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Optimal Threshold Estimation Using Cultural Algorithm for EMD-DWT based ECG Denoising

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Abstract: The electrocardiogram (ECG) signal is widely used as one of the most important for analysis of cardiac condition of patients. It is necessary to filter the non-stationary noise from source to find clean ECG. This work falls within the overall framework of digital processing of the physiological signal. AT first data driven EMD method is chosen to get the IMFS and these IMFS further passed though DWT for filtration. To achieve the adaptive filtering process better further optimal threshold is calculated based on cultural algorithm. Denoising is performed on MIT-BIH database and evaluated with parameter called SER, MSE, and cross correlation. It is found that the hybrid algorithm EMD + DWT + Cultural based yield better results than traditional methods.

Keywords: EMD, DWT, IMF, SER, MSE, Cultural algorithm.

1. Introduction

Automated processing of ECG signals has gained widespread interest in the last few years in both medical and signal processing environments. The challenge is very interesting: given the "sensitivity" of the field, the final goal of automatic processing (to complete or even substitute the physician's contribution) remains a particularly delicate task.

During the acquisition process, ECG signals are affected by multiple sources of distortion. The pre-processing step should minimize the effect of these interfering interferences, while conserving the useful components of the signal with great attention. Among the most common disturbances are interferences with the electrical network (the "50 Hz"), baseline fluctuations (due to breathing or patient movements) and so called "electromyographic noise" "(EMG) caused by muscle activity [1]. ECGs are superposing in this domain. other researchers have used spatial filters based on the fact that the maternal and they use a number of electrode signals, to find a linear combination between the observations, and determine the best coefficients to model a weighted sum of these observation signals. EMD (empirical mode decomposition) based approach is proposed to remove high frequency noise and base line wandering in MIT-BIH database [2]. Suggested work has few deficiencies regarding the discard of unwanted IMFs, hence hybrid approach with ensemble empirical mode decomposition along with Wiener filter is proposed. [3-4] hence further adaptive techniques adopted to justify the non-stationary behaviour of ECG signals are explored with nonlinear Bayesian filtering framework with adaptive Gaussian noise [5].

Beside the mentioned methods, adaptive filter has also been applied successfully on the problem of ECG extraction [6]. This filter is generally based on adapting the coefficients of a linear filter through several iterations in order to estimate the adaptive filters may be sensitive to the temporal shape of the reference signal especially if only one reference is used; therefore, it normally requires multi reference signals [7-8].

Some studies have formulated the ECG extraction as a blind source separation (BSS) problem [9]. BSS is based on the assumption that the abdominal ECG channel is composed of independent components. The two main approaches which exist in this regard are Principal Component Analysis (PCA) and Independent Component Analysis (ICA). PCA tries to project the mixing signal onto the principal axis of its covariance matrix. Therefore, the PCA components are geometrically orthogonal by construction and also statistically orthogonal. This method is thus based on the removal of second order dependencies of the observation signals [10]. ICA approach looks for components which are not necessarily geometrically orthogonal, but are statistically independent, and tries to remove the higher order statistics of the sources [11].The aim of ICA is to find the mixing matrix in equation (2.4) such that the sources are mutually statistically independent. The aim of ICA is to find the mixing matrix [12] such that the sources are mutually statistically independent. ICA is compared to PCA [13] and is proved to perform better in the literature [14-15].

The wavelet transform (WT) is another approach that has been proposed for the problem of ECG denoising. Different techniques for noise removal and/or detection of ECG waveforms have been used using Shannon and Tsallis entropy [16]. Non-local wavelet transform domain filtering [17] and optimal selection of wavelet thresholding algorithm for ECG signal denoising [18] has been proposed. The threshold selection was major issue while denoising the ECG, to overcome the problem various hybrid model has been proposed, electrocardiogram extraction based on non-stationary ICA and wavelet denoising [19] which claim better extraction of noise free ECG compare to traditional DWT method. Denoising of weak ECG signals by using wavelet analysis and fuzzy thresholding [20] claims optimal threshold calculation according to signal nature. Genetic algorithm and wavelet hybrid scheme is further proposed for denoising the ECG [21]. ECG signal denoising by functional link artificial neural network (FLANN) [22], An adaptive filtering approach for electrocardiogram (ECG) signal noise reduction using neural networks [23], has been proposed with limitation of predefined training information. PSO combined partial differential equation filtering based approach is suggested for ECG [24]. Further Modified PSO is suggested for denoising [25]. The soft computing based approaches ensures the optimal solutions of threshold estimation [26-29]. This paper proposes the hybrid approach of denoising the ECG signals.

2. Pre-Processing of ECG Signal

During the automatic processing of the ECG signal, consisting of the succession of a few steps (segmentation, analysis, classification), a pre-processing stage often imperatively necessary. It can include all processing to eliminate the various perturbations which degrade the quality of the recording: the interference with the baseline oscillations due to movements or respiration of the patient, noise induced by the electrical activity of the muscles etc. Except the quality of the signal to be treated (this whole category of processing is sometimes grouped under the generic name of "denoising) manuscript in different sections.

2.1. Denoising of the ECG

The ECG signal is subjected to a set of disturbances caused by the movements or breathing, muscle electrical activity, inappropriate positioning electrodes, interference with the electrical network etc. All these undesirable phenomena lead to a degradation of the quality of the recorded ECG signal and make it automatic processing. Therefore, preliminary signal processing is strongly necessary in most cases. Given the peculiarities of the field, the quality of such a pre-processing must be irreproachable: it must consider the elimination of disturbing influences, while faithfully keeping the essential characteristics of the useful waves that make up the signal. These characteristics (including form, duration, and spectrum) will later be used to extract the parameters that "decide" the classification, therefore their slightest degradation can affect the automatic "verdict", that is to say the classification of the patient. This clearly explains the importance of denoising quality.

