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Optimized Noise Canceller for ECG Signals

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ABSTRACT

During the acquisition of Electrocardiogram Signals (ECG), various interferences distort the signal. Adaptive filters have been widely used as noise cancellers. Traditional optimization techniques have been very popular because of their advantages. Least Mean Square (LMS) is a traditional optimization technique which is gradient based. This method converges very quickly to an optimal solution and is easy to understand. But this technique does not provide solutions for non-differentiable and discontinuous problems. Bio-inspired optimization algorithms such as genetic algorithm (GA) and Memetic algorithm (MA) can optimize complex and hard problems. In this paper, the adaptive noise canceller has been optimized with Modified Memetic Algorithm (MMA) to remove power line interference in the ECG signals. The performance of these algorithms has been analyzed on the basis of parameters viz., improvement in signal to noise ratio, normalized correlation coefficient (NCC) and root mean square error (RMSE). The results show that (MMA) outperforms both LMS and GA algorithms. Simulation results of GA and MA on benchmark functions viz. Greiwank and Rastrigin show that MMA is more effective for the optimization process.

Keywords

Empirical Mode Decomposition, Genetic algorithm, Least Mean Square Algorithm, Memetic Algorithm, Benchmark Functions.

1. INTRODUCTION

Electrocardiogram (ECG) signals are a measure of the electrical activity of the heart. These electrical signals are collected using the electrodes. The amplitude and the timing of the various waves in ECG viz, P, Q, R, S and T, give the vital information about the heart's working. A physician can detect a heart problem from this information and can suggest timely measures. But during the acquisition of ECG signal, it may get corrupted by different types of noises [1] which make it difficult for the physician to give his diagnosis. Power Line Interference (PLI) is one such kind of noise which superimposes on the vital information. The frequency range of ECG signal is 0.05Hz to 150Hz, and the frequency of the PLI noise is 50/60 Hz which lies within the frequency spectrum of the ECG signal, so PLI noise need to be removed for proper diagnosis.

In the literature, various methods have been applied to remove PLI noise in the ECG signals. Earlier notch filters were used, but it failed when there is deviation in input line frequency. Wavelets have been used by many authors but prior information about the ECG signal is needed [2]. LMS algorithm has the disadvantage of getting stuck to local optimum. Also choice of step size is also important in the search process.

A block diagram for denoising the corrupted signal is shown in fig.1. Here the noisy ECG is decomposed using Empirical Mode Decomposition (EMD). This EMD is a decomposition process used for the non-linear and non-stationary signals.

Least Mean Square (LMS) is a classical method of finding an optimum solution and uses gradient based method of steepest descent algorithm. It is suitable only for the differentiable problems. As compared to other classical techniques LMS is relatively simple and easy to implement. But it suffers from the problem that it may get stuck in to local optimum point.

Genetic Algorithm (GA) is a nature inspired optimization technique which utilizes the parallel search process. The best solution is found from the large search space, randomly generated which removes the risk of getting struck in the local optimum solution and finds the global optimum solution. It involves the process as evaluation, selection, cross over and mutation.

Memetic algorithm (MA) is also based on the biological processes. But in this, the individual learns from the neighbors and surroundings and improves itself. These learned cultures, traits are not transferred to the next generation but is used only for the improvement of the individual.

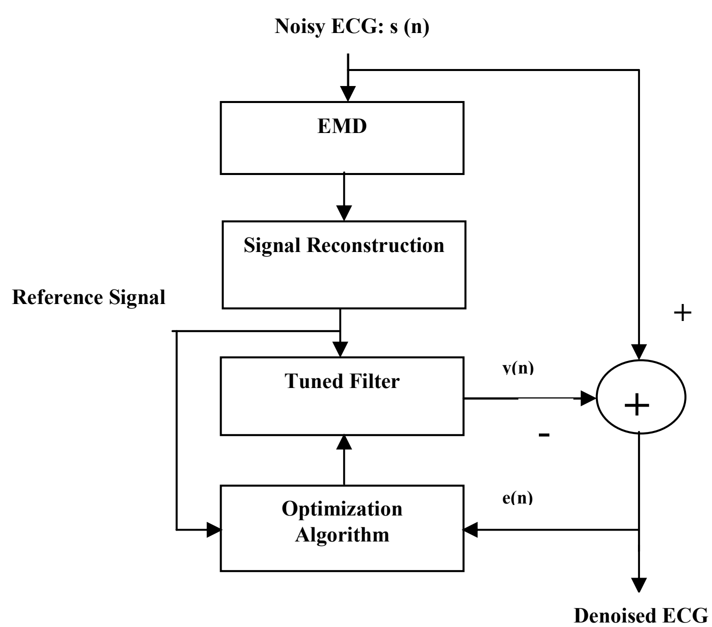

Fig 1: Denoising Method for ECG

The performance of these algorithms has also been evaluated on the basis of root mean square error (RMSE), normalized correlation coefficient (NCC) [3] and improvement in signal to noise ratio [4].

The Genetic algorithm and Modified Memetic algorithm has also been experimented on two benchmark functions viz. Griewank and Rastrigin. Both are multimodal functions have many local minimas. The global minima of both the functions are at zero.

