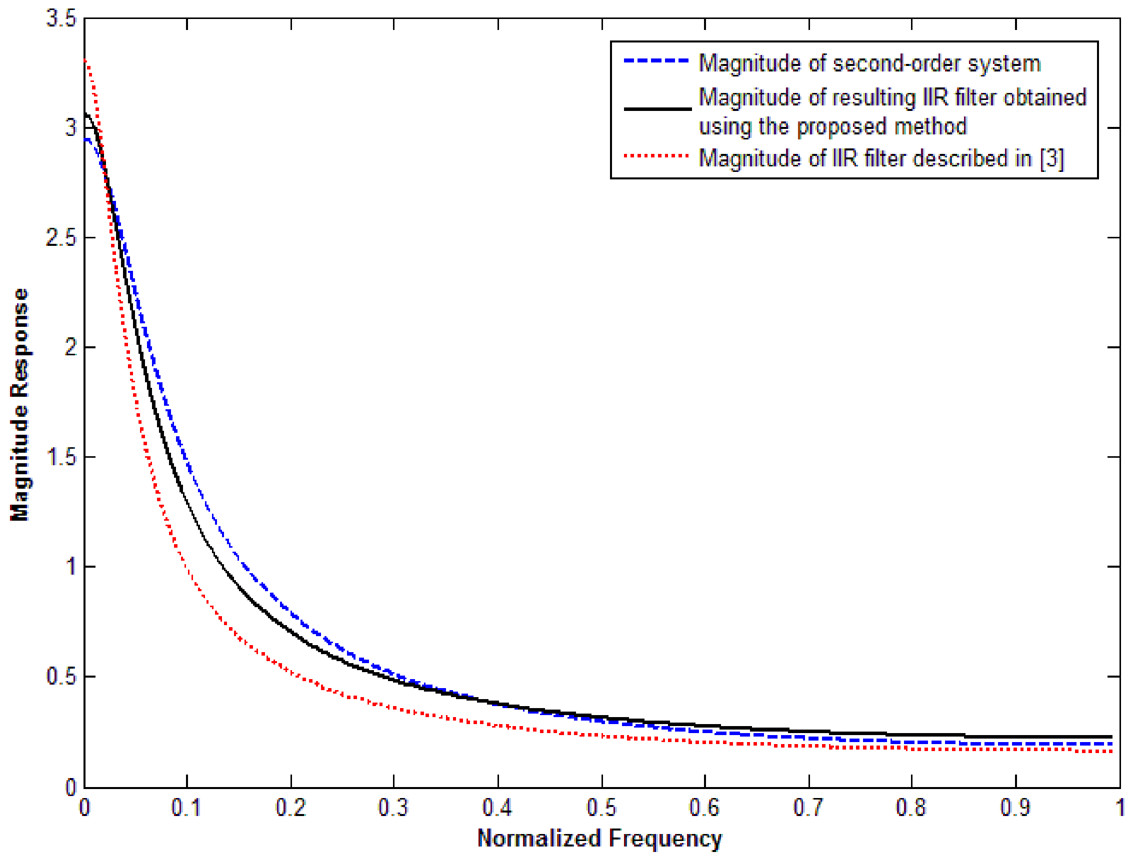

FIGURE 19: The magnitude responses of second-order system and IIR filter

Example 5:

This example is also considered in [3] for solving system identification problem. It is required to approximate a second order system by IIR filter with the same order. The system and the filter are described respectively by the following transfer functions [3]:

$$H_p\left(z^{-1}\right)=\frac{1}{1-1.2z^{-1}+0.6z^{-2}} \quad \text{and} \quad H_f\left(z^{-1}\right)=\frac{1}{1-b_1z^{-1}-b_2z^{-2}} \tag{10}$$

Using the same control parameters of example 1, the optimal solution (b_1= -1.1966, b_2= -0.59522) is obtained after 1503 objective function evaluations with MSE=0.393x10-3. However, the solution in [3] is obtained after 3000 objective function evaluations with MSE=0.5x10-3.

Example 6:

This example is considered in [12], for finding the global solution of the following test function:

$$f_4=\frac{1}{4000}\sum_{i=1}^{N}x_i^2-\prod_{i=1}^{N}\cos\left(\frac{x_i}{\sqrt{i}}\right)+1 \tag{11}$$

The proposed IA is used to solve this function with 30 dimensions (i.e. N=30) in solution space [-600, 600]. In Table (4), the control parameters selected based on the study described in previous section and that used in [12] are given.

IA Parameters	The selected parameters based on the above study	The selected parameters in [12]
Population size	200	200
Replication rate	0.2	0.1
Mutation rate	0.02	0.02
Clone rate	0.06	0.01
Hypermutation rate	0.8	0.01

Table 4: The IA Control Parameters Of Example 3

Using the proposed IA, the solution is obtained after 13120 function evaluations; however in [12] is reached after 15743 function evaluations. So, the IA control parameters are having significant effect on the convergence speed.

6 CONCLUSIONS

In this paper, general rules on speeding up the convergence of the IA are discussed. The convergence speed of the IA is important issues and heavily depends on its main control parameters. In spite of the research carried out up to date, there are no general rules on how the control parameters of the IA can be selected. In literature [12]-[13], the choice of these parameters is still left to the user to be determined statically prior to the execution of the IA. Here, we investigate the effect of the parameters variation on the convergence speed by adopting three different objective optimization examples (2-D recursive filter design, minimization of simple function, and banana function). From the studied examples, the following general heuristics on immune algorithm parameters that guarantee the convergence speed are concluded: 1) the population size should be greater than 100; 2) the replication rate should be higher than 0.2; 3) the clonal rate should be small in the range (0.05≤ p_c <0.1); 4) the hypermutation rate should be high in the range (0.5≤ p_h <1); and 5) the mutation rate should be between 1/ p_s and 1/L. These heuristics are applied to study cases solved in [3] and [12] to show effect of control parameter selection on the IA performance. Numerical results show that the good selection of the control parameters of the IA have significant effect on the convergence speed of the algorithm.

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Performance Study of Various Adaptive Filter Algorithms for Noise Cancellation in Respiratory Signals

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Abstract

Removal of noises from respiratory signal is a classicl problem. In recent years, adaptive filtering has become one of the effective and popular approaches for the processing and analysis of the respiratory and other biomedical signals. Adaptive filters permit to detect time varying potentials and to track the dynamic variations of the signals. Besides, they modify their behavior according to the input signal. Therefore, they can detect shape variations in the ensemble and thus they can obtain a better signal estimation. This paper focuses on (i) Model Respiratory signal with second order Auto Regressive process. Then synthetic noises have been corrupted with respiratory signal and nullify these noises using various adaptive filter algorithms (ii) to remove motion artifacts and 50Hz Power line interference from sinusoidal 0.18Hz respiratory signal using various adaptive filter algorithms. At the end of this paper, a performance study has been done between these algorithms based on various step sizes. It has been found that there will be always tradeoff between step sizes and Mean square error.

Keywords: Adaptive filter, Least Mean Square (LMS), Normalized LMS (NLMS), Block LMS (BLMS), Sign LMS (SLMS), Sign-Sign LMS (SSLMS), Signed Regressor LMS (SRLMS), Motion artifact, Power line interference

1. INTRODUCTION

Various biomedical signals are present in human body. To check the health condition of a human being it is essential to monitor these signals. While monitoring these signals, various noises interrupt the process. These noises may occur due to the surrounding factors, devices connected and physical factors. In this paper, noises associated with the respiratory signals are taken into account. The monitoring of the respiratory signal is essential since various sleep related disorders like sleep apnea (breathing is interrupted during sleep), insomnia (inability to fall asleep), narcolepsy can be detected earlier and treated. Also breathing disorders like snoring, hypoxia (shortage of O_2), hypercapnia (excess amount of CO_2) hyperventilation (over breathing) can be treated. The respiratory rate for new born is 44 breathes/min for adults it is 10-20 breathes/min. Various noises affecting the respiratory signal are motion artifact due to instruments, muscle contraction, electrode contact noise, powerline interference, 50HZ interference, noise generated by electronic devices, baseline wandering, electrosurgical noise.

One way to remove the noise is to filter the signal with a notch filter at 50 Hz. However, due to slight variations in the power supply to the hospital, the exact frequency of the power supply might (hypothetically) wander between 47 Hz and 53 Hz. A static filter would need to remove all the frequencies between 47 and 53 Hz, which could excessively degrade the quality of the ECG since the heart beat would also likely have frequency components in the rejected range. To circumvent this potential loss of information, an adaptive filter has been used. The adaptive filter would take input both from the patient and from the power supply directly and would thus be able to track the actual frequency of the noise as it fluctuates.

Several papers have been presented in the area of biomedical signal processing where an adaptive solution based on the various algorithms is suggested. Performance study and comparison of LMS and RLS algorithms for noise cancellation in ECG signal is carried out in [1]. Block LMS being the solution of the steepest descent strategy for minimizing the mean square error is presented in [2]. Removal of 50Hz power line interference from ECG signal and comparative study of LMS and NLMS is given in [3]. Classification of respiratory signal and representation using second order AR model is discussed in [4]. Application of LMS and its member algorithms to remove various artifacts in ECG signal is carried out in [5]-[7]. Mean square error behavior, convergence and steady state analysis of different adaptive algorithms are analyzed in [8]-[10]. The results of [11] show the performance analysis of adaptive filtering for heart rate signals. Basic concepts of adaptive filter algorithms and mathematical support for all the algorithms are taken from [12].

In [13] the authors present a real-time algorithm for estimation and removal of baseline wander noise and obtaining the ECG-derived respiration signal for estimation of a patient's respiratory rate. In [14], a simple and efficient normalized signed LMS algorithm is proposed for the removal of different kinds of noises from the ECG signal. The proposed implementation is suitable for applications requiring large signal to noise ratios with less computational complexity. The design of an unbiased linear filter with normalized weight coefficients in an adaptive artifact cancellation system is presented in [15]. They developed a new weight coefficient adaptation algorithm that normalizes the filter coefficients, and utilize the steepest-descent algorithm to effectively cancel the artifacts present in ECG signals. The paper [16] describes the concept of adaptive noise cancelling, a method of estimating signals corrupted by additive noise. In [17], an adaptive filtering method is proposed to remove the artifacts signals from EEG signals. Proposed method uses horizontal EOG, vertical EOG, and EMG signals as three reference digital filter inputs. The real-time artifact removal is implemented by multi-channel Least Mean Square algorithm. The resulting EEG signals display an accurate and artifact free feature.

The results in [18] show that the performance of the signed regressor LMS algorithm is superior than conventional LMS algorithm, the performance of signed LMS and sign-sign LMS based realizations are comparable to that of the LMS based filtering techniques in terms of signal to noise ratio and computational complexity. An interference-normalized least mean square algorithm for robust adaptive filtering is proposed in [19].The INLMS algorithm extends the gradient-adaptive learning rate approach to the case where the signals are nonstationary. It is shown that the INLMS algorithm can work even for highly nonstationary interference signals, where previous gradient-adaptive learning rate algorithms fail. The use of two simple and robust variable step-size approaches in the adaptation process of the Normalized Least Mean Square algorithm in the adaptive channel equalization is investigated in [20].In the proposed algorithm in [21], the input power and error signals are used to design the step size parameter at each iteration. Simulation results demonstrate that in the scenario of channel equalization, the proposed algorithm accomplishes faster start-up and gives better precision than the conventional algorithms. A novel power-line interference (PLI) detection and suppression algorithm is presented in [22] to preprocess the electrocardiogram (ECG) signals. A distinct feature of this proposed algorithm is its ability to detect the presence of PLI in the ECG signal before applying the PLI suppression algorithm. An efficient recursive least-squares (RLS) adaptive notch filter is also developed to serve the purpose of PLI suppression. In [23] two types of adaptive filters are considered to reduce the ECG signal noises like PLI and Base Line Interference. Various methods of removing noises from ECG signal and its implementation using the Lab view tool was referred in [24]. Results in [25] indicate that respiratory signals alone are sufficient and perform even better than the combined respiratory and ECG signals.

2. MATHEMATICAL MODEL OF RESPIRATION SIGNALS

The respiratory systems' function is to allow gas exchange to all part of the body. In addition to supplying oxygen, the respiratory system aids in removing of carbon dioxide. It prevents the lethal buildup of this waste product in body tissues. The respiratory system carries out its life-sustaining activities through the process of respiration. Respiration is the process by which the atmospheric oxygen is inhaled in to the body and the unwanted carbon dioxide is exhaled out through the nostrils and mouth.

Respiratory signals are not a constant signal with common amplitude and regular variations from time to time. Hence to estimate the signal it is necessary to frame an algorithm which can analyze even the small variations in the input signal. Respiratory signal is modeled in to a second order AR equation so that the parameters can be utilized for determining the fundamental features of the respiratory signal. The autoregressive (AR) model is one of the linear prediction formulas that attempt to predict an output Y(n) of a system based on the previous inputs {x(n), x(n-1), x(n-2)...}. It is also known in the filter design industry as an infinite impulse response filter (IIR) or an all pole filter, and is sometimes known as a maximum entropy model in physics applications.

The respiration signal can be modeled as a second order autoregressive model [4] as the following,

$X(n)=a_1X(n-1)+a_2X(n-2) + e(n)$ (1)

Where e (n) is the prediction error and $\{a_1,a_2\}$ are AR model coefficients to be determined through burgs method.

3. NOISES IN RESPIRATORY SIGNALS

Methods of respiration monitoring fall into two categories. Devices such as spirometers and nasal thermocouples measure air flow into and out of the lungs directly. Respiration can also be monitored indirectly, by measuring body volume changes; transthoracic inductance and impedance plethysmographs, strain gauge measurement of thoracic circumference, pneumatic respiration transducers, and whole-body plethysmographs are examples of indirect techniques. When the doctors are examining the patient on-line and want to review the respiratory signal waveform in real-time, there is a good chance that the signal has been contaminated by baseline wander (BW), power line interference (PLI), muscle artifacts (MA) and electrode motion artifacts (EM) etc., mainly caused by patient breathing, movement, power line noise, bad electrodes and improper electrode site preparation. All these noises mask the tiny features of the signal and leads to false diagnosis. To allow doctors to view the best signal that can be obtained, we need to develop an adaptive filter to remove the artifacts in order to better obtain and interpret the respiratory signal data.

