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Optimal Order of the Differentiator Selection in Noise Removal of ECG Signals

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Abstract: ***A recording of the heartbeat known as the Electrocardiogram (ECG), sometimes may get corrupt by the noise from various sources. The actual frequency of power and also its harmonics can vary based on the device and its location. A simple way to be able to eliminate the noise is the filtering of a signal using a notch filter which is based on its frequency and vicinity that may bring down the quality of an ECG since there may be components of frequency in the heartbeat as well. In order to circumvent such a loss of information, there is an optimal order for the filter that needs to be used. Fractional calculus is that branch of Mathematics that consists of the differentiation and the integrations belonging to a non-integer order. This has been migrating from the mathematicians and their theoretical realms and are also applied to several branches of engineering that may be interdisciplinary. This type of transfer functions of a Fractional Order (FO) based filters has been represented by the Fractional Order Differential (FOD) equations. The filters will then be realized by using some order elements that are fractional. For the purpose of this work, a Shuffled Frog Leaping Algorithm (SFLA), a Particle Swarm Optimization (PSO) along with a hybrid SFLA-PSO have been proposed. This proposed filter obtains input from the source of noise and the patients and the results proved that the proposed technique was able to achieve better performance than the other techniques.***

Index Terms: Electrocardiogram (ECG) signal, Fractional Order Differentiator (FOD), Fractional Order Filter, Shuffled Frog Leaping Algorithm (SFLA) and Particle Swarm Optimization (PSO).

I. INTRODUCTION

The signal of an Electrocardiogram (ECG) is an approach to diagnostics for detecting the diseases of the heart. The signals give a significant amount of information regarding the functional conditions of the heart and the circulation system. Placing the electrodes on the surface of the body, it is possible to extent the electrical activity in the muscles of the heart. Additionally, the ECG records may get corrupt owing to different types of noise like respiration owing to baseline drift, effects of the electromyogram, motion artefacts and power line interference. This noise normally is generated from that of the used equipment and sometimes from the bioelectric activity of the body. Thus, this high-resolution signal extraction uses signals from various recordings that have been contaminated because of background noise and has to be investigated. The primary goal of the signal enhancement of the ECG was to separate different components of valid signals from some of the undesired artefacts in order to be able to present the ECG which helps in its accurate and easy interpretation [1].

The ECG tracing used typically has been characterized by means of a recurrent sequence of the waves that include the P, the QRS and the T waves. This will correspond to the atria and its depolarization, the ventricles and their repolarization [2]. The P wave here represents an electric signal which marks the heartbeat’s initiation, the atrial depolarization spreading from a Sinoatrial Node (SAN) in the direction of the atria and also the Atrio-Ventricular Node (AVN) that has a 0.08-0.11s time period. A QRS complex will reflect a combination of three of the graphical deflections that are noticed on an electrocardiogram marking the ventricle and its depolarization. The T wave now signifies repolarization (or a recovery) of ventricles that have a period of about 0.05–0.25 s. A typical signal segment of the ECG obtained from an MIT-BIH arrhythmia database (with an ECG 100 recording) is depicted in figure 1.

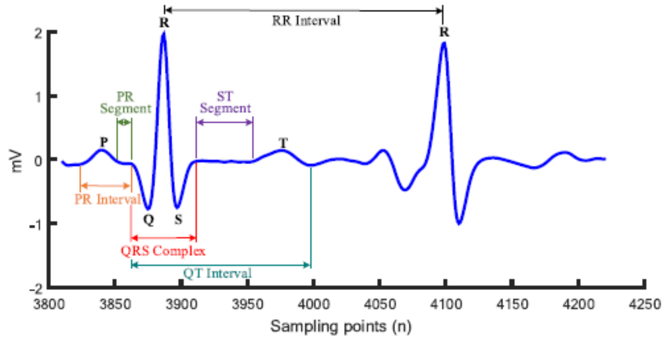

Figure 1 A typical cardiac cycle (heartbeat) from MIT-BIH arrhythmia database (ECG 100 recording)

A QRS complex is the orientation waveform designed for analysing the ECG signals and also helps in an accurate and dependable detection that can affect the presentation of an algorithm for automatic ECG analysis depending on heart rate and its variability (a variation in the RR intervals) to diagnose cardiac diseases. For the purpose of detecting a QRS complex in an accurate manner, it is important to be able to classify the R-peak locations as of the ECG data recorded.