In this paper, section 1 gives the introduction, section 2 discusses the empirical mode decomposition, section 3 describes and gives different optimization algorithms used for the removal of PLI, section 4 gives the testing of the proposed algorithm on benchmark functions, section 5 describes the implementation of the denoising of ECG signals, section 6 gives the results and discussion, and finally section 7 concludes the paper.

2. EMPIRICAL MODE DECOMPOSITION

Empirical Mode Decomposition (EMD) is a method of decomposing the non-stationary and non-linear signals into its oscillatory components. The process is data driven and the components so obtained are called intrinsic mode function (IMF) and this process is called sifting process [5] [6] [7]. In EMD no prior knowledge about the signal is required. In each process an IMF and a residue is produced then the residue is further processed to get another IMF and a residue. This process stops when no further IMF can be obtained from the residue. So signal can be represented as:

$$s(t) = \sum_{k=1}^{N} C_k(t) + r(t) \tag{1}$$

where $s(t)$ is the signal to be decomposed, $C_k(t)$ the IMFs and $r(t)$ is the residue [8].

3. OPTIMIZATION ALGORITHMS

In order to remove the noise due to power line interference an adaptive filter is used, the weights of which are optimized by an optimizing algorithm. In this section, least mean square algorithm, genetic algorithm and proposed Modified Memetic algorithm are discussed.

3.1 Least Mean Square (LMS) Algorithm

Least Mean Square (LMS) algorithm is a traditional method of optimization given by Widrow and Hoff. It is based on the gradient descent technique [9] and starts from a point. It finds the set of weights for which minimum error can be achieved. The weight updation [10] is as follows:

$$y(n) = d(n) \times w(n) \tag{2}$$

$$e(n) = s(n) - y(n) \tag{3}$$

$$w(n+1) = w(n) + \mu \times d(n) \times e(n) \tag{4}$$

where y(n) is the output of the filter, d(n) is the reference signal for the filter, e(n) is the error from the noise canceller and w(n) are the weights of the adaptive FIR filter. LMS has the disadvantage of getting struck to a local minimum point. Also the tracking of the changes in the input of the filter depends on the step size [11].

3.2 Genetic Algorithm

Genetic algorithm (GA) is a method for finding the optimum solution based on the biological phenomenon. It is based on the survival of the fittest phenomenon. So from the population of solutions best fit individuals are selected and then crossover is done to form the next generation [12]. To add diversity to the population, mutation process takes place. The operators used are evaluation, selection, crossover and then mutation. The pseudo code of the genetic algorithm is:

```
(i) Generate the solution population.
(ii) (a) Set pop_size, max_gen, gen=0.
     (b) Set cross_rate, mutate_rate;
(iii) while max_gen>= gen
    evaluate fitness
    for (i=1 to pop_size)
        select (mate1,mate2)
        child = crossover(mate1,mate2)
        child = mutation( )
    end for
        replace offspring to new generation
        gen = gen+1
end while
(iv) return best chromosomes.
```

3.3 Modified Memetic Algorithm (MMA)

Memetic Algorithm (MA) is an evolutionary algorithm in which global search techniques are combined along with the local search to improve the quality of the solution. So, the best attributes are passed on to the next generations. Also the individuals in each generation have the quality of adapt from the environment and neighbors to improve them [13]. So these traits are taken from the neighbors *i.e.* locally. Local search reduces the computation and helps in early convergence.

For the removal of PLI, in this work, genetic algorithm has been used for global search and within this local search is embedded to make the convergence to optimal solution. This local search is done by particle swarm optimization (PSO) technique. The modification in the inertia parameter used in the PSO equation. In the classical PSO, the inertia is fixed but here, it is changing with the current value of the particle and the global best value of the population. The equation for the local search is:

$$v(t+1) = v(t) \times \mu \times rand + c_1 \times rand \times (pbest - current) + c_2 \times rand \times (gbest - current) \tag{5}$$

$$x(t+1) = x(t) + v(t+1) \tag{6}$$

where $c_1 = c_2 = 2$, and **μ=(1-current/gbest)**, v(t) is the current velocity of the agent, v(t+1) is the updated velocity, x(t) is the present position, x(t+1) is the next position, c_1, r_1, c_2, r_2 are control parameters, μ is the inertia weight, "pbest" is the particle's best position, "current" is the particle's current position and "gbest" is the global best position of the population. The pseudo code of the Modified Memetic Algorithm is:

```
(i) (a) set pop_size, max_gen, gen=0, cross_rate,
        mutate_rate, meme;
    (b) set v, c1, c2, r1, r2.
(ii) initialize population
(iii) while max_gen > gen
```

for i=1:pop_size
evaluate fitness of agents.
select best agents.
find the best agent of the population as 'gbest'.
find the local best agent as 'pbest'.
end
for i=1:pop_size
for j=1: meme
update the velocity of the meme according to eqn. 5.
update the position of the meme according to eqn. 6.
end
end
for i=1:pop_size
select two agents for crossover.
perform crossover.
perform mutation.
end
replace offspring to new population.
gen = gen+1
end while
(iv) return best agent.
(v) generate neighbor for the best agent.
for j=1: meme
update the velocity of the meme according to eqn 5.
update the position of the meme according to eqn 6.
end.
(vi) return best optimum agent.

