A NOVEL QRS COMPLEX DETECTION ON ECG WITH MOTION ARTIFACT DURING EXERCISE

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ABSTRACT

We present a novel QRS complex detection scheme from ECG with motion artifact. The algorithm relies on subspace learning and template matching. QRS complex detection during exercise is a challenging problem because multiple artifacts affect the ECG measurement. Motion artifact is considered to be the main disturbance added to the measurement during exercise. To deal with the problem, we train a dictionary to represent motion artifact using information from a tri-axis accelerometer, and then remove the artifact contribution from noisy ECG measurements. We select the GCC-PHAT filter for efficient QRS detection on the denoised ECG measurements. We show that the proposed algorithm has appreciably higher motion artifact reduction capability and lower computational complexity than competing algorithms. It is therefore a preferred alternative for implementation in mobile health monitoring systems.

Index Terms— ECG, QRS complex, motion artifact, dictionary learning, GCC-PHAT

1. INTRODUCTION

Wearable bio-sensing is gaining importance in daily life due to the increased interest in personal health care and the wide spread of smart mobile devices. The application of such devices is broad ranging from drug delivery to setting up a fitness plan. Amongst many of bio-signals, electrocardiogram (ECG) delivers vital information because of its direct connection to cardiac activities. ECG signal is represented by five distinct (P-Q-R-S-T) complexes, and each individual complex provides information on part of the heart activity. The QRS complex has the most distinct shape of the whole interval of ECG, and the waveform makes ECG monitoring convenient and accurate. Successful detection of QRS complexes enables accurate bio-identification [1], heart rate (HR) computation [2], and arrhythmia detection [3]. However, during exercise, multiple sources of additive artifacts affect the ECG measurement and they make the cardiac monitoring difficult in practice. Motion artifacts are considered to be the main obstruction, and they are generated by skin deformation which changes the electrical property of interface between skin and electrodes [4, 5]. Because of that, accurate recording of ECG during exercise is difficult since motion causes severe baseline wander. To avoid such artifacts, mechanically and electrically stable measurement is necessary, but it limits the subject's mobility.

The previous study shows that motion artifacts can possibly be removed by use of accelerometry. The accelerometer based artifact reduction is extensively studied in EEG and other bio-signal measurements. The method estimates motion artifact indirectly using the information from accelerometer, and removes the estimated artifact using adaptive filters, such as LMS and RLS filters [6]. However, this approach requires a measurement system with strict synchronization between ECG and accelerometer measurements to obtain proper cancellation results. In addition, the method uses adaptive filtering with no access to the true ECG signal, and leads to filtering out ECG information as well. Wavelet and dictionary learning techniques are studied to reconstruct clean ECGs using prior information [7]. Yet, these approaches can not produce proper denoising performance if the measurements are highly contaminated by motion artifacts that are correlated with the trained data. Recently, a direct cancellation method by monitoring the impedance change between skin and electrode is reported [8]. However, the method requires a specially designed circuit [9] for injection of known high frequency signal, to avoid interference with ECG signals, and results in high sampling rate which is not desirable in wearable devices.

We propose, in this paper, a novel QRS detection scheme for wearable bio-sensing devices during exercise. The proposed approach consists of dictionary learning based artifact reduction and template based QRS detection methods. The proposed approach can be configured by combining off-the-shelf electronics; dry electrodes, amplifier, and an accelerometer. The low hardware cost for implementation is an advantage of the proposed system.

This paper is organized as follows: Section 2 introduces our motivation, the proposed artifact reduction, and QRS detection methods. In Section 3 we present the experiment results of the proposed scheme. We suggest expected applications of the proposed approach in Section 4.

2. PROPOSED METHOD

2.1. Motivation

Detecting ECG signal using portable dry-electrode is a challenging problem because the measurement is highly subject to motion artifact. Despite the variability of ECG appearance, the QRS complex is less vulnerable to the change in heart rates and motion artifact due to its high peak-to-peak waveform in the appearance.

