A Multi-Channel Electrode Tissue Impedance Detection Approach for Motion Artifact Suppression in Ambulatory Electrocardiography

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Abstract

In ambulatory electrocardiography recording, the motion artifact can contaminate the signal and disrupt the normal functioning of the automatic analysis algorithm. The objective of this study is to evaluate an approach for measuring the electrode tissue impedance (ETI) variation for motion artifacts suppression application. The proposed approach injects an additional common mode signal though the reference electrode. Motion artifact suppression is performed using adaptive filter with the reference signal generated by ETI.

1. Introduction

Ambulatory electrocardiography (AECG) monitoring is a portable non-invasive technique to monitor electrical activity of the heart by measuring voltage difference between electrodes. The relative movement between the electrode and the conductive adhesive, and the stretch of skin generate MA [1]. MA is the biggest source of noise in AECG and can vary skin potential up to several millivolts [2]. This contaminates AECG signal and makes it difficult to be identified. Filtering MA from AECG is highly difficult because they have similar frequency spectra [3]. Using basic filter to suppress MA could not efficiently remove MA from AECG without distorting original AECG signal [4]. Blind source separation techniques were used to selectively remove MA from AECG [5], but they suffered from high computationally cost [6]. In order to solve this problem, adaptive filter (AF) had been widely used [7]. In the existing approaches, the reference signal of AF was generated by single channel electrode tissue impedance (SC-ETI) detection approach [8-10]. To monitor high quality SC-ETI and AECG signal simultaneously, SC-ETI needs a complex system design to ensure the high input impedance of amplifiers. More research is required to find a supplementary approach.

In this paper, we present a multi-channel electrode tissue impedance (MC-ETI) detection approach [11] to generate the reference signal of AF and use AF to suppress MA from AECG.

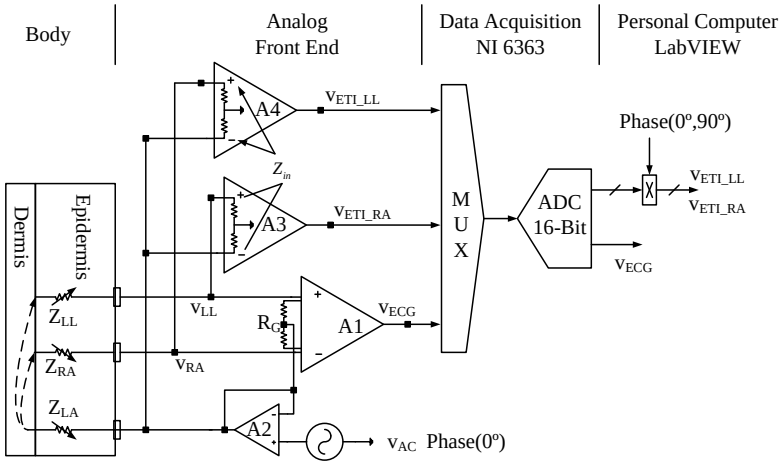

Figure 1. MC-ETI detection approach

2. Method

2.1. MC-ETI detection

In order to reduce the MA in AECG, AF requires a reference signal which has high correlation with MA and low correlation with AECG. In Fig. 1, MC-ETI detection approach can generate the reference signal for the AF without any extra sensors.

Amplifier A2 forces an 1kHz AC voltage though the driven right leg circuit and electrode Z_{LA}. There are two current paths though the body. One path flows through Z_{LA}, Z_{RA}, Z_{in} to the ground and the other path flows through Z_{LA}, Z_{RA}, Z_{in} to the ground. Z_{in} is the input impedance of instrument amplifier. Actually, RA places several millimetres below the right collarbone and LA places several millimetres below the left collarbone and LL places several millimetres below the left breast.

When Z_{LA}, Z_{LL}, Z_{RA} vary with the electrode movement, the divided voltages v_{LL}, v_{RA} will vary simultaneously. A3 and A4 amplify these voltages differentially and generate two AC voltage v_{ETI_LL}, v_{ETI_RA}. At the same time, A1 detects AECG signal v_{ECG}. A analog digital convertor (ADC) samples these voltages with 80kHz sampling rate and transports the data to the person computer (PC). A digital lock-in amplifier extracts the DC component from v_{ETI_LL}, v_{ETI_RA} and calculate the MC-ETI signal by the following equations:

$$Z_{ETI\_LL} \approx Z_{LL} \approx (Z_{in} - 2Z_{LA})V_{ETI\_LL}/2V_{AC} - 2Z_{LA}$$
$$Z_{ETI\_RA} \approx Z_{RA} \approx (Z_{in} - 2Z_{LA})V_{ETI\_RA}/2V_{AC} - 2Z_{LA} \quad (1)$$

We chose commercial silver/silver chloride electrodes as LL, LA and RA, and pasted them on the corresponding part of the body. We used a Philips® M1603A ECG lead set to connect the electrodes to the analog front-end. We measured the impedance when we pushed one of the electrode of LL and RA.

