AUTOMATION OF ECG SIGNAL ANALYSIS USING EMD AND CNN

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ABSTRACT:

Hybrid approach is proposed in this concept to remove noise presented in ECG signal with more efficient accuracy. The electrocardiogram ECG signal plays an important role in the primary diagnosis, prognosis and survival analysis of heart diseases. The ECG signal contains an important amount of information that can be exploited in different manners. However, during its acquisition it is often contaminated with different sources of noise making difficult its interpretation. In this paper, a new approach based on Morphological Top-Hat Transform (MTHT) is developed in order to suppress noises from the ECG signals. Notch filtering also used here along with MTHT for better signal recovery. The experimental results indicated that the proposed methods in this work were better than the compared methods in terms of retaining the geometrical characteristics of the ECG signal, SNR. Due to its simplicity and its fast implementation, the method can easily be used in clinical medicine.

KEYWORDS: Electro Cardiogram, Notch Filter**,** Morphological operations, Top-Hat Transform, Signal to Noise Ratio

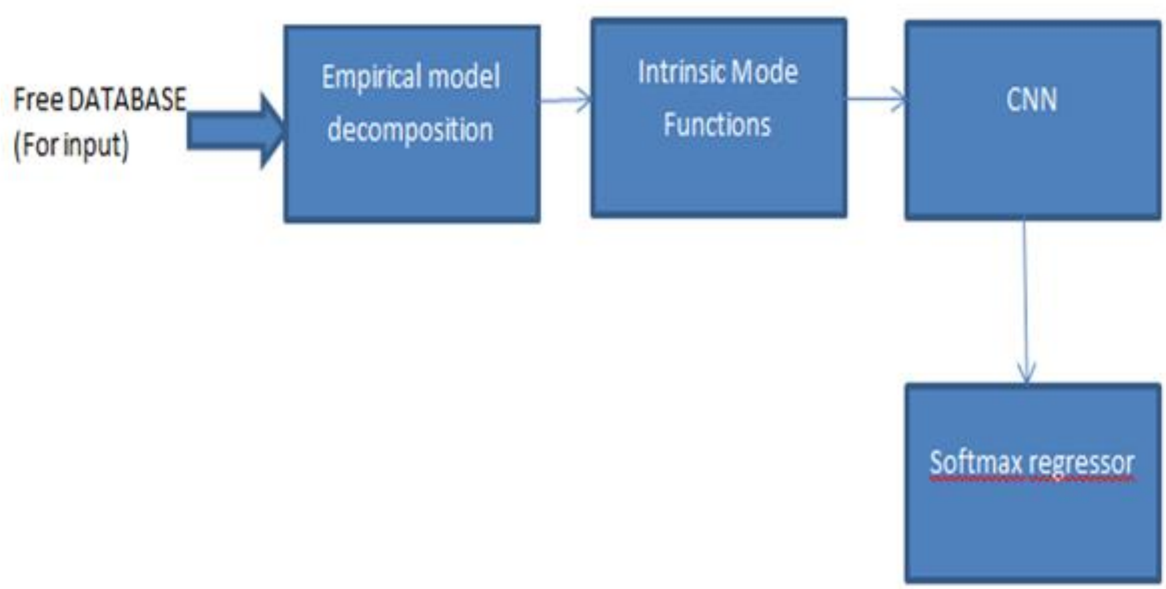
INTRODUCTION:

During its acquisition the ECG signal is corrupted with different types of noises. Noises such as the power line interference (50 Hz), the muscle artifact due to the EMG (electromyogram), the baseline wandering due to the rythmic inhalation and exhalation during respiration are examples of noises which corrupt tthe ECG signals [1-2]. In order to reduce the noise in ECG signals many techniques are available such a digital filters (FIR or IIR), adaptive method, wavelet transform thresholding and Empirical Mode Decomposition methods [3]. However, digital filters and adaptive methods can be applied to signal whose statistical characteristics are stationary in many cases. Recently the wavelet transform has been proven to be an useful tool for non-stationary signal analysis [4]. Thresholding is used in wavelet domain to smooth out or to remove some coefficients of wavelet transform subsignals of the measured signal. The noise content of the signal is reduced, effectively, with in the nonstationary environment. The denoising method that applies thresholding in wavelet domain has been proposed by Donoho [5-6]. It has been proved has Been proved that the Donoho’s method for noise reduction works well for a wide class of one dimensional and two dimensional signals. Other approaches for threshold value estimators can be found in [7-10]. VisuShrink [9, 11] utilizes the universal threshold estimator, which is $2\log(N)$ for a vector $i\ d$ of the detail coefficients of length N . Sure Shrink is based onStein’s unbiased risk estimator [12]. Sure Shrinkhs serious drawbacks in situations of extreme sparsity of the wavelet coefficients [13]. In [11], Bayes Shrink was used for the threshold estimator, which is a data-driven sub and adaptive technique. Others methods, which has also been widely used is the Least Mean Squar adaptive algorithm (LMS) [9]. But this algorithm is not able to track the rapidly varying non-stationary signals such as ECG signal within each heart beat; this causes excessive low pass filtering of mean parameters such as QRS complex. The ECG signal is characterized by fi ve peaks and valleys labelled by the letters P, Q, R, S, T as shown in fi gure 1.The QRS complex is the most prominent wave component within the electrocardiogram. It refl ects the electrical activity of heart during the ventricular contraction and the time of its occurrence. A great number of methods were proposed for detection of the waves of ECG signal [1-7]. The majority of these method sare based on fi ltering or the thresholding adaptive, which shows the limitation of the application.

LITERATURE SURVEY:

A single normal cycle of ECG represents the consecutive atrial and ventricular depolarization and repolarization during every heartbeat which is associated with the peaks and troughs of ECG waveform (Dupre et al., 2005; Fathima et al., 2012; Karthiket al., 2013, Labate et al., 2013). ECG signals are frequently plagued by impulse and Gaussian noise in diverse forms. Power line interference of 50/60 Hz is a common artifact corrupting the raw ECG which appears as a sinusoidal wave (Gupta et al., 2010; Lay-Ekuakille etal., 2013). Another artifact is baseline wander where the baseline (of ECG waveform) start to drift up and down in a sinusoidal pattern due to respiration. One more significant artifact is Electromyographic noise (EMG) where muscle contraction signals interfere with the ECG. Baseline correction and noise elimination forms an important module in preliminary analysis of ECG signals (Lay-Ekuakille et al., May 2013;Sep 2013). It is important to limit the distortionby the baseline correction and noise suppressionalgorithms for further analysis such as QRS detection and temporal alignment for proper diagnosis. This highlights the significance of pre-processing module to catalyze the procedure of computer-aided disease diagnosis (Bhatejaet al., 2010; 2011; Mar 2013; May 2013; Jun2013; Aug 2013) to facilitate the subsequent detection of cardiovascular disease. Computer based diagnosis have been demonstrated fertile for various other diseases especially which arebased on accumulation of fluid (M. Khan et al.,2007; S. Urooj et al., 2010; 2011). In this regard, the reliability issues of the computer-based biophysical model reported in (S. Urooj et al., May2011; Jun 2011; 2012) are of great importance. Multiresolution techniques in wavelet domain for ECG signal conditioning include wavelet packet, multi-wavelet, bionic wavelet and lifting wavelet (Sayadi et al., 2007; Srivastava et al., 2011). Techniques employing mathematical morphology for noise and baseline removal in ECG signals include works of Chu et al. (1996), Sun et al. (2002), Lay-Ekuakille et al. (2008), Liu et al. (2011) and Casciaro et al. (2012) for removal of above mentioned artifacts. Morphological operators have been widely used in the signal- and image-processing 'elds because of their robust and adaptive performance in extracting the shape information in addition to their simple and quick sets computation [12–15].Chu and Delp used the combined opening and closing operators for baseline correction and noise suppression of ECG signals and good 'ltering performance was obtained [16].However, their morphological 'ltering (MF) algorithm distorts the characteristic points in ECG signal.This makes it diGcult for the subsequent processing to reliably detect the signi'cant ECG components or intervals.In this paper, a modi'ed morphological 'ltering (MMF) algorithm is proposed for baseline correction and noise suppression of ECG signals.For baseline correction, the same operators are used in the MF algorithm and the MMF algorithm.For noise suppression, modi'ed morphological operators are used in the MMF algorithm.Better signal conditioning performance has been obtained. The Fourier transform-based approach has been developed in [13] to extract ECG signal features in the frequency domain. But, this method omits the time resolution, which affects the estimation accuracy. This issue has been circumvented in some other works by providing the time-frequency analysis without significantly affecting the resolution. In [14–12], the wavelet transform-based algorithms were developed to find applications in some medical areas. In the wavelet domain, a compromise between the frequency and time resolutions is achieved easier and one can select a proper wavelet to provide a reasonable accuracy. However, a choice of an optimal wavelet is still challenging [10] and the approach has low efficiency in smoothing ECG signals.

