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ECG SIGNAL DENOISING: A NEW APPROACH

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ABSTRACT

ECG signal plays a crucial role in diagnosis of a Varity of diseases. At the time of diagnosis the proper information from the ECG signals helps to make a proper and efficient diagnosis for the patient. Most often it is found that treatment of the patient suffers due to improper information of ECG signals. The cause behind this problem is the noise added in the ECG signals at the time of signal acquisition. Hence to overcome this problem efficient denoising of ECG signals is required. An algorithm for suppression artifacts from the electrocardiogram (ECG) using SASS algorithm has been investigated. An improvement of the traditional technique is proposed by involving Time-frequency dependent threshold for calculation of the pilot estimate in the first stage. The appropriate choice of the wavelet basis functions used in each stage has been stressed. The strong relationship between the wavelet function's support and the ECG morphology has been emphasized. The preliminary assumptions have been argued by experiments on a wide range database. They have shown that an appropriate choice of the decomposing wavelets for the two algorithm stages can considerably improve the quality of the denoised signal.

KEYWORDS: *Electrocardiogram, Denoising, signal acquisition, ECG.*

I. INTRODUCTION

The presence of parasite interference signals could cause serious problems in the registration of the ECG signals. Most common are power line interference, EMG signals, motion artifacts, and base line (drift) interference. While there are well-developed methods for power line interference and drift suppression there are still problems in EMG signal suppression, due to considerable overlapping of the frequency spectra of both types of signals. Thus, the automatic interpretation, following accurate detection of characteristic ECG points and waves and measurement of signal parameters is, be- come extremely difficult, sometimes virtually impossible task.

Adequate ECG denoising algorithms and procedures should:

Improve signal-to-noise ratio (SNR) for obtaining clean and readily observable recordings, yielding the subsequent use of straightforward approaches for correct automatic detection of characteristic points in the ECG signal and recognition of its specific waves and complexes;

Preserve the original shape of the signal and especially the sharp Q, R and S peaks, without distorting the P and T waves and the smooth transition of the ST-T segment.

Recently some new techniques based on global and local transforms have become popular in connection with signal denoising. As a first step the signal is de- composed into a transform domain where filtering procedures are applied. The noise-free signal is obtained by an inverse transform. Choosing appropriate basis functions for successful decorrelation of the signal and de- signing transform domain filters accommodated to the ECG signal morphology could turn this techniques into powerful means for ECG signal denoising.

This paper has been organized as follows: Section-I is giving a brief introduction about the paper, section-2 is about the various type of noise encountered in the ECG signal, section-III is about SAA

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algorithm and section-V is provided with the results and discussion after the preprocessing and denoised signal.

II. NOISE

Noise is present in almost all environments, and can be defined as an undesirable signal that interferes with the desired signal. A noise itself is a signal that can be generated from several sources. These interference signals include interferences from power supplies, motion artefacts due to patient movement, radio frequency interference, defibrillation pulses, pace maker pulses, interferences from other monitoring equipment, etc.[12]. The big challenge of noise in biomedical signals is closely related with amplitude of the desired signals face to the noise, i.e. the Signal-to-Noise Ratio (SNR). For instance, an ECG measurement gets challenging due to the presence of the large DC offset and various interference signals. This potential can be up to 300 mV for a typical electrode, which is several times larger than ECG signal.

Noise reduction is a crucial task to unravel in biological signals and for this reason, the understanding the characteristics of noise is that the focus of the contents during this chapter. The chapter can begin with noise properties and characteristics as SNR and separability, followed by most typical noises sources associated to EKG.

2.1 Noise Properties

Depending on its frequency or time characteristics, a noise method will be classified in many categories:

- Narrowband noise
- Band-limited noise
- Colored noise
- Impulsive noise
- Transient noise pulse

Narrowband noise may be a noise method with a slender information measure akin to a 50Hz hum from the ability lines. Noise is only random noise that contains a power spectrum. Noise on paper contains all frequencies in equal intensity.

Band-limited noise it's a noise with at spectrum and restricted information measure that typically covers the restricted spectrum of the device or the signal of interest.

Colored noise it's nonwhite noise or any broadband noise whose spectrum contains a non-at shape; examples square measure pink noise, brown noise and autoregressive noise.

Impulsive noise is having pulses of small-duration and random amplitude and length. Transient noise pulses is comprising of relatively noise pulses of long length.

