Denoising of Continuous Glucose Monitoring signal with Adaptive SG Filter

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Abstract. This paper aims at simulating an intelligent Savitzky Golay (SG) filter which can automatically adjust its parameters in accordance with the changes in sampling or cut off frequency. The filter is implemented on signals obtained from Continuous Glucose Monitoring (CGM) device. The Continuous Glucose Monitoring devices can indicate any life threatening (hyperglycemic or hypoglycemic) event, so that a preventive action may be taken to control blood glucose. The accuracy of these devices is generally not very good due to factors like sensor electronics and movement artefacts. In the present research work, data obtained from GlucoSim simulator is used, which is an educational software to simulate glucose and insulin levels in blood and their dynamics in healthy or diabetic (Type-1) individuals. Genetic Algorithm and Particle Swarm Optimization techniques are used to tune the parameters of Savitzky Golay filter leading to GA-SGF and PSO-SGF filters. Continuous Glucose Monitoring signal is denoised using the adaptive Savitzky Golay filters. It is observed from the results that PSO-SGF provides fast and efficient filtering.

Keywords: SG (Savitzky Golay), CGM (Continuous Glucose Monitoring), PSO (Particle Swarm Optimization), GA (Genetic Algorithm), Intelligent SG Filter.

1 Introduction

Many diabetic patients need to monitor their glucose level multiple times in a day [1]. Regular glucose monitoring with the help of CGM devices improves the health conditions as well as the life span of a diabetic patient. Earlier invasive blood monitoring devices were used which required finger pricking to test the blood and are sufficiently accurate. The newer devices are non-invasive CGM devices, which are held in patient's hands or put on other body parts from where accurate glucose levels can be acquired. However random noise and occasional spikes corrupt the signal and increase signal irregularities which may affect the accuracy of CGM devices. The noise and spikes may originate from sensor electronics and movement artifacts. Therefore, CGM signal should be filtered before it can be used for any diagnosis or treatment. The SG filter is usually used for data smoothing and denoising in spectrum analysis, biomedical signal processing, image processing [2] etc. Heise et al. [3] explained the effects of data pretreatment on glucose measurement signals, using SG Filters and filter coefficients are computed using hit and trial method. Schafer [4] discussed the problems of calculating the filter coefficients of SG filter accurately during the filter design. In the present work, SGF is selected to smooth and denoise the CGM signals. SG filter has capacity to retain shape of the signal and thus avoid signal distortion. The performance of SG outperforms the conventional filters if proper polynomial order and frame size is selected. The selection of appropriate values of SGF parameters is made using hit and trial basis or prior experience is required which is a cumbersome task and is thus a shortcomings of SGF filter [4-5].

Researchers have used various heuristic and meta-heuristic evolutionary optimization methods to overcome above discussed drawback of filter designing [6-7]. These include GA, PSO, Differential Evolution algorithm (DE), Simulated annealing algorithm etc. Optimization algorithms are executed iteratively until an optimum solution is found. These algorithms aim at minimizing the cost of a product/function or maximizing its efficiency. GA seems to be a promising candidate for digital filter design [8]. However GA does not guarantee the global solution and it has complex structure, takes longer time to operate & also suffers from local optimal solutions. Kumar et al. [6] designed optimal digital filter using PSO technique. PSO shows fast convergence speed and error function is also minimum while optimizing the filter parameters. Various other researchers have also utilized PSO for filter design and results obtained are promising [7] which motivates for the design of filter parameters using optimization techniques. In this paper GA and PSO are explored to evaluate the filter parameters and devise an adaptive SG filter which automatically tunes its parameters for efficient filtering.

This paper is organized as follows. “Introduction” section presents brief overview of the prior work done by other researchers. “Materials and Methods” section describes the concepts, tools and techniques used in the present work. The experimental data, results and analysis are presented under “Results and Discussion” section. Finally the concluding remarks are given the “Conclusion” section.

