CHAPTER-1
INTRODUCTION

1.1 INTRODUCTION

ElectroCardioGram (ECG) is the record of the electrical potentials produced by the heart during contraction and expansion. It is very essential tool used by medical practioners especially cardiologists to inspect the cardiac malfunctioning or pathological condition of the heart [1].The Electrocardiogram signal usually is in the range of 2 mV having the bandwidth of 0.1Hz to 120 Hz. In normal conditions, Electrocardiogram waveform is having a very expected duration, amplitude and direction. So that it can be easily recognized, assessed, identified and interpreted for a usual or unusual functioning of the heart. The Electrocardiogram signal and heart rate reveals the cardiac fitness of human heart. Any change in heart rate or variation in the morphological form of Electrocardiogram signal is a sign of cardiac arrhythmia. It is noticed and analyzed by investigation of the recorded electrocardiogram waveform. The amplitude and duration of the P-Q-R-S-T-U wave more specifically QRS complex contains the first hand information of the heart disease.

➢ ECG MORPHOLOGY

The Electrocardiogram signal is a graphical demonstration of the Electro-Mechanical action of the heart pumping that recorded within specific period of time. Fig.1.1 shows an example of electrocardiogram waveform which consists of a P, QRS, T and small U wave is noticeable in certain cases. In the regular heartbeat, the key parameters are examined which comprise the duration, shape, R-R interval and QRS complex wave of electrocardiogram signal as whole. The fluctuation in these parameters leads to illness of the heart.

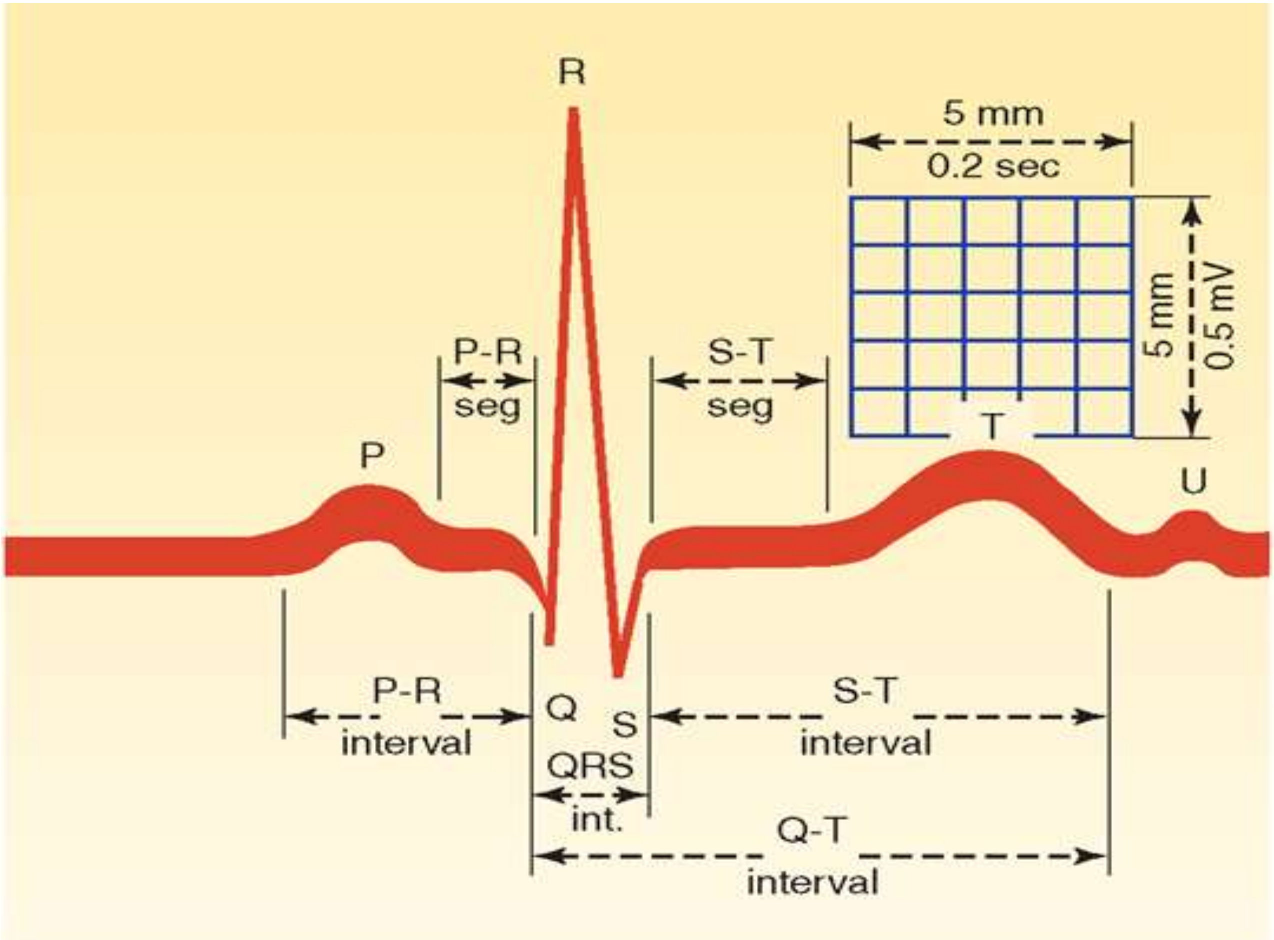

FIG. 1.1 TYPICAL ECG WAVEFORM

P wave: When the electrical impulse is conducted from the SA node towards the AV node and spreads from right to left atrium, the depolarization of atria occurs.The depolarization (contraction) of atria results the P Wave in the ECG.

QRS complex: It consists of three waves, sequentially known as Q, R and S. The rapid depolarization of both the ventricles results this complex. The muscles of the ventricles have large muscle mass than that of atria, hence its amplitude is much larger than that of P wave.

T wave: Ventricular re-polarization results the preceding of ST segment and the T-wave.

U wave: The source of U wave is not clear and rarely seen. It is probably produced due to the repolarization of the papillary muscles.

➢ ARTIFACTS

The Electrocardiogram is frequently contaminated through noise and artifacts.
Various artifacts are:

1. **Power Line Interference (PLI):** Power line interference or artifacts consists of 50-60 Hz power line frequencies and bandwidth of less than 1 Hz. The amplitude of power line interference fluctuates up to 50% of FSD level**.**

2. **Baseline wander:** Baseline wander artifact occurs mainly due to respiration at the drifting frequencies between 0.15 Hz to 0.3 Hz. Baseline wander artifact is also known as Baseline shift or drift.

3. **Muscle noise/ Electromyographic artifact:** Electrical bio-potential due to EMG or muscle contraction adulterates the electrocardiogram signal. The amplitude of muscle noise fluctuates up to 10% of FSD level with frequency of 10 KHz**.**

4. **Motion artifacts:** Motion artifacts are produced due to motion of electrode or change in impedance between electrodes, when it is superimposed on the Electrocardiogram activity then it is known as motion artifact.

5. **Electrode contact noise:** Contact noise originates due to loss of contact between the subject's skin and the electrodes.

6. **Data gathering device and Electrosurgical noises:** It is generated through medical apparatus and signal processing hardware at frequencies between 100 kHz and 1 MHz.

1.2 METHODOLOGY

In this proposed study, programming of MATLAB software has been utilized to develop an algorithm for de-noising of ECG signal. Use of Genetic Particle Filter (GPF) diminishes the degeneracy problem of Particle Filter (PF). EEMD is used in this thesis instead of EMD because it solves the EMD mode mixing problem. Ensemble EMD symbolizes a major improvement with great adaptability, flexibility, versatility and robustness in noisy ECG signal filtering method. EEMD consists of EMD and taking corresponding IMFs average of an ensemble of ‘n’ number of trials. This outputs treats final true result of EEMD. Ensemble EMD methods are used to decompose the electrocardiogram signal into its true Intrinsic Mode Functions (IMFs).

1.3 OBJECTIVES OF THIS DISSERTATION

Objectives of this dissertation are:-

1. First Objective is to develop an algorithm for de-noising of ECG signal. EEMD methods are used to decompose the ECG signal into ‘n’ number of Intrinsic Mode Functions (IMFs). Then the IMFs which are dominated by noise are automatically determined using Fuzzy Thresholding (FT) and then these are filtered using Genetic Particle Algorithms to remove the noise.

2. Second objective is to improve the computational efficiency of signal processing. Signal to Noise Ratio (SNR) and Root Mean Square Error (RMSE) are used to measure and compare the performance of proposed methods with different existing techniques for different artifacts.

1.4 DISSECTION OF DISSERTATION

The material of this dissertation has been organized in six chapters. The contents of the chapters are briefly outlined as:-

Chapter-1 Discusses the introduction to ECG signal, ECG Morphology and various types of artifacts and gives a brief objective of the thesis.
Chapter-2 Discusses the Literature Review.
Chapter-3 Discusses the introduction to basics concept such as EEMD, EMD, Genetic Particle Filter and Fuzzy Thresholding.
Chapter-4 Discusses about the implementation of proposed approach and flow chart diagram &algorithms used.
Chapter-5 Results of the proposed technique elaborated. These results are shown and compared with other techniques in terms of their SNR.
Chapter-6 Discusses the conclusion and future work or scope.

1.5 SUMMARY

This chapter gives brief introduction about ECG signal, ECG morphology and its graphical representation, brief idea about artifacts in ECG signal, discusses various types of artifacts and discusses on the objectives of the thesis and gives brief outline of the project design.

CHAPTER-2

LITERATURE REVIEW

2.1 INTRODUCTION

Many investigators have tried various approaches for de-noising of ECG signal. Nature of the technique used largely depends on the application domain. Many researchers have worked on development of method for reduction of various noises in ECG signal.This review includes applicability of such methods to ECG de-noising, their advantages and limitations and the scope of any future work, if possible, in these methods.

2.2 HISTORICAL PERSPECTIVE OF DENOISING OF ECG SIGNAL

With the advances in signal processing, accordingly spontaneous signal processing, computer vision and smart filtering systems were implemented for de-noising of electrocardiogram signal. Over the years, the electrocardiogram signal investigation has been considered very challenging issue for both the signal processing and biomedical diagnostics.

2.3 DEVELOPMENT HISTORY OF MATLAB AND ITS FEATURES

MATLAB (Matrix Laboratory) is mathematical computing software. It is a forth generation programming language. MATLAB (Matrix Laboratory) was developed by Math co-works.It allows plotting of function, implementation of algorithms and matrix manipulations etc. It contains several tools for managing files, codes, variables, data and applications inside the Matrix Laboratory.

Following are the three important windows that exist in Matrix Laboratory(MATLAB):-

1. **Command window**: commands are entered or written in this window

2. **Edit/Debug Window**: generate new M-files/modify the program
3. **Figure window**: displays images,2D and 3D plots ,graphs

MAJOR TOOLIN MATLAB:-

1. Help browser
2. Current directory browser
3. Workspace
4. Array Editor
5. Command history window
6. Launch Pad
7. Three window i.e. Command, Figure, Edit/debug window

DIFFERENT TOOLBOXES IN MATLAB:-

1. Aerospace
2. Bioinformatics
3. Communication
4. Control System
5. Curve Fitting
6. Data Acquisition
7. Database
8. Distributed Computing
9. Filter Design
10. Financial
11. Fuzzy logic
12. Image Acquisition
13. Image Processing

2.4 LITERATURE SURVEY ON DENOISING OF ECG SIGNAL

- **ECG DE-NOISING BASED ON HYBRID TECHNIQUE**

B. Pradeep Kumar, S. Balambigai and Dr. R. Asokan **[1]** proposed a hybrid technique which combined Empirical Mode Decomposition and Wavelet thresholding. EMD is used for decomposing the noisy electrocardiogram signal into sequences of intrinsic mode functions (IMF). Wavelet thresholding is used for removing the noise from decomposed signal. Hybrid Technique has been improved the performance of de-noising signal. The hybrid technique also provides improved SNR than wavelet transform approach. It removes both power line noise and base line wander noise.

- **DE-NOISING OF ECG SIGNALS USING EMPIRICAL MODE DECOMPOSITION BASED TECHNIQUE**

Anil Chacko* and Samit **Ari [2]** proposed de-noising approach for electrocardiogram signals built on Empirical Mode Decomposition. The noisy ECG signal is initially decomposed into sequences of Intrinsic Mode Functions (IMFs) with the help of EMD method. The IMFs which are ruled by noise are spontaneously determined through Spectral Flatness (SF).These noisy IMFs are filtered with the help of Butterworth filters to eliminate noise. It performs better Signal to Noise Ratio (SNR) and lower Root Mean Square Error (RMSE) as compared to Wavelet Transform de-noising technique.

- **ECG SIGNAL DE-NOISING USING UN-DECIMATED WAVELET TRANSFORM**

V. Naga Prudhvi Raj and Dr. T. Venkateswarlu **[3]** proposed a de-noising approach which contains un-decimated wavelet Transform. This transform is used to decompose the raw electrocardiogram signal.In this method, the shrinkage action is used to eliminate the noise from the noisy electrocardiogram signal. In the shrinkage phase, Semi-soft and stein thresholding are used with traditional soft and hard thresholding. It confirmed the suitability of different wavelet for electrocardiogram signals de-noising. It provided a better smoothness, stability and accuracy as compared to DWT.

- **GENETIC PARTICLE FILTERING FOR DE-NOISING OF ECG CORRUPTED BY MUSCLE ARTIFACTS**

Guojun Li, Xiao pin Zeng, Jinzhao Lin and Guojun Li, Xiaona Zhou **[4]** proposed de-noising method is based on particle filter along with Genetic algorithm. A Genetic algorithm (GA) is embedded into the Standard Particle Filter (S-PF) is known as GA-PF which is used to overcome the degeneracy problem. GA-PF can effectively track and suppressed the EMG artifacts while conserving the desired ECG signal.

- **WAVELET DOMAIN WIENER FILTERING FOR ECG DE-NOISING USING IMPROVED SIGNAL ESTIMATE**

N. Nikolaev and A. Gotchev **[5]** presented a two-phase algorithm for suppression of electromyogram (EMG) artifacts from the electrocardiogram (ECG) using Wavelet Domain Wiener Filtering.

- **A NOVEL ECG SIGNAL DE-NOISING METHOD BASED ON HILBERT-HUANG TRANSFORM**

Changnian Zhang, XiaLi and Mengmeng Zhang **[6]** proposed an algorithm for electrocardiogram (ECG) signal de-noising based on Hilbert-Huang Transform. This transform presents two phases for signal processing. Firstly, Original dataset is converted into an ‘n’ (number of) intrinsic mode functions through EMD method and then these IMFs components are passed through Hilbert transforms. It is simpler approach as compared to wavelet de-noising method.

- **ECG SIGNAL DE-NOISING BASED ON MORPHOLOGICAL FLITERING**

Zhongguo Liu, Jinliang Wang and Boqiang Liu **[7]** proposed a morphological methodology to eliminate the noise of the electrocardiogram signals. The structuring elements exist in different sizes. These structuring elements are used to process the different environment of electrocardiogram signal and noise. This filter is very effective in removing noise and correct baseline drift. This method is modest, fast and simple. It also supports the real-time processing.

- **ECG SIGNALS DE-NOISING USING NEIGHBOURING COEFFICIENTS**

Yang Ying and Xi An **[8]** proposed a method for ECG signals de-noising using neighboring coefficients method with help of level dependent thresholding. This neighboring coefficients method gives better results than hard thresholding.

- **ECG SIGNAL DE-NOISING USING NOISE INVALIDATION**

N. Nikvand, H. Bagherzadeh Rafsanjani and M.A Khalilzadeh **[9]** proposed a method for ECG signal de-noising using noise invalidation. In wavelet shrinkage,the coefficients which are smaller than threshold are considered as noisy coefficients. These noisy coefficients are discarded from the signal. The electrocardiogram signal is reconstructed through remaining coefficients in time domain.

- **NON-LOCAL MEANS DE-NOISING OF ECG SIGNALS**

Brian H. Tracey and Eric L. Miller **[10]** proposed a non-local means method for de-noising of ECG Signals. NLM-based de-noising scheme provides improved signal-to-noise ratio.

- **APPLICATION OF S-TRANSFORM FOR REMOVING BASELINE DRIFT FROM ECG**

AlarkaSanyal, ArijitBaral and AbhijitLahiri **[11]** proposed a method for removal of baseline drift using Stock-well Transform or simply S-transform. It also high-points the advantages of Stock-well transform over Discrete Wavelet Transform for elimination of baseline shift from an Electrocardiogram signal**.**

- **PARABOLIC FILTER FOR REMOVAL OF POWERLINE INTERFERENCE IN ECG SIGNAL USING PERIODOGRAM ESTIMATION TECHNIQUE**

G. Kavya and Dr. V.Thulasibai **[12]** proposed a parabolic filter method for elimination of power-line interference (PLI) in electrocardiogram Signal through periodogram estimation method. This new filter (Parabolic) is used to eliminate the power line interference 50Hz (PLI) in the electrocardiogram signal. It contains high SNR and minimum MSE as compared with the other existing filters.

- **ECG SIGNAL DE-NOISING BASED ON EMPIRICAL MODE DECOMPOSITION AND MOVING AVERAGE FILTER**

Sonali, Omkar Singh and Ramesh Kumar Sunkaria **[13]** proposed a system for Electrocardiogram Signal De-noising Based on Empirical Mode Decomposition and Moving Average Filter. It is an enhancement of the existing EMD based de- noising algorithms. Electrocardiogram signal is initially decomposed into 'n' (number of) Intrinsic Mode Functions (IMFs), then high frequency noises are eliminated using lower order IMFs followed by the reconstruction of the ECG signal.

- **DE-NOISING OF ECG SIGNAL BASED ON IMPROVED ADAPTIVE FILTER WITH EMD AND EEMD**

J.Jenitta and Dr. A.Rajeswari **[14]** proposed an improved method of de-noising Electrocardiogram (ECG) signal established on adaptive filter with Empirical mode Decomposition (EMD) and Ensemble Empirical mode Decomposition (EEMD). Three different methods used for eliminating baseline wander and power-line interference noise in electrocardiogram signal.

- **DE-NOISING OF WEAK ECG SIGNALS BY USING WAVELET ANALYSIS AND FUZZY THRESHOLDING**

M. Ustundag, M. Gokbulut and A. Sengur **[15]** proposed a weak ECG signal de-noising method based on fuzzy thresholding and wavelet packet analysis. Firstly, the weak electrocardiogram signal is decomposed into various level using wavelet packet transforms. Then, the threshold value is determined using the fuzzy s-function. The reconstruction of the ECG signal from the retained coefficients is achieved by using inverse wavelet packet transform.

- **A COMPLETE ENSEMBLE EMPIRICAL MODE DECOMPOSITION WITH ADAPTIVE NOISE**

Maria E. Torres, Marcelo A. Colominas, Gaston Schlotthauer and Patrick Flandrin **[16]** proposed method of electrocardiogram de-noising on the ensemble empirical mode decomposition (EEMD). It provides an exact rebuilding of the original signal .It also delivers better spectral separation of the modes. It also provides a lesser computational cost. It solves EMD mode mixing problem.

- **WAVELET BASED MOTION ARTIFACT REMOVAL FOR ECG SIGNALS**

Fakroul Ridzuan Hashim, John Soraghan, Lykourgos Petropoulakis and Sairul Izwan Safie **[17]** proposed a combined method of wavelet based de-noising and high-pass/low-pass filtering. In the first stage wavelet de-noising techniques with several threshold methods are used. In the second stage and in order to remove motion artifact noise, a combination of a high and low frequency filters are employed.

- **ECG DE-NOISING BY SPARSE WAVELET SHRINKAGE**

Zhao Zhidong and Pan Min **[18]** proposed a novel sparse wavelet shrinkage method for de-noising for ECG signal. It is based on maximum likelihood estimation of sparse data corrupted with Gaussian noise. It utilizes the prior information on the probability density of the data. This method has better performance than traditional hard and soft shrinkage functions.

- **A SURVEY ON ECG SIGNAL DE-NOISING TECHNIQUES**

Sarang L. Joshi, Rambabu A. Vatti and Rupali V.Tornekar **[19]** presented a survey of various types of noises corrupting ECG. Several methodologies used for de-noising the ECG signal are adaptive filtering, Fuzzy logic, FIR filtering, Wavelet transform and

Empirical Mode Decomposition. Adaptive filtering is the most widely used technique for de-noising. Wavelet transform is the modern approach with different types of thresholding systems such as hard thresholding, soft thresholding and semi-thresholding.

2.4 SUMMARY

An extensive literature review carried out of ECG de-noising using different method and techniques has been discussed briefly in this chapter.

