Adaptive motion artifacts reduction algorithm for ECG signal in textile wearable sensor

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Abstract: For ubiquitous healthcare system, it is very important to measure a bio-signal without any discomfort. The electro-conductive fabric can be a good application for biomedical sensor. However, it is difficult to measure the bio-signal because of its sensitivity variation caused by contact impedance change, especially by motion of the subject. In this paper, adaptive noise reduction algorithm on motion artifacts is described to measure electro-cardiogram using lead II configuration conducted with both Ag/AgCl electrode as a reference signal and electro-conductive fabric.

Keywords: adaptive filtering, motion artifacts, wearable sensor, ECG

Classification: Science and engineering for electronics

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1 Introduction

Nowadays, ubiquitous environment is a popular topic among researchers. Digital convergence enables people to connect to any device with ease, anywhere and anytime. Particularly, in bio-medical engineering, new trend using ‘e’ of electronic and ‘u’ of ubiquitous, called e-Health or u-Health is emerging. Novel systems and applications using information and communication technology (ICT) are required to measure bio-signals without any discomforts or time-space limitation.

Researchers are interested in wearable devices for ubiquitous healthcare environment on the ground of its portability, flexibility and connectivity [1]. This type of sensor has an advantage for the patient who is in rehabilitation therapy, or for a person who needs all-day nursing, to monitor one’s health status with relatively less cost and without any or little limitation in space and time [2].

In this point of approach, wearable sensor with electro-conductive fabric has comfortable texture and is easy to use because it is a wearing type rather than the existing bio-signal sensor of the adhesive type conventional ECG electrode [3]. However, the sensor also has some issues that it is weak to AC power line interference (e.g. 50/60 Hz), thermal noise and motion artifacts, because of very low impedance characteristic.

Among theses weaknesses, motion artifacts caused by the subject’s movement have such various frequency ranges that their reduction is harder than the others which have specific frequency ranges. In addition, its magnitude is relatively large that meaningful bio-signals can be buried in it. This can lead to a wrong diagnosis result and improper follow-up [4].

There are several researches on reducing motion artifacts by considering it as a simple sinusoidal noise in conventional ECG electrode. Gary M. Friesen, *et al.* [5] compared noise sensitivity in detecting QRS mentioning that motion of ECG electrode caused electrode-skin impedance changes inducing baseline changes with its duration of 100 ~ 500 ms. Antti Ruha, *et al.* [6] proposed real-time QRS detector system for measuring ambulatory HRV. The motion artifacts were considered to be lower than 5 Hz sinusoidal wave and filtered

using over-sampled (2 kHz) ECG signal for better timing-resolution.

Some researchers are interested in motion artifacts as a more complicated noise source. D. A. Tong, *et al.* [4] proposed adaptive filter for electrode motion artifact caused by relation between the subject's skin and electrode. Yan Liu and Michael G. Pecht [7] also proposed adaptive filtering for motion artifacts considered as a skin stretch using LED and optical sensor.

In spite of more complex situation than the conventional electrode mentioned above, there are few considerations on motion artifacts, so far, in ECG signal acquired by means of electro-conductive fabrics. To reduce the motion artifacts for ECG measured by electro-conductive textile wearable sensor, we suggest adaptive filter method using motion artifacts model in 2 motion types and its quantitative evaluation using statistical analysis.

2 Mathematical background

2.1 Adaptive filter system

Fig. 1 (a) shows the system block diagram of adaptive filter. Let $\mathbf{x}(n)$ be the signal input consisting of the original ECG signal source $\mathbf{v}(n)$ and the unknown motion artifacts noise source $\mathbf{m}(n)$ added by a subject. Let the desired input $\mathbf{r}(n)$ be correlated with $\mathbf{m}(n)$ but not correlated with $\mathbf{v}(n)$. The $\mathbf{y}(n)$ is the adaptive filter output. Suppose that $\mathbf{v}$, $\mathbf{r}$ and $\mathbf{m}$ have zero mean in stationary random properties.

