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A Software Tool for ECG Denoising with Adaptive Filtering

Uyarlamalı Filtrelemeyle EKG Gürültü Temizleme için Yazılım Aracı

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Abstract

The electrocardiogram (ECG) is a biomedical signal used to check heart functions and diagnose some diseases. In order for these assessing to be made correctly, the relevant signals must be well cleared of noise. Many methods have been developed for this purpose. In this study we designed a new software tool by collecting many adaptive algorithms for ECG denoising. This tool was developed with a user-friendly graphical interface and comprises the loading of signals, their preprocessing, visualization, and single or comparative denoising. Some of the strengths and different aspects of the developed tool are that it contains many adaptive algorithms, can add different noise types with specified characteristics to the signals, can perform single or comparative denoising operations, can calculate and present many evaluation parameters, can recommend the most successful method in comparative analysis, and shows detailed spectrums of signals. Additionally, this tool provides detailed theoretical information about adaptive algorithms, noises and denoising processing. With its rich content, it is also useful in education of adaptive algorithms in denoising processes.

Keywords: *ECG Denoising, Adaptive Filtering, Software Tool*

Öz

Elektrokardiyogram (EKG), kalp fonksiyonlarını kontrol etmek ve bazı hastalıkları teşhis etmek için kullanılan biyomedikal bir sinyaldir. Değerlendirmelerin doğru bir şekilde yapılabilmesi için ilgili sinyallerin gürültüden iyi bir şekilde arındırılmış olması gerekir. Bu amaçla birçok yöntem geliştirilmiştir. Gerçekleştirilen çalışmada, EKG gürültü temizleme için birçok uyarlamalı algoritmayı bir araya getirerek yeni bir yazılım aracı tasarlanmıştır. Kullanıcı dostu grafiksel bir arayüze sahip bu araç, sinyal yükleme, ön işleme, görselleştirme ve tek veya karşılaştırmalı gürültü temizleme işlemlerini içermektedir. Geliştirilen aracın bazı güçlü ve farklı yönleri, birçok uyarlanabilir algoritma içermesi, sinyallere belirtilen özelliklere sahip farklı gürültü türleri ekleyebilmesi, tek veya karşılaştırmalı gürültü temizleme işlemleri gerçekleştirebilmesi, birçok değerlendirme parametresini hesaplayıp sunabilmesi, karşılaştırmalı analizde en başarılı yöntemi önerebilmesi ve sinyallerin ayrıntılı spektrumlarını göstermesidir. Ayrıca, bu araç uyarlamalı algoritmalar, gürültüler ve gürültü temizleme işlemleri hakkında ayrıntılı teorik bilgiler de sağlamaktadır. Bunun yanında zengin içeriğiyle, gürültü temizleme süreçlerinde uyarlanabilir algoritmaların eğitiminde de faydalıdır.

Anahtar Kelimeler: *EKG Gürültü Temizleme, Uyarlamalı Filtreleme, Yazılım Aracı*

1. Introduction

Biomedical signals contain a lot of information about organs. One of the most important of these is ECG signals. However, different noise types are contaminated to the ECG signal measurements and cause its misrepresentation. There are mainly four types of noises/artifacts that have dominant characteristics and distort the ECG waveform during measurement. These are Power Line Interference (PLI) noise, Baseline Wander (BW) noise, Muscle Artifact (MA) noise and Electrode Motion (EM) artifacts. The recordings of ECG can also consist a mixed version of these noise types, such as a mixture of varying amounts of PLI, BW, MA and EM [1-4]. The PLI noise is a sinusoidal signal about 50 Hz (or 60 Hz) frequency arise from the electromagnetic field of the power lines. The BW noise is a signal with low frequency about $0.15-0.6\ Hz$. This noise occurs by the patient's breathing or body movements and shifts the baseline of the ECG signal. The MA noise or electromyogram (EMG) noise varies in the range of $1-500\ Hz$ and is caused by the waves generated from the electrical activity of muscle movements near the electrodes. The EM noise appears by very slow changes in the impedance of the skin electrode with electrode movements and therefore a temporary baseline shift occurs in the ECG signal at a very low frequency of about $1-10\ Hz$. These undesired noises/artifacts make the analysis of cardiac functions and the diagnosis of some heart diseases more difficult by distorting the P-QRS-T waves in the cardiac loop of an ECG signal, or can also lead to incorrect analysis and diagnosis.

ECG denoising is a noise reduction/cancellation process and is defined as estimating the clean ECG signal from its noisy measurement with lowest possible error. Several methods for biomedical signal processing have been proposed to overcome the noise problem and to obtain an acceptable ECG waveform [1-4]. The common methods in the literature are based on linear filtering, optimal filtering, Bayesian filtering, adaptive filtering, mathematical transforms (wavelet transforms etc.), decomposition methods (empirical mode decomposition, variational mode decomposition etc.) and hybrid usage of some of them. Adaptive noise cancellation (ANC) which is based on the use of adaptive filters (AFs) is an effective noise reduction technique [5]. An AF contains a digital filter and an adaptive algorithm adjusts the filter coefficients [6]. Adaptive FIR filtering is widely preferred in applications to avoid the stability problem that arises in adaptive IIR filtering. Adaptive algorithms commonly used can be grouped as gradient-based and least squares-based. The most popular gradient-based algorithms are the Least Mean Squares (LMS) and the Normalized LMS (NLMS)

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algorithms. The Recursive Least Squares (RLS) algorithm is the most used least squares-based algorithm in adaptive filtering applications.

Generally, in studies given in the literature, one or few adaptive filtering methods have been presented or examined and their performance evaluations have been made. To the best of our knowledge, there is no comprehensive literature review that combines multiple methods. In addition, comprehensive software tools have not been designed to implement these methods, use them in applications and analyze their performance. The basic principle is that the software tool to be designed should be in a structure that can easily be used in applications/practice by users who do not have technical knowledge. In addition, comprehensive multimedia-supported computer tools are needed to better understand and teach adaptive filters, which are used extensively in many fields. Based on this, the aims and main contributions of this study can be summarized as follows under two headings: theoretical knowledge/education and application/practice.

Theoretical knowledge / Education	Application/Practice
i. Researching many adaptive filtering methods and collecting them in a comprehensive resource ii. Designing a user-friendly software tool that explains adaptive filtering methods with multimedia support and interactive applications. iii. Detailed numerical and graphical analysis of denoising process with adaptive filters	i. Performing single denoising processing with adaptive filters ii. Performing comparative denoising processing with adaptive filters and realizing performance evaluations iii. As a result of comparative denoising processes, presenting the method with the highest performance to the user according to the selected criterion iv. By testing all methods, presenting the most appropriate method to the user according to the selected criteria v. Detailed numerical and graphical analysis of denoising process with adaptive filters vi. Providing in-depth information with powerful numerical and graphical supports

In the literature, to the best of our knowledge, no studies on software tool design that performs denoising process with only a large number of adaptive algorithms have been found. In this study, many adaptive algorithms have been collected and a new software tool was designed for ECG denoising, which can also be used for educational purposes. With this tool, which denoised the measured/recorded or synthesized (5 different types) noisy ECG signals with many different adaptive algorithms, single and multiple (comparative) results can be obtained. Also, the tool can scan all/selected algorithms and obtain the best one for choosing the performance criteria with its default parameters. In addition, with its detailed numerical (powers, errors, SNRs, percentages, cross-correlation coefficients, etc.) and graphical (measured/recorded data signal, noise signal, clean-noisy-filtered ECG signals, frequency and power spectrums, spectrogram etc.) results and user-friendly interface, ECG denoising operations can be performed easily, quickly and effectively. Since making evaluations on noise-free data is much more efficient, it provides great convenience to decision makers in the medical field and reduces the possibility of making incorrect evaluations.

This paper is organized as follows: the variants of classical adaptive filtering algorithms are summarized in Section 2; the ECG denoising process and selected adaptive algorithms are explained in Section 3; the designed software tool with sample applications and evaluations are given in Section 4 and the results are discussed in Section 5.

2. Adaptive Filtering Algorithms

There are many studies in the literature in the area of ECG denoising. The gradient-based algorithms are widely used for ECG denoising and have taken the attention of many researchers. The algorithms with their abbreviations used in the designed tool and mentioned in this section are given in Table 1 [7-38].

