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ECG denoising by EMD and EEMD improved with an adaptive RLS filter

My Hachem El yousfiAlaou[1,2], Haoidhu Assane[1,2],Benayad Nsiri[1,2]
[1]Biomedical Engineering, Higher National School of Arts and Crafts of Rabat (ENSAM),
Mohammed V University in Rabat, Morocco
[2]Research Center STIS, M2CS, National School of Arts and Crafts of Rabat (ENSAM),
Mohammed V University in Rabat, Morocco
hachem.alaoui@um5s.net.ma, haoidhassane@gmail.com, benayad.nsiri@enst-bretagne.fr

ABSTRACT

The ECG is collected as a variation over time of the electrical potential generated by the heart. Once acquired this signal is contaminated by several artifacts and noises which can be biological or instrumental. Hence the need to properly filter the ECG signals before its processing. In this paper two filtering methods are proposed, which are the empirical mode decomposition (EMD) associated with an RLS filter and the ensemble empirical mode decomposition (EEMD) associated with an RLS filter. This two are used to filter the noises and artifacts present in the ECG.As we observed through the qualitative indicator MSE that filtering through the combination of EMD or EEMD with the RLS adaptive filter is much better for filtering out ECG noises and artifacts than other combinations.

Key words: ECG; empirical mode decomposition (EMD); ensemble empirical mode decomposition EEMD; adaptive RLS filter.

1.INTRODUCTION

The electrocardiogram (ECG) is the recording of the electrical activity of the heart. It is a two-dimensional plot that varies with time. this ECG signal once collected it is contaminated by several noises and artifacts of different nature[1]. Which are either of instrumental origin such as the noise introduced by the 50 / 60 Hz sector, the noise generated by bad contacts between electrodes and skin subject. But also, can beings of biological origin like the artifact caused by the fluctuation of the baseline generated by the breathing of the patient which is in the signal ECG or the artifact of the muscular signal electromyogram (EMG). Some of these noises and artifacts are easy to eliminate by simple linear filter, but others have frequencies included in the frequency band of the ECG, therefore by filtering them with the conventional linear filters, one risks also deleting parts of the signal ECG. There are therefore several methods in the literature to filter the ECG, starting with the simple linear filters (band pass) [2], then the adaptive filters like LMS, RLS, NLMS [3], [4] which are the most used ,and finally there are the different approaches based on the wavelet transform (TO) [5], [6] which also shows good results.

This paper describes two methods of filtering non-stationary signals which the EMD (empirical modal decomposition) [7]and the EEMD (ensemble empirical modal decomposition) both associated with an adaptive RLS filter[8], [9]. EMD and EEMD were introduced by Huang[10], [11]. EMD and EEMD decompositions are methods characterized by a process called Sifting allowing to temporally decompose a signal into a sum of oscillating components called Empirical Modes known as Intrinsic Mode Function (IMF). These methods are adaptive and do not depend on the starting signal or on a choice of a frequency band. They are suitable for non-stationary signals. Thus, after the decomposition of the noisy ECG signal in IMFs by the EMD and the EEMD. The filtered signal was reconstituted with these two methods associated with an adaptive RLS filter, because this combination with the RLS gives better results thanother combinations. In the method part of this work is described the proposed filtering tools and algorithms, then the result part which includes the results performed on a test signal generated from EMD and EEMD algorithms and the results on a noisy real ECG signal.

2.METHOD

a. The empirical Mode Decomposition (EMD)

EMD was introduced in 1998 by Huang [10], the EMD approach seeks to decompose the given signal S(t), into successions of several oscillating functions of different frequencies classified from rapid oscillations (high frequencies) to slower oscillations (low frequencies). These oscillations which are unique for each signal are called IMFs (intrinsic mode function), and the process by which we identify these IMFs is called the sifting process[12], [13]. We can illustrate the decomposition into EMD of the signal S(t) of the form:

$$S(t) = \sum_{i=1}^{N}(IMF_i(t)) + r(t) \quad (1)$$

All these IMFi(t) are oscillating functions intrinsic to the signal, r(t) is the residue which is a constant monotonic function and N the number of MFIs contained in the signal.