The modifications have been done in the local search in the memetic algorithm. The inertia of the particle has been modified so that optimum result is achieved in less iteration. As the inertia is made dependent on the current and the global positions, the next position now will be near to the optimum one.

4. TESTING ON BENCHMARK FUNCTIONS

In order to test the performance of Genetic and Modified Memetic algorithms, two benchmark functions have been chosen. Griewank function (F1) and Rastrigin function (F2) both are non linear and multimodal functions. Both these functions have many local minimas. Griewank function is a good function for the testing of the Genetic algorithm. Rastrigin is a difficult problem for the Genetic Algorithm [14].

$$F1 = 1 + \sum_{i=1}^{n}\left(\frac{x_i^2}{4000}\right) - \prod_{i=1}^{n}\left(\cos\left(\frac{x_i}{\sqrt{i}}\right)\right) \quad (7)$$

$$F2 = \sum_{i=1}^{n}\left[x_i^2 - 10\cos(2\Pi x_i) + 10\right] \quad (8)$$

'n' is the dimension.

These functions have been tested with population size of 80 and dimension is 20. The crossover rate is 80%. The generations are varied from 50 to 400. For the Memetic algorithm, in the local search, the acceleration constants c1, c2 are fixed at 2 and the maximum velocity is fixed at the upper range of the search [15]. The range of search space is [-600, 600] for the Griewank function and [-5.12, 5.12] for the Rastrigin function.

The mean optimum value is taken for 50 runs [16]. Table 1 and table 2 show the Griewank and Rastrigin function values corresponding to the number of generations. The logarithmic value is plotted as shown in the figures 2(a) & 2 (b) for both F1 and F2. As shown the Memetic algorithm is able to reach the optimum value which is near to origin as compared to Genetic algorithm. The stopping criterion is fixed as the maximum generation.

Table 1 Griewank Function

Generation	Modified Memetic Algorithm	Genetic Algorithm
50	0.00020152	1.2946
100	0.00018252	1.0007
150	0.00016692	0.9108
200	0.00014199	0.6875
250	0.00011785	0.5101
300	0.00012457	0.3198
350	0.00012494	0.3208
400	0.00012415	0.3196

Table 2. Rastrigin Function

Generation	Modified Memetic Algorithm	Genetic Algorithm
50	1.2127	10.0718
100	1.1513	9.6535
150	1.1265	8.9594
200	1.0108	7.5757
250	0.9744	6.6755
300	0.8802	6.5816
350	0.7151	5.9055
400	0.6910	5.8298

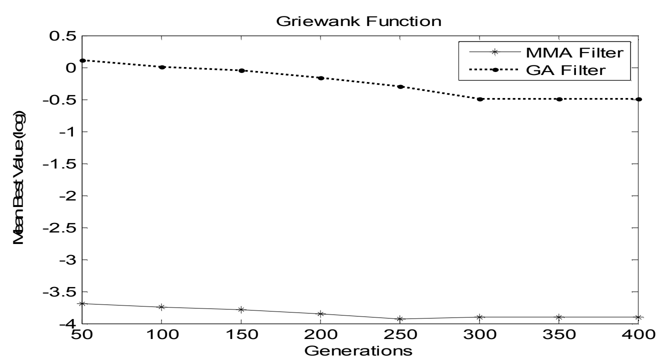

Fig 2(a): Griewank Function Values

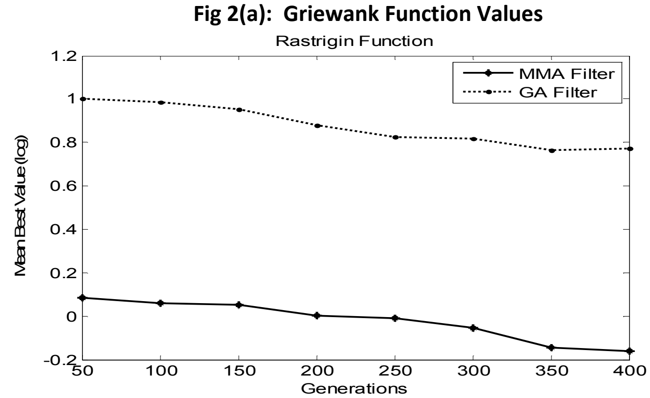

Fig 2(b): Rastrigin Function Values

5. ECG DENOISING

Experiments have been performed on ECGs taken from the MIT-BIH data base [17], according to the method shown in fig. 1. The ECG signals considered are 116. dat, 117.dat and 201.dat and have a sampling frequency of 360Hz, ADC resolution of 11 bits, 1800 samples of the ECG signal have been taken.

In order to analyze the performance of the method, noise of 0.20V, 0.24V and 0.15V of 50Hz have been added to the clean ECGs respectively. These corrupted ECGs are then decomposed by the EMD process. Eleven Intrinsic Mode Functions (IMFs) and a residue have been obtained. The IMF containing the PLI is used for the reconstruction of the reference for the adaptive filter. Filter then produces the exact estimate of its reference signal which is then subtracted from the corrupted signal to get the denoised ECG. The optimization algorithm helps to get the best estimate by changing the weights of the filter according to the changes in the input and the error produced.

