Method for QRS Complex Detection by RLS

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Abstract: *An original technique for QRS complex detection of electrocardiogram signals, by atom swarm optimization (PSO)-AF Savitzky–Golay filter, is used to make the feature. A useful detection algorithm, containing search-backs for missed peaks, is also proposed. In the experiment, AF-RLS, achieves the best results with sensitivity, positive productivity and detection error rate of 99.75, 99.83 and 0.42%, in that order. Usefulness of the proposed method is validating by comparing fidelity parameter of the proposed method with state-of-the-art methods.*

Index Terms *- RLS, Adaptive filtering, QRS, PSO.*

I. Introduction

In this paper, a novel combination of particle swarm optimization (PSO) algorithm with AF (PSO-AF), for QRS complex detection, is proposed. In this PSO-AF combination, used for QRS feature generation, gives the benefit of system adaptation to incoming signal variations and PSO algorithm, used for coefficients' adaptation process, offers the advantage of fast convergence and accurate optimization[1]-[3]. The AF, in its linear-prediction model, is used. The proposed method is data-independent, as it does not require any data-dependent parameter initialization [4]. Utilization of PSO algorithm concept with AF, for QRS detection application, is the state-of-the-art presented in this paper.

The k-means method and the many variants and additions of it had been used for classification, data clustering, and VQ codebook design since the introduction several decades ago. In k-means a set of class centers, called a codebook, which here corresponds to the dictionary, is learned from a larger set of training data [5-7]. The k-means variants may be divided into two main classes, batch and continuous, depending on how often the codebook is updated. The batch-methods, i.e., the (generalized) Lloyd algorithm (GLA) which is also known as the Linde Buzo-Gray (LBG) algorithm, update the codebook only after (re)-classification of all the training vectors in the training set [8]–[10]. The continuous method, the Macqueen variant [19], updates the codebook after classification of each training vector. Both variants have been widely referred, cited, refined, analyzed and used, but the GLA is perhaps easier to understand and analyze and thus has been more used. The reference to k-means is highly relevant when explaining how the new method, RLS-DLA, relates to other methods, especially ILS-DLA. In short: As ILS-DLA reduces to the batch variant of k-means when used for VQ codebook design, RLS-DLA reduces to the continuous variant of k-means [11].

In the rest of this paper, a direct approach for simultaneous estimation of mass and time-varying grade is pursued. We first formulate vehicle longitudinal dynamics and explain experimental setups and validation of the longitudinal model. We then investigate the implementation of a recursive least square (RLS) method for simultaneous online mass and grade estimation. We briefly discuss the recursive least square scheme for time-varying parameters and review some key papers that address the subject. The difficulty of the traditional RLS with single forgetting is discussed next. For estimation of multiple parameters that vary with different rates, RLS with vector-type forgetting is previously proposed in a few papers. We analyze this approach and propose an ad hoc modification of the updated law for the gain in the RLS scheme. Although we could not prove the algorithm convergence nor define a region of convergence for the algorithm, we demonstrate, with both simulated and test data that incorporating two distinct forgetting factors is effective in resolving the difficulties in estimating mass and time-varying grade. The experimental setup and particular issues with experimental data are also discussed [12-14].

II. Existing Methods

An adaptive filter is a system with a linear filter that has a transfer function controlled by variable parameters and a means to adjust those parameters according to an optimization algorithm. Because of the complexity of the optimization algorithms, almost all adaptive filters are digital filters. Adaptive filters are required for some applications because some parameters of the desired processing operation (for instance, the locations of reflective surfaces in a reverberant space) are not known in advance or are changing. The closed-loop adaptive filter uses feedback in the form of an error signal to refine its transfer function [13-15].

Generally speaking, the closed loop adaptive process involves the use of a cost function, which is a criterion for optimum performance of the filter, to feed an algorithm, which determines how to modify filter transfer function to minimize the cost on the next iteration. The most common cost function is the mean square of the error signal [13-16].