In recent years, new techniques based on the wavelets have become popular in the context of signal denoising. Indeed, this transformed has the remarkable property of "concentrating" most of the signal energy useful in a reduced number of high energy coefficients in the "transformed" domain. By against, the coefficients representing the image of the noise in the domain of the transformed wavelets will be numerous, but of low energy. In view of the above observations, the principle of a denoising system based on the wavelet transform results quickly. It consists of three successive steps:

1. Application of the wavelet transform to the signal affected by noise.
2. The filtering of the coefficients thus obtained, according to a certain criterion.
3. The calculation of the inverse transform, starting from the coefficients resulting from step former.

Such a denoising algorithm was originally proposed by Donoho [30] for the case of additive noise. It relies on the use of the discrete wavelet transform (DWT) for steps 1 and 3 and on non-linear adaptive filtering of the coefficients in step 2, known filtering on the name of "thresholding". The threshold value is set taking into account the estimate of the variance of the noise which affects the useful signal. In fact, this modality of choosing the threshold constitutes the weak point of the algorithm, since it does not take not consider any information regarding the useful signal. In attempting to overcome this disadvantage, an alternative approach has been implemented for step 2 of the algorithm. It includes a category of techniques of optimized threshold using cultural algorithm. In this case, cultural algorithm will predict threshold based on fitness function, which can further filter of the useful signal coefficients and the noise coefficients. The filtering will be the direct implementation of the analytical solution that maximizes the conditioned probability of useful coefficients, being "Noisy" observations. In order to implement the denoising of the ECG signals, this approach, given its rigorous mathematical bases and the experimental results obtained on working time. Towards such an approach, also carried out by experimental and theoretical studies on the particular case of ECG signals.

2.2. Soft Filtering in the Domain of the Wavelet Transform Applied for the ECG Signals

In the case of a soft filtering of the wavelet coefficients, the performance of the method are determined by two factors:

- The accuracy of a proper prediction of local and statistical property of the wavelet coefficients, both for the useful signal and for the noise.
- The quality of the prediction of the parameters for the two components (useful and disruptive) of a wavelet coefficient.

Of particular interest for the case of ECG signals is the Wiener filter says "Empirical" in the field of DWT, filter proposed in [31] and presented as an improvement of the "classical" Wiener filtering in the transformed domain. Given the importance of transformed into different wavelets. The estimation of the parameters of the useful signal is made thus using a "pilot signal", obtained by the hard thresholding of the wavelet coefficients resulting from the application of the first DWT. This is the first step of the algorithm. The Soft threshold based filtering of the coefficients is done in the domain of the second DWT, under the hypothesis of a Gaussian distribution for both the useful and noise coefficients. This filtering is the second step of the algorithm. The idea has been implemented under different forms in the [32-34] case of ECG signals and the results been satisfactory. The benefits of such an approach have been stated and verified empirically by the authors in [35]. First, it is the ability of the system to properly preserve the forms of the useful waves of the ECG signal. Indeed, the conventional disadvantages of the denoising by the thresholding of the DWT in its usual form (sometimes called "DWT Decimated ") can be found in the case of ECG signals, with disturbing effects. Reconstruction of useful waves could be severely damaged by artefacts such as parasitic oscillations at the beginning and at the end of the QRS complex (the phenomenon of Gibbs, attributed to the translational variance of the decoded DWT) [35-37] or by the deformation of the "slow" waves of the signal (the P and T waves). In [35], the authors use a wavelet mother well localized in time to obtain the pilot signal, wavelet having the role of correctly reproducing the exact form of the QRS complex. The negative effect of such a choice for the shape of the P and T waves (which have a relatively slow temporal evolution) is corrected by the second step of the algorithm, where wavelets are well localized in frequency are preferred.

3. Proposed Method

The architecture for denoising method is shown in Fig.1.

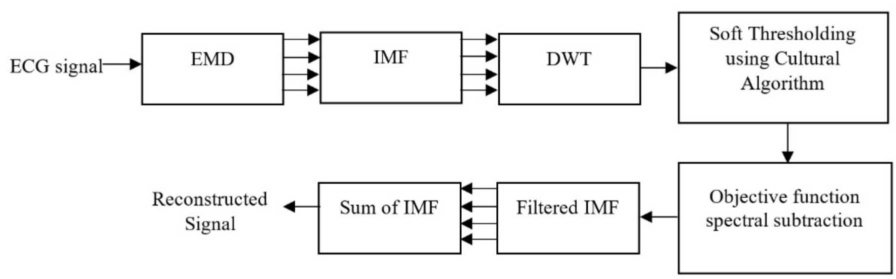

Fig. 1. Architecture for denoising method.

3.1. EMD: Original Method

Empirical Mode Decomposition (EMD) is a tool for Decomposition of non-linear, non-stationary signals proposed by Huang and his Colleagues [38]. It is defined by an empirical decomposition algorithm, without genuine theoretical evaluation. Despite its limited theoretical foundations, the method is applied to several types of real signals, including physiological signals and Biomedical, where promising results are obtained. The EMD is used to extract descriptors from speech signals to classify emotions. It also used to extract descriptors of physiological signals, As well as to analyse the gastro-oesophageal information. The first time that the EMD method was tested on cardiac ECG signals, it was in the [9], who applied this method on simulated S_1 and S_2signals [39]. Liu et al. [40] used the Hilbert-Huang transformation, which is based on the Decomposition EMD, to extract features of cardiac sounds [40].