The number of generations is fixed at 200; the size of the population is kept at 30. The cross over probability and mutation probability set at 0.8 and 0.01 respectively. The selection is rank based. The fitness function for the filter is:

$$f(t) = \sum_{n=1}^{N} \frac{(s(n) - Y(n))^2}{N} \tag{9}$$

where f(t) is the fitness function to be minimized, s(n) is the noisy ECG signal, Y(n) is the output of the adaptive filter and N is the number of samples in the ECG signal.

These optimization algorithms viz. LMS, GA and MMA have been analyzed on the basis of the improvement in the signal to noise ratio in dB, by RMSE, and the normalized correlation coefficient (NCC). RMSE defines the average magnitude of noise which still remains in the denoised signal. NCC is the association between the two signals in time series.

$$RMSE = \sqrt{\frac{\sum_{n=1}^{N} (x(n) - z(n))^2}{N}} \tag{10}$$

Imp [SNR] = $SNR_{output} - SNR_{input}$

$$\mathrm{Im}\,p[SNR] = 10\log 10\left(\frac{\sum_{n=1}^{N} (s(n) - x(n))^2}{\sum_{n=1}^{N} (z(n) - x(n))^2}\right) \tag{11}$$

$$NCC = \frac{\sum_{n=1}^{N} x(n) z(n)}{\sum_{n=1}^{N} x^2(n) \sum_{n=1}^{N} z^2(n)} \tag{12}$$

where z(n) is the denoised ECG signal. s(n) is the ECG signal with noise, x(n) is the signal without noise and N is the number of samples.

6. RESULTS

Original ECG 201.dat and the corrupted ECG along with their frequency spectrum have been shown in fig. 3 & 4 respectively. The Fourier spectrum of the clean ECG shows that there is no 50/60 Hz frequency component present in the signal and when the noise is added as shown in fig. 4(b) the component at 50Hz is present. The IMFs of ECG 201 have been shown here. Twelve IMFs have been obtained from the EMD process. Some of these have been shown in the fig. 5(a) and 5(b). The left side shows the IMFs and their frequency spectrum is shown on the right side.