The algorithm the EMD decomposition is schematically shown in Figure 1.

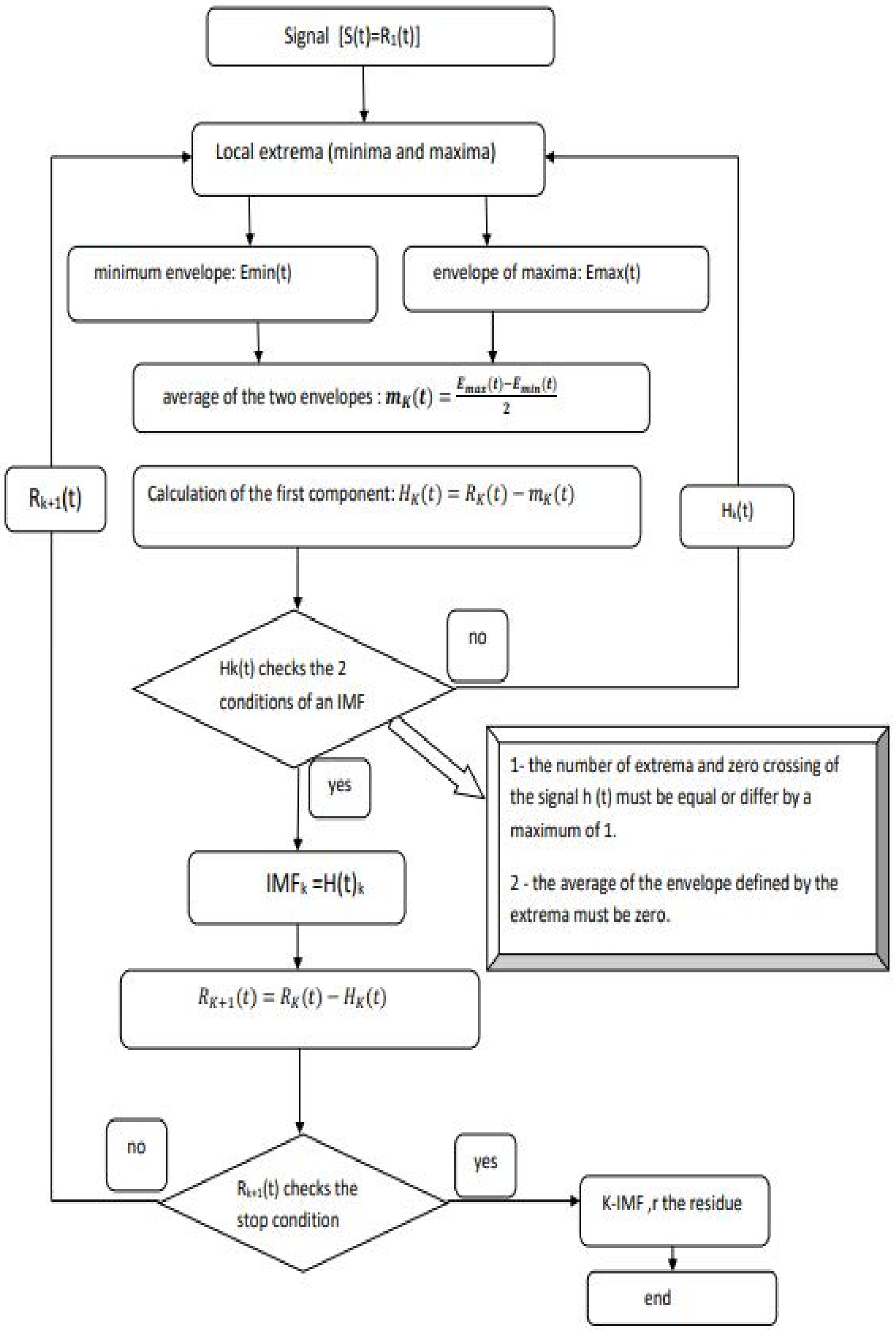

Figure 1: EMD algorithm

b. The EEMD method (ensemble empirical mode of decomposition)