TABLE 2.1: SUMMARY OF LITERATURE REVIEW

S.No.	Name of paper and Author	Method	Advantages	Improvements and Future Work
1	ECG de-noising based on hybrid technique *B. Pradeep Kumar, S.Balambigai and Dr. R. Asokan*	1. Empirical Mode Decomposition 2. Wavelet thresholding.	1. The proposed method removes both power line noise and base line wander noise. 2.EMD has good ability to decompose the signal. 3.Wavelet thresholding is good in removing the noise from decomposed signal	Some other combination of hybrid techniques can be implemented. Also VLSI implementation of hybrid techniques has a great scope in future.
2	De-noising of ECG signals using Empirical Mode Decomposition based technique *Anil Chacko and Samit Ari**	1. Empirical Mode Decomposition 2. Butterworth filter.	1. In the proposed approach,automatic detection of noisy IMFs is done using spectral flatness measure. 2.It shows better SNR performance and lower RMSE compared to Wavelet Transform based technique.	Mode mixing consequence can be improved in future.

3	ECG Signal De-noising Using Un-decimated Wavelet Transform *V. Naga Prudhvi Raj and Dr. T. Venkateswarlu*	1.Undecimated Discrete Wavelet Transform 2. Wavelet Shrinkage.	1.The proposed method shows better balance between smoothness and accuracy than the DWT.	
4	Genetic Particle Filtering for De-noising of ECG Corrupted by Muscle Artifacts *Guojun Li, Xiaopin Zeng, Jinzhao Lin and Guojun Li, Xiaona Zhou.*	1. Genetic Particle filter.	1.The proposed method is used to mitigate the sample degeneracy of PF.	Modification of the GAPF algorithm is under investigation to tackle the adaptive parameters adjustment.
5	Wavelet domain wiener filtering for ECG de-noising using improved signal estimate. *N. Nikolaev,Z. Nikolov, A. Gotchev and K. Egiazarian*	1. Translation-invariant wavelet transforms. 2.Wiener filter	1.The proposed technique shows better algorithm capabilities in comparison with other thresholding algorithms	
6	A novel ECG signal de-noising method based on Hilbert-Huang Transform *Changnian Zhang, XiaLi and Mengmeng Zhang*	1.Hilbert-Huang Transform	1.The proposed method is suitable for nonlinear and non-stationary signal processing.	There are several future directions of research. HHT method in ECG Signal processing has broad application prospects in future.

7	ECG Signal De-noising Based on Morphological Filtering *Zhongguo Liu, Jinliang Wang and Boqiang Liu*	1.Morphological filtering techniques.	1. Morphological filtering approach is simple, fast and real-time in processing. .	Combination of morphological filters and adaptive filters are used for most appropriate structuring element in future.
8	ECG signals de-noising using neighbouring coefficients *Yang Ying and Xi An*	1. Neighboring coefficients with a level dependent threshold estimator.	1. The neighboring coefficients scheme performance is better than the hard thresholding.	
9	ECG signal de-noising using noise invalidation *N.Nikvand , H Bagherzadeh Rafsanjani and M.A Khalilzadeh*	1. Noise in-validation method. 2.Adaptive Thresholding,	1. The method exploits second order statistics of noise to remove additive noise.	
10	Nonlocal Means De-noising of ECG Signals *Brian H. Tracey and Eric L. Miller*	1. Non-local means method.	1. NLM-based de-noising scheme provides improved signal-to-noiseRatio than wavelet based method.	NLM de-noising should be applicable to a wider range of biomedical signals such as EMG or evoked potentials in future.
11	Application of S-Transform for Removing Baseline Drift from ECG *AlarkaSanyal ,ArijitBaral and AbhijitLahiri*	1.S-Transform	1.The advantage of S-transform based method is due to its inherent properties for which it directly conveys the time-frequency information of a signal while the later does not.	Also VLSI implementation of hybrid Techniques with S - Transform have a great scope in future.

12	Parabolic Filter For removal of power-line interference in ECG Signal Using periodogram estimation technique *G. Kavya and Dr. V.Thulasibai*	1. Parabolic Filter 2.Periodogram Estimation	1.Parabolic Filter is used to eliminate the power line interference50Hz (PLI) in the electrocardiogram signal.	The proposed work may be extended for implementation in Field Programmable Gate Array (FPGA).
13	ECG Signal De-noising Based on Empirical Mode Decomposition and Moving Average Filter. *Sonali, Omkar Singh and Ramesh Kumar Sunkaria*	1. Empirical Mode Decomposition 2. Moving Average Filter.	1.The enhancement to the existing EMD based approach with an additional work including moving average filtering to improve the QRS quality .	The combination of the modified EMD approach and smoothing makes the algorithm very much realistic and applicable and can be applied in long term examination of the ECG signal in practical stress test as well as in Holter monitoring that may get affected by the prominent noises.
14	De-noising of ECG Signal based on ImprovedAdaptive filter with EMD and EEMD *J.Jenitta and Dr.A.Rajeswari*	1. Empirical mode Decomposition (EMD) 2. Ensemble Empirical mode Decomposition (EEMD)	1. Least mean square (LMS) algorithm used with EMD and EEMD to improve the computational efficiency of adaptive processing.	
15	De-noising of weak ECG signals by using wavelet analysis and fuzzy thresholding *M.Ustundag , M.Gokbulut and A.Sengur*	1.Wavelet transform 2.Fuzzy thresholding	1. Threshold value is determined using the fuzzy s-function to remove the additive noise.	

16	A complete ensemble empirical mode decomposition with adaptive noise *Maria E. Torres, Marcelo A. Colominas, Gaston Schlotthauer and Patrick Flandrin*	1. Complete ensemble empirical mode decomposition	1. It delivered better spectral separation of the modes. 2. It also provides a lesser computational cost. 3. It solves EMD mode mixing problem.	In future works statistical studies will be carried out in order to determine the proper ensemble size and the amplitude of the added noise.
17	Wavelet Based Motion Artifact Removal for ECG Signals *FakroulRidzuanHashim,LykourgosPetropoulakis, John Soraghan and SairulIzwanSafie*	1. Wavelet with high-pass/ low-pass filtering.	1. Wavelets have the capability to reduce the effects of motion artifact noise.	The proposed method is used to de-noise both the low frequency and high frequency noise leaving behind the important information of the original signal .It has been improved in future.
18	ECG De-noising by Sparse Wavelet Shrinkage *Zhao Zhidong and Pan Min*	1.Sparse wavelet shrinkage	1. It not only decreases the noise, but also preserves the signal singularity. This method has better performance than traditional hard and soft shrinkage functions. .	
19	A Survey on ECG Signal De-noisingTechniques *Sarang L. Joshi, Rambabu A. Vatti and RupaliV.Tornekar*	1.Wavelet Transform 2.Fuzzy Logic 3.FIR filter 4.Empirical mode Decomposition	1.Equi-ripple notch filter is the best choice to remove power line interference. 2. Empirical mode Decomposition is used to remove baseline wander.	Some methods are focussed to remove power line interference while others are aimed at removing baseline wander and other types of noise. Every method has some disadvantages associated with it. Future research should aim at removing all types of noises from ECG signal using a single hybrid approach which can be the combination of existing approaches.

CHAPTER-3

BRIEF DISCUSSION ON BASIC CONCEPTS

3.1 INTRODUCTION

A brief description of various techniques used such as EEMD, EMD, Genetic Particle Filter etc. is represented in this thesis without extensive elaboration.

3.2 HILBERT-HUANG TRANSFORM

Hilbert-Huang Transform (HHT) is the combination of Hilbert Transform andEMD. It is very much appropriate for non-stationary and nonlinear signal processing. This transform presents two phases for signal processing. First, Original dataset is converted into an ‘n’ (number of) Intrinsic Mode Functions (IMFs) through EMD method and then these IMFs components are passed through Hilbert Transform.

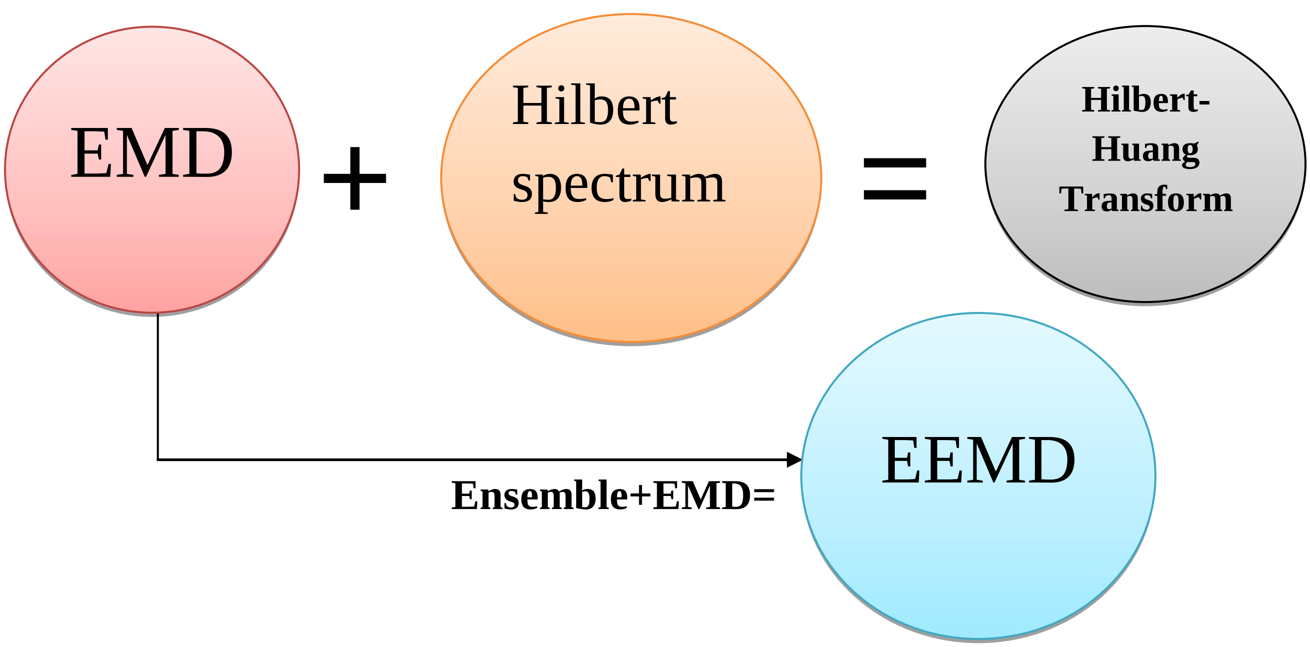

FIG. 3.1 HILBERT-HUANG TRANSFORM (HHT)

3.3 EMPIRICAL MODE DECOMPOSITION(EMD)

Empirical Mode Decomposition (EMD) decays a signal *y(n)* into sequence of 'n' number of sub-components known as Intrinsic Mode Functions (IMFs).Intrinsic Mode Functions represent oscillatory nature of signal. It is obtained by a organized process known as **sifting**.

CONDITIONS FOR IMF

(1) Number of zero crossings and extremes must fluctuate (differ) at most by 1.

(2) The average of the greater and lower envelopes respectively should be zero.

SIFTING ALGORITHM

IMFs of a signal are obtained by an iterative process known as **Sifting Step.**

Step1: Extremas Identification

Detect all the highest and lowest of y*(n).*

Step2: Interpolation

Insert between maxima to get $y_{max}(n)$ and insert between minima to get $y_{min}(n)$.

Step3: Average Envelope

Calculate average between envelopes

$$y_{avg}(n) = (y_{min}(n)+ y_{max}(n))/2$$

Step4: IMF Extraction

Extract details

$$d_1(n) = y(n) - y_{avg}(n)$$

$d_1(n)$ is assumed as input to the coming repetitions of sifting.

Step5: Stopping Condition

The $r_1(n)$ is assumed as input to coming repetitions and repetitions are stopped when $r(n)$ becomes a monotonic function. This is ensured by limiting Standard Derivation (SD) between k^{th} and $(k\text{-}1)^{th}$ iterations.

$$\text{SD} = \sum_{n=0}^{L-1}[(d_{k-1}(\text{n}) - d_k(\text{n})]^2 \div d^2{}_{k-1}(\text{n})$$

Typical value of SD: 0.2-0.3Sifting.

Step6: Reconstruction

If ‘N’ round of sifting procedure is done on the given signal $y(n)$,then it is decomposed into a sequences of ‘n’ number of IMFs.

Signal can be reconstructed as:

$$\text{y(n)} = \sum_{k=1}^{N}[(h_k(\text{n}) - r_N(\text{n})]$$

Where $h_k(n)$ are IMFs and $r_N(n)$ is the residue after ‘N’ sifting repetitions.

- **<u>DRAWBACKS OF EMD</u>**

The major shortcoming of EMD is the mode mixing consequence. Mode-mixing indicates that oscillations of different time scales co-exist in a given IMF or oscillations with the similar time scale have been allocated to different IMFs.

3.4 ENSEMBLE EMPIRICAL MODE DECOMPOSITION (EEMD)

Ensemble EMD (EEMD) is used to eliminate the mode-mixing consequence. It overcomes mainly the mode mixing problem of the original EMD through addition of white noise into the targeted signal frequently. It is also known as a Noise-Assisted Data Analysis system (NADA). EEMD consists of EMD and taking corresponding IMFs ensemble average of 'n' number of trials. These ensemble averages output treats as final result of EEMD. Ensemble EMD methods are used to decompose the electrocardiogram signal into true intrinsic mode functions (IMFs).

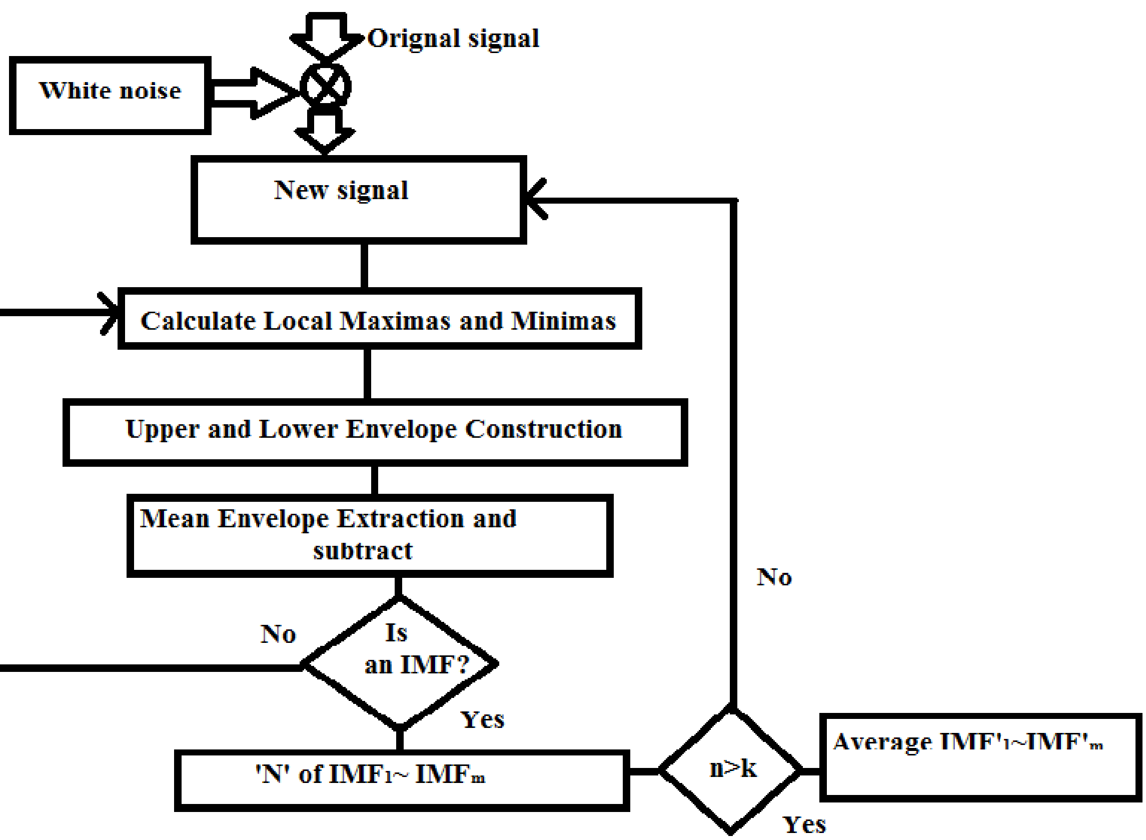

FIG. 3.2 FLOW CHART OF EEMD

- **ADVANTAGES OVER EMD**

(1) EEMD utilizes the complete benefit of the statistical features and also uniform scattering of frequency of white noise to improve the EMD process.

(2) It has more focused and band limited components.

3.5 GENETIC ALGORITHM (GA)

The GA is based on natural selection and genetic recombination. The Genetic Algorithm works by choosing solutions from the current population and then applying genetic operators (such as mutation and crossover) to create a new population set.Genetic Algorithm exploits historical information to speculate on new search areas with improved performance. Overall it performs global search**.**The Genetic Algorithm (GAs) performs a random search of a defined N-dimensional solution space. The Genetic Algorithm (GAs) mimics the processes in nature that leads to evolution of higher organisms.

The Genetic Algorithm has the following steps:-

- **Natural selection ("survival of the fittest")**
- **Reproduction**
- **Crossover**
- **Mutation**

- **ROULETTE WHEEL SELECTION:**

The selection process is to stochastically select from one generation to create the basis of the further generation. The necessity is that the fittest individuals have a greater chance of survival than lower ones. This also repeats itself in nature that fittest individuals will tend to have a better probability of survival and will go forward to form the mating pool for the further generation. Parents are chosen according to their fitness. The superior the chromosomes are, the more chances to be selected they have. A Roulette Wheel where are placed all chromosomes in the population, every has its place large accordingly to its fitness function.

- **GENETIC OPERATORS:**

The Crossover and mutation are two basic operators of Genetic Algorithm.

Crossover: New chromosomes are generated by combining portions of two existing chromosomes.

One point crossover - one crossover point is chosen, binary string from beginning of chromosome to the crossover point is copied from one parent, the rest is copied from the second parent.

Two point crossover -Two crossover point are chosen, binary string from beginning of chromosome to the first crossover point is copied from one parent, and the part from the first to the second crossover point is copied from the second parent and the rest is copied from the first parent.

Uniform crossover - bits are randomly copied from the first or from the second parent

Arithmetic crossover - some arithmetic operation is done to make a new offspring

Mutation: New chromosomes are generated by randomly changing some bits in existing chromosomes.

Elitism:It is a method which copies the best chromosome to new population. Elitism can improve the performance of Genetic Algorithm because it prevents losing the best found solution.

➤ GENETIC PARTICLE FILTER:

A Genetic Algorithm (GA) is embedded into the Standard Particle Filter (S-PF) is known as GA-PF which is used to overcome the degeneracy problem.It improves the self-evolution and self-adaptation.