As the power of digital signal processors has increased, adaptive filters have become much more common and are now routinely used in devices such as mobile phones and other communication devices, camcorders and digital cameras, and medical monitoring equipment.

Block diagram

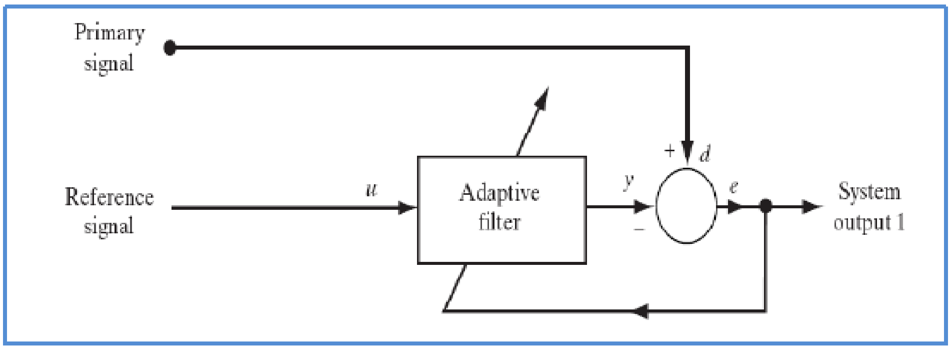


Figure 1: Adaptive filter

Savitzky–Golay filters:

A Savitzky–Golay filter is a digital filter that can be applied to a set of digital data points for the purpose of smoothing the data, that is, to increase the signal-to-noise ratio without significantly distorting the signal. This is achieved, in a process known as convolution, by fitting successive sub-sets of adjacent data points with a low-degree polynomial by the method of linear least squares. When the data points are equally spaced, an analytical solution to the least-squares equations can be found, in the form of a single set of "convolution coefficients" that can be applied to all data subsets, to give estimates of the smoothed signal, (or derivatives of the smoothed signal) at the central point of each sub-set. The method, based on established mathematical procedures, was popularized by Abraham Savitzky and Marcel J. E. Golay who published tables of convolution coefficients for various polynomials and sub-set sizes in 1964. Some errors in the tables have been corrected. The method has been extended for the treatment of 2- and 3-dimensional data.

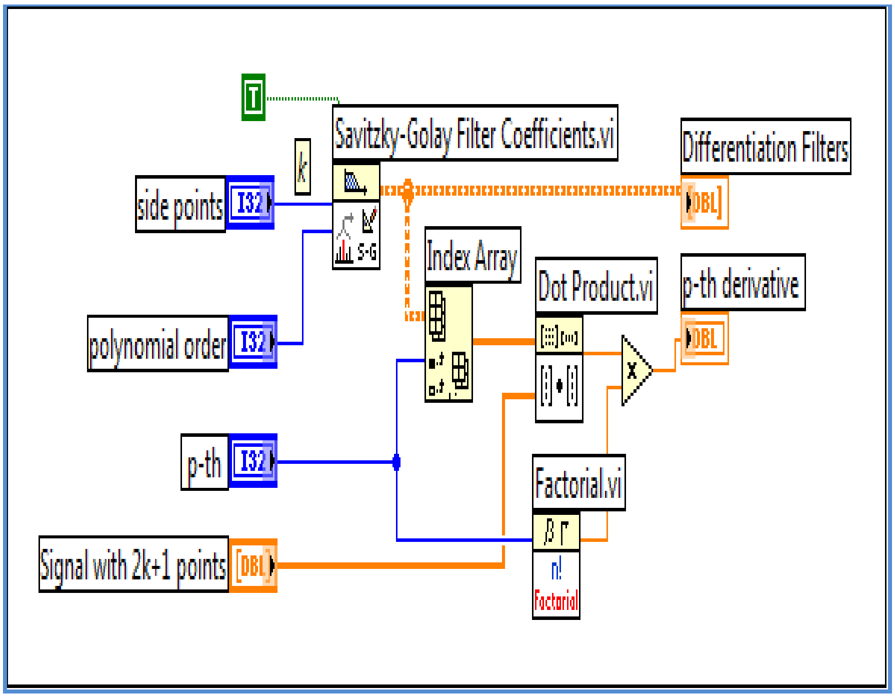


Figure 2: Block diagram of Savitzky–Golay filter

Savitzky and Golay's paper is one of the most widely cited papers in the journal *Analytical Chemistry* and is classed by that journal as one of its "10 seminal papers" saying "it can be argued that the dawn of the computer-controlled analytical instrument can be traced to this article."

