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RLS Filter Optimization for Non-Invasive Fetal Electrocardiogram Extraction Using the PSO Algorithm

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Abstract: Non-invasive fetal electrocardiogram (fECG) extraction is still a challenging task due to the overbearing preponderance of the maternal ECG (mECG) and the presence of noise and interferences. Adaptive filtering techniques, particularly the Recursive Least Squares (RLS) algorithm, have been shown to work well for this issue. However, RLS performance largely depends on a few of its parameters (filter order, forgetting factor, and regularization term), typically tuned empirically, thus limiting robustness and generalizability. In this work, we introduce an automatic parameter optimization process based on the Particle Swarm Optimization (PSO) algorithm. The proposed method was validated using simulated signals generated on MATLAB, including abdominal recordings (aECG), maternal thoracic signals (mECG), and a reference fECG for comparison. Quantitative outcomes, using Mean Squared Error (MSE) and Signal-to-Noise Ratio (SNR) metrics, indicate that PSO-based optimization improves the quality of the resultant fECG compared to the optimal empirical settings, eliminating residual maternal interference. These findings show the potential of PSO for robust fECG extraction and its potential feasibility for real clinical data in the future.

Keywords: Non-invasive fECG extraction, Adaptive filtering, RLS, Optimization, PSO algorithm

Introduction

Prenatal monitoring increasingly relies on non-invasive methods of estimation of fetal health and development (Behar, 2016; Sameni, 2007). Among them, fetal electrocardiogram (fECG) analysis represents an essential component, since it provides valuable information concerning the cardiac activity and aids in the earliest possible diagnosis of rhythmical or structural pathologies. However, extracting fECG from abdominal electrodes remains an arduous task owing to the overwhelming dominance of maternal ECG (mECG), noise, and physiological interferences (Vennila, 2014; Clifford, 2006; Sweeney, 2012).

Among the suggested methods, adaptive filters are proving to be an effective solution, with the Recursive Least Squares (RLS) algorithm being particularly attractive because of its high convergence speed and resilience to non-stationary signals (Haykin, 1991; Widrow, 1985). Nevertheless, RLS performance is based on several key parameters (filter order, forgetting factor, regularization term), whose tuning is usually performed empirically, hence decreasing the method's performance and viability (Ciochina, 2009). To address this issue, metaheuristic optimization techniques provide a viable alternative since they automatically perform the parameter selection and explore the space in a better way. Particle Swarm Optimization (PSO), inspired by the collective behavior of bird flocks or schools of fish, is particularly well suited to this task (Eberhart, 2000; Ekanem, 2025; Kennedy, 2002; Poli, 2007; Mendes, 2004; Talbi, 2009).

Here, we propose the application of PSO to automatically optimize the RLS filter parameters for fECG extraction from MATLAB-generated simulated signals. The objective is to compare the performance obtained through automatic optimization to that achieved by using empirical parameter values based on quantitative metrics such as the MSE and SNR to determine the added value of PSO in the process. The rest of this paper is organized in the following manner: Section 2 presents the proposed methodology, starting with the fundamentals of the RLS filter and its PSO optimization. Section 3 describes simulations and results generated on test signals. Finally, Section 4 concludes the paper and offers outlooks for future work.

Methodology

RLS Adaptive Filter

Figure 1 depicts the representation of fECG extraction using RLS adaptive filter.

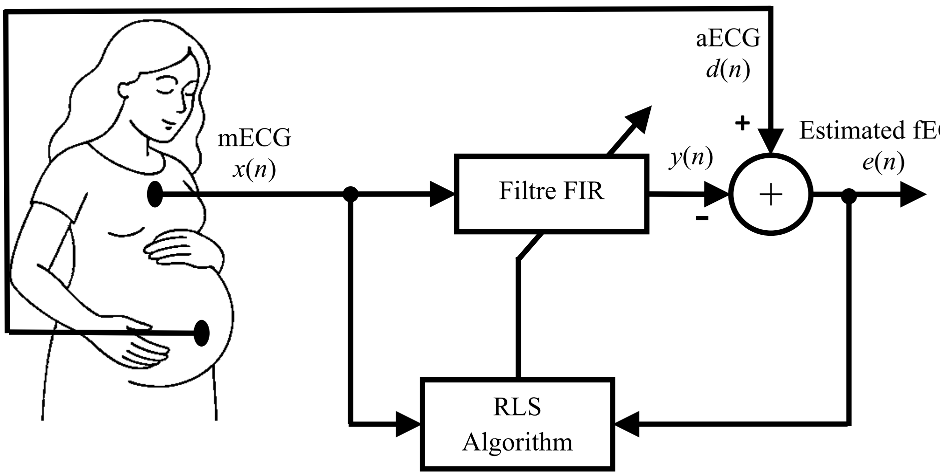

Figure 1. General representation of fetal ECG extraction using adaptive filter.

