ECG Denoising based on PCA and using R Peaks Detection

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Keywords: Electrocardiogram, R Peaks, Multi-Scale Product, Undecimated Wavelet Transform, Principal Component Analysis.

Abstract: In this paper, we propose a new Electrocardiogram (ECG) Denoising technique based on Principal Component Analysis (PCA) and using R peaks detection. This technique consists at first step in cutting the entire ECG signal into frames then the denoising is performed frame by frame by using PCA. Each frame is located between two successive R peaks. The R peaks detection is performed by using a new detection method based on multi-scale product of the undecimated wavelet coefficients. The Reconstructed ECG signal is obtained by concatenating all the denoised frames. The evaluation of the proposed technique is performed by comparing it to the denoising technique based on PCA and applied to the entire noisy ECG signal. The two techniques are tested on four ECG signals taken from MIT-BIH database. The used criteria in this evaluation of these two techniques are the SNR improvement and the mean square error (MSE). The obtained results from this evaluation show clearly that the denoising technique based on PCA and applied to the entire noisy ECG signal, is slightly better than the proposed technique. However this latter has the advantage of working in real-time because the processing is performed frame by frame and not on the entire noisy ECG signal. Concerning the new proposed technique of R peaks detection, it is very accurate because it permits a perfect reconstruction of the ECG signal when concatenating all the frames.

1 INTRODUCTION

The Electrocardiogram (ECG) signal is a graphical representation of cardiac activity and it is used for the identification of heart abnormalities and different heart diseases. Generally, an ECG signal has unique morphological characteristics (P-QRS-T complex) and it is highly significant than other biological signals (P. Karthikeyan, 2012; Er. Manpreet Kaur, 2014; Lei Lei, 2013). This high significance is justified by the fact that it is possible to diagnose many cardiac diseases by analyzing the variations of this morphology visually. While ECG results have made major contributions to cardiac diagnosis (B. Babloyantz, 1996), the electroencephalogram (EEG) is useful in neurological diagnosis, but to a lesser degree (A. Blanco, 1997).

It is possible to have diagnostics of various cardiac diseases through the analysis of the morphology visually variations.The presense of noises in an elctrocardiogram signal, will however severely affect features extraction and visual diagnosis of various application such as emotion estimation and stress measurement (P. Karthikeyan, 2012). For suppressing noises and extracting the efficient morphology of an electrocardiogram signal, various processing techniques have been recently proposed (M. Benmaiekl, 2010; K. M. Chang, 2011; M. P. S. Chawla, 2008; S. C. Mahesh, 2008; S. M. M. Martens, 2006). Many research works have used digital Infinite Impulse Response (IIR) filter in order to remove the effects of baseline wander and power line interference from the ECG signal (S. C. Mahesh, 2008; Mbachu C.B, 2011). Thanks to the simplicity of the IIR filter design, higher order IIR filters are performing well for removing the noises from ECG signals. However, it has the drawback of increased filtering time, memory and unable to filter the highly non linear signals in the entire ECG range (P. Karthikeyan, 2012). Recently, adaptive filtering techniques are used for suppressing the power line interference and other noises from an ECG signal (S. M. M. Martens, 2006; F. Chang, 2007; D. Dobrev, 2008). This technique is more well-known due to its smaller residual errors and faster filtering response (P. Karthikeyan, 2012; S. G. Tareen, 2008). However, this technique needs the reference signal (either noise or signal characteristics) information for the efficient filtering process (P. Karthikeyan,

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2012). In reference (Taigang He, 2006), the temporal averaging filter is adopted for noise cancellation and it needs a large number of time frames for efficient noise reduction (P. Karthikeyan, 2012). Independent Component Analysis (ICA) is for suppressing the noises from physiological signals in reference (S. G. Tareen, 2008). On the other hand, the linear filtering is also adopted for concelling the baseline wander from an ECG signal in the frequency range of 0.5Hz (E.-S. El-Dahshan, 2010). This technique introduces the ringing effect (Gibbs phenomenon) on the ECG signal analysis (P. Karthikeyan, 2012). For rectifying this limitation, polynomial fitting (PF) or namely cubic spline filter was introduced for suppressing noise from an ECG signal. P. Karthikeyan (P. Karthikeyan, 2012) has used the Principal Component Analysis (PCA) for ECG signal denoising and in this work we have also used PCA for the same goal. Our proposed denoising technique exploits the R-peaks detection in ECG denoising and the processing of denoising is performed frame by frame. Each frame is located between two consecutive R-peaks. In the rest of this paper, we will detail with the proposed technique and we will study the Principal Component Analysis (PCA). We will also expose our new proposed technique of R-peaks detection which is based on multi-scale product of the undecimated wavelet coefficients. Then we will give some simulation results obtained from the application of the proposed technique to four ECG signals taken from MIT-BIH database. Finally we will interpreted these results and give the conclusion.