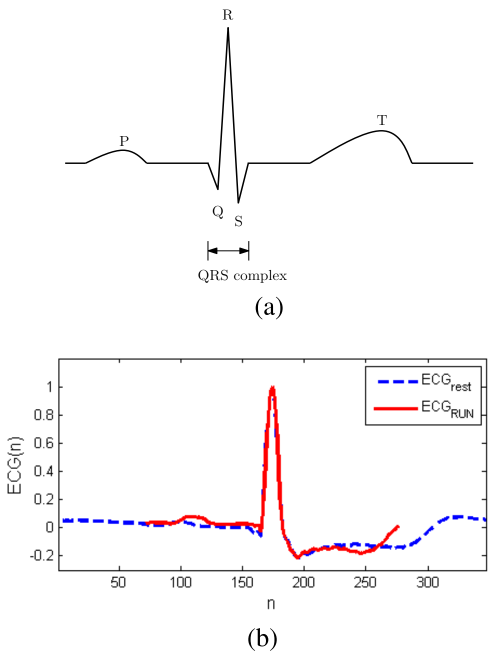

Fig. 1. ECG waveform and QRS complex (a), and ECG waveforms before (dashed line) and after exercise (solid line) (b).

Fig.1 (a) illustrates the portion of QRS complex from one cycle of ECG, and Fig.1 (b) shows the persistent shape of QRS complex at both low (88 bpm) and high (155 bpm) heart rates, dashed and solid lines respectively. Leveraging the fact, a QRS template can provide a robust signature to heart rate changes and additive artifacts.

2.2. Problem formulation

Taking ECG measurements during time T, which is enough to include at least one QRS complex, then we can express the measurement signal $x(t)$ during $t \in (0, T)$ as

$$x(t) = \gamma s(t - \tau) + m(t) + v(t), \tag{1}$$

where $s(t-\tau)$ is a QRS complex centered at time τ with gain γ, motion artifact $m(t)$, and $v(t)$ is the measurement noise. In this model, we are given $x(t)$, and extract $s(t)$ before exercise; but $m(t)$, τ, and γ are unknown information to be estimated for accurate QRS detection. We will explain our approach about how to find these unknown information through the rest of this paper.

2.3. Motion artifact cancellation

We highlight the dictionary training scheme which learns subspaces to represent motion artifacts rather than ECG waveforms different from the conventional approaches. After subspace leaning, the artifact contribution is removed from the corrupted ECG measurements by sparse coding. Clearly, this is the opposite approach to the previous studies, but more efficient in cleaning motion artifacts. The acceleration signals during exercise are much sparser than ECG signals because they are highly localized in the frequency domain (below 10Hz in general). In contrast, ECG signals are widely spread (below 120Hz) regardless of the heart rate. Via the proposed dictionary learning scheme, the propagation delay between ECG and motion artifact will be compensated due to translation and modulation duality between the time and frequency domain.

Assuming the motion artifact on the ECG measurements are spanned by the same subspaces of the acceleration signals, the artifact signals can be removed by subtracting the artifact contribution from the corrupted ECG measurements using the learned subspaces. Stationary or quasi-stationary signal can be effectively reconstructed using subspace learning method such as K-SVD [10] and its variants. Because the K-SVD performs singular value decomposition (SVD), it requires $\mathcal{O}(N^3)$ complexity for each computation, and thus it is expensive to apply for wearable devices. As an alternative, iterative subspace identification (ISI) provides comparative performance as that of K-SVD but requires one eighth of computation time [11]. The ISI harvests the union of subspaces which is expressed by linear combination of observations, and the subspaces of input signals are learned recursively from the training set until the set is empty. Readers may refer [11] for more details about the ISI algorithm.