III. PROPOSED METHOD

RLS:

The Recursive least squares (RLS) is an adaptive filter which recursively finds the coefficients that minimize a weighted linear least squares cost function relating to the input signals. This is in contrast to other algorithms such as the least mean squares (LMS) that aim to reduce the mean square error. In the derivation of the RLS, the input signals are considered deterministic, while for the LMS and similar algorithm they are considered stochastic. Compared to most of its competitors, the RLS exhibits extremely fast convergence. However, this benefit comes at the cost of high computational complexity.

Algorithm

1. Calculates the output signal y (n) of the adaptive filter.
2. Calculates the error signal $e(n)$ by using the following equation: $e(n) = d(n) – y(n)$.
3. Updates the filter coefficients by using the following equation:

   $\vec{W}(N+1) = \vec{W}(n) + e(n).\vec{K}(n)$

   Where $\vec{W}$ is the filter coefficients vector and $\vec{K}(n)$ is the gain vector. $\vec{K}(n)$ is defined by the following equation:

   $$\vec{K}(n) = \frac{P(n).\vec{U}(n)}{\lambda + \vec{U}(n).P(n).\vec{U}(n)}$$

   Where λ is the forgetting factor and $P(n)$ is the inverse correlation matrix of the input signal. Refer to the book Adaptive Filter Theory for more information about the inverse correlation matrix.

   $P(n)$ has the following initial value $P(0)$:

   $$P(0) = \begin{bmatrix} \delta^{-1} & \cdots & 0 \\ \vdots & \ddots\ \delta^{-1} & \vdots \\ \cdots & 0 & \delta^{-1} \end{bmatrix}$$

   Where δ is the regularization factor. The standard RLS algorithm uses the following equation to update this inverse correlation matrix.