2.2. Adaptive filtering

In noise cancellation applications, the AF updates its coefficients $w_1(k), w_2(k)$ continuously to minimize the error energy of the output signal. Fig. 2 shows the AF to suppress MA in AECG, the primary input of the AF is an MA contaminated AECG signal $S_{ecg}(k) = V_{ecg}(k) + n_0(k)$. The reference inputs $n_{ref\_1}(k), n_{ref\_1}(k)$ are the MC-ETI signal related with MA. By iterated operation, AF can automatically remove the noise from the contaminated signal, leaving a clean AECG signal $E_{ecg}(k)$ [12]. Where $V_{ecg}(k)$, $n_0(k)$, $Y_{ref}(k)$ and $E_{ecg}(k)$ represent the original AECG signal, MA signal, filter output and clean AECG signal after MA removing, respectively.

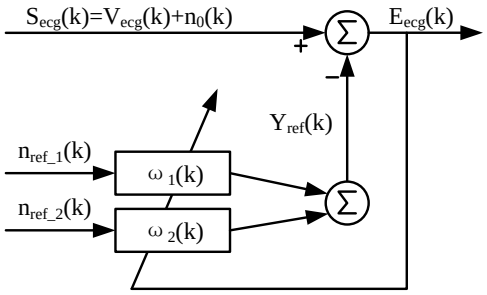

Figure 2. Adaptive filter to suppress MA in AECG

3. Results and discussion

3.1. Artifacts and correlated signals

Ten tests were carried out on five male subjects with each of two tests. A single test involved three steps to imitate MA in AECG: a motionless wait for 30 seconds (the subject sat on a chair), pushing and releasing the electrode by hand in turn for 6 times, and a motionless rest for 30 seconds before stop. We employed the pushing and releasing operations to simulate the force condition in motion state. Both of the pushing and releasing lasted 1s, with 3s interval between each time.

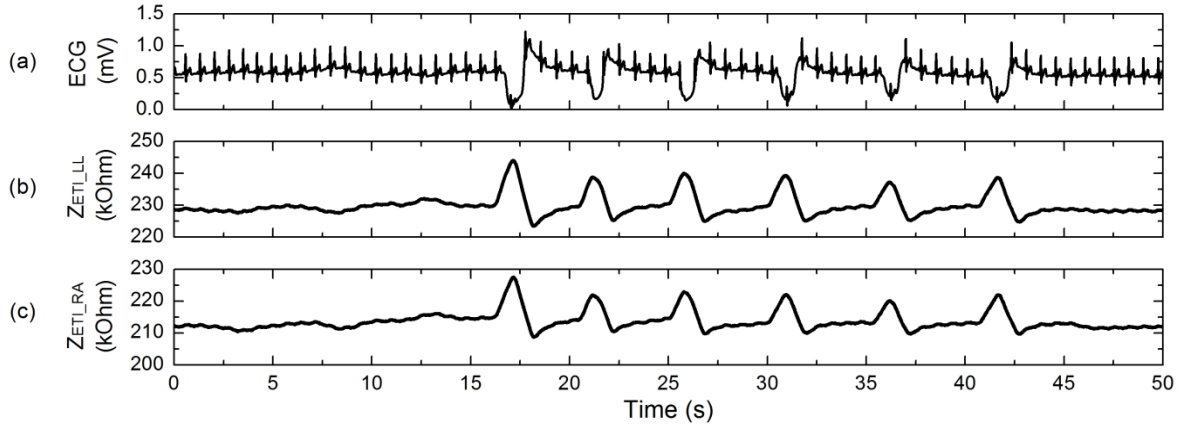

Figure 3. AECG (a), and impedance modulus |Z| of Z_{ETI_LL}, Z_{ETI_RA} (b,c)

Fig. 3 shows a section of the AECG and reference signals generated by MC-ETI over a period of 50 seconds with signals in the motionless and motion state. In the motionless state (0-15s and 45-50s), the AECG and MC-ETI signals are stable, but have no correlation. In the motion state (15-45s), these signals are strongly correlated.

Fig. 4 shows the correlation coefficient between MC-ETI and the AECG signal over time offset. In motion state, the peak of red curve at zero time offset shows the good correlation between these two signals. However, there is no obvious peak of black curve at zero time offset in the motionless state.