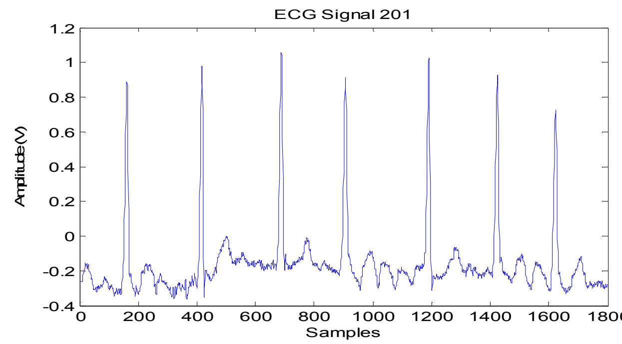

Fig 3(a): Clean ECG

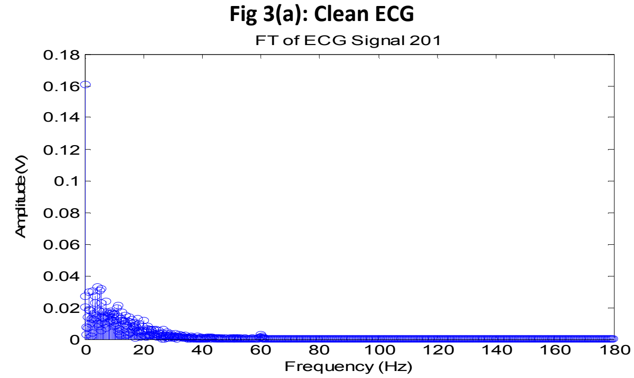

Fig 3(b): Frequency Spectrum of Clean ECG

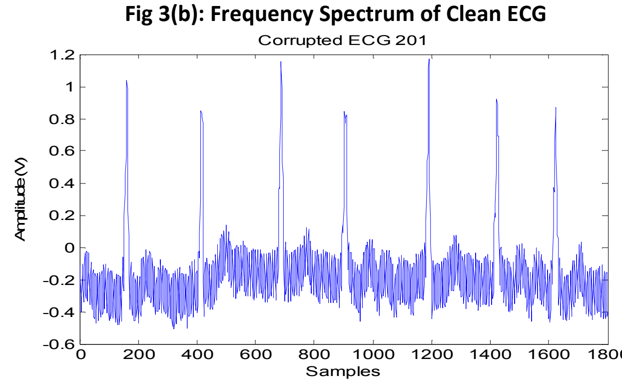

Fig 4(a): Corrupted ECG

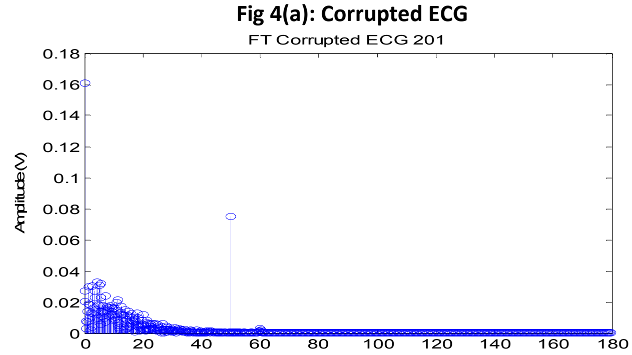

Fig 4(b): Frequency Spectrum of Corrupted ECG

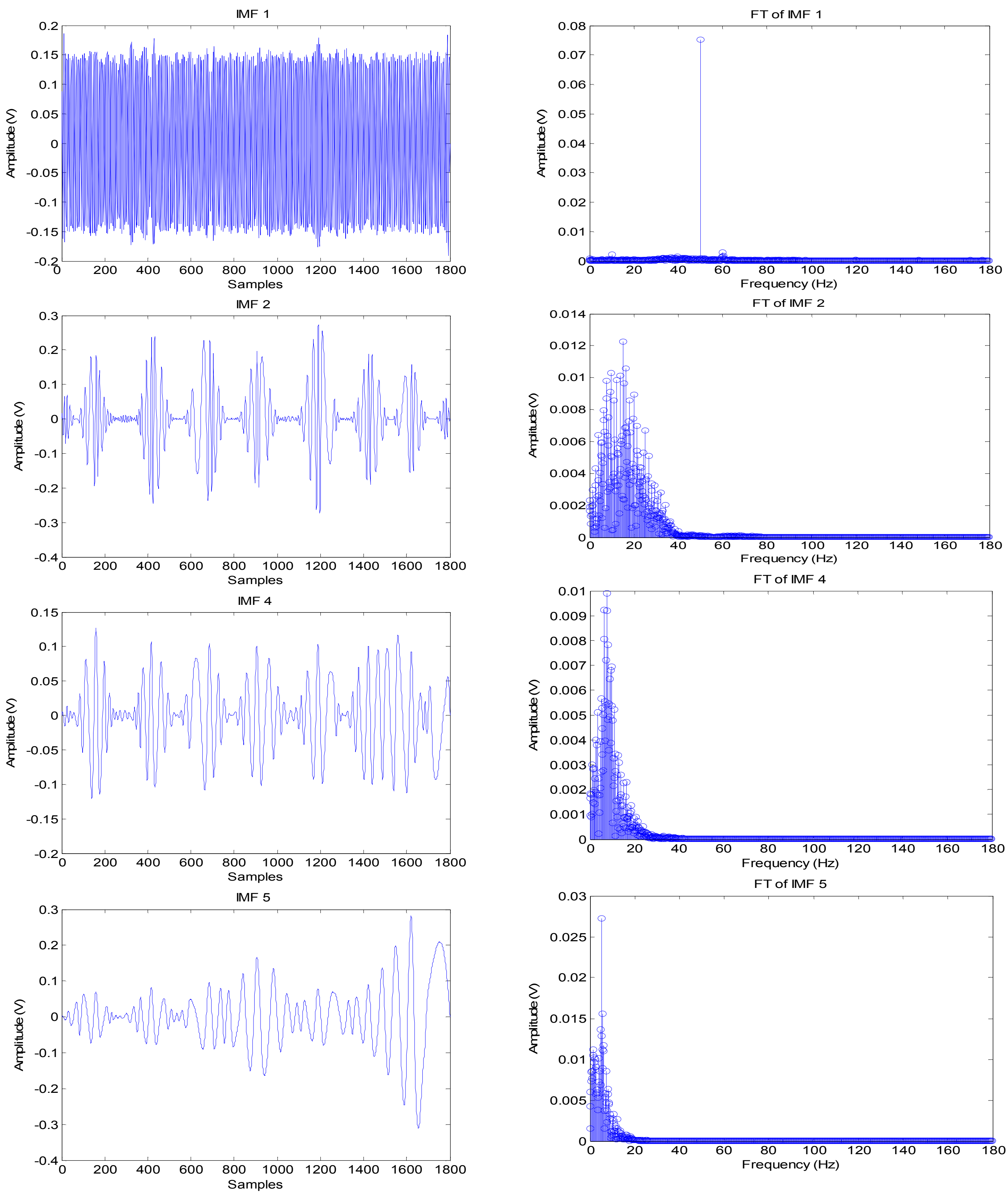

Fig 5(a) IMFs 1, 2, 4, & 5 (left side) and their frequency spectrum (right side)