Table 1. Adaptive filtering algorithms

Algorithm	Abbreviation	Weight Update Equations	Ref.
Least Mean Square	LMS	$\hat{\boldsymbol{w}}(n+1) = \hat{\boldsymbol{w}}(n) + \mu\, \boldsymbol{x}(n)e(n)$ $e(n) = d(n) - \boldsymbol{x}^T(n)\hat{\boldsymbol{w}}(n)\ \ ,\ \ 0 < \mu < 2/\lambda_{max}\{\mathbf{R}_x(n)\}$	[7]
Sign-Regressor LMS	SRLMS	$\hat{\boldsymbol{w}}(n+1) = \hat{\boldsymbol{w}}(n) + \mu\, sign\{\boldsymbol{x}(n)\}e(n)$	[7]
Sign-Error LMS	SELMS	$\hat{\boldsymbol{w}}(n+1) = \hat{\boldsymbol{w}}(n) + \mu\, \boldsymbol{x}(n)sign\{e(n)\}$	[7]
Sign-Sign LMS	SSLMS	$\hat{\boldsymbol{w}}(n+1) = \hat{\boldsymbol{w}}(n) + \mu\, sign\{\boldsymbol{x}(n)\}sign\{e(n)\}$	[7]
Normalized LMS	NLMS	$\hat{\boldsymbol{w}}(n+1) = \hat{\boldsymbol{w}}(n) + \frac{\mu}{\alpha + \boldsymbol{x}^T(n)\boldsymbol{x}(n)}\boldsymbol{x}(n)e(n)$	[8]
Normalized SRLMS	NSRLMS	$\hat{\boldsymbol{w}}(n+1) = \hat{\boldsymbol{w}}(n) + \frac{\mu}{\alpha + \boldsymbol{x}^T(n)\boldsymbol{x}(n)}sign\{\boldsymbol{x}(n)\}e(n)$	[8]
Normalized SELMS	NSELMS	$\hat{\boldsymbol{w}}(n+1) = \hat{\boldsymbol{w}}(n) + \frac{\mu}{\alpha + \boldsymbol{x}^T(n)\boldsymbol{x}(n)}\boldsymbol{x}(n)sign\{e(n)\}$	[8]
Normalized SSLMS	NSSLMS	$\hat{\boldsymbol{w}}(n+1) = \hat{\boldsymbol{w}}(n) + \frac{\mu}{\alpha + \boldsymbol{x}^T(n)\boldsymbol{x}(n)}sign\{\boldsymbol{x}(n)\}sign\{e(n)\}$	[8]
Modified LMS	MLMS	$\hat{\boldsymbol{w}}(n+1) = \hat{\boldsymbol{w}}(n) + \frac{\mu(n)}{\boldsymbol{x}^T(n)\boldsymbol{x}(n)}\boldsymbol{x}(n)sign\{e(n)\}$ $\mu(n+1) = \alpha\mu(n) + \beta e^2(n)\ \ ,\ \ 0 < \alpha < 1\ \ ,\ \ \beta > 0$	[9]
Error Normalized LMS	ENLMS	$\hat{\boldsymbol{w}}(n+1) = \hat{\boldsymbol{w}}(n) + \frac{\mu}{\alpha + \boldsymbol{e}^T(n)\boldsymbol{e}(n)}\boldsymbol{x}(n)e(n)$	[10]
Error Normalized SRLMS	ENSRLMS	$\hat{\boldsymbol{w}}(n+1) = \hat{\boldsymbol{w}}(n) + \frac{\mu}{\alpha + \boldsymbol{e}^T(n)\boldsymbol{e}(n)}sign\{\boldsymbol{x}(n)\}e(n)$	[10]
Error Normalized SELMS	ENSELMS	$\hat{\boldsymbol{w}}(n+1) = \hat{\boldsymbol{w}}(n) + \frac{\mu}{\alpha + \boldsymbol{e}^T(n)\boldsymbol{e}(n)}\boldsymbol{x}(n)sign\{e(n)\}$	[10]
Error Normalized SSLMS	ENSSLMS	$\hat{\boldsymbol{w}}(n+1) = \hat{\boldsymbol{w}}(n) + \frac{\mu}{\alpha + \boldsymbol{e}^T(n)\boldsymbol{e}(n)}sign\{\boldsymbol{x}(n)\}sign\{e(n)\}$	[10]
Variable Step-Size LMS	VSSLMS	$\hat{\boldsymbol{w}}(n+1) = \hat{\boldsymbol{w}}(n) + \mu_1(n)\boldsymbol{x}(n)e(n)\ ,\ \mu_1(n) = \frac{1-\mu}{2(1-\mu^{n+1})}\ \ ,\ \ 0.5 < \mu < 1$	[11]

Sign-Regressor VSSLMS	SRVSSLMS	$\widehat{\boldsymbol{w}}(n+1)=\widehat{\boldsymbol{w}}(n)+\mu_1(n)sign\{\boldsymbol{x}(n)\}e(n)\ ,\quad 0.5<\mu<1$	[11]
Sign-Error VSSLMS	SEVSSLMS	$\widehat{\boldsymbol{w}}(n+1)=\widehat{\boldsymbol{w}}(n)+\mu_1(n)\boldsymbol{x}(n)sign\{e(n)\}\ ,\quad 0.5<\mu<1$	[11]
Error Normalized VSSLMS	ENVSSLMS	$\widehat{\boldsymbol{w}}(n+1)=\widehat{\boldsymbol{w}}(n)+\dfrac{\mu_1(n)}{\alpha+\boldsymbol{e}^T(n)\boldsymbol{e}(n)}\boldsymbol{x}(n)e(n)\ ,\quad 0.5<\mu<1$	[11]
Error Normalized Sign-Regressor VSSLMS	ENSRVSSLMS	$\widehat{\boldsymbol{w}}(n+1)=\widehat{\boldsymbol{w}}(n)+\dfrac{\mu_1(n)}{\alpha+\boldsymbol{e}^T(n)\boldsymbol{e}(n)}sign\{\boldsymbol{x}(n)\}e(n)\ ,\quad 0.5<\mu<1$	[11]
Data Error Normalized VSS-LMS	DENVSS-LMS	$\widehat{\boldsymbol{w}}(n+1)=\widehat{\boldsymbol{w}}(n)+\mu_2(n)\boldsymbol{x}(n)e(n)$ $\mu_2(n)=\dfrac{\mu}{(1-\alpha)\lVert\boldsymbol{x}(n)\rVert^2+\alpha\lVert\boldsymbol{e}(n)\rVert^2}\ ,\quad 0<\alpha<1$	[12-13]
Data Error Normalized VSS-SRLMS	DENVSS-SRLMS	$\widehat{\boldsymbol{w}}(n+1)=\widehat{\boldsymbol{w}}(n)+\mu_2(n)sign\{\boldsymbol{x}(n)\}e(n)$	[12-13]
Data Error Normalized VSS-SELMS	DENVSS-SELMS	$\widehat{\boldsymbol{w}}(n+1)=\widehat{\boldsymbol{w}}(n)+\mu_2(n)\boldsymbol{x}(n)sign\{e(n)\}$	[12-13]
Data Error Normalized VSS-SSLMS	DENVSS-SSLMS	$\widehat{\boldsymbol{w}}(n+1)=\widehat{\boldsymbol{w}}(n)+\mu_2(n)sign\{\boldsymbol{x}(n)\}sign\{e(n)\}$	[12-13]
Normalized Variable Step-Size LMS	NVLMS	$\widehat{\boldsymbol{w}}(n+1)=\widehat{\boldsymbol{w}}(n)+\dfrac{\mu_v(n)}{\alpha+\boldsymbol{x}^T(n)\boldsymbol{x}(n)}\boldsymbol{x}(n)e(n)$ $\mu_v(n)=\mu_{max}+(\mu_{min}-\mu_{max})e^{-\beta\sigma_e^2(n)}$	[14]
Normalized Variable Step-Size SRLMS	NVSRLMS	$\widehat{\boldsymbol{w}}(n+1)=\widehat{\boldsymbol{w}}(n)+\dfrac{\mu_v(n)}{\alpha+\boldsymbol{x}^T(n)\boldsymbol{x}(n)}sign\{\boldsymbol{x}(n)\}e(n)$	[14]
Normalized Variable Step-Size SELMS	NVSELMS	$\widehat{\boldsymbol{w}}(n+1)=\widehat{\boldsymbol{w}}(n)+\dfrac{\mu_v(n)}{\alpha+\boldsymbol{x}^T(n)\boldsymbol{x}(n)}\boldsymbol{x}(n)sign\{e(n)\}$	[14]
Normalized Variable Step-Size SSLMS	NVSSLMS	$\widehat{\boldsymbol{w}}(n+1)=\widehat{\boldsymbol{w}}(n)+\dfrac{\mu_v(n)}{\alpha+\boldsymbol{x}^T(n)\boldsymbol{x}(n)}sign\{\boldsymbol{x}(n)\}sign\{e(n)\}$	[14]
Leaky LMS	LLMS	$\widehat{\boldsymbol{w}}(n+1)=(1-\mu\gamma)\widehat{\boldsymbol{w}}(n)+\mu\,\boldsymbol{x}(n)e(n)\ ,\quad 0\le\mu\gamma<1$	[15]
Leaky NLMS	LNLMS	$\widehat{\boldsymbol{w}}(n+1)=(1-\mu\gamma)\widehat{\boldsymbol{w}}(n)+\dfrac{\mu}{\alpha+\boldsymbol{x}^T(n)\boldsymbol{x}(n)}\boldsymbol{x}(n)e(n)\ ,\quad 0\le\mu\gamma<1$	[15]
Least Mean Fourth	LMF	$\widehat{\boldsymbol{w}}(n+1)=\widehat{\boldsymbol{w}}(n)+\mu\,\boldsymbol{x}(n)e(n)^3$	[16-17]
Normalized LMF	NLMF	$\widehat{\boldsymbol{w}}(n+1)=\widehat{\boldsymbol{w}}(n)+\dfrac{\mu}{\alpha+\boldsymbol{x}^T(n)\boldsymbol{x}(n)}\boldsymbol{x}(n)e(n)^3$	[16-17]
Error Normalized LMF	ENLMF	$\widehat{\boldsymbol{w}}(n+1)=\widehat{\boldsymbol{w}}(n)+\dfrac{\mu}{\alpha+\boldsymbol{e}^T(n)\boldsymbol{e}(n)}\boldsymbol{x}(n)e(n)^3$	[16-17]
Leaky LMF	LLMF	$\widehat{\boldsymbol{w}}(n+1)=(1-\mu\gamma)\widehat{\boldsymbol{w}}(n)+\mu\,\boldsymbol{x}(n)e(n)^3\ ,\ 0\le\mu\gamma<1$	[16]
Normalized Leaky LMF	NLLMF	$\widehat{\boldsymbol{w}}(n+1)=(1-\mu\gamma)\widehat{\boldsymbol{w}}(n)+\dfrac{\mu}{\alpha+\boldsymbol{x}^T(n)\boldsymbol{x}(n)}\boldsymbol{x}(n)e(n)^3$	[16]
Error Normalized Leaky LMF	ENLLMF	$\widehat{\boldsymbol{w}}(n+1)=(1-\mu\gamma)\widehat{\boldsymbol{w}}(n)+\dfrac{\mu}{\alpha+\boldsymbol{e}^T(n)\boldsymbol{e}(n)}\boldsymbol{x}(n)e(n)^3$	[16]
Least Mean Logarithmic Square	LMLS	$\widehat{\boldsymbol{w}}(n+1)=\widehat{\boldsymbol{w}}(n)+\mu\,\dfrac{\alpha\boldsymbol{x}(n)e^3(n)}{1+\alpha e^2(n)}$	[18]
Normalized LMLS	NLMLS	$\widehat{\boldsymbol{w}}(n+1)=\widehat{\boldsymbol{w}}(n)+\mu\,\dfrac{\alpha\boldsymbol{x}(n)e^3(n)}{\lVert\boldsymbol{x}(n)\rVert^2[\lVert\boldsymbol{x}(n)\rVert^2+\alpha e^2(n)]}$	[18]
Sign-Regressor NLMLS	SRNLMLS	$\widehat{\boldsymbol{w}}(n+1)=\widehat{\boldsymbol{w}}(n)+\mu\,sign\{\boldsymbol{x}(n)\}\,\dfrac{\alpha e^3(n)}{\lVert\boldsymbol{x}(n)\rVert^2[\lVert\boldsymbol{x}(n)\rVert^2+\alpha e^2(n)]}$	[18]
Sign-Error NLMLS	SENLMLS	$\widehat{\boldsymbol{w}}(n+1)=\widehat{\boldsymbol{w}}(n)+\mu\,sign\{e^3(n)\}\,\dfrac{\alpha\boldsymbol{x}(n)}{\lVert\boldsymbol{x}(n)\rVert^2[\lVert\boldsymbol{x}(n)\rVert^2+\alpha e^2(n)]}$	[18]
Sign-Sign NLMLS	SSNLMLS	$\widehat{\boldsymbol{w}}(n+1)=\widehat{\boldsymbol{w}}(n)+\mu\,sign\{e^3(n)\}\,sign\{\boldsymbol{x}(n)\}\,\dfrac{\alpha}{\lVert\boldsymbol{x}(n)\rVert^2[\lVert\boldsymbol{x}(n)\rVert^2+\alpha e^2(n)]}$	[18]
Median LMS	MLMS	$\widehat{\boldsymbol{w}}(n+1)=\widehat{\boldsymbol{w}}(n)+\mu\,med[\mathbf{x}(n)e(n)\ \cdots\ \mathbf{x}(n-L+1)e(n-L+1)]$	[19]
Normalized MLMS	NMLMS	$\widehat{\boldsymbol{w}}(n+1)=\widehat{\boldsymbol{w}}(n)+\mu(n)\,med[\mathbf{x}(n)e(n)\ \cdots\ \mathbf{x}(n-L+1)e(n-L+1)]$	[19]
Sign-Regressor NMLMS	SRNMLMS	$\widehat{\boldsymbol{w}}(n+1)$ $=\widehat{\boldsymbol{w}}(n)+\mu(n)\,med[sign\{\boldsymbol{x}(n)\}e(n)\ \cdots\ sign\{\boldsymbol{x}(n-L+1)\}e(n-L+1)]$	[19]
Sign-Error NMLMS	SENMLMS	$\widehat{\boldsymbol{w}}(n+1)=\widehat{\boldsymbol{w}}(n)+$ $\mu(n)\,med[\mathbf{x}(n)sign\{e(n)\}\ \cdots\ \mathbf{x}(n-L+1)sign\{e(n-L+1)\}]$	[19]
Sign-Sign NMLMS	SSNMLMS	$\widehat{\boldsymbol{w}}(n+1)=\widehat{\boldsymbol{w}}(n)+\ \mu(n)med[sign\{\boldsymbol{x}(n)\}sign\{e(n)\}\ \ldots$ $\ldots\ sign\{\boldsymbol{x}(n-L+1)\}sign\{e(n-L+1)\}]$	[19]
Kalman LMS	KLMS	$\widehat{\boldsymbol{w}}(n+1)=\widehat{\boldsymbol{w}}(n)+\dfrac{\boldsymbol{x}(n)e(n)}{\lVert\boldsymbol{x}(n)\rVert^2+q_v(n)/\sigma_w^2(n)}$	[20]
Kalman Sign-Regressor LMS	KSRLMS	$\widehat{\boldsymbol{w}}(n+1)=\widehat{\boldsymbol{w}}(n)+\dfrac{sign\{\boldsymbol{x}(n)\}e(n)}{\lVert\boldsymbol{x}(n)\rVert^2+q_v(n)/\sigma_w^2(n)}$	[20]
Kalman Sign-Error LMS	KSELMS	$\widehat{\boldsymbol{w}}(n+1)=\widehat{\boldsymbol{w}}(n)+\dfrac{\boldsymbol{x}(n)sign\{e(n)\}}{\lVert\boldsymbol{x}(n)\rVert^2+q_v(n)/\sigma_w^2(n)}$	[20]
Kalman Sign-Sign LMS	KSSLMS	$\widehat{\boldsymbol{w}}(n+1)=\widehat{\boldsymbol{w}}(n)+\dfrac{sign\{\boldsymbol{x}(n)\}sign\{e(n)\}}{\lVert\boldsymbol{x}(n)\rVert^2+q_v(n)/\sigma_w^2(n)}$	[20]
Proportionate LMS	PLMS	$\widehat{\boldsymbol{w}}(n+1)=\widehat{\boldsymbol{w}}(n)+\mu\,\mathbf{G}(n)\boldsymbol{x}(n)e(n)$ $\mathbf{G}(n)=diag\{[g_0(n)\ \cdots\ g_{M-1}(n)]\}\ ,\quad g_l(n)=\dfrac{\gamma_l(n)}{\frac{1}{M}\sum_{i=0}^{M-1}\gamma_i(n)}$ $\gamma_l(n)=\max\{\gamma_{min}(n),\lvert\widehat{w}_l(n)\rvert\}\ ,\quad l=0,\ldots,M-1$ $\gamma_{min}(n)=\rho\max\{\delta_p,\lvert\widehat{w}_0(n)\rvert,\ldots,\lvert\widehat{w}_{M-1}(n)\rvert\}$, Typical vaues: $\rho=5/M$, $\delta_p=0.01$	[21]
Sign-Regressor PLMS	SRPLMS	$\widehat{\boldsymbol{w}}(n+1)=\widehat{\boldsymbol{w}}(n)+\mu\,\mathbf{G}(n)sign\{\boldsymbol{x}(n)\}e(n)$	[21]
Sign-Error PLMS	SEPLMS	$\widehat{\boldsymbol{w}}(n+1)=\widehat{\boldsymbol{w}}(n)+\mu\,\mathbf{G}(n)\boldsymbol{x}(n)sign\{e(n)\}$	[21]
Sign-Sign PLMS	SSPLMS	$\widehat{\boldsymbol{w}}(n+1)=\widehat{\boldsymbol{w}}(n)+\mu\,\mathbf{G}(n)sign\{\boldsymbol{x}(n)\}sign\{e(n)\}$	[21]