3.1 Motion Artifact

Motion artifact cause false alarms during patient monitoring, which can reduce clinician confidence in monitoring equipment alarms and, consequently, slow response time. When motion artifact is introduced to the system, the information is skewed. Motion artifact causes irregularities in the data. Motion artifact can be reduced by proper design of the electronic circuitry and set-up. The shape of the baseline disturbance caused by motion artifacts can be assumed to be a biphasic signal resembling one cycle of a sine wave. The peak amplitude and duration of the artifact are variables since the respiratory unit is a sensitive device, it can pickup unwanted electrical signals which may modify the actual respiratory signal.

3.2 Power line interference

Power line interference consists of 50Hz pickup and harmonics which can be modelled as sinusoids and combination of sinusoids**.** Characteristics which might need to be varied in a model of power line noise include the amplitude and frequency content of the signal. These characteristics are generally consistent for a given measurement situation and, once set, will not change during a detector evaluation. Power line interference is often a nuisance in bio potential measurements, mostly because of the long wires between the subject and the amplifier, the separation between the measurement points (electrodes), capacitive coupling between the subject (a volume conductor) and power lines, and the low amplitude of the desired signals. High-resolution measurements searching for potentials as small as 1 V further exacerbate the problem. It is a common interference source with low frequency and weak amplitude in signal detection and transmission.

3.3 Electrode Contact Noise

Electrode contact noise occurs due to the loss of contact between electrode and skin. The measurement of bioelectric events is exposed to various sources of noise. The reactions that take place at the electrode make the electrode itself a source of noise. Electrode contact noise can be modeled as a randomly occurring rapid baseline transition (step) which decays exponentially to the baseline value and has a superimposed 50 Hz component. This transition may occur only once or may rapidly occur several times in succession. Characteristics of this noise signal include the amplitude of the initial transition, the amplitude of the 50 Hz component and the time constant of the decay.

3.4 Baseline Drift

The wandering of baseline results from the gross movements of the patients or from mechanical strain on the electrode wires. If there is no proper application of jelly between the electrode and the skin, during that time also baseline wandering occurs. Respiration, muscle contraction, and electrode impedance changes due to perspiration or movement of the body are the important sources of baseline drift. The drift of the baseline with respiration can be represented as a sinusoidal component at the frequency of respiration. The amplitude and frequency of the sinusoidal component should be variables. The amplitude of the respiratory signal also varies by about 15 percent with the original signal. The variation could be reproduced by amplitude modulation of the respiratory by the sinusoidal component which is added to the baseline.

4. ADAPTIVE FILTER ALGORITHMS

A system is said to be adaptive when it tries to adjust its parameters with the aid of meeting some well-defined goal or target that depends upon the state of the system and its surroundings. So the system adjusts itself so as to respond to some phenomenon that is taking place in its surroundings. An event related signal could be considered as a process, which can be decomposed into an invariant deterministic signal time locked to a stimulus and an additive noise uncorrelated with the signal. The most common signal processing of this type of bioelectric signal separates the deterministic signal from the noise. Several techniques can be considered of which we are considering the adaptive signal processing technique. Adaptive filters are self-designing filters based on an algorithm which allows the filter to “learn” the initial input statistics and to track them if they are time varying. These filters estimate the deterministic signal and remove the noise uncorrelated with the deterministic signal. The principle of adaptive filter is as shown in Figure 1.

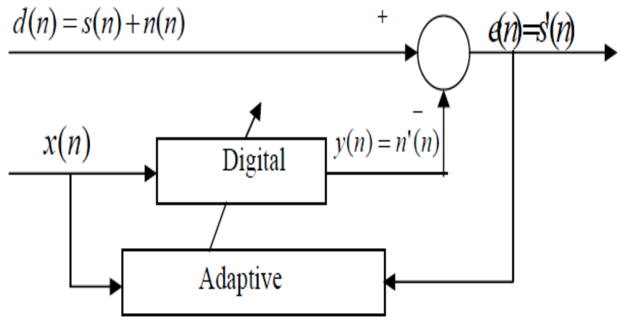


FIGURE 1: Principle of Adaptive Filter

Obtained signal d (n) from sensor contains not only desired signal s (n) but also undesired noise signal n (n). Therefore measured signal from sensor is distorted by noise n (n). At that time, if undesired noise signal n(n) is known, desired signal s(n) can be obtained by subtracting noise signal n(n) from corrupted signal d(n). However entire noise source is difficult to obtain, estimated noise signal n' (n) is used. The estimate noise signal n' (n) is calculated through some filters and measurable noise source X(n) which is linearly related with noise signal n(n). After that, using estimated signal n' (n) and obtained signal d (n), estimated desired signal s' (n) can be obtained. If estimated noise signal n' (n) is more close to real noise signal n(n), then more desired signal is obtained. In the active noise cancellation theory, adaptive filter is used. Adaptive filter is classified into two parts, adaptive algorithm and digital filter. Function of adaptive algorithm is making proper filter coefficient. General digital filters use fixed coefficients, but adaptive filter change filter coefficients in consideration of input signal, environment, and output signal characteristics. Using this continuously changed filter coefficient, estimated noise signal n' (n) is made by filtering X (n). The different types of adaptive filter algorithms can be explained as follows.

4.1 LMS Algorithm

The LMS algorithm is a method to estimate gradient vector with instantaneous value. It changes the filter tap weights so that e (n) is minimized in the mean-square sense. The conventional LMS algorithm is a stochastic implementation of the steepest descent algorithm. It simply replaces the cost function $\xi(n) = E[e^2(n)]$ by its instantaneous coarse estimate.

The error estimation e(n) is

$$e(n) = \mathbf{d}(n) - w(n)\,X(n) \qquad (2)$$

Coefficient updating equation is

$$\mathbf{w}(n+1) = \mathbf{w}(n) + \mu\, x(n)\, e(n), \qquad (3)$$

Where μ is an appropriate step size to be chosen as $0 < \mu < 0.2$ for the convergence of the algorithm. The larger step sizes make the coefficients to fluctuate wildly and eventually become unstable. The most important members of simplified LMS algorithms are:

4.2 Signed-Regressor Algorithm (SRLMS)

The signed regressor algorithm is obtained from the conventional LMS recursion by replacing the tap-input vector x (n) with the vector sgn{x(n)}.Consider a signed regressor LMS based adaptive filter that processes an input signal x(n) and generates the output y(n) as per the following:

$$y(n) = \mathbf{w}^t(n)x(n) \qquad (4)$$

where, $\mathbf{w}(n) = [\, w0(n), w1(n), \ldots , wL\text{-}1(n)\,]^t$ is a L-th order adaptive filter. The adaptive filter coefficients are updated by the Signed-regressor LMS algorithm as,

$$\mathbf{w}(n+1) = \mathbf{w}(n) + \mu\, \mathrm{sgn}\{x(n)\}e(n) \qquad (5)$$

Because of the replacement of x(n) by its sign, implementation of this recursion may be cheaper than the conventional LMS recursion, especially in high speed applications such as biotelemetry these types of recursions may be necessary.

4.3 Sign Algorithm (SLMS)

This algorithm is obtained from conventional LMS recursion by replacing e(n) by its sign. This leads to the following recursion:

$$\mathbf{w}(n+1) = \mathbf{w}(n) + \mu\, x(n)\, \mathrm{sgn}\{e(n)\} \qquad (6)$$

4.4 Sign – Sign Algorithm (SSLMS)

This can be obtained by combining signed-regressor and sign recursions, resulting in the following recursion:

$$\mathbf{w}(n+1) = \mathbf{w}(n) + \mu\, \mathrm{sgn}\{x(n)\}\, \mathrm{sgn}\{e(n)\}, \qquad (7)$$

Where sgn{ . } is well known signum function, e(n) = d(n) – y(n) is the error signal. The sequence d (n) is the so-called desired response available during initial training period. However the sign and sign – sign algorithms are both slower than the LMS algorithm. Their convergence behavior is also rather peculiar. They converge very slowly at the beginning, but speed up as the MSE level drops.

4.5 Block LMS (BLMS) Algorithm

To reduce the computational requirements of LMS algorithm, block LMS is introduced. Here the filter coefficients are held constant over each block of L samples, and the filter output y(n) and the error e(n) for each value of n within the block are calculated using the filter coefficients for that block. Then at the end of each block, the coefficients are updated using an average for the L gradients estimates over the block.

4.6 Normalized LMS (NLMS) Algorithm

In NLMS, the step size takes the form of,

$$\mu(n) = \frac{\beta}{\left\| x(n) \right\|^2} \qquad (8)$$

Where β is a normalized step size with 0< β<2. When x(n) is large, the LMS experiences a problem with gradient noise amplification. With the normalization of the LMS step size by $||x(n)||^2$ in the NLMS, noise amplification problem is diminished.

5. SCOPE OF THE PROPOSED WORK

The work carried out in [1]-[7], [13]-[18], [24] analyzes the removal of noises in ECG and EMG signal using adaptive filter algorithm. An ECG recording requires more number of electrodes on the skin and people may wear it continuously for effective monitoring. EEG measurements are always random in nature. For the complete detection, we need more number of samples for analysis. Also, the mathematical modeling of EMG signals is very complex. Removal of motion artifacts and power line interference from ECG or EMG is complex since it requires more number of electrodes for measurement. From the results in [25], the respiratory signals alone are sufficient and perform even better than ECG, EEG and EMG. In our paper, we consider only the respiratory signal for noise removal since it is more convenient and do not require more number of electrodes on the skin. We studied the performance of various adaptive filter algorithms for the removal of noises in respiratory signal. Autoregressive **(AR)** spectral estimation techniques are known to provide better resolution than classical periodogram methods when short segments of data are selected for analysis. In our study, we adopted the Burg's method to compute AR coefficients. The major advantage of Burg method for estimating the parameters of the AR model are high frequency resolution, stable AR model and it is computationally efficient.

6. SIMULATION RESULTS

This section presents the results of simulation using MATLAB to investigate the performance behaviors of various adaptive filter algorithms in non stationary environment with two step sizes of 0.02 and 0.004. The principle means of comparison is the error cancellation capability of the algorithms which depends on the parameters such as step size, filter length and number of iterations. A synthetically generated motion artifacts and power line interference are added with respiratory signals. It is then removed using adaptive filter algorithms such as LMS, Sign LMS, Sign-Sign LMS, Signed Regressor, BLMS and NLMS. All Simulations presented are averages over 1000 independent runs.

6.1 Removal of Motion Artifacts

Respiratory signal is represented by second-order autoregressive process that is generated according to the difference equation,

$$x(n)=1.2728x(n-1) - 0.81x(n-2) + v(n) \qquad (9)$$

Where v (n) is randomly generated noise.

Figure 2 and Figure 3 shows the convergence of filter coefficients and Mean squared error using LMS and NLMS algorithms. An FIR filter order of 32 and adaptive step size parameter (μ) of 0.02 and 0.004 are used for LMS and modified step sizes (β) of 0.01 and 0.05 for NLMS. It is inferred that the MSE performance is better for NLMS when compared to LMS. The merits of LMS algorithm is less consumption of memory and amount of calculation.

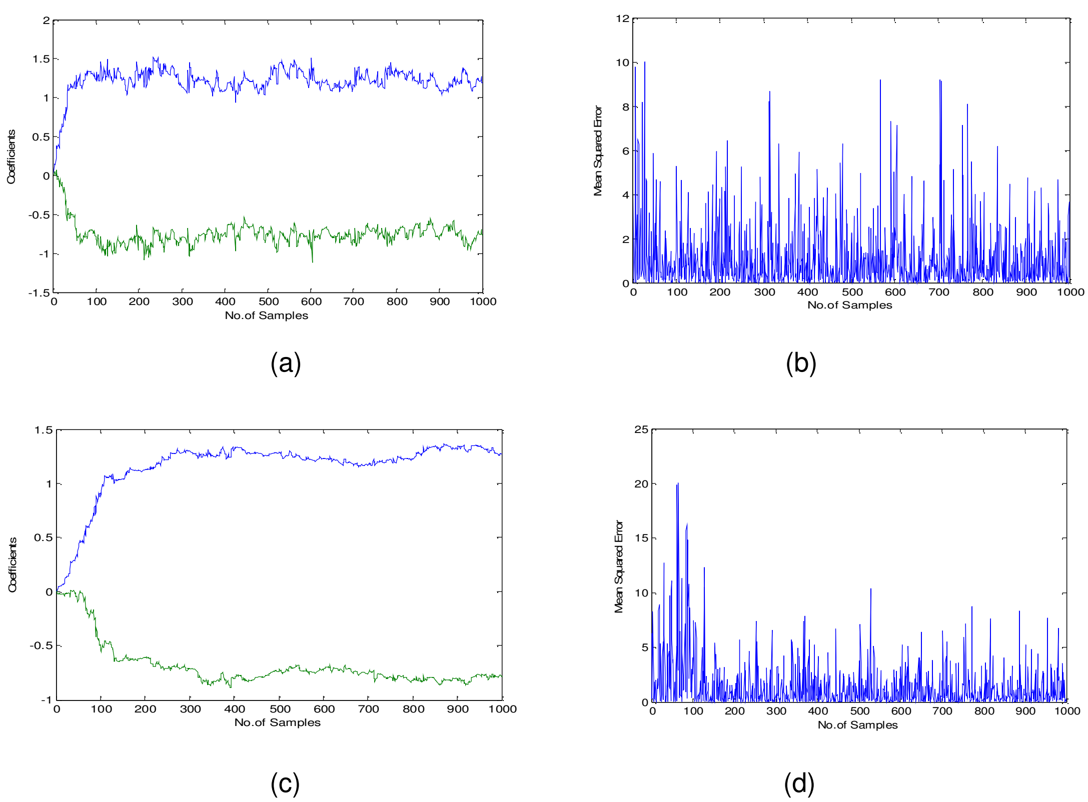
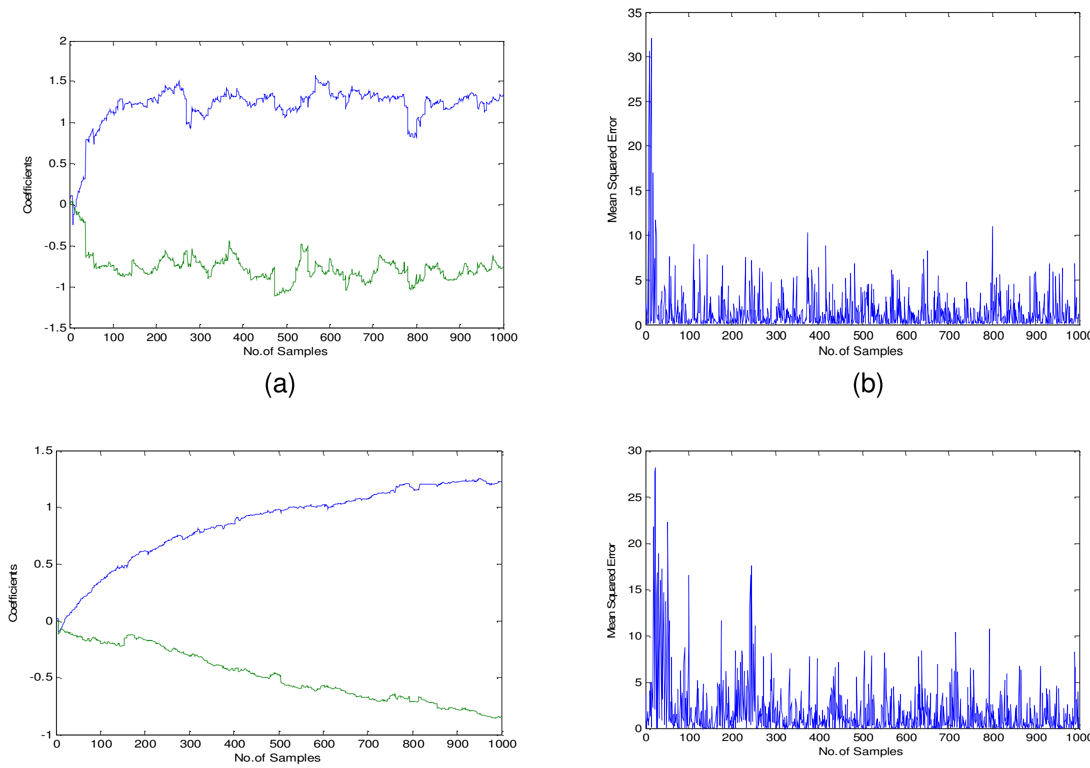