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Also, there is a need for an exact delineation of the ECG waves that is based on this. At the time the QRS complex location has been detected, other ECG signals and their components like the P and the T waves are determined by the QRS complex and its position [3]. But in practice, the ECG records are generally corrupted using different noises and artefacts. Thus, de-noising with the enhancement of signals are needed for accurately analysing the ECG. A generalisation of the integer calculus using similar concepts is known as Fractional calculus. Only a few years back, fractional calculus created a breakthrough in various fields such as engineering and science [4]. This included electrical engineering, biomedical engineering, electromagnetics, robotics and control engineering. A very often used definition for these general derivatives was the Caputo definition that was described as (1):

$$D_0^{\alpha} f(t) = \frac{1}{\Gamma(m-\alpha)} \int_0^t f^{(m)}(u)(t-u)^{m-\alpha-1} du \qquad (1)$$

Wherein α denotes a fractional order, m denotes an integer so that (m − 1) < α < m, and Γ (.) denotes its gamma function. The system that has been defined using the FOD equations has been termed as the FO system. The primary advantage of that of the FO systems compared to their counterpart systems of integer order is an infinite memory and the integer order systems, on the other hand, are consideredas of a finite memory. The result of this is a model with a real-world phenomenon that makes use of the FO calculus has now been receiving a lot of attention. Literature has shown different natural phenomena modelled using FOD equations for producing better results. There are several other applications that have been based on the FO systems discussed recently in control theorems, Smith charts, agriculture, chaotic systems, bioengineering, and electromagnetic systems. Even though there has been a realization of these fractional elements that are not commercial as yet, there has been many research articles introduced in the recent decades like topics of fractal behaviour of an insulator solution interface that is metal based where there are some dynamic mass diffusion processes that also include heat conduction. Further, in the domain of the analogue, this operation is known as the fractance device [5]. The FO filters have been represented using the FOD equations and these are taken to be a generalized care of integer-order filters. There were some FO filters that were proposed, wherein the processes for the design of filters with fractional elements had been introduced. Normally, there were two different techniques that were introduced for designing an FO filter. The first will depend on the actual analysis that makes use of the FO elements and the next process was dependent on the integer estimation for fractional elements that are easily realized. Such processes had introduced a Fractional-Order Low-Pass Filter (FLPF), a Fractional-Order High-Pass Filter (FHPF), a Fractional-Order Band-Pass Filter (FBPF), and finally a Fractional-Order All-Pass Filter (FAPF) based filters that also had some design equations. Thus, there was also a need for one single fractional element. Therefore, we see a need for some generalized work that had to be introduced for designing an FO filter having two different fractional elements of a similar order to decrease the degree of freedom of design. All such techniques of design had been presented and this was based on making use of an equivalent function for transfer which was on a Field Programmable Analogue Array (FPAA). This was employed through a transfer function of a higher order once additional zeros were inserted to the poles to obtain similar traits of fractional filters [6].

Further, a set of continuous-time current-mode FO filters were also published. All these structures that were proposed had offered benefits of realizations that were resistor-less and also had an electronic adjustment of the characteristics and their frequency along with the capacity of an ultra-low voltage operation. The compounding had an increased complexity of a circuit related to their linear counterparts and the current-mirror filters were resultant by an assumption of a small-signal operation. The discrete-time techniques to perform an analogue signal processing was the Switched-Capacitor (SC) and the Switched-Current (SI) [7]. The SC filters were then realised by employing some operational amplifiers (op-amps) and some capacitors, and the SI filters made use of a Metal–Oxide–Semiconductor (MOS) transistor. The time constants were then formed to be the produce of the period of the clock and the actual ratio of its associated capacitances and sometimes the characteristic relations of the MOS transistors. It was because of this, both filters had offered some frequency traits at the time of implementation in an integrated form. There are several noise reduction methods along with the removal of motion artefacts that have been proposed and these were the band pass filters, the de-noising methods, Hop- Field Neural Network (HNN), the Wavelet Neural Networks (WNN), the Particle Swarm Optimization (PSO) and the ensemble averaging technique. The rest of the investigation has been organized thus. Section 2 discusses all related work in literature. The different methods used are explained in Section 3. The results of the experiments have been analysed in Section 4 and the conclusion duly made in Section 5.

II. RELATED WORKS

Tsirimokou et al., [8] had brought about some novel configurations of the topologies of FO filters that were realised by the concept of some companding filtering. The first step was to design this in an algorithmic manner and for the next step, there were some straightforward building blocks of the sinh-domain and also the log-domain based integrators that were proposed. Engaging of the MOS transistors that had been operated in its subthreshold region, the filter structures derived could offer the operational capability in an environment of an ultra-low-voltage. These technologies were reconfigurable so as to ensure that the filter was selected by means of an appropriate bias of current sources.