In primary step, the algorithm for EMD technique will be presented. The second step consists in applying the algorithm to real signals S1 and S2, in order to propose a method for extracting descriptors that discriminates between S1 and S2. The EMD is a recursive algorithm that aims to separate any signal *x*(t) into two components: approximation component which is the low frequency component (slow variations) and a second high frequency component (fast variations) called detail. These components are IMFs (Intrinsic mode functions). The main motivation for empirical modal decomposition is that it does not depend on the choice of a particular basis, such as wavelets, for example; The EMD is totally adaptive. The EMD algorithm, applied to the signal *x*(t), can be illustrated by the following steps:

EMD Algorithm

1. Initialization, $r(t) = x(t)$and $k = 1$.
2. Determine the extrema (maxima and minima) of the signal $r(t)$.
3. Interpolate by a cubic spline the minima and maxima to generate an envelope $e_{min}(t)$ and $e_{max}(t)$, respectively.
4. Calculate the mean $\mathrm{m(t)} = \frac{[\mathrm{e_{min}(t)+e_{max}(t)}]}{2}$ and extract intermediate functions:
$p_i = r(t) - m(t)$ and let $r(t) = m(t)$
5. As long as p_i does not satisfy the conditions of an IMF (Intrinsic Mode Function), repeat:
   - Calculate the mean $m_i(t)$ of $p_i(t)$
   - $p_{i+1}(t) = p_i(t) - m_i(t)$; $i = i + 1$
6. $d_k(t) = p_i(t) and\ r(t) = r(t) - d_k(t)$
7. If $r(t)$ is not monotone, return to step 2 and apply the increment in k as $(k = k + 1)$. Otherwise, the decomposition is complete.

At the end of the decomposition, $x(t)$ can be reconstructed as follows:

$$x(t) = \sum_{k=1}^{N} d_k(t) + r(t) \tag{1}$$

The theoretical basis of the EMD method and to solve some disadvantages. For example, the spline interpolation, which aims to construct the envelopes of maxima and minimas respectively, generates in some cases "overshoot"; where the envelope constructed has an amplitude greater than the maximum of the signal, which introduces artefacts in step 5 of the algorithm, which is normally referred to as "Shifting Process" (SP). The individual IMFs are further samples to the cultural optimized soft thresholding.

3.2. Discrete Wavelet Transform

The different IMFs obtained from EMD (in case of mixed signals) holds some noise content as the abrupt peaks in signals. Every IMF is further transformed into frequency domain for more localize information about noise by DWT. It gives Detailed Coefficients (DC) and Approximate Coefficients (AC) of signals according to high and low pass filtration accordingly.

$$X_i = \frac{1}{\sqrt{M}} \sum_n x(t) \varphi_i\,(n) \tag{2}$$

$$X_j = \frac{1}{\sqrt{M}} \sum_n x(t) \psi\,(n) \tag{3}$$

where $i \geq j$, $x(t)$ is the output and $\varphi_i(n), x(t)\psi(n)$ depends upon $n = 0,1, \dots M - 1$. Equation (2) represents the approximate coefficients and Equation (3) represents detailed coefficients. This method corresponds to the objective set out at the beginning of the course and is the result of a theoretical and practical study on the subject of the processing of ECG signals.

3.3. Working Hypotheses

We consider the case of an ECG signal (s) perturbed by noise in an additive way (p). Since the classical white noise assumption is not realistic in the case of real physical noises that disrupt the ECG signal, the assumption is that the noise is additive, coloured, Gaussian and of zero mean. While the Gaussian and zero-mean PDF does not reduce the generality of the method, the hypothesis of a coloured noise predominantly considers the broadband type noise produced by the electrical activity of the muscles. This type of noise, called EMG (electromyography) noise, is the most difficult to remove, because its spectrum is partially coincident with the frequency band occupied by the useful ECG signal. Generally, it is considered as a random, wide-band noise (the phrase "almost white" is sometimes used in the literature) and having a non-stationary character. It should also be noted that for real ECG signals, an accurate characterization of the noise is not available. This means that even if one knows the possible sources of disturbance (listed above), neither the noise statistic nor its power spectral density is known. In practice, all the characteristics of the noise can vary between two separate ECG signals and even for recording from a single individual over time. We are then obliged to make the most general assumptions a priori, to place ourselves within a sufficiently broad and generic framework.

As for the signal, the authors in [32-34] take into account a Gaussian PDF of the DWT coefficients of the ECG signal. The hypothesis, on which the possibility of filtering Wiener is based, is not sufficiently realistic. In fact, the ECG signal has a highly non-stationary character: there are some "prominent" waves (P, QRS, T) separated by intervals that mark the lack of electrical activity (the isoelectric segments). In the domain of the wavelet transform, this results in the existence of a relatively small number of high-energy coefficients (marking especially the "breaks" in the signal, i.e. the beginnings and ends of the waves) and a large number of low-energy coefficients, corresponding to the isoelectric segments and the slow variation portions of the signal. Therefore, the hypothesis of a Gaussian distribution seems inappropriate for realistic modeling of the useful coefficient statistics. To take into account the observations presented above, it was considered that a heavy-tailed distribution for the coefficients PDF is more realistic, and the particular case of a Laplacian distribution becomes very attractive given its Simplicity of calculation [41-42]. In order to illustrate the plausibility of this a priori assumption, the empirical observations (the histogram of the wavelet coefficients) and the theoretical curve representing a PDF. It should be remembered that the mathematical form of a Laplacian law is:

$$p_W(w) = \frac{1}{\sqrt{2}\sigma_w} \exp\left(-\frac{\sqrt{2}|w|}{\sigma_w}\right), \quad (4)$$

where σ_w is the standard deviation of the wavelet coefficients w.

The proposed denoising algorithm consists of two distinct steps:

Step 1: Obtaining the processed signal

The processed signal represents an estimate of the useful ECG signal. It is used to calculate the optimal threshold according fitness function of cultural algorithm, with the necessary statistical estimates of the useful wavelet coefficients. To obtain the processed signal, the noisy signal is sampled with EMD decomposition and obtained IMFs are transformed in the domain of the DWT W_1 and its coefficients are threshold. The inverse transform is then applied to obtain the processed signal. For this step, it is better to choose a well-located mother wavelet in time [32]: it has been determined empirically that the daubechies wavelet provides the best results. The filtering in the domain W1 is non-linear and consists in the simple application of a thresholding strategy: either soft-thresholding or hard thresholding [30]. Since no white noise has been assumed, this thresholding must be adapted to each decomposition scale of the DWT (the power of the noise is not equally distributed in all the frequency sub-bands corresponding to the different decomposition scales).