FIGURE 2: Performance of LMS adaptive filter. (a),(b) Plot of trajectories of filter coefficients and Squared error for μ=0.02 (c),(d) Plot for μ=0.004



(c) (d)

FIGURE 3: Performance of NLMS adaptive filter. (a),(b) Plot of trajectories of filter coefficients and Squared error for μ=0.02 (c),(d) Plot for μ=0.004

6.2 Removal of Power line Interference

A synthetic power line interference of 50 Hz with 1mv amplitude is simulated for PLI cancellation. Power line interference consists of 50Hz pickup and harmonics which can be modeled as sinusoids and combination of sinusoids. Figure 4 shows the generated power line interference.

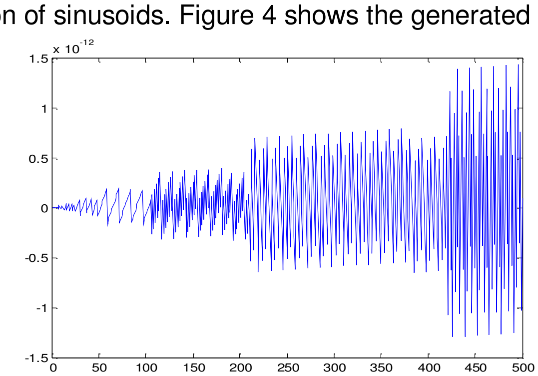
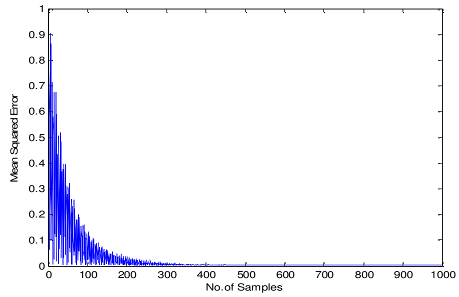
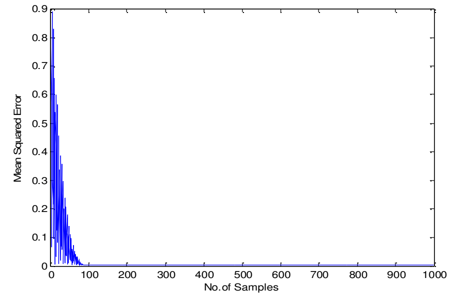


FIGURE 4: Power line interference

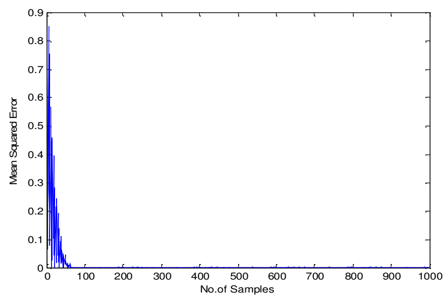
The mean square learning curves for various algorithms are depicted as shown in Figure 5. The input x(n) is 0.18Hz sinusoidal respiratory signal. It is observed that minimization of error is better with BLMS compared with other algorithms.



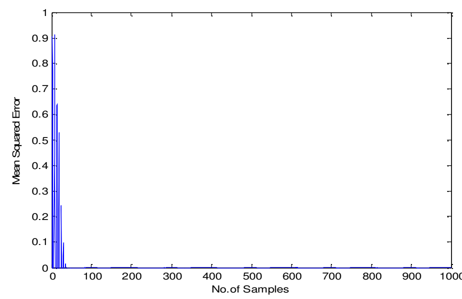
(a) LMS



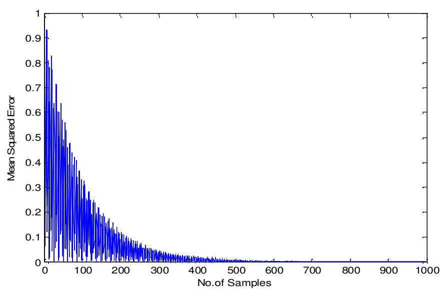
(b) SRLMS



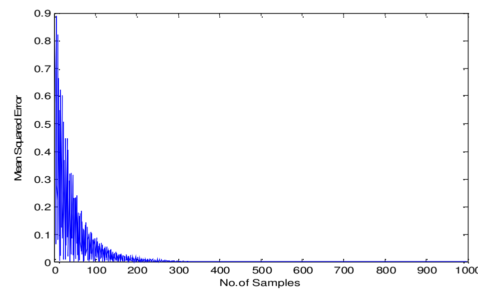
(c) Sign-Sign LMS



(d) BLMS



(e) NLMS



(f) Sign LMS

FIGURE 5: Mean Squared Error Curves for various Adaptive filter algorithms

7. COMPARITIVE EVALUATION AND DISCUSSION

Table 1 provides the comparison of mean squared error (MSE) and Convergence rate (C in terms of number of iterations that the filter coefficients converge) of different algorithms. It is observed from Figure 2 and Figure 3, the convergence speed for μ =0.02 is faster than μ=0.004. But MSE performance is comparatively better for μ=0.004 than μ=0.02. Convergence rate of LMS algorithm is better when μ=0.02 and low MSE value when μ=0.004. It is also inferred that the MSE performance of Sign Regressor LMS (SRLMS) at the step size of 0.02 is better when compared to other algorithms. But there is always tradeoff between convergence rate and mean squared error. Hence choosing an algorithm depends on the parameter on which the system has more concern.

Algorithm	μ=0.02		μ=0.004	
	MSE	C	MSE	C
LMS	2.3873e-004	100	5.4907e-005	250
SRLMS	8.5993e-006	100	5.3036e-004	550
SIGN LMS	1.3406e-004	100	4.9436e-005	550
SIGN-SIGN LMS	4.9514e-004	200	8.7072e-004	500
NLMS	β=0.05, 6.8306e-004	100	β=0.01, 0.0012	700

TABLE 1: Comparison of MSE and Convergence Rate

Table 2 shows the comparison of resulting mean square error while eliminating power line interference from respiratory signals using various adaptive filter algorithms with different step sizes. The observed MSE for LMS as shown in Figure 5 (a) is very low for μ =0.02 compared with μ =0.004. The performance of BLMS depends on block length L and NLMS depends on the normalized step size β. Observing all cases, we can infer that choosing μ =0.02 for the removal of power line interference is better when compared to μ =0.004. The step size μ =0.004 can be used unless the convergence speed is a matter of great concern. It is found that the value of MSE also depends on the number of samples taken for analysis. The filter order is 32.

Algorithm	Motion Artifacts		Power line interference	
	μ=0.02	μ=0.004	μ=0.02	μ=0.004
	MSE	MSE	MSE	MSE
LMS	1.5973e-007	2.6776e-005	8.7683e-009	8.8808e-005
BLMS	3.1966e-004	0.0160	3.2675e-004	0.0160
SR LMS	5.3616e-007	2.1528e-007	3.8242e-010	4.8876e-005
SIGN LMS	1.9924e-007	1.2130e-005	2.1145e-007	5.7397e-010
SIGN-SIGN LMS	3.7528e-006	5.5596e-007	1.9290e-007	4.2355e-008
NLMS	β=0.05, 2.1528e-007	β=0.01, 1.0570e-008	β=0.05, 4.7339e-012	β=0.01, 3.6219e-005

TABLE 2: Comparison of MSE in removing motion artifacts and power line interference

From the simulation results, the proposed adaptive filter can support the task of eliminating PLI and motion artifacts with fast numerical convergence. Compared to the results in [23], the mean square value obtained in this work is found to be very low by varying the step sizes and increasing the number of iterations. An FIR filter order of 32 and adaptive step size parameter (μ) of 0.02 and 0.004 are used for LMS and modified step sizes (β) of 0.01 and 0.05 for NLMS. It is inferred that the MSE performance is better for NLMS when compared to LMS. The merits of LMS algorithm is less consumption of memory and amount of calculation. It has been found that there will be always tradeoff between step sizes and Mean square error. It is also observed that the performance depends on the number of samples taken for consideration.

7. CONCLUSION & FUTURE WORK

This study has revealed useful properties of various adaptive filter algorithms. The objective is to optimize different adaptive filter algorithms so that we can reduce the MSE so as to improve the quality of eliminating interference. It is inferred that the MSE performance is better for NLMS when compared to LMS. The merits of LMS algorithm is less consumption of memory and amount of calculation. It has been found that there will be always tradeoff between step sizes and Mean square error. It is also observed that the performance depends on the number of samples taken for consideration. Choosing an algorithm depends on the parameter on which the system has much concern. The future work includes the optimization of algorithms for all kinds of noises and to use the optimized one in the implementation of DSP Microcontroller that estimates the respiratory signal.

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Single-Channel Speech Enhancement by NWNS and EMD

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Abstract

This paper presents the problem of noise reduction from observed speech by means of improving quality and/or intelligibility of the speech using single-channel speech enhancement method. In this study, we propose two approaches for speech enhancement. One is based on traditional Fourier transform using the strategy of Noise Subtraction (NS) that is equivalent to Spectral Subtraction (SS) and the other is based on the Empirical Mode Decomposition (EMD) using the strategy of adaptive thresholding. First of all, the two different methods are implemented individually and observe that, both the methods are noise dependent and capable to enhance speech signal to a certain limit. Moreover, traditional NS generates unwanted residual noise as well. We implement nonlinear weight to eliminate this effect and propose Nonlinear Weighted Noise Subtraction (NWNS) method. In first stage, we estimate the noise and then calculate the Degree Of Noise (DON1) from the ratio of the estimated noise power to the observed speech power in frame basis for different input Signal-to-Noise-Ratio (SNR) of the given speech signal. The noise is not accurately estimated using Minima Value Sequence (MVS). So the noise estimation accuracy is improved by adopting DON1 into MVS. The first stage performs well for wideband stationary noises and performed well over wide range of SNRs. Most of the real world noise is narrowband non-stationary and EMD is a powerful tool for analyzing non-linear and non-stationary signals like speech. EMD decomposes any signals into a finite number of band limited signals called intrinsic mode function (IMFs). Since the IMFs having different noise and speech energy distribution, hence each IMF has a different noise and speech variance.

These variances change for different IMFs. Therefore an adaptive threshold function is used, which is changed with newly computed variances for each IMF. In the adaptive threshold function, adaptation factor is the ratio of the square root of added noise variance to the square root of estimated noise variance. It is experimentally observed that the better speech enhancement performance is achieved for optimum adaptation factor. We tested the speech enhancement performance using only EMD based adaptive thresholding method and obtained the outcome only up to a certain limit. Therefore, further enhancement from the individual one, we propose two-stage processing technique, NWNS+EMD. The first stage is used as a pre-process for noise removal to a certain level resulting first enhanced speech and placed this into second stage for further removal of remaining noise as well as musical noise to obtain final enhancement of the speech. But traditional NS in the first stage produces better output SNR up to 10 dB input SNR. Furthermore, there are musical noise and distortion presented in the enhanced speech based on spectrograms and waveforms analysis and also from informal listening test. We use white, pink and high frequency channel noises in order to show the performance of the proposed NWNS+EMD algorithm.

Keywords: speech enhancement, non linear weighted noise subtraction, degree of noise, empirical mode decomposition, adaptive thresholding.

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1. INTRODUCTION

In many speech related systems like mobile communication in an adverse environment, the desired signal is not available directly; rather it is mostly contaminated with some interference sources of noise. These background noise signals degrade the quality and intelligibility of the original speech, resulting in a severe drop in the performance of the applications. The degradation of the speech signal due to the background noise is a severe problem in speech related systems and therefore should be eliminated through speech enhancement algorithms. In our previous study, we have proposed a two stage noise reduction algorithm by noise subtraction and blind source separation [1]. In that report, we recommended further research to improve the algorithm over wide ranges of SNRs as well as noise reduction performance for narrow-band noises.