Khateb et al., [9] had proposed both design and implementation of the FO filters that were based on some promising Complementary MOS (CMOS) structures with a Differential Difference Current Conveyor (DDCC), designed and invented with the process of 0.35 µm CMOS AMIS.
The filter derivation was achieved with a second-order approximation of the fractional-order transfer functions. These filters propose an advantage of a very low voltage (±500 mV) operation along with some grounded and passive elements. Proposed a method for quickly deriving some high-order filters which. Experimental results had proved that the proposed filters performed attractively. Freeborn et al., [10] had proposed usage of some nonlinear least squares and their optimization for approximating a passband ripple of traits of some traditional Chebyshev and low pass filters using the FO steps in a stopband. The simulations of the MATLAB of $(1+\alpha),(2+\alpha)$ *and* $(3+\alpha)$ order the low pass filters along with fractional steps that are from $\alpha=0.1$ to $\alpha=0.9$ that have been provided as examples. The SPICE simulations of the 1.2, 1.5, and the 1.8 order low pass that made use of the approximated FO capacitors found in a new Tow-Thomas biquad circuit will validate the filter circuit implementation.

Tripathy et al., [11] had presented a hardware realization along with a performance investigation of the fractional inductors of the order of $0 < \alpha < 2$. These fractional inductors were realised along with a impedance and converter circuit along with fractional capacitors. This description of the impedance of the fractional inductors along with various exponents was experimentally carried out. Further, there was also a generalized approach for designing the fractional-order band pass filter that has been discussed here. This fractional-order band pass filter contains a set of fractional capacitor of an order of $0 < \beta < 1$. The final presentation of the fractional-order based band pass filters was investigated and then related to the integer-order filters by means of simulation and experimentation.

Adhikary et al., [12] had introduced a new tunable Fractional Order Parallel Resonator (FOPR) that had a frequency of resonating which may be tuned by the FO element coefficient. And the Q-factor could be set at a high (infinite) by means of varying its resistors. By making use of an FOPR circuit, there are two simple FO filters (the FO band pass and the FO notch) that were established. This work also included a detailed analysis of the sensitivity of circuits of circuit parameters describing the manner in which they were proposed for the FOPR and the FO filters. The FOPR and FO filters proposed were replicated in the MATLAB and this was recognized in the hardware. These hardware circuits had also been tested and some detailed results were duly provided.

Sahu et al., [13] had proposed a design of the FO Multi-Input–Single-Output (MISO)–type Static Synchronous Series Compensator (SSSC) that had a goal of improving the system of power and its stability that made use of a Modified Whale Optimization Algorithm (MWOA). This MWOA proposed had achieved a proper balance between the stages of exploitation and its exploration for the original Whale Optimization Algorithm (WOA). The MWOA and its performance was validated by means of employing benchmark test functions. They were also contrasted using the WOA and some more heuristic algorithm such as the Differential Evolution (DE), the Particle Swarm Algorithm (PSO) and the Gravitational Search Algorithm (GSA). The FO MISO SSSC controller that was proposed had been enhanced by an MWOA technique and this was verified using a single-machine system of infinite bus and this is prolonged to a framework of multi-machine. Khanna and Upadhyay [14] had made presentations of some optimal designs of the FO low pass along with high pass filters that had a Butterworth estimation isattained using a PSO along with some suitable scaling. The analysis of errors of these designed filters compared to the other filters in stopband and pass band were considered. Finally, an improved FO with low pass and high pass filters were employed for designing the FO band pass filters. Ates et al., [15] had made a presentation of a new and discrete Infinite-Impulse Response (IIR) method of filter design aimed at the realisation of the FO continuous filters found in the digital systems. The method known as the Fractional Order Darwinian Particle Swarm Optimization (FODPSO) was improved to offer an improved fit of discrete filter functions of IIR filters. For this purpose, the authors had been executed a new hybrid version of this FODPSO method. This was done by a technique of arithmetical candidate point selection with the Base Optimization Algorithm (BaOA). Such a modification will expand the range of search of an FODPSO and so an optimized and discrete IIR filter will be able to provide some better approximation for the amplitude response of the FO continuous filter functions.

Xie et al., [16] had proposed another new algorithm for job scheduling. An intuition of this algorithm was based on the SFLA and the PSO. The trust model was also introduced for improving resource trust. These comprehensive simulations were conducted through the CloudSim. The results of the experiments proved the algorithm to be able to improve the trustworthiness of a comparison with the TD-Min-Min and the Genetic Algorithm (GA). Zhu et al., [17] had presented a target recognition that was based on the Ultra-Wide Band (UWB) that was realized in rainy weather with the Support Vector Machine (SVM). For the purpose of removal of features, a Principal Component Analysis (PCA) was used for reducing the dimension that was able to shorting the time taken for running the algorithm. For improving the rate of recognition, the SVM parameter had to be optimized and on the basis of the PSO and the SFLA, the work had proposed the PSO-SFLA that promised a better performance in its speed of convergence and optimal ability.