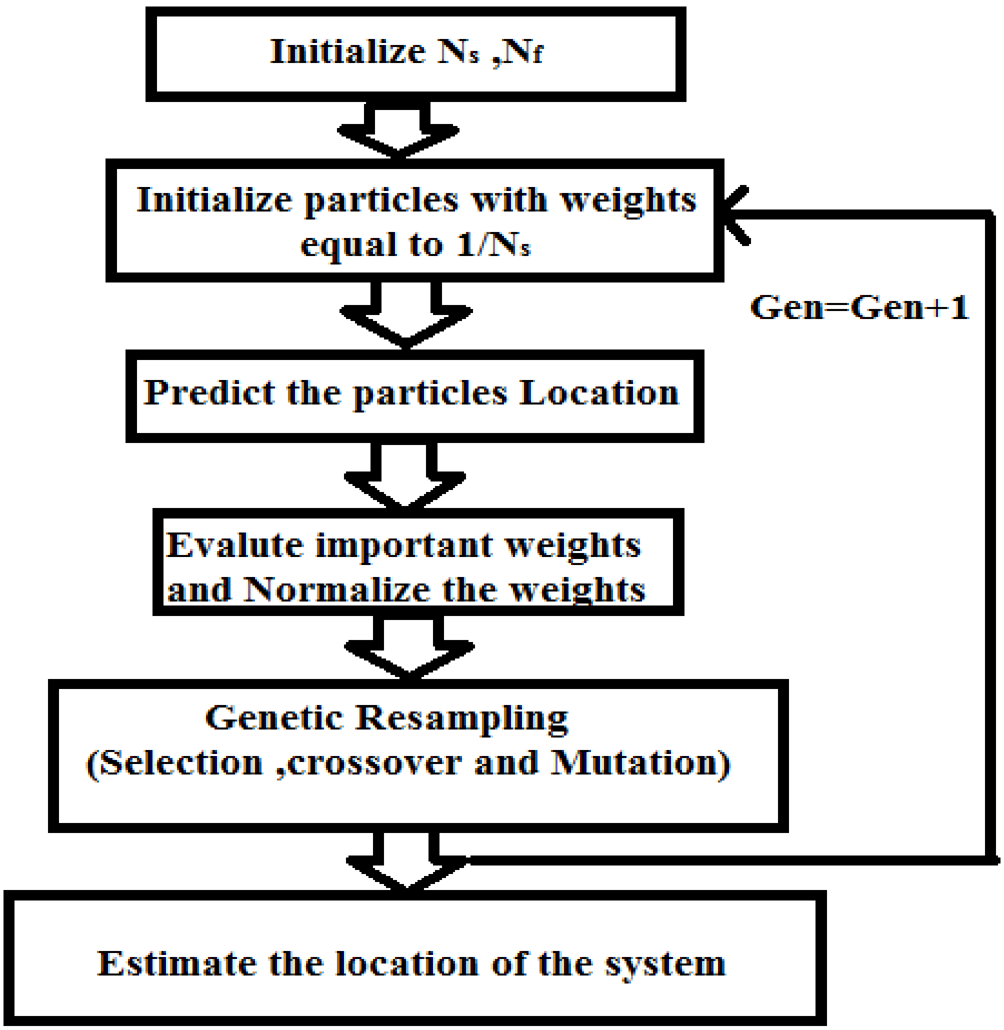

FIG. 3.3 FLOW CHART OF GENETIC PARTICLE FILTER

- **<u>The GA-PF ALGORITHM steps are following:-</u>**

1. Set particles and its weights.
2. Evaluate the importance weights.
3. Normalize importance weights.
4. **Genetic Resample**:

   Selection: Compute the individual's weighs as fitness function of the particles and then chooses the individuals through high fitness function with the help of Roulette selection. The individual greatest fitness is directly reserved to the coming generation.

   Crossover: Within probability of mutation 'P_c', stochastically pick two individuals from the beyond particles to create two recombinants using recombination principle.

   Mutation: Pick certain individuals stochastically from population under a smallmutation probability. Then mutate them.

5. New particles, the following repetition are determined until evolving generation 'T'.
6. Update the estimation of system state is the final output of GA-PF algorithms.

- **<u>ADVANTAGES OVER PARTICLE FILTER</u>**

(1) Genetic algorithm is used to overcome the degeneracy problem of Particle Filter (PF).

(2) Genetic algorithm filter improves the self–evolution and self–adaptation process.

3.6 FUZZY

- **FUZZY LOGIC**

The Fuzzy sets are being extensively used in computer vision and machine intelligence. A fuzzy set deals with the uncertainty and vagueness. Fuzzy logic is a good problem solving technique to handle uncertainty present in the problems. Fuzzy Logic provides a simple way to draw definite and correct conclusions from vague, uncertain, ambiguous or imprecise information. In a sense, fuzzy logic also resembles human decision capability with its ability to work with approximate, imprecise and uncertain data and find precise definite solutions. Fuzzy logic allows expressing the knowledge with subjective concepts such as, Low, Medium and High, which are then mapped into exact numeric ranges. In the example, Low, Medium and high are linguistic variables

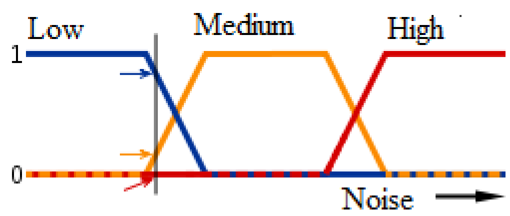

FIG. 3.4 LINGUISTIC VARIABLES INDICATED AS LOW, MEDIUM AND HIGH

- **FUZZY SET THEORY**

The crisp-set theory is based upon the binary memberships that are either 0 or 1 which means either a member belong to a particular set or it does not. A crisp set is defined as a set whose element fully belongs to the set and also have similar properties which can be measured quantitatively. In contrast with crisp sets, Fuzzy set does not have binary membership. Each element belongs to the set with some membership degree which shows the strength to which the member belongs to the set. The membership values lies between zero (0) and one (1) where zero (0) means no membership to the set and one (1) means entire membership to the set.

➢ SOURCES OF FUZZY CONTROL RULES:

The following are sources of fuzzy control rules:-

- Proficient knowledge.
- Control engineering knowledge.
- Fuzzy model of the process: linguistic depiction of the active properties.
- Self-establishing Learning: learning from previous learning or self-shaping learning.

➢ FUZZY PROCESSING

The following are steps of Fuzzy processing:-

- Fuzzification: transforms input crisp data into fuzzy data.
- Rule-base: comprises a knowledge or information of the application field
- Decision-making logic rule: executes inference for fuzzy control activities
- De-fuzzification:Reverse process of Fuzzification

Fuzzification means to transform crisp data sets into fuzzy data set. Fuzzification can be applied on fuzzy data sets to increase the fuzziness of the data set. While de-fuzzification is the reverse process. It means transforming fuzzy data set into discrete values. The strength of fuzzy thresholding processing lies in its middle step i.e. modification of membership values. After the data is fuzzified, appropriate fuzzy techniques modifies the membership function values. It can be a fuzzy rule based approach or fuzzy clustering and a fuzzy integration approach and so on.

➢ FUZZY THRESHOLDING

Fuzzy rules are well-defined in terms of statistical properties which determine the required range of thresholds is known as Fuzzy Thresholding.

The threshold value is determined using the fuzzy function.

- **ADVANTAGES OVER OTHER METHODS**

(1) Fuzzy logic is very easy to implement, use and understand. The mathematical concepts of fuzzy reasoning are very simple.

(2) Threshold value is determined using the fuzzy logic to remove the unwanted signal or noise. It provides the better SNR than other thresholding method such as soft and hard thresholding.

3.7 SUMMARY

An extensive basic concept such as Genetic Particle Filter, EEMD, EMD, Hilbert Transform etc. related to proposed approach used for ECG de-noising has been presented in this chapter.

CHAPTER-4
PROPOSED APPROACH

4.1 INTRODUCTION

This chapter discusses the implementation of first and second objectives i.e. for de-noising of ECG signal. EEMD methods are used to decompose the ECG signal into intrinsic mode functions. Then intrinsic mode functions which are dominated by noise are automatically determined using fuzzy thresholding and then filtered using Genetic Particle Algorithms to remove noise and improve the computational efficiency of adaptive processing. Signal to Noise Ratio (SNR) and Root Mean Square Error (RMSE) are used to measure and compare the performance of proposed methods with different techniques for different artifacts.

4.2 FLOW CHAT DIAGRAM

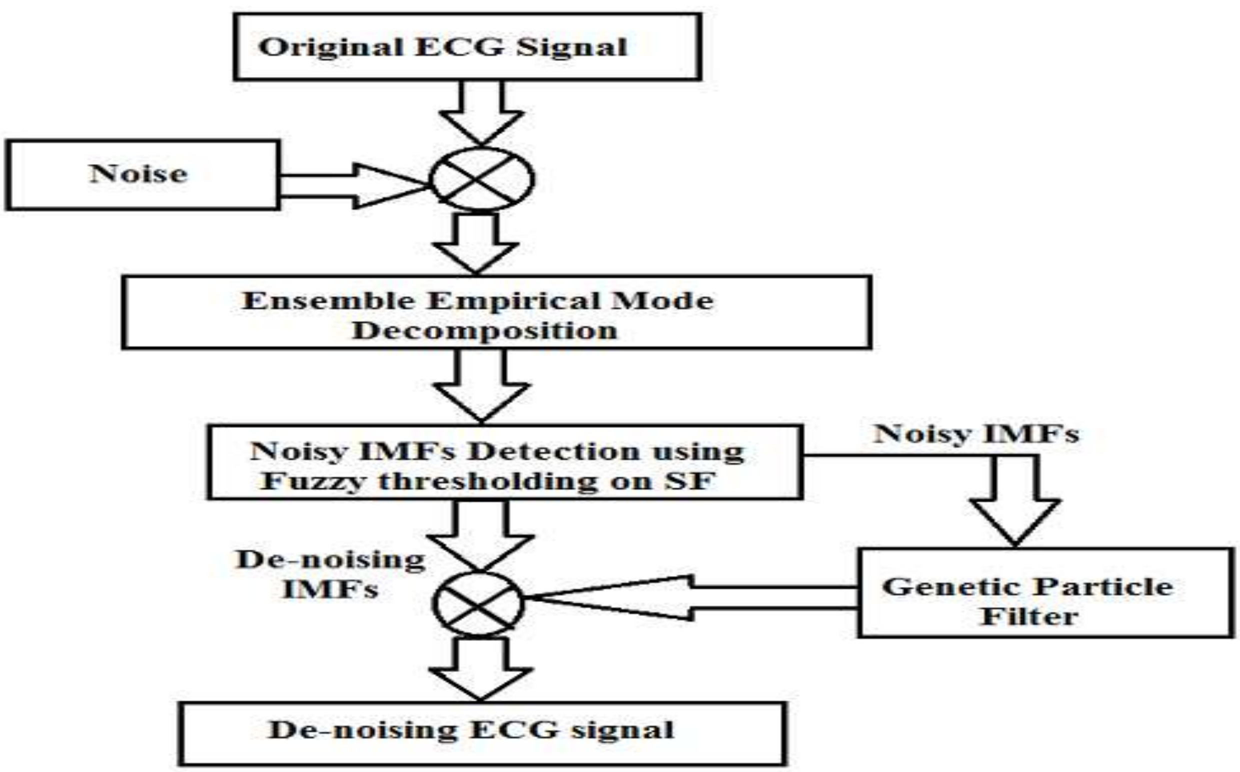

FIG. 4.1 FLOW CHART OF PROPOSED METHOD

4.3 ALGORITHM FOR PRESENTED METHOD:

1. $y^i[n]=y[n]+w^i[n]$
   where $w^i[n]$ i.e. i=1,2…………I are different realization of white Gaussian.

2. Each $y^i[n]$ i=1, 2…………….I is decomposed into modes using EMD.
   $IMF_k^i[n]$ where k=1, 2………..K indicates the modes.
3. Assign IMF_k as the k-th mode of y[n].
   Obtained as average of the corresponding IMF_k^i

   $\overline{IMF_k}[n]= 1/I \sum_{i=1}^{I} IMF^i k[n]$

4. Residue $R[n]=y[n]-\overline{IMF_k}[n]$

5. The number of noisy intrinsic mode functions is acquired by using the Spectral Flatness (SF) of individual IMF.

$$\text{spectral flatness measure} = \sqrt[l]{\prod_{n=0}^{L-1} G(n)} \div \left(\sum_{n=0}^{L-1} G(n)\right)/L$$

6. Fuzzication
   3 Trapezoidal membership functions 'low','medium','high'

   Rule base:

   1. **IF SPF is high range THEN IMF is noiseless.**
   2. **IF SPF is medium range THEN IMF is noisy.**
   3. **IF SPF is low range THEN IMF is noisy.**

      Condition:

      Take min of membership function of spectral flatness.
      Noisy=min (0.09, 0.08) =0.08
      Take min of membership function of spectral flatness.
      Noisy=min (0.03, 0.05) =0.03

      For combining the rules, according to fuzzy max-min implication, 'min' membership is noisy.

7. Defuzzication method
8. Output: 2 output :- one for noisy
   Second for noiseless
9. Noisy IMFs is passed through the **GA-PF algorithms.**

- Set (Initialize) particles and its weights:
  K=0, make particles $\{y_0^i\}_{i=1}^{Ns}$based on the prior probability density p_{y0}
  Ns=100
- Evaluate the importance weights are 1/Ns.
- Predict the particle location
  $U_k^i=U_{k-1}^i p(Z_k|y_k^i)$
  i=1,2……………Ns.
- Normalize importance weights.

  $U_k^{i=}U_k^i/ \sum_{i=1}^{Ns}U_k^i$

- Output of PF
- **Genetic Resample**:

  Starting generation=0 and Maximal Acceptable generation T=20

  - **Selection**: Compute the individual's weighs as fitness function of the particles and then choice the individuals through high fitness function with the help of Roulette Selection. The individual greatest fitness is directly reserved to the coming generation.
  - **Crossover**: Within mutation probability 'Pc', stochastically pick two individuals from beyond particles to create two recombinants using recombination principle.
  - **Mutation:** Pick certain individuals stochastically from population within slight mutation probability. Then it mutates them as $y_k^{new}=y_k^A+\eta$
- New particles, the succeeding repetition are determined until evolving generation T.
- Update the valuation of system state is the final output

10. ECG signal is reconstructed by adding clean IMFs and the remaining signal IMFs.

4.4 IMPLEMENTATION:

The Electrocardiogram signals have been taken from Hospital database. The noisy signal n(t) is acquired as n(t) = y(t) + m(t) where y(t) is the original ECG and m(t) is the noise signal. The n(t) signal is decomposed into Intrinsic Mode Functions using EEMD process. Noisy signal is passed through EMD method to obtain the IMFs. True IMFs taken as targeted signal is obtained by ensemble means of corresponding IMFs.

The number of noisy intrinsic mode functions is acquired by using the Spectral Flatness (SF) of individual IMF. The Spectral flatness is the relationship between the Geometric mean (GM) and Arithmetic mean (AM). It is defined as the ratio of geometric mean to its arithmetic mean of the power spectrum.

Spectral Flatness (SF) =Geometric mean (GM) /Arithmetic mean (AM)

Spectral Flatness measure is fuzzied to detect whether the IMFs are noisy or not. Linguistic variable used are low, medium and high. Membership function for Spectral Flatness is shown.

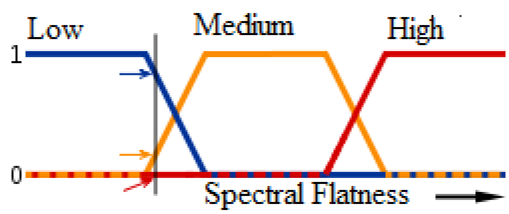

FIG. 4.2 LINGUISTIC VARIABLES AS LOW, MEDIUM AND HIGH

When spectral flatness of an IMF lies in the high range then this IMF is classified as noisy.

The rules for spectral flatness are:

Rule 1: IF SF is in high range THEN IMF is clean
Rule 2: IF SF is in medium range THEN IMF is noisy
Rule 3: IF SF is in low range THEN IMF is noisy

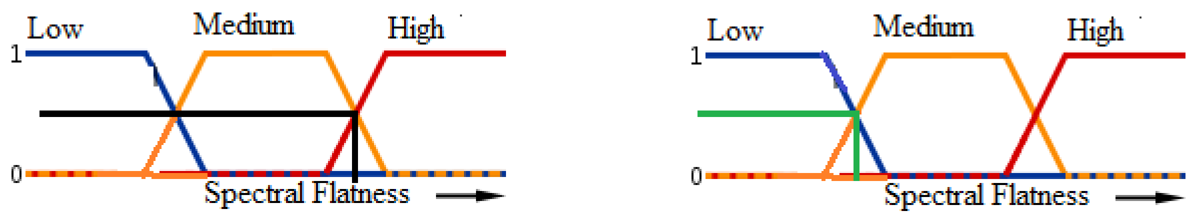

FIG. 4.3 MEMBERSHIP FUNCTION LIES BETWEEN MEDIUM AND HIGH OR LOW AND MEDIUM

Now applying Rule 1,

Take minimum of membership of Spectral Flatness

Noisy = min (0.09, 0.08) = 0.08

Now applying Rule 2,

Take minimum of membership of Spectral Flatness

Noisy= min (0.03, 0.05) = 0.03

For combining the rules, according to fuzzy max-min implication, 'min' membership is noisy. Automatic determination of noisy intrinsic mode functions is done using spectral flatness. The noisy IMFs are cleaned using Genetic Particle Filter to remove the noise.

4.5 SUMMARY

Both objectives i.e. First objective and second objective of this thesis have been implemented in this chapter. It also provides the brief explanation of the proposed approach with flow chart and algorithm.

CHAPTER-5

RESULTS AND DISCUSSION

5.1 PREVIEW

In this method, De-noising of ECG signal is done in such a way so that to suppress impulsive noises at several level while conserving the original ECG signals. It is not possible to remove noise completely, but we have tried to eliminate it as much as possible.

We tested the proposed method on ECG signal that are corrupted with three type of noise i.e. Muscle Artifacts, Electrode Artifacts and mixed noise.

5.2 RESULT OF PRESENTED APPROACH

The proposed method is tested on five databases with different types of artifacts. Electrocardiogram (ECG) signals are processed in MATLAB software.

Parameters [4] of Proposed algorithm listed as follows:-

Number of particles =100

Crossover probability=0.8

Mutation probability=0.1

Maximal Acceptable generation ‘T’=20

RESULT OF FIRST DATABASE.

Elapsed time is 48.136103 seconds.

SNR =

17.720505346041993

Number of NOISY IMFs: 5

Number of CLEAN IMFs: 9

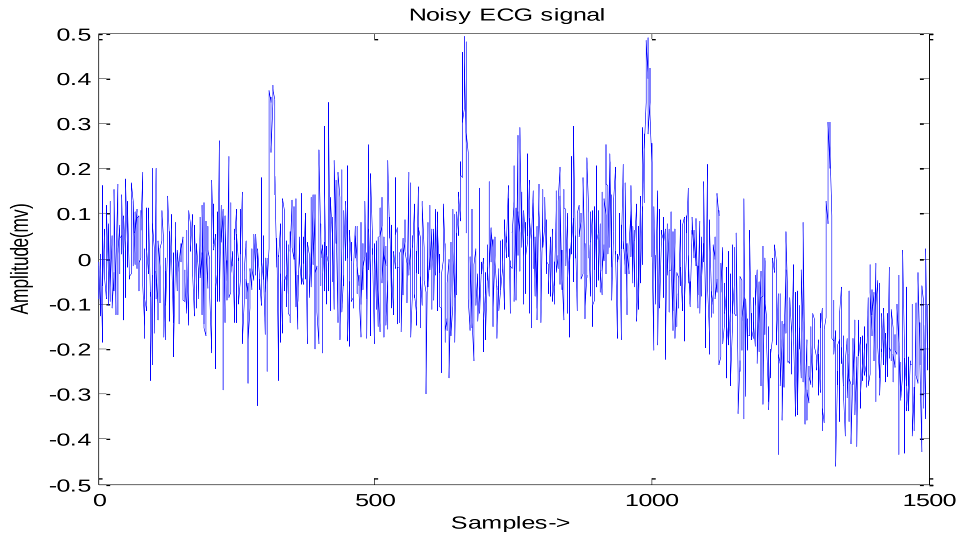

FIG. 5.1 NOISY ECG SIGNAL (DATABASE1)

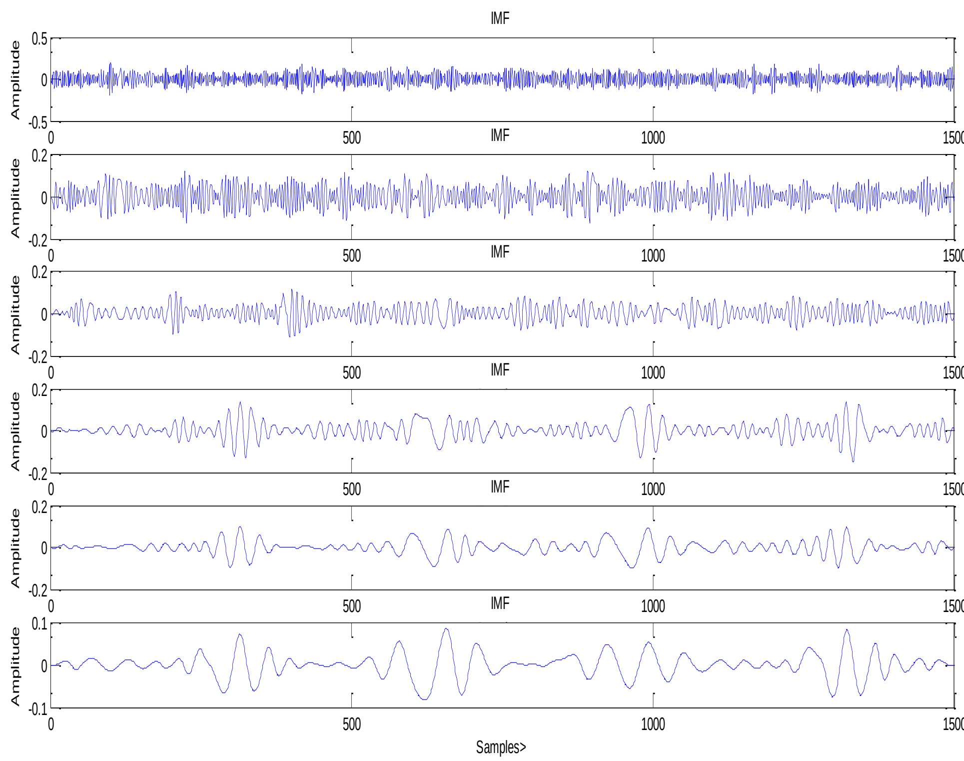

FIG. 5.2 SIX INTRINSIC MODE FUNCTIONS (IMFs) (DATABASE1)

