Evaluation of a Combined Approach for Denoising ECG Measurements Using Unconventional Sensors

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Abstract

The human electrocardiogram is a key indicator to examine the electrical heart condition and function. A common problem is that its recording can be impacted by external sources of noise. In this paper, we focus on the reduction of powerline interference in ECG measurements using a combined approach. We discuss the typical noise types affecting ECG recordings and describe several filtering techniques currently used to denoise ECG measurements. We propose an approach that combines unconventional ECG electric field sensors with Wiener filtering to improve the ECG denoising performance. Validation tests are performed though an experimental system using both pre-recorded ECG and ambient noise signals. We show that our approach can lead to an overall improved noise cancelling and the corresponding retrieval of the desired ECG signal reducing the noise levels from – 25dB down to -52dB.

1. Introduction

The human electrocardiogram (ECG) provides information of the heart electrical activity using electrodes placed in contact with the skin. The ECG signal is represented by a non-linear quasi-periodic time series, and it is the key indicator to examine the electrical function and condition of the heart. However, the fidelity of the ECG signals is often degraded by noise, which might alter the morphological features (P,Q,R,S, T waves) and time dependent metrics such as the heart rate variability.

Real time assessment applications such as cardiorespiratory monitoring, analysis of ECG and heart rate variability rely on the determination of the morphology and time interval characteristics. However, common sources of noise such as base-line wander (BW), muscle artefacts and power-line interferences (PLI) can severely affect ECG measurements [1] , leading to inaccurate diagnosis and treatment. Thus, the real-time ECG noise detection and elimination still remains a challenge [2].

1.1. Noise in ECG signals

The ECG denoising methods have been classified into six main groups according to [1,2]. The first group belongs to ECG denoising using *Empirical mode decomposition* (EMD), which is a local and adaptive method in the frequency–time analysis. EMD is a data-driven mechanism which is suited for non-linear and non-stationary signals [3,4]. The second group includes *deep learning based autoencoder models* (DAEs), which aim at regenerating a clean ECG signal from a corrupted version of the same by optimising the objective function. The wavelet-based methods fall into the third group. These use the *wavelet transform* (WT) to decompose the signal, to determine the type of thresholding required, followed by the signal reconstruction. The DAEs and WT are statistical methods and are used to extract a statistical-based model of the noise signal [5]. The fourth group utilises the sparsity property of ECG for *sparse optimisation t*o denoise ECG signals. Here, the signal is split into segments, and every segment is broken into sparse parts and residues to denoise ECG signals [7].

Even though several denoising approaches have been established in the literature, studies show that a single signal processing technique is not adequate to remove different sources of noise and artifacts present when collecting ECG signals [6]. Therefore, other advanced denoising approaches based on a*daptive filtering* have been proposed. The basic approach uses *model-based Bayesian filters* such as the extended Kalman filter (EKF), Extended Kalman Smoother (EKS), and unscented Kalman Filter(UKF). The fifth group uses *Bayesian filters* to introduce changes in the conventional dynamic ECG model of Kalman filter to denoise ECG signals. The last group is defined as *hybrid systems* combining various denoising methods previously reported in literature [7]. It has been shown that combined approaches including filtering techniques like conventional filtering [8] and adaptive filtering [9] can offer an improved reduction of noise in ECG signals. However, the results obtained using hybrid models, showed that these filtering techniques introduce different kinds of waveform distortion [7].

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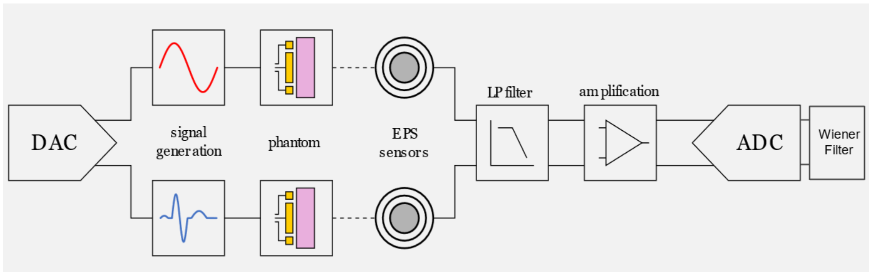

Figure 1: Block diagram of the experimental set up for the combined ECG denoising system

Therefore, a robust and reliable method to extract the noises present in ECG recordings becomes important [2].

In this paper we present a combined approach for the reduction of powerline interference in ECG signals. We propose a method which uses unconventional electric field sensors as ECG detectors combined with Wiener filtering to provide a unique real time ECG PLI denoising technique. Experimental tests were carried out using a custom-made device that mimics the ECG signal propagation using tissue like phantoms. The developed system is used to assess the effectiveness of the proposed method to reduce PLI and its harmonics.