2 Material and method

2.1 Savitzky Golay Filter

SG filter de-noises the signal by fitting a polynomial structure to data samples. It removes the noise component while retaining important features of the signal so that signal distortion is not caused. In this process a polynomial is fitted onto the input data samples. After this the noise is reduced by estimating the input to signal space [2]. Further the fitted polynomial is processed through a linear function to extract the desired output. It is revealed from literature [3] that cascade application of 2-stages of SGF can be actualized through a simple Linear Time Invariant (LTI) filtering scheme which leads to an efficient and simple filtering.

Least Squares polynomial smoothing is depicted in Fig. 1 where black dots represent samples of input data. A polynomial is fitted to the set of input samples using Least Square smoothing of signals [1].

$$S(n) = \sum_{k=0}^{N} b_k \, n^k \qquad (1)$$

The mean-squared approximation error is minimized,

$$C_N = \sum_{n=-M}^{M} (S(n) - x(n))^2 \qquad (2)$$

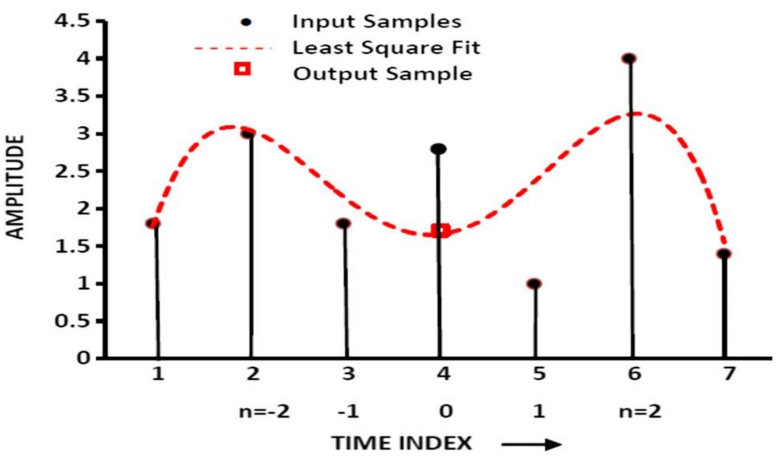

Fig. 1. Least square polynomial fitting [1]

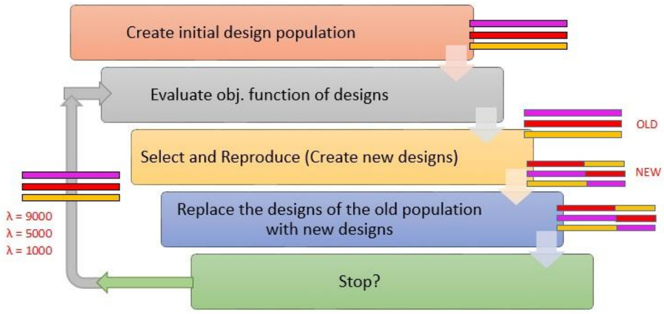

Fig. 2. Flowchart of Genetic Algorithm

The analysis is viable for approximation interval of "half width" M. The result is the zeroth polynomial coefficient. The least square polynomial fitting and calculation of the filter coefficients is explained in this reference. [2]

Y_0=S (0) = b_0 (3)

2.2 Optimization Techniques

Optimization is a method of finding the finest possible solution for a particular query, under defined conditions. In past few decades researchers have successfully solved many complex engineering problems e.g. process control, biomedical signal processing and image processing [6] using optimization techniques. There are many nature-inspired optimization algorithms, which emulate some biological or physical phenomena such as GA [9], Simulated annealing (SA), and PSO [8], and Ant Colony Optimization (ACO) etc. GA is one of the most well-known population based optimization method. [10, 11] Therefore it is used in the present work to automatically compute filter coefficients instead of hit and trial method.

An algorithm will converge to an appropriate solution or will not converge at all, depends on the design of fitness function. The weighted sum of two objectives i.e. minimization of MSE and maximization of SNR is considered as fitness function in this work.