Research on speech enhancement techniques started more than 40 years ago at AT&T Bell Laboratories by Schroeder as mentioned in [2]. Schroeder proposed an analog implementation of the spectral magnitude subtraction method. Then, the method was modified by Schroeder’s colleagues in a published work [3]. However, more than 15 years later, the spectral subtraction method as proposed by Boll [4] is a popular speech enhancement techniques through noise reduction due to its simple underlying concept and its effectiveness in enhancing speech degraded by additive noise. The technique is based on the direct estimation of the short-term spectral magnitude. Recent studies have focused on a non-linear approach to the subtraction procedure [5-7]. In Martin [5] algorithm modifies the short time spectral magnitude of the corrupted speech signal such that the synthesized signal is perceptually as close as possible to the clean speech signal. The estimating noise is obtained as the minima values of a smoothed power estimate of the noisy signal, multiplied by a factor that compensates the bias. The algorithm eliminates the need of speech activity detector by exploiting the short time characteristics of speech signal. Martin’s study compared the result with Malah [6], and found an improved SNR. However, this noise estimation is sensitive to outliers, and its variance is about twice as large as the variance of a conventional noise estimator. These approaches have been justified due to the variation of signal-to-noise ratio across the speech spectrum. Unlike white

Gaussian noise, which has a flat spectrum, the spectrum of real-world noise is not flat. Thus, the noise signal does not affect the speech signal uniformly over the whole spectrum. Some frequencies are affected more adversely than others. In high frequency channel noise (HF channel), for instance, in the low frequencies, where most of the speech energy resides, are affected more than the high frequencies. Hence it becomes imperative to estimate a suitable factor that will subtract just the necessary amount of the noise spectrum from each frequency bin (ideally), to prevent destructive subtraction of the speech while removing most of the residual noise. Then it is usually difficult to design a standard algorithm that is able to perform homogeneously across all types of noise. For that, a speech enhancement system is based on certain assumptions and constraints that are typically dependent on the application and the environment.

There are some crucial restrictions of the Fourier spectral analysis [8]: the system must be linear; and the data must be strictly periodic or stationary; otherwise the resulting spectrum will make little physical sense. From this point of view, Fourier filter methods will fail when the processes are nonlinear. The empirical mode decomposition (EMD), proposed by Huang *et.al* [9] as a new and powerful data analysis method for nonlinear and non-stationary signals, has made a new path for speech enhancement research. EMD is a data-adaptive decomposition method, which decompose data into zero mean oscillating components, named as intrinsic mode functions (IMFs). It is mentioned in [10] that most of the noise components of a noisy speech signal are centered on the first three IMFs due to their frequency characteristics. Therefore EMD can be used for effectively identifying and removing these noise components. Xiaojie et. al. [11] proposed EMD that effectively identify and remove noise components. Recently there are many speech enhancement methods [12-14] have been developed in dual-channel and single-channel modes using EMD. In [12] EMD based speech enhancement is achieved by removing those IMFs whose energies exceeded a predefined threshold value. The IMFs, which represent empirically, observed applying EMD in observed speech contaminated with white Gaussian noise generates noise model. In [13] speech enhancement based on EMD-MMSE is performed by filtering the IMFs generated from the decomposition of speech contaminated with white Gaussian noise. In [14], an optimum gain function is estimated for each IMF to suppress residual noise that may be retained after single-channel speech enhancement algorithms.

In our previous study, Hamid [1] proposed noise subtraction (NS) technique where noise is estimated using minimum value sequence (MVS) and the noise floor is updated with the help of estimated degree of noise (DON). The main drawback of this method is that we estimate DON on the basis of pitch period over the frame and the pitch period of unvoiced sections is not accurately estimated. To solve this problem, in this paper, we estimate EDON on the basis of estimated SNRs of clean and noisy speech spectrums. Then, the EDON is estimated in two stages from a function, which is previously prepared as the function of the parameter of the degree of noise [1]. We consider the valleys of the observed smoothed power spectrum of a noisy speech signal to estimate noise power. This spectrum is tuned by EDON to adjust the noise level for a particular SNR. We also perform suitable steps to minimize the residual noise problem. Now the estimated noise spectrum with a controlled non-linear factor is subtracted from the observed spectrum in time domain to obtain noise reduced speech. This paper presents a parametric formulation to estimate noise weight on the basis of EDON. The weighting factor increases with increasing SNRs, and results non-linear weighting factor with speech activity. Although Fourier transform and wavelet analysis make great contributions, they suffer from many shortcomings in case of nonlinear and nonstationary signals. For this reason, for further enhancement, EMD technique has been used for robust noisy speech analysis in this work.

Since the IMFs in EMD having different noise and speech energy distribution, hence each IMF has a different noise and speech variance. These variances change for different IMFs. Therefore an adaptive threshold function is used, which is changed with newly computed variances for each IMF. Moreover, since IMFs are generated from EMD and therefore, we call the proposed method as EMD based adaptive thresholding technique. To enhance the speech, EMD based adaptive thresholding algorithm applied into each IMFs for removing the noise embedded in the underlying

IMFs. In the adaptive threshold function, adaptation factor is the ratio of the square root of added noise variance to the square root of estimated noise variance. It is experimentally observed that the better speech enhancement performance is achieved for optimum adaptation factor. We tested the speech enhancement performance using only EMD based adaptive thresholding method and obtained the outcome only up to a certain limit. Moreover, each individual method has some performance limitations.

Therefore, further enhancement from the individual one, we propose two-stage processing technique, namely, a time domain NS or NWNS followed by an EMD based adaptive thresholding. The first stage is used as a pre-process for noise removal to a certain level resulting first enhanced speech and placed this into second stage for further removal of remaining noise as well as musical noise to obtain final enhancement of the speech. But traditional NS in the first stage produces better output SNR up to 10 dB input SNR. Furthermore, there are musical noise and distortion presented in the enhanced speech based on spectrograms and waveforms analysis and also from informal listening test. EMD based adaptive thresholding does not work well on distorted speech and not be able to recover the speech from the distorting speech when it cascaded with NS. As a result, the overall performance of enhanced speech obtained from NS+EMD based adaptive thresholding is not so good based on the objective and subjective measures. In the first stage, the performance of speech enhancement improves by introducing nonlinear weight in NS, namely NWNS, to control the noise level and improves its overall performance for wide range of input SNRs provide first enhanced speech without distortion and with minimum effect of musical noise. Moreover, the overall performance is further improved by cascading NWNS in the first stage and EMD based adaptive thresholding in the second stage. In this two-stage processing, NWNS is influenced to increase the performance of EMD based adaptive thresholding. The advantage of the method is the effective removal of noise and produces better output SNR for wide range of input SNR and also improves the speech quality with reducing residual noise.

2. NOISE ESTIMATION AND SUBTRACTION

The main component of speech noise reduction is noise estimation that is a most difficult task for a single-channel enhancement system. The noise estimate can have a major impact on the quality of the enhanced speech. That is, with a better noise estimation, a more correct SNR is obtained, resulting in the enhanced speech with low distortion. We have assumed that speech and noise are uncorrelated to each other. We further assume that signal and noise are statistically independent.

2.1 Estimating Minimum Value Sequence (MVS)

The sections of consecutive samples are used as a single frame l(320 samples) and spaced l'(100 samples) achieving an almost 62.75% overlap. The short-term representation of a signal $y(n)$ is obtained by Hamming windowing and analyzed using N=512 point Discrete-Fourier transform (DFT) at sampling frequency 16KHz. Initially, noise spectrum is estimated from the valleys of the amplitude spectrum [1]. The algorithm for noise estimation is as follows:

Compute the RMS value Y_{rms} of the amplitude spectrum $Y(k)$. We detect the minima of $Y(k)$ by obtaining the vector k_{min} such that $Y(k_{min})$ are the minima in $Y(k)$. Then the interpolation is performed between adjoining minima positions to obtain $Y_{min}(k)$ representing the minimum value sequences (MVS). We smooth the sequences by taking partial average called smoothed minimum value sequences (SMVS). An estimation of noise from the SMVS is survived by an overestimation and underestimation of the SNR which is controlled by proposed EDON. The block diagram of the noise estimation process is shown in Figure 1.

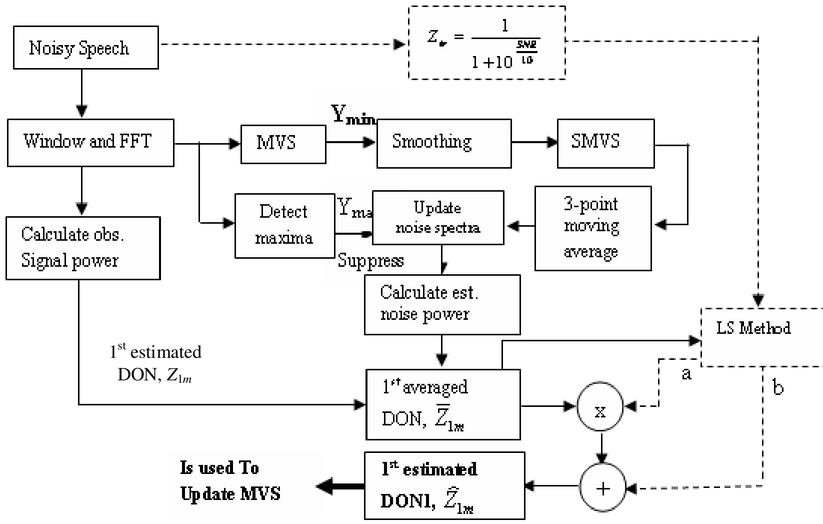


FIGURE 1: Block diagram of the 1st estimated DON, Z_{1m}.

2.2 Estimation of the Degree Of Noise (EDON)

In a single-channel method, we only know the power of the observed signal. To obtain EDON, we estimate noise of the observed signal in every analysis frame *m*. First white noise of various SNR is added to voiced vowel sounds. Now for each SNR, DON of each phoneme is estimated and averaged which corresponds the input SNR. Then each of these estimated 1st averaged DONs of each frame *m* for corresponding input SNR expressed as $\overline{Z}_{1m}$. The estimated $\overline{Z}_{1m}$ is aligned with the true DON (Z_{tr}) using the least-square (LS) method results the 1st estimated DON $Z_{1m}$of that frame. The true DON (Z_{tr}) is given by

$$Z_{tr} = \frac{P_d}{P_s + P_d} = \frac{1}{1+10^{\frac{dB}{10}}} \tag{1}$$

where *dB* is input SNR. The 1st averaged DON is

$$\overline{Z}_{1m} = \frac{1}{M}\sum_{m=1}^{M}\frac{P_\eta(m)}{P_{obs}(m)} \tag{2}$$

where, *M* are the noise added frames; $P_\eta(m)$and $P_{obs}(m)$ are the powers of noise and observed signals, respectively. Here it obvious that we consider only the voiced phonemes in our experiment. So the value of $\overline{Z}_{1m}$should be limited to voiced portion of a speech sentence. We used the same experiment with unvoiced speech. Practically the unvoiced portion contaminated with higher degree of noise. Hence the estimated noise is higher for unvoiced frame than from voiced frame. Consequently higher DON value is obtained from unvoiced frame than from voiced frame that is logically resemblance. The degree of noise estimated from a function using least square method is given as

$$Z_{tr} = a \times \overline{Z}_{1m} + b$$

here *a* and *b* are unknown. We estimate *a* and *b* via LS method, yielding $\overline{a}$ and $\overline{b}$and the estimated degree of noise is given by

$$Z_{1m} = \overline{a} \times \overline{Z}_{1m} + \overline{b} \tag{3}$$

where Z_{1m} is the 1st estimated DON of frame m. The value os Z_{1m} is applied to update the MVS. Next, the noise level is re-estimated and updated with the help of Z_{1m}. Finally, from the estimated noise, we again estimate 2nd averaged DON ($\bar{Z}_{2m}$) and similarly the 2nd estimated DON (Z_{2m}) which is used to estimate the noise weight for non linear weighted noise subtraction.

2.3 Noise Spectrum Estimation

We detect the minima $Y_{\min}(k_{\min}) \leftarrow \min(Y(k))$ values of amplitude spectrum $Y(k)$ when the following condition ($Y(k)<Y(k-1)$ and $Y(k)<Y(k+1)$ and $Y(k)<Y_{rms}$) is satisfied. The $k_{\min}$ expresses the positions of the frequency bin index of minima values. Then interpolate between adjoining minima positions $(k_{\min} \leftarrow k)$ to obtain the minima value sequence (MVS) $Y_{\min}(k)$. Now we smooth the sequences by taking partial average called smoothed minima value sequence (SMVS). This process continuously updates the estimation of noise among every analysis frames. Now the noise spectrum is estimated from the SMVS and 1st estimated DON according to the condition

$$D_m(k) = Y_{\min}(k) + \left(\sqrt{Z_{1m}} \times Y_{rms}\right) \tag{4}$$

where Y_{rms} is the rms value of the amplitude spectrum. Then we made some updates of $D_m(k)$, the updated spectrum is again smoothed by three point moving average, and lastly the main maximum of the spectrum is identified and are suppressed [1]. Figure 2 shows the spectrums.

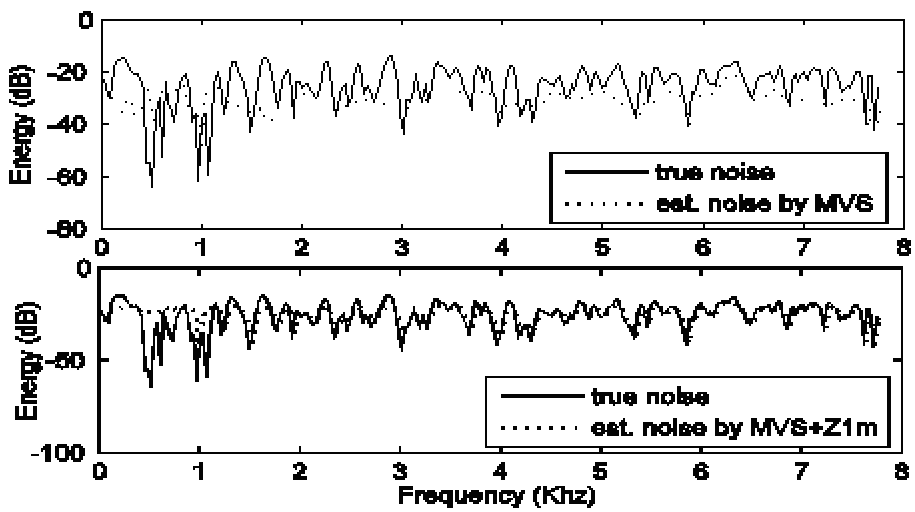


FIGURE 2: Noise spectrums (true and estimated).