   $P(n+1) = \lambda^{-1}P(n) - \lambda^{-1}\vec{K}(n).U^{-T}(N).P(n)$

IV. RESULTS

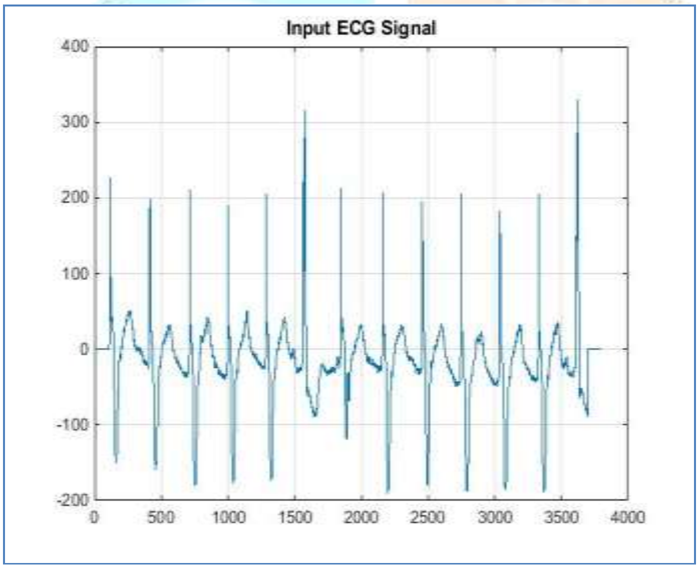


Figure 3: Input ECG Signal

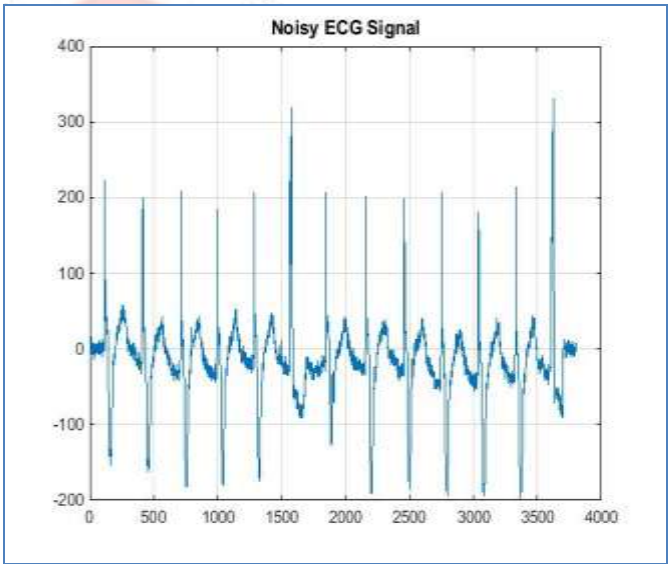
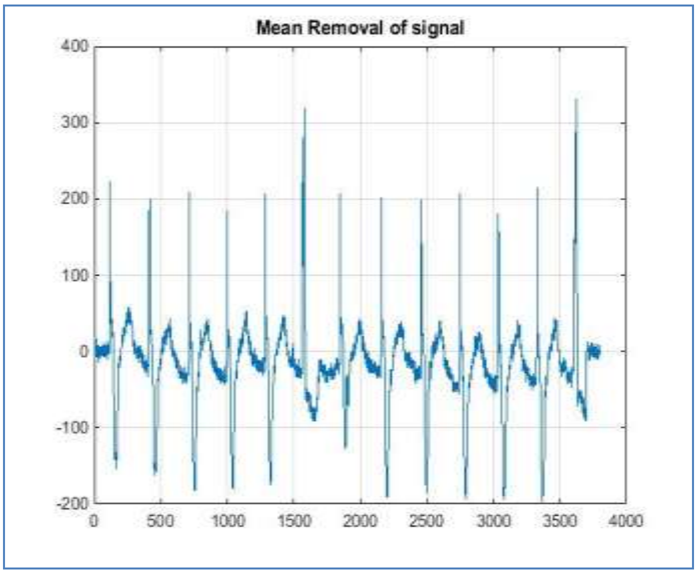


Figure 4: Noisy ECG Signal



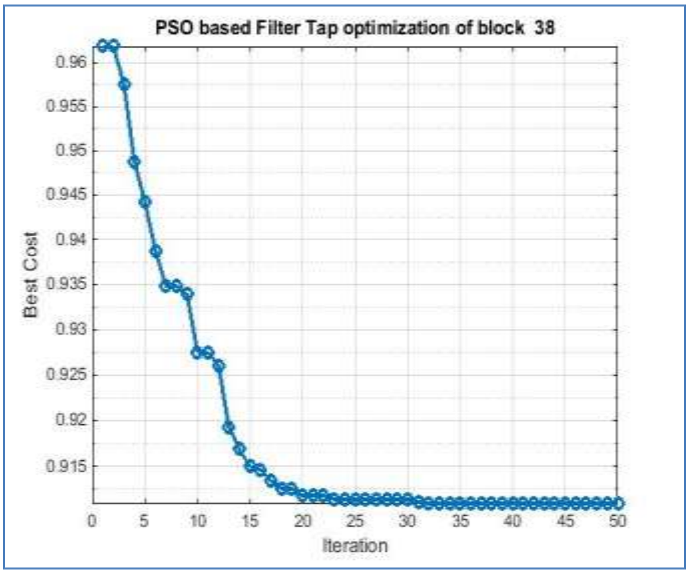
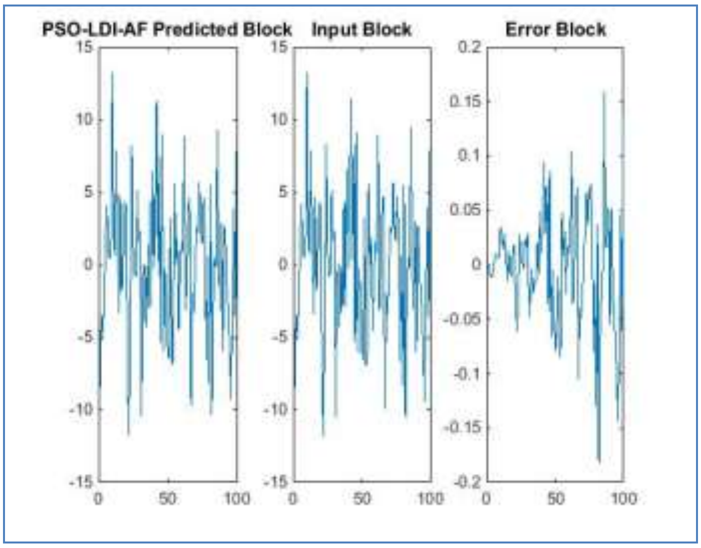