Fitness function=*W1*MSE - W2 *SNR* (4)

Where W1+W2 = 1

GA is based on Darwin's theory of natural evolution and uses the concept of 'survival of the fittest'. The algorithm is used to repeatedly modify a population of individual solutions [9] by randomly selecting from an existing population. The selection of population is based on fitness function which is used to produce the next generation. The population "evolves" towards an optimal (fittest) solution over successive generations. A general flowchart for implementation of GA is shown in Fig.2.

In this work PSO is also used for tuning the filter parameters. In PSO every solution is denoted as a point in the search space which is called a "particle". All the "particles" are assigned a unique fitness value, as shown in Fig. 3. The fitness value is calculated using a fitness function to be optimized as in GA. The particles move in the problem space with some velocity by pursuing the current optimum particles. Flowchart depicting pseudo code of PSO is shown in Fig. 4.

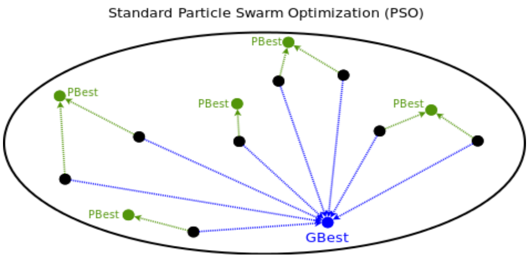

Fig. 3. Standard PSO

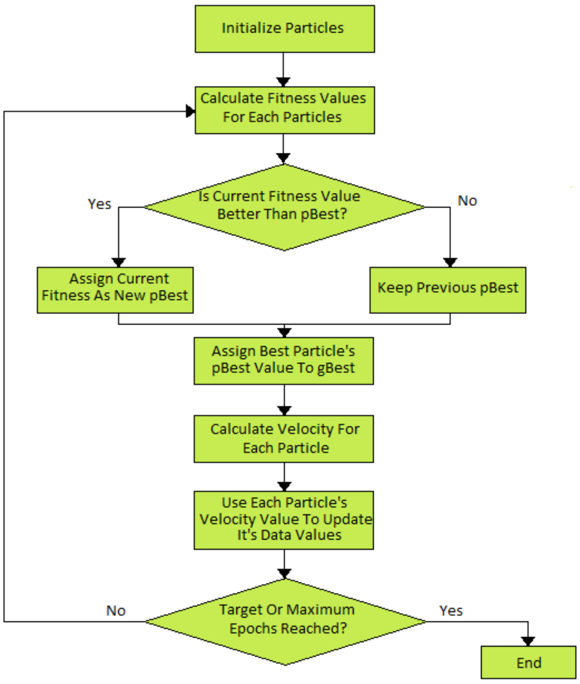

Fig. 4. Flowchart of PSO

2.3 Continuous Glucose Monitoring (CGM)

CGM device reports the patient's blood glucose levels in real time and alert them when their glucose levels hit a high or low limit, thus provides insight into glucose trends [12, 13]. Nowadays various types of CGM devices are manufactured by different companies which are either invasive or non-invasive. A newer type of economic CGM device, called as "flash" CGM is used for monitoring blood glucose levels. These CGMs don't have alarms, transmitter and are not required to be calibrated using a standard meter. The patient needs to hold the device next to the sensor to get the readings. The glucose levels are displayed on a screen in real time. Fig. 5 shows a real time CGM signal.