Proportionate Normalized LMS	PNLMS	$\hat{\boldsymbol{w}}(n+1)=\hat{\boldsymbol{w}}(n)+\frac{\mu\,\mathbf{G}(n)\boldsymbol{x}(n)e(n)}{\alpha+\boldsymbol{x}^T(n)\mathbf{G}(n)\boldsymbol{x}(n)}$	[22]
Proportionate Normalized SRLMS	PNSRLMS	$\hat{\boldsymbol{w}}(n+1)=\hat{\boldsymbol{w}}(n)+\frac{\mu\,\mathbf{G}(n)sign\{\boldsymbol{x}(n)\}e(n)}{\alpha+\boldsymbol{x}^T(n)\mathbf{G}(n)\boldsymbol{x}(n)}$	[22]
Proportionate Normalized SELMS	PNSELMS	$\hat{\boldsymbol{w}}(n+1)=\hat{\boldsymbol{w}}(n)+\frac{\mu\,\mathbf{G}(n)\boldsymbol{x}(n)sign\{e(n)\}}{\alpha+\boldsymbol{x}^T(n)\mathbf{G}(n)\boldsymbol{x}(n)}$	[22]
Proportionate Normalized SSLMS	PNSSLMS	$\hat{\boldsymbol{w}}(n+1)=\hat{\boldsymbol{w}}(n)+\frac{\mu\,\mathbf{G}(n)sign\{\boldsymbol{x}(n)\}sign\{e(n)\}}{\alpha+\boldsymbol{x}^T(n)\mathbf{G}(n)\boldsymbol{x}(n)}$	[22]
Non-Negative LMS	N^2LMS	$\hat{\boldsymbol{w}}(n+1)=\hat{\boldsymbol{w}}(n)+\mu\boldsymbol{D}(n)\boldsymbol{x}(n)e(n) \quad , \quad \boldsymbol{D}(n)=diag\{\hat{\boldsymbol{w}}(n)\}$	[23]
Exponential Non-Negative LMS	eN^2LMS	$\hat{\boldsymbol{w}}(n+1)=\hat{\boldsymbol{w}}(n)+\mu\boldsymbol{x}(n)e(n)\hat{\boldsymbol{w}}^{\gamma}(n) \quad , \quad 0<\gamma<1$	[23]
Sign-Regressor Exponential Non-Negative LMS	SReN^2LMS	$\hat{\boldsymbol{w}}(n+1)=\hat{\boldsymbol{w}}(n)+\mu sign\{\boldsymbol{x}(n)\}e(n)\hat{\boldsymbol{w}}^{\gamma}(n) \quad , \quad 0<\gamma<1$	[23]
Sign-Error Exponential Non-Negative LMS	SEeN^2LMS	$\hat{\boldsymbol{w}}(n+1)=\hat{\boldsymbol{w}}(n)+\mu\boldsymbol{x}(n)sign\{e(n)\}\hat{\boldsymbol{w}}^{\gamma}(n) \quad , \quad 0<\gamma<1$	[23]
Sign-Sign Exponential Non-Negative LMS	SSeN^2LMS	$\hat{\boldsymbol{w}}(n+1)=\hat{\boldsymbol{w}}(n)+\mu sign\{\boldsymbol{x}(n)\}sign\{e(n)\}\hat{\boldsymbol{w}}^{\gamma}(n) \quad , \quad 0<\gamma<1$	[23]
Normalized Non-Negative LMS	N^3LMS	$\hat{\boldsymbol{w}}(n+1)=\hat{\boldsymbol{w}}(n)+\mu(n)\boldsymbol{D}(n)\boldsymbol{x}(n)e(n)$ $\boldsymbol{D}(n)=diag\{\hat{\boldsymbol{w}}(n)\} \quad , \quad \mu(n)=\frac{\mu}{\alpha+\boldsymbol{x}^T(n)\boldsymbol{x}(n)}$	[23]
Sign-Regressor Normalized Non-Negative LMS	SRN^3LMS	$\hat{\boldsymbol{w}}(n+1)=\hat{\boldsymbol{w}}(n)+\mu(n)\boldsymbol{D}(n)sign\{\boldsymbol{x}(n)\}e(n)$	[23]
Sign-Error Normalized Non-Negative LMS	SEN^3LMS	$\hat{\boldsymbol{w}}(n+1)=\hat{\boldsymbol{w}}(n)+\mu(n)\boldsymbol{D}(n)\boldsymbol{x}(n)sign\{e(n)\}$	[23]
Sign-Sign Normalized Non-Negative LMS	SSN^3LMS	$\hat{\boldsymbol{w}}(n+1)=\hat{\boldsymbol{w}}(n)+\mu(n)\boldsymbol{D}(n)sign\{\boldsymbol{x}(n)\}sign\{e(n)\}$	[23]
Dead-Zone LMS	DZLMS	$\hat{\boldsymbol{w}}(n+1)=\hat{\boldsymbol{w}}(n)+\mu\,g[e(n)]\boldsymbol{x}(n) \;,\; g(e)=\begin{cases} e-t \;, & e>t \\ 0 \;, & -t<e<t \\ e+t \;, & e<-t \end{cases}$	[24]
Sign-Regressor Dead-Zone LMS	SRDZLMS	$\hat{\boldsymbol{w}}(n+1)=\hat{\boldsymbol{w}}(n)+\mu\,g[e(n)]sign\{\boldsymbol{x}(n)\}$	[24]
Normalized Dead-Zone LMS	NDZLMS	$\hat{\boldsymbol{w}}(n+1)=\hat{\boldsymbol{w}}(n)+\mu(n)g[e(n)]\boldsymbol{x}(n)$	[25]
Sign-Regressor Normalized Dead-Zone LMS	SRNDZLMS	$\hat{\boldsymbol{w}}(n+1)=\hat{\boldsymbol{w}}(n)+\mu(n)g[e(n)]sign\{\boldsymbol{x}(n)\}$	[25]
Sign-Error Normalized Dead-Zone LMS	SENDZLMS	$\hat{\boldsymbol{w}}(n+1)=\hat{\boldsymbol{w}}(n)+\mu(n)sign\{g[e(n)]\}\boldsymbol{x}(n)$	[25]
Sign-Sign Normalized Dead-Zone LMS	SSNDZLMS	$\hat{\boldsymbol{w}}(n+1)=\hat{\boldsymbol{w}}(n)+\mu(n)sign\{g[e(n)]\}sign\{\boldsymbol{x}(n)\}$	[25]
Dead-Zone Leaky LMS	DZLLMS	$\hat{\boldsymbol{w}}(n+1)=(1-\mu\gamma)\hat{\boldsymbol{w}}(n)+\mu\,g[e(n)]\boldsymbol{x}(n)$	[26]
Sign-Regressor Dead-Zone Leaky LMS	SRDZLLMS	$\hat{\boldsymbol{w}}(n+1)=(1-\mu\gamma)\hat{\boldsymbol{w}}(n)+\mu\,g[e(n)]sign\{\boldsymbol{x}(n)\}$	[26]
Sign-Error Dead-Zone Leaky LMS	SEDZLLMS	$\hat{\boldsymbol{w}}(n+1)=(1-\mu\gamma)\hat{\boldsymbol{w}}(n)+\mu\,sign\{g[e(n)]\}\boldsymbol{x}(n)$	[26]
Sign-Sign Dead-Zone Leaky LMS	SSDZLLMS	$\hat{\boldsymbol{w}}(n+1)=(1-\mu\gamma)\hat{\boldsymbol{w}}(n)+\mu\,sign\{g[e(n)]\}sign\{\boldsymbol{x}(n)\}$	[26]
Sign-Regressor Leaky LMF	SRLLMF	$\hat{\boldsymbol{w}}(n+1)=(1-\mu\gamma)\hat{\boldsymbol{w}}(n)+\mu\,sign\{\boldsymbol{x}(n)\}e(n)^3$	[26]
Sign-Error Leaky LMF	SELLMF	$\hat{\boldsymbol{w}}(n+1)=(1-\mu\gamma)\hat{\boldsymbol{w}}(n)+\mu\,\boldsymbol{x}(n)sign\{e(n)^3\}$	[26]
Sign-Sign Leaky LMF	SSLLMF	$\hat{\boldsymbol{w}}(n+1)=(1-\mu\gamma)\hat{\boldsymbol{w}}(n)+\mu\,sign\{\boldsymbol{x}(n)\}sign\{e(n)^3\}$	[26]
Median Leaky LMS	MLLMS	$\hat{\boldsymbol{w}}(n+1)=(1-\mu\gamma)\hat{\boldsymbol{w}}(n)+\mu\,med[\mathbf{x}(n)e(n) \quad \cdots \quad \mathbf{x}(n-M+1)e(n-M+1)]$	[26]
Sign-Regressor Median Leaky LMS	SRMLLMS	$\hat{\boldsymbol{w}}(n+1)=(1-\mu\gamma)\hat{\boldsymbol{w}}(n)+$ $\mu\,med[sign\{\boldsymbol{x}(n)\}e(n) \quad \cdots \quad sign\{\boldsymbol{x}(n-M+1)\}e(n-M+1)]$	[26]
Sign-Error Median Leaky LMS	SEMLLMS	$\hat{\boldsymbol{w}}(n+1)=(1-\mu\gamma)\hat{\boldsymbol{w}}(n)+$ $\mu\,med[\mathbf{x}(n)sign\{e(n)\} \quad \cdots \quad \mathbf{x}(n-M+1)sign\{e(n-M+1)\}]$	[26]
Sign-Sign Median Leaky LMS	SSMLLMS	$\hat{\boldsymbol{w}}(n+1)=(1-\mu\gamma)\hat{\boldsymbol{w}}(n)+\;\mu\,med[sign\{\boldsymbol{x}(n)\}sign\{e(n)\} \;\ldots$ $\ldots \;\; sign\{\boldsymbol{x}(n-M+1)\}sign\{e(n-M+1)\}]$	[26]
Sign-Regressor LMF	SRLMF	$\hat{\boldsymbol{w}}(n+1)=\hat{\boldsymbol{w}}(n)+\mu\,sign\{\boldsymbol{x}(n)\}e(n)^3$	[27]
Least Mean Mixed-Norm	LMMN	$\hat{\boldsymbol{w}}(n+1)=\hat{\boldsymbol{w}}(n)+\mu\,\boldsymbol{x}(n)e(n)[\lambda+(1-\lambda)e^2(n)] \;\;, 0<\lambda<1$	[27]
Sign-Regressor LMMN	SRLMMN	$\hat{\boldsymbol{w}}(n+1)=\hat{\boldsymbol{w}}(n)+\mu\,sign\{\boldsymbol{x}(n)\}e(n)[\lambda+(1-\lambda)e^2(n)]$	[27]
Delayed LMS	DLMS	$\hat{\boldsymbol{w}}(n+1)=\hat{\boldsymbol{w}}(n)+\mu\,\boldsymbol{x}(n-D)e(n-D) \quad , \quad D$: D step delay $e(n-D)=d(n-D)-y(n-D) \;,\; y(n-D)=\boldsymbol{x}^T(n-D)\hat{\boldsymbol{w}}(n-D)$	[28]
Variable Step-Size DLMS	VSS-DLMS	$\hat{\boldsymbol{w}}(n+1)=\hat{\boldsymbol{w}}(n)+\mu(n)\boldsymbol{x}(n-D)e(n-D)$	[28]
Delayed Normalized LMS	DNLMS	$\hat{\boldsymbol{w}}(n+1)=\hat{\boldsymbol{w}}(n)+\frac{\mu}{\alpha+\boldsymbol{x}^T(n-D)\boldsymbol{x}(n-D)}\boldsymbol{x}(n-D)e(n-D)$	[29]
Delayed Error Normalized LMS	DENLMS	$\hat{\boldsymbol{w}}(n+1)=\hat{\boldsymbol{w}}(n)+\frac{\mu}{\alpha+\boldsymbol{e}^T(n-D)\boldsymbol{e}(n-D)}\boldsymbol{x}(n-D)e(n-D)$	[29]
Log-LMS	Log-LMS	$\hat{\boldsymbol{w}}(n+1)=\hat{\boldsymbol{w}}(n)+\mu\,Q[e(n)]\boldsymbol{x}(n) \quad , \quad Q[z]=2^{log_2(z)}sign(z)$	[30]
Modified Log-LMS	MLMS	$\hat{\boldsymbol{w}}(n+1)=\hat{\boldsymbol{w}}(n)+\mu\,Q[e(n)]\boldsymbol{x}(n)$ $Q[z]=\alpha 2^{\theta(z)}sign(z)$, α is a small power $-$ of $-$ two value and less than 1 $\theta(z)=\begin{cases} 0 & when\ \lvert z/\alpha\rvert<1 \\ log_2(z/\alpha) & at\ converging\ state \\ -log_2(z/\alpha) & at\ extracting\ state \end{cases}$ These stages are switched when two consecutive error values satisfy $\lvert e(n)-e(n-1)\rvert<\varepsilon$, where $\varepsilon>0$ is a threshold value and $e(n)=d(n)-y(n)$	[30]
Modified Normalized Log-LMS	MNLMS	$\hat{\boldsymbol{w}}(n+1)=\hat{\boldsymbol{w}}(n)+\frac{\mu}{\boldsymbol{x}^T(n)\boldsymbol{x}(n)}\,Q[e(n)]\boldsymbol{x}(n)$	[31]