2 MATERIAL AND METHODS

As mentioned previously, in this paper, we propose a new method of ECG denoising based on Principal Component Analysis (PCA). This technique consists at first step in cutting the noisy ECG signal into frames where each frame is located between two consecutive R-peaks. Then the denoising is performed frame by frame by using PCA. The denoised ECG signal is finally obtained by concatenating all the denoised frames. For detecting R peaks, we propose in this paper, a new technique of R-peaks detection based on undecimated wavelet transform and computing multi-scale product and then computing the modulus maxima.

2.1 Principal Component Analysis

Principal Component Analysis (PCA) is a method that is usually employed in multivariate statistical analysis (I Romero). Its aim is to reduce the number of dimensions from a numerical measurement of several variables (I Romero). With this dimensional reduction, this technique looks for simplifying a statistical problem with the minimal lost of information. This technique is also used in signal processing for separating a linear combination of signals generated from sources that are statistically independent. This is performed by representing the data with a new coordinate system where its aim consists in maximizing the signal, measured by the variance, and minimizing redundancy, measured by the covariance magnitude (Shlens Jonathan, 2009; Joachim.behar). Note that others measures can be used with such statistically based techniques for discovering the axes. For example in the case of ICA, the measure is based on non-Gaussianity (Joachim.behar). The final PCA aim consists in decorrelating the signal by projecting data onto a particular orthogonal basis (Joachim.behar). PCA is completely non-parametric and there is no assumption on the structure of a model. We will say that the new axis set is discovered in the case of PCA. Note that this is different from Fourier based techniques where the axes onto which the data are projected, are fixed. Therefore with PCA, the new basis depends completely on the structure of the data being analyzed and the founded basis function with PCA may overlap in the frequency domain (Gari D. Clifford). PCA and ICA are named techniques of blind source separation (BSS). 'Blind' expresses that the new axes on which the data are projected are completely determined by the data i.e without prior knowledge of the data structure (Gari D. Clifford). Joachim et al (Joachim.behar) have projected the ECG sample onto the new set of axes determined by PCA, separate signal and noise component within this new domain before projecting back the signal to the original space.

PCA identifies the most 'meaningful' basis in which to re-express our data set; the aim consists in minimizing redundancy, measured by the covariance magnitude, and to maximize the signal that is measured by the variance (Shlens, Jonathan, 2009).

PCA assumes (Joachim.behar):

- Linearity.
- Large variance represents interesting structure; which means that we suppose that the SNR is high enough such that the signal is associated with principal components having a high variance and noise with components having a lower

variance.

- Principal components are orthogonal.

In order to find the principal components of a multidimensional signal, one can use singular value decomposition (SVD). Suppose X is an $N \times M$ real observation matrix that can be decomposed as follow:

$$X = USV^T \quad (1)$$

Where S is an $N \times M$ diagonal matrixwith nonnegative real numbers on the diagonal; $S = diag(s_1,\ s_2, s_3, \dots, s_m)$ with $s_i = \sqrt{\lambda_i}$ and where a common convention is to list the singular values λ_i in descending order. The smallers the s_i are, the smaller the amount of energy carried along the corresponding eigenvector. Therefore, small eigenvalues are frequently associated with the noise (Gari D. Clifford, 2006). V is an $M \times M$ matrix of column vectors corresponding to the eigenvectors of the covariance matrix XX^T and which constitutes a new Basis B' (Joachim Behar). The matrix U is of dimension $N \times N$ and it is a matrix of projections of X onto the eigenvectors of C (Golub, G. H., 1989).

In this section we start with an example taken from (Joachim Behar) where N = 2 (in other word, just two ECG cycles are considered) and M = 240 (i.e we have 240 data points per ECG cycle). The cycles are represented as a stack (Fig.1.).