PROPOSED TECHNIQUE:

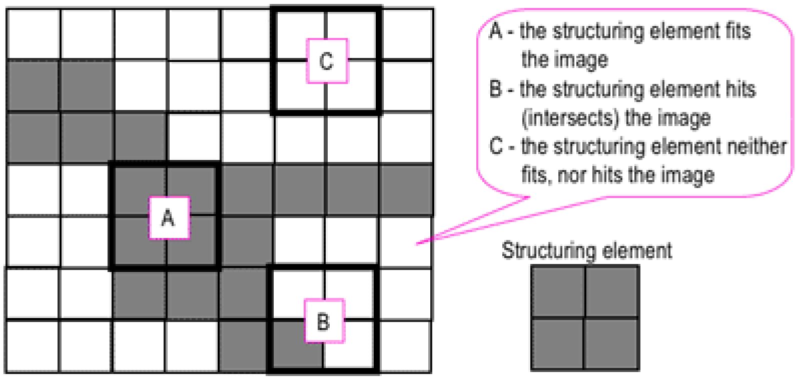


MORPHOLOGICAL PROCESSING:
Binary images may contain numerous imperfections. In particular, the binary regions produced by simple thresholding are distorted by noise and texture. Morphological image processing pursues the goals of removing these imperfections by accounting for the form and structure of the image. These techniques can be extended to greyscale images.

BASIC CONCEPTS

Morphological processing is a collection of non-linear operations related to the shape or morphology of features in an image. Morphological operations rely only on the relative ordering of pixel values, not on their numerical values, and therefore are especially suited to the processing of binary images. Morphological operations can also be applied to greyscale images such that their light transfer functions are unknown and therefore their absolute pixel values are of no or minor interest.

Morphological techniques probe an image with a small shape or template called a **structuring element**. The structuring element is positioned at all possible locations in the image and it is compared with the corresponding neighbourhood of pixels. Some operations test whether the element "fits" within the neighbourhood, while others test whether it "hits" or intersects the neighbourhood:



Probing of an image with a structuring element (white and grey pixels have zero and non-zero values, respectively).

A morphological operation on a binary image creates a new binary image in which the pixel has a non-zero value only if the test is successful at that location in the input image.

