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Comparison of moving average and Savitzky-Golay filters for noise removal in electrocardiograms

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Abstract
This paper presents the results of independently applying two filters to eliminate noise from an ECG signal: Moving Average Filter (MAF) and Savitzky-Golay Filter (S-G). These filters were applied to 45 ECGs from the Physionet database, all diagnosed with sinus bradycardia. A Python script was developed for automatic application of the filters using the following parameters: MAF was applied using three window sizes (7, 14, and 21), and S-G with a window size of 21 and polynomial orders of 7, 9, and 11. Results indicate that MAF performs best with a window size of 7. However, the S-G filter (21,11) significantly outperforms MAF in noise removal. Statistical parameters used were MSE (MAF = 0.0435; S-G = 0.0062), SNR (MAF = 16; S-G = 25), and Correlation Coefficient (MAF = 0.988; S-G = 0.9944); these values indicate that the S-G filter achieves better noise removal and minimal signal distortion, making it the best option for such processes. It is important to note that six filter configurations were compared, with S-G (21,11) being the best. A test hypothesis points out that there are meaningful differences between SG (21,11) and MAF (7).

Keywords: Noise removal, Electrocardiograms, Moving Average Filter, Savitzky-Golay Filter, signal quality

Introduction
The heart is a vital organ for our body, so identifying any abnormality that could indicate disease is critical. Cardiovascular diseases cause interruption of oxygen supply to heart muscles due to some type of blockage, with an estimated 18 million deaths per year caused by such diseases [1]. An electrocardiogram (ECG) represents the electrical activity of the human heart, making it a very useful tool for detecting various heart problems [2]. The heart's electrical impulses can be used to diagnose cardiac conditions such as arrhythmias, cardiac arrest [3,4], coronary artery blockage, atrial fibrillation, among others [5]. Due to the presence of various interferences during ECG recording, the signal can be corrupted by different noise sources such as electrical power lines, axis deviation due to involuntary muscle movements, breathing, among others. These can affect the accuracy of ECG interpretation, leading to incorrect diagnoses and treatments [6]. Gaussian noise acquired during signal transmission due to electrode conditions must also be considered [7]. Proper ECG noise removal remains a challenge for current researchers. Many filters and algorithms have been developed to reduce or eliminate ECG noise, but the search continues for those yielding better results [8]. Various ECG denoising methodologies include Kalman filters [9], discrete wavelet transforms [10,11], singular value decomposition, and independent component analysis [12]. Some authors [13] propose a hybrid method combining wavelet transform and FIR filters. This study focuses on analyzing two specific filter types: Moving Average Filter and Savitzky-Golay Filter.

Moving Average Filter
This type of filter (MAF) is simply a Finite Impulse Response (FIR) filter used to smooth a data array or signal. Input samples and their average are used to produce the output signal. As the window size increases, the output smoothing also increases. In [14], this filter was used for ECG noise removal, and it was found that the Signal-to-Noise Ratio (SNR) reached considerably good values. Similarly, in [15] noted that this digital filter behaves like a bandpass filter of 5-18 Hz and highlighted its advantages, including low computational cost, simple mathematical operations, ease of implementation, and preservation of midrange

frequencies. One of its disadvantages is the attenuation of the QRS complex, which can affect diagnosis. Mathematically, it is represented as follows:

$$y[n] = \frac{1}{7}\sum_{-3}^{3} x[n-k]$$

where x, y, and t represent the input data, output signal, and time index, respectively. This method enables smoothing the signal for better analysis [16].