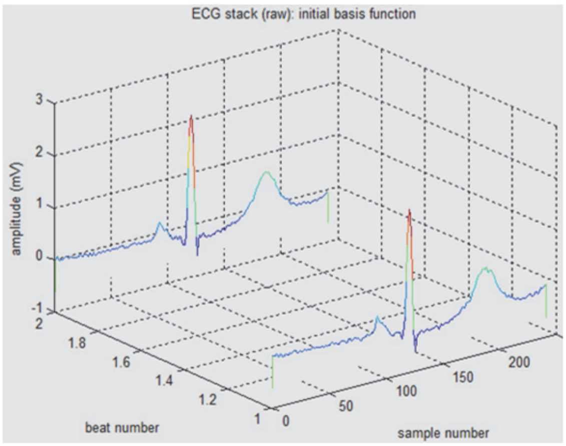

Figure 1: Plot of the basis functions expressed in B (joachim.behar).

For building this stack, QRS detection is performed on the initial ECG sample (this detection was performed by using a Pan and Tompkins algorithm for example (Pan, Jiapu, 1985) which is then 'cut' into its different cycles. The initial ECG stack can be seen as observations (over time) of the same state variable but along two different axes. The initial basis is $B = (e_1, e_2)$ and the basis found by PCA is $B' = (p_1, p_2)$. If we represent the initial data onto a plot which axis are directed against e_1 and e_2 respectively then the blue points are obtained on Fig.2.

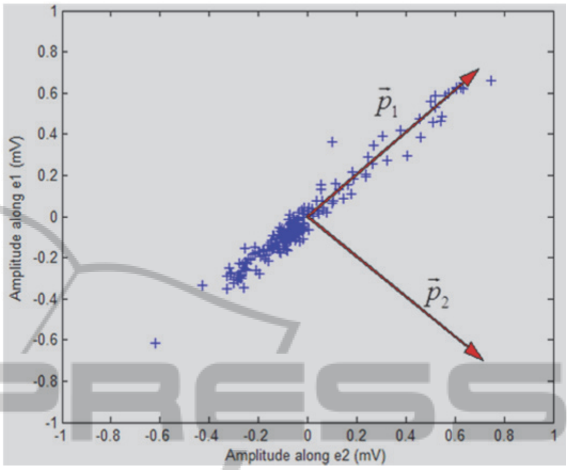

Figure 2: Plot of the first ECG cycle against the second ECG cycle (joachim.behar).

Note that if the two cycles were precisely the same then all the points would be aligned. Then the PCA is applied for finding the most representative manner of the data representing:

The red arrows on the plot represent the principal components that PCA finds (2 in our case since N = 2). Note that the founded axis for B' are orthogonal as expected. Again the purpose with PCA consists in minimizing redundancy, measured by the covariance magnitude, and maximizing the signal, measured by the variance. As we can see this is what we can obtain by determining p_1 and p_2.

The data are now represented within this new set of axis directed along p1 and p2 (i.e the observations are projected onto the new basis B′) to obtain Fig.3.

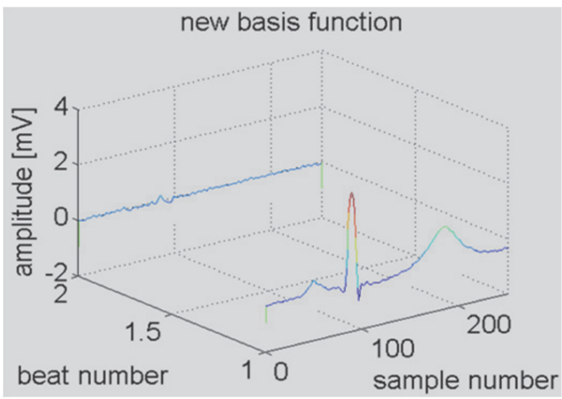

Figure 3: Plot of the basis functions in B′ (joachim.behar).

The first basis function (along p1) carries the signal information while the second basis function (along p2) would be considered as carrying the residual information which in our case will be attributed to process and observation noise. Note that each slice of the initial stack (here N=1 or N=2) is a linear combination of the slices expressed in B′.