The process is founded on the use of the maternal thoracic ECG (mECG), denoted by x(n), as the reference signal (filter input) and the abdominal ECG (aECG), denoted by d(n), as the desired output. The goal of the filter is to estimate the maternal component contained in the abdominal signal and then subtract it to arrive at the fetal component (D, 2022) (Andreotti, 2014) (Niknazar, 2013). Among various adaptive filtering algorithms, the Recursive Least Squares (RLS) algorithm is well known for its fast convergence, and it can adapt to change in the signal (Ciochina, 2009) (Kahankova, 2017). Mathematically, for a vectorized input at instant *n*:

$$\mathbf{x}(n) = \left[x(n)\ x(n-1)\ ...\ x(n-M+1)\right]^T \tag{1}$$

For the filter coefficients vector at instant *n*:

$$\mathbf{w}(n) = \left[w_0(n)\ w_1(n)\ ...\ w_{M-1}(n)\right]^T \tag{2}$$

Where *M* is the filter order.

The RLS algorithm updates the coefficient vector by minimizing the squared error:

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

$$e(n) = d(n) - \mathbf{w}^T(n-1)\mathbf{x}(n) \tag{4}$$

Table 1 summarizes the RLS algorithm:

Table 1. Summary of the RLS algorithm.

Parameters:	M= filter order. λ= forgetting factor. δ= positive constant.
Initialization:	$\mathbf{w}(0) = \mathbf{0}_{M\times 1}$ $\mathbf{Q}(0) = \delta^{-1}\mathbf{I}$
Computing:	For: $n=0,1,2,\ldots,N-1$ $\mathbf{k}(n) = \dfrac{\lambda^{-1}\mathbf{Q}(n-1)\mathbf{x}(n)}{1+\lambda^{-1}\mathbf{x}^{T}(n)\mathbf{Q}(n-1)\mathbf{x}(n)}$ $e(n) = d(n) - \mathbf{x}^{T}(n)\mathbf{w}(n-1)$ $\mathbf{w}(n) = \mathbf{w}(n-1) + \mathbf{k}(n)e(n)$ $\mathbf{Q}(n) = \lambda^{-1}\mathbf{Q}(n-1) - \lambda^{-1}\mathbf{k}(n)\mathbf{x}^{T}(n)\mathbf{Q}(n-1)$

Where:
- λ is the forgetting factor ($0<\lambda\leq 1$),
- $Q(n)$ is the inverse correlation matrix (initialized with δI),
- δ is a regularization parameter.

It is important to select properly λ, M, and δ, as they a direct impact on the convergence rate, the numerical stability, and the quality of the extracted fECG. This calls for an optimization algorithm to adjust these parameters.

Optimization Using PSO

The Particle Swarm Optimization (PSO) algorithm is a metaheuristic technique inspired by the social behavior of flocking birds and schooling fish. Each candidate solution, called a particle, explores the RLS filter parameter space by flying according to its own experience and the experience of neighboring particles (Ekanem, 2025; Poli, 2007). In our study, the RLS filter parameters define the search vector:

- λ (forgetting factor),
- M (filter order),
- δ (regularization factor).

Each particle evaluates the quality of its position using a cost function based on the Mean Squared Error (MSE) between the extracted fetal signal and the reference signal. The optimization process thus aims to minimize this MSE.

The interest of PSO is twofold:
1. To automate the selection of RLS parameters, which are often empirically determined.
2. To improve the robustness and accuracy of fECG extraction by allowing adaptation to variations in real signals.

PSO Algorithm for RLS Parameter Optimization

1. **Initialization**
   - Randomly generate a set of particles with parameters (λ, M, δ).
   - Initialize velocities and define the search boundaries.
2. **Evaluation**
   - For each particle, apply the RLS with its parameters.
   - Compute the cost function:
     $J = MSE\left(fECG_{extracted}, fECG_{real}\right)$
3. **Update of Best Solutions**

- Update the personal best position (pBest).
- Update the global best position (gBest).