Rajamohana and Umamaheswari [18] had proposed another hybrid approach for an improved binary PSO along with the SFLA for decreasing the feature sets and their high dimensionality. The approach had helped customers in disregarding all fake reviews and in enhancing the performance classification by means of offering some trustworthy reviews. The Naive Bayes (NB), the K Nearest Neighbour (KNN) and the SVM classifiers had been employed for the purpose of classification.

The outcomes proved that the hybrid method proposed had an optimized feature subset and was also able to obtain a higher accuracy of classification. Bao and Han [19] had further proposed another hybrid multi-swarm PSO algorithm that had three different techniques which were the multi-swarm method, the update technique and finally the cooperation approach.

There was also another new way to group particle swarms that had been put forth by means of a calculation of the particles and their fitness values. For every group, the particles tend to update in accordance with the formula that has been morphed using the SFLA. Furthermore, there was a new strategy of communication used. Cooperation of all these strategies will maintain the algorithm and its diversity for improving their search ability. Lastly, the results of the experiment based on benchmark functions were able to verify the proposed PSO and its effectiveness.

Narimani et al., [20] had obtainable another novel hybrid algorithm depending on the SFLA and the PSO to solve an Optimal Power Flow (OPF) in the power systems. This problem of optimization has taken into consideration all real power generation conditions that involve the prohibit zones, a valve point effect along with the generation units of a multi-fuel type. The increase in the anxieties over all the environmental problems had now required the operators of power systems to take into consideration of the problem of emission to be a consequential matter aside from the other economic issues to ensure the problem of OPF to become a problem of multi-objective optimization.

III. METHODOLOGY

The FO filter circuits were electronic circuits using the concepts of fractional calculus referring to a branch of mathematics that is concerned with a non-integer differentiation along with integration for realizing the magnitude and the phase traits that were not achievable easily. For the purpose of this section, FO generalized filters (the order α), the SFLA FOD order optimized and also the hybrid SFLA-PSO methods were discussed.

A. Fractional-Order Generalized Filters (Order α)

The integrators and the differentiators were valuable in the building blocks found in biomedical applications. The FO digital implementations in these circuits were published duly in the literature. Utilization of all second-order expressions used in the CFE was a suitable tool to realise the fractional-order differentiators and also the integrators for approximating variables $(\tau s)^{\alpha}$ that make use of the formula shown in (2). If in case α = 1, the transfer function will represent a new differentiator, while in the case of α = -1 denotes an integrator. For the range (0 < α < 1), the element can be taken as representing the FOD and in a range (-1 < α < 0), this is a FO integrator [21].

$$(\tau s)^{\alpha} = \frac{\alpha_0(\tau s)^2 + \alpha_1(\tau s) + \alpha_2}{\alpha_2(\tau s)^2 + \alpha_1(\tau s) + \alpha_0} \qquad (2)$$

The FOD: a transfer function, with a magnitude response of integer-order differentiator, was shown as in formula H (s) = τs, and H (ω) = ω/ωo. The frequency of unity gain was ωo = 1/τ, wherein the τ was the corresponding time-constant. Additionally, a phase response was constant and was also equal to π/2. So, a transfer function for the FOD is shown as in (3):

$$H(s) = (\tau s)^{\alpha} \qquad (3)$$

Wherein (0 < α < 1) denotes the direction of its differentiator. Its magnitude response has been specified as H (ω) = (ω/ωo)α. In this particular case, there is a phase response which is constant and also equal to the απ/2 that predicts the reliance of the phase which is from a fractional-order α. The actual value of the α found in the FO generalized filter has been optimized by making use of the SFLA and the hybrid SFLA. Input was taken from the source of noise and the patient along with an optimal value of the order filter that is chosen.

B. Shuffled Frog Leaping Algorithm (SFLA) Order Fod Optimized

The Shuffled Frog Leaping (SFL) was motivated using the memetic evolution of frogs while examining for the actual food location. The frogs that belong to various groups known as memeplexes use a strategy especially when the resources are scattered in areas. Each memeplex has a certain number of frogs having a similar structure then with other compliances. At the same time, the process of shuffling will cause each frog in earlier experiences at the time of searching for food. This SFL combination is one that has both random and deterministic approaches. A deterministic strategy will further permit this algorithm to make use of a response surface information in an effective manner to guide this type of a heuristic search. All these random elements tend to make sure there is robustness and flexibility for the patterns of search [22]. There are three stages to the SFL which are partitioning, local search and its shuffling. Once there is a generation of its random initial population the members of this population were sorted in decreasing order based on their function evaluation value. After this, the population gets partitioned into various subsets. All memeplexes are perceived to be a set of some parallel cultures to achieve an independent local search for a certain number of iterations. Once this is done, all the memeplexes will shuffle together where the stopping criteria is checked and in case of it not being met, partitioning, local search and process of shuffling will be continued. Based on the process of evolution of the SFL, the frog that is the worst in each update of memeplex will be based on the best frog position or the best frog that is found until now.