Step 2: The optimal threshold from cultural algorithm in the domain of the W_2 wavelet transform

In general, an optimal threshold maximizes the a posteriori probability of obtaining the useful values, given the noisy observations. In Fig. 2, the steps taken to implement the second stage of the denoising algorithm were explained.

The Discrete wavelet transform (DWT) [43-44] was used for this step. The source of diversity is the wavelet wave selected for the calculation of the DWT. Generally, obtaining diversity is desirable because in each variant of the signal obtained by diversity there remains the same original signal (useful signal, signal to be estimated), affected by several variants of the noise. In fact, the transform proposed in [43-44] consists practically in different L DWT applied to the same input signal (see Fig. 2). For the particular case of an ECG signal, it is better to use in this step wavelet functions which are well localized in frequency (which may well preserve the forms of the P and T waves) and at the same time which are not Implemented by means of filters with an extremely long impulse response (these filters would introduce oscillations around the QRS complex) [32]. A compromise must therefore be secured in this respect. Another source of possible diversity is represented by the circular permutations of the signal samples.

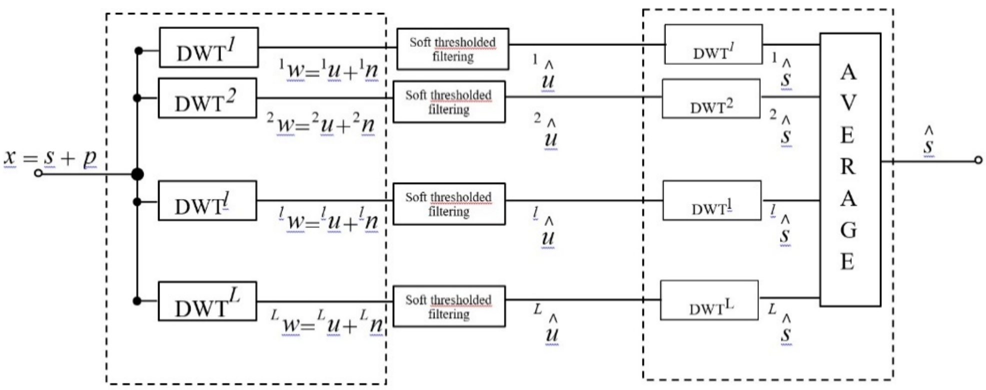

Fig. 2. Illustration of the second stage of the denoising algorithm.

The signal at the input of the system (x) is considered as composed of a useful signal (s) affected by additive noise (p):

$$X = s + p \quad (5)$$

After the application of the DWT, one obtains at its output L sequences of wavelet coefficients, each sequence corresponding to the mother wavelet used for the calculation of the DWT:

$$l_w = l_u + l_n, \tag{6}$$

where l_u is the useful coefficients and l_n is the noise coefficients, with $l = 1, \ldots, L$. The cultural algorithm gives the optimal threshold value according to fitness function of power spectral subtraction. The optimal threshold provides a filter maximizes the a posteriori probability of obtaining the useful coefficients (l_u), given the observations disturbed by the noise (l_w). The goal is to find for each DWT coefficients and hence the solution of the equation:

$$l_u(l_w) = \underset{l_u}{\arg\max}\, p_{u/w}\left(\frac{l_u}{l_w}\right) \tag{7}$$

Using the Bayes rule, equation (4) becomes:

$$l_u(l_w) = \underset{l_u}{\arg\max}\left(p_{w/u}\left(\frac{l_w}{l_u}\right).p_u(l_u)\right) = \underset{l_u}{\arg\max}(p_n(l_w - l_u).p_u(l_u)) \tag{8}$$

This equation expresses the estimation of the useful coefficients as a function of the probability densities respectively of the coefficients of the noise (p_n) and of the useful coefficients (p_u). The signals are in transformed domain only hence under consideration that a Gaussian distribution for the noise and Laplacian coefficients for the useful coefficients. Under these assumptions, the analytical solution of equation (7) [41-43] is:

$$l_{\hat{u}} = \frac{\left(l_w - \frac{\sqrt{2^l}\sigma_n^2}{l_{\sigma u}}\right)_+}{l_w}.l_w, l = 1,,,,, L, \tag{9}$$

where $(X)_+ = \begin{cases} X, si\ X > 0 \\ 0, others \end{cases}$. It can easily be seen that equation (9) actually represents a soft thresholding operation of the noisy coefficients, the threshold value being:

$$l_S = \frac{\sqrt{2^l}\sigma_n^2}{l_{\sigma_u}}, \tag{10}$$

Where σ_u is the variance of the noise and l_{σ_u} is the estimated value of the coefficients of the useful signal for the DWT with the index 1. Indeed, the exact values of these parameters are not known (this would have solved our problem ideally) and must be estimated. The value of the useful coefficients, it will not remain constant across a decomposition scale. It is the non-stationary character of the ECG signal which leads to such a consequence: there will be breaks in the signal, marked by groups of high-energy wavelet coefficients, with successive zones of low-amplitude coefficients. Therefore, the local evaluation of this parameter is necessary, and the fact that a pilot signal is available facilitates this evaluation: instead of the standard deviation (equation 9) we take the absolute value of each DWT coefficient of the pilot signal. In practice, the value of the threshold will be particularized for each coefficient: thus, the filtering becomes adaptive. In terms of noise variance, it is usually evaluated using the well-known median estimator:

$$\sigma_n^2 = \frac{median\,(w(j,k))}{0.6745} \tag{11}$$

where $k = 1, \ldots., M/2^j$ and $j = 1$, $w(j,k)$ is the wavelet coefficient that occupies the position k in the decomposition scale j and M is the length of the DWT. In the case of a white and Gaussian noise, the estimate is made only for the coefficients of detail obtained after the first iteration of the DWT (j = 1): given the white character of the noise, this estimate remains valid for the others Scales, because σ_n^2 do not depend on the scale j. On the other hand, if we consider the case of a noise that is not AWGN, the situation changes and the estimate must be made on each scale in particular.