2.2 Noise Characteristics

Noise is generally signified as a random variable, known as x(n), and relating its properties as a function of time it is not very useful. Therefore, a more common approach for the evaluation of its probability distribution, range of variability, or frequency characteristics should be used.[20].

While noise can take a variety of different probability distributions, the Central Limit Theorem 1implies that noises will have a Gaussian or normal distribution.

The probability p(x) of a Gaussianly distributed variable, x, is specified by the normal or Gaussian distribution equation:

$$p(x) = \frac{1}{\sigma\sqrt{2\pi}} e^{\frac{-(x-a)^2}{2\sigma^2}}$$

Where, a it is the mean, or average value, and σ^2 is the variance. The arithmetic quantities of mean and variance are frequently used in signal processing algorithms.

The mean value of a discrete array of N samples is evaluated as:

$$\overline{x} = \frac{1}{N}\sum_{k=1}^{N} x_k$$

And the variance, σ2, is calculated as:

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$$\sigma^2 = \frac{1}{N-1}\sum_{k=1}^{N}(x_k - \overline{x})^2$$

From above Equations we grasp the standard deviation σ, which is just the square root of the variance.

2.3Separability of Signal and Noise

A signal is utterly retrievable from noise if the spectra of the signal and the noise don't overlap. An example of a loud signal with dissociable signal and noise spectra is shown in Figure 4.2(a). During this case, the signal and noise square measure placed in numerous components of the frequency spectrum, and signal will be denoised with a low- pass filter. Although, Figure 4.2(b) illustrates a lot of common example of signal and noise, with overlapping spectra. For these cases, it's out of the question to utterly separate the signal from the noise; but, the results of the noise will be a lot of or less reduced relying on the filter technique used.

2.4 Noise Sources

The Noise that emanates from moving, vibrating, or colliding sources and is that the most presence of noise is consummated in numerous degrees in the majority environments. The foremost famous and customary are: Acoustic acquainted variety of noise gift in everyday environments; magnetism Noise, that is gift in any respect frequencies and particularly at radio frequencies; process Noise that results from the signal process, e.g. quantization noise in digital writing, or lost knowledge packets in digital knowledge communication systems.

2.4.1 Biomedical Noises Sources

Noise frequently is a limitation factor in the performance of medical instrumentation, producing variability. In biomedical measurements, variability has four different origins:

1. Physiological variability;
2. Transducer artifact;
3. Environmental noise or interference;
4. Electronic noise.

Physiological Variability: Physiological variability is due to the presence of other sources of biological influences than those of interest. For example, assessment of respiratory function based on the measurement of blood pO23 could be confounded with other physiological mechanisms that change blood PO2[20]. Physiological variability can be a very difficult problem to solve, where to solve it, sometimes it is required information provided by different sources to help in validation.

Transducer Artefact: Transducer artefact has been appeared while the transducer is responsible to mold the desired signal. The perfect example is non-invasive measurements of various electrical potentials using electrodes placed on the skin are sensitive to motion artefact.

Environmental Noise: Environmental noise is generated from existing sources, either external or internal to the body. Maybe, during a craniate EKG recording, the craniate EKG is corrupted by the mother EKG. In these cases it isn't attainable to describe the precise characteristics of environmental noise.

Electronic Noise: Electronic noise falls into two broad classes: thermal or Johnson noise, and shot noise. The previous is created primarily in resistance or resistance materials whereas the latter is said to voltage barriers associated with semiconductors. Each sources manufacture noise with a broad vary of frequencies usually extending from DC to $10^{12} - 10^{13}$ cycles/second.

2.5 ECG Noises Sources

ECG signals continually have background noise associated, and noise sources area unit numerous that noise reduction became a vital frontend signal process task for bio- medical signals. The most common noises that typically ought to be thought-about are: cable interference, muscular contraction (EMG), Instrumentation noise generated by electronic devices, Baseline drift and EKG amplitude modulation [22, 23]. Power line interference could be a narrow-band noise centered at fifty cycles/second with an information measure of below one cycles/second. This sort of noise typically contains harmonics due to parasite currents through human body. Cable interference is comparatively constant throughout the EKG measure. Cables employed in electrodes connections area unit another supply of cable noise [24].

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Muscular contractions manufacture artefacts inside millivolts level potentials. This signal is generally transient bursts of zero mean band-limited Gaussian noise [22]. The worst case of muscular contractions interference is once the measurements area unit created at same time as muscular activity, i.e., in sports or jobs with intense body activity. In these cases, the muscular amplitude signal will fully overlaps the EKG signals. While not muscular activity the noise created is negligible because of its insignificant amplitude.