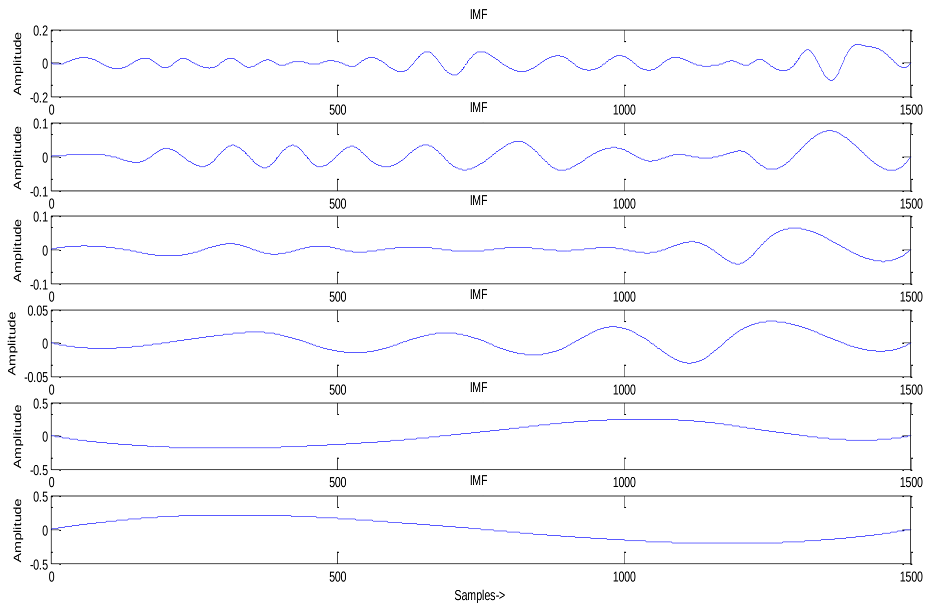

FIG. 5.3 REMAINING SIX INTRINSIC MODE FUNCTIONS (IMFs) (DATABASE1)

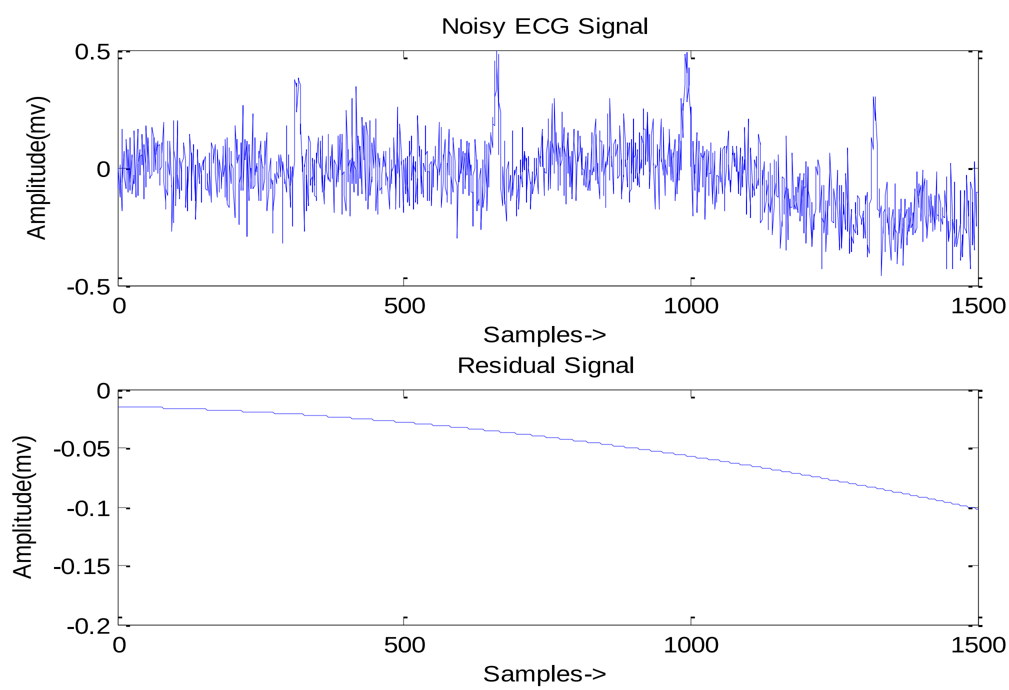

FIG. 5.4 NOISY ECG SIGNAL AND RESIDUAL SIGNAL (DATABASE1)

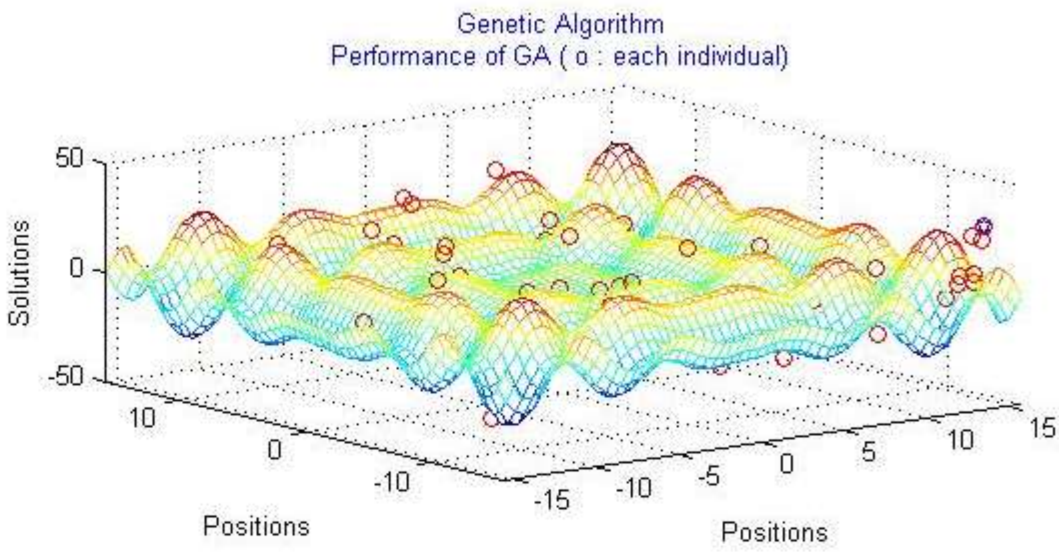

FIG. 5.5 PERFORMANCE OF GA (O: EACH INDIVIDUAL)(DATABASE1)

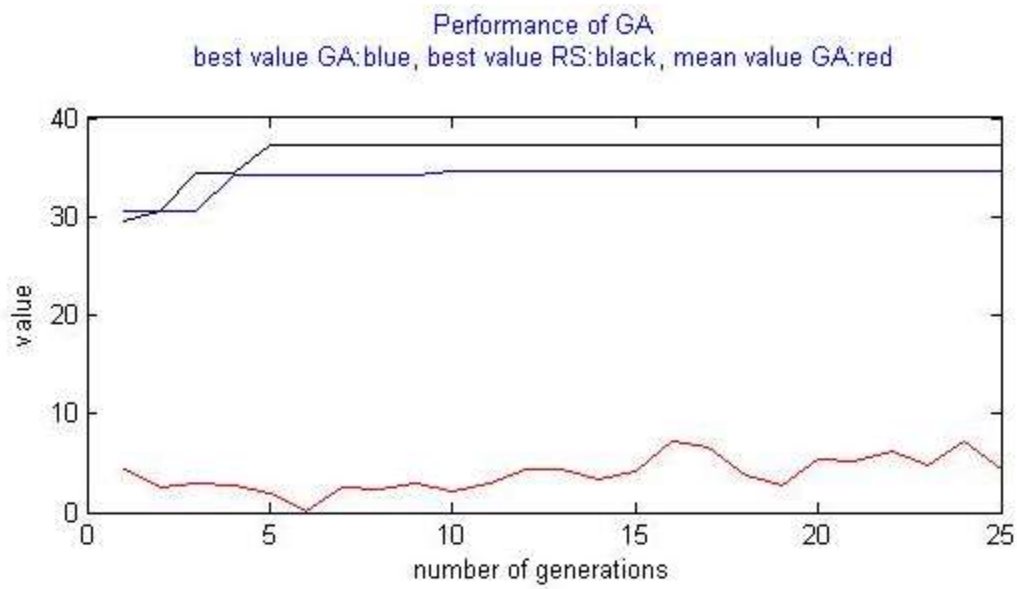

FIG. 5.6 VALUE (BEST SOLUTION) Vs NUMBER OF GENERATIONS (DATABASE1)

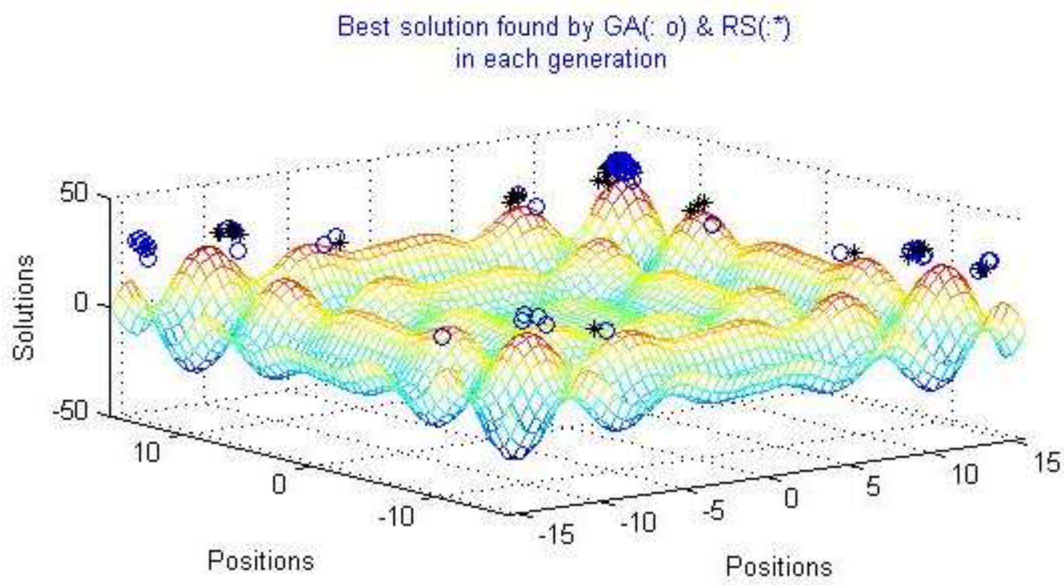

FIG. 5.7 BEST SOLUTION BY GA (: o) AND RS (: *) IN EACH GENERATIONS (DATABASE1)

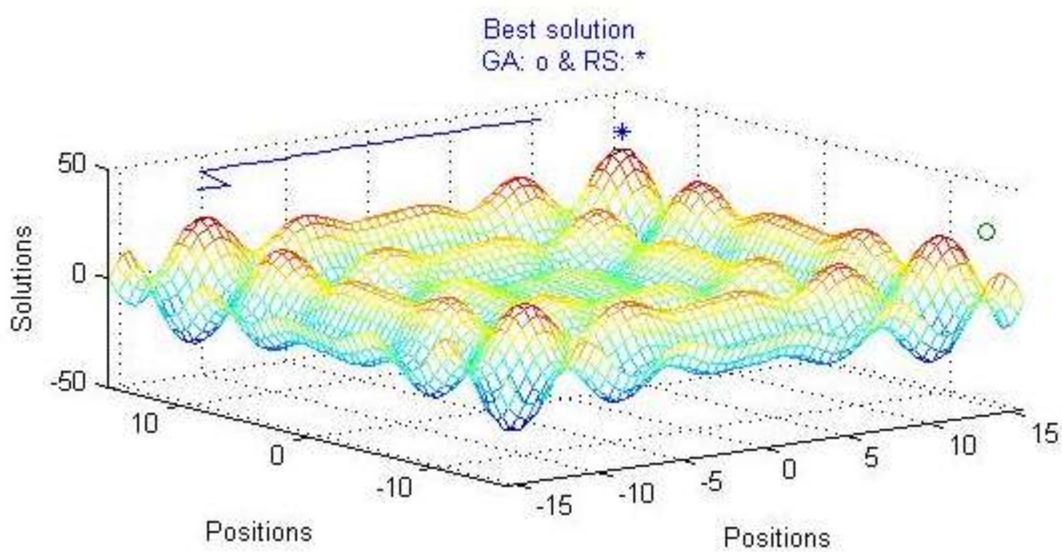

FIG. 5.8 BEST SOLUTION BY GA (: o) AND RS (: *) FOR OVERALL (DATABASE1)

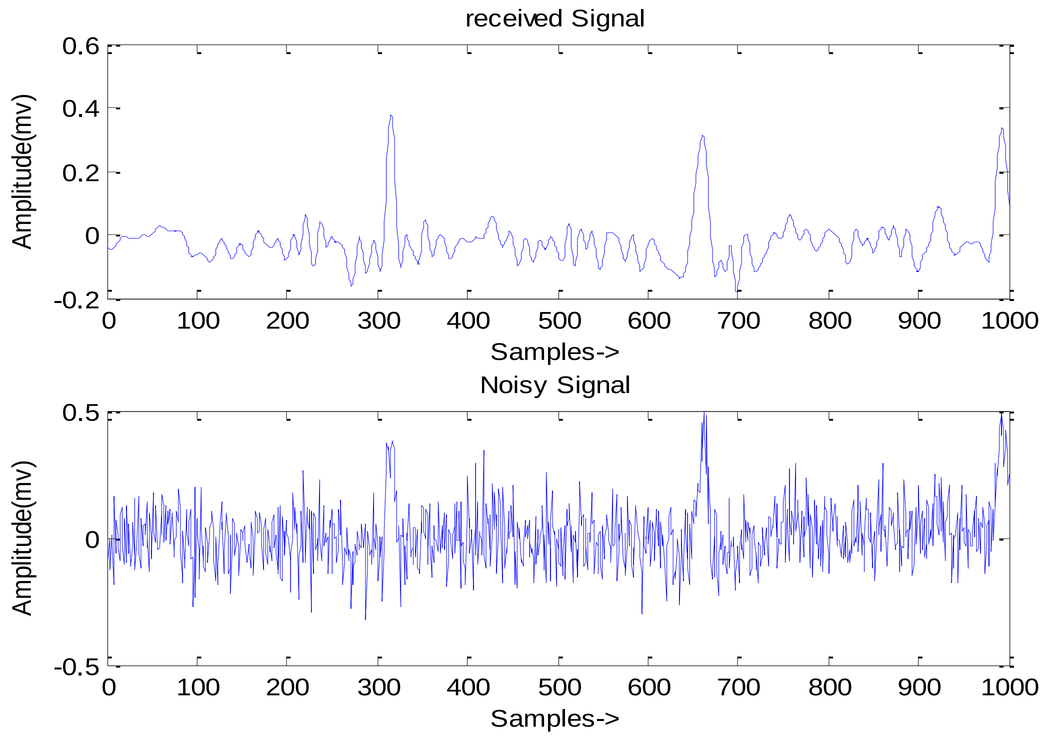

FIG. 5.9 DE-NOISED ECG AND NOISY ECG SIGNAL (DATABASE1)

RESULT OF SECOND DATABASE

Elapsed time is 56.791631 seconds.

SNR =

18.805832618785590

Number of NOISY IMFs: 4

Number of CLEAN IMFs: 10

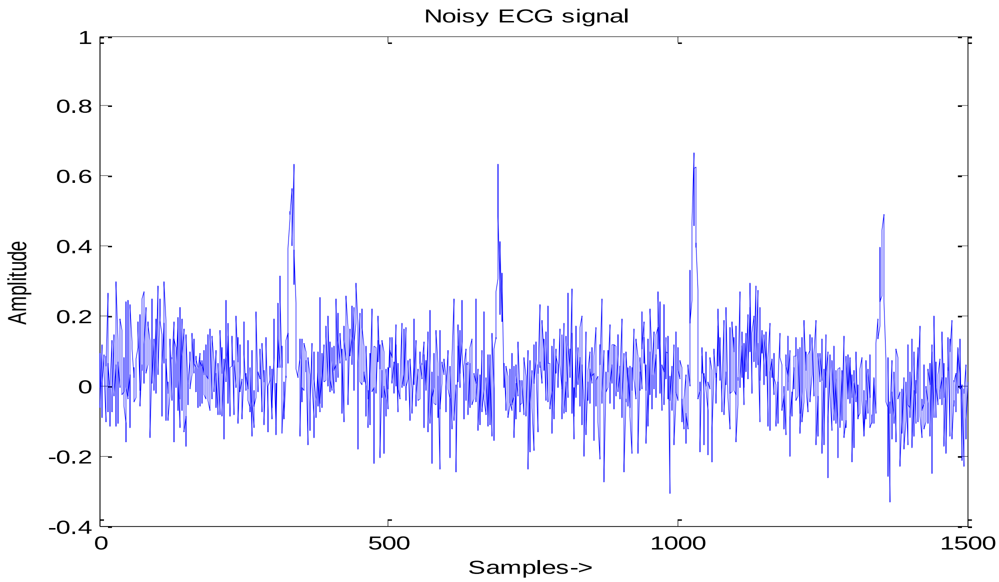

FIG. 5.10 NOISY ECG SIGNAL (DATABASE2)

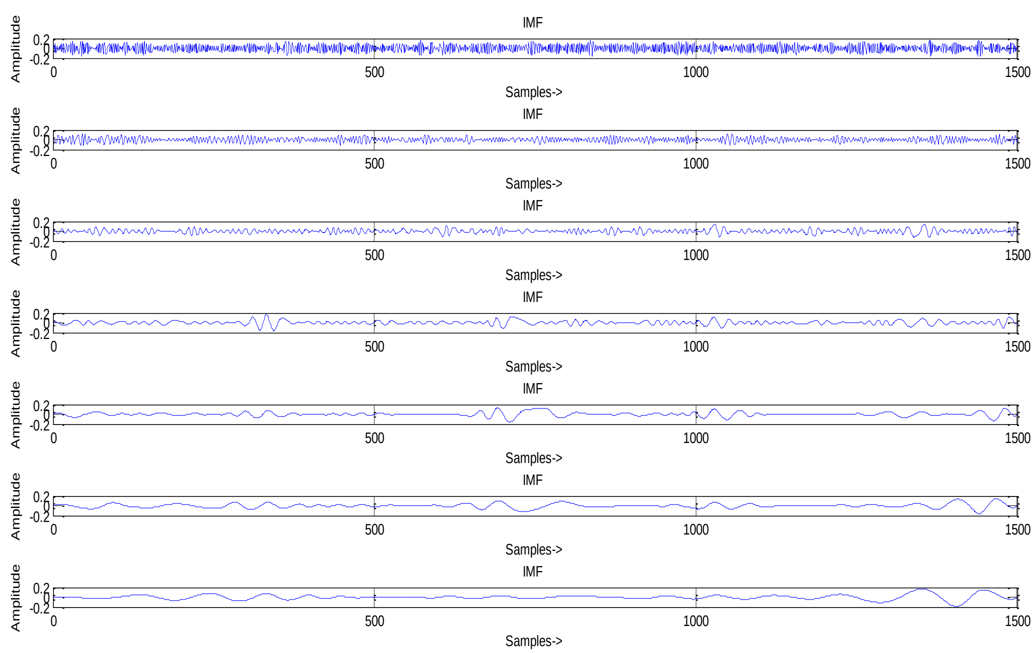

FIG. 5.11 SIX INTRINSIC MODE FUNCTIONS (IMFs) (DATABASE2)