TOP-HAT TRANSFORM:

In mathematical morphology and digital signal processing, top-hat transform is an operation that extracts small elements and details from given signal. There exist two types of top-hat transform: the white top-hat transform is defined as the difference between the input image and its opening by some structuring element, while the black top-hat transform is defined dually as the difference between the closing and the input image. Top-hat transforms are used for various image processing tasks, such as feature extraction, background equalization, image enhancement, and

others. In the morphological Top-Hat transform algorithm, the noise suppression is performed as follow

$$\begin{aligned} f &= f_o \bullet B - f_o \circ B \\ &= \left(f_o \bullet B - f_o\right) + \left(f_o - f_o \circ B\right) \\ &= \left(f_o \oplus B_1 \Theta B_2 - f_o\right) + \left(f_o - f_o \Theta B_1 \oplus B_2\right) \end{aligned}$$

$f_o \bullet B - f_o$ and $f_o - f_o \circ B$ are two types of the morphological Top-Hat Transform [21]. The morphological Top-Hat transform is a high-pass filter with good performances. $f_o \bullet B - f_o$ is called theBlack Top-Hat transform, which is used to extractnegative impulsive features; $f_o \circ B - f_o$ is called theWhite Top-Hat transform, which is used to extract positive impulsive features. Thus filter can be used to extract the positive and negative featuressimultaneously. Figure3. illustrates a bloc diagram describing the structure of the morphological Top-Hat transform of the ECG signals. It consists of three blocs: The first is concerned with the acquisition of ECGsignals (*o f* : original ECG signal). This step is followedby another step which allows the detection of the noise. This detection is achieved using the morphological operators defined in equation 1 *B* and 2 *B* are structuring elements for opening and closing. These operations are used simultaneously on the original signal. The following step is the subtraction of the resulted closing and opening operations.

NOTCH FILTERING:

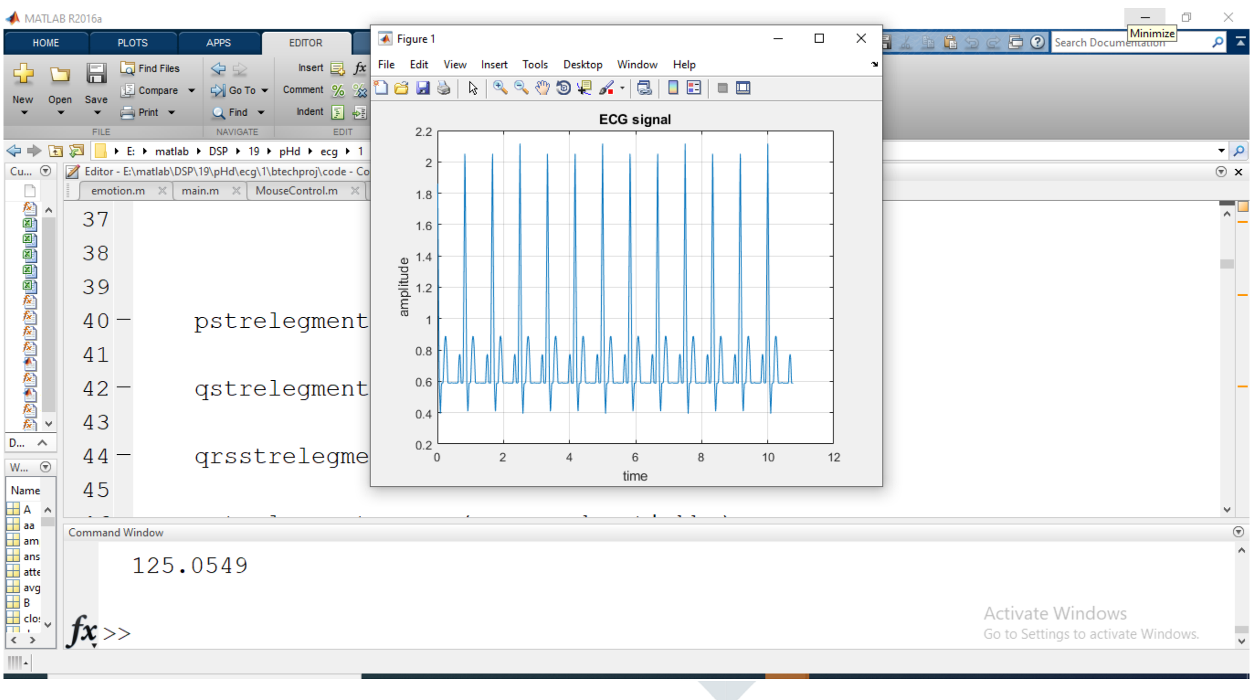
In signal processing, a **band-stop filter** or **band-rejection filter** is a filter that passes most frequencies unaltered, but attenuates those in a specific range to very low levels.[1] It is the opposite of a band-pass filter. A **notch filter** is a band-stop filter with a narrow stopband (high Q factor).