The next step consists in suppressing the noisy component(s) in the domain found by PCA and then project back the signal to the original space B. It is therefore expected that the signal will be retrieved in the original space will be 'cleaner'. On this example (Joachim behar) and as we are only dealing with N=2 then we only keep the first principal component in B′ before projecting back onto B. As this is not very representative with N=2, we will see what kind of results are obtained on an example with higher dimensionality.

A stack of 20 ECGs cycles is considered and represented in Fig.4. PCA is applied in order to find the new basis B′ which cardinality is equal to 20. A singular value is associated to each vector which constitutes the basis and represents the energy amount that is carried out by the corresponding vector (Fig.4.). Suppose that the signal is represented by the vectors having the highest singular values we filter our data in the B′ domain by just conserving the five most representative principal components. Generally the signal/noise boundary will be taken to be at the knee of the eigenspectrum (P. Karthikeyan, 2012). Fig.4. indicates 'how much' those vectors contribute to the raw signal and Fig.5. shows the data projected onto the new axis.

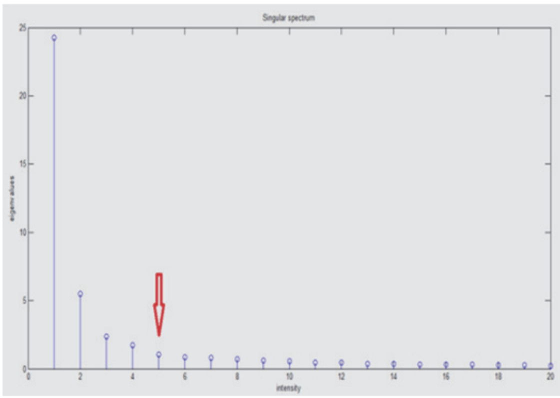

Figure 4: Discovered principal components (joachim.behar).

The only the first five principal components are kept in this case since they contain most of the energy (fig.4).

As we can see the signal is cleaner than what it was initially. Finally Fig.6. shows a few ECG cycles from the initial sample and the corresponding PCA filtered cycles.

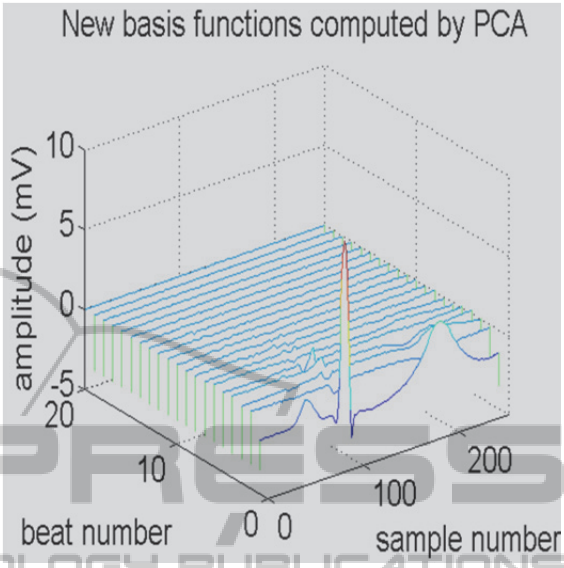

Figure 5: ECG stack after filtering by keeping only the first 5 principal components within the B′ domain (Joachim Behar).

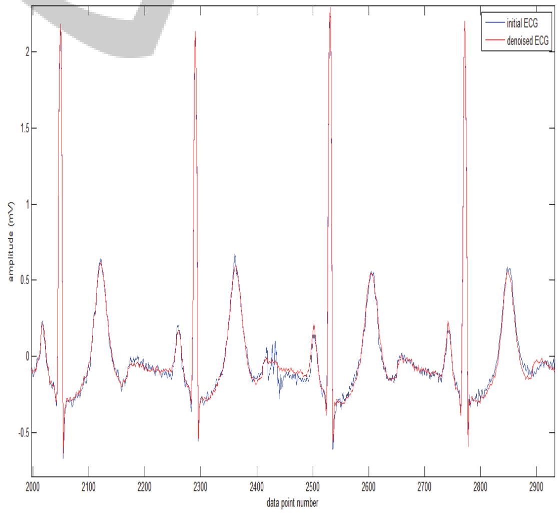

Figure 6: A few ECG cycles after backprojection and reconstruction from the ECG stack (Joachim Behar).