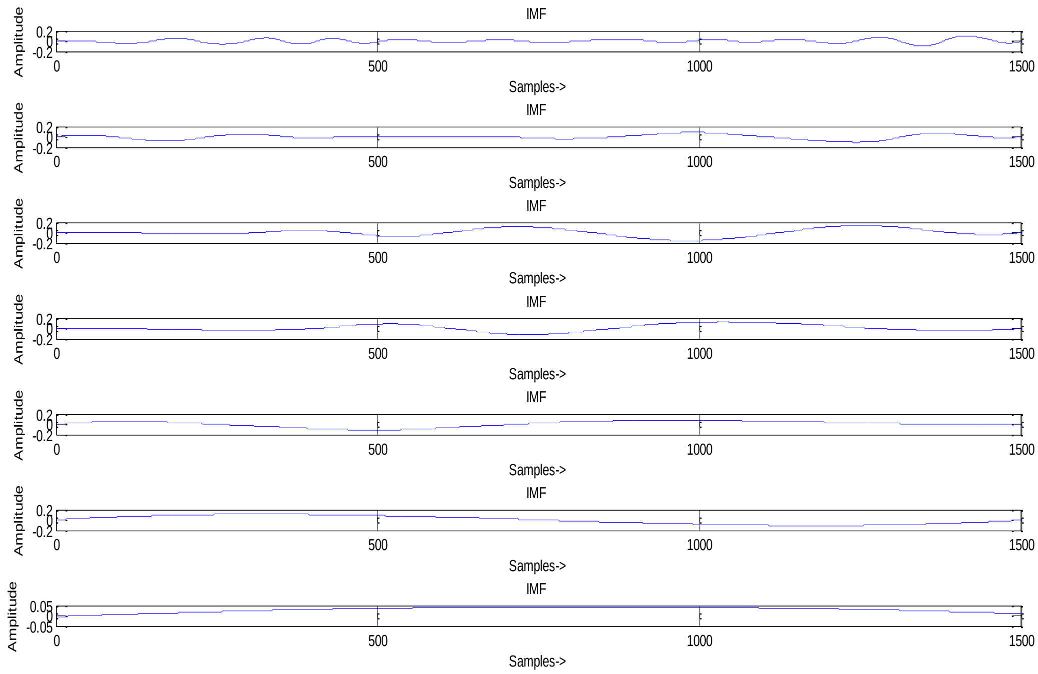

FIG. 5.12 REMAINING SIX INTRINSIC MODE FUNCTIONS (IMFs) (DATABASE2)

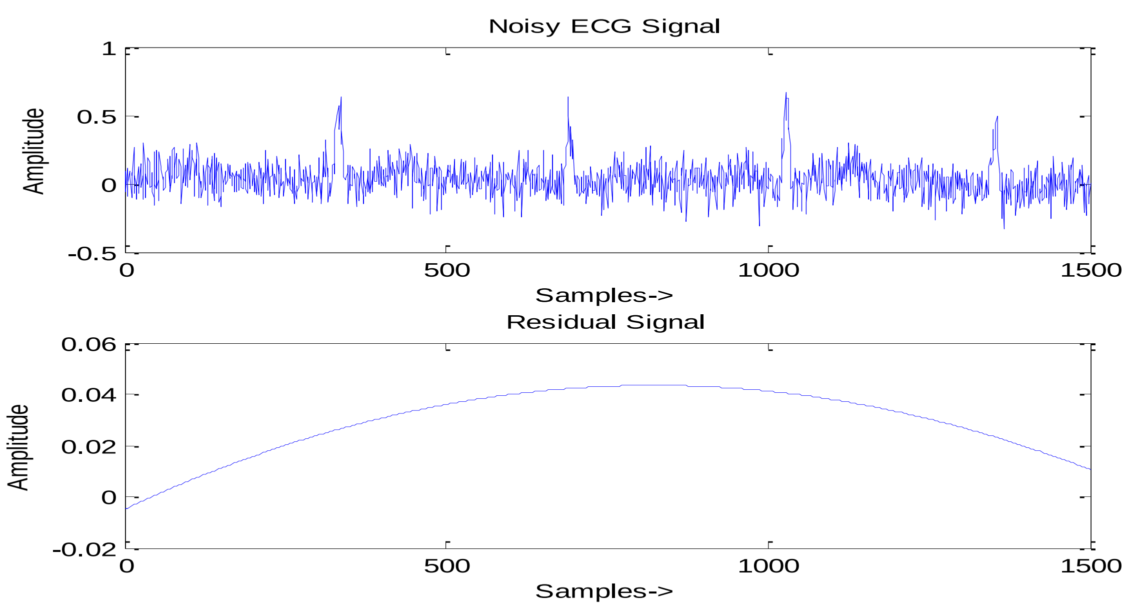

FIG. 5.13 NOISY ECG SIGNAL AND RESIDUAL SIGNAL (DATABASE2)

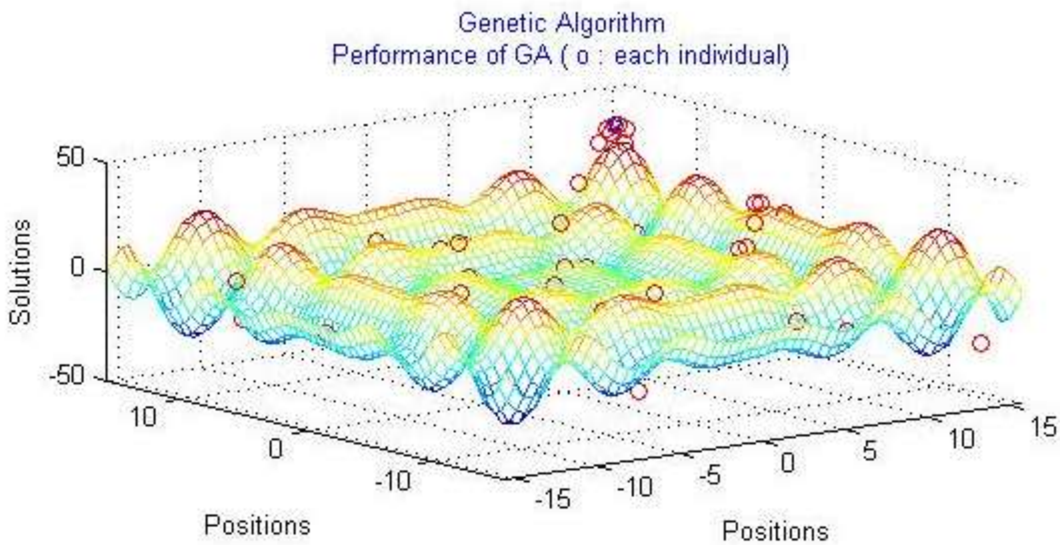

FIG. 5.14 PERFORMANCE OF GA (O: EACH INDIVIDUAL)(DATABASE2)

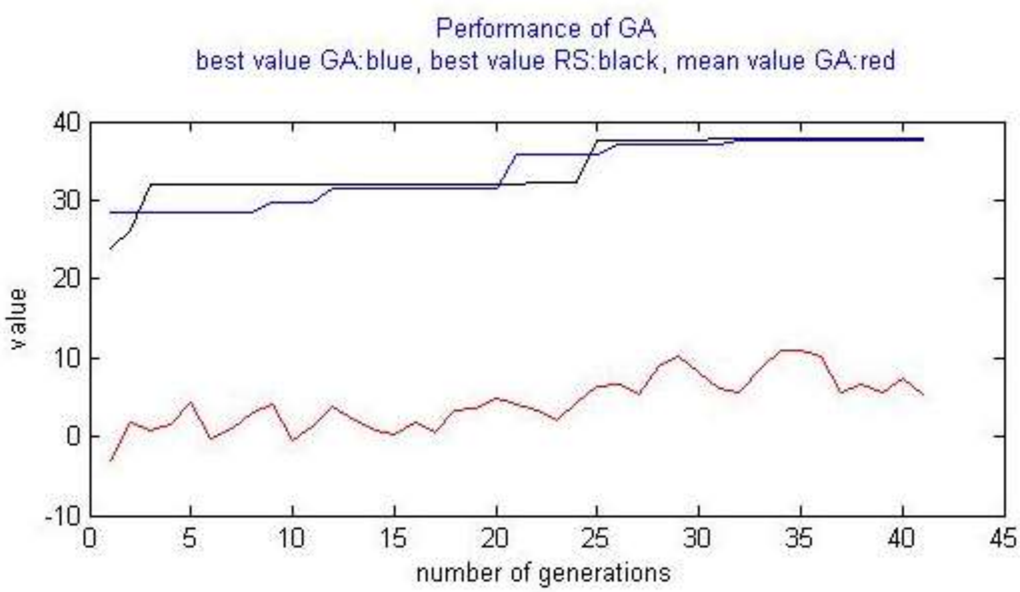

FIG. 5.15 VALUE (BEST SOLUTION) Vs NUMBER OF GENERATIONS (DATABASE2)

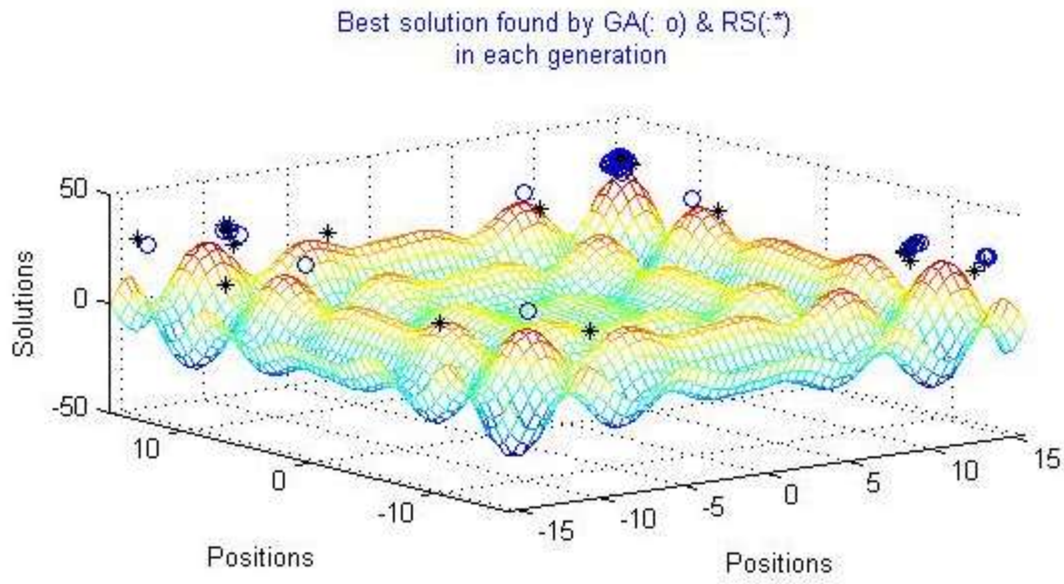

FIG. 5.16 BEST SOLUTION BY GA (: o) AND RS (: *) IN EACH GENERATIONS (DATABASE2)

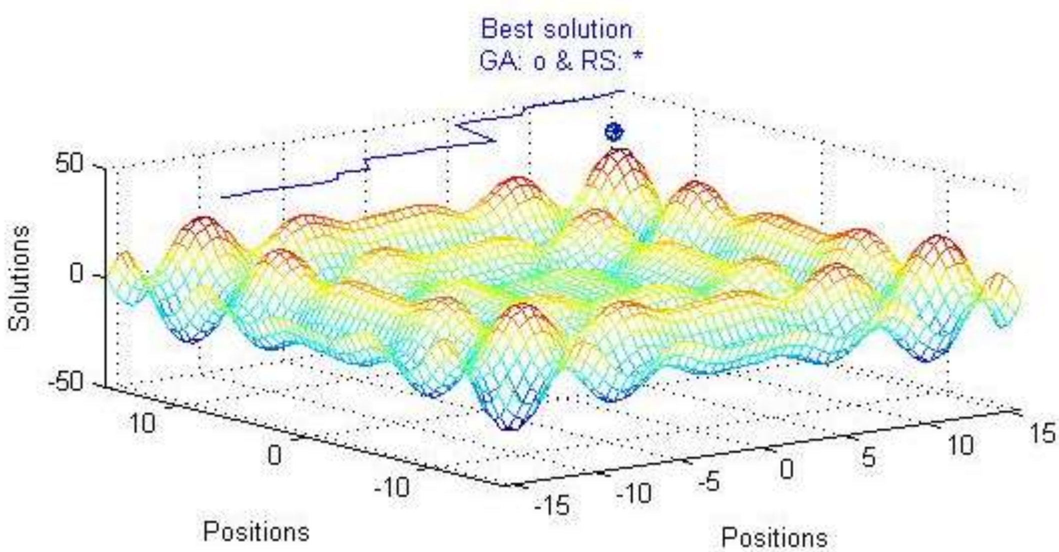

FIG. 5.17 BEST SOLUTION BY GA (: o) AND RS (: *) FOR OVERALL (DATABASE2)

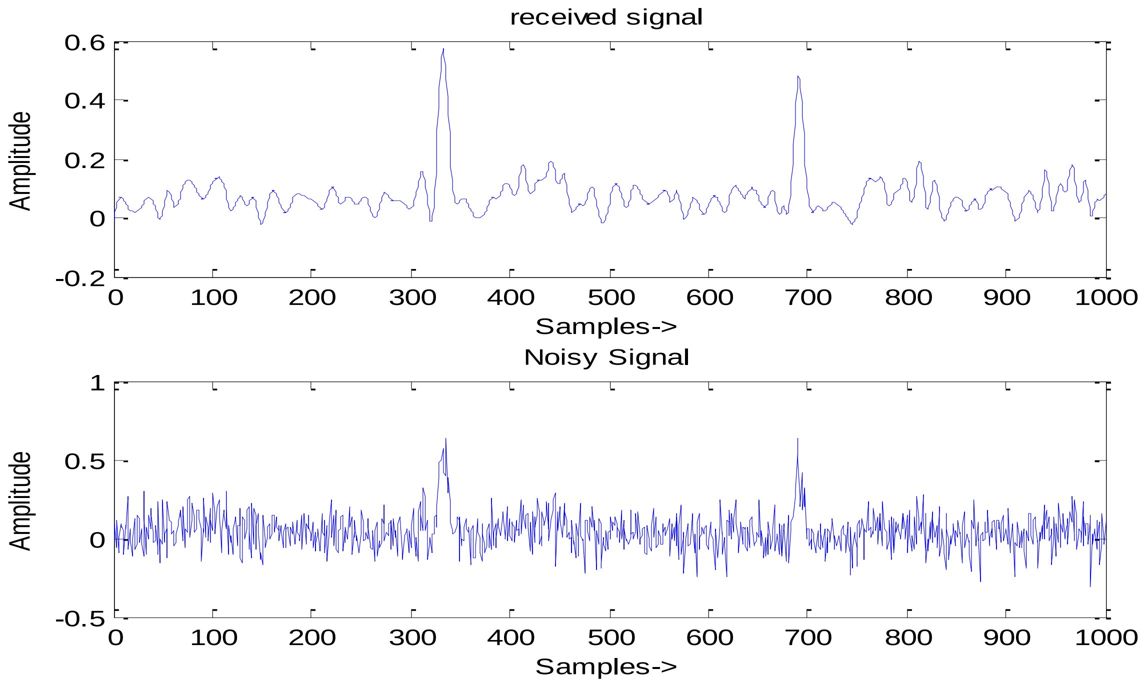

FIG. 5.18 DE-NOISED ECG AND NOISY ECG SIGNAL (DATABASE2)

RESULT OF THIRD DATABASE

Elapsed time is 29.112299 seconds.

SNR =

19.998679996791846

Number of NOISY IMFs: 5

Number of CLEAN IMFs: 9

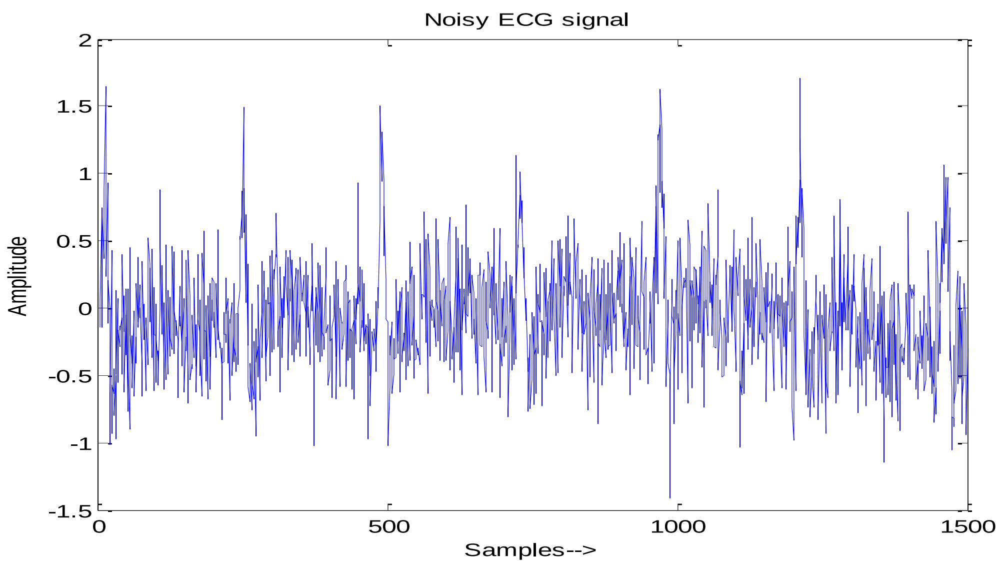

FIG. 5.19 NOISY ECG SIGNAL (DATABASE3)

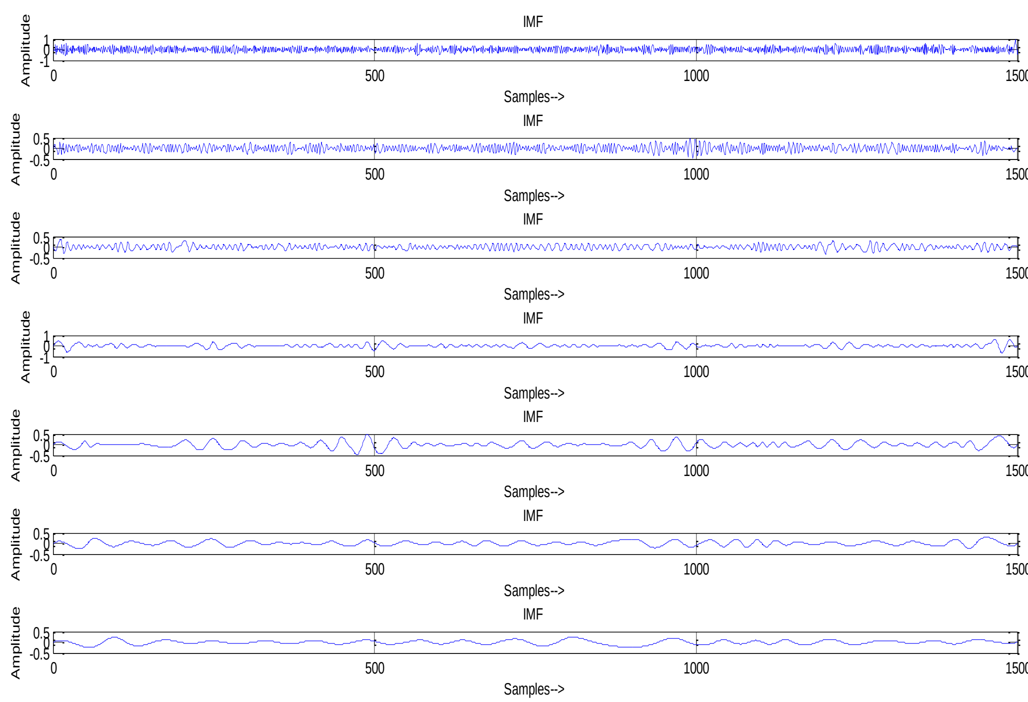

FIG. 5.20 SIX INTRINSIC MODE FUNCTIONS (IMFs) (DATABASE3)