In the SFLA, the NP frog population was generated for representing initial solutions. Every solution which is X_i known as a frog was signified by the D-dimension vector $X_i = (x_{i1}, x_{i2}, ..., x_{iD})$, I ∈ {1, 2……NP}. After this, the objective function was designed for every frog and this was sorted in descending order.

The total population was separated into a number of parallel subsets namedas the m memeplexes. For this, the first frog will go to its first memeplex, the next frog will go into the second memeplex and the frog m will go to its mth memeplex, and the frog m+1 will go into its first memeplex. It is set as the Mk to be the kth memeplex of frog population. The method of division is termed as in (4):

$$M^k = \{X_{k+m(l-1)} \in P \mid 1 \le l \le n\},\ 1 \le k \le m \tag{4}$$

Today every memeplex will contain a set of n frogs and it is evident that the NP=m*n.

For generating a new frog for every memeplex, the SFL will generate another new frog for every memeplex and the SFL applies the equations (5) and (6) that fall between Xb and Xw for producing Xn.

$$\Delta X_w = \lambda(X_b - X_w),\ -\Delta X_{w\max} \le \Delta X_w \le \Delta X_{w\max} \tag{5}$$

$$X_n = X_w + \Delta X_w,\ f_w = f(X_w) \tag{6}$$

Wherein Xb denotes the best frog of the existing memeplex, Xw denotes the worst frog of the current memeplex, λ denotes a random number and the ΔXw max will be the upper bound for the ΔXw. By applying such a method, a maximum acceptable step size for the Xw will be limited. Once this is done, if there is a newly generated frog, which means Xn does not have a better quality compared to the Xw, Equations (4) and (5) will be repeated between the Xg and the Xw wherein the Xg will be the best frog in the population. In the stage of partitioning, a m memeplex has to be generated each one consisting of n frogs. For the purpose of doing this, the population has to be sorted in decreasing order based on the cost function value. After this, the first frog of each memeplex is assigned and the ranking 1 will go to the memeplex 1 and the frog that ranks 2 will go to memeplex 2 and so on until frog ranking m goes to memeplex m, the second frog in every memeplex will be assigned to be : frog ranking (m + 1) will go to the memeplex 1, frog ranking (m + 2) will go to the memeplex 2, …, frog ranking (m + m) will go to the memeplex m. The method continues n times for assigning them to all the frogs into the memeplexes.

C. Particle Swarm Optimization (PSO) Algorithm

It is swarm intelligence based algorithm, has the social behaviour of the birds that has been qualified originally by Kennedy and Eberhart (1995). Every solution or a bird will be signified by one particle or a collection called a swarm. Every particle will attempt at achieving either the preeminent or an optimal position within the decision space having two different types of velocity (the Pbest and the Gbest). These are the best positions in the particle and in the history of the swarm. The algorithm will begin by means of generating random and uniform particles [23]. In case the decision variables are D, its current position will be (Xk) and the velocity (Vk) of that of the kth particle will be signified by the D-dimensional vector which is as in (7 and 8):

$$X_k = (x_{k1}, x_{k2}, \ldots, x_{kD}) \tag{7}$$

$$V_k = (v_{k1}, v_{k2}, \ldots, v_{kD}) \tag{8}$$

The actual velocity of that of the kth particle will be designed as per (9):

$$v_{kd}^{n+1} = w.v_{kd}^{n} + c_1.r_1^n(Pbest_{kd}^n - x_{kd}^n) + c_2.r_2^n(Gbest_d^n - x_{kd}^n)$$
$$for\ k = 1, 2, \ldots, N\ and\ d = 1, 2, \ldots., D \tag{9}$$

Wherein, v_{kd}^{n+1} =velocity of that of the dth dimension of its kth particle found in (n + 1)th iteration; w = denotes the inertia weight parameter and this has a crucial role in the convergence of the swarm and will also control the properties of its current velocity (the values that are larger and smaller resulting in a search within a wide and also a narrow space); v_{kd}^{n} = the actual velocity of a dth dimension belonging to the kth particle found in its nth iteration; c1 = a cognitive parameter; c2 = a social parameter (where the c1 and c2 control the Pbest and the Gbest movement to its optimal point); r_1^n and r_2^n = the random numbers that are distributed uniformly within [0,1]; $Pbest_{kd}^n$ = the best position of that of the dth dimension for its kth particle up to its nth iteration; and $Gbest_d^n$ = dth dimension for the best swarm position up to its nth iteration. To regulate the particle and its velocity, the lower and the upper-velocity bounds will be incomplete (10):

$$v_d^{\min} \le v_{kd}^{n+1} \le v_d^{\max} \tag{10}$$

Wherein, $v_d^{\min}$ and $v_d^{\max}$ = are the lower and the upper bounds of velocity for the dth dimension.