Figure 5: Mean Removal of Signal   Figure 6: PSO based Filter Tap Optimization of block 38



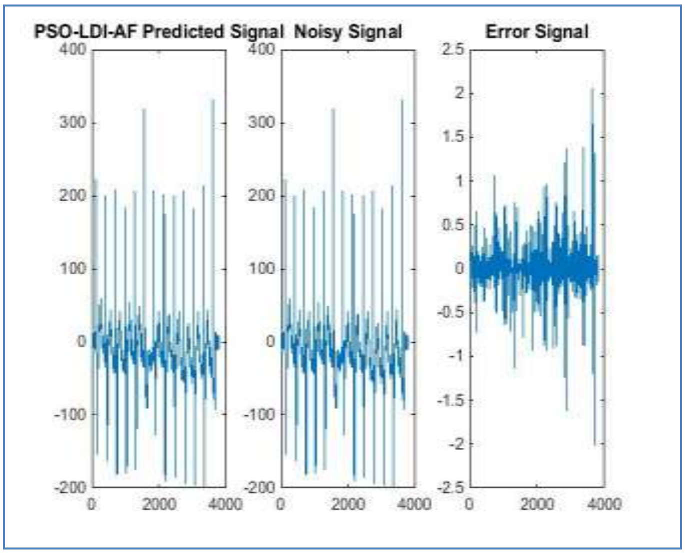
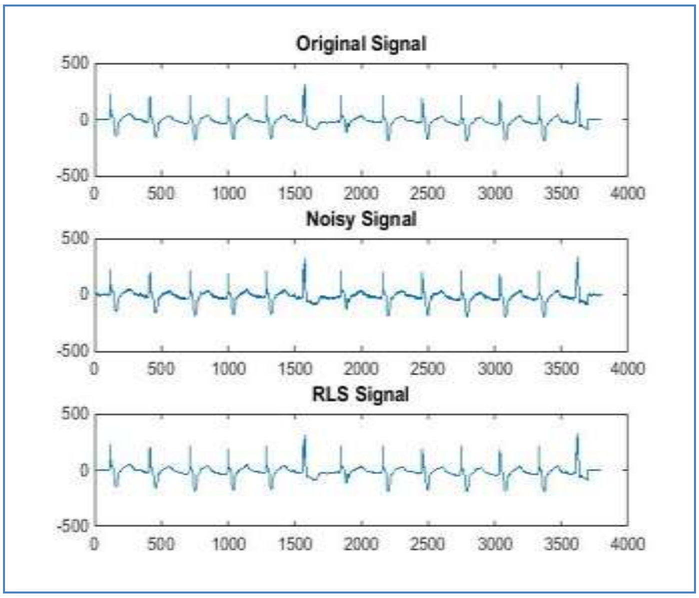