2.4 Non-linear Weighted Noise Subtraction (NWNS)

Noise reduction in the front-end is based on implementation of the traditional spectral subtraction (SS) require an available estimation of the embedded noise, here, in time domain we named noise subtraction (NS). The goal of this section is to modify the noise subtraction process by adopting a non linear weight for minimizing the effect of residual noise in the processed speech and then to improve the performance by using EMD.

For subtraction in time domain, the estimated noise in the previous section is recombined with the phase of the noisy speech and inverse transformed one. Then we obtain $\hat{d}_{ss}(n)$ by withdrawing the effect of the window. The NWNS is given by:

$$s_1(n) = y(n) - \sqrt{\alpha \times Z_{tr}} \times \hat{d}_{ss}(n) \tag{5}$$

where $\alpha = 0.3019 + 6.4021 \times Z_{2m} - 14.109 \times Z_{2m}^2 + 9.8273 \times Z_{2m}^3$ is nonlinear weighting factor. We use least-square method for the estimation process. We find that for each input SNR, certain weight is required for best noise reduction results over wide ranges of SNR. In this experiment, we used 7 male and 7 female speakers of 10 different sentences at different SNR levels, randomly selected from the TIMIT database. We use 3rd degree polynomials to derive the above formulation. It is observed from Eq. (1) that it needs the input SNR. The input SNR can be estimated using variance is given by

$$SNR_{input} = 10 \log_{10}\left(\frac{\sigma_s^2}{\sigma_\eta^2}\right) \tag{6}$$

where, σ_s^2 and σ_η^2 are the variances of speech and noise respectively. We assume that due to the independency of noise and speech, the variance of the noisy speech is equal to the sum of the speech variance and noise variance. It is found that by adopting nonlinear weighted in NS, a good noise reduction is obtained. Although with the NWNS, we find the good performance with less musical noise by informal listening test but for further enhancement we cascade another method EMD and get better results.

3. CASCADE OF NWNS AND EMD

The general block diagram of the proposed system is shown in Figure 3. In the block diagram, first stage is incorporated a Noise Subtraction (NS) method with weight and second stage a Empirical Mode Decomposition (EMD) based adaptive thresholding method.

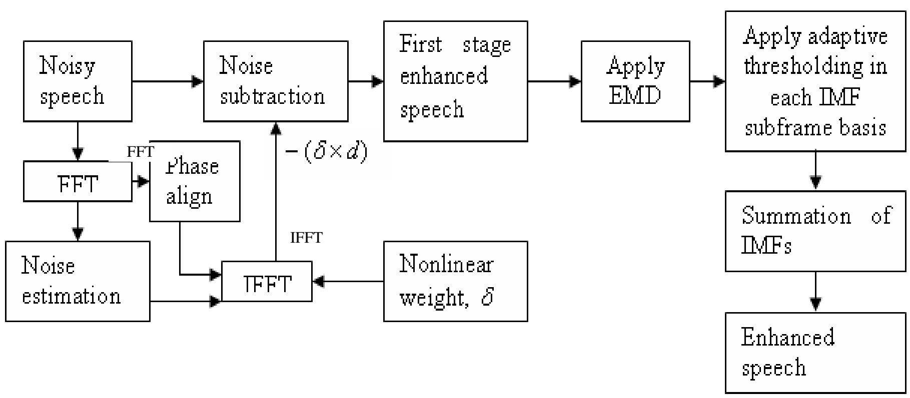


FIGURE 3: The block diagram of the two-stage NWNS+EMD method.

3.1 Empirical Mode Decomposition (EMD)

The principle of EMD technique is to decompose any signal $y(n)$ into a set of band-limited functions, which are the zero mean oscillating components, called simply the intrinsic mode functions (IMFs) [9]. Although a mathematical model has not been developed yet, different methods for computing EMD have been proposed after its introduction [15]. The very first algorithm, called as the sifting process, is adopted here to find the IMF's include the following steps;

1. Identify the extrema of $y(n)$
2. Generate the upper and lower envelopes ($u(n)$ and $l(n)$) by connecting the maxima and minima points by interpolation
3. Calculate the local mean $\mu_1(n)=[u(n)+l(n)]/2$
4. Since IMF should have zero local mean, subtract out $\mu_1(n)$ from $y(t)$ to obtain $h_1(t)$
5. Check whether $h_1(t)$ is an IMF or not
6. If not, use $h_1(t)$ as the new data and repeat steps 1 to 6 until ending up with an IMF.

Once the first IMF is derived, we should continue with finding the remaining IMFs. For this purpose, we should subtract the first IMF $c_1(n)$ from the original data to get the residue signal $r_1(t)$. The residue now contains the information about the components of longer periods. We should treat this as the new data and repeat the steps 1 to 6 until we find the second IMF.

3.2 Soft-thresholding

The soft thresholding strategy proposed in [16] for a frame, *m* of length *L* in transform-domain as

$$\hat{Y}_q = \begin{cases} Y_q, & if \quad \phi \geq \sigma_n^2 \\ sign(Y_q)\left[\max\{0, (|Y_q| - j\gamma)\}\right], & otherwwise \end{cases} \tag{7}$$

where $\phi = \frac{1}{L}\sum_{q=1}^{L}|Y_q|^2$ denotes the average power of the frame, and σ_n^2 is the global noise variance of the speech, Y_q is qth coefficient of the frame obtained by the required transformation and $\hat{Y}_q$ denotes to the thresholded samples of the frame. The multiplication factor $j\gamma$ is the linear threshold function while j being the sorted index-number of $|Y_q|$. An estimated value of γ can be obtained as:

$$\gamma = \frac{\lambda\sigma_n}{\sqrt{\frac{1}{Q}\sum_{q=1}^{Q} q^2}} \tag{8}$$

where λ is an adaptation factor and its value is determined experimentally such that $0<\lambda<1$. It is observed that the first part of Eq. (7) is for signal dominant frame when the condition satisfies, and second part is for noise dominant frame where soft thresholding will have to apply. So the classification of frames either to be signal dominant or noise dominant depends on average power of a frame and global noise variance of the given noisy speech. In this paper, we apply this soft thresholding strategy adaptively in each IMF, as discuss in the next section.

3.3 Adaptive thresholding

Soft thresholding strategy performs better on wide range of input SNR due to thresholded noise dominant frames only and kept remain the same in case of signal dominant frames but the misclassification of frames is a major drawback that causes musical noise [9]. Therefore this method is mainly appropriate for white noise. All the drawbacks can be significantly reduced with the proposed EMD based adaptive thresholding strategy with some modification of frame classification criteria. Since the IMFs will have different noise and speech energy distribution, so it suggests that each IMF will have a different noise and speech variance. After applying EMD, the soft thresholding technique is applied on each sub-frame of each IMF based on the computed variances. It is obvious that the variances will be changed for different sub-frames as well as with the individual IMF. The threshold will also be changed with newly computed variances and hence this technique is termed as adaptive thresholding. The proposed EMD based adaptive thresholding strategy for r^{th} subframe of $(i')^{th}$ IMF as:

$$\hat{Y}_{q,i'}^{(r)} = \begin{cases} Y_{q,i'}^{(r)}, & if\ \varphi_{i'}^{(r)} \geq 2\sigma_{n,i'}^2 \\ sign(Y_{q,i'}^{(r)})\left[\max\{0, (|Y_{q,i'}^{(r)}| - j'\hat{\gamma})\}\right], & otherwise \end{cases} \tag{9}$$

Here, $\hat{Y}_{q,i'}^{(r)}$ denotes to the thresholded samples of r^{th} subframe of the $(i')^{th}$ IMF, $Y_{q,i'}^{(r)}$ is q^{th} coefficient of r^{th} subframe of $(i')^{th}$ IMF and the multiplication $j'\hat{\gamma}$ is the adaptive threshold function while j' being the sorted index-number of $|Y_{q,i'}^{(r)}|$. The threshold factor $\hat{\gamma}$ is varied adaptively for individual IMF according to its variance. An estimated value of $\hat{\gamma}$ can be obtained as:

$$\hat{\gamma} = \frac{\sigma_{-n,i'}}{\sqrt{\frac{1}{Q}\sum_{q=1}^{Q} q^2}} \quad \text{or,} \quad \hat{\gamma} = \frac{\lambda\sigma_{n,i'}}{\sqrt{\frac{1}{Q}\sum_{q=1}^{Q} q^2}}$$

where, $Q = 64$, $\sigma_{-n,i'} = \lambda\sigma_{n,i'}$, $\lambda =$ adaptation factor and $\sigma^2_{n,i'} =$ noise variance of the $(i')^{th}$ IMF. Since global noise variance is estimated from silent frames, therefore, it assumes each frame as well as subframe belong that variance. That is why; the boundary for the classification of subframes should be set to two times of the globally estimated noise variance when noise variance and speech variance of that subframe are same. The enhanced speech signal of the EMD based adaptive thresholding is given by

$$s_2(n) = \sum_{i'=1}^{I}\left[\sum_{r=1}^{R}\left(\sum_{q=1}^{Q}\hat{Y}^{(r)}_{q,i'}\right)\right] \tag{10}$$

where, I=total number of IMFs,
R=total number of subframe and
Q=length of a subframe.

4. EXPERIMENTAL RESULTS AND DISCUSSION

We study the effectiveness of the proposed NWNS+EMD based adaptive thresholding algorithm are tested on the speech data corrupted by three different types of additive noise like white, pink and HF channel noise are taken from NOISEX database. N=56320 samples of the clean speech /she had your dark suit in greasy wash water all year/ from TIMIT database were used for all simulations. The noises are added to the clean speeches at different SNRs from –10dB to 30dB of step 5 to obtain noisy speech signals.

For evaluating the performance of the method, we are used the overall output and average segmental SNRs that are graphically represented as for measuring objective speech quality. The results of the average output SNR obtained from for white noise, pink noise and HF channel noise at various SNR levels are given in Table 1 for pre-processed speech in the first stage and final enhanced speech in the second stage respectively. Since in the real world environments, the noise power is sometimes equal to or greater than the signal power or the noise spectral characteristics sometimes change rapidly with time, NS or NWNS is not so effective in such situations. Because, there have to introduced large errors in the noise estimation process. EMD based adaptive thresholding method plays a vital role for the above case as found in Table 1. Table 2 presents a comparison the overall average output SNR among our previous method WNS and WNS+BSS with proposed method NWNS+EMD.

Input SNR	White noise		HF channel noise		Pink noise	
	NWNS	EMD	NWNS	EMD	NWNS	EMD
-10dB	-1.57	2.06	-7.47	-0.58	-7.06	-6.69
-5dB	2.39	5.69	-2.66	3.03	-2.32	-1.92
0dB	5.26	8.85	1.91	6.29	2.14	2.82
5dB	8.66	11.94	6.42	9.74	6.33	7.22
10dB	11.64	15.15	10.77	13.46	10.73	11.71
15dB	15.77	18.72	15.42	17.42	15.40	16.26
20dB	20.37	22.62	20.22	21.64	20.22	20.91
25dB	25.17	26.85	25.11	26.12	25.11	25.64
30dB	30.05	31.27	30.02	30.77	30.02	30.44

TABLE 1: The average output SNR for various types of noises at different input SNR by NWNS and NWNS+EMD (indicated as EMD).

Input SNR	White noise			HF channel noise			Pink noise		
	WNS	WNS+BSS	EMD	WNS	WNS+BSS	EMD	WNS	WNS+BSS	EMD
0dB	0.66	8.1	8.9	0.4	4.3	6.3	0.4	2.1	2.8
5dB	6.0	10.2	11.9	5.5	7.8	9.7	5.5	6.8	7.2
10dB	11.1	11.2	15.2	10.5	10.9	13.5	10.4	10.2	11.7
15dB	15.7	13.8	18.7	15.1	13.1	17.4	15.0	13.2	16.3
20dB	19.2	15.2	22.6	18.6	14.9	21.6	18.8	15.1	10.1
25dB	21.3	15.7	26.9	20.8	15.7	26.1	21.4	15.8	25.6
30dB	22.3	16.0	31.3	21.8	15.8	30.8	22.7	16.1	30.5

TABLE 2: The average output SNR for various types of noises at different input SNR by WNS, WNS+BSS (previous methods) and NWNS+EMD (indicated as EMD).