Artefacts generated by electronic devices will manufacture many totally different interferences, conducing to unpredictable noise shapes, leading to complete signal distortion or instrumentation saturation. If they are doing not contemplate these things, these artefacts can be thought-about like Gaussian noise.

Baseline drift and EKG with respiration happens throughout the respiratory cycle. The amplitude of EKG signal varies principally influenced by relative distance between heart and electrodes. This distance is multiplied once lungs fill and reduces at time of lungs become empty. The impact is discovered as a slow modulation of the EKG amplitude with same frequency because the respiratory cycle. The amplitude of the EKG signal conjointly varies by concerning V-day with respiration [25, 26, 27, 28].

In addition, physiological and environmental noise affects the EKG power spectrum. EKG power spectrum will give helpful info concerning cardiovascular disease, and if EKG signal is impure with noise for overall spectrum, becomes tough to aim this info with sensible accuracy. Figure 4.3 summarizes the relative power spectra of the EKG, QRS complexes, P and T waves, motion whole thing, and muscle noise. This graph reveals that the EKG signal has their energy principally focused in frequencies below than twenty five cycles/second, wherever the QRS advanced assumes the most important space.

III. PROPOSED ALGORITHM

Noise cancellation requires different strategies for different noise sources or types.

Since the focus of this thesis is a non-classical method, the approaches covered in this section are all included in the non-classical methods used by several authors. A useful method for removing power line and baseline disturbances is the application of a digital linear phase filtering [30]. This method can be used to reduce signal magnitude spectrum while preserving the signal time domain as much as possible. The disadvantage of this method is the computational requirements. This is mainly caused by linear phase narrow-band filtering, that requires a long impulse response, and the corresponding number of filter coefficients caused by a large number of multiplications involved in the time domain [31].

Random and stationary noise can be removed using a temporal averaging method. Noise reduction by temporal averaging method is proportional to the square root of the number of frames or beats taken into the average [32]. This method only offers effective performance if a large number of samples is used. Moreover, due to heartbeats variability, it can cause considerable errors, producing distorted results, or extremely smooth waves.

To increase signal quality, some authors refer the performance of spatial averaging [33, 34, 35]. But spatial averaging requires a large number of electrodes in the same region, which cause the main drawback of the method for portable equipment. This not only causes a discomfort to the users, as well as an amount of signals to be recorded and treated. Meanwhile, solutions like wearable sensors might be the answer to discomfort, but at time these solutions produces high noise levels due to a bad contact of electrodes at skin surface producing high levels of noise.

the SVD (Singular Value Decomposition) method has been proposed to remove muscle noise artifacts in exercise ECG's, [36]. SVD filtering do not requires prior information for a satisfactory performance, about the onset or the set points of ECG signal. This is very important since in the presence of a noisy ECG signal it wouldn't be possible to grasp the right position of the wave. SVD method is based on matrix factorization, and the problem of this technique is the matrix dimension and computational calculations before a possible reduction of the matrix. However, the authors of [36] mentioned that with a minimum value of matrix size, the results performance of the MSE (mean square error) are identical to the results of the Wiener filter MSE using a discrete cosine transform.

One promising solution for noise reduction is the use of adaptive filters. There are several advantages for adaptive filtering approaches: adapting filtering do not needs a priori knowledge of the statistical or

spectral properties of the signal and noise; constantly adapt the weights of filter for better performance; when applied to a set of samples does not require higher power computation requirements. For some applications, the drawback of adaptive filtering approach is that requires the correlation of noise with signal. For the case of ECG, this is not a problem due to the possibility to obtain this correlation from the electro in the leg. Several authors, e.g.[37, 38, 39], have done their works in this field of signal processing, but mainly with ECG signals from databases as MIT-BIH.A method for ECG denoising based on Wavelet Shrinkage approach [1] using Time-Frequency Dependent Threshold (TFDT) has been proposed in [2]. Generally speaking, the TFDT is high for the non-informative wavelet coefficients, and low for the informative coefficients representing the important signal features. Although giving better results in comparison with other ECG denoising methods, the latter has certain disadvantages: some oscillations may occur in the ends of the QRS complexes using long-length decomposition filters due to the poor time localisation of the basis functions; and in opposite – very short-length filters may corrupt the shapes of the “slow” P and T waves.
The method, called 'sparsity-assisted signal smoothing' (SASS), is based on modeling a signal as the sum of a low-pass component and a piecewise smooth component. The problem is formulated as a sparse-regularized linear inverse problem. We provide simple direct methods to set the regularization parameter and the non-convexity parameter, the later if a non-convex penalty is utilized. We derive an iterative optimization algorithm that harnesses the computational efficiency of fast solvers for banded systems. The SASS approach performs a type of wavelet denoising, but does so through sparse optimization rather than through wavelet transforms.
In the present study we aim to improve the denoising procedure by SASS algorithm:
1. Assuring good pilot estimation of the QRS areas using algorithm with short sup- port (short length filters), and
2. Refinement the shapes of the P and T waves using medium length filters.