4. **Update of Velocities and Positions**

$$v_i \leftarrow w.v_i + c_1 r_1 \left(pBest_i - x_i \right) + c_2 r_2 \left(gBest_i - x_i \right)$$

$$x_i \leftarrow x_i + v_i$$

5. **Iteration**
   - Repeat steps 2 to 4 until the maximum number of iterations is reached or convergence is achieved.
6. **Output**

   The optimal parameters (λ^*, M^*, δ^*) are provided by *gBest*.

Results and Discussion

The proposed method is tested on these generated synthetic signals. First, three distinct signals were generated in MATLAB:

- an abdominal signal simulating the mixture of maternal ECG and fetal ECG,
- a thoracic signal representing only the maternal ECG,
- a reference fetal signal used to evaluate the extraction quality.

These signals constitute the testing environment employed for the evaluation of the method. Figure 2 illustrates an example of the synthetic signals used in our simulations.

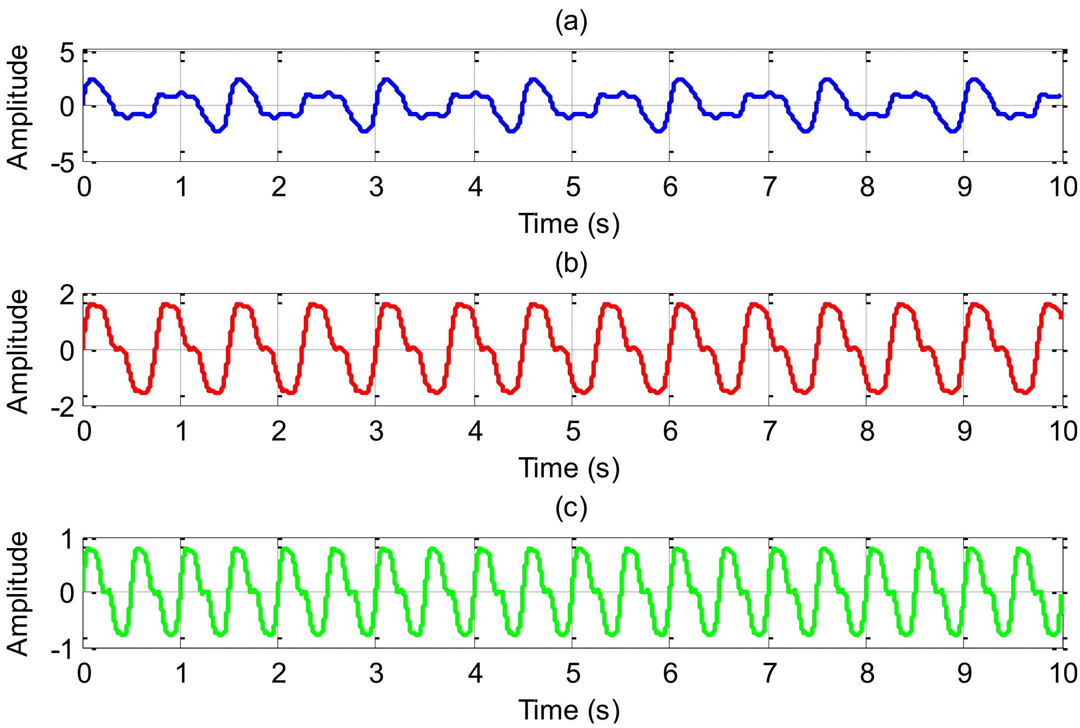

Figure 2. Signals used in the simulation. (a) abdominal signal, (b) thoracic signal, (c) reference fECG signal.

The performance of the RLS filter was first evaluated using empirically chosen parameters, and then with parameters optimized by PSO. The comparison was carried out using the Mean Squared Error (MSE) between the extracted fetal signal and the reference fetal signal, as well as the Signal-to-Noise Ratio (SNR), calculated as follows:

$$MSE = \frac{1}{N} \sum_{n=1}^{N} \left(fECG(n) - f\hat{ECG}(n) \right)^2 \tag{5}$$

$$SNR(dB) = 10\log_{10}\left(\frac{\sum_{n=1}^{N} fECG(n)^2}{\sum_{n=1}^{N}\left(fECG(n) - f\widehat{ECG}(n)\right)^2}\right) \tag{6}$$

With $fECG$ denoting the reference fetal signal and $f\widehat{ECG}$ the extracted fetal signal.

Table 2 summarizes the results obtained using empirical selections of the RLS filter parameters (12 empirical combinations from c1 to c12) and the result obtained with optimal parameters achieved through the PSO method.

Table 2. Comparison between 12 empirical configurations and PSO-based optimization.