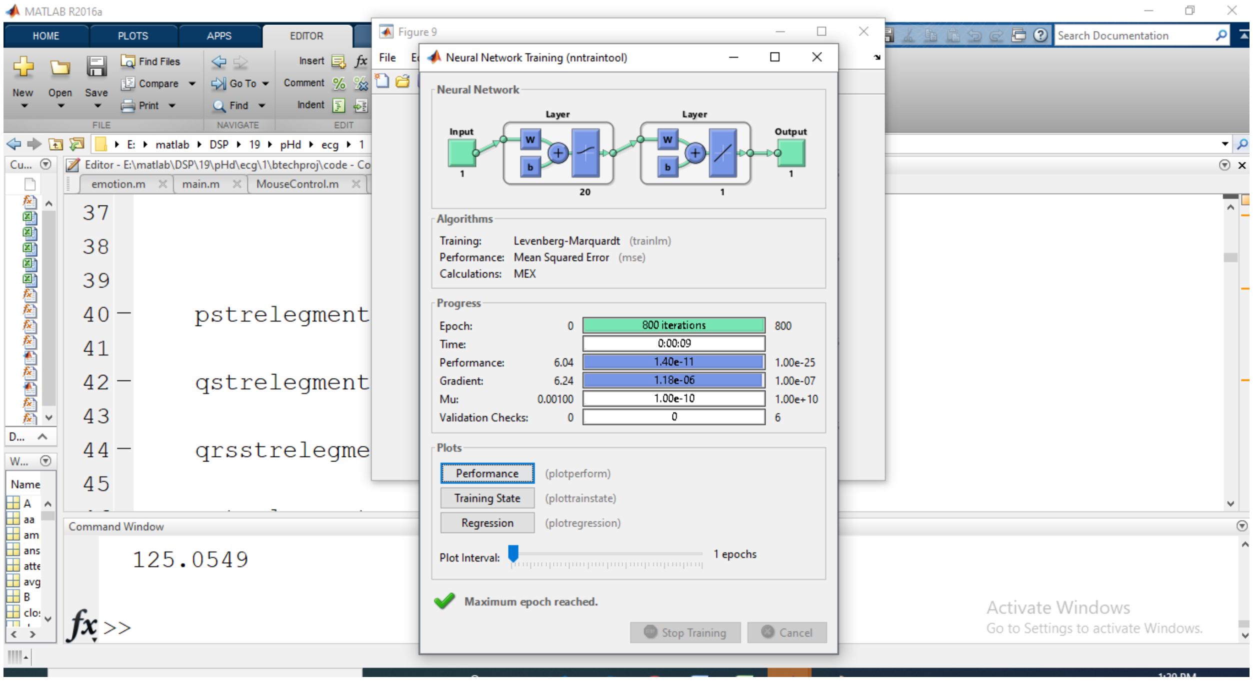
Narrow notch filters (optical) are used in Raman spectroscopy, live sound reproduction (public address systems, or PA systems) and in instrument amplifiers (especially amplifiers or preamplifiers for acoustic instruments such as acoustic guitar, mandolin, bass instrument amplifier, etc.) to reduce or prevent audio feedback, while having little noticeable effect on the rest of the frequency spectrum (electronic or software filters). Other names include 'band limit filter', 'T-notch filter', 'band-elimination filter', and 'band-reject filter'.