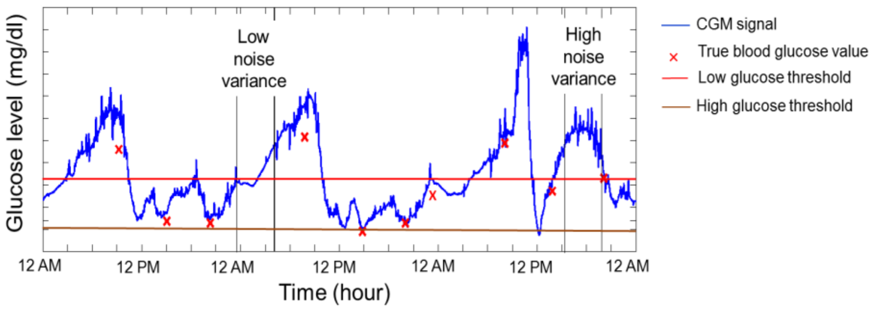

Fig. 5. Real time CGM Signal

The glucose monitoring signal acquired from CGM device can be described as,

$$X\ (k) = Y\ (k) - N\ (k)$$

Where Y (k) is the acquired CGM signal, X (k) is the unknown glucose value at time instant 'k' and N (k) denotes the noise interference due to measurement error. The noise is generally a high frequency component of a signal resulting in signal distortion and thus causes inaccuracy and delay. Low pass filtering is the most appropriate to remove such noise from CGM signals.

In SG filers, the filter parameters "N" (order of fitting polynomial) and "M" (length of frame) are tuned to get required filter output. Manually selecting these parameters is a very tedious and time consuming process. Further if the sampling frequency changes these parameters are to be re-evaluated. Therefore in this work automatic tuning of filter parameters is carried out using optimization techniques.

2.4 Source of Data:

Glucose-insulin dynamics are simulated using a rigorous model based on pharmacokinetic of insulin- glucose, as explained in Fig. 6 [13]. The simulator has a graphical user interface to offer a user-friendly environment for carrying out virtual experiments in various conditions i.e. diet and exercise.

It is surmised in the simulation that variations in blood glucose-insulin concentrations at tissue level are fast and the balances are in quasi-steady state just after a disturbance. This model is capable of simulating the dynamics of blood glucose-insulin for a diabetic/healthy subjects. The user interface of GlucoSim software is shown in the Fig. 7.

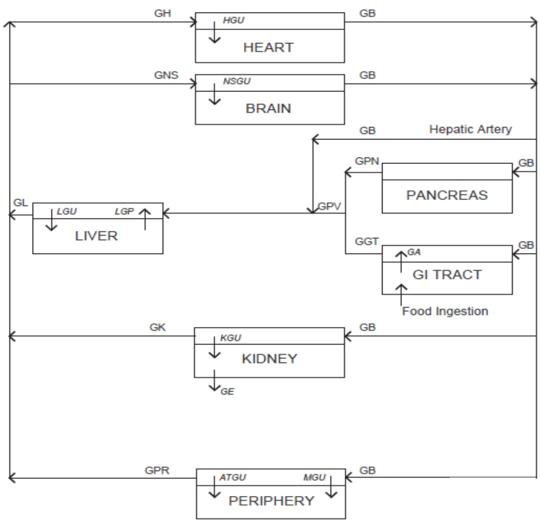

Fig. 6. Pharmacokinetic diagram of GlucoSim [13]

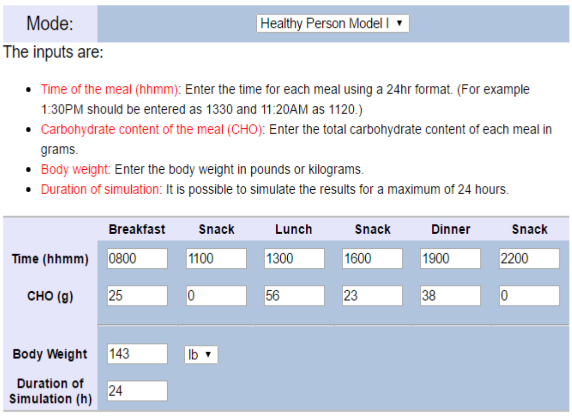

Fig. 7. Front panel of GlucoSim

3 Intelligent SG filter

Fig. 8 shows the block diagram and flowchart of the proposed adaptive SG filtering system. The synthetic data is taken using GlucoSim and white Gaussian noise is added to the signal. The noisy signal is then passed to the filter for denoising. The optimization of filter parameters is carried out using GA and PSO. The GA and PSO algorithms are used for automatic selection of parameters of the Intelligent SG filter. Using these optimization techniques the SG filter can accurately modify its parameters according the set objectives, defined by GA or PSO.