Savitzky-Golay Filter

S-G filters have been widely used to remove noise from signals such as EEG, ECG, elastography, infrared spectroscopy, MRI images, and eye movement analysis [17]. The basic idea is to perform local approximations in a signal by moving a window with a fixed-order polynomial [18]. Polynomial coefficients can be calculated using least squares, and data is smoothed by computing the polynomial value at the center index of the dynamic window. This process is repeated for each data point, producing high SNR values while maintaining the original signal shape [19]. According to Sultana [20], the S-G filter is typically used to smooth signals and improve data accuracy without distorting the original signal; it uses a convolution process to fit data to a low-degree polynomial. The polynomial can be expressed as follows:

$$\rho(r_i) = c_0 + c_1^r + \cdots + c_p^{rp}$$

Building an Savitzky-Golay filter involves initial conditions such as filter length, polynomial order, and window size [21]. Filter effectiveness is measured by comparing the original and filtered signal. Common parameters include Mean Square Error (MSE) [22], Signal-to-Noise Ratio (SNR) [23], and correlation [24]. MSE is defined as:

$$MSE = \frac{1}{N}\sum_{i=1}^{N}[x(i) - \hat{x}(i)]^2$$

SNR is defined as:

$$SNR = 10log_{10}(\frac{\sum_{i=1}^{N}(x(i))^2}{\sum_{i=1}^{N}[x(i) - \hat{x}(i)]^2})$$

The correlation coefficient [25], indicates that a value of 1 implies perfect correlation between signals, with optimal window size and polynomial order:

$$CORR = \frac{\sum_{i=1}^{N}(X_i - \tilde{X})(Y_i - Y)}{\sqrt{\sum_{i=1}^{N}(X_i - \tilde{X})^2 (Y_i - \tilde{Y})^2}}$$

In general, good filtering results in low MSE, SNR above 20 dB, and correlation coefficients close to 1.

Materials and Methods

A total of 45 electrocardiograms from the Physionet database [26] were analyzed, specifically a set of ECGs diagnosed with sinus bradycardia. Each file contains the 12 leads, sampled at 500Hz with a 10-second duration. This set was supported by Chapman University and Shaoxing People's Hospital. To compare filter effectiveness, a Python script (See Annex 1) was developed for automatic analysis of each ECG. Libraries used include scipy, neurokit2, matplotlib, numpy, among others. The algorithm starts by reading the ECG and extracting lead DII values, which commonly yield heart rate, rhythm, and electrical axis, among other parameters. The MAF is applied to the original signal using window sizes 7, 14, and 21. Subsequently, MSE, SNR, and CORR are calculated. The process is repeated using the S-G filter with polynomial orders 7, 9, and 11, all with a window size of 21. For each case, average values for each parameter are computed and compared to determine the most effective filter for ECG noise removal (see Figure 1), without causing significant signal distortion.

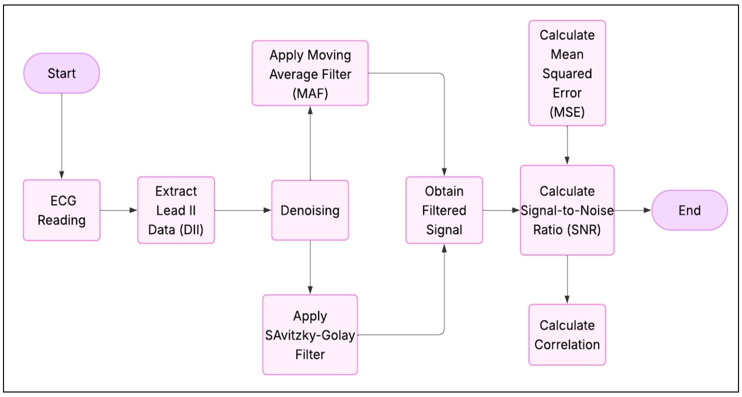

Fig1: Denoising ECGs´ Flowchart

Results

Qualitative analysis. - The algorithm from Figure 1 was applied to 45 ECGs from the Physionet database, but for simplicity, graphical results for two ECGs, JS0013 (Figure 2) and JS0019 (Figure 3), are shown. Both are from the Physionet dataset. In Figure 2, the original signal, the signal filtered by S-G (order 11, window 21), and the signal filtered by MAF (window 7) are displayed from top to bottom. It appears that MAF better removes noise visually; however, upon closer inspection, MAF produces distortions in the original QRS complex. Specifically, there is a slight variation in the R and S wave amplitudes compared to the original signal, potentially affecting precise calculations. The R wave amplitude is approximately 5 units, a value preserved by S-G, while MAF reduces it to 4 units.