The EEMD is an improvement of the EMD introduced to resolve the gaps noted on the EMD[11], especially the problem of mode mixing. "The mixture of modes consists in the appearance of more than one IMF of the same local oscillation, on the one hand, on the other hand the dramatic disappearance of the low amplitude oscillations caused by the non-identification of their extrema and consequently the resulting IMF is presented as a mixture of more than one frequency over a duration of analysis, which makes it lose its physical meaning "[14].

The EEMD method solves this problem of mode mixing but requires a lot of computation time. It is based on the addition of white Gaussian noise to the signal before being decomposed into IMFs with a sufficient number of repetitions. Ideally the number of iterations should be greater than or equal to 100 according to these studies[15], [16]. However in this paper an improvement of the EEMD was used in the framework for reducing this number of repetitions to 40[17], [18], which is on a small optimization tip by first filtering the Gaussian noise added to the signal by a low pass filter (the cutoff frequency of the low pass filter is the maximum frequency present in the ECG which is 150Hz).

c. Flowchart of the EEMD algorithm

Fig 2 shows the EEMD decomposition algorithm which is the subject in this study. It is based on the EMD algorithm to which a noise insertion step has been added into the signal in several.

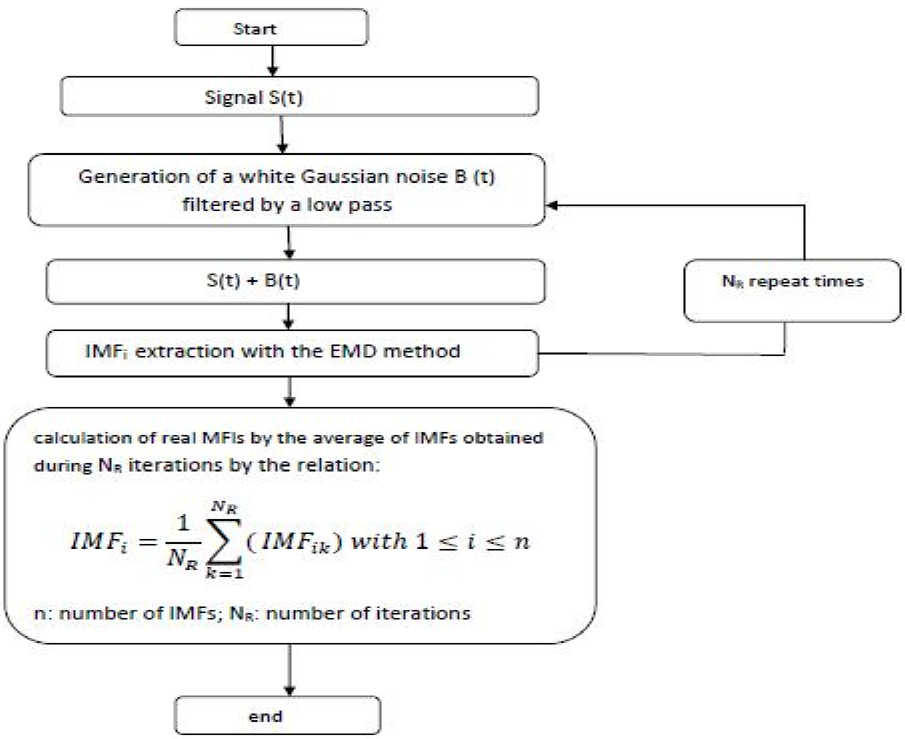

Figure 2: EEMD algorithm.

d. Adaptive filter

An adaptive filter is a filter which takes as input a noisy signal x(n) and a reference d(n) to give as output signal y(n) by adjusting y(n) with each new input via an error e(n). This error is calculated between y(n) and d(n) by the expression e(n) = d(n) - y(n). The latter is taken to adjust the coefficients of the adaptive filterfor each new entry. In general, an adaptive filter can be illustrated by the following diagram:

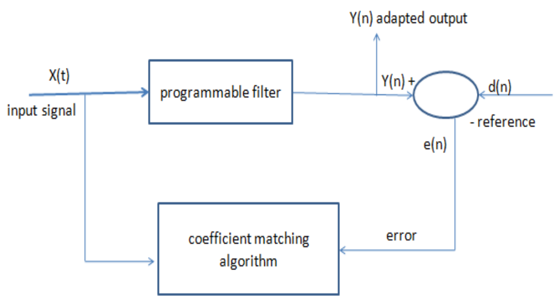

Figure 3: Adaptive filter

Figure 3 shows a general block diagram of an adaptive filter. In this work the algorithm of the recursive least squares filter (RLS) was chosen thanks to its superior stability and its fast convergence [4] ,[8], [17].

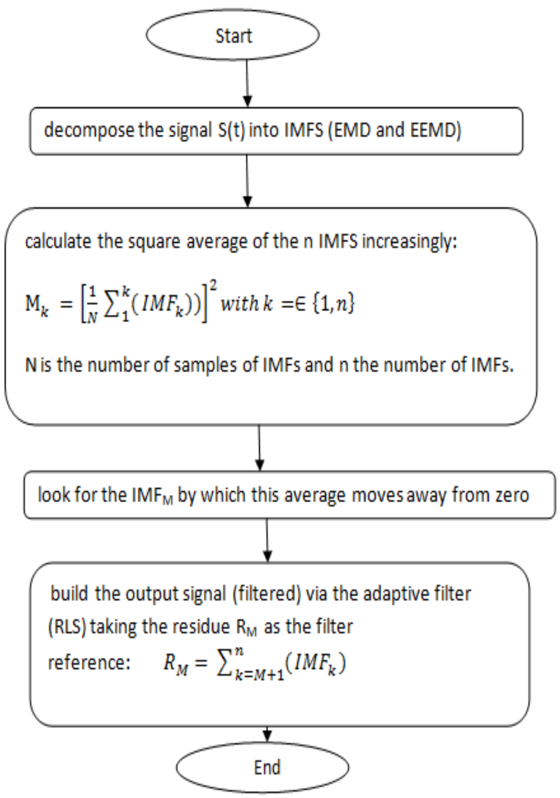

Figure 4: Proposed filtering method

Figure 4, shows the algorithm of the filtering method proposed in this paper.

e. The mean square error (MSE)

To be able to compare the effectiveness of the reconstruction methods based on EMD or EEMD, we opted for the use of the MSE indicator, calculated by the following formula:

$$\text{MSE} = \frac{1}{\text{N}} \sum_{\text{i}=1}^{\text{N}} (\text{desired signal} - \text{filtered signal})^2 \quad (2)$$

Where N is the sample number of the signal.

f. Signal to noise ratio

The signal to noise ratio (SNR), is a qualitative indicator which quantifies the amount of contamination of a signal given by noise, it is expressed in decibels (dB) [19]. it is calculated by the following relation:

$$SNR = 10\log_{10}\left(\frac{Psignal}{Pbruit}\right) \quad (3)$$

where Psignal is the signal strength and Pnoise, the noise power. This power is obtained by the relation:

$$P = \sum_{i=1}^{N} \left(\frac{X_i^2}{N}\right) \quad (4)$$

with N, the number of signal samples.

g. Description of the database used

The ECG-ID Database is a database created by Tatiana lugovaya during her master's (Biometric human identification based on electrocardiogram) available on PhysioNet. It contains 300 ECG recordings obtained from 90 people. this database contains 3 files (a File (*. mat) which contains the ECG data, a 20 second recording of an ECGI which is a noisy ECG and an ECGI filter which filters the ECG I; a File (* .info) which contains the duration of the recording, the sampling frequency (important data), and the gain and finally a File (* .hea) which contains the age, sex and date for each recording The number of records for each person varies from 2 (collected over one day) to 20 (collected periodically over 6 months).