2.2 Modulus Maxima

Wavelet modulus maxima are used to locate characterizing singularities in the signal. Let wf(x) is the wavelet transform of a function f(x) then we have:

- Any point x_0 such that $\frac{\partial(wf(x))}{\partial x}$ has a zero crossing at $x = x_0$ is named a local extremum; when x varies.
- Any point x_0 such that $|wf(x)| \leq |wf(x_0)|$ when x belongs to the other side of the neighborhood of x_0 and $|wf(x)| < |wf(x_0)|$ when x belongs to either a right or left neighborhood of x_0 is named modulus maximum.
- Any corrected curve in the scale space x along which all points are modulus maxima is called maxima line (Samar Krimi, 2005).

2.3 Multiscale Products

The singularity detection can be performed via the product of the wavelet coefficients instead of local maxima of the wavelet coefficients. Rosenfeld and Cowoerkers suggested forming multiscale pointwise products (A. Rosenfeld, 1970; B. M. Sadler, 1999). This is intended to enhance multiscale peaks due to edges, while cancelling noise, by exploiting the multiscale correlation due to the desired signal presence. The multiscale product of the first k scales is expressed as follow:

$$p_k(n) = \prod_{j=1}^{k} W_{w_2^j} x(n) = \prod_{j=1}^{k} y_j(n) \qquad (2)$$

The maxima in $W_{w_2^j} x(n)$ due to edges in x(n) will tend to propagate across scales; so that p(n) will tend to reinforce the signal response and not the noise.

2.4 R Peaks Detection

In this paper, we propose a new method of R-peaks detection based on undecimated wavelet transform by using multi-scale product and modulus maxima. The different steps of this method are:

- Apply the undecimated wavelet transform to the ECG signal.
- Compute a multi-scale product, p_{123} from the product of undecimated wavelet coefficients, w_1, w_2, w_3 of successive scales (scale 1, scale 2, scale 3) as follow:

$$p_{123} = w_1 \cdot w_2 \cdot w_3 \qquad (3)$$

- Compute the modulus maxima of p_{123}.
- Extract the R peaks of the ECG signal.

For determining the modulus maxima of the multi-scale product p_{123}, we need to compute a threshold thr. For this, we have applied in this work the rule of Donho (D. L. Donoho, I. M. Johnstone, G. Kerkyacharian, 1995, D. L. Donoho and I. M. Johnstone, 1995) which is used for calculating the global threshold. Hence, we have used in this work, the following expression to compute this thr:

$$thr = \sigma \cdot \sqrt{2 \cdot \log(length(p_{123}))} \qquad (4)$$

With:

$$\sigma = MAD(abs(p_{123}))/0.6745 \qquad (5)$$

where MAD represents the median.

Here is an example of R peaks detection using the proposed technique (Fig.8.).

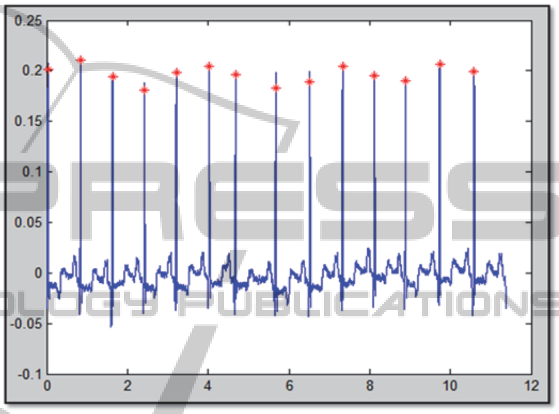

Figure 8: An example of R peaks detection using the proposed technique.

This figure shows the marked R-peaks using the proposed technique.

2.5 Evaluation Criteria

The evaluation of the proposed ECG denoising technique is performed by comparing it to the denoising technique based on PCA which applied to the entire noisy ECG signal. The two techniques are tested on four noisy ECG signals taken from MIT-BIH database. The used criteria in this evaluation are the SNR improvement and the mean square error (MSE). These criteria are expressed as follow:

$$\begin{aligned} imp(dB) &= SNR_{output} - SNR_{input} \\ &= 10 \cdot \log \left[\frac{\sum_i |s_d(i) - s(i)|^2}{\sum_i |s(i) - s_n(i)|^2}\right] \end{aligned} \qquad (6)$$

Where s, s_n and s_d are respectively the clean, the noisy and the denoised signals.

$$\begin{aligned} MSE &= E\left[\left(s(n) - \tilde{s}(n)\right)^2\right] \\ &= \frac{1}{N} \sum_{n=0}^{N-1} \left(s(n) - \tilde{s}(n)\right)^2 \end{aligned} \qquad (7)$$

Where s(n) and $\tilde{s}(n)$ are respectively the clean and the denoised signal.