2. Materials and Methods

2.1. Experimental approach

The experimental denoising approach considers the use of unconventional electric field sensors (EPS) [10] as a non-invasive tool for the detection of both: ECG and noise signals. The EPS sensors falls within the category of capacitive sensing that operate based on displacement currents. In this way, high resolution ECGs can be recorded with and without the need for sensor attachment allowing for rapid and accurate ECG analysis. Besides this, our proposal uses an additional pair of EPS sensors as noise detectors, due to their susceptibility to ambient noise, to detect PLI and its harmonics plus any other sources of noise affecting the ECG recording.

The structure of the EPS sensor has been previously described in [10, 11]. Briefly, the EPS sensor is an electrometer-based amplifier insulating electrode that does not require galvanic contact with the body to acquire biopotential signals. Instead, it operates with displacement currents and the traditional electrode-skin interface is replaced with a dielectric material.

The block diagram of the proposed experimental denoising system is shown in Fig. 1. The system includes a pair of antennas embedded in a tissue phantom to emulate the ECG signal passing through various layers of tissue. Two pairs of EPS sensors are used, the first one for ECG collection and the second one for noise detection. A signal conditioning stage is used for pre-filtering and amplification. An analog-to-digital converter (ADC National Instruments) is used for signal digitalisation and finally, a Wiener filter algorithm is used to retrieve the ECG and noise signals from the measurements using our experimental sensing system.

State-of-the-art literature has shown that Wiener filtering provides an effective method for noise reduction and ECG signal quality improvement [12,13]. Most of the denoising methods based on Wiener filtering rely on an estimation of the noise using a statistical approach as discussed on [12,13]. Given the known spectral properties (the power distribution of the signal in the frequency domain) of the signal of interest and the added noise, several iterations are required to approximate the transfer function of the Wiener filter to produce an output closely matching the signal of interest. However, ideal Wiener filtering requires to either have knowledge of the noise level or the signal of interest.

As opposed to a noise estimate, in this work, we propose to use EPS sensors for recording an accurate replica of the noise. By using a reference sine wave alongside with the ECG, an accurate noise reading can be obtained. The combined approach presented in this paper considers the combination of EPS sensors and Wiener filtering for ECG denoising which is an adapted version of a method used for the reduction of PLI noise in geophysical magnetic resonance sounding measurements [14]. Such technique has shown to be effective in removing power line and short electromagnetic interference such as the characteristic bursts of cellular and Wi-Fi data transmission. The presented method is validated using pre-recorded ECG signals passing through a tissue phantom in which two signals are generated a) simulated ECG and b) reference sine wave to be measured by the EPS detectors as shown in Fig. 1.

2.2. Phantom cardiac model

For evaluating the proposed combined approach, a tissue phantom model was developed for testing. This tissue phantom serves two purposes: a) to mimic the interfacing layers of tissue between signal source (noise and ECG) and the EPS sensor, and b) to provide a signal ground path to emulate a conductivity similar to human tissue. The phantom consists of several layers including: a) foam block & weight, b) insulating constraint layer, c) EPS, d) agar phantom, e) ground loop and f) e-field source emitter used to radiate the ECG signal emulating its propagation through the human tissue. The stack of layers modelling the voltage of the heart and the signal propagation through the human tissue is shown in Fig 2.

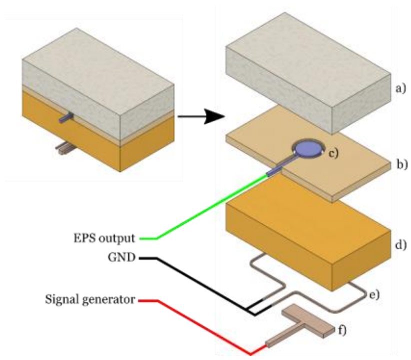

Figure 2. The tissue phantom with an embedded e-field source emitter. The stack consists of a) foam block & weight, b) insulating constraint layer, c) EPS sensors, d) agar phantom, e) ground loop, f) e-field source emitter.

Agarose gel is routinely used to mimic brain tissue in phantoms for magnetic resonance (MR) imaging [15]. Pharmaceutical-grade agar powder (Intralabs UK) was used and mixed with a saline solution at various concentrations to increase the conductivity. Agarose concentration at 4% was used to approximate a Young's modulus of bulk tissue in the body of approximately 1 MPa. When cast into a known volume, the conductivity at a range of frequencies can be determined using Eq. 1.

$$Conductivity,\ \sigma = \frac{1}{\rho} = \frac{l}{R \times A} \quad \text{........... Eq. 1}$$

where, σ is the electrical conductivity in Siemens/m, ρ is the electrical resistivity (Ohms-m), R is the electrical resistance (Ohms), *A* is the cross-sectional area of the gel sample in m^2 and *l* is the length of gel sample in meters.

The EPS electrodes were held in place (as shown in Fig 2c) by an insulating central layer to constrain any movement of the sensors and ensure repeatable placement and data collection.