Parameters selection	***M***	***λ***	***δ***	***MSE***	***SNR***
Empiric c1	16	0,9997	0,1	0.001855	18.48
Empiric c2	16	0,9997	0,5	0.001455	18.83
Empiric c3	16	0,9997	0,7	0.001457	18.81
Empiric c4	16	0,9999	0,1	0.000426	20.12
Empiric c5	16	0,9999	0,5	0.000424	20.06
Empiric c6	**16**	**0,9999**	**0,7**	**0.000423**	**20.04**
Empiric c7	32	0,9997	0,1	**33.29**	**-20.13**
Empiric c8	32	0,9997	0,5	0.001301	19.09
Empiric c9	32	0,9997	0,7	0.001314	19.07
Empiric c10	32	0,9999	0,1	0.000416	20.21
Empiric c11	**32**	**0,9999**	**0,5**	**0.000413**	**20.21**
Empiric c12	32	0,9999	0,7	0.000413	20.20
Optimized PSO	**32**	**1**	**1**	**0.000255**	**20.42**

The obtained results show that PSO-based optimization significantly improves the quality of the extracted signal by reducing the residual maternal component and enhancing the visibility of the fetal peaks.Figure 3 depicts the convergence curve of PSO compared to those of the empirical combinations c1, c6, and c11, which provide the best MSE/SNR trade-offs, as well as combination c7, which exhibits filter divergence.

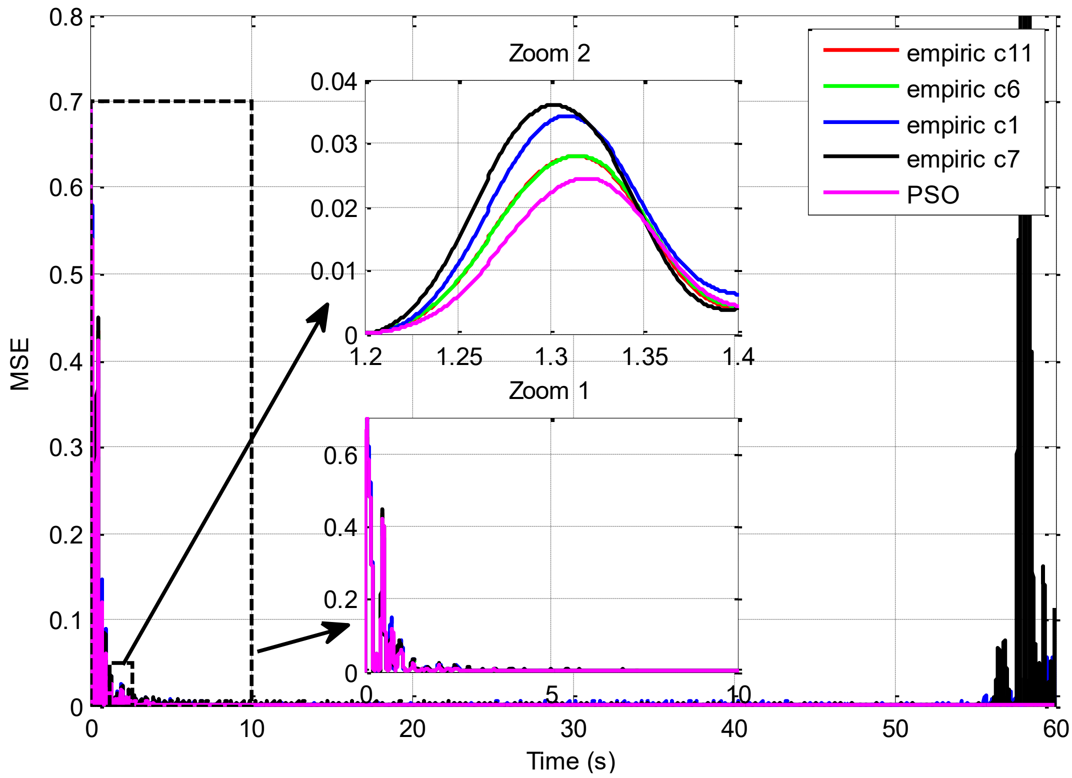

Figure 3. Convergence curve of PSO compared with empirical configurations.

Figure 4 illustration of the real fECG signal and the extracted signals obtained using the best empirical configuration and the PSO-based configuration.