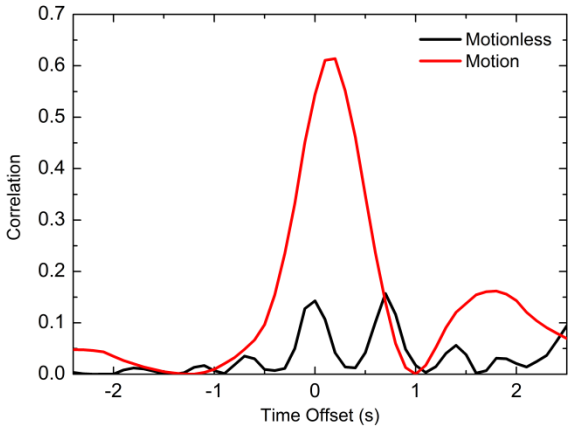

Figure 4. Correlation over time offset

Table 1 shows the correlation coefficient at zero time offset for MC-ETI of the overall ten tests. The correlation in motion state is clearly much higher than motionless state. This result means MC-ETI can reflect the MA in AECG and it is uncorrelated with the AECG signal. Thus we can use it as the reference signal of AF to suppress the MA in AECG signal.

Table 1. Correlation of MC-ETI and AECG at zero time offset

	Motion	Motionless
Data1	0.479	0.110
Data2	0.679	0.074
Data3	0.672	0.149
Data4	0.653	0.129
Data5	0.662	0.369
Data6	0.479	0.382
Data7	0.679	0.424
Data8	0.620	0.399
Data9	0.692	0.224
Data10	0.616	0.276
Mean	0.598	0.247
Standard Deviation	0.079	0.112

3.2. Motion artifact suppression

We used a fixed step size LMS AF with 100 coefficients to filter MA signal from AECG. Fig. 5 shows a segment of signal with ten seconds MA contaminated AECG and the MA filtered AECG.

The black curve shows noticeable baseline fluctuation resulted from MA. The red curve shows less fluctuation, as AF removed most of MA.

We used signal to artifact ratio (SAR) of the ten tests to evaluate the performance of AF:

$$\mathrm{SAR} = \delta^2_{\mathrm{ecg}} / \left(\delta^2_{\mathrm{ecg\_MA}} - \delta^2_{\mathrm{ecg}}\right) = \delta^2_{\mathrm{ecg}} / \delta^2_{\mathrm{MA}} \qquad (2)$$

where δ^2_{ecg} is the variance of the MA free AECG signal and δ^2_{MA} is the variance of the MA. The former is estimated from the first three seconds in MA free segment and the latter is estimated by subtracting δ^2_{ecg} from the variance $\delta^2_{\mathrm{ecg\_MA}}$ of the MA contaminated segment of the same test.

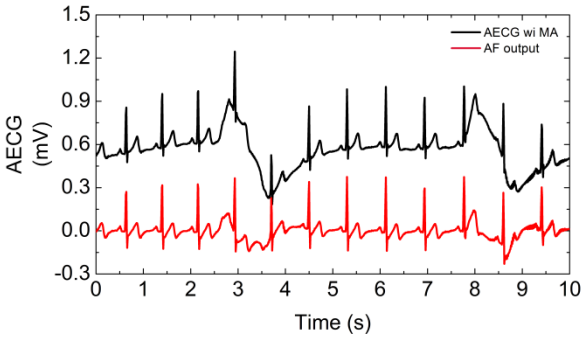

Figure 5. MA contaminated AECG (top), MA filtered AECG (bottom)

In Fig. 6, AF increases the SAR from MA contaminated AECG (-15.81 dB) to AF output (19.22 dB), with almost 35 dB improvement.

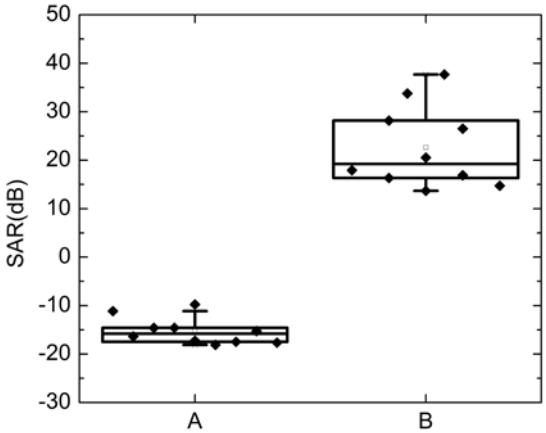

Figure 6. SAR of MA contaminated AECG (A), SAR of AF output (B)

4. Conclusion

This paper investigated the performance of MC-ETI detection approach and its MA suppression performance. Results showed that MC-ETI was highly correlated with MA in AECG. With MC-ETI generated reference signal, the SAR was improved by 35 dB by adaptive filtering.

Preliminary experiment indicate MC-ETI can be used as the reference signal of AF and significantly suppress MA in AECG recording. The future work will be the performance comparison of SC-ETI and MC-ETI and the design of a portable MC-ETI detection system. Furthermore, we will evaluate the performance of using MC-ETI to detect multi-electrodes tissue impedance.

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