The system output $\mathbf{e}(n)$ can be formulated as follows:

$$\begin{aligned}\mathbf{e}(n) &= \mathbf{x}(n) - \mathbf{y}(n) \\ &= \mathbf{v}(n) + \mathbf{m}(n) - \mathbf{y}(n)\end{aligned}\quad (1)$$

Squaring followed by mean of Eq. (1) is

$$E\{\mathbf{e}(n)^2\} = E\{\mathbf{v}(n)^2\} + E\{(\mathbf{m}(n) - \mathbf{y}(n))^2\} \quad (2)$$

The right-hand side term of Eq. (2) must be minimized for minimizing $E\{\mathbf{e}(n)^2\}$, so optimal solution is

$$\mathbf{y}(n) = \mathbf{m}(n) \quad (3)$$

That is, when the desired motion input $\mathbf{r}(n)$ is chosen to high correlation with $\mathbf{m}(n)$, if we find $\mathbf{y}(n)$ by $\mathbf{r}(n)$ then the system output $\mathbf{e}(n)$ will be close to the original ECG signal source $\mathbf{v}(n)$ with its motion artifacts reduced.

2.2 LMS algorithm

Fig. 1 (b) represents the multi-input linear combiner. Least mean square (LMS) algorithm is based on the steepest descent approach [8]. Let filter weight $\mathbf{w}$ have the relation at time $(k + 1)$ as follows:

$$\mathbf{w}_{k+1} = \mathbf{w}_k + \mu(-\nabla) \quad (4)$$

Approximation of ∇ can be expressed as

$$\begin{aligned}-\nabla &= 2\mathbf{r}_k \mathbf{r}_k^T \mathbf{w}_k - 2\mathbf{r}_k \mathbf{x}_k \\ &= 2\mathbf{r}_k (\mathbf{y}_k - \mathbf{x}_k) = 2\mathbf{r}_k \mathbf{e}_k\end{aligned}\quad (5)$$

Therefore,

$$\mathbf{w}_{k+1} = \mathbf{w}_k + 2\mu \mathbf{r}_k \mathbf{e}_k \quad (6)$$

Generally, μ or 2μ is called as *step size*. In this paper, 2μ is chosen as it.

Fig. 1. (a) System diagram of adaptive noise filter, (b) Linear combiner representing adaptive filter in (a)

3 Methods

3.1 Specification of sensors

A round-type conventional Ag/AgCl electrode (generally, $2\text{ k}\Omega @ 10\text{ Hz}$) and the electro-conductive fabric (conductive coated on polyester, $3\text{ cm} \times 3\text{ cm}$, $0.15 \sim 0.20\ \Omega/\text{sq.inch}$) are used for the experiment. Its appearance and microscopic image are in Fig. 2 (a)–(b).

3.2 System configuration

Lead II configuration is conducted with both sensors, and ECGs are acquired by BIOPAC® MP 150 with ECG amplifier module (ECG100C, set its gain to 1,000 times) simultaneously. This configuration is illustrated in Fig. 2 (c). The sampling frequency is 1,000 Hz, higher than general cases ($250 \sim 500\text{ Hz}$) in ECG acquisition. This is for other feature extraction and future study like [6], such as QRS detection or HRV calculation in better time-resolution condition.

3.3 Activity control

In the experiment, subject movement is restricted to 2 types:

1. Sitting down a chair and standing (small z-axis movement, every 10 seconds)
2. Squatting and standing (big z-axis movement, every 4 seconds)

Fig. 2. (a) Electro-conductive fabric surface, (b) Its microscopic sectional view by scanning electron microscope (SEM, x100), (c) Main experimental configuration illustration

3.4 Signal manipulation

Input ECG signals are normalized by z-score normalization to make its mean value zero, as shown bellow:

$$\text{Normalized signal} = \frac{(\text{signal} - E\{\text{signal}\})}{\sigma_{\text{signal}}} \quad (7)$$

Where, $E\{\mathbf{x}\}$ is the mean value of signal $\mathbf{x}$ and σ_x is the standard deviation of signal $\mathbf{x}$, which is assumed to have a Gaussian distribution.