3.RESULTS

a. Simulation Results

To test the correct functioning of the algorithms studied in this paper. We generated a on synthetic signals to be able to check if the filtering is well done and also if the noise variance (signal to noise ratio) had an influence on the reconstruction of the signal filtered by EMD and EEMD decompositions.

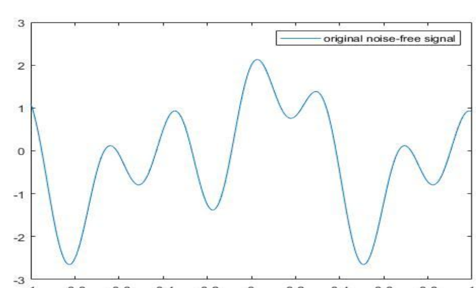

Figure 5: Synthetic signal

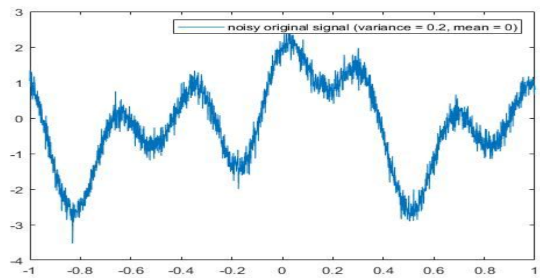

Figure 6: Noisy synthetic signal

The figure 6 shows the noisy synthetic signals (Gaussian noise with variance 0.2 and mean 0).

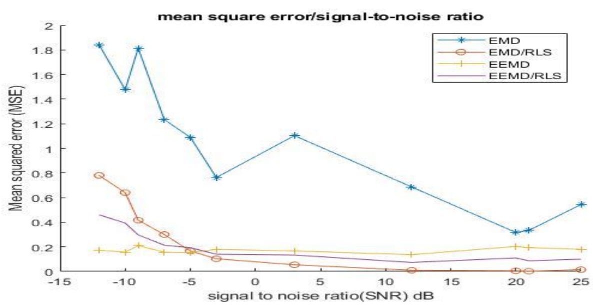

Figure 7: MSE comparison of filtered signals.

The figure 7, is a representation obtained by calculating the MSE between the noisy synthetic signals and the filtered test signal by the four methods EMD, EMD/RLS, EEMD, EEMD/RLS according to the SNR. We notice on this representation that the best results are obtained by the EMD/RLS and EEMD/RLS.

With the tests carried out on the algorithms with the synthetic signals, it could be affirmed that the EMD and the EEMD are well adapted and robust methods to filter signals with a strong presence of noise without altering the useful information contained in the signal. Because the variance of the noise almost does not influence the reconstruction of the filtered signal and that the association EMD or EEMD with the adaptive filter RLS is much better than other combinations to reconstruct the filtered signal.

b. Real-Data Experiments

The data of the person number 1 of the database were taken for the decomposition EMD and EEMD:

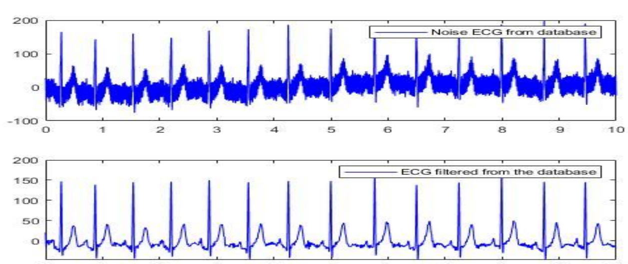

Figure 8: ECG and filtered ECG from database

The figure 8, shows the two ECG signals from the database of person number 1 with the first value which is the ECG signal collected with noise, and the second value which is this same ECG signal but filtered and made available also in this same database.

b.1 - EMD filtering method associated with the adaptive RLS filter

We have decomposed by the EMD the noisy ECG signal from person number 1 in the database. We have obtained six MFIs, here is the average of these six MFIs and the reference signal of the RLS filter deduced**:**