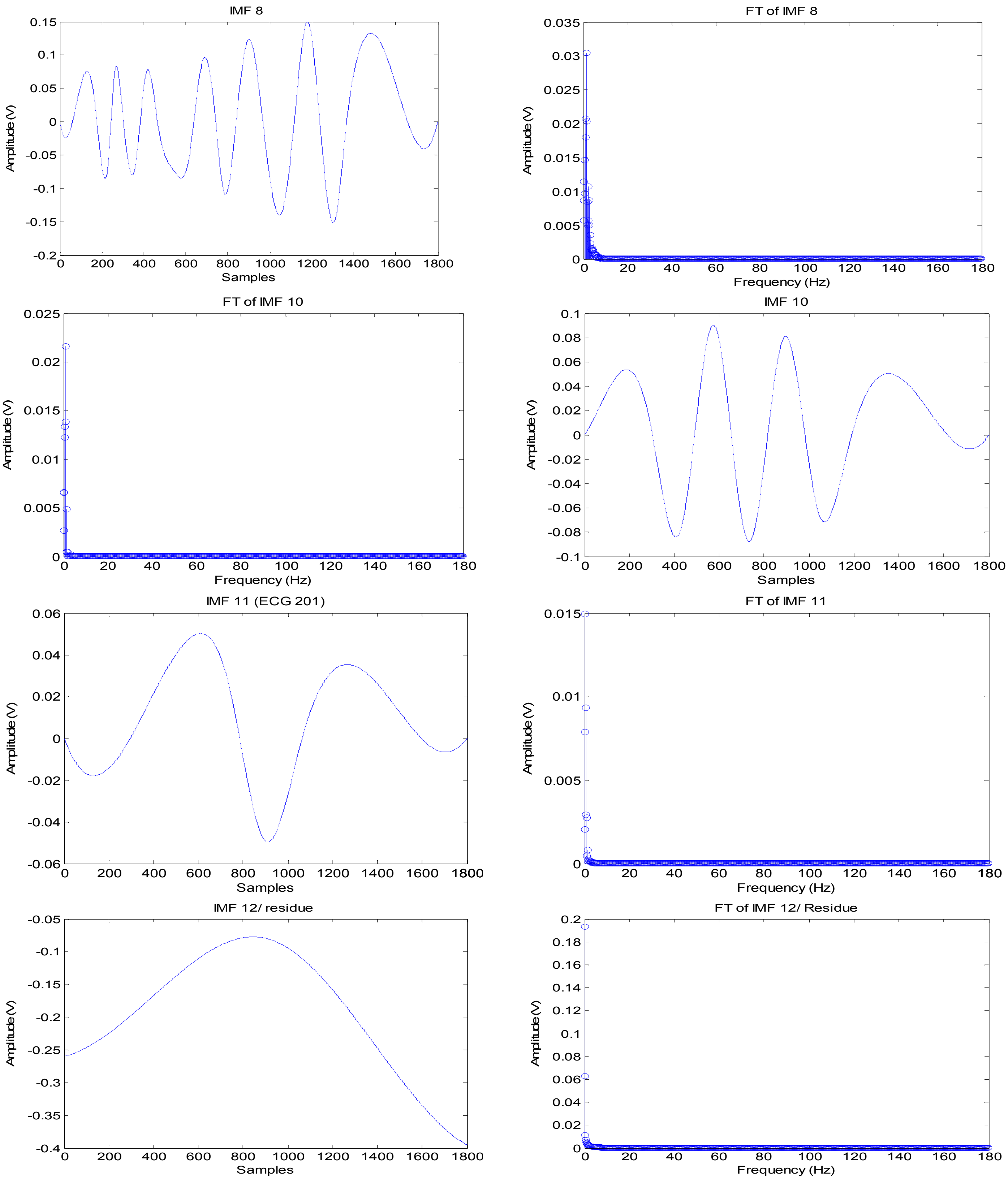

Fig 5(b) IMF 8, 10, 11 and 12 (left side) and its frequency spectrum (right side)

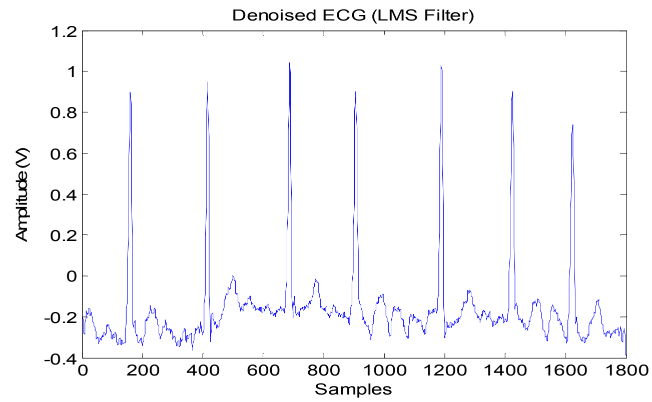

Fig 6(a) Denoised ECG (LMS Filter)

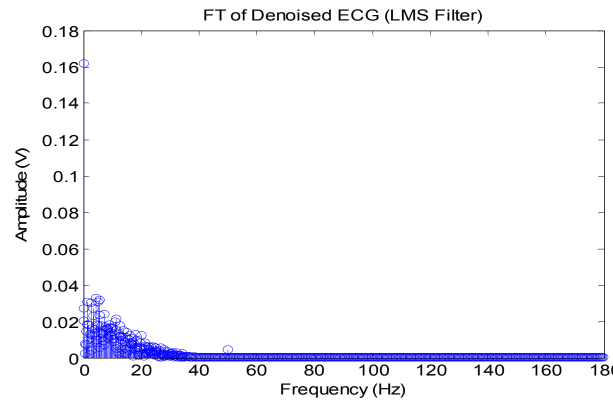

Fig 6(b) Frequency Spectrum of Denoised ECG (LMS Filter)