Constrained Stability LMS	CSLMS	$\widehat{\boldsymbol{w}}(n+1)=\widehat{\boldsymbol{w}}(n)+\mu\left[\frac{\delta\boldsymbol{x}(n)\delta e(n)}{\alpha+\Vert\delta\boldsymbol{x}(n)\Vert^2}\right]$ $\delta\boldsymbol{x}(n)=\boldsymbol{x}(n)-\boldsymbol{x}(n-1)$, $\delta e(n)=e(n)-e(n-1)$, $0<\mu<2/\lambda_{max}\{\mathbf{R}_{\delta x}(n)\}$, $\alpha>0$	[32-33]
Modified Constrained Stability LMS	MCSLMS	$\widehat{\boldsymbol{w}}(n+1)=\widehat{\boldsymbol{w}}(n)+\mu_3(n)\left[\frac{\delta\boldsymbol{x}(n)\delta e(n)}{\alpha+\Vert\delta\boldsymbol{x}(n)\Vert^2}\right]$ $\delta\boldsymbol{x}(n)=\boldsymbol{x}(n)-\boldsymbol{x}(n-1)$, $\delta e(n)=e(n)-e(n-1)$, $\mu_3(n)=b(1-exp(-a\vert e(n)\vert^2))$	[34]
Recursive Least Squares	RLS	$\boldsymbol{q}(n)=\mathbf{P}(n)\boldsymbol{x}(n)$, $\mathbf{k}(n)=\frac{\boldsymbol{q}(n)}{\lambda+x^T(n)\boldsymbol{q}(n)}$, $e(n)=d(n)-\boldsymbol{x}^T(n)\widehat{\boldsymbol{w}}(n)$ $\widehat{\boldsymbol{w}}(n+1)=\widehat{\boldsymbol{w}}(n)+\mathbf{k}(n)e(n)$, $\mathbf{P}(n+1)=\frac{1}{\lambda}[\mathbf{P}(n)-\mathbf{k}(n)\boldsymbol{q}^T(n)]$	[6, 35]
Affine Projection Algorithm (P-th order)	APA (P-th order)	$\widehat{\boldsymbol{w}}(n+1)=\widehat{\boldsymbol{w}}(n)+\mu\,\mathbf{X}(n)[\epsilon\mathbf{I}+\mathbf{X}^T(n)\mathbf{X}(n)]^{-1}\boldsymbol{e}(n)$ $\boldsymbol{e}(n)=\boldsymbol{d}(n)-\mathbf{X}^T(n)\widehat{\boldsymbol{w}}(n)$, $0<\mu\le 1$, $\epsilon>0$ (small constant) $\boldsymbol{d}(n)=[d(n)\quad d(n-1)\quad\cdots\quad d(n-P+1)]^T$ $\mathbf{X}(n)=[\boldsymbol{x}^T(n)\quad \boldsymbol{x}^T(n-1)\quad\cdots\quad \boldsymbol{x}^T(n-P+1)]$	[36-37]
Affine Projection Sign Algorithm (P-th order)	APSA (P-th order)	$\widehat{\boldsymbol{w}}(n+1)=\widehat{\boldsymbol{w}}(n)+\frac{\delta\,\mathbf{X}(n)sign\{\boldsymbol{e}(n)\}}{\sqrt{sign\{\boldsymbol{e}(n)\}\mathbf{X}^T(n)\mathbf{X}(n)sign\{\boldsymbol{e}(n)\}}}$, $0<\delta<1$	[37]