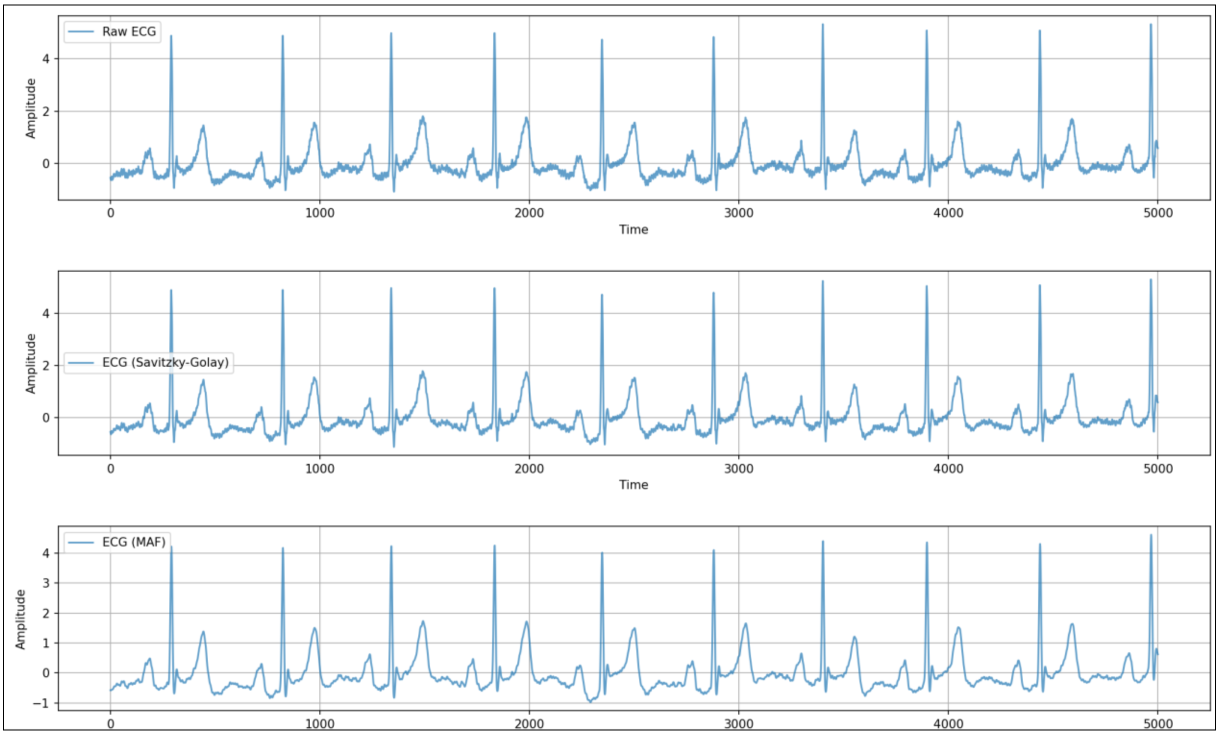

Fig 2: Visual comparison of the original signal and filters.

Similar observations were noted as in ECG JS0019. Although the signal appears smoother with MAF, variations in the QRS complex amplitude are evident. No temporal distortion is observed; thus statistical parameters are necessary to validate the filtering results. After denoising ECGs, the waveform must not change in order to obtain correct values in the intervals PR, for example, because this value is useful to detect some kind of blockage.