3. Experimental evaluation

3.1. Phantom cardiac model

For the proposed experiments, five agar formulation samples with a range of salt concentrations were cast into 20 mm diameter ABS tubing. After cooling and solidification samples were placed in a test jig. These where then subjected to a 10 V peak to peak input voltage at room temperature (~25°C). The output voltage and current values were measured and used to calculate the resistance. Fig. 3 shows the conductivity results of the five formulations vs. a frequency sweep ranging from 0 to 10 KHz. The final concentration of 1 mg/100 ml for an approximate conductivity of ≈ 0.5 Siemens/m was selected being similar to the dielectric properties of biological tissues [16] aiming to emulate human tissue.

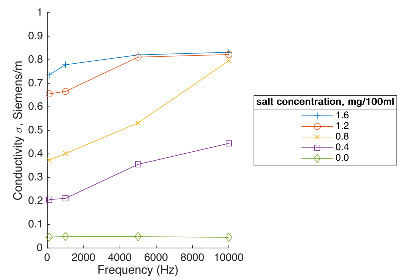

Figure 3. Conductivity results of five different phantom formulations vs frequency.

3.2. Results after applying the combined approach (EPS sensors and Wiener filter) for ECG denoising

The method is validated considering the experimental setup implementing the EPS detectors shown in Fig. 1 and the cardiac tissue phantom shown in Fig. 2. For this experiment two signals were generated a) a simulated ECG and b) a reference sine wave at a frequency of 7 Hz. Both signals were radiated though the e-field source emitter with an amplitude of 5 mV, with 5 minutes of data recorded for each tested frequency. The predominant source of noise present in the laboratory environment was 50 Hz, and it was sensed through the EPS sensors (Fig 1).

The combined denoising approach (EPS sensors and Wiener filter) works as follows: firstly, the reference sine wave is subtracted from the EPS collected output signal to derive the noise estimate. Secondly, the recorded ECG and noise estimate are both fast Fourier transformed (FFT) at 1 kHz sampling rate giving a FFT frequency resolution of 1 Hz for signal processing purposes. Thirdly, based on the noise estimate, the ideal Wiener filter transfer function is generated and then applied into the ECG signal detected by the second pair of EPS sensors.

Fig 4. shows the resulting signals measured before and after applying the combined denoising approach. In Fig. 4a) the reference sine wave (red line) is shown. The sine wave containing PLI, and ambient electrical noise recorded using EPS is depicted in blue. The yellow trace is the resulting noise estimate. Fig. 4b) shows the ECG signal results at the output of EPS sensors (blue line) and after noise reduction using Wiener filtering (red line). As it can be observed, the method allows the removal of the noise present in the ECG signal. Fig. 4c) shows the results of 50 Hz attenuation when testing a range sine waves with frequencies ranging from 1 to 200 Hz.

Fig. 5 shows the power spectral density (PSD) results measured after applying the combined denoising approach. The plot shows the results from an ECG trace where the predominant 50 Hz noise is attenuated from -25 to -52 dB after applying the proposed method.

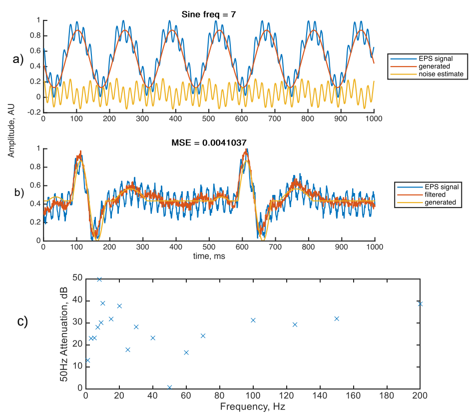

Figure 4. Results before and after applying the combined denoising approach, 4a) reference sine wave and noise estimate; b) ECG signal before/after filtering; c) results of 50 Hz attenuation when testing a range of sine waves with frequencies ranging from 1 to 200 Hz.

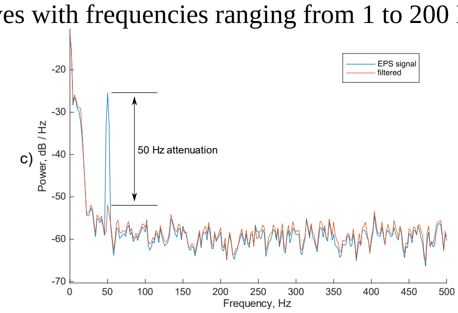

Figure 5: PSD results measured after applying the combined denoise approach.

4. Conclusions

This experimental work shows that the proposed combined approach is suitable for de-noising pre-recorded electrocardiograms from PLI using unconventional EPS sensors. Through the subtraction of the recorded noise signals using a reference EPS, a noise estimate is calculated and used to generate the ideal Wiener filter settings, thus providing adaptative noise cancelling capabilities showing that the predominant 50 Hz noise is attenuated from -25 to -52 dB after applying the proposed method.

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