3. ECG Denoising

The adaptive filters, which have self-adjusting characteristics, can be implemented as analog, digital or hybrid. The fundamental application classes of these filters can be summarized as identification (modeling), inverse modeling, interference canceling and prediction. Many different algorithms can be used in adaptive filter applications [38].

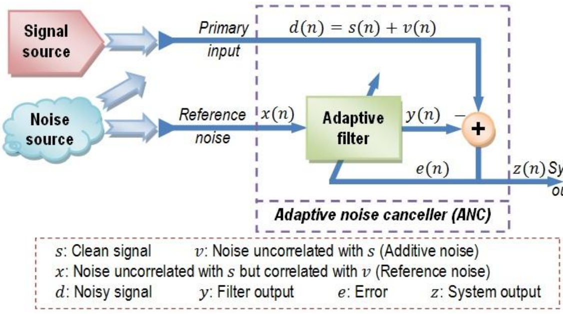


Figure 1. The block diagram of adaptive noise cancellation.

Adaptive noise cancellation, whose block diagram is given in Figure 1, is used to reduce/cancel noise from a corrupted/distorted signal. The fundamental mission of this process is to cancel the undesired disturbances from a signal adaptively to improve the SNR. The system output in Figure 1 is written by Eq. (1) [5-6]:

$$z=s+v-y \tag{1}$$

If both sides of Eq. (1) are squared, Eq. (2) is obtained.

$$\left.\begin{aligned} z^2 &= s^2+2s(v-y)+(v-y)^2 \\ E\{z^2\} &= E\{s^2\}+E\{(v-y)^2\} \end{aligned}\right\} \tag{2}$$

The minimum output power of system is

$$min[E\{z^2\}]=E\{s^2\}+min[E\{(v-y)^2\}] \tag{3}$$

In order to provide $E\{z^2\}$ to be minimum, $E\{(v-y)^2\}$ must also be minimum in Eq. (3), hence

$$z-s=v-y \tag{4}$$

The implementation steps of the adaptive noise cancellation process using the adaptive algorithm can be summarized as follows:

i. Set adaptive filter initial parameters
ii. Collect the samples $d(n)$ and $x(n)$
iii. Update the filter parameters
iv. Estimate the noise signal $y(n)\cong v(n)$ by using updated filter parameters
v. Obtain the clean ECG signal $e(n)=d(n)-y(n)$
vi. Go to step ii and repeat the same steps of adaptive noise cancellation process from step ii to vi.

4. Designed Software Tool and Applications

The new software tool, which can perform adaptive filtering with algorithms given in Table 1, was designed using MATLAB App Designer [39]. All adaptive algorithms in the program are coded without using built-in functions. The general equations in Table 2 can be used for the performance evaluations as a result of the denoising process.

The general flowchart of filtering process and login screen of the designed software tool are given in Figure 2 and 3, respectively. After entering the valid username and password, one can select the "Filtering" or "Topic descriptions" modules (Figure 4). When the "Topic descriptions" button is clicked, the topic selection screen comes (Figure 5) and the relevant topic is selected from here, and its explanation is presented in the style of a web page (Figure 6). When the "Filtering" button is clicked, the ECG signal loading and editing screen appears (Figure 7). This loading can be done in two ways: loading a noisy ECG signal or loading a clean ECG signal by adding noise. On this screen, if desired, the ECG signal can be cropped in terms of time or samples number. After the noisy ECG signal is loaded or created, the filtering process is started with selection of denoising method.

For the first application, the "105m.mat" [40] ECG signal is loaded, its length is reduced to 1800 samples and PLI noise with 0.5 V amplitude and 50 Hz frequency is added to it (Figure 8a). After clicking "Single method" button the screen for single analysis is opened (Figure 8b). Clean and noisy ECG signals are automatically transferred to this screen. After the algorithm is selected, a dialog box opens to enter the appropriate parameters (Figure 8b). By clicking the OK button, the analysis (denoising) is concluded (Figure 8c). The result screen in Figure 8c allows evaluating the denoising performance of a selected algorithm for both time and frequency domains graphically. The performance parameters in Table 2 are also included in this screen. These parameters allow evaluating the denoising performance of the selected algorithm numerically. In addition to the clean, noisy and filtered ECG signal graphics and frequency spectrums, the user can also display the power spectrums and spectrograms optionally (Figure 8d-e). The power spectrums in Figure 8d show the power contents versus frequency of clean, noisy, and denoised signals. The spectrogram plots in Figure 8e allow also to analyzing how the frequency content of these signals varies over time.

Table 2. The parameters used for performance evaluations.

Parameters	Expression		
	Clean signal	*Noisy signal*	*Filtered signal*
Power (dB)	$P_{cs} = 10\log_{10}\left\{\sum_{n=1}^{N}\lvert s(n)\rvert^2\right\}$	$P_{ns} = 10\log_{10}\left\{\sum_{n=1}^{N}\lvert d(n)\rvert^2\right\}$	$P_{fs} = 10\log_{10}\left\{\sum_{n=1}^{N}\lvert e(n)\rvert^2\right\}$
	Mean Absolute Error (MAE)	*Mean Square Error (MSE)*	*Root Mean Square Error (RMSE)*
Error (%)	$MAE = \frac{1}{N}\sum_{n=1}^{N}\lvert s(n) - e(n)\rvert$	$MSE = \frac{1}{N}\sum_{n=1}^{N}\lvert s(n) - e(n)\rvert^2$	$RMSE = \sqrt{\frac{1}{N}\sum_{n=1}^{N}\lvert s(n) - e(n)\rvert^2}$
SNR (dB)	*Input SNR*	*Output SNR*	*SNR improvement*
	$SNR_{in} = 10\log_{10}\left\{\frac{\sum_{n=1}^{N}[s(n)]^2}{\sum_{n=1}^{N}[v(n)]^2}\right\}$	$SNR_{out} = 10\log_{10}\left\{\frac{\sum_{n=1}^{N}[e(n)]^2}{\sum_{n=1}^{N}[s(n) - e(n)]^2}\right\}$	$SNR_{imp} = SNR_{out} - SNR_{in}$
	RMS Difference	*Noise Retention*	
Percentage (%)	$PRD = \sqrt{\frac{\sum_{n=1}^{N}[s(n) - e(n)]^2}{\sum_{n=1}^{N}[s(n)]^2}} \times 100$	$PNR = \frac{\lvert P_{fs} - P_{cs}\rvert}{P_{cs}} \times 100$	
	Between clean signal and noisy signal	*Between clean signal and filtered signal*	
Cross-correlation coefficient	$\rho_1 = \frac{\sum_{n=1}^{N}[s(n) - \bar{s}][d(n) - \bar{d}]}{\sqrt{\sum_{n=1}^{N}[s(n) - \bar{s}]^2 \sum_{n=1}^{N}[d(n) - \bar{d}]^2}}$	$\rho_2 = \frac{\sum_{n=1}^{N}[s(n) - \bar{s}][e(n) - \bar{e}]}{\sqrt{\sum_{n=1}^{N}[s(n) - \bar{s}]^2 \sum_{n=1}^{N}[e(n) - \bar{e}]^2}}$	

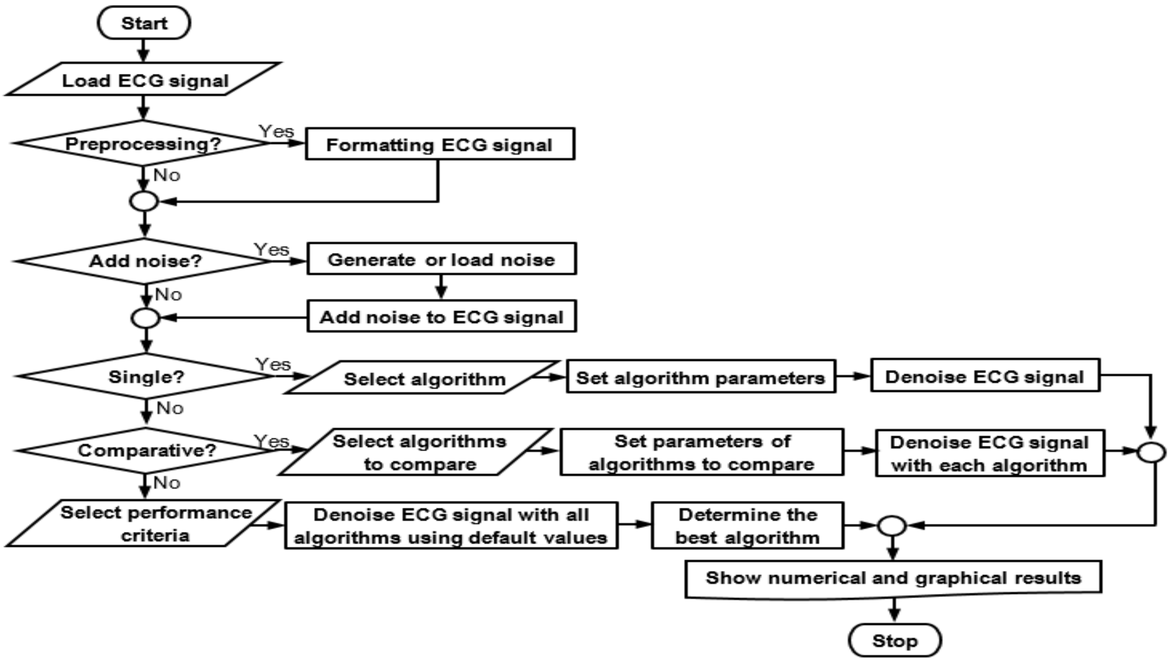


Figure 2. The flowchart of filtering process in the designed software tool.