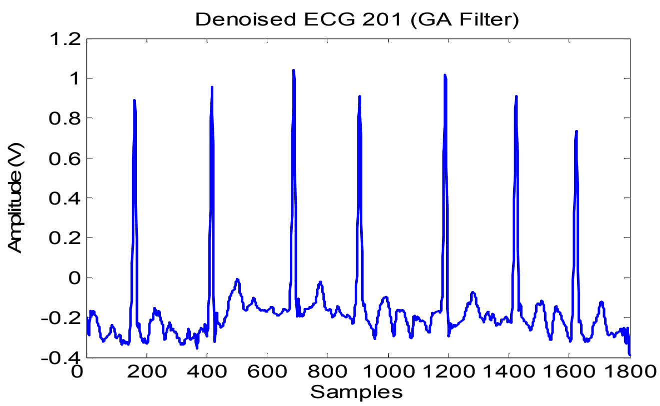

Fig 7(a) Denoised ECG (GA Filter)

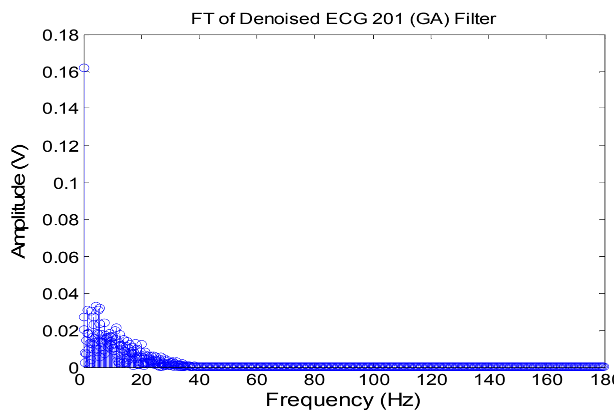

Fig 7(b) Frequency Spectrum of Denoised ECG (GA Filter)

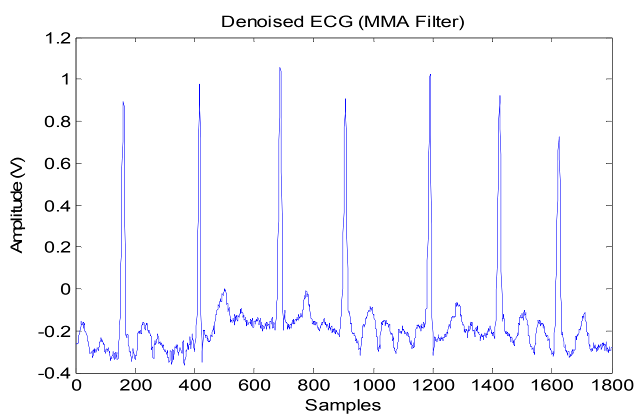

Fig 8(a) Denoised ECG (Modified MA Filter)

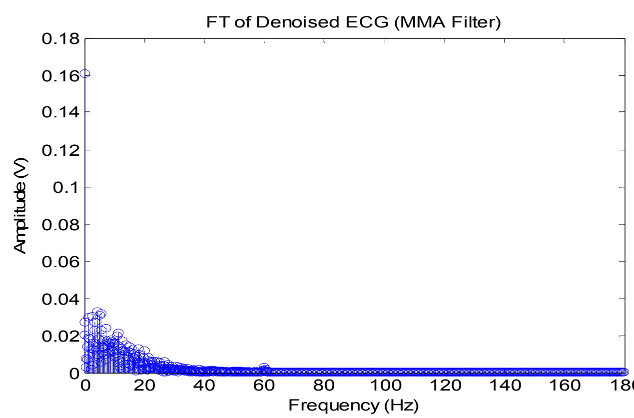

Fig 8(b) Frequency Spectrum of Denoised ECG (MMA Filter)

IMF1 contains the PLI component at the 50Hz frequency. IMF 2 and rest of the IMFs do not contain the noise component as shown in fig.5. So only IMF 1 has been used for the reconstruction of the reference signal for the adaptive canceller. The frequency components are decreasing as the order of IMF is increasing and the residue IMF12 is a monotonic signal as shown in fig.5(b).

The denoisd ECGs from the LMS filter and GA filter has also been shown in fig.6(a &b) and fig. 7(a & b) respectively. The denoised ECG from the Modofied Memetic algorithm (MMA) filter and its frequency spectrum has been shown in fig. 8 (a) and 8 (b). The PLI component at 50Hz has been effectively removed from the signal.

TABLE 3.
COMPARISON OF LMS, GA AND MMA FILTERS

ECG		RMSE	NCC	Improvement in SNR (dB)
ECG 116	LMS	0.0055	1.0000	28.3848
	GA	0.0054	1.0000	28.4182
	MMA	0.0015	1.0000	39.3113
ECG 117	LMS	0.0082	1.0000	26.4712
	GA	0.0080	1.0000	26.5382
	MMA	0.0059	1.0000	29.2487
ECG 201	LMS	0.0057	0.9999	25.1118
	GA	0.0054	0.9999	25.7949
	MMA	0.0009	1.0000	41.0421

Figures 6, 7 & 8 shows that the PLI component has been removed by all the filters. The quantitative analysis of the results from these three filters is shown in table 3. The results given in table 3 show that the GA filter results are slightly good as compared to the LMS filter and the performance of Modified Memetic filter in case of ECG 201, shows approximaterly 16dB improvement in SNR as compared to GA filter, with RMSE decreased by 0.0045.