Figure 7: PSO-LDI-AF P, Input, Error block   Figure 8: PSO-LDI-AF P, Noisy, Error signal



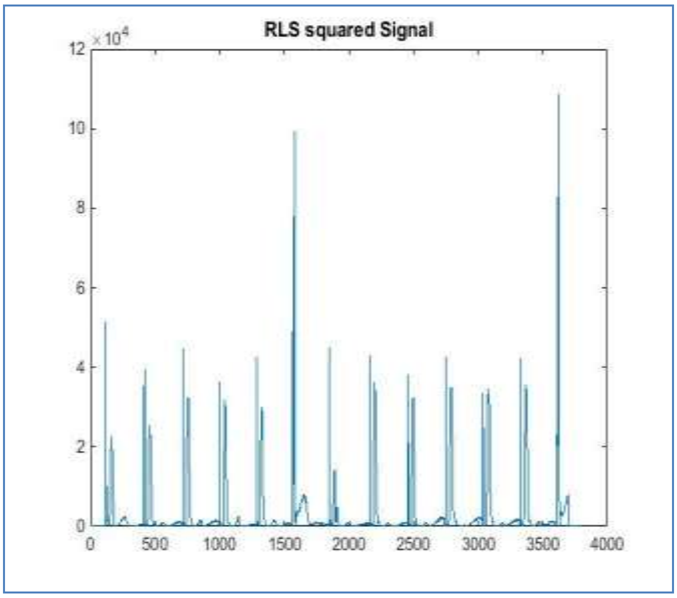
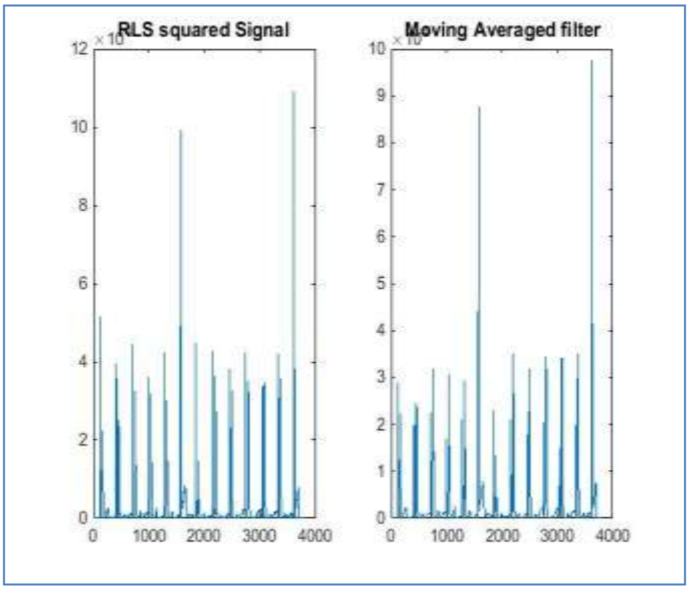


Figure 9: Original, Noisy, RLS Signal   Figure 10: RLS Squared Signal



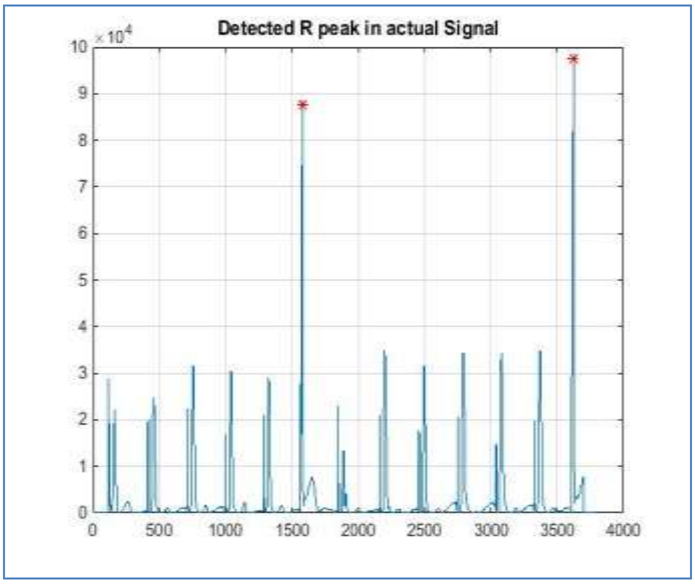


Figure 11: Moving Average Filtered Signal   Figure 12: Detected R Peak In Actual Signal