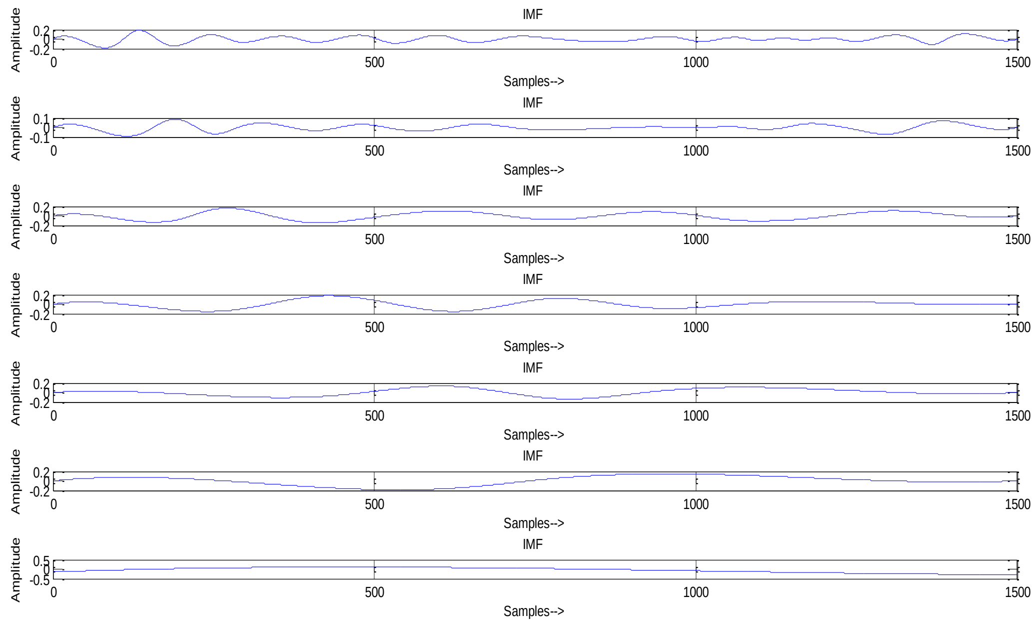

FIG. 5.21 REMAINING SIX INTRINSIC MODE FUNCTIONS (IMFs) (DATABASE3)

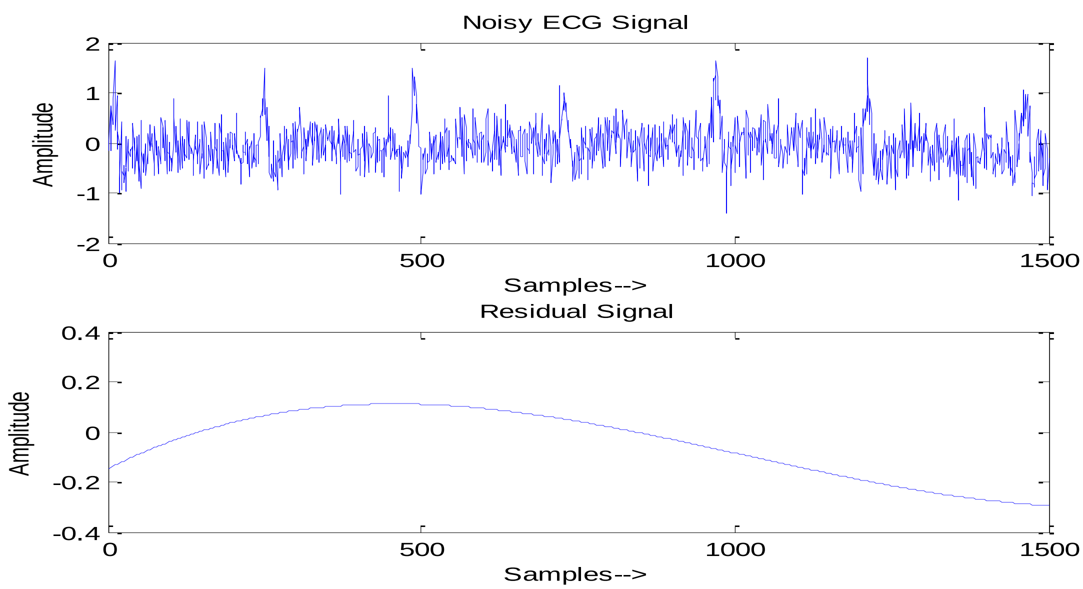

FIG. 5.22 NOISY ECG SIGNAL AND RESIDUAL SIGNAL (DATABASE3)

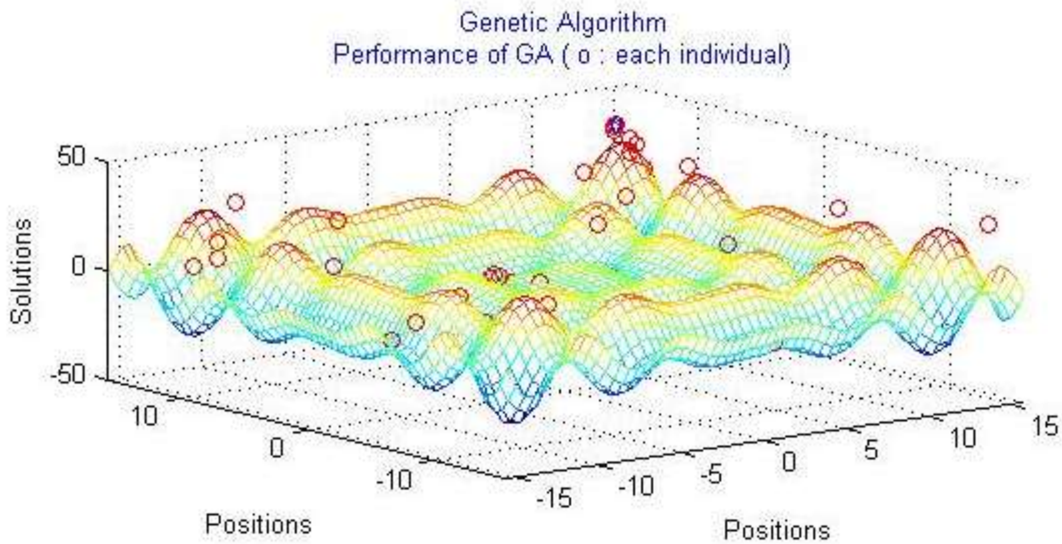

FIG. 5.23 PERFORMANCE OF GA (O: EACH INDIVIDUAL)(DATABASE3)

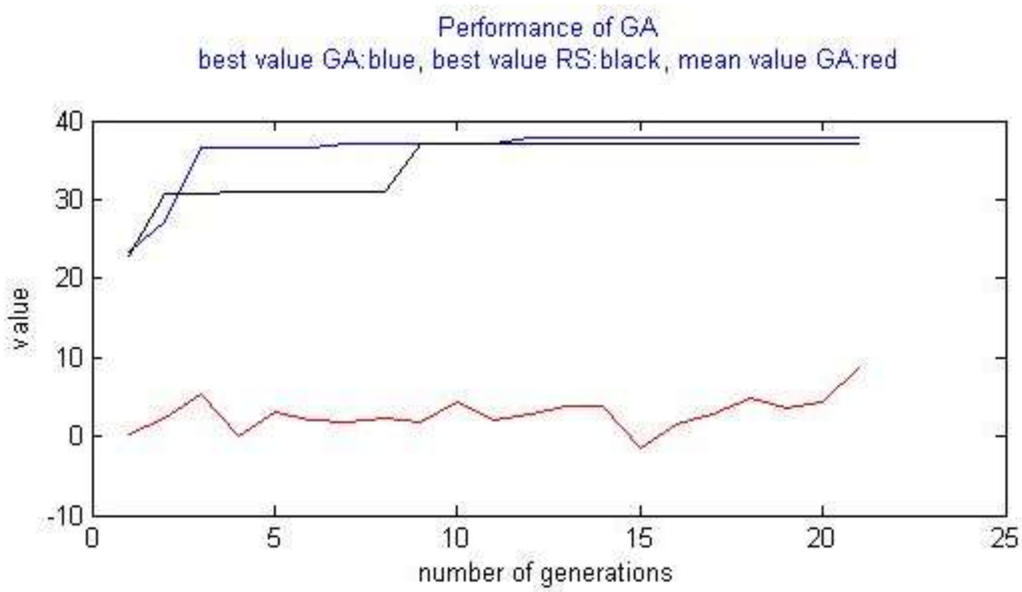

FIG. 5.24 VALUE (BEST SOLUTION) Vs NUMBER OF GENERATIONS (DATABASE3)

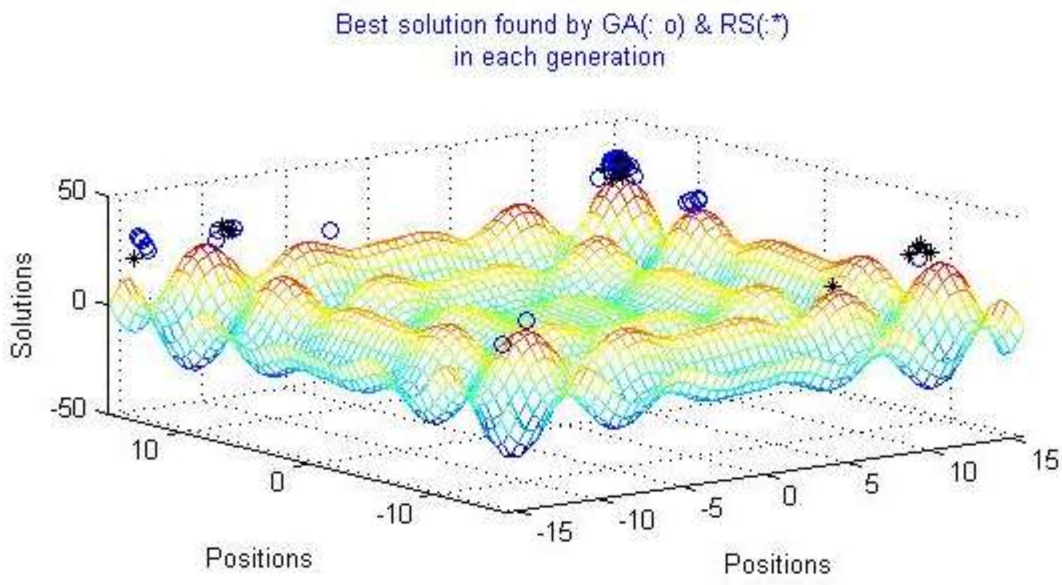

FIG. 5.25 BEST SOLUTION BY GA (: o) AND RS (: *) IN EACH GENERATIONS (DATABASE3)

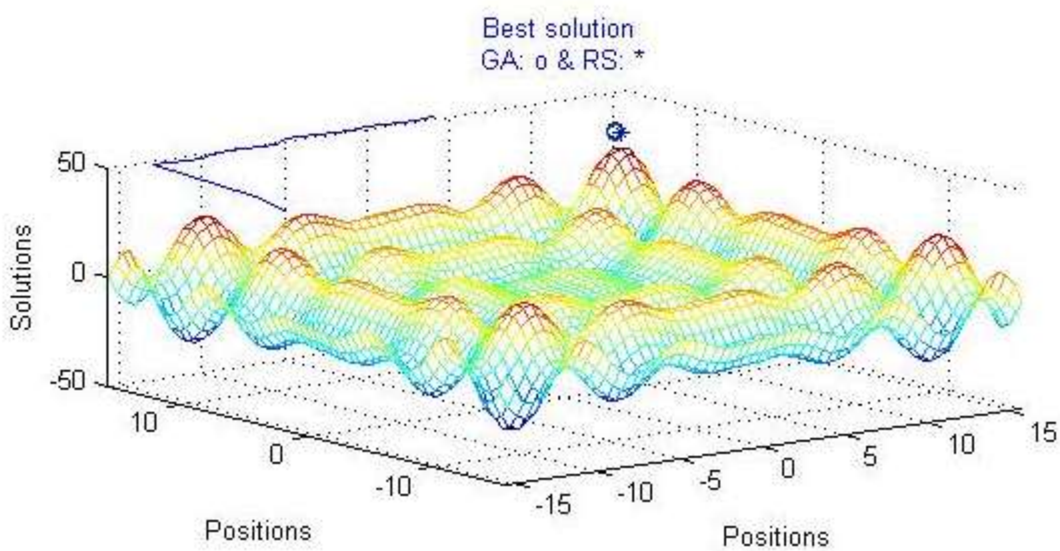

FIG. 5.26 BEST SOLUTION BY GA (: o) AND RS (: *) FOR OVERALL (DATABASE3)

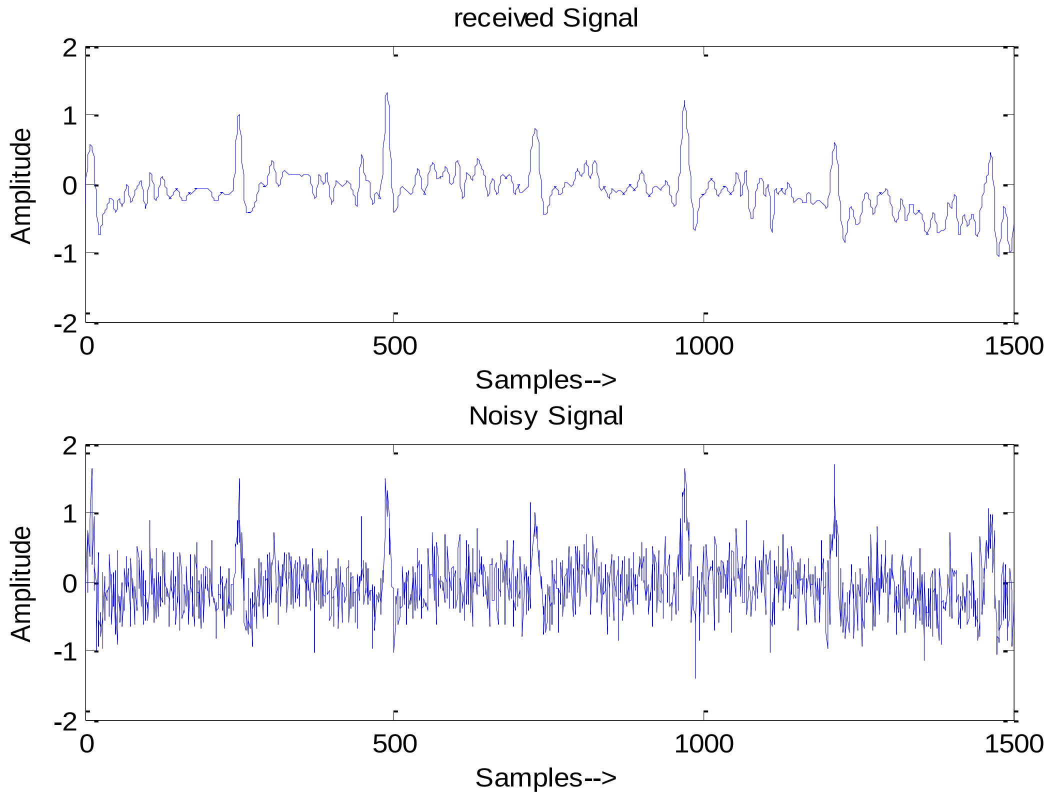

FIG. 5.27 DE-NOISED ECG AND NOISY ECG SIGNAL (DATABASE3)

RESULT OF FOURTH DATABASE

Elapsed time is 18.12064 seconds.

SNR =

18.5141

Number of NOISY IMFs: 4

Number of CLEAN IMFs: 8

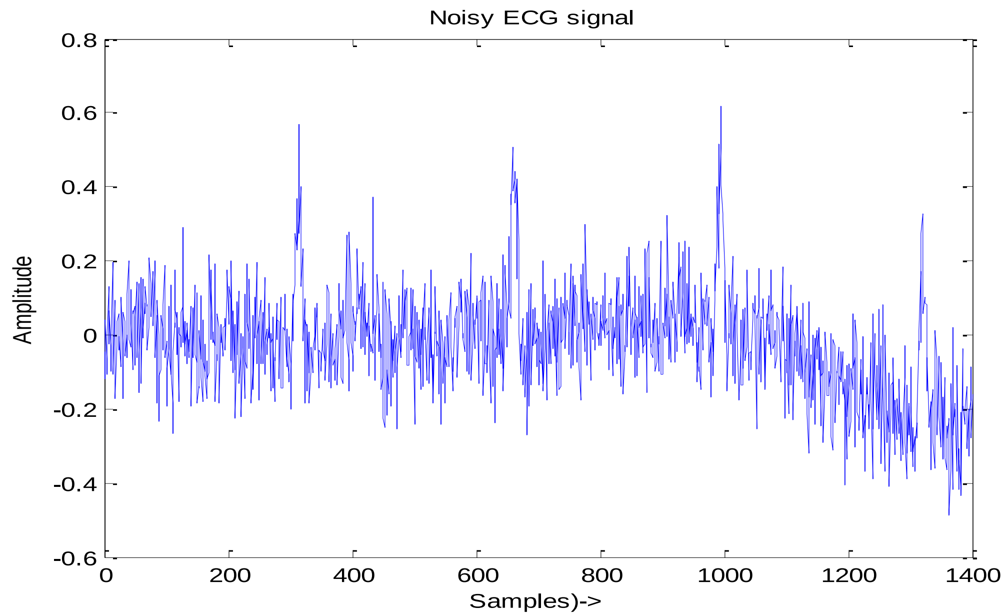

FIG. 5.28 NOISY ECG SIGNAL (DATABASE4)

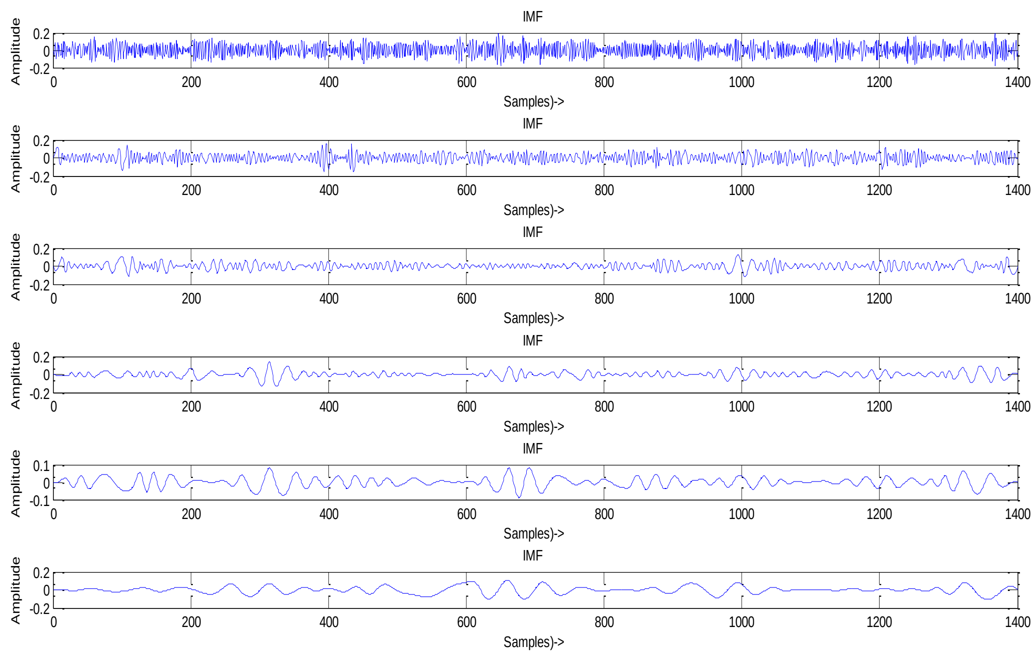

FIG. 5.29 SIX INTRINSIC MODE FUNCTIONS (IMFs) (DATABASE4)

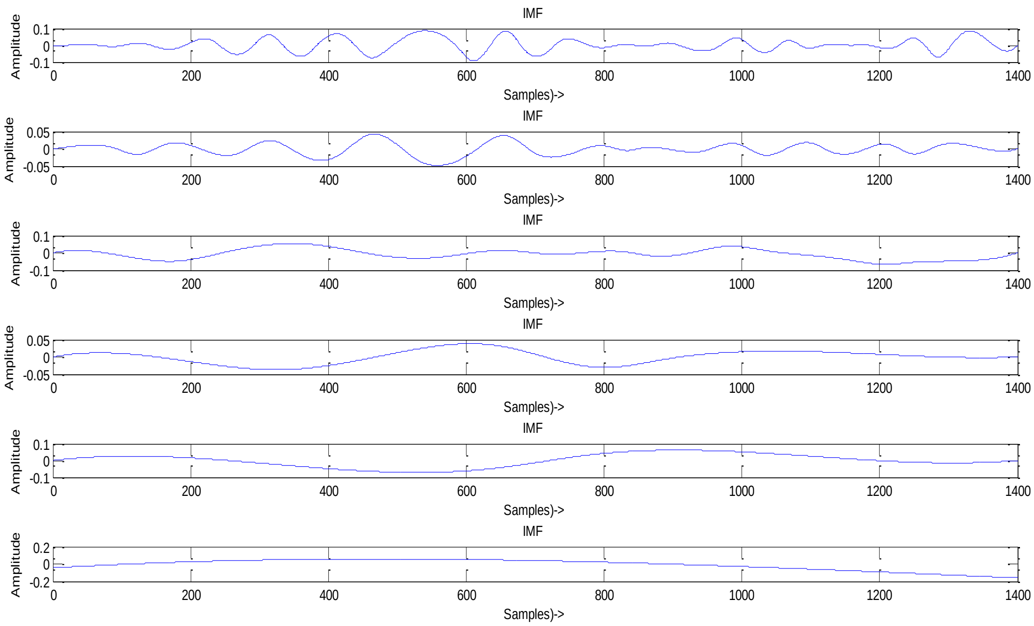

FIG. 5.30 REMAINING SIX INTRINSIC MODE FUNCTIONS (IMFs) (DATABASE4)