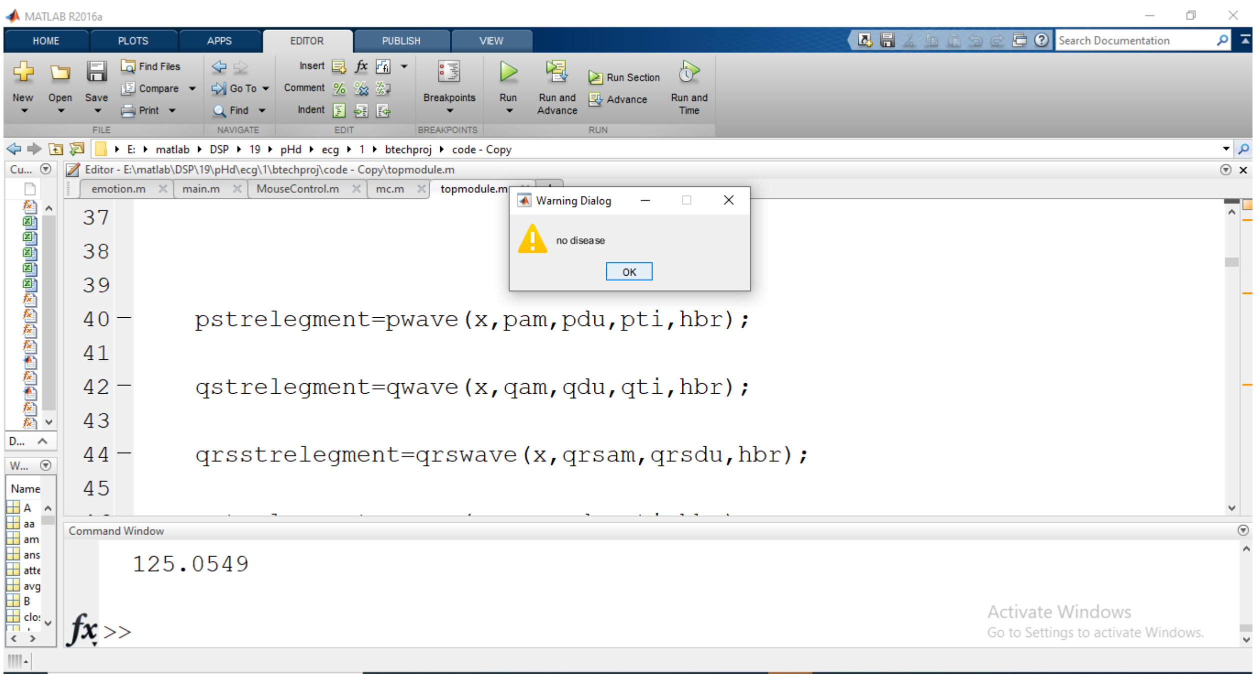
Typically, the width of the stopband is 1 to 2 decades (that is, the highest frequency attenuated is 10 to 100 times the lowest frequency attenuated). However, in the audio band, a notch filter has high and low frequencies that may be only semitones apart.

A Notch Filter is also known as a Band Stop filter or Band Reject Filter. These filters reject/attenuate signals in a specific frequency band called the stop band frequency range and pass the signals above and below this band. For example, if a Notch Filter has a stop band frequency from 1500 MHz to 1550 MHz, it will pass all signals from DC to 1500 MHz and above 1550 MHz. It will only block those signals from 1500 MHz to 1550 MHz.

RESULTS:







CONCLUSION:

The paper summarizes the current state of the art in empirical mode decomposition. It is obvious that the method is still in its infancy, nonetheless a respectable and quickly growing number of applications to analyze biomedical time series already exists. The method provides specific advantages due to its applicability to non-stationary and non-linear time series. Perhaps the most difficult problem yet to solve is Also biomedical time series often are recorded over long time spans extending over days and even weeks. No appropriate EMD method yet exists to allow an online evaluation of suc long going recordings. Undoubtedly the future will show the potential of this heuristic to analyze and interpret huge and complex time series data sets the interpretability of the extracted IMFs in physical terms.

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