In terms of speech quality and intelligibility, the proposed two-stage (NWNS+EMD based adaptive thresholding method has to given a better tradeoff between noise reduction and speech distortion. We investigate this effect from the enhanced speech waveforms obtained from various methods as shown in Figure 4. It is observed from the waveforms that the enhanced speech is distorted in low voiced parts due to remove the noise in NS method whereas NWNS does not. A little amount of noise is removed from the corrupted speech by NWNS method. So in NS method there is a loss of speech intelligibility while NWNS maintains it. Although the EMD based adaptive thresholding can be able to successfully remove the noise from voiced parts but there is some noise remaining in the silent parts because of misclassification of subframes as signal-dominant. This remedy can be avoided using the proposed method. We also observed that by NS+EMD based adaptive thresholding method, there is loss of information in lower voiced parts and as a result speech intelligibility reduced. Moreover, the wavefrom obtained by NWNS+EMD based adaptive thresholding, it can be seen that there is no loss of information in lower voiced parts and maintains the speech intelligibility. We use two perceptually motivated objective speech quality assessments, namely the average segmental SNR (ASEGSNR) and the Perceptual Evaluation of Speech Quality (PESQ) to study the effectiveness of the proposed method. In Figures 5 and 6, it is observed that our proposed NWNS+EMD based adaptive thresholding approach achieve comparable improvements of speech quality. The PESQ scores of the speech at –10dB and –5dB (pink and HF channel noise) are almost equal to input PESQ scores. This is due to the presence of musical noise in first stage

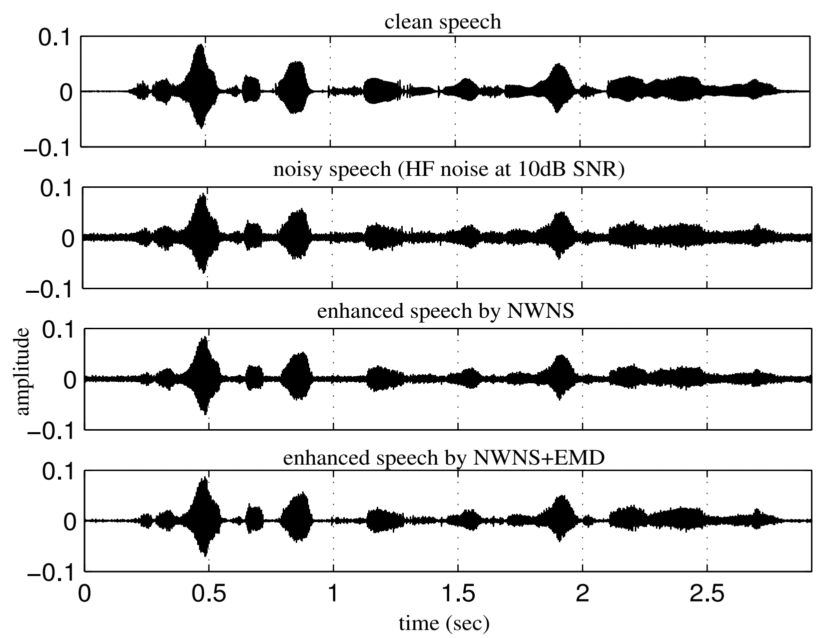
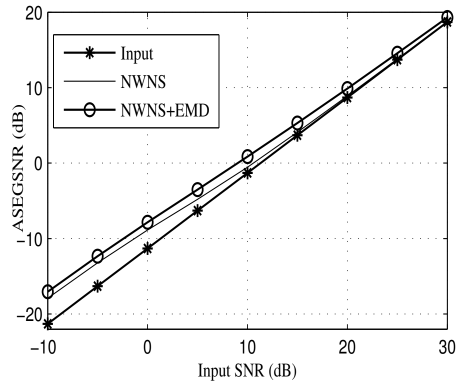


FIGURE 4: Speech waveforms of (from top) clean, noisy (HF noise at 10dB), enhanced by NWNS and NWNS+EMD.



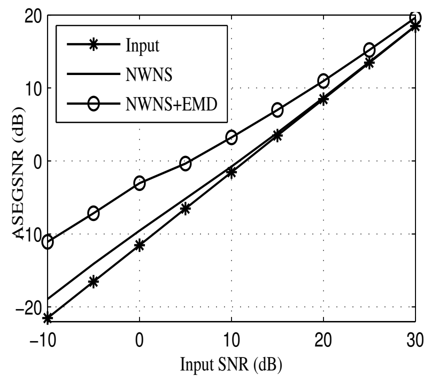
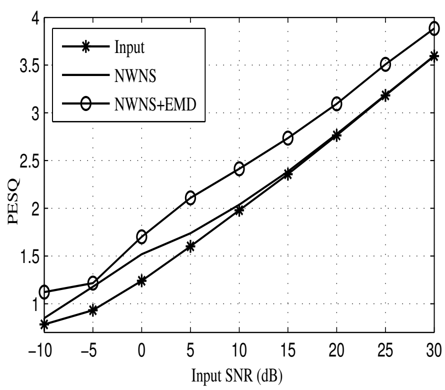


FIGURE 5: Comparisons of the average output segmental SNR (ASEGSNR) by NWNS and NWNS+EMD methods for pink noise (left) and HF channel noise (right).



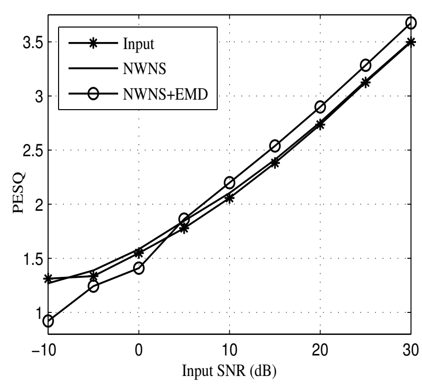


FIGURE 6: Comparison of PESQ scores by NWNS and NWNS+EMD methods for pink noise (left) and HF channel noise (right).

5. CONCLUSION & FUTURE WORK

In this paper, we presented a new algorithm to effectively remove the noise components in all frequency levels of a noisy speech signal. Our aimed to improve SNR of noise contaminated speech by removing and/or reducing noise using a two-stage processing technique; namely, a time domain nonlinear weighted noise subtraction (NWNS) followed by an Empirical Mode Decomposition (EMD) based adaptive thresholding. The first enhanced speech became as input of the second stage for further enhancement and obtained final enhanced speech after second stage processing. We introduced the degree of noise (DON1 and DON2) estimation process. DON1 was used to improve noise estimation accuracy and DON2 to calculate nonlinear weighting factor for NWNS in order to reduce musical noise. The parameters of DON1 and DON2 were estimated for white noise and we used the same parameters for all color/real world noises. Since the empirical mode decomposition (EMD) was fully data adaptive and highly effective for nonlinear and nonstationary data, it overcame inadequacy effect of the first stage for assumption as stationary of nonstationary speech segment. We combined NWNS+EMD based adaptive thresholding enhancement algorithm which worked most efficiently for wide range of input SNR. It was found that the amount of this improvement decreased when the interfering source power was minimal. This was because the algorithm was dependent upon the interfering noise signal estimation in the first stage and also dependent upon the adaptation factor and adaptive threshold factor in the second stage. When the interfering noise power was increased (up to 0dB), the proposed methods were able to perform better noise estimation. However, as the interfering noise power became much larger, as was true for extremely small SNR's (<0dB), the algorithm did not perform well in the case of color noises due to the inability of the method to obtain an adequate estimate of the original signal. The performance of the proposed method over speech contaminating with white noise or color noise was good based on objective measures and spectrograms and waveforms analysis.

Since in single channel speech enhancement method, there was difficulty removing all the noise components from speech without introducing musical noises or distortions, hence in this regard further research can be conducted to increase the accuracy of noise estimation (DON1) and also the more adjustment needed of the nonlinear weight (DON2) for voiced/unvoiced sections for underlying noisy speech to reduce musical noise and to improve speech quality. All EMD based algorithm suffers from computational complexity and the empirical process takes long time and is not applicable for real time processing. Therefore, it is suggested that more research can be conducted on insight the EMD making it less empirical and more mathematical.

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Consistent Nonparametric Spectrum Estimation Via Cepstrum Thresholding

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Abstract

For stationary signals, there are number of power spectral density estimation techniques. The main problem of power spectral density (PSD) estimation methods is high variance. Consistent estimates may be obtained by suitable processing of the empirical spectrum estimates (periodogram). This may be done using window functions. These methods all require the choice of a certain resolution parameters called bandwidth. Various techniques produce estimates that have a good overall bias Vs variance tradeoff. In contrast, smooth components of this spectral required a wide bandwidth in order to achieve a significant noise reduction. In this paper, we explore the concept of cepstrum for non parametric spectral estimation. The method developed here is based on cepstrum thresholding for smoothed non parametric spectral estimation. The algorithm for Consistent Minimum Variance Unbiased Spectral estimator is developed and implemented, which produces good results for Broadband and Narrowband signals.

Keywords: Cepstrum, Consistency, Cramer Rao Lower Bound, Unbiasedness.

1. INTRODUCTION

The main objective of spectrum estimation is the determination of the Power Spectral density (PSD) of a random process. The estimated PSD provides information about the structure of the random process, which can be used for modeling, prediction, or filtering of the deserved process. Digital Signal Processing (DSP) Techniques have been widely used in estimation of power spectrum. Many of the phenomena that occur in nature are best characterized statistically in terms of averages [20].

Power spectrum estimation methods are classified as parametric and non-parametric. Former one a model for the signal generation may be constructed with a number of parameters that can be estimated from the observed data. From the model and the estimated parameters, we can compute the power density spectrum implied by the model. On the other hand, do not assume any specific parametric model of the PSD. They are based on the estimate of autocorrelation sequence of random process from the observed data. The PSD estimation is based on the assumption that the observed samples are wide sense stationary with zero mean. Traditionally four techniques are used to estimate non parametric spectrum such as Periodogram, Bartlett method (Averaging periodogram), Welch method (Averaging modified periodogram) and Blackman-Tukey method (smoothing periodogram) [18] and [19].

2. CEPSTRUM ANALYSIS

The cepstrum of a signal is defined as the Inverse Fourier Transform of the logarithm of the Periodogram. The cepstrum of $\{y(t)_{t=0}^{t=N-1}\}$ can be defined as [7],[8] and [13]

$$c_k = \frac{1}{N}\sum_{p=0}^{N-1}\ln(\phi_p)e^{j\omega_k p}\ ; k = 0,......N-1 \tag{1}$$

Consider a stationary, discrete-time, real valued signal $\{y(t)_{t=0}^{t=N-1}\}$, the Periodogram estimate is given by

$$\hat{\phi}_p = \frac{1}{N}\left|\sum_{t=0}^{N-1} y(t)e^{-j2\pi ft}\right|^2 \tag{2}$$

A commonly used cepstrum estimate is obtained by replacing ϕ_p with the periodogram $\hat{\phi}_p$.

$$\hat{c}_k = \frac{1}{N}\sum_{p=0}^{N-1}\ln(\hat{\phi}_p)e^{j\omega_k p}\ ; \quad k = 0,......, N-1 \tag{3}$$

to make unbiased estimate the cepstrum coefficients only at origin is modified, remaining are unchanged.

$$\begin{cases} \bar{c}_0 = \hat{c}_0 + 0.577126 \\ \bar{c}_k = \hat{c}_k \qquad k = 1,......N/2 \end{cases} \tag{4}$$

In this approach, we smooth $\left\{\ln \hat{\phi}_p\right\}$ by thresholding the estimated cepstrum $\{\bar{c}_k\}$, not by direct averaging of the values of $\left\{\ln \hat{\phi}_p\right\}$. The following test can be used to infer whether c_k is likely to be equal or close to zero and, there fore, whether $\overline{c_k}$ should be truncated to zero [9]-[12].

$$\tilde{c}_k = \begin{cases} 0 & if\left|\bar{c}_k\right| \le \dfrac{\mu\pi}{(d_k N)^{1/2}} \\ \bar{c}_k & else \end{cases} \tag{5}$$

The spectral estimate corresponding to $\{\tilde{c}_k\}$ is given by

$$\tilde{\phi}_p = \exp\left[\sum_{k=0}^{N-1}\tilde{c}_k e^{-j\omega_p k}\right]; \quad p = 0,........N-1 \tag{6}$$

The proposed non parametric spectral estimate is obtained from $\tilde{\phi}_p$ by a simple scaling

$$\hat{\hat{\phi}}_p = \hat{\alpha}\tilde{\phi}_p,\ p = 0,.....N-1 \tag{7}$$

where $\hat{\alpha} = \dfrac{\sum_{p=0}^{N-1} \hat{\phi}_p \tilde{\phi}_p}{\sum_{p=0}^{N-1} \tilde{\phi}_p^{\;2}}$; $\hat{\alpha}$ *is a scaling factor*

Statistics of log periodogram

The mean and variance of the k th component of the log periodogram of the signal, $\log\left|\overline{Y}_k\right|^2$, assuming that the spectral component $\overline{Y}_k$ is Gaussian, are, respectively, given by [1]-[6],

$$E\{\log\left|\overline{Y}_k\right|^2\} = \begin{cases} \log(\lambda_{Y_k}) - \gamma - \log 2 & k = 0, K/2 \\ \log(\lambda_{Y_k}) - \gamma & k = 1, \ldots\ldots\ldots K/2-1 \end{cases} \tag{8}$$

where $\gamma = 0.57721566490$ is the Euler constant, and

$$\operatorname{var}(\log\left|\overline{Y}_k\right|^2) = \begin{cases} \sum_{n=1}^{\infty} \dfrac{n!}{(0.5)_n} \dfrac{1}{n^2} & k = 0, K/2 \\ \sum_{n=1}^{\infty} \dfrac{1}{n^2} & k = 1, \ldots . K/2-1 \end{cases} \tag{9}$$

where $(a)_n \cong 1.a.(a+1).(a+2)\ldots\ldots..(a+n-1)$. Furthermore,

$$\sum_{n=1}^{\infty} \frac{n!}{(0.5)_n} \frac{1}{n^2} = \frac{\pi^2}{2}; \; \sum_{n=1}^{\infty} \frac{1}{n^2} = \frac{\pi^2}{6};$$

Note from (8) that the expected value of the k th component of the log-periodogram equals the logarithm of the expected value of the periodogram plus some constant. This surprising linear property of the expected value operator is of course a result of the Gaussian model assumed here. From (9) the variance of the k th log-periodogram component of the signal is given by the constant.