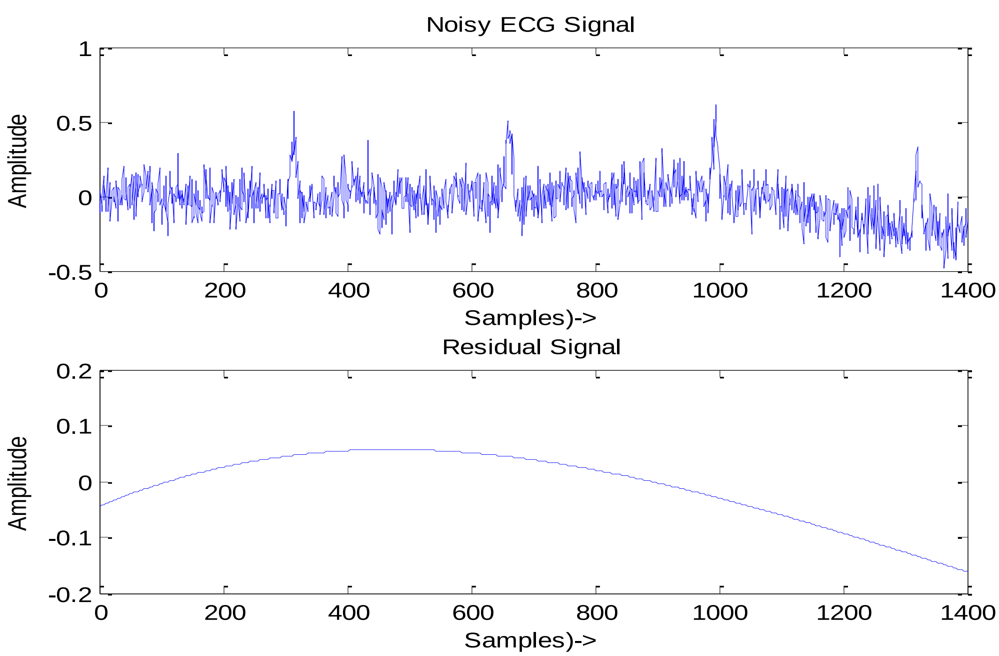

FIG. 5.31 NOISY ECG SIGNAL AND RESIDUAL SIGNAL (DATABASE4)

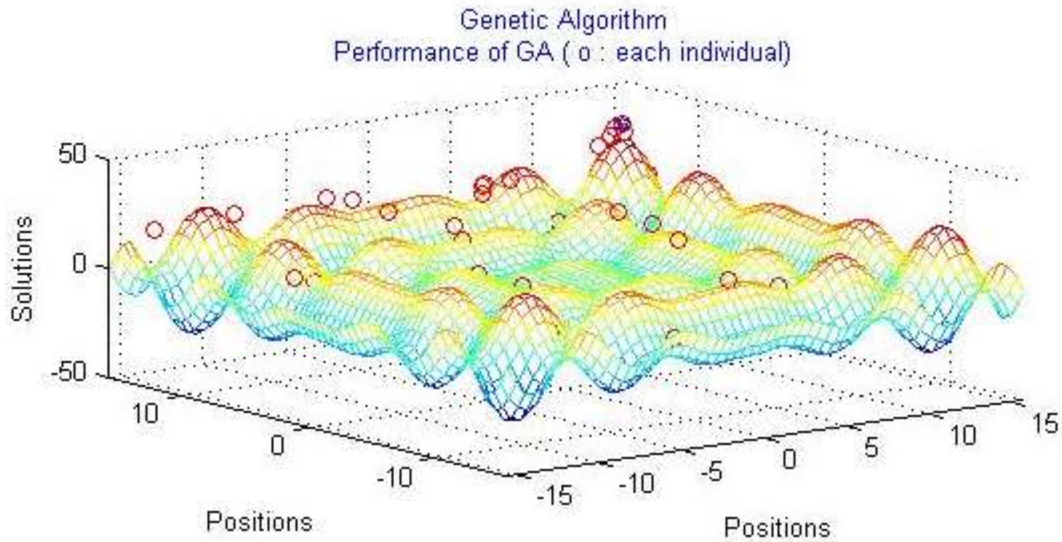

FIG. 5.32 PERFORMANCE OF GA (O: EACH INDIVIDUAL)(DATABASE4)

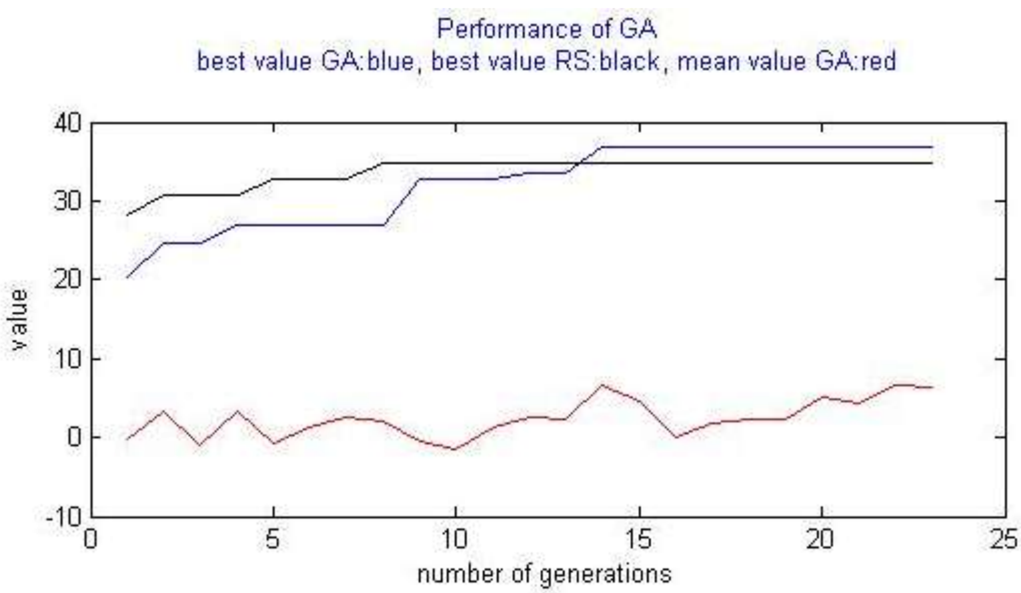

FIG. 5.33 VALUE (BEST SOLUTION) Vs NUMBER OF GENERATIONS (DATABASE4)

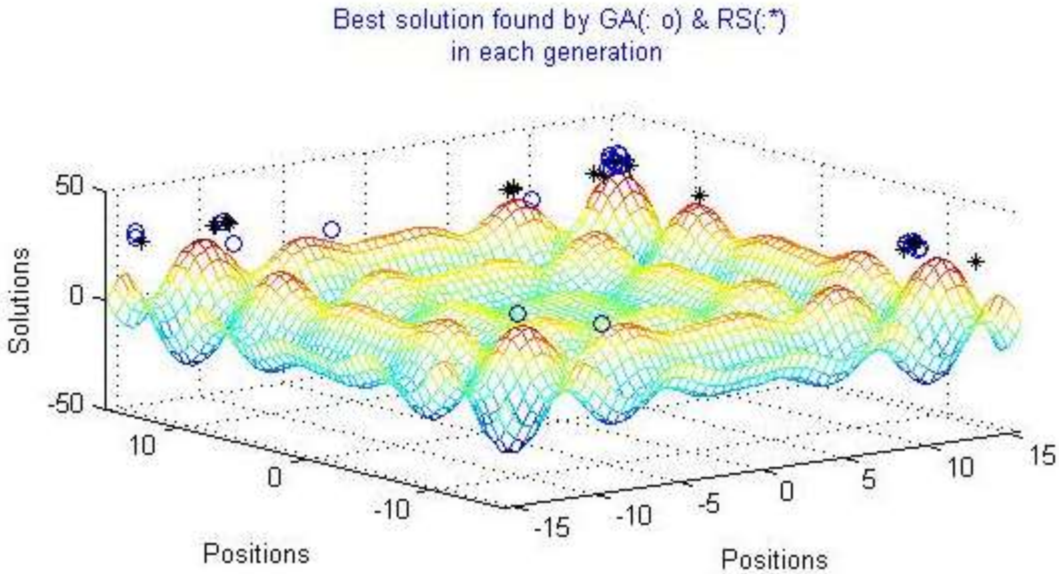

FIG. 5.34 BEST SOLUTION BY GA (: o) AND RS (: *) IN EACH GENERATIONS (DATABASE4)

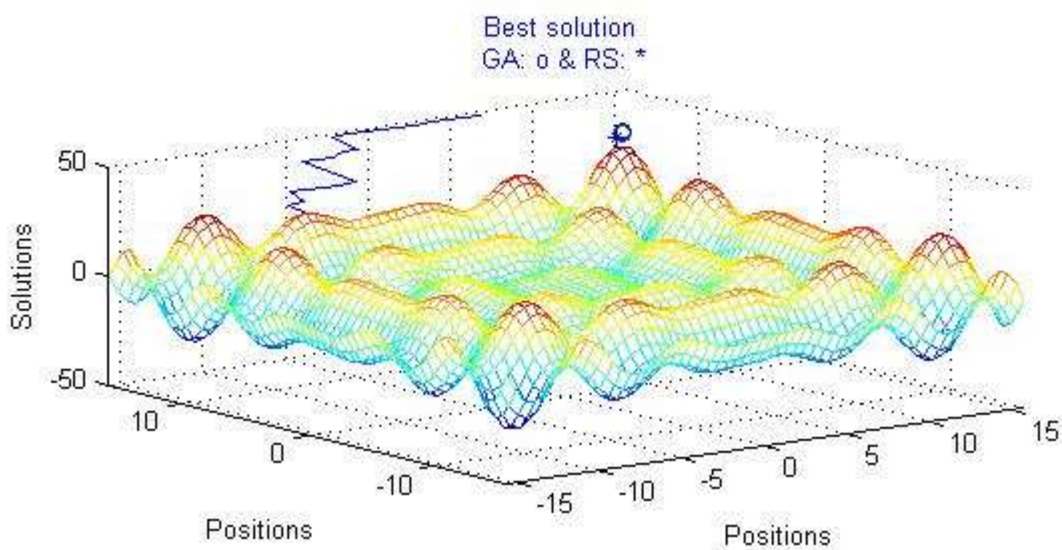

FIG. 5.35 BEST SOLUTION BY GA (: o) AND RS (: *) FOR OVERALL (DATABASE4)

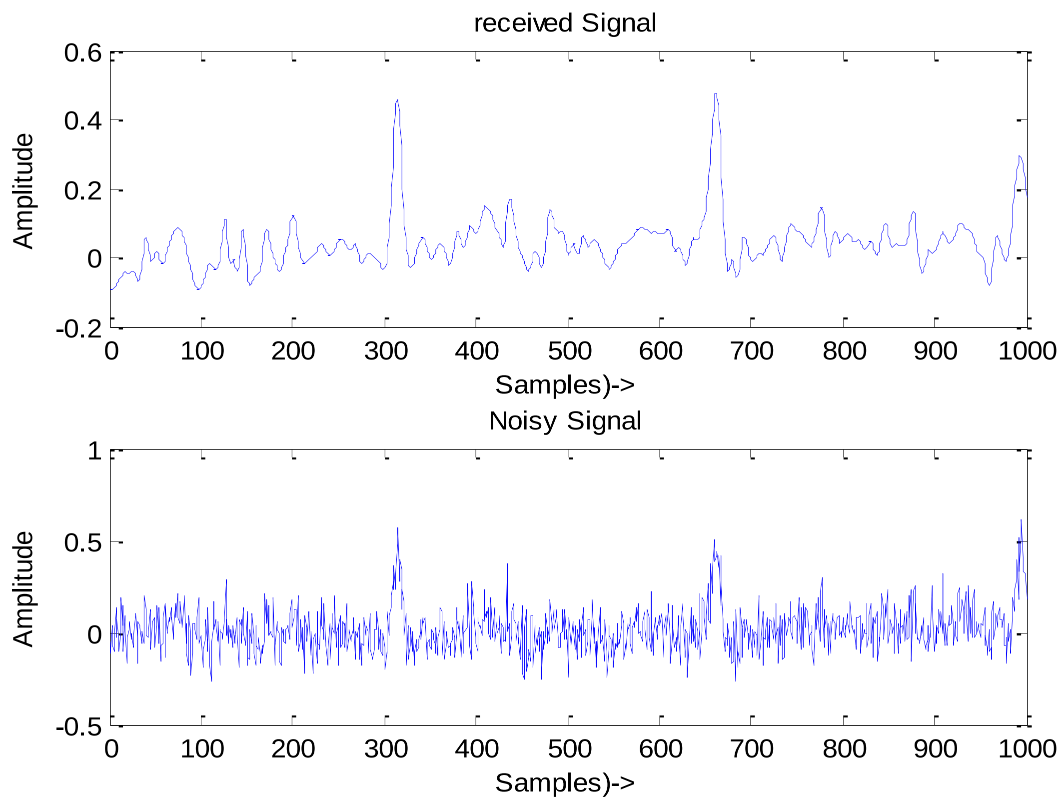

FIG. 5.36 DE-NOISED ECG AND NOISY ECG SIGNAL (DATABASE4)

RESULT OF FIFTH DATABASE

Elapsed time is 22.025525 seconds.

SNR =

17.6858

Number of NOISY IMFs: 4

Number of CLEAN IMFs: 9

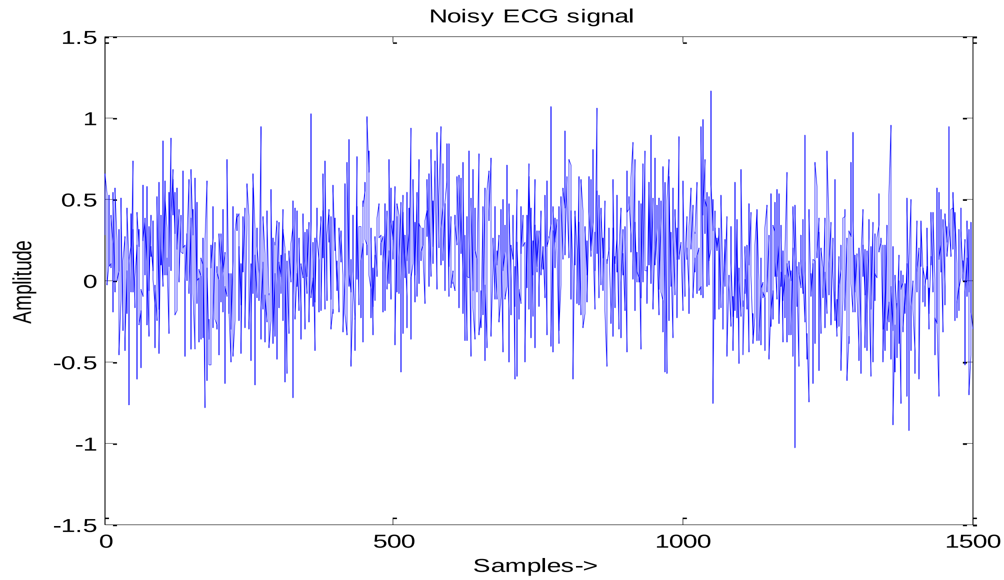

FIG. 5.37 NOISY ECG SIGNAL (DATABASE5)

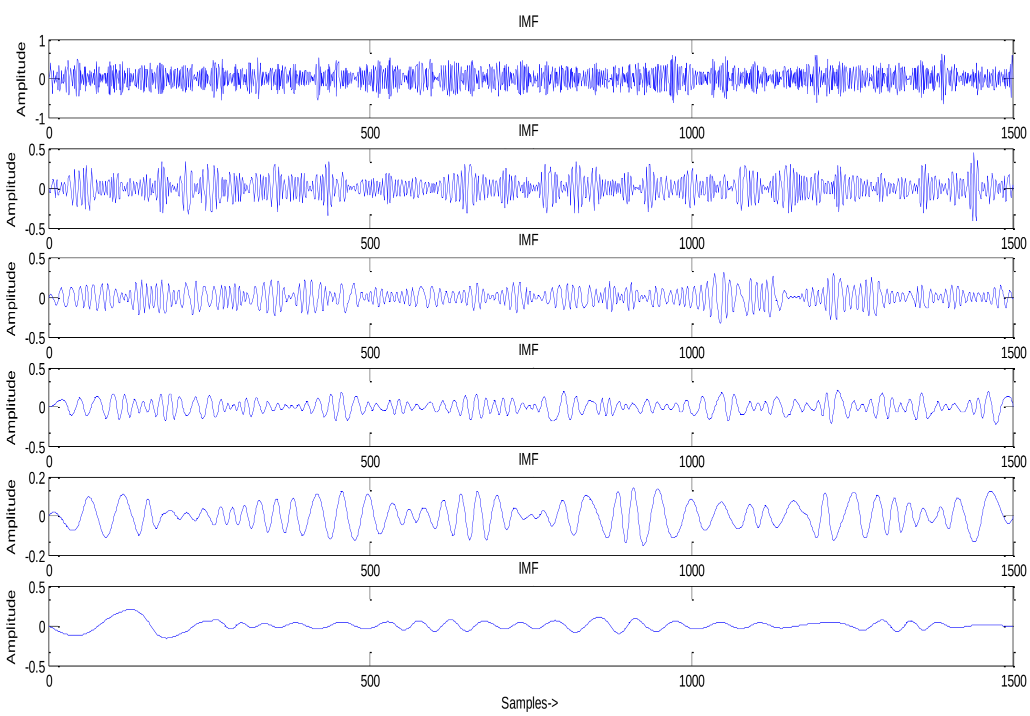

FIG. 5.38 SIX INTRINSIC MODE FUNCTIONS (IMFs) (DATABASE5)

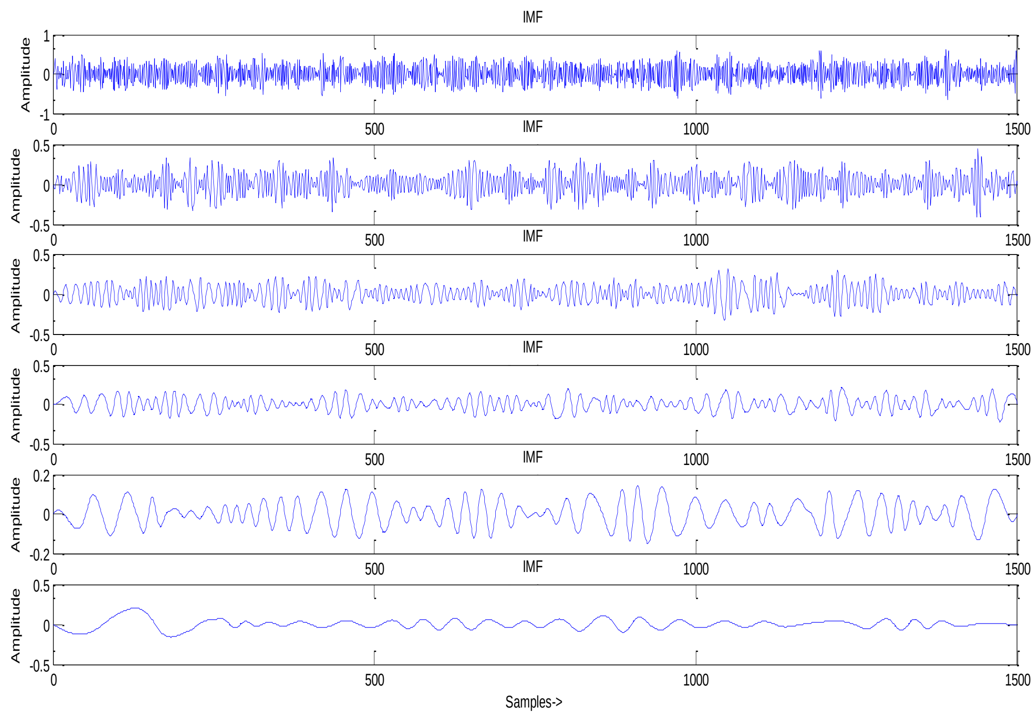

FIG. 5.39 REMAINING SIX INTRINSIC MODE FUNCTIONS (IMFs) (DATABASE5)