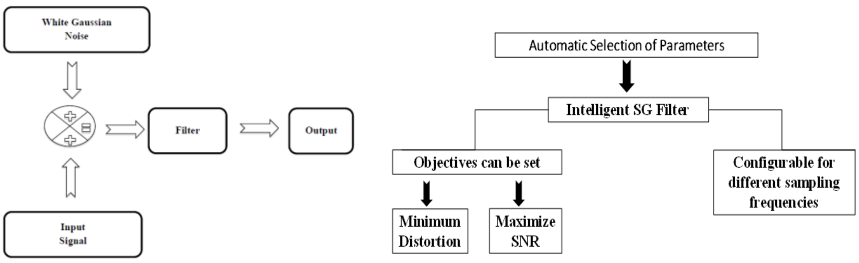

Fig. 8(a). Block Diagram for filtering of noisy CGM signal; **Fig. 8(b).** Selection of filter parameters using optimization techniques

This helps to give best possible solution for the filter coefficients N and M, while minimizing the distortion and maximizing the Signal to Noise Ratio. GA and PSO are used to find the best possible solution for filter coefficients N and M. The filter parameters N and M vary with cut off frequency of the signal. The desired cut-off frequency is 10Hz. Equation (5) gives relationship between cut off frequency and filter parameters.

$$Fc = \frac{\mathrm{N}+1}{3.2\ \mathrm{M}-4.6} \qquad \text{Where } \mathrm{M} \geq 25 \text{ and } \mathrm{N} < \mathrm{M}. \qquad (5)$$

4 Results and Discussion

The present work is performed using MATLAB (R2016) software to denoise the CGM signal. The experimentation is performed on continuous glucose monitoring signal in order to verify the application of adaptive SG filter. The CGM signal is simulated using GLUCO SIM simulator [13] and the signal obtained is shown in Fig. 9. White Gaussian noise (WGN) of 10 dB SNR is added to the CGM signal. The noisy CGM signals is filtered with intelligent SGF. The filter parameters i.e. N (order of fitting polynomial) and M (length of frame) are tuned using GA and PSO leading to GA-SGF and PSO-SGF filters.

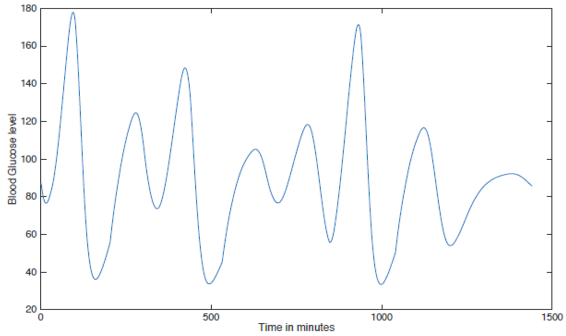

Fig. 9. CGM signal obtained from GlucoSim

The objective function under consideration is aggregation of maximum SNR and minimum distortion. Fig. 10 shows the GA-SGF filtered and noisy CGM signal. Convergence plot of GA is shown in Fig. 11. GA-SGF filter shows convergence in almost 50 iterations. Fig. 12 shows the magnitude response of GA-SGF filter output.