7. CONCLUSION

The conclusion from the results is that the performance of Modified Memetic filter is better as compared to the Genetic filter and LMS filter. The Power Line Interference has been effectively and efficiently removed by the memetic filter without any loss of the valuable information in the ECG signals. In case of ECG 201, with Modified Memetic algorithm there has been approximately 16dB increase in the SNR and 0.0045 reductions in RMSE. MMA is able to achieve minima at approximately 0.0001of Griewank function and, which is very near to its global minima as compared to GA. Also the convergence to global optima is early with MMA and is an effective algorithm for the optimization.

8. REFERENCES

[1] Tang Jing-tian, Zou Qing, Tang Yan, Liu Bin, Zhang Xiao-kai, "Hilbert-Huang Transform for ECG De-noising" *Bioinformatics and Biomedical Engineering, ICBBE*, Year: 2007, pp. 664 – 667.

[2] Zhao Zhidong, Pan Min, "ECG Denoising by Sparse Wavelet Shrinkage" *Bioinformatic and Biomedical Engineering, ICBBE, The 1st International Conference* on 6-8 July2007, pp.786–789.

[3] Yunfeng Wu, Rangayyan, R.M., "An Algorithm for Evaluating the Performance of Adaptive Filters for the Removal of Artifacts in ECG Signals" *Electrical and Computer Engineering, CCECE, Canadian Conference* on, Year: 2007, pp. 864–867.

[4] Omid Sayadi, Mohammad Bagher Shamsollahi, "ECG Denoising and Compression Using a Modified Extended Kalman Filter Structure", *Biomedical Engineering, IEEE Transactions,* Volume 55, Issue: 9, 2008, pp. 2240-2248.

[5] Delechelle, E., Lemoine, J., Oumar Niang, "Empirical Mode Decomposition: An Analytical Approach for Sifting Process", *Signal Processing Letters, IEEE* Volume 12, Issue: 11, Year: 2005, pp. 764 – 767.

[6] Nianqiang Li, Ping Li, "An Improved Algorithm Based on EMD-Wavelet for ECG Signal De-noising", *International Joint Conference on Computational Sciences and Optimization, IEEE Computer Society*, Year: 2009, pp. 825-827.

[7] Nimunkar, A.J., Tompkins, W.J., "EMD-based 60-Hz Noise Filtering of the ECG" *Engineering in Medicine and Biology Society EMBS*, *29th Annual International Conference of the IEEE,* Year: 22-26 Aug. 2007, pp.1904 - 1907.

[8] Boudraa, A.-O., Cexus, J.-C., "EMD-Based Signal Filtering", *Instrumentation and Measurement, IEEE Transactions* on Volume: 56, Issue: 6 Year: 2007, pp. 2196 – 2202.

[9] Widrow, B., Glover, J.R., Jr., McCool, J.M., Kaunitz, J., Williams, C.S., Hearn, R.H., Zeidler, J.R., Eugene Dong, Jr., Goodlin, R.C., "Adaptive Noise Cancelling: Principles and Applications". *Proceedings of the IEEE* Volume 63, Issue: 12, Year: 1975, pp. 1692 – 1716.

[10] Zhao Zhidong, Ma Chan, "A Novel Cancellation Method of Powerline Interference in ECG Signal Based on EMD and Adaptive filter", *Communication Technology, ICCT, 11th IEEE International Conference* on 10-12 Nov. 2008, pp.517 – 520.

[11] Soroor Behbanani, "Investigation of Adaptive Filtering for Noise Cancellation in ECG Signals" *Second International Multisymposium on Computer and Computational Sciences, IEEE Computer Society*, Year: 2007, pp.144 – 149.

[12] M. Srinivas and Lalit M. Patnaik, "Genetic Algorithms: A Survey", Computer Volume 27, Issue: 6, Year: 1994, pp. 17 – 26.

[13] Nguyen, Q.H., Ong, Y.S., Krasnogor, N., "A Study on the Design Issues of Memetic Algorithm", *Evolutionary Computation, CEC*, Year: 2007, pp. 2390 – 2397.

[14] Digalakis, J.G.; Margaritis, K.G.; "An experimental study of benchmarking functions for genetic algorithms," *IEEE International Conference on Systems, Man, and Cybernetics, 2000,* vol.5, no., pp.3810-3815.

[15] Pant, M.; Thangaraj, R.; Abraham, A., "Particle Swarm Based Meta-Heuristics for Function Optimization and Engineering Applications," *Computer Information Systems and Industrial Management Applications, 2008. CISIM '08. 7th*, vol., no., 26-28 June 2008, pp.84-90.

[16] Ratnaweera, A.; Halgamuge, S.K.; Watson, H.C.;, "Self-organizing hierarchical particle swarm optimizer with time-varying acceleration coefficients," *IEEE Transactions on Evolutionary Computation*, vol.8, no.3, June 2004, pp. 240-255.

[17] Database:www.physionet.org/physiobank/database/**mit**db.