The empirical study of the denoising of ECG signals has led to a different method for estimating this variance of noise. The reasoning is as follows: since the pilot signal is an approximation of the useful signal and since the noise is additive, it can be stated that the difference between the input signal and the pilot signal will be an approximation of the noise. Therefore, in order to obtain the variance of the noise at decomposition level j (of the DWT), this transform will be applied to the "noise" signal and the variance will simply be computed at j for the noise coefficients obtained, which will provide us The desired estimate. Considering all the observations made before, equation (6) becomes:

$$l_u(j,k) = \frac{\left[l_w(j,k) - \sqrt{2^l}\sigma_n^2 / l_{\xi_u}(j,k)\right]_+}{l_w(j,k)}.l_w(j,k), \tag{12}$$

where $l_{\xi_u}(j,k)$ is the coefficients of the DWT (using the mother wavelet with the index l) of the pilot signal. The relation in equation (12) shows that the Soft threshold based filtering is applied to each sample in particular ("sample-by-sample" processing), which is in agreement with the non-stationary character of the ECG signal (the threshold value must be variable in time) and with the colour spectrum of the noise (the threshold value must be "adapted in frequency").

As we have already discussed before, the use of the DWT in this stage of the algorithm provides a gain in diversity. Concretely, we have L different estimates for the key parameters of equation (9) instead of a single one. In our case, variance of the noise and the standard deviation are the useful coefficients. To measure this dependence, we define the sensitivity of the estimate of the coefficients:

$$S_u(\sigma_u) = \frac{du}{d\sigma_u}\frac{\sigma_u}{u} \tag{13}$$

For coefficients which are greater than the threshold defined by (10), substituting equation (9) in equation (13), this becomes:

$$S_u(\sigma_u) = \frac{\sqrt{2}\sigma_n^2}{\sigma_u w - \sqrt{2}\sigma_n^2} \quad (14)$$

The function defined in (14) is decreasing in σ_u. The wavelet coefficients have a small local variation in the zones corresponding to the slow evolution of the signal (for example, P wave). For these zones, with small values of the parameter σ_u, equation (14) indicates a greater approximation error. In this context, the use of L distinct estimates for σ_u can improve the results especially for these portions of the signal. This helps us to preserve the shape of the P wave, which is the most sensitive to noise and denoising (because of its low amplitude and its varied morphology).

Returning to Fig. 2, after the Soft threshold based filtering, the denoised signal is obtained via the discrete wavelet transform (DWT). This consists of calculating each inverse DWT (corresponding to the DWTs used in the DWT). The output signal is obtained by calculating the mean of the L variants denoised by l_{sc} from the following relation.

$$s(n) = \frac{1}{L}\sum_{l=1}^{L} l_{sc}(n), n = 1, \dots, M \quad (15)$$

Note that by means of the results of the various filtration given by (12). It can be assumed the residual noise is a Gaussian random process with zero mean. Its different realizations are the sequences of residual noise (which has "survived" soft threshold filtering) which disturb the useful signal. On the other hand, each sample can be considered as the summation of a useful sample (which, theoretically, is always the same since there is only one useful signal) and a residual noise sample (which is different for each branch of the DWT). Consequently, the calculation of the average of the corresponding samples at a fixed time point will result in the reciprocal cancellation of the remaining portion of noise in each sample. On the other hand, the useful signal will be well preserved (under the condition that the signal does not vary very quickly).

A "second iteration" of our algorithm could further improve the results. This iteration would consist in the reuse of the denoised signal as a better version of the processed signal. The signal resulting from the output of the system is returned to the input of the filtration process, where it will act as the processed signal for this second iteration.

Fitness function of cultural algorithm:

Spectral flatness: [44]

The spectral flatness is calculated by dividing the geometric mean of the power spectrum by the arithmetic mean of the power spectrum, i.e.:

$$\mathrm{Flatness} = \frac{\sqrt[N]{\prod_{n=0}^{N-1} x(n)}}{\frac{\sum_{n=0}^{N-1} x(n)}{N}} = \frac{\exp\left(\frac{1}{N}\sum_{n=0}^{N-1} \ln x(n)\right)}{\frac{1}{N}\sum_{n=0}^{N-1} x(n)} \quad (16)$$

where $x(n)$ represents the magnitude of binary number n.

Cultural algorithm will evaluate the optimal threshold according to following fitness function.

$$Er = min(1 - Flatness) \quad (17)$$

After spectral subtraction, filtered IMFs are summed up to get the reconstructed signal.

3.4. Cultural Algorithm

Inspired by the process of social and cultural changes, the CA was developed to enhance evolutionary computation. Cultural algorithms (introduced by Robert G. Reynolds) [44] modelling inspired by the evolution of human culture at two levels of scale:

- The micro level corresponding to a space describing a population of individuals;
- The macro level corresponding to a belief space.

The interactions between these two levels are described on the one hand by a validation / acceptance of the evolution of the population towards the space of belief and on the other by the influence of beliefs on population.

As Fig. 3 shows, the population space and the belief space can evolve respectively. The population space consists of the autonomous solution agents and the belief space is considered as a global knowledge repository. The evolutionary knowledge that stored in belief space can affect the agents in population space through influence function and the knowledge extracted from population space can be passed to belief space by the acceptance function.

In the process of the CA evolution, the population space is initialized with candidate solution agents at random, meanwhile, the initial knowledge sources in the belief space are built. At first the two spaces evolve independently. Then the selected agents from the population space are used to update the belief space. After the knowledge sources being updated, the belief space will reversely guide the evolution of the population space.