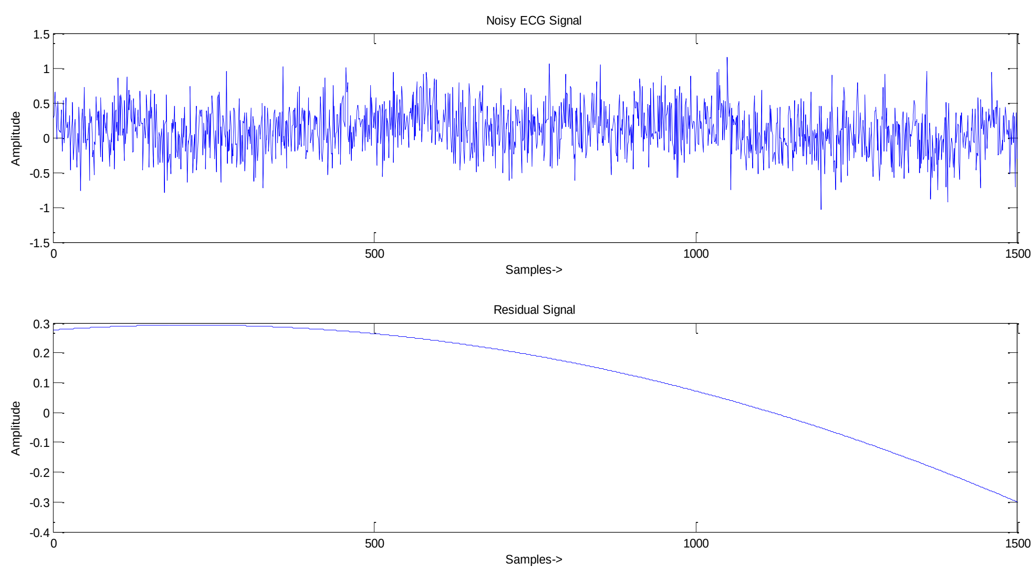

FIG. 5.40 NOISY ECG SIGNAL AND RESIDUAL SIGNAL (DATABASE5)

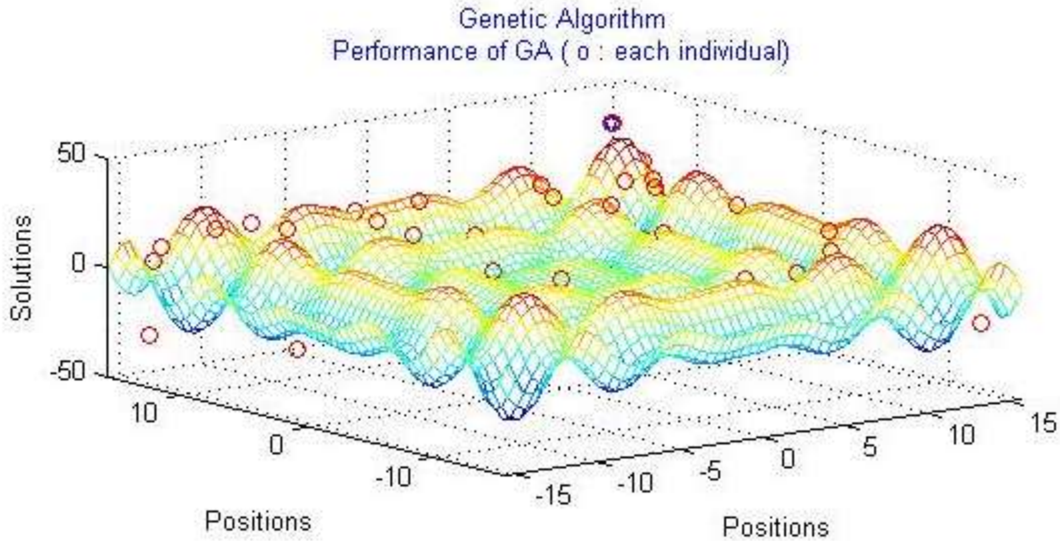

FIG. 5.41 PERFORMANCE OF GA (O: EACH INDIVIDUAL)(DATABASE5)

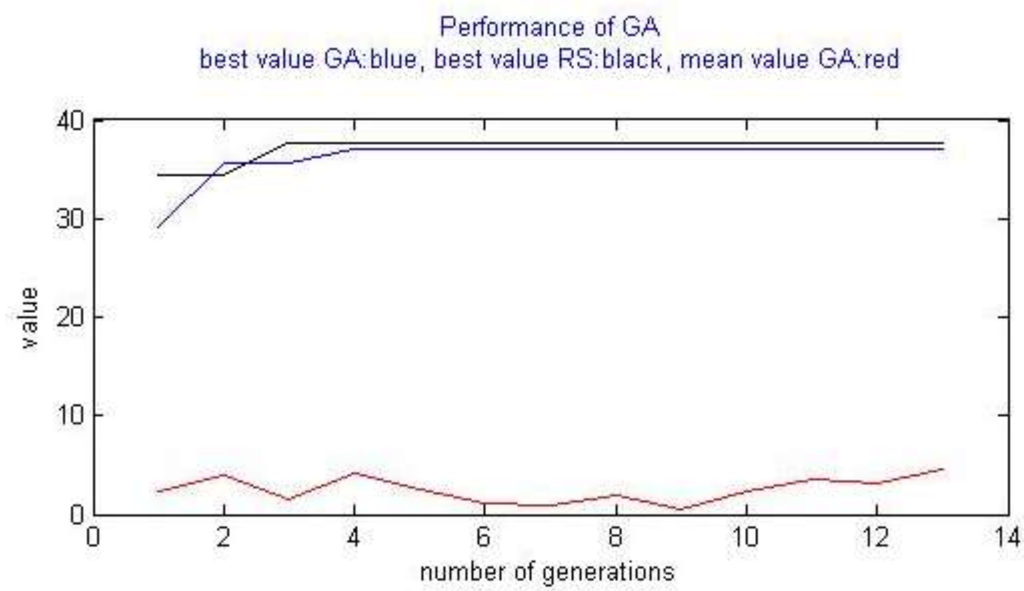

FIG. 5.42 VALUE (BEST SOLUTION) Vs NUMBER OF GENERATIONS (DATABASE5)

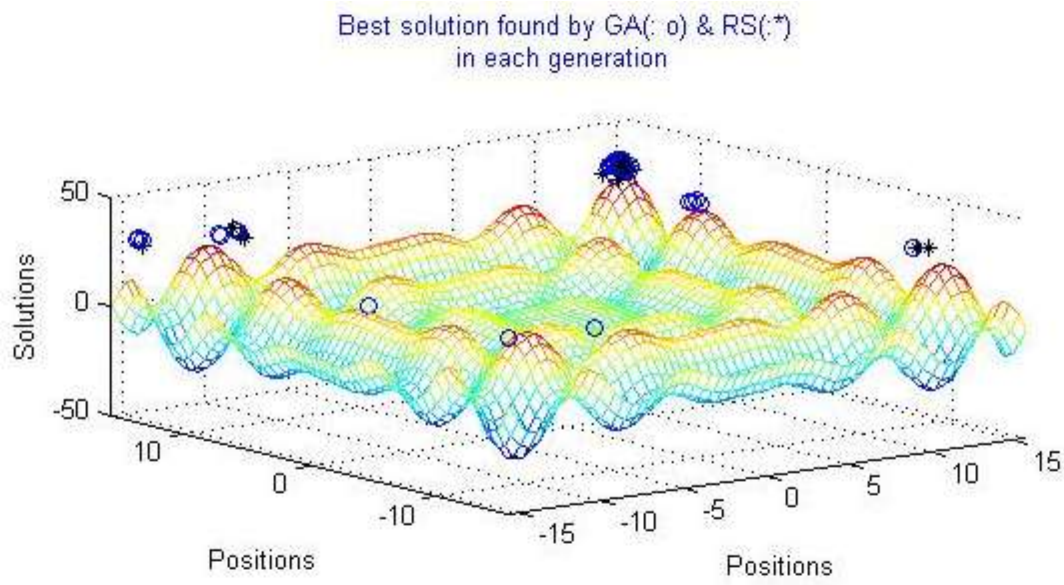

FIG. 5.43 BEST SOLUTION BY GA (: o) AND RS (: *) IN EACH GENERATIONS (DATABASE5)

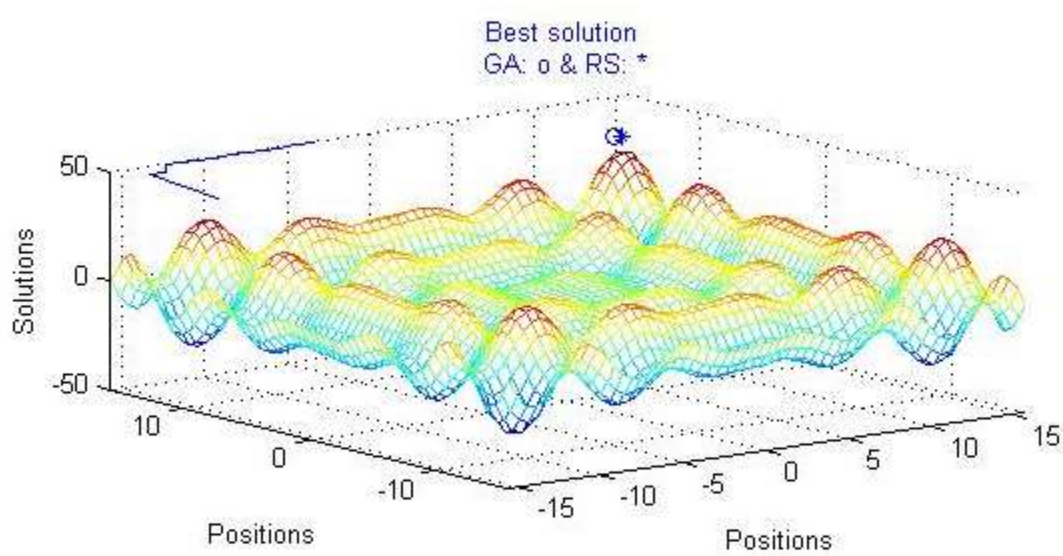

FIG. 5.44 BEST SOLUTION BY GA (: o) AND RS (: *) FOR OVERALL (DATABASE5)

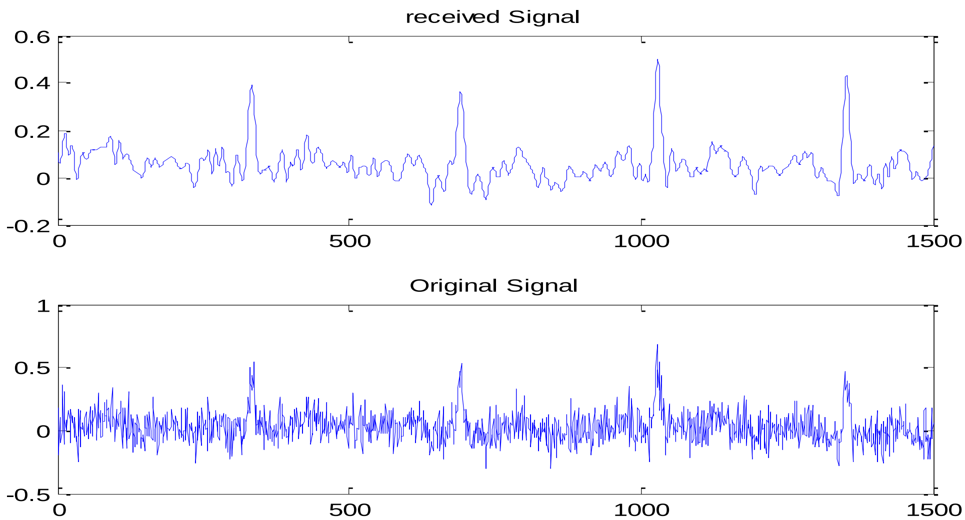

FIG. 5.45 DE-NOISED ECG AND NOISY ECG SIGNAL (DATABASE5)

5.3 COMPARISON WITH OTHER METHODS

The performance of this approach is estimated based on the Signal to Noise Ratio (SNR) and Root Mean square Error (RMSE). These parameters are used to compare existing method with proposed method.

The SNR can be calculated as the follow:

SNR=10*log 10 (output^2/ (input - output) ^2)

The RMSE can be calculated as the follow:

$$\mathbf{RMSE} = \sqrt{\sum_{t=0}^{L-1} [(\mathbf{original\ signal} - \mathbf{reconstructed\ signal})^2]/\mathbf{L}}$$

where L is the length of signal

The Table I represent the values of SNR measure for the results of various existing approaches such as EMD based technique, Particle Filter and Wavelet etc. with proposed method.

TABLE5.1: COMPARISON OF SNR VALUES FOR DIFFERENT DATABASE OF EXISTING METHODS WITH PROPOSED METHOD

Database	Wavelet Based Techniques (SNR in dB)	EMD Based Techniques (SNR in dB)	Particle Filter Method (SNR in dB)	Proposed Method(SNR in dB)	Percent improvement in comparison to Particle filter method (%)
Database1	10.9142	12.9997	14.0853	17.7205	25.80
Database2	11.1984	13.8093	15.2512	18.8058	23.30
Database3	10.1845	13.8138	15.9588	19.9987	25.31
Database4	10.4252	14.0839	16.0254	18.5141	15.52
Database5	11.9732	14.3374	14.8569	17.3418	16.72
Average	**10.9391**	**13.8088**	**15.2355**	**18.4761**	**21.33**

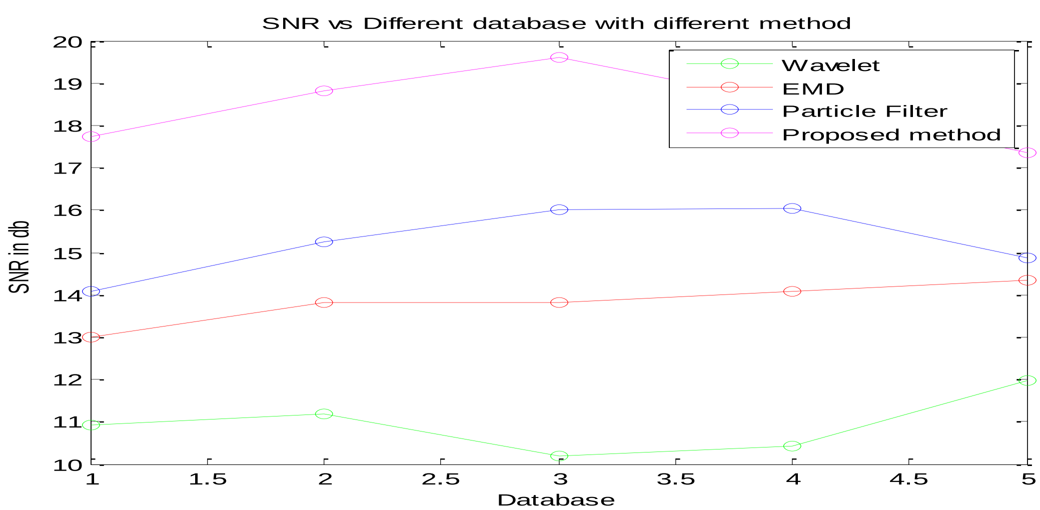

FIG. 5.46 SNR Vs DIFFERENT DATABASE WITH DIIFERENT METHOD AND PROPOSED METHOD

The Table II represents the values of RMSE measure for the results of various existing approaches with proposed method.

TABLE5.2: COMPARISON OF RMSE VALUES FOR DIFFERENT DATABASE OF EXISTING METHODS WITH PROPOSED METHOD

Database	Wavelet Based Techniques (RMSE in dB)	EMD Based Techniques (RMSE in dB)	Particle Filter Method (RMSE in dB)	Proposed Method (RMSE in dB)	Percent improvement in comparison to Particle filter method (%)
Database1	0.299	0.224	0.198	0.131	- 33.83
Database2	0.271	0.215	0.179	0.112	- 37.43
Database3	0.310	0.212	0.162	0.105	-35.18
Database4	0.302	0.199	0.152	0.119	- 21.71
Database5	0.255	0.191	0.187	0.137	- 26.73
Average	**0.287**	**0.208**	**0.175**	**0.120**	**-30.97**

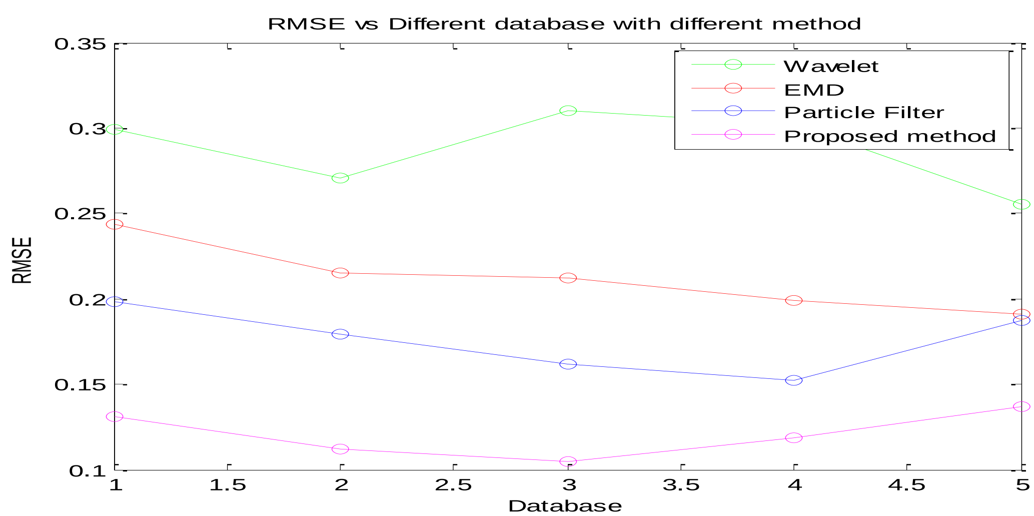

FIG. 5.47RMSE Vs DIFFERENT DATABASE WITH DIIFERENT METHOD AND PROPOSED METHOD

5.4 DISSCUSSION

From the both tables and figures 1 and 2, it is evident that the performance of the presented algorithm is better than the existing algorithms with different types of artifacts. The SNR results of the proposed algorithm show better results and lower Root Mean square Error(RMSE) compared to EMD, Wavelet, and Particle Filter based techniques which are usually used as an ECG signal de-noising method with five different type of Database. The average SNR and RMSE improvement of the results de-noised by the proposed method has been **improved by 21.33% and -30.97% respectively** to Particle Filter method.

CHAPTER-6

CONCLUSION AND FUTURE WORK

6.1 CONCLUSION

Genetic algorithm based ECG signal De-noising using EEMD and Fuzzy Thresholding is our proposed technique. It gives better performance in comparison with EMD based technique and other existing noise removal algorithms in terms of SNR. The EEMD methods are used to split the ECG signal into IMFs. The Ensemble EMD (EEMD) symbolizes a major improvement with great adaptability,flexibility,versatility and robustness in noisy ECG signal filtering method.The EEMD is better than EMD because it removes the mode-mixing effect from the signal. The Fuzzy Thresholding is used for automatic detection of Intrinsic Mode Functions (noisy) using Spectral Flatness. The remaining noisy intrinsic mode functions are filtered using Genetic Particle Filter to obtain clean ECG signal. The Genetic Algorithm Particle Filter improves the self–evolution and self–adaptation process. By using advantages of the EEMD over EMD technique and Genetic Particle Filter over the Particle Filter de-noising performance has been improved. It removes the muscle artifacts,baseline wander artifact, electrode artifact and high frequency noise from noisy ECG signal. The experimental output results showed that our proposed method to de-noise the signal is better both in terms of qualitative and quantitative measures. The proposed method shows lower RMSE and better SNR than other techniques with good quality output ECG signal.The average SNR and RMSE improvement of the results de-noised by the proposed method has been **improved to 21.33% and -30.97% respectively** with the Particle Filter method. The proposed method provides the better accuracy compared to other methods.

6.2 FUTURE WORK

The future work is possible in the following directions as described below:-

- The proposed method can be extended to other bio-medical signal such as ElectroMyoGraphs (EMG) and ElectroEncephaloGraphs (EEG).These are the signals that records the activities of body muscles and brain respectively.
- Today, the importance of developing the large scale ICs is growing tremendously; we can also implement the proposed algorithms in hardware using Verilog or VHDL. In other words, the proposed hybrid method can be realized in hardware by the converting the code for Genetic Algorithms and Fuzzy logic into hardware architecture.
- Miniaturized portable hand held ECG devices is another possibility or even it can be embedded in wearable gadgets like watches, wrist bands. Moreover it can also be incorporated in mobile phones etc. for continuous monitoring of the cardiac activity.