IV. RESULTS AND DISCUSSIONS

The proposed work has been successfully implemented in the MATLAB. This section presents the results obtained and comparative analysis with SaSS algorithm. For the testing phase, we have used MIT-BIH ECG data base. Figure (4.1) is presenting the ECG signal and Noise mixed ECG Signal. Figure 4.2 is showing Preprocessed ECG signal.

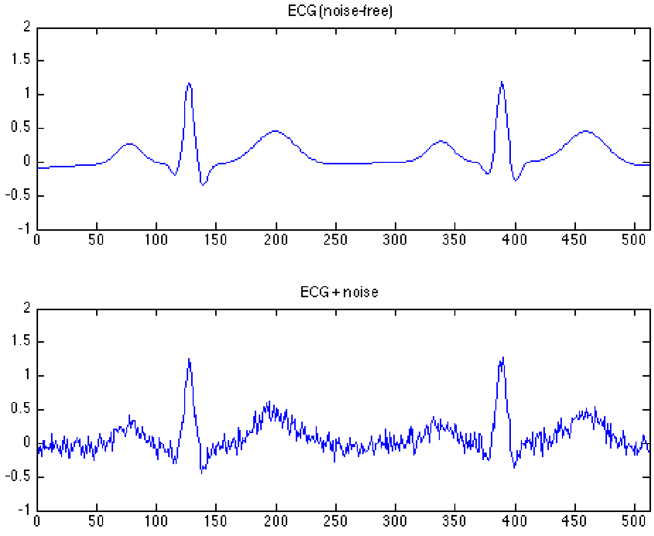

Figure 4.1 : ECG signal and Noise mixed ECG Signal

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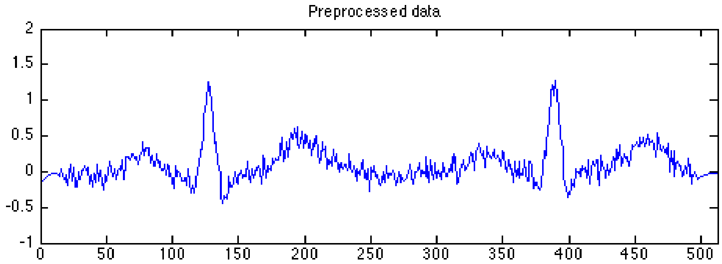

Figure 4.2: Preprocessed ECG signal

Figure 4.3 shows the results obtained after ECG signal denoising using SASS algorithm.

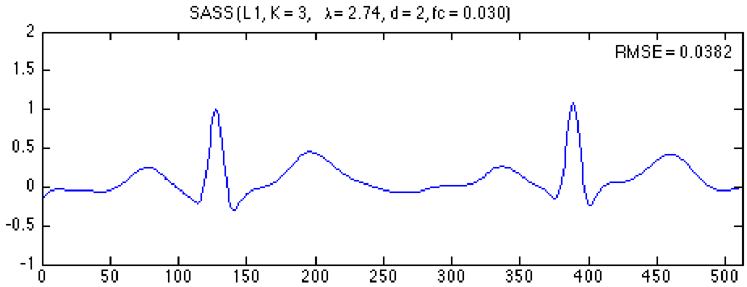

Figure 4.3: Denoised ECG signal

V. CONCLUSION

As a conclusion the experimental results have showed that the proposed two-stage denoising approach leads to very effective suppression of the noise signals that may be parasite EMG signal.

The results of the simulation show that it has advantages comparing with the wavelet analysis based on hard and soft threshold. All computer simulations were performed in MATLAB environment. The results are evaluated by calculating the RMSE and the correlation coefficient. It can be noted that the interval-dependent thresholds of wavelet analysis a better result than soft and hard thresholding methods. In all SNR rates, the SASS method shows superior performance of the ECG signals.

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