Sensitivity: 99.9221%
Positive productivity: 100.000%
Average productivity: 99.9606%
Total detection error: 0.0789%
Total process time: 0.2816seconds

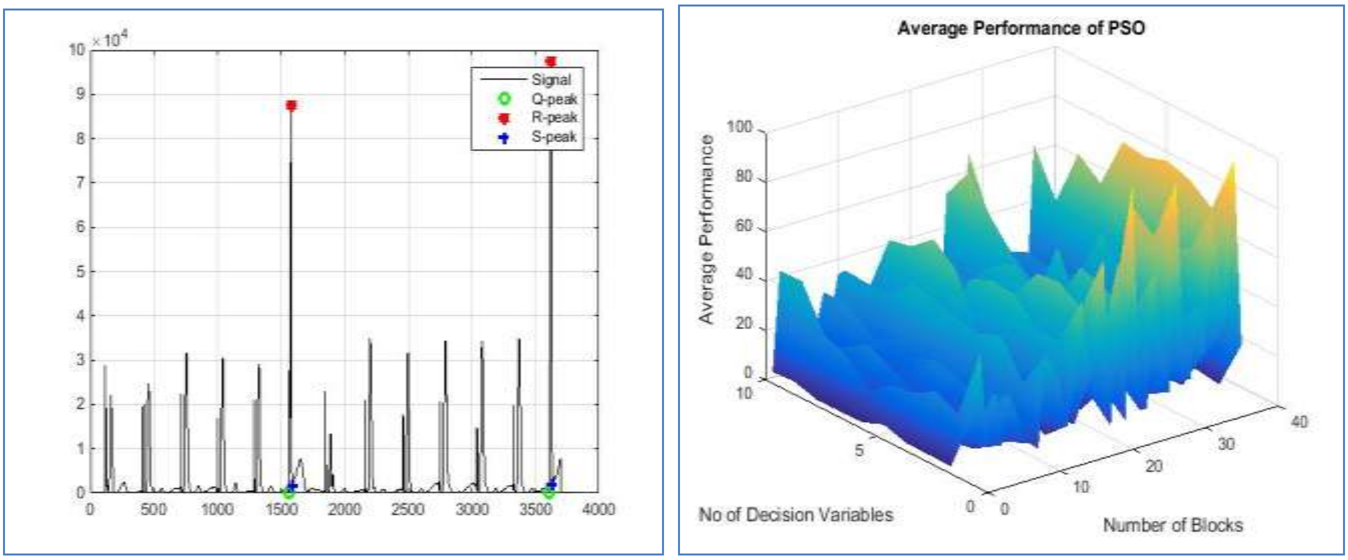


Figure 13: Average Performance of PSO

Table 1. comparison between Savitzky–Golay filters and Recursive least square

S.No	Savitzky–Golay filters	Recursive least squares
1	Linear least squares	least mean squares (LMS)
2	Generate the smoothed signal	Reduce mean square errors

V. CONCLUSION

An original technique for QRS complex detection of electrocardiogram signals, by atom swarm optimization (PSO) -AF Savitzky–Golay filter, is used to make the feature. A useful detection algorithm, containing search-backs for missed peaks, is also proposed. In the experiment, AF-RLS, achieves the best results with sensitivity, positive productivity and detection error rate of 99.75, 99.83 and 0.42%, in that order. Usefulness of the proposed method is validating by comparing fidelity parameter of the proposed method with state-of-the-art methods.

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