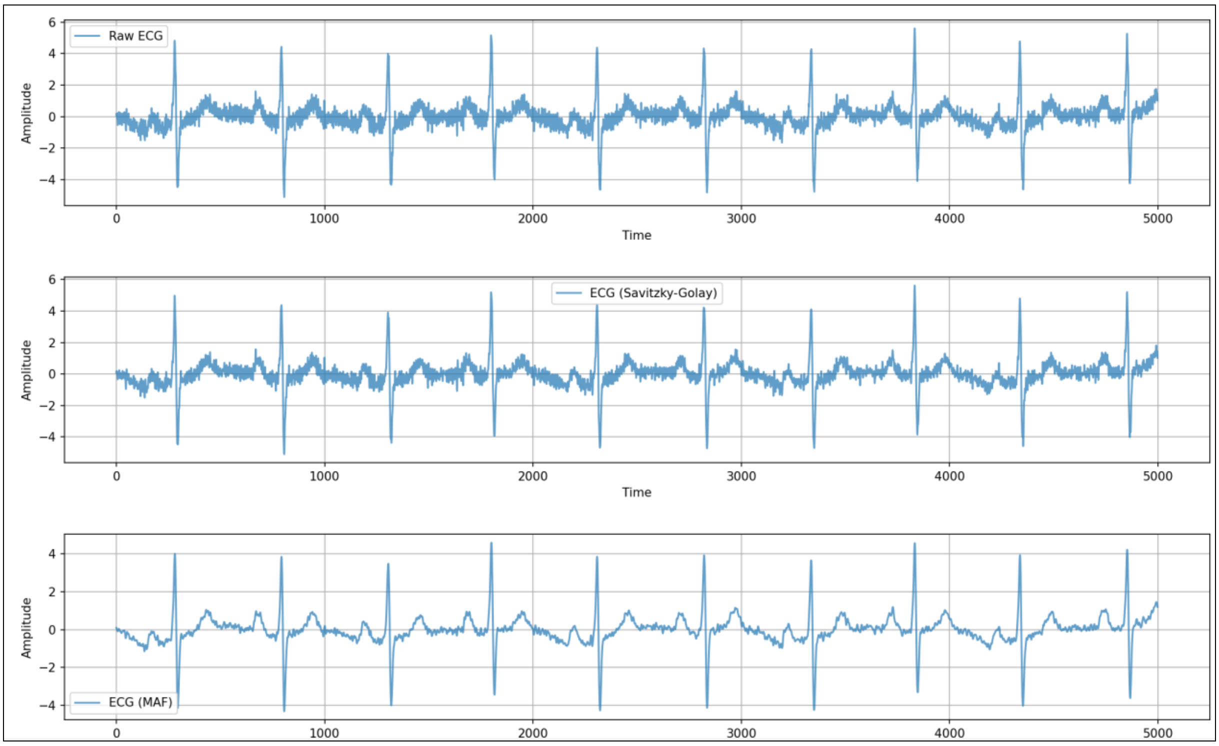

Fig 3: Filter comparison for the ECG labeled JS0019.

Quantitative analysis. - To enhance the analysis of the original ECG signal filtering, the metrics Mean Square Error (MSE), Signal-to-Noise Ratio (SNR), and Correlation coefficient were used. According to the literature, good filtering is based on low MSE values and high SNR values; likewise, a correlation value close to one indicates highly effective filtering without altering the original signal. Two filtering processes were applied. The first involved the S-G filter, using a window size of 21 and polynomial orders of 7, 9, and 11, respectively, applied to 45 ECGs diagnosed with sinus bradycardia. Then, the MAF was applied using window sizes of 7, 14, and 21 to the same ECGs. In other words, six types of filters were applied to the ECGs to determine which produced better noise elimination results. For each case, MSE, SNR, and Correlation were calculated. Table 1 shows the average of each parameter for every filter used. For MAF, the best results were obtained with a window size of 7, and as the window size increased, the values of MSE, SNR, and Correlation declined to levels not acceptable for filtering purposes, as observed with window sizes 14 and 21. On the other hand, the S-G filter performed better even with a polynomial order of 7 compared to any MAF window. The best S-G results were achieved with a polynomial order of 11 and a window size of 21. In this case, the MSE reached its lowest value (0.0062), the SNR its highest (25.03), and the correlation was very close to one (0.9984), making it the best filter among the six filter studied.

Table 1: Comparison of parameters among filters

Parameters	**Savitzky-Golay**			**Moving Average**		
Order	7	9	**11**	**7**	14	21
MSE	0.0155	0.0106	0.0062	0.0435	0.1871	0.3331
SNR	21.694	23.463	25.030	16.224	9.9026	7.5526
Correlation	0.9948	0.9971	0.9984	0.9862	0.9468	0.9077

These results indicate that MAF with a window size of 7 represents a good filter, as it yields a very low MSE and a correlation of around 98%. However, the S-G filter produces significantly better values than MAF, making it a superior option for filtering. These parameters suggest that, with the S-G filter, the original signal does not undergo major variations in the shape of the ECG waveforms. In Figures 2 and 3, it can be observed that the QRS complex is almost identical to the one shown in the original signal, unlike what is seen with MAF.