Figure 3. The login window of tool.

Figure 4. The module selection window of tool.

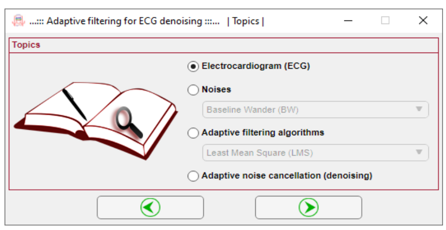


Figure 5. The topic selection window of tool.

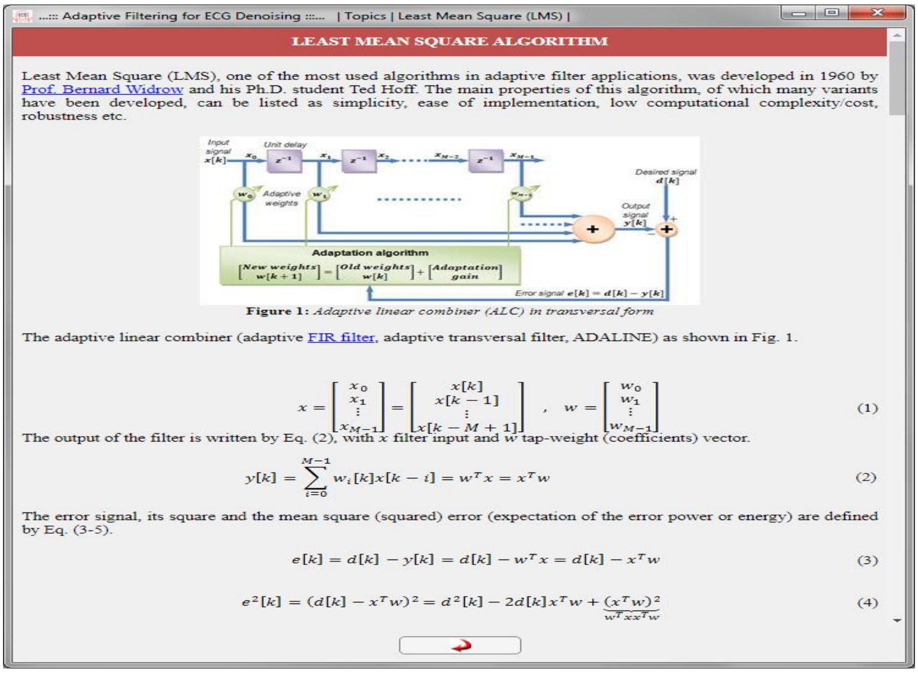


Figure 6. The sample topic description page from tool.

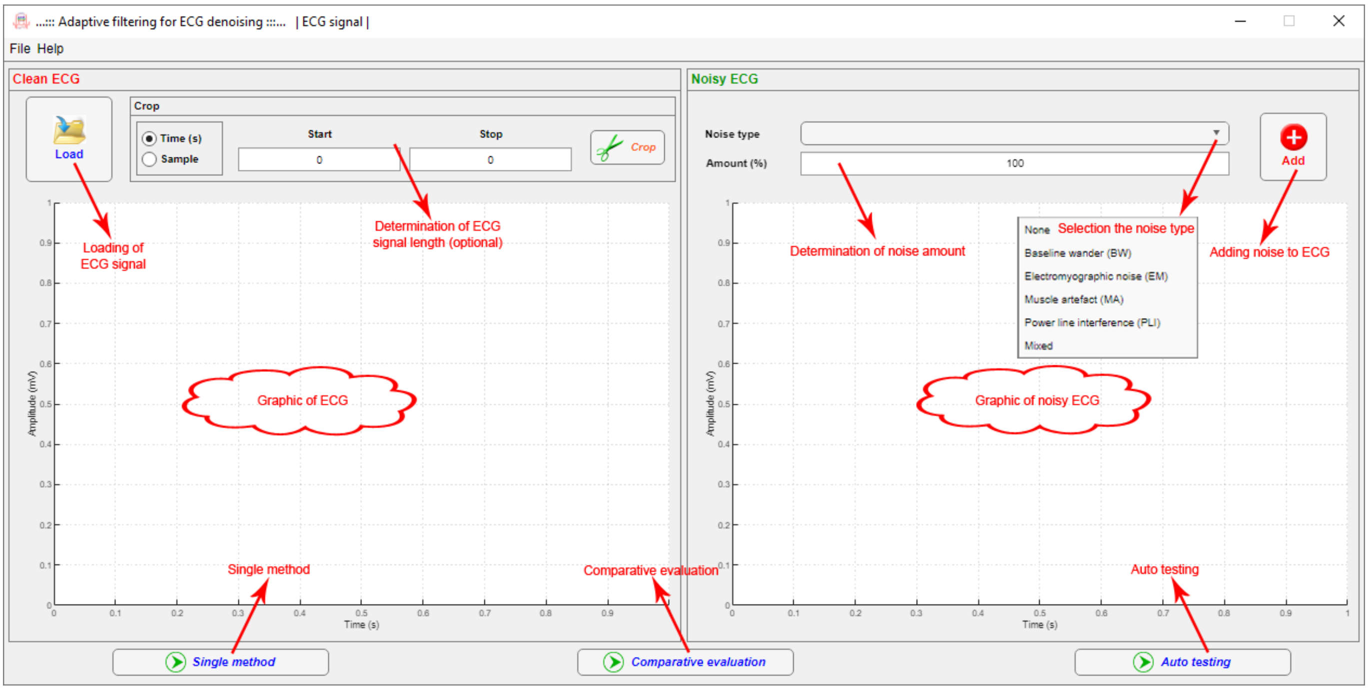
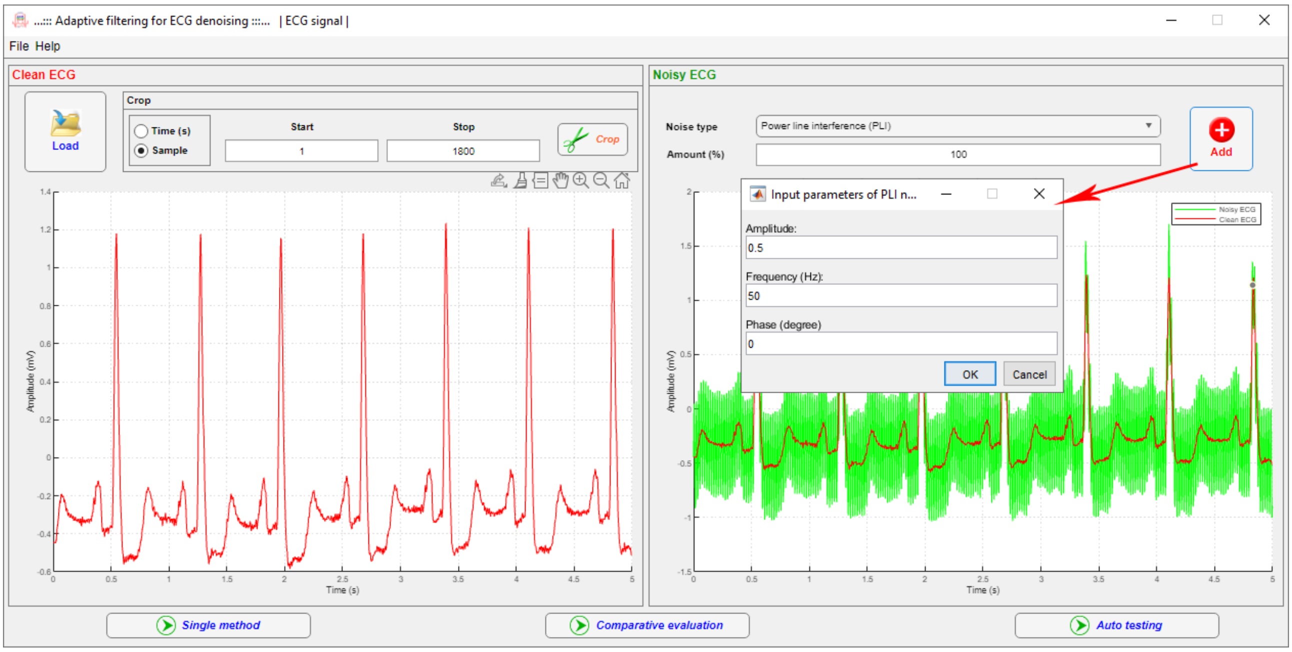