The position of the particle isrestructuredlike (11):

$$x_{kd}^{n+1} = x_{kd}^{n} + v_{kd}^{n+1} \tag{11}$$

Here a variable w in the equation (9) will control the impact of all earlier velocities. The big w will facilitate a global optimization (looking out for new areas) and the small w will help in local exploration. Thus, there is a proper w value helping in reducing the iterations needed for locating an optimum solution. Based on this variable w the computation is as per (12):

$$w = 0.4 + 0.5*(IterMax - iter) / IterMax \tag{12}$$

Wherein the iter refers to the current number of iterations and the IterMax denotes the actual number of acceptable iterations.

D. Proposed Hybrid SFLA-PSO

In the procedure of the SFLA evolution, the frogs that have the worst fitness will learn data from memeplex best Xb, or the frog that is the best in the whole population Xg, or will be replaced by a randomly identified solution. The shuffling takes place after the memeplex that evolves for a particular number of iteration is in parallel.

The PSO is an algorithm of fast search than other techniques of evolution constantly facing the risk of premature convergence of search when discovering the complex functions. This type of behaviour is attributed to the particle diversity loss in the population towards the end of the process of evolution. The goal was to integrate the SFLA and the PSO for combining all the benefits of a high-speed PSO with the SFLA's global skill of exploration.

This SFLA-PSO has been described as below [24]:

Step 1: Initiating all variables so that the number of memeplexes (m); the number of frogs found in each memeplex (n); the number of actual solutions (NP=n*m); the number of iteration (IterMax, Lmax, T, iter) are identified.

Step 2: Generating the NP frogs randomly as the initial population;

Step 3: Calculating the frog's fitness in the population; finding the one having the best fitness and denoting Xg; sorting the population in decreasing order on the basis of fitness and dividing them into m memeplexes as per (4);

Step 4: For every memeplex, identify frogs with the best and worst fitness and then denote Xb and Xw,; Based on equations (5) and (6), operate the memetic evolutions without a constraint ||D||≤Dmax; Now go to Step 4 for Lmax times;

Step 5: Finding a frog that has the best fitness in the entire population and then denotes the Xg, Now, go to Step 4 for about T times;

Step 6: Shuffle all memeplexes in order to form a population POP; now find the one frog that has the worst fitness and this is denoted as Xwg;

Step 7: For a population POP, now apply the wPSO using an iteration number set which is 20*Lmax, and for this, a variable w will be computed as in equation (12); Now find a particle that has the best fitness and denotes it as XgPSO;

Step 8: The frog that is the worst in the POP Xwg will be substituted by a particle XgPSO; now check if its merging conditions are met. Then stop. Else, go to Step 3 with population POP.

IV. RESULTS AND DISCUSSION

In this section, the ECG, actual, SFLA order optimized and hybrid SFLA order optimized methods are used. The ECG signal without noise, ECG signal with noise, ECG signal with SFLA FOD order optimized, ECG signal with hybrid SFLA FOD order optimized, order optimized FIR-FOD magnitude response and order optimized FIR-FOD phase response as shown in figures 2 to 7.