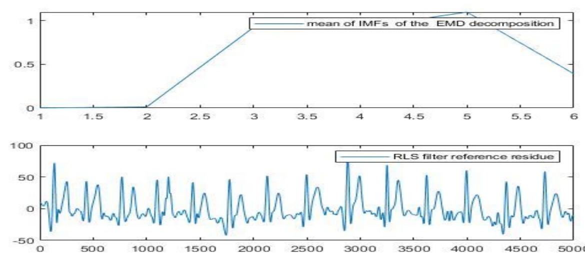

Figure 9: Average of the IMFs and the RLS reference

The figure 9, shows as a first signal the average of the six IMFs obtained by the EMD decomposition of the noisy ECG signal, we see that from the second IMF (IMF2), this average becomes increasing and quickly moves away from zero, so the residue (which is the sum of the IMFs remaining after the IMF2) is taken as the reference of the adaptive RLS filter.

Results of the adaptive RLS filter

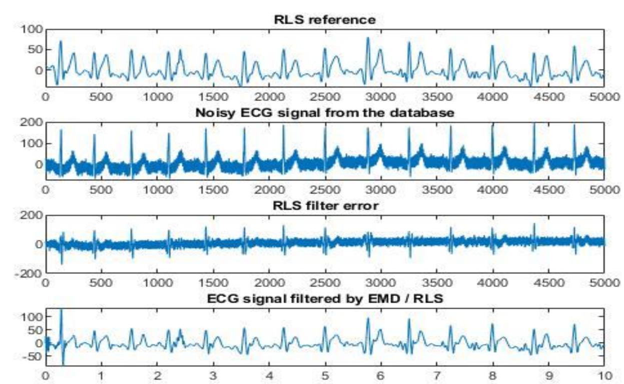

Figure 10: RLS results

This figure 10, shows the input signals of the adaptive RLS filter (which are the noisy ECG signal from the database and the reference of the RLS which is the residue of the EMD decomposition of the noisy ECG after the MFI_2) and the output signals of the RLS filter (which are the error estimated by the RLS filter and the ECG signal filtered by the RLS.

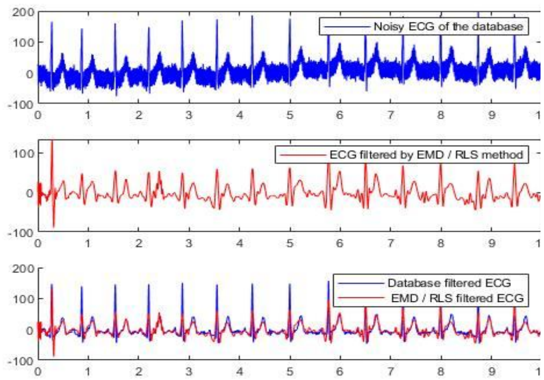

Figure 11: Noisy ECG, filtered ECG from database and filtered ECG by EMD/RLS.

This figure 11 shows the noisy ECG signal from the database and the filtered signal obtained by the EMD decomposition combined with the reconstitution by adaptive RLS filter.

b.2 - EEMD filtering method associated with the adaptive RLS filter.

After EEMD decomposition of the noisy ECG signal of person number 1 in the database, we obtained six IMFs, here is the average of these six IMFs and the reference signal of the RLS filter deduced:

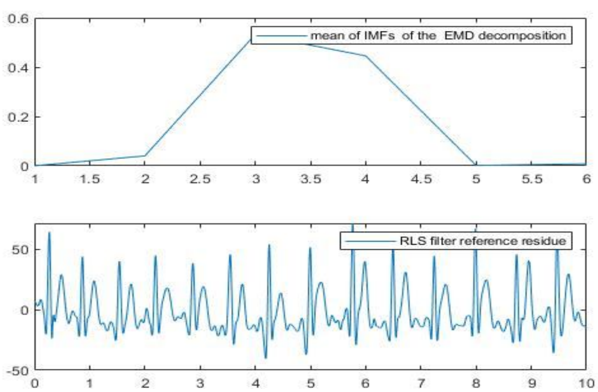

Figure 12: Average of IMFs and the RLS reference**.**

This figure 12, shows as a first signal the average of the six IMFs obtained by the EEMD decomposition of the noisy ECG signal, we see that from the second IMF (IMF2), this average becomes increasing and quickly moves away from zero, therefore the residue (which is the sum of the MFIs remaining after the MFI2) is taken as the reference of the adaptive RLS filter.

RLS adaptive filter result

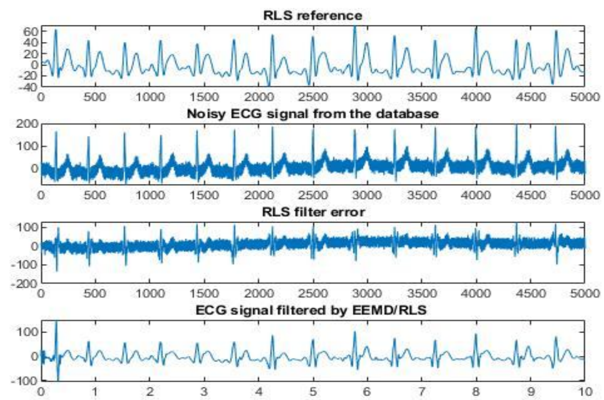

Figure 13: Results of RLS filter

This figure 13, shows the input signals of the adaptive RLS filter (which are the noisy ECG signal from the database and the reference of the RLS which is the residue of the EEMD decomposition of the noisy ECG after the IMF_2) and the output signals of the RLS filter (which are the error estimated by the RLS filter and ECG signal filtered by the RLS).

EEMD filtered signal/RLS filter

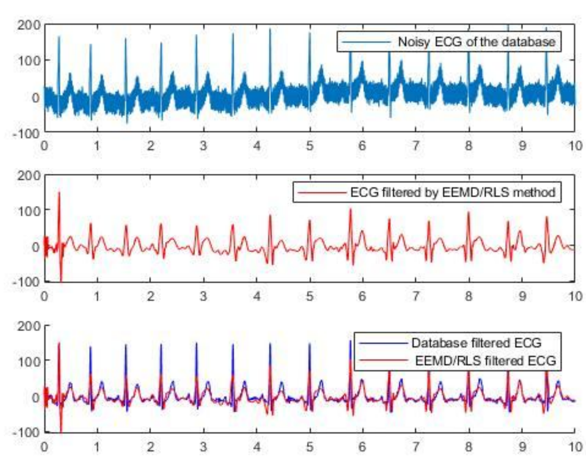

Figure 14: Noisy ECG, filtered ECG from database and filtered ECG by EEMD/RLS**.**

Figure 14 shows the noisy ECG signal from the database and the filtered signal obtained by the EEMD decomposition combined with the reconstitution by adaptive RLS filter.

4. CONCLUSION

In this work, we found that EMD and EEMD are suitable and effective methods to automatically filter non-stationary signals like the noisy ECG signal studied in this case. We could confirm that EMD or EEMD filtering associated with the RLS is more effective for filtering than other combinations via the MSE. Moreover, with the EMD or EEMD decomposition we can directly isolate the baseline from the noisy signal because it constitutes the residue of the decomposition.

However, the filtering by the EMD or EEMD methods associated with the RLS filter have certain limits. The EEMD algorithm is slow compared to the EMD because of the high number of repetitions of the decomposition process,. There has also been a decrease in amplitude of the peaks R of the ECG signal filtered by the two methods EMD/RLS and EEMD/RLS which is explained by the fact of the elimination of the first IMFs considered to be noisy whereas it is also them which contains these peaks R. Thus, a future perspective opens which is to seek to solve this problem of the amplitudes of the R peaks and to understand if this only occurs with the ECG.

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