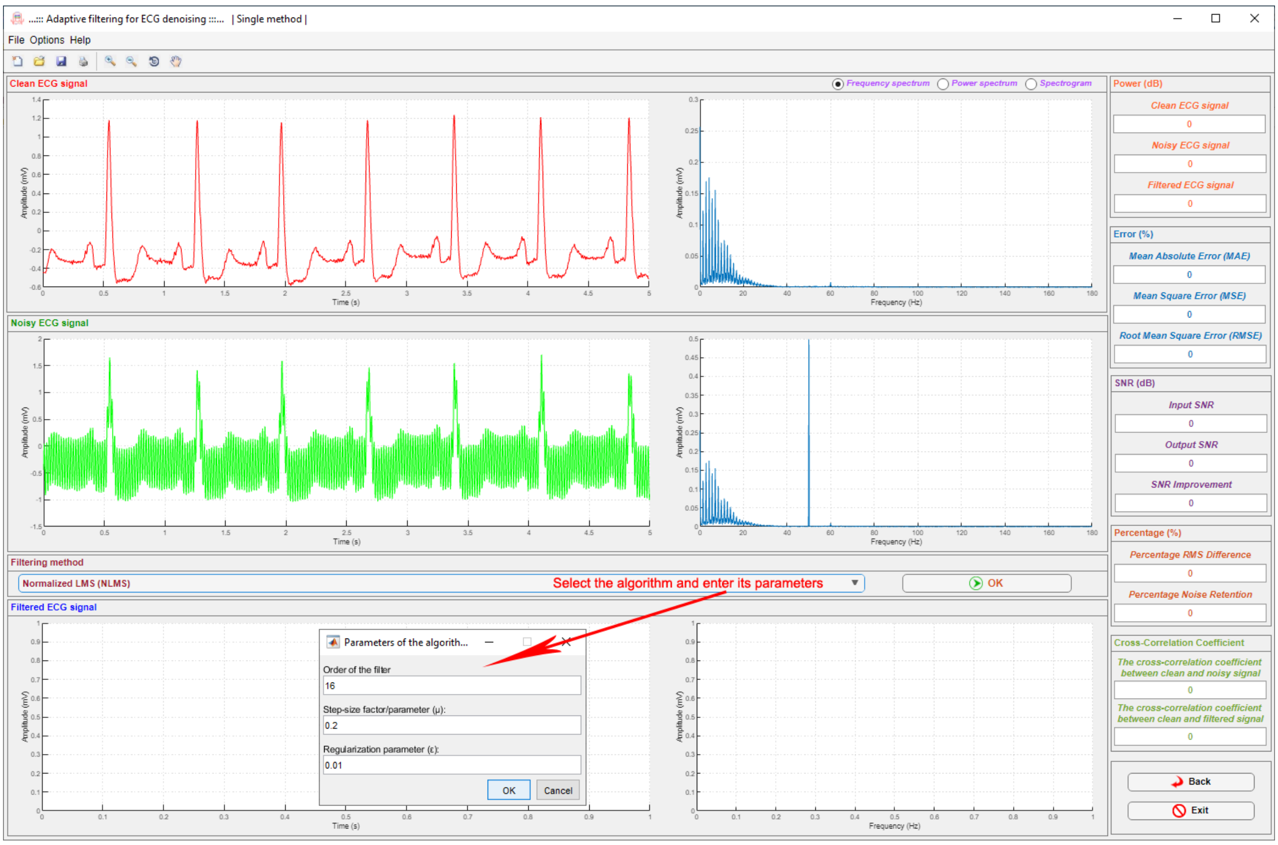
Figure 7. The ECG loading and editing screen of tool.

For the second application, the "103m.mat" [40] ECG signal is loaded, its length is reduced to 6 s and is mixed with noise (%30 Baseline wander [41], %40 Electromyographic noise [41], %25 Muscle artefact [41] and %50 Power line interference with 1 V amplitude and 50 Hz frequency is added to it (Figure 9a). The comparative results for LMS, NLMS, ENLMS and RLS algorithms are given in Figure 9b. In all algorithms, the filter length and the step-size are $M = 16$ and $\mu = 0.05$, respectively in the LMS, NLMS and ENLMS. In RLS algorithm forgetting factor is $\lambda = 0.9995$ and $\beta = 1$. The clean, noisy and filtered ECG signal graphics, frequency spectrums, power spectrums and spectrograms for each method are displayed optionally. Also, the performance parameters obtained for each method are given in the comparative table and the most successful method(s) are highlighted. According to the comparative denoising results in this simulation, it is seen that the RLS algorithm is more successful than the others selected. This window allows to comparing the 4 selected algorithms both graphically and numerically in the time domain, frequency domain, power spectra and spectrograms, respectively.

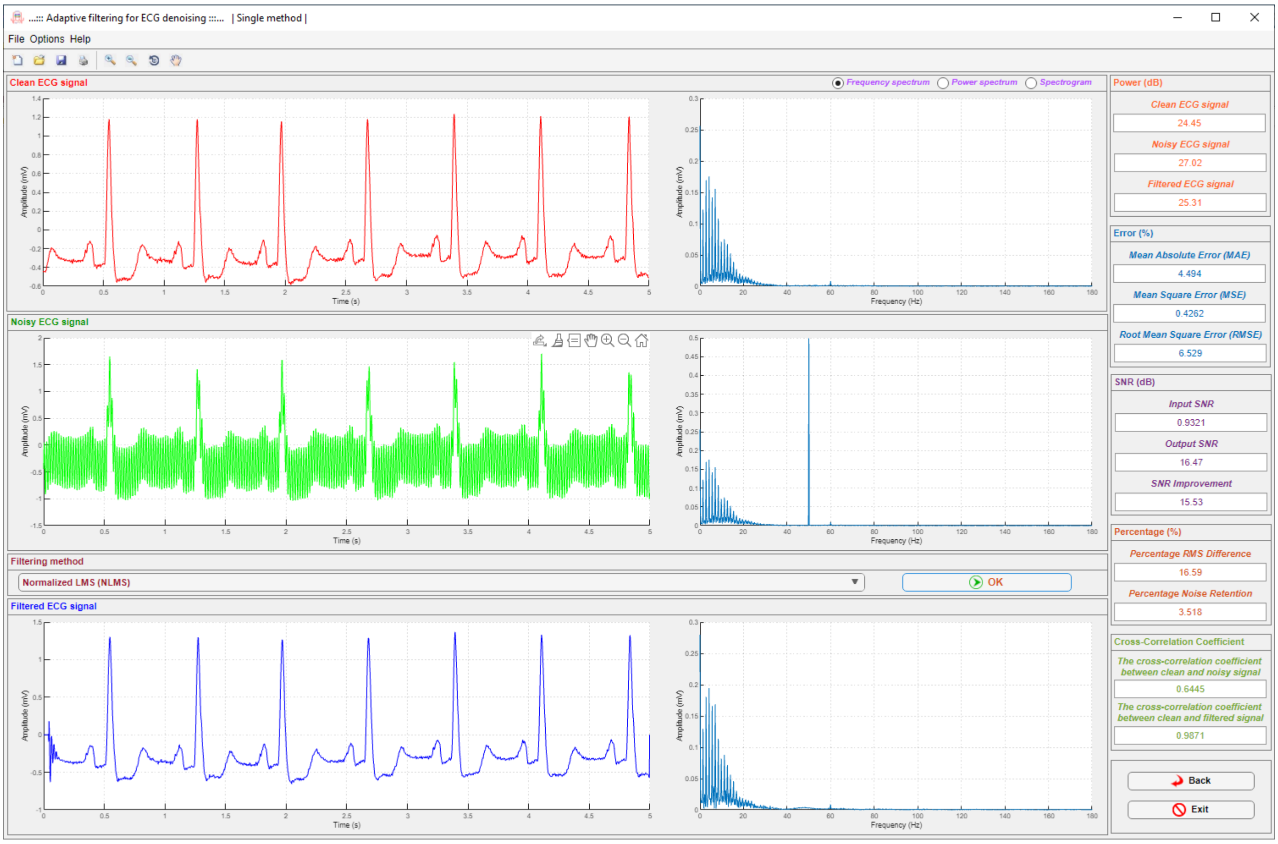
Similarly, by clicking the "Auto testing" button, the screen where automatic denoising options are set is displayed (Figure 10). On this screen, the performance criteria and the methods to be scanned are selected, and the method with the best results is obtained. Although the processing time is long, it can determine the most appropriate adaptive filter to clean the noise in the loaded signal because it scans selected or all methods.



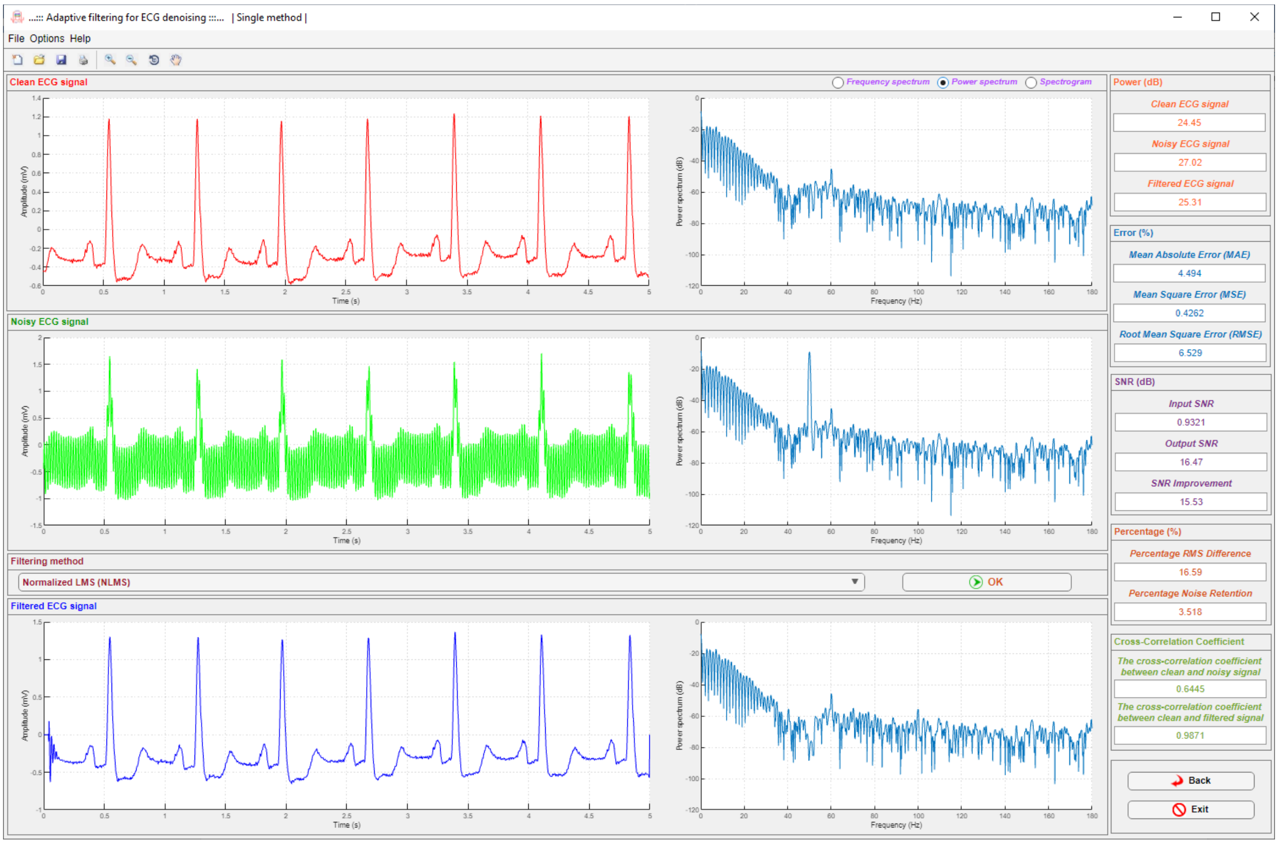
(a) Loading and cutting the ECG signal and adding noise to it.