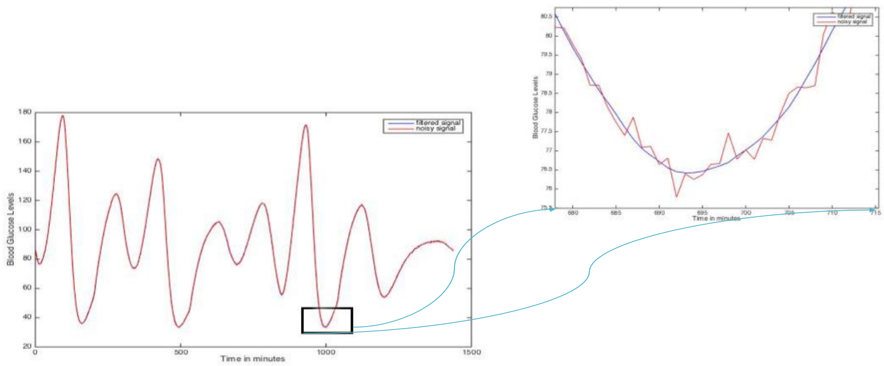

Fig. 10. Plot of filtered and noisy CGM signal using GA-SGF

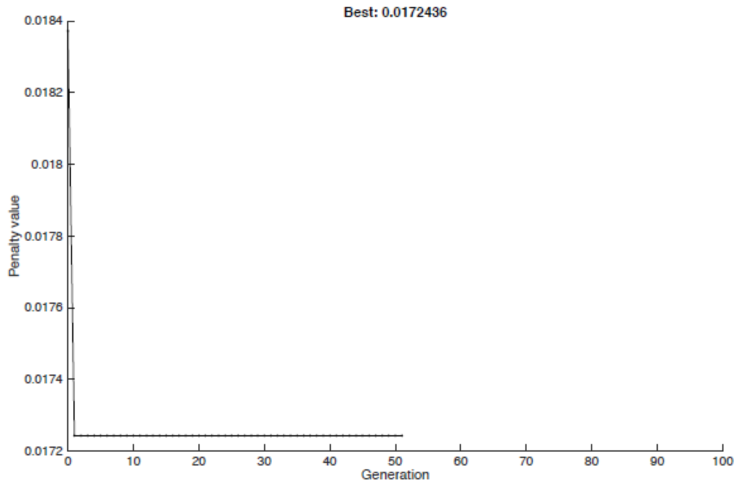

Fig. 11. Convergence curve of GA-SGF

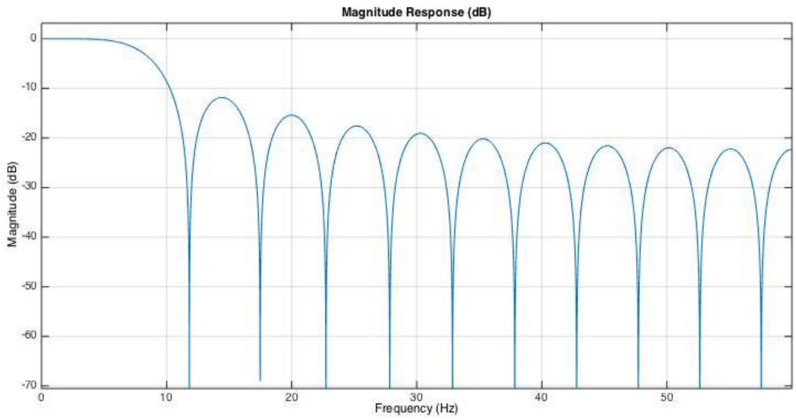

Fig. 12. Magnitude Response of GA-SGF

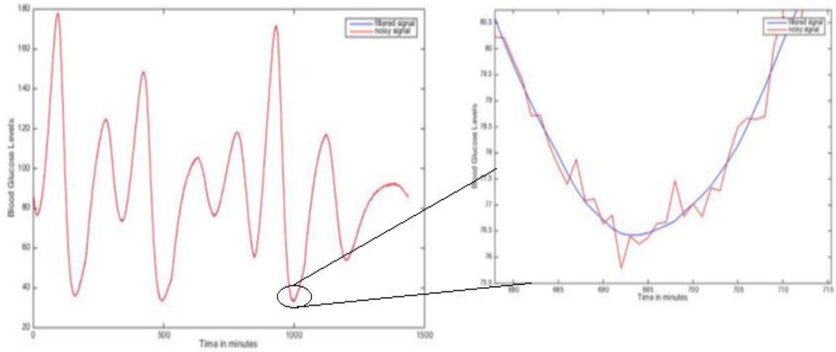

Fig. 13. Filtered and noisy signal using PSO-SGF

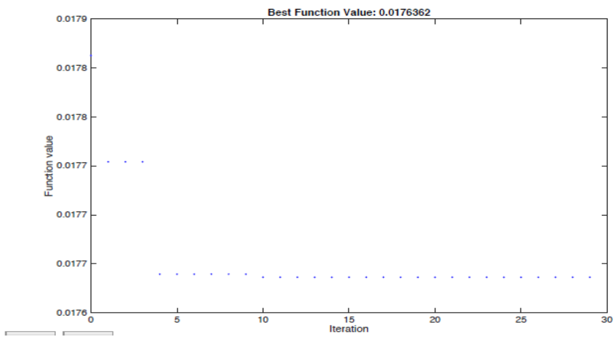

Fig. 14. Convergence curve of PSO-SGF

Fig. 13 shows the plot of filtered and noisy CGM signal using PSO-SGF filter. Fig. 14 and 15 show the convergence and magnitude plot of PSO-SGF filter. It is observed that PSO converges in almost 29 iterations and thus takes lesser time in designing the SGF filter. The parameters of the output obtained by the two algorithms are recorded in Table 1.

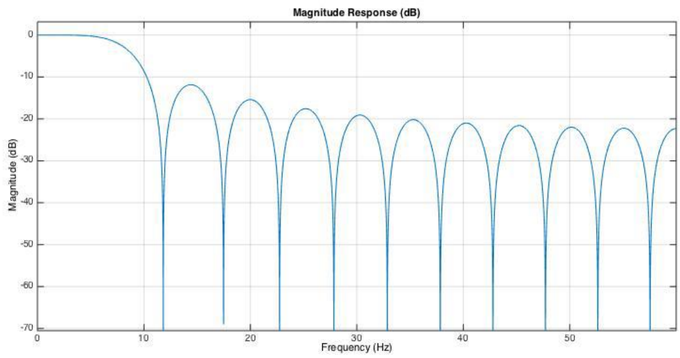

Fig. 15. Magnitude response using PSO-SGF

Table 1. Comparative results of GA-SGF and PSO-SGF filters.

Output	Noise-added Signal	Filter Optimised GA	Filter Optimised PSO
SNR	49.6263	50.3260	50.3260
MSE	0.0969	0.0175	0.0175
Order of filter(k)	NA	5.00	5.0000
Length of frame	NA	25.0000	25.0000
Minimum Number of iterations	NA	51	29

It is observed from the Table 1 that SNR and MSE of GA-SGF and PSO-SGF filters are same, whereas PSO tunes SGF filter in 29 iterations which is quite less as compared to GA tuned SGF. In PSO the ‘best’ particle guides the others and does not utilize genetic operators such as crossover and mutation therefore it provides better results for this application. Another advantage of PSO is that it is easy to implement and there are few parameters to adjust as compared to GA.

5 Conclusion:

This work investigates the filtering ability of adaptive SG filter for denoising CGM signal. In conclusion, since the filter parameters are dependent on the sampling frequency and the cut off frequency of the signal, and are generally calculated using hit and trial method which is a very tedious and time consuming task. As these parameters need to be calculated repeatedly for changes in sampling frequency or cut off frequency, therefore an adaptive SG filter is employed to solve this issue. In this work, GA and PSO are utilized for the optimization of filter parameters. The results indicate that computation time of PSO is lesser as compared to GA optimized filter. GA and PSO algorithms are used for automatic selection of parameters of the Intelligent SG filter, with the help of the set objectives. Results reveal a good magnitude response of designed filters and MSE is also reduced which indicates that signal distortion is less. Thus is it is concluded that PSO-SGF filter provides a better solution for denoising CGM signals with variable sampling or cut off frequency.

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