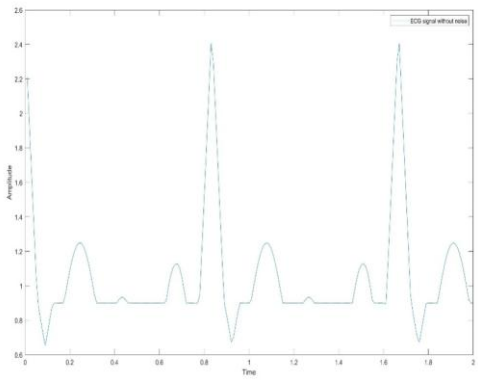

Figure 2 ECG Signal without Noise

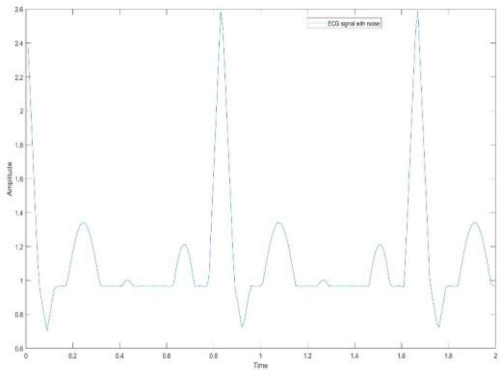

Figure 3 ECG Signal with Noise

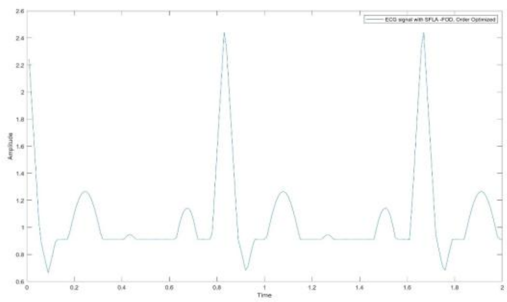

Figure 4 ECG Signal with SFLA FOD Order Optimized

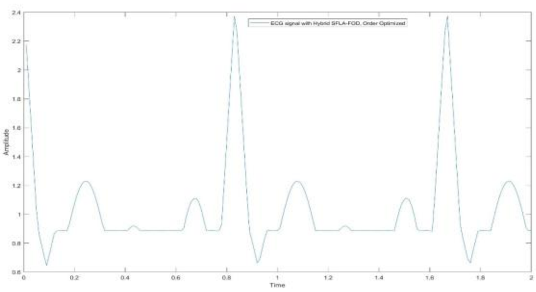

Figure 5 ECG Signal with Hybrid SFLA FOD Order Optimized

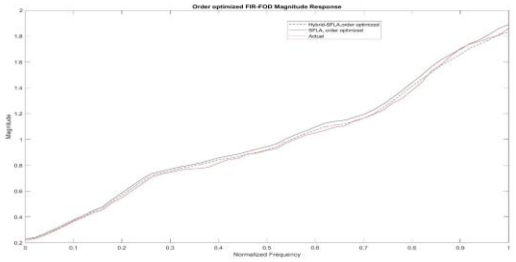

Figure 6 Order Optimized FIR-FOD Magnitude Response

From the figure 6, it can be observed that the order optimized FIR-FOD magnitude response for proposed hybrid SFLA order optimized has better performance than actual.

The order optimized FIR-FOD magnitude response for proposed hybrid SFLA order optimized has lower performance than SFLA order optimized method.

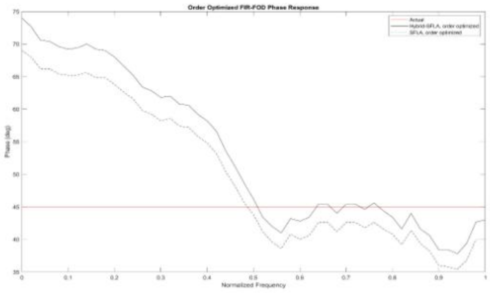

Figure 7 Order Optimized FIR-FOD Phase Response

From the figure 7, it can be observed that the order optimized FIR-FOD phase response for proposed hybrid SFLA order optimized has better performance than actual and SFLA order optimized method.

V. CONCLUSION

ECG will generally be employed for diagnosing cardiovascular diseases. Sometimes it becomes necessary to be able to remove noise from the ECG recordings. There are many adaptive filter structures proposed for cancellation of noise. The advent of FO based devices has brought about a major interest in examining the FO filters since they have many applications in non-linear system identification, controller design and signal processing. For this, the hybrid SFLA-TS FOD was proposed. The SFLA made use of a grouping strategy of search to provide proper exploration. An independent local search was able to provide good exploitation. This hybrid SFLA-PSO has been proposed in order to solve an ECG signal noise. There is a convergence of the original SFLA to the local optima. For avoiding such a shortcoming, a new method for improving local search near global optima was proposed. The chances of merging to the global optima thus improved. The results have proved that the order optimized FIR-FOD phase response that was used for the proposed hybrid SFLA order had a better performance compared to the original method of SFLA.