3 RESULTS AND DISCUSSION

In Tables 1 and 2, are reported the results obtained from SNR improvement and MSE computation and this for the two techniques (the proposed technique and the denoising technique based on PCA applied on the entire ECG).

Table 1: SNR improvement computation in case of ECG signal 103.

	Signal: 103	
	imp(dB)	
SNRi (dB)	The proposed Technique	Entire ECG denoising technique based on PCA
-5	10.1452	9.5192
0	11.9834	12.2626
5	12.8148	12.8499
10	13.1325	13.5676
15	12.1903	13.8807

Table 2: MSE computation in case of ECG signal 103.

	Signal: 103	
	MSE	
SNRi	The proposed Technique	Entire ECG denoising using PCA
-5	0.0064	0.0074
0	0.0012	0.0013
5	3.3973e-04	3.2636e-04
10	1.0164e-04	9.3075e-05
15	3.9933e-05	2.7020e-05

These obtained results (Tables 1 and 2) show clearly that the denoising technique based on PCA and applied to the entire noisy ECG, is slightly better than the proposed technique. However, the advantage of the proposed technique consists in working in real time.

Figures 9 and 10 illustrates two examples of ECG denoising using the proposed.technique.

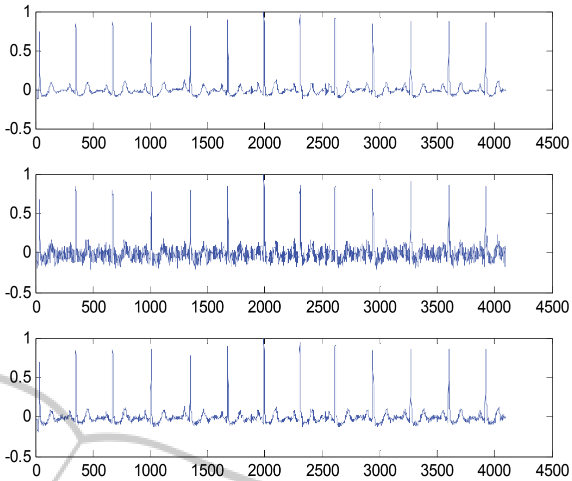

Figure 9: Noisy ECG signal (101 corrupted by Gaussian White Noise with SNR= 7.3835) denoised by the proposed technique to obtain a denoised ECG signal with SNR= 19.2953.

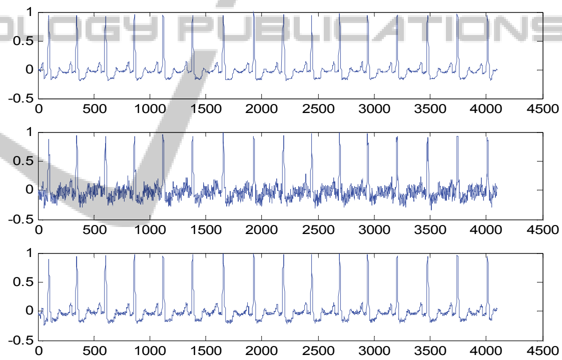

Figure 10: Noisy ECG signal (105 corrupted by Gaussian White Noise with SNR= 10.6282) denoised by the proposed technique to obtain a denoised ECG signal with SNR= 21.3125.

5 CONCLUSIONS

In this paper, we have proposed a new ECG denoising technique based on Principal Component Analysis (PCA). This technique consists at first step in cutting the noisy ECG signal into frames where each frame is located between two successive R-peaks. Then the denoising is performed frame by frame and the denoised ECG signal is obtained by concatenating the different denoised frames. In our evaluation, we have compared the proposed technique to the denoising technique based on PCA and applied to the entire noisy ECG signal. This comparison is performed by the SNR improvement (imp(dB)) and the Mean Square Error (MSE) computations. The obtained results from this evaluation show clearly that the denoising technique based on PCA and applied to the entire noisy ECG, is slightly better than the proposed technique but the advantage of the proposed technique lies in working in real-time.

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