These procedures repeat till a termination condition has been reached. The CA pseudo code presented by [44] is given as follows:

t=0; no of iteration i=0;
Define initial value of Population size p(i)
Define initial value of Belief Space B(i)
Repeat sequence
Evaluate Population size P(i);
Define new B(i),
Accept (P(i));
Adjust (B (i));
Variation (P (i) to P(i-1));
Stop until condition achieved

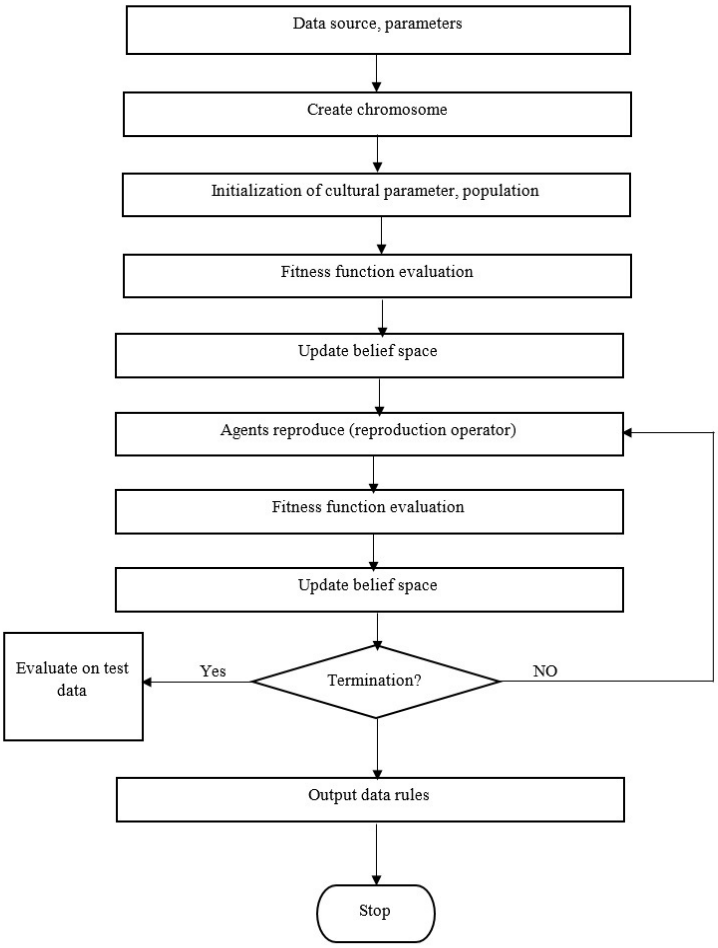

Fig. 3. CA framework.

3.5. Evaluation Parameters

3.5.1. Signal-to-Noise Ratio (SNR)

The signal-to-noise ratio (SNR) is the ratio between the signal strength and the noise power.

$$\boldsymbol{SNR}(dB) = 10\, log \frac{\sum_{n=1}^{N} s^2(n)}{\sum_{n=1}^{N}[S(n) - \hat{S}(n)]} \quad (18)$$

3.5.2. Signal-to-Error Ratio (SER)

Signal to error ratio defined as

$$\mathbf{SER} = \frac{\sum_{t=0}^{L-1} \mathbf{S}^2(t)}{\sum_{t=0}^{L-1}[S(t) - \hat{S}(t)]^2} \quad (19)$$

where $S(t)$ and $\hat{S}(t)$ are the clean and reconstructed ECG signal respectively and L or N is the length of the signal.

3.5.3. MSE

$$MSE = \sum_{n=1}^{N}\left[S(n) - \hat{S}(n)\right]^2 / \sum_{n=1}^{N}[S(n)]^2 \quad (20)$$

3.5.4. Cross Correlation

Correlation is a measurement of the linear relationship between two continuous variables. The calculation of the correlation coefficient is covariance between two continuous variables. The coefficient of correlation is in fact the normalization of covariance. This normalization makes it possible to obtain a value which will always vary between -1 and +1, independent of the scale of the variables considered [45].

5. Experimental Setup

The MIT-BIH database [46] is a universal database containing 48 half-hour two-way records (DII and V5). It has been collected by researchers to be used as a reference for the validation and comparison of algorithms on the ECG signal.

- Each ECG recording is sampled at a frequency of 360 Hz.
- The main advantage of this database is that it contains a large number of cardiac pathologies, which makes it possible to validate the algorithms on a large number of ECG signal cases.

- The records correspond to subjects that are 25 men aged 32 to 89 years, and 22 women aged 23 to 89 years.
- The signals are numbered from 100 to 124 for the first group that includes a variety of waveforms and from 200 to 234 for the second group that includes a variety of pathological cases.
- In order to objectively evaluate the quality of the proposed methodology, to the usual measures used in this sense, noise was added generated artificially under MATLAB on a number of 5 signals from MIT-BIH database.

The signals were chosen from among the most "clean" possible and with morphologies different. To evaluate the results, the SNR was calculated. The noise was generated via a second order AR process, the signal disturbance thus resulting being a coloured noise, intended to simulate the physical noise broadband of the EMG type.

To calculate the SNR at the output of the system, we have considered as "signal error" the difference between the original signal and the denoised signal and the evaluation criterion that we used is the percentage of normalized squared error (SER) between the various reconstructed signals and the original signal not noisy.

Finally an ECG signal evaluate the robustness of our method by adding noise to the signals to obtain reports Signal / noise (SNR) of 6, 8, 10, 12, 14, 16 and 18 dB. We compared the performance of the method Classical to those of our approach. We have also looked at the error of our approach without adding signal part of the MFI 1 in the reconstruction, in order to apprehend in isolation the effect of the correction of threshold estimation on signal reconstruction interest. Simulation is carried out using MATLAB 2014.