A hypothesis test was considered, using a significance level of 5% and the standardized value for two samples (z = ±1.96):

$$z = \frac{(\overline{x_1} - \overline{x_2}) - (\mu_1 - \mu_2)}{\widehat{\sigma_{12}}}$$

Where

$$\widehat{\sigma_{12}} = \sqrt{\frac{\sigma_1^2}{n_1} + \frac{\sigma_2^2}{n_2}}$$

It represents the estimated standard error of the two samples. The null hypothesis is defined as $H_0: \mu_{MAF} = \mu_{SG}$, and the alternative hypothesis as $H_1: \mu_{MAF} \neq \mu_{SG}$. Considering the values corresponding to the best filters in each case, SG (21,11) and MAF (7), the standardized value is presented in Table 2.

Table 2: Standardized value for hypothesis test

	MSE	**SNR**	**CORR**
sigma	0.00383	0.82964	0.0016
z	9.74015	10.6144	7.36764

From Table 2, it can be observed that when analyzing the standardized values of the two samples (MAF and SG), each of them falls outside the acceptance region of H_0. Therefore, the alternative hypothesis is accepted, indicating that there are significant differences between the calculated parameters. This confirms that the SG (21,11) filter presents statistically significant differences when compared to MAF (7).

Discussion

The findings of this study are consistent with previously reported research, which indicates that one of the most effective digital filters for removing noise from electrocardiogram signals, without causing significant attenuation of the original signal, is the Savitzky-Golay filter. In particular, when compared to the Moving Average filter, the advantages of the Savitzky-Golay filter are significantly greater. For this case, the optimal configuration was a filter with a window size of 21 and a polynomial order of 11.

Conclusion

Noise removal from a signal is a very important process for the quantitative analysis of a given signal. Applying it to an ECG is even more relevant due to its complexity and its usefulness in the classification of certain heart diseases. The automation of ECG reading and its corresponding diagnosis must employ highly efficient models to achieve predictions with a low margin of error. Noise removal from an ECG is crucial to ensure high-quality quantitative analysis. The parameters obtained in this work indicate that the S-G filter with a polynomial of order 11 and a window size of 21 produces the best results for noise removal in the ECGs studied. An MSE value of 0.0062 and an NSR value of 25 are representative of very acceptable noise removal, and a Correlation value of 0.9984 indicates that the distortion of the signal is minimal. Hypothesis test, indicated there is meaningful differences between SG (21,11) and MAF (7). These values ensure that the S-G filter (21,11) is far superior to the MAF (7). It should be mentioned that in the visual representation of the signals, the MAF improves the smoothness of the signal with the window size, but it causes greater distortion in the original signal, which is undesirable for filtering purposes.

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Annex 1

Python script for Denoising ECGs

```python
import neurokit2 as nk
import numpy as np
import matplotlib.pyplot as plt
from scipy.io import loadmat
import scipy.signal as signal
from scipy.stats import pearsonr
from scipy.signal import savgol_filter

def mse(original, processed):
    return np.mean((original - processed)**2)

def snr(original, processed):
    signal_power = np.sum(original**2)
    noise_power = np.sum((original - processed)**2)
    return 10 * np.log10(signal_power / noise_power)

data = loadmat("C:/JS00019.mat")
frecuency = 500  # En Hz
val_data = np.array(data["val"])
filas = val_data[1, :] / 100
ecg_smoothed = signal.savgol_filter(filas, window_length=21, polyorder=13)
ecg_smoothed1 = nk.signal_smooth(filas, method="moving_average", size=7)
mse_val = mse(filas, ecg_smoothed)
snr_val = snr(filas, ecg_smoothed)
correlation, _ = pearsonr(filas, ecg_smoothed)
```