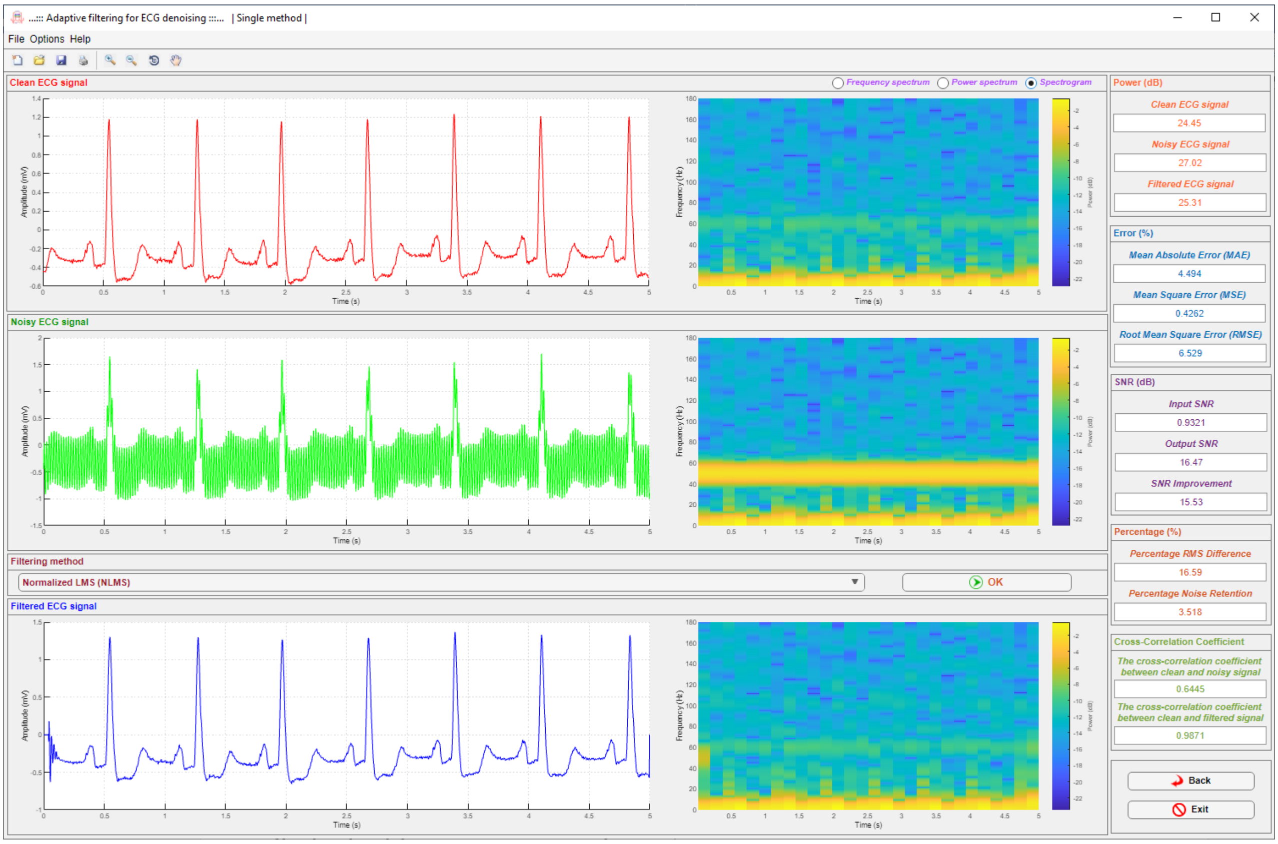
(b) The “single method” screen of tool.



(c) The result screen with frequency spectrums.

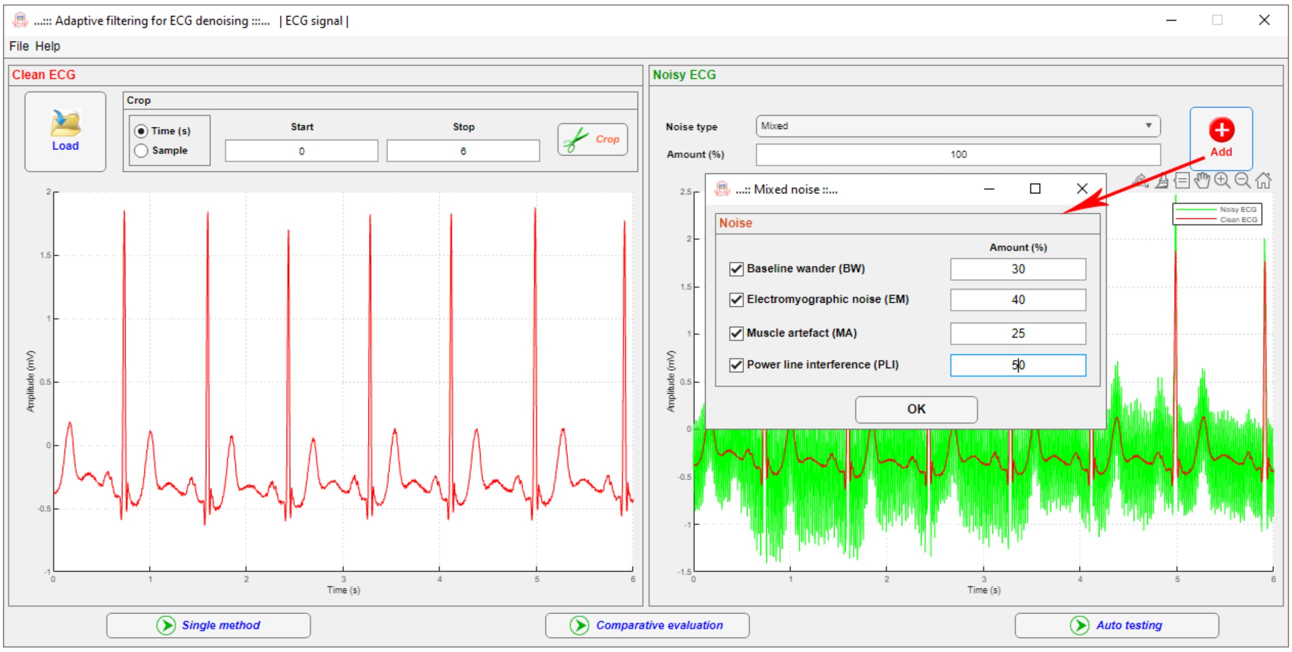


(d) The result screen with power spectrums.



(e) The result screen with spectrograms.

Figure 8. The screenshots for first application.



(a) The creating/adjusting mixed noise and adding to ECG signal.

	Least Mean Square (LMS)	Normalized LMS (NLMS)	Error Normalized LMS (ENLMS)	Recursive Least Squares (RLS)
Power of clean ECG (dB)	25.5439	25.5439	25.5439	25.5439
Power of noisy ECG (dB)	28.6439	28.6439	28.6439	28.6439
Power of filtered ECG (dB)	25.8843	25.7771	26.6371	25.5271
MAE (%)	8.4031	4.9242	15.9886	4.4512
MSE (%)	1.3601	0.5912	4.2402	0.4834
RMSE (%)	11.6622	7.6890	20.5917	6.9525
Input SNR (dB)	-0.0265	-0.0265	-0.0265	-0.0265
Output SNR (dB)	11.2022	14.7132	7.0167	15.3378
SNR Improvement (dB)	11.2287	14.7397	7.0432	15.3643
Percentage RMS Difference (%)	28.6361	18.8801	50.5623	17.0715
Percentage Noise Retention (%)	1.3328	0.9130	4.2797	0.0656
Clean and noisy ECG cross-correlation	0.6142	0.6142	0.6142	0.6142
Clean and filtered ECG cross-correlation	0.9452	0.9725	0.8347	0.9768

(b) The comparative result screen in time domain.

Figure 9. The screenshots for second application.

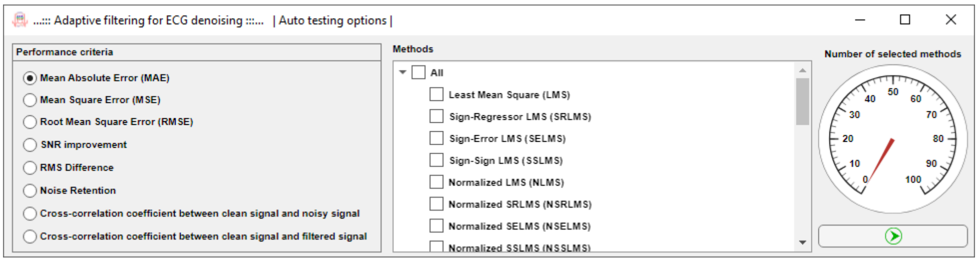


Figure 10. The auto testing options screen.

5. Conclusions

One of the most important steps of signal preprocessing is noise cancellation/reduction (denoising). After removing or reducing unwanted noise from the signals, they present more accurate information about their source. There are many denoising methods in the field of signal processing. The most important of these are adaptive filtering techniques. In the field of medicine, it is necessary to reduce the noises from the relevant signals at high rates in the correct evaluation of the functions of the organs and in the correct diagnosis of the diseases. Computer aided software tools are widely used in recent years and very helpful in many application areas that especially require heavy theoretical information, practical applications, concepts, mathematical operations, examples, problem solving etc. In this study, a new software tool with a user-friendly graphical user interface and rich contains was designed using MATLAB to ECG denoising area with many adaptive algorithms. This tool, which is convenient for adding new algorithms, contains a signal loading/editing module to be used for denoising the ECG signal corrupted by five different noise types, their visualization and preprocessing. It contains basically single, comparative and automatic denoising modules, which can be used to obtain an acceptable ECG waveform from the noisy ECG signal with many adaptive algorithms. Furthermore, this tool produces more numerical and graphical results about the denoising processes performed by using many adaptive filtering algorithms for analysis and comparison purposes. It can also scan all or selected algorithms and suggest the most successful one according to the selected performance criteria. In addition, with its rich content, it can be used effectively in the education of subjects in this field.

Author Contribution Statement

Metin Hatun: Conceptualization, Methodology, Investigation, Validation, Visualization, and Writing. Fahri Vatansever: Conceptualization, Methodology, Investigation, Software, Validation, Visualization, Writing-Reviewing and Editing.

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