Table 1 represents the different ECG signal against varying SNR value in dB. The observation shows the increase in SER value according increase in SNR. Lowest SER achieved when signal strength is high. Table 2 represents the comparative study of different methods proposed , EMD + DWT + Cultural gives better performance against varying SNR compare to other tradition al method .Approximately 2-3 dB gain is achieved in proposed method.

Therefore we use cross correlation as a measurement of denoising impact on ECG based on different SNR, Cross correlation obtained after input ECG signal further normalized to get output between 0 to 1.The correlation coefficient value near to 1 resemble nearest match to the reference signal. Fig. 10 shows the maximum cross correlation at 18 dB SNR compare to lower order SNR value.

Fig. 11 claims the mean square value according SNR. It is observed that MSE value is high when noise power is more, gradually it is decreasing, according to decrement in noise power. At 18 dB minimum MSE is achieved i.e. .98. Fig. 12 shows the performance of signal to noise ratio over different input noise power. When input noise power (dB) increases the SNR increases. The performance of proposed method shows better than EMD and EMD + Wavelet methods.

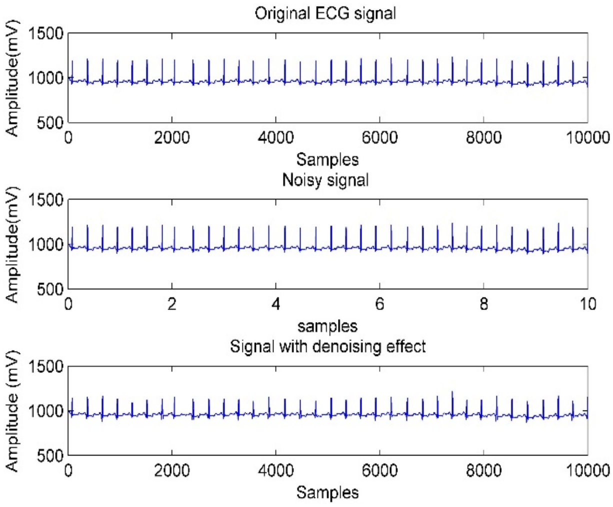

Fig. 4. Original ECG (100 m), noise with 14 dB SNR and denoised signal with proposed method.

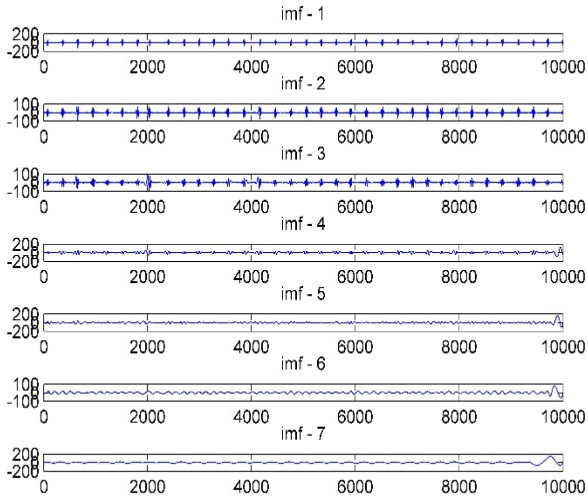

Fig. 5. Generated 1 to 8 IMFs after EMD.

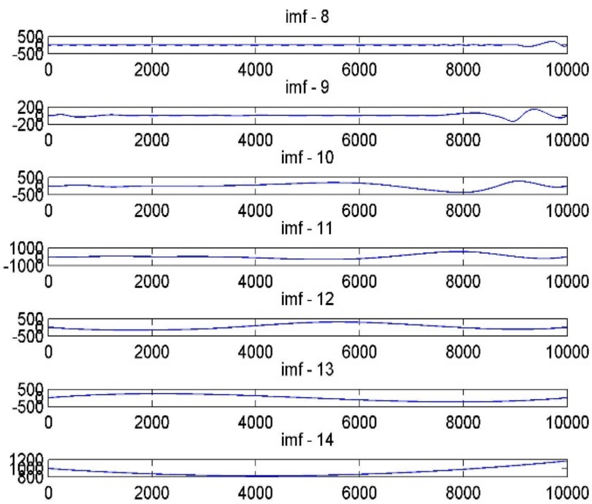

Fig. 6. Generated 9 to 14 IMFs after EMD.

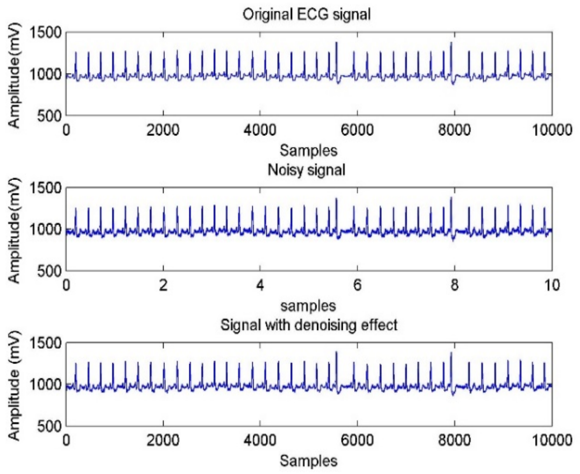

Fig. 7. Original ECG (105 m), noise with 18 dB SNR and denoised signal with proposed method.

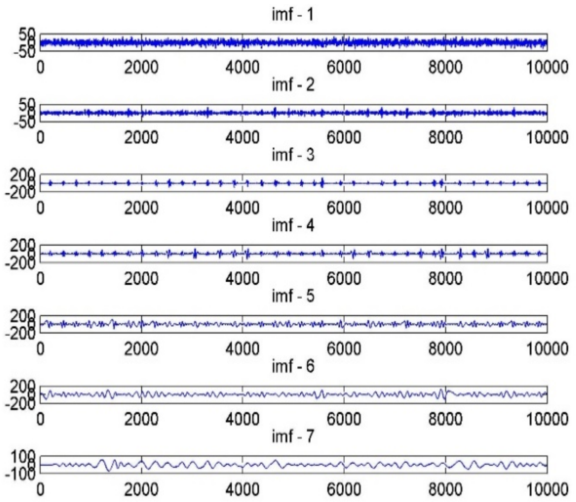

Fig. 8. Generated 1 to 8 IMFs after EMD.