In order to estimate motion artifacts $\mathbf{m}(n)$, desired motion input $\mathbf{r}(n)$ is set to the difference between motion-added signal $\mathbf{x}(n)$ and motion-free signal $\mathbf{v}(n)$. The $\mathbf{v}(n)$ is considered as the original ECG signal source from Ag/AgCl electrodes and it is supposed to have little or no correlation with $\mathbf{r}(n)$. System output $\mathbf{e}(n)$ is the refined signal from the electro-conductive fabric with its motion artifacts term reduced. Finally, in this experiment, the motion-added $\mathbf{x}(n)$ from the electro-conductive fabric and motion-reduced system output $\mathbf{e}(n)$ are compared to the motion-free signal source $\mathbf{v}(n)$ from the Ag/AgCl electrode.

LMS algorithm is used for reducing motion artifacts with 128 coefficients and 0.001 step size, coded with MATLAB® R14.

3.5 Motion artifacts model

The motion artifacts to be reduced are restricted only to a variation of contact impedance caused by a subject's movement in electro-conductive fabric. Therefore, in this experiment, the ECG signal from Ag/AgCl electrode is used as the reference signal compared with the system output $\mathbf{e}(n)$ and is assumed to be un-related or less-related with the variability of contact impedance focused on subject's motion.

In this paper, desired motion artifacts signal $\mathbf{r}(n)$ is modeled as:

- Motion artifacts are the difference between motion-free signal and motion-added signal.

- Maximum frequency of motion artifacts is smaller than 5 Hz.

4 Results and discussion

The motion-free ECG source signal $v(n)$, motion-added ECG signal $x(n)$, filter output $y(n)$ as the estimated motion-artifacts signal and the system output $e(n)$ as the motion-reduced ECG signal, are recorded and analyzed in this experiment.

The experiment results are presented in Table I. It shows the relations on each signal using the correlation value (r) in 95% confidence level p-test.

Table I. Correlation with each signal

	Relation between	Subject movement type	
		Type 1	Type 2
Correlation (r) with p-value < 0.05	$r(n)$ and $v(n)$	−0.217	−0.172
	$r(n)$ and $x(n)$	0.283	0.215
	$r(n)$ and $y(n)$	0.832	0.834
	$v(n)$ and $x(n)$	0.854	0.871
	$v(n)$ and $e(n)$	0.941	0.916

The motion artifacts reduction algorithm proposed in this paper increases the correlation value between reference ECG source $v(n)$ and system output $e(n)$. The correlation between modeled motion $r(n)$ and adaptive filter out $y(n)$ shows that adaptive filter using LMS follows the motion trend ($r = 0.832$ in type 1, $r = 0.834$ in type 2). These explain that motion from textile wearable sensor can be reduced by the proposed algorithm indirectly.

The motion model $r(n)$ has little correlation with ECG signal ($v(n)$ or $x(n)$) because the $r(n)$ comes from the difference between motion-free and motion added ECG signal, and motion-free ECG source $v(n)$ has little correlation with subject motion in the experiment, even though Ag/AgCl electrode has been attached firmly to the subject body.

From this result, it is thought that better choice and modeling of motion input is needed without any correlation with ECG signal source for system improvement in the future. In this paper, we choose relatively high sampling frequency in ECG acquisition for future uses, and minimal low frequency range in modeling of motion artifacts from the previous researches ([5, 6]). In this point of view, frequency band of proposed motion artifacts occupies such a small portion of total frequency range that this may not be an efficient analysis in energy compactness manner. The frequency in both data acquisition and motion artifact model will be optimized and the system will be enhanced based on this study.

Also, the variation of contact impedance, not by the motion artifacts, will have to be considered and analyzed, which is possibly caused by various factors, such as variability of body temperature in the contact area, fabric condition (dry or wet and fabric size), in-between contact condition (skin

status, sweat), *etc.*

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