Motion artefact removals for wearable ECG using stationary wavelet transform

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Wearable Electrocardiogram (ECG) is attracting much attention in daily healthcare applications. From the viewpoint of long-term use, it is desired that the electrodes are non-contact with the human body. In this study, the authors propose an algorithm using the stationary wavelet transform (SWT) to remove motion artefact superimposed on ECG signal when using non-contact capacitively coupling electrodes. The authors evaluate the effect on motion artefact removal of this algorithm by applying it to various ECG signals with motion artefacts superimposed. As a result, the correlation coefficients of ECG signals with respect to the clean ones have been improved from 0.71 to 0.88 on median before and after motion artefact removal, which demonstrates the validity of the proposed SWT-based algorithm.

1. Introduction: In recent years, the demand on information and communication technology is increasing in healthcare and medical applications. Body area network (BAN) has been proposed for this purpose. BAN is a wireless network constructed by connecting various vital sensors on human body to collect and monitor health states in daily life [1, 2]. Wearable electrocardiogram (ECG) is one of typical vital sensors. By adding a wireless communication function in the wearable ECG, the ECG signal can be detected and sent to a coordinator of BAN in real time. Such a wearable ECG can be used to grasp the health state and to trigger an alarm at impending state of life. As an example, it may be used to monitor driver’s ECG in an automobile.

Current ECG sensors usually employ gel electrodes that contact the skin directly. Although the gel electrodes are strong to noise, they are not suitable to long term use because of the deterioration of detection sensitivity with the drying of gel, allergic reaction to the person who has weak skin, and discomfort of contact. It is obvious that non-contact capacitively coupling electrodes are more promising for long term daily use. However, the body’s movement may be easily superimposed on the detected ECG signal.

Fig. 1 shows an example of ECG signal with movement of upper body for a sitting person, measured by our developed upper body for a sitting person, measured by our developed

2. Algorithm: The wavelet transform of a signal \( x(t) \) is defined by

\[
W(b, a) = \int_{-\infty}^{\infty} x(t) \frac{1}{\sqrt{a}} \psi\left(\frac{t-b}{a}\right) dt
\]

Here, \( a \) is the scale parameter, \( b \) is the shift parameter, \( \psi^\prime(t) \) is the complex conjugate of mother wavelet \( \psi(t) \) which satisfies the admissibility condition,

\[
C_0 = 2\pi \int_{-\infty}^{\infty} |\hat{\psi}(\omega)|^2 \frac{1}{\omega} d\omega
\]

where \( \hat{\psi}(\omega) \) is Fourier transform of \( \psi(t) \).

In the case of discrete wavelet transform, the scale parameter and the shift parameter take discrete value, \( a = 2^j \), and \( b = 2^k \). The discrete wavelet transform of \( x(t) \) is defined by:

\[
W(k, j) = \int_{-\infty}^{\infty} x(t) \frac{1}{\sqrt{2}} \psi^\prime(2^{-j}t-k) dt
\]

The discrete wavelet transform with Mallat devised algorithm can be obtained by combining high-pass filters \( H_0 \) and low-pass filters \( L_0 \) [7]. However, Mallat’s algorithm carries out down-sampling. In the SWT [8], as shown in Fig. 2, by up-sampling the filter coefficients of the high-pass filters and the low-pass filters, it is possible to perform time-invariant wavelet transform. This is important in order to find outliers such as the artefact due to body movement and the specified signal components such as the QRS complex. The wavelet coefficients are given by the sequences \( \{d_{1j}, d_{2j}, ..., d_{nj}\} \) and the scaling coefficient is given by the sequence \( a_j \). Where \( J \) represents the order of SWT. Since the ECG signal has a frequency component of 0–100 Hz, we set \( J = 9 \). Fig. 3 shows the SWT result of the ECG signal in Fig. 1.