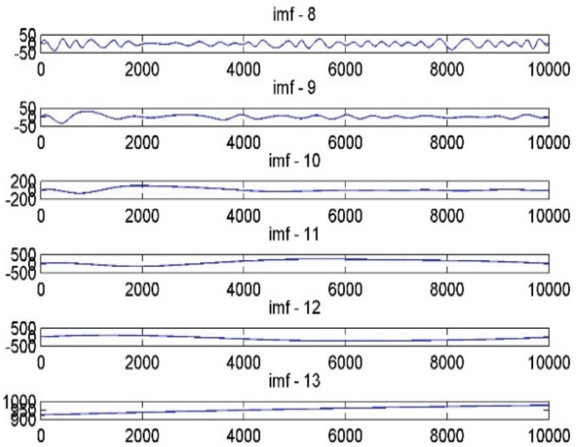

Fig. 9. Generated 9 to 14 IMFs after EMD.

Table 1. Experiments carried out for the several records from MIT-BIH arrhythmia database for additive white Gaussian noise (AWGN).

I/P SNR(dB)	ECG 100	ECG 103	ECG 105	ECG 119	ECG 212
6	26.6130	33.5129	37.9481	30.7114	25.1185
8	24.0910	33.8904	39.2179	21.4330	33.4391
10	35.9229	33.8653	40.357	32.6768	25.6640
12	28.0034	34.3316	41.3822	33.1530	34.5457
14	26.4311	34.4010	42.2049	33.6560	25.1798
16	36.0674	34.5119	43.1465	32.2159	34.6279
18	35.1695	34.4138	43.4989	34.2534	28.1049

Table 2. Comparisons various denoising methods for ECG record 105 model from MIT- BIH arrhythmia database.

SNR (dB)	EMD (dB)	EMD-DWT(dB)	EMD-CL-DWT(dB)
6	26.6130	29.234	37.9481
8	28.498	31.4534	39.2179
10	32. 229	34.8653	40.357
12	34.005	36.4556	41.3822
14	36.5511	38.4010	42.2049
16	38.0344	40. 119	43.1465
18	40.145	42.4338	43.4989

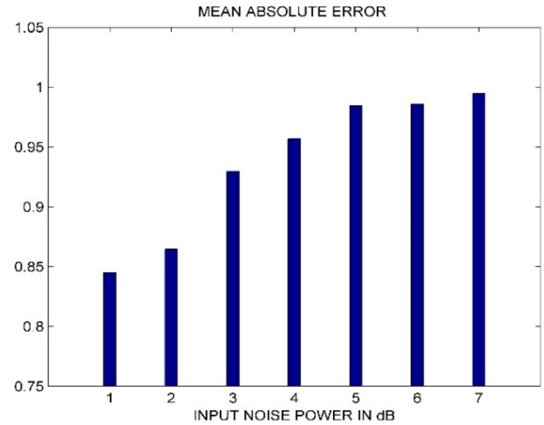

Fig. 10. Cross correlation calculation under different SNR (6-18) in MIT-BIH (100.mat) data.

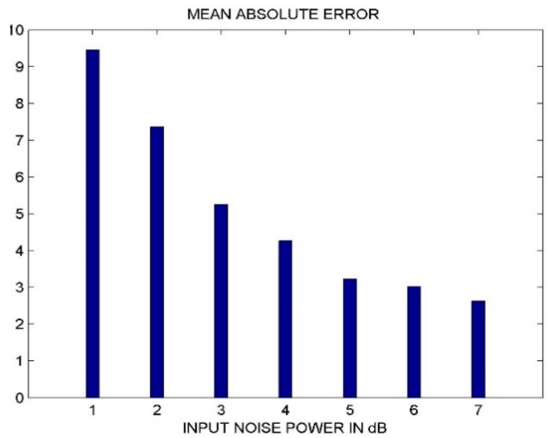

Fig. 11. Mean square error calculation under different SNR (6-18) in MIT – BIH (100.mat) data.

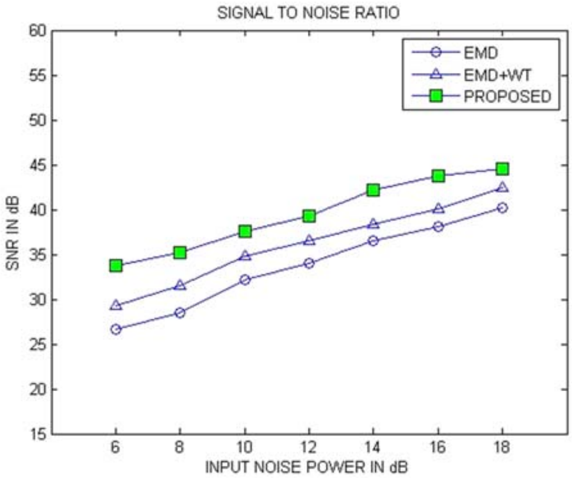

Fig. 12. Comparison of SNR for different methods with different input noise power.

6. Conclusion

The result of the work on this subject was the implementation of a denoising method which relies on the statistical properties of the SNR of the ECG signal. Some variants different from the proposed method have been tested under a variety of conditions and results have always been satisfactory. The tests carried out were aimed at bringing the more possible of the actual conditions from which such processing must operate. In this context, we have studied the influence of denoising on ECG signal, the synthetic noise ranges from 6 dB to 18 dB. The optimal selection of threshold using cultural algorithm yield better results than traditional results. Approximately 15 % of gain is achieved in proposed method.

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