Statistics of Cepstrum

The mean of the cepstral component of the signal is obtained from (8) and is given by [1], [2] and [7]

$$E\{c_y(n)\} = \frac{1}{K} \sum_{k=0}^{K-1} \log(\lambda_{Y\,k}) \exp\{ j \frac{2\pi}{K} kn\} - \frac{1}{K} \xi_n \tag{10}$$

where $\xi_n = \begin{cases} 2\log 2, \; \text{if } n = 0 \text{ or } n \text{ even} \\ 0, \; \text{if } n \text{ odd} \end{cases}$

the variance of the cepstral components is obtained from (9) and given by for $n = 0, \ldots\ldots\ldots\ldots K/2$

$$\begin{aligned} \operatorname{var}(c_y(n)) &= \operatorname{cov}(c_y(n), c_y(n)) \\ &= \begin{cases} \dfrac{2}{K} k_1 + \dfrac{2}{K^2}(k_0 - 2k_1), \; \text{if } n = 0, \dfrac{K}{2} \\ \dfrac{1}{K} k_1 + \dfrac{2}{K^2}(k_0 - 2k_1), \; \text{if } 0 < n < \dfrac{K}{2} \end{cases} \end{aligned} \tag{11}$$

and for $n, m = 0, 1, \ldots\ldots\ldots\ldots, K/2, n \neq m$

$$\operatorname{cov}(c_y(n), c_y(m)) = \begin{cases} \frac{2}{K^2}(k_0 - 2k_1) & if\ n-m = \pm 2, \pm 4, \ldots\ldots\ldots \pm \frac{K}{2} \\ 0, & otherwise \end{cases} \tag{12}$$

where $k_0 = \frac{\pi^2}{2}$; $k_1 = \frac{\pi^2}{6}$

The covariance matrix of cepstral components of the signal, assuming the spectral components of the signal are statistically independent complex Gaussian random variables. The covariance matrix of cepstral components given by (11) and (12) is independent of the underlying power spectral density which characterizes the signal under the Gaussian assumption. The covariance of cepstral components under the Gaussian assumption is a fixed signal independent matrix that approaches, for large K a diagonal matrix given by

$$\operatorname{cov}(c_y(n), c_y(m)) = \begin{cases} \frac{1}{K}\frac{\pi^2}{3}, & if\ n = m = 0, \frac{K}{2} \\ \frac{1}{K}\frac{\pi^2}{6}, & if\ 0 < n = m < \frac{K}{2} \\ 0, & otherwise \end{cases} \tag{13}$$

Cepstrum algorithm

1. Let a stationary, discrete-time, real valued signal $\{y(t)_{t=0}^{t=N-1}\}$
2. Compute the periodogram estimate of ϕ_p using FFT.

$$\hat{\phi}_p(\omega) = \frac{1}{N} \left| \sum_{t=0}^{N-1} y(t) e^{-j\omega t} \right|^2$$

3. First apply natural logarithm and take IFFT to compute the cepstrum estimate.

$$\hat{c}_k = \frac{1}{N} \sum_{p=0}^{N-1} \ln(\hat{\phi}_p) e^{j\omega_k p};$$

$$k = 0, \ldots\ldots, N-1$$

4. Compute the threshold by choosing the appropriate value of μ depending on the type of signal and determine the cepstral coefficients

$$\tilde{c}_k = \begin{cases} 0 & if \left|\bar{c}_k\right| \le \frac{\mu\pi}{(d_k N)^{1/2}} \\ \bar{c}_k & else \end{cases}$$

5. Compute the spectral estimate corresponding to $\{\tilde{c}_k\}$ is given by

$$\tilde{\phi}_p = \exp\left[\sum_{k=0}^{N-1} \tilde{c}_k e^{-j\omega_p k}\right]; \quad p = 0, \ldots\ldots\ldots N-1$$

6. Obtain the proposed non parametric spectral estimate by a simple scaling

$$\hat{\hat{\phi}}_p = \hat{\alpha}\tilde{\phi}_p, \; p = 0, \ldots\ldots N-1$$

Simulation Results

In this section, we present experimental results on the proposed algorithm for simulated data to estimate the power spectrum. The performance of proposed method is verified for simulated data, generated by applying Gaussian random input to a system, which is either broad band or narrow band.The MA broad band signal is generated by using the difference equation [18]

$$\begin{aligned} & y(t)-1.3817y(t-1)+1.5632y(t-2)-0.8843y(t-3)+ \\ & 0.4096y(t-4)=e(t)+0.3544e(t-1)+0.3508e(t-2)+ \\ & 0.1736e(t-3)+0.2401e(t-4), \\ & \quad t=0,1,\ldots N-1 \end{aligned} \tag{14}$$

where $e(t)$ is a normal white noise with mean zero and unit variance. The ARMA narrow band signal is generated by using the difference equation

$$\begin{aligned} & y(t)-0.2y(t-1)+1.61y(t-2)-0.19y(t-3)+ \\ & 0.8556y(t-4)=e(t)-0.21e(t-1)+0.25e(t-2), \\ & \quad t=0,1,\ldots N-1 \end{aligned} \tag{15}$$

The number of samples in each realization is assumes as N=256.

After performing 1000 Monte Carlo Simulations, the comparison of the mean Power Spectrum, Variance and Mean Square Error for the broad band signal and narrow band signals, obtained using periodogram and cepstrum approach along with the true power spectrum are shown in Figure 1 (a) , (b) and (c) and Figure 2 (a), (b) and (c) respectively.