The main features of QRS complex are observed in the wavelet coefficients from \( d_{1j} \) to \( d_{7j} \). Compared with the existing SWT-based algorithm only using the energy of ECG signal, we also consider the time periodicity of ECG signal and introduce it to the QRS complex detection part of the existing algorithm. The flowchart of the proposed algorithm for motion artefact removal is shown in Fig. 4. First of all, to detect the QRS complex from the energy of ECG signal, we calculate the energy \( e(n) \) of the ECG signal within a time period (0.1 s) and detect the local maximum value \( e(N) \) of the energy.
Fig. 5 shows the calculated result of energy for the ECG signal in Fig. 1. The threshold $e_{th}$ is determined from the value obtained by multiplying the median value of all $e(N)$ by $\alpha$ to avoid overlooking the QRS complex. If $e(N)\cdot e_{th}$, we define $k = N$, and calculate the time interval $T(k)$ between $e(k)$ and $e(k - 1)$. The threshold $T_{th}$ is defined from the median value of $T(k)$. Since the QRS complex should periodically appear in the ECG signal normally, if $T(k)$ and $T(k+1)$ are both larger than $T_{th}$, $e(k)$ is determined as the energy of the QRS complex. On the other hand, the SWT is performed for the ECG signal. The Haar wavelet is used as the mother wavelet. Since the time width of the QRS complex is about 0.1 s, the wavelet coefficients $\{d_1, d_2, ..., d_6\}$ during the determined QRS complex period are replaced with 0. Next, P wave and T wave rise more slowly compared with the QRS complex. Hence, we focus on the wavelet coefficients $\{d_6, d_7, d_8, d_9\}$ that correspond to low-frequency component. Since the heart rate of an adult is 60–90 times within one minute usually, we detect the local maximum values and minimum values of wavelet coefficients $\{d_6, d_7, d_8, d_9\}$ every one second. The thresholds $D_{min}$ and $D_{max}$ are defined by the medians of the local maximum values and the local minimum values, respectively. Then, if $D_{min} < d_j(n) < D_{max}$, the wavelet coefficients $\{d_6, d_7, d_8, d_9\}$ during this time period are replaced with 0. Thereafter, by the inverse SWT, the motion artefact can be extracted, and then we can remove the motion artefact from the ECG signal by subtracting the extracted one.

### 3. Results

To verify the validity of the proposed algorithm, we produced an artificial ECG signal by superimposing a motion artefact as shown in Fig. 6b to a measured clean ECG signal in Fig. 6a. We assumed that the motion artefact was caused by electrode slippage and obtained the motion artefact by attaching the electrode on the arm and moving it up and down. Fig. 6c shows the artificial ECG signal with superimposed motion artefact. Comparing the two waveforms in Figs. 6c and 1, it can be said that the artificial ECG waveform with superimposed motion artefact is similar to the actual one. Fig. 6d shows the

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**Fig. 1** Measured ECG signal with motion artefact

**Fig. 2** Stationary wavelet transform

**Fig. 3** SWT of the ECG signal in Fig. 1

**Fig. 4** Flowchart of motion artefact extraction
A quantitative evaluation was conducted by calculating the correlation coefficients between the ECG signal after motion artefact removal and the clean ECG signal. Compared with the correlation coefficient of 0.76 between Figs. 6a and c, the correlation coefficient has been improved to 0.93 between Figs. 6a and d. In addition, we produced 16 artificial ECG signals by superimposing four measured motion artefact as shown in Fig. 8 on four clean ECG signals as shown in Fig. 7. The four clean ECG signals were selected from the ECG-ID database [9, 10] (Fig. 8). Our algorithm was quantitatively evaluated by the correlation coefficients between the ECG signals after motion artefact removal and the clean ECG signals. Fig. 9 shows the cumulative distribution of the correlation coefficients before and after applying the algorithm for the 16 ECG signals with motion artefacts. In all of the cases, the motion artefacts have been significantly removed so that the correlation coefficient has been improved from 0.71 to 0.88 on median.

Next, we investigated the optimal value of the factor α for the threshold e\(_{th}\) which detects the QRS complex. We applied our algorithm to 20 different ECG signals selected from the ECG-ID database. By comparing the number of R waves, we determined the appropriate α for each ECG signal and made their average as the optimal value of α. As a result, α = 0.6 is likely most suitable as the optimal value.

To illustrate the performance of our algorithm, we also compared the motion artefact removal effect by applying our algorithm and Strasser et al.'s algorithm [6] to the ECG signal in Fig. 1.
Several ECG signals with the PVC, selected from the MIT-BIH Arrhythmia Database [10, 11]. We attempted to apply our algorithm to these ECG signals, but it did not work well in removing the motion artefacts. This may be due to that our algorithm requires the time interval of QRS complex.

4. Conclusion: Wearable ECG integrated with non-contact ECG detection and human body communication can provide a lot of convenience in daily monitoring of ECG signal. In this study, we paid attention to the motion artefact in the ECG signal measured by our wearable ECG, and proposed a SWT-based algorithm for motion artefact removal. To evaluate the validity of the motion artefact removal algorithm, we applied it to various ECG signals with motion artefact superimposed artificially. Then we calculated the correlation coefficients between the ECG signals before and after the motion artefact removal and the clean ECG signals, respectively. It is found that the correlation coefficients have been improved from 0.71 to 0.88 on median before and after the motion artefact removal, which demonstrates the validity of the proposed SWT-based algorithm.

The future work is to investigate the influence of other mother wavelet on motion artefact removal and to devise an algorithm which is valid even in the existence of a PVC beat.

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