REFERENCES

1. Ebrahimzadeh, E., Pooyan, M., Jahani, S., Bijar, A., &Setaredan, S. K. (2015). ECG Signals noise removal: Selection and optimization of the best adaptive filtering algorithm based on various algorithms comparison. Biomedical Engineering: Applications, Basis and Communications, 27(04), 1550038.
2. Fedotov, A. A. (2016). Selection of Parameters of Bandpass Filtering of the ECG Signal for Heart Rhythm Monitoring Systems. Biomedical Engineering, 50(2), 114-118.
3. He, R., Wang, K., Li, Q., Yuan, Y., Zhao, N., Liu, Y., & Zhang, H. (2017). A novel method for the detection of R-peaks in ECG based on K-Nearest Neighbors and Particle Swarm Optimization. EURASIP Journal on Advances in Signal Processing, 2017(1), 82.
4. Said, L. A., Ismail, S. M., Radwan, A. G., Madian, A. H., El-Yazeed, M. F. A., & Soliman, A. M. (2016). On the optimization of fractional order low-pass filters. Circuits, Systems, and Signal Processing, 35(6), 2017-2039.
5. Soltan, A., Radwan, A. G., & Soliman, A. M. (2012). Fractional order filter with two fractional elements of dependant orders. Microelectronics Journal, 43(11), 818-827.
6. Ali, A. S., Radwan, A. G., & Soliman, A. M. (2013). Fractional order Butterworth filter: active and passive realizations. IEEE Journal on emerging and selected topics in circuits and systems, 3(3), 346-354.
7. Tsirimokou, G., Psychalinos, C., &Elwakil, A. S. (2016, May). Switched-current fractional-order filter designs. In Circuits and Systems (ISCAS), 2016 IEEE International Symposium on (pp. 682-685). IEEE.
8. Tsirimokou, G., Laoudias, C., &Psychalinos, C. (2015). 0.5-V fractional-order companding filters. International Journal of Circuit Theory and Applications, 43(9), 1105-1126.
9. Khateb, F., Kubánek, D., Tsirimokou, G., &Psychalinos, C. (2016). Fractional-order filters based on low-voltage DDCCs. Microelectronics Journal, 50, 50-59.
10. Freeborn, T., Maundy, B., &Elwakil, A. S. (2015). Approximated fractional order Chebyshev lowpass filters. Mathematical Problems in Engineering, 2015.
11. Tripathy, M. C., Mondal, D., Biswas, K., & Sen, S. (2015). Experimental studies on realization of fractional inductors and fractional-order bandpass filters. International Journal of Circuit Theory and Applications, 43(9), 1183-1196.
12. Adhikary, A., Sen, S., & Biswas, K. (2016). Practical realization of tunable fractional order parallel resonator and fractional order filters. IEEE Transactions on Circuits and Systems I: Regular Papers, 63(8), 1142-1151.
13. Sahu, P. R., Hota, P. K., & Panda, S. (2018). Modified whale optimization algorithm for fractional-order multi-input SSSC-based controller design. Optimal Control Applications and Methods, 39(5), 1802-1817.
14. Khanna, T., & Upadhyay, D. K. (2015, December). Design and analysis of improved fractional order Butterworth filters. In India Conference (INDICON), 2015 Annual IEEE (pp. 1-6). IEEE.
15. Ates, A., Alagoz, B. B., Kavuran, G., & Yeroglu, C. (2017). Implementation of fractional order filters discretized by modified Fractional Order Darwinian Particle Swarm Optimization. Measurement, 107, 153-164.
16. Xie, X., Liu, R., Cheng, X., Hu, X., & Ni, J. (2016). Trust-Driven and PSO-SFLA based job scheduling algorithm on Cloud. Intelligent Automation & Soft Computing, 22(4), 561-566.
17. Zhu, G., Jiang, T., & Zhou, Z. (2016, September). A fusion method for object identification in rainy weather based on PSO-SFLA and UWB. In Communications and Information Technologies (ISCIT), 2016 16th International Symposium on (pp. 537-541). IEEE.
18. Rajamohana, S. P., & Umamaheswari, K. (2018). Hybrid approach of improved binary particle swarm optimization and shuffled frog leaping for feature selection. Computers & Electrical Engineering. Vol. 67, pp. 497-508.
19. Bao, H., & Han, F. (2017, September). A Hybrid Multi-swarm PSO Algorithm Based on Shuffled Frog Leaping Algorithm. In International Conference on Intelligent Science and Big Data Engineering (pp. 101-112). Springer, Cham.

20. Narimani, M. R., Azizipanah-Abarghooee, R., Zoghdar-Moghadam-Shahrekohne, B., &Gholami, K. (2013). A novel approach to multi-objective optimal power flow by a new hybrid optimization algorithm considering generator constraints and multi-fuel type. Energy, 49, 119-136.
21. Tsirimokou, G., Psychalinos, C., &Elwakil, A. (2017). Procedure for Designing Fractional-Order Filters. In Design of CMOS Analog Integrated Fractional-Order Circuits (pp. 13-39). Springer, Cham.
22. AliniaAhandani, M., &Kharrati, H. (2018). Chaotic shuffled frog leaping algorithms for parameter identification of fractional-order chaotic systems. Journal of Experimental & Theoretical Artificial Intelligence, 1-21.
23. Orouji, H., Haddad, O. B., Fallah-Mehdipour, E., &Mariño, M. A. (2013). Extraction of decision alternatives in project management: Application of hybrid PSO-SFLA. Journal of Management in Engineering, 30(1), 50-59.
24. Lin, M. J., Luo, F., Xu, Y. G., & Luo, L. (2013). A Novel Hybrid Optimization Method of Shuffled Frog Leaping Algorithm and Particle Swarm Optimization. In Advanced Materials Research (Vol. 717, pp. 433-438). Trans Tech Publications.

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