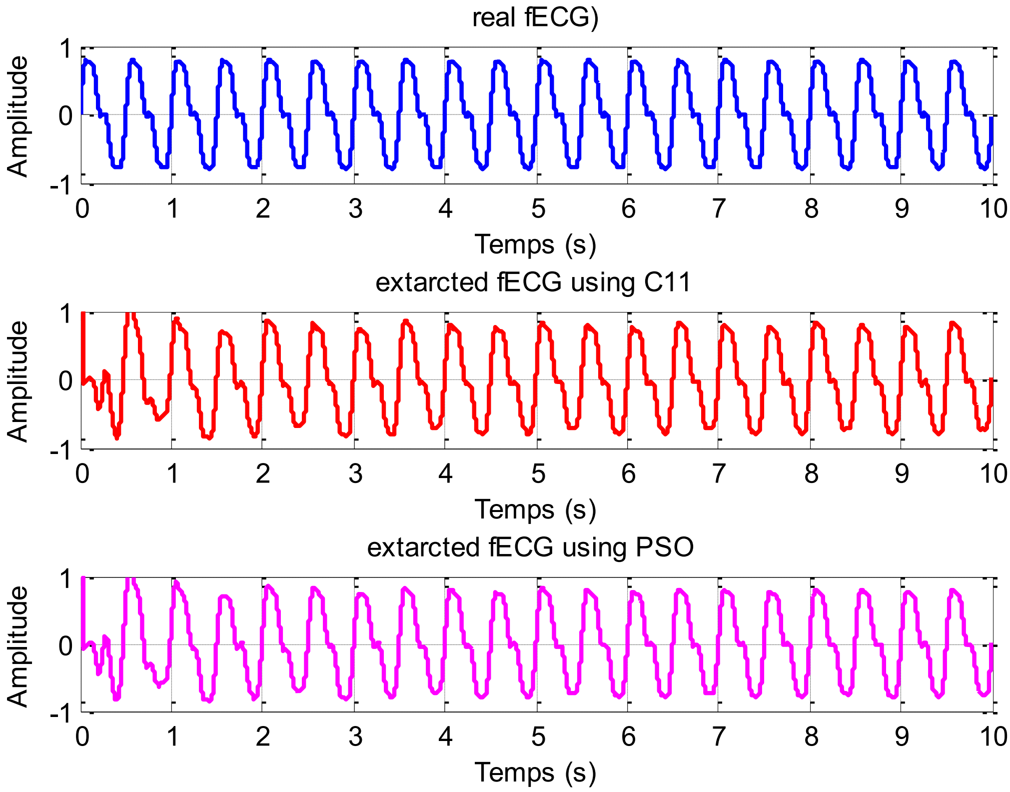

Figure 4. Real fECG and extracted signals obtained with both methods

The findings identify the constraint of an empirical choice of RLS filter parameters against a systematic one with the use of the PSO algorithm. Among the 12 hand-trial configurations, the best one is configuration C11, which provides an acceptable trade-off between MSE and SNR. Still, its performance cannot compete with that obtained by PSO, which can automatically identify a set of parameters with a significant MSE reduction and improvement in SNR. The curve of convergence also demonstrates the ability of PSO in achieving an optimal solution in a robust and effective manner, while empirical parameters depict more dispersed and sometimes weaker plots. Whereas PSO optimization did the best overall, it must be noted that empirical configuration C11 also produced results very close. This similarity may be explained by the fact that several parameter combinations were manually tested before arriving at C11, thereby narrowing the gap with the optimized solution. These findings confirm the relevance of integrating a metaheuristic optimization method such as PSO for tuning adaptive filter parameters in the context of fECG extraction.

Conclusion

In this work, we investigated the extraction of the fetal electrocardiogram (fECG) using an adaptive Recursive Least Squares (RLS) filter. After evaluating several empirical configurations, we introduced an automatic parameter optimization of the filter based on the Particle Swarm Optimization (PSO) algorithm. The results demonstrated that PSO improves the extraction quality by reducing the mean squared error (MSE) and increasing the signal-to-noise ratio (SNR), compared to manual parameter tuning, while providing a systematic parameterization procedure.

As future perspectives, it would be of great interest to apply this approach to real signals from clinical databases in order to confirm its robustness under practical conditions. In addition, other metaheuristic optimization methods (such as Genetic Algorithms or Ant Colony Optimization) could be explored and compared with PSO. Finally, the integration of clinically relevant criteria, beyond MSE and SNR, would represent a step forward toward more comprehensive medical validation.

Scientific Ethics Declaration

* The author declares that the scientific ethical and legal responsibility of this article published in EPSTEM journal belongs to the author.

Conflict of Interest

* The authors declare that they have no conflicts of interest

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