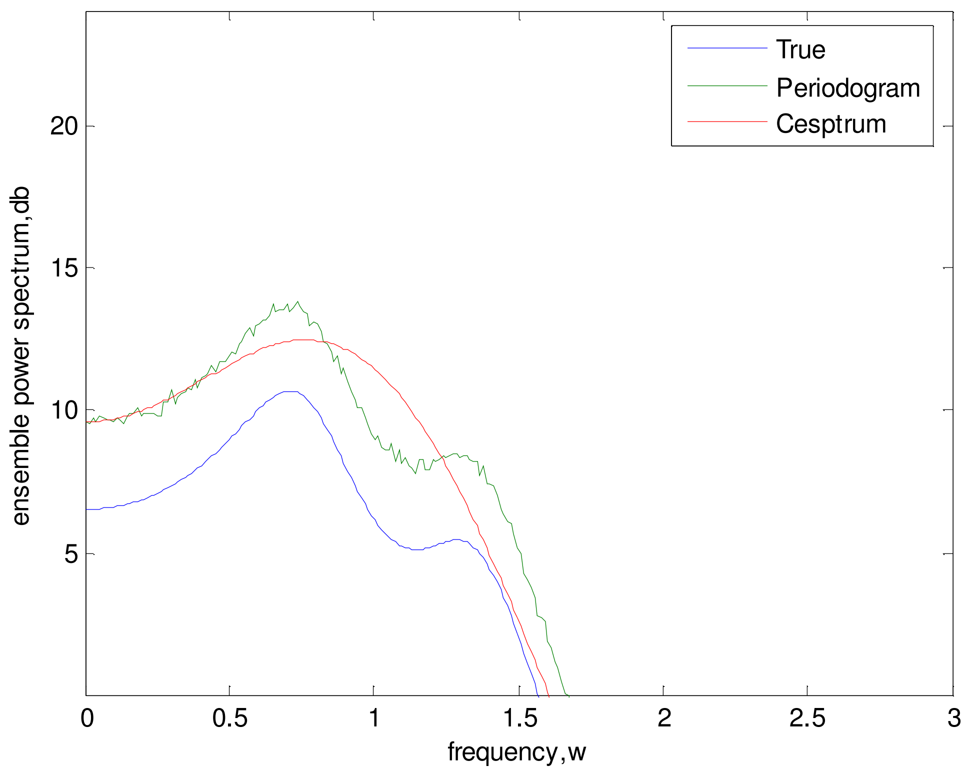

FIGURE 1: (a) PSD vs frequency for broadband signal

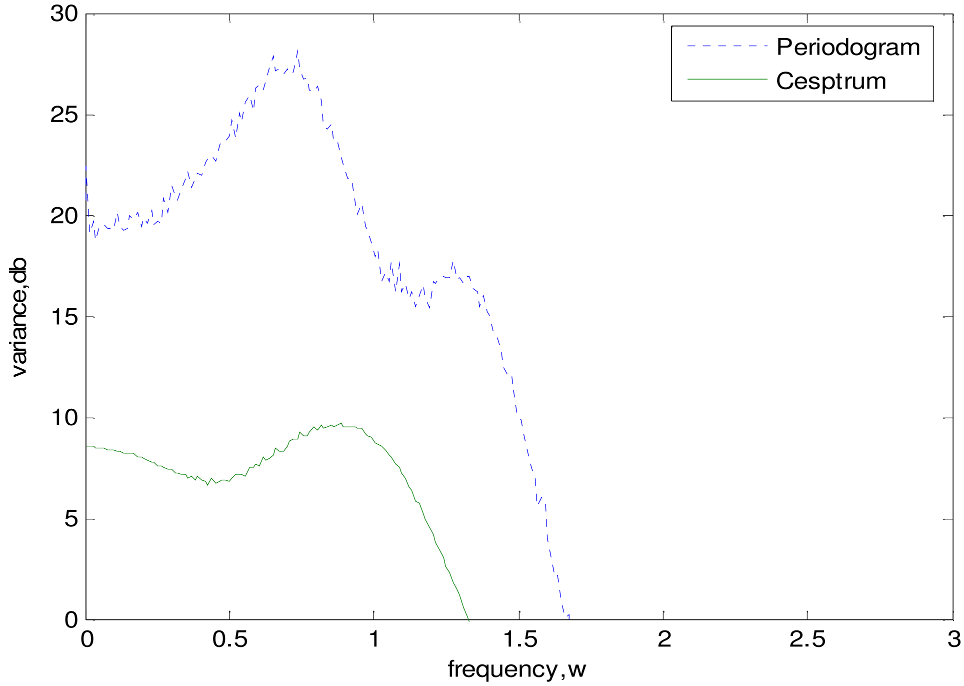

FIGURE 1: (b) Variance vs frequency for broadband signal

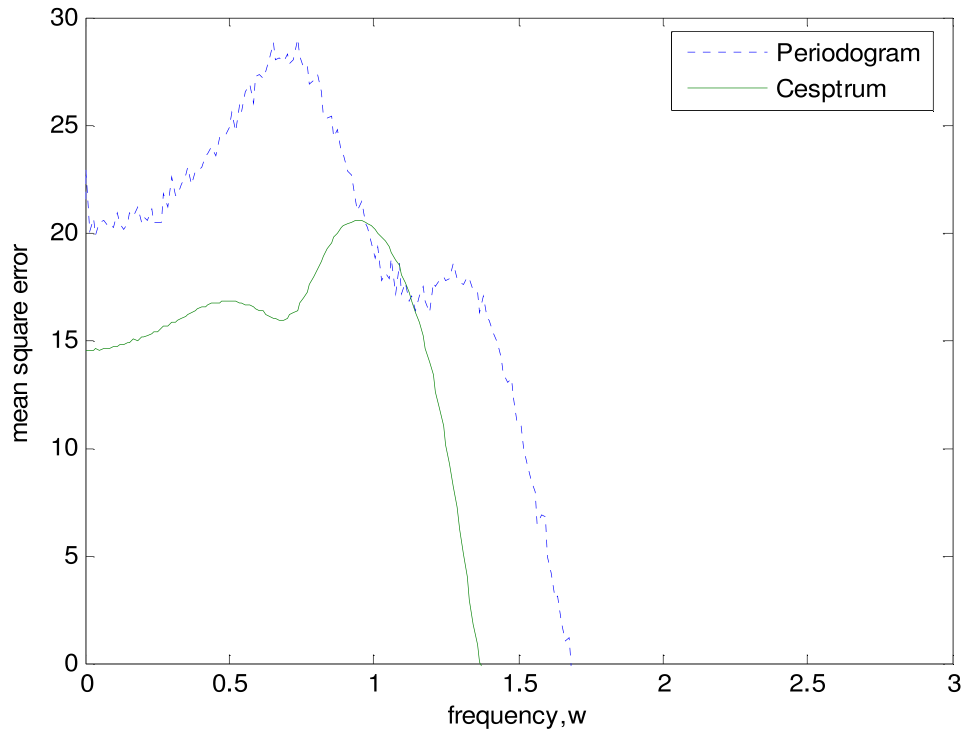

FIGURE 1: (c) Mean Square Error vs frequency for broadband signal

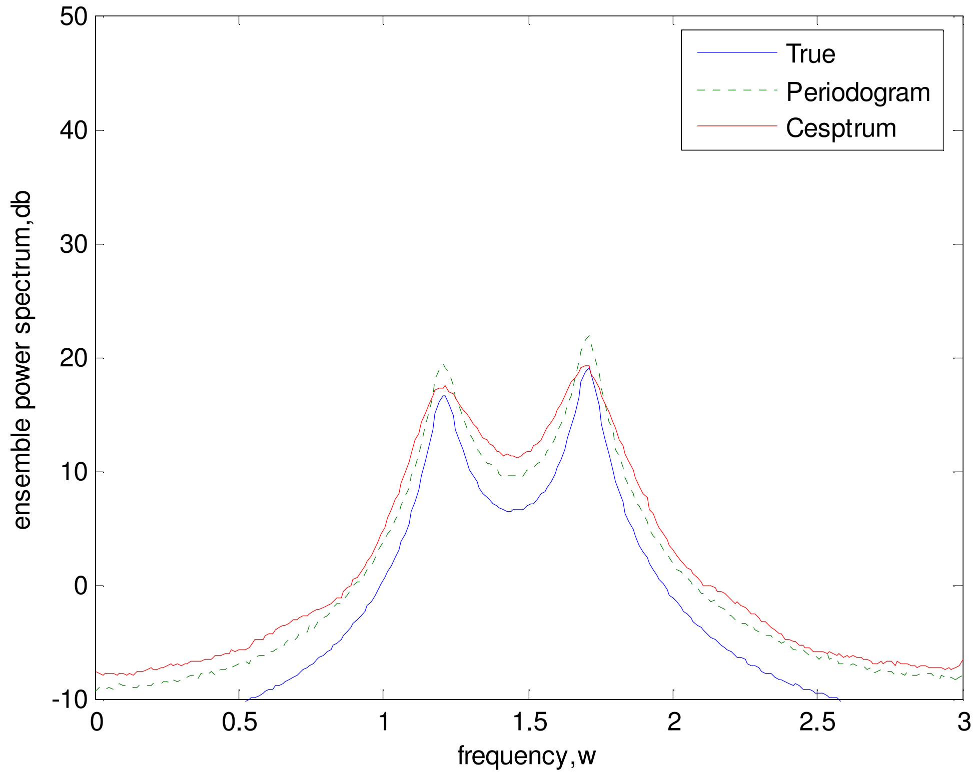

FIGURE 2: (a) PSD vs frequency for narrowband signal

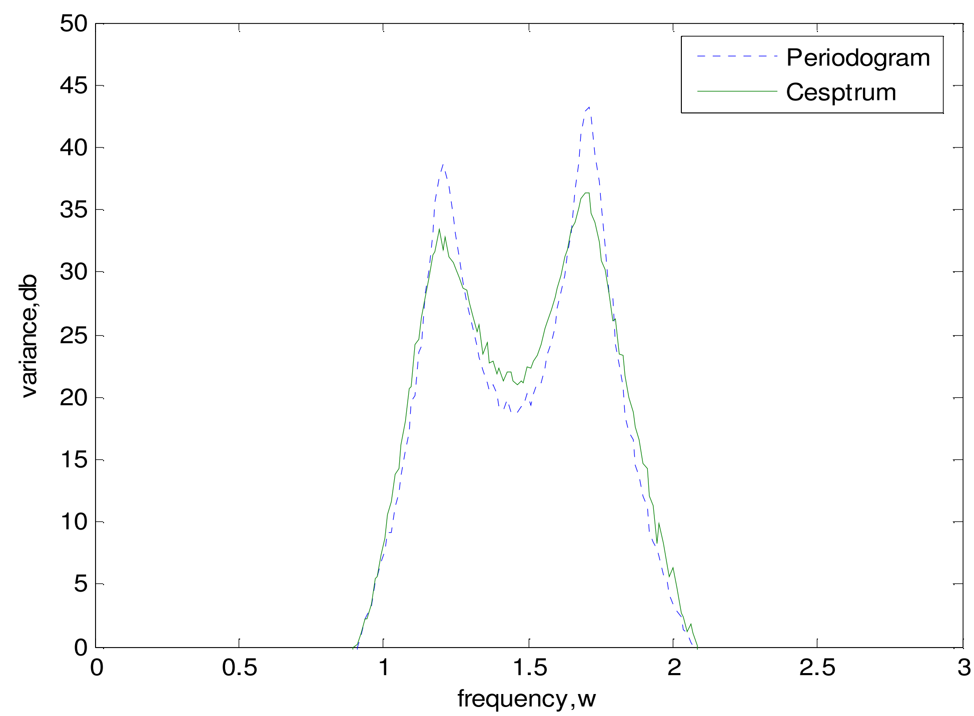

FIGURE 2: (b) Variance vs frequency for narrowband signal

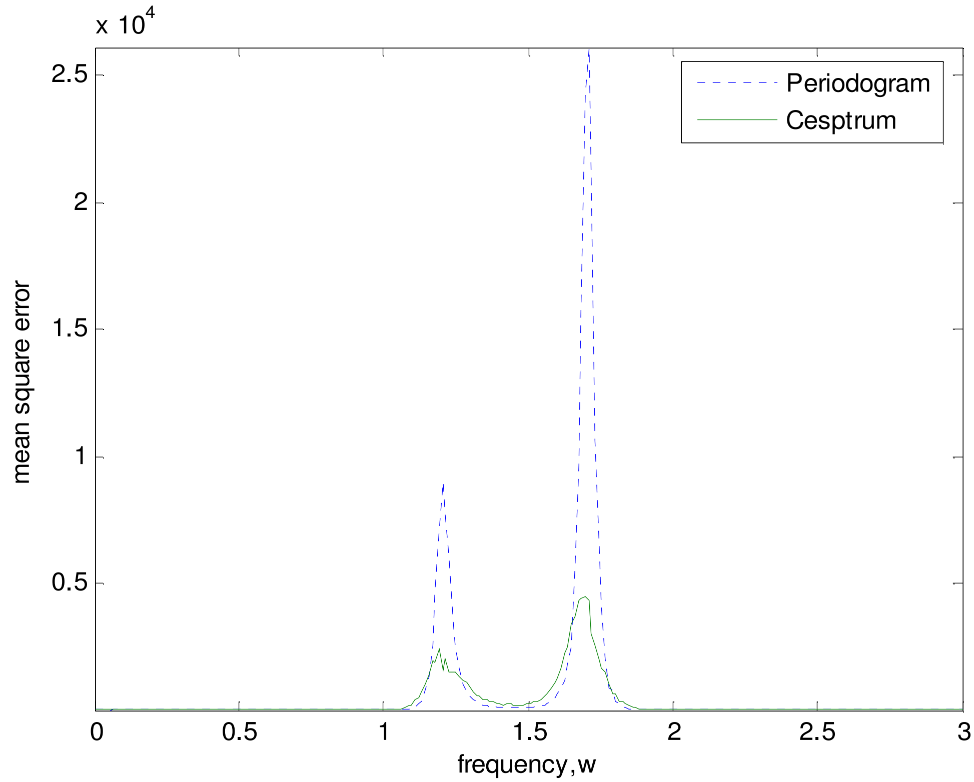

FIGURE 2: (c) Mean Square Error vs frequency for narrowband signal

From the above results we can say that

1. In the case of broad band signal the spectral estimates through cepstrum approach has very smooth response compared to the periodogram approach. However it can be observed that the mean square error is more in the case of periodogram and least with cepstrum thresholding approach.
2. In the case of broad band signals, variance obtained through cepstrum thresholding approach is very small as compared to the periodogram approach.
3. It is also observed that the mean square error estimated through cepstrum approach for narrowband signals is less compared to broadband signals.

Comparison among the traditional methods and the cepstrum method

In order to evaluate the performance of the cepstrum technique, which is compared with the traditional methods such basic Peridogram, Bartlett method, Welch method and Blackman and Tukey [21] for simulated ARMA narrow band signal, which is generated by using equation (15).

The various PSD techniques	Mean	Variance
Cepstrum	0.0090	2.4023e-004
Periodogram	0.0092	4.8587e-004
Black-man and Tukey	0.0521	0.0047
Welch	0.0138	8.9491e-004
Bartlett	0.2474	0.0637

TABLE 1: Comparison table for the parameters mean and variance (Record length N=128).

From the comparison table 1, for short record length, with respect to mean and variance, the cepstrum technique produces better results in comparison with the traditional methods. For longer record length, with reduced computational complexity, the cepstrum method produces the values of mean and variance as same as that of the Welch method, but these methods are better than the remaining techniques. For 1000 Monte carlo simulations, the ensemble power spectrum for various techniques is shown in figure 3.

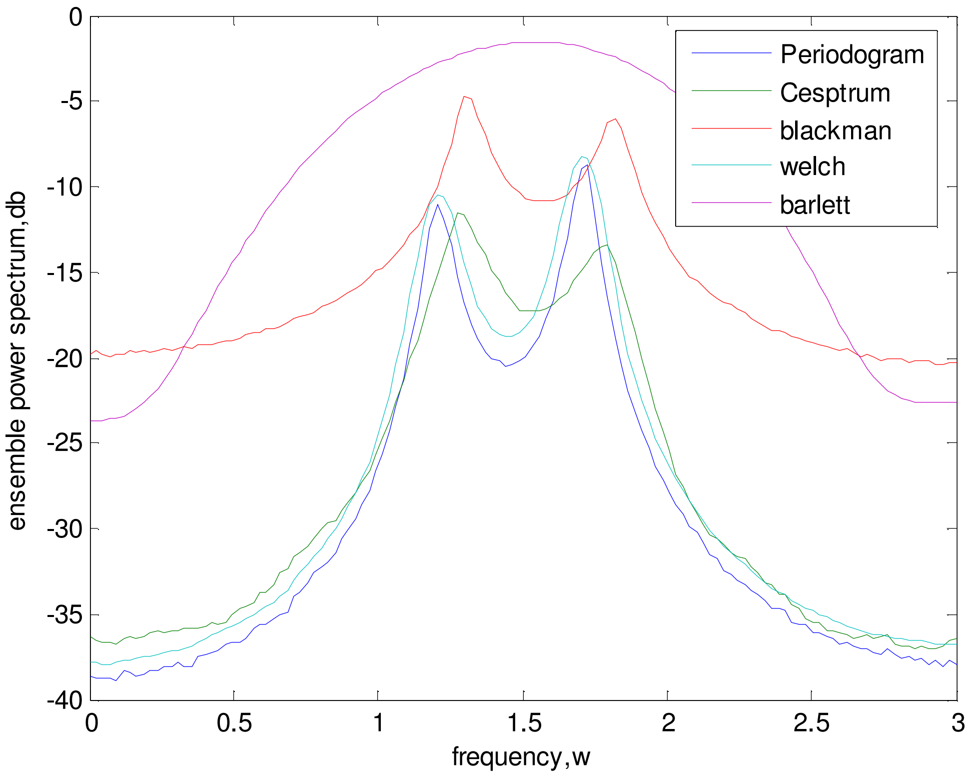

FIGURE 3: an ensemble power spectrum of an ARMA narrowband signal by using the traditional methods and the cepstrum method

Results for MST Radar data

The concept of cepstrum is applied to atmospheric data collected from the MST Radar on 10^{th} August 2008 at Gadhanki, Tirupati, India. 150 sample functions, each having 256 samples are used to know the performance of cepstrum in comparison with the standard periodogram. The better results are obtained through the cepstrum than the periodogram. The comparison of the mean Power Spectrum, Variance for Radar data, obtained using periodogram and cepstrum approach are shown in Figure 4 (a) and (b) respectively. It is observed that the smooth power spectra and less variance in cepstrum than that of the periodogram.

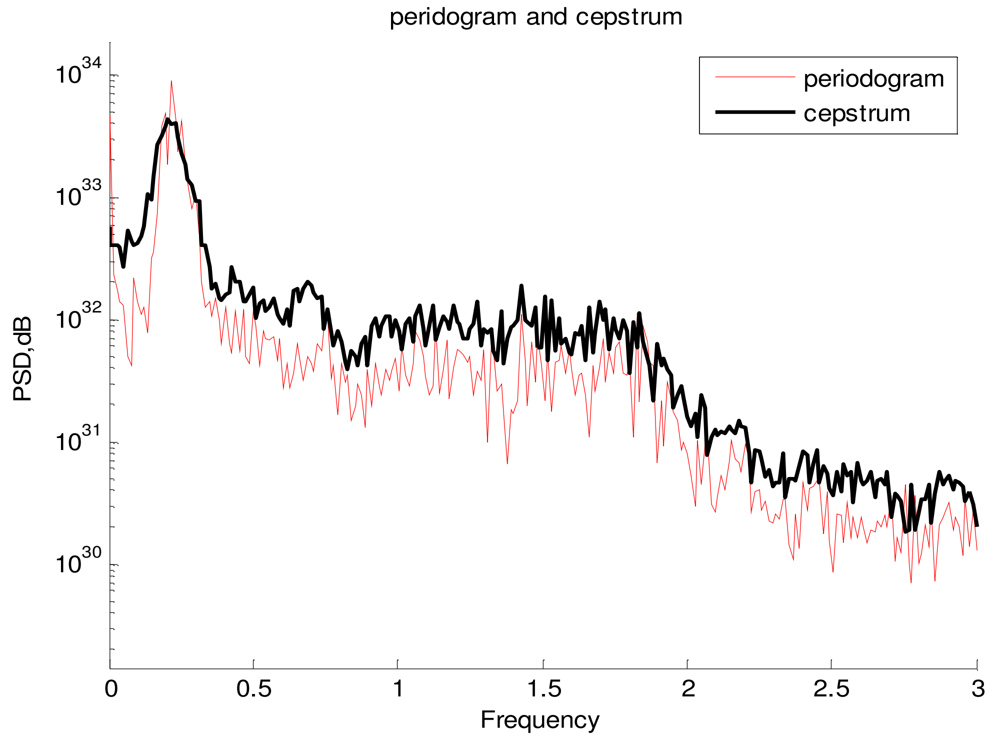

FIGURE 4: (a) Mean Power Spectra Vs Frequency for MST Radar data

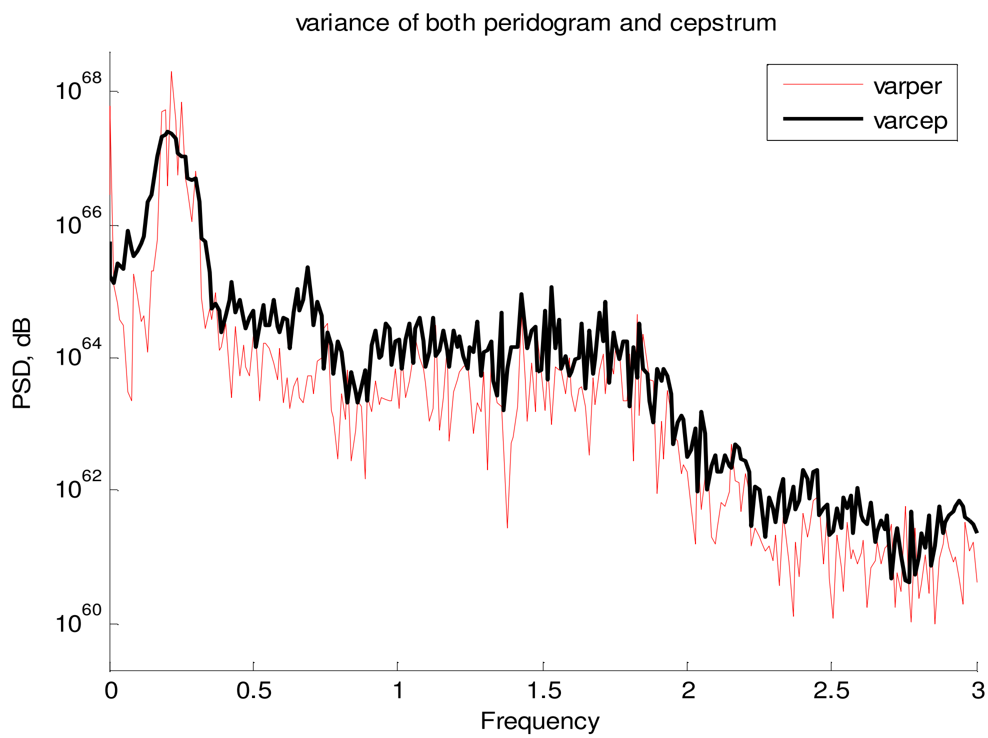

FIGURE 4: (b) Variance Vs Frequency for MST Radar data

3. CONSLUSION & FUTURE WORK

The problem in traditional methods is that the variance becomes proportional to square of power spectrum instead of converging into zero, thus the estimated spectrum is an inconsistent. In this paper the new technique has been proposed, called cepstrum, which gives reduce variance while evaluating the smoothed nonparametric power spectrum estimation. The expression for mean and variance of the cepstrum has been presented. The total variance reduction is more through broadband signals when compared to narrowband signals. All results are verified by using MAT lab 7.0.1. The concept of Cepstrum can be also extended for higher order spectral estimations.

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IMPORTANT DATES

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