We choose the acceleration signal of gravitational direction $g \in \{x, y, z\}$ which shows the biggest cross-correlation with the measured ECG signals [6]. A sampled N acceleration signal vector $\vec{a}_g$ can be expressed with a matrix-vector product as

$$\vec{a}_g = \Phi\vec{\alpha} + \epsilon \tag{2}$$

where Φ is an $N \times K$ overcomplete matrix with $K \gg N$, $\vec{\alpha}$ is an $K \times 1$ vector, and ϵ is the approximation error. The sparse representation problem can be expressed as

$$\text{minimize } ||\vec{\alpha}||_0, \quad \text{s.t } ||\vec{a}_g - \Phi\vec{\alpha}||_2 \leq \epsilon \tag{3}$$

where $||\cdot||_0$ denotes the number of nonzero entries in α. The coefficient vector $\vec{\alpha}$ is sparse since the acceleration signals are quasi-periodic and thus highly localized in the frequency domain during exercise. The ISI process provides the minimum subsets of subspaces to represent the signal vector of $\vec{a}_g$:

$$\vec{a}_g = \Phi_s\vec{\alpha}_s + \epsilon. \tag{4}$$

Now, with the trained dictionary Φ_s, one can find the coefficient $\vec{\beta}_s$ to represent the artifact contribution to the measured

ECGs by solving a least square problem:

$$\underset{\vec{\beta}_s}{\text{minimize}} \quad ||\vec{a}_g - \Phi_s \vec{\beta}_s||_2. \tag{5}$$

Thus, the motion artifact can be estimated as $\hat{m} = \Phi_s \vec{\beta}_s$, and we obtain denoised ECGs by computing the residual: $\hat{x} = \vec{x} - \hat{m} = \vec{x} - \Phi_s \vec{\beta}_s$. In Fig.2, the first slot illustrates

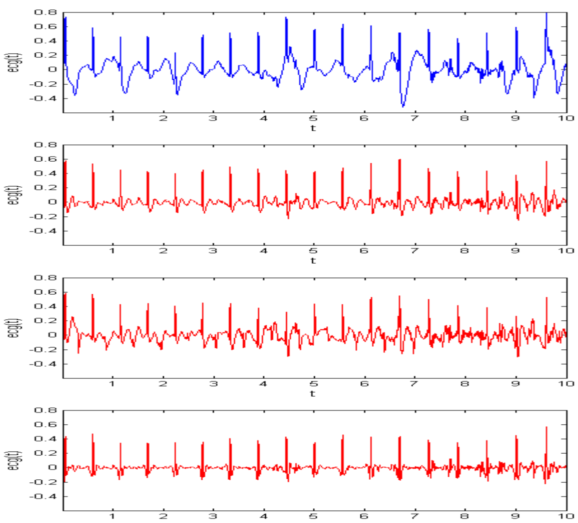

Fig. 2. Denosing results of corrupted ECG signal (1st slot) using adaptive filters (LMS: 2nd and RLS: 3rd slots), and subspace based method (4th slot).

ECG signal corrupted by motion artifact. The second and third slots are the artifact cancellation results using LMS and RLS filters respectively. The fourth slot represents denoising results by the proposed subspace based method. We compare the artifact reduction capability of the ISI based method with adaptive filtering methods. For comparison, we compute the artifact power reduction using the adaptive filtering and the proposed methods in dB scale as $10\log_{10}(||\hat{x}||^2/||\vec{x}||^2)$ after artifact cancellation, and the results are presented in Table1. In the table, the numbers inside parentheses indicates heart rate in bit-per-minute (bpm). Clearly, the ISI based approach

Table 1. Power reduction after removing motion artifacts

Methods	Walk (94-120)	Jog (102-139)	Run (121-163)
LMS	-4.7	-0.9	-0.5
RLS	-3.6	2.3	-0.3
ISI	-6.6	-6.1	-6.8

shows the highest reduction of motion artifact. However, dictionary learning is costly in computation. Thus, as compensation of the rigorous processing, we design a fast running algorithm to detect QRS complexes which is introduced in following subsections.

2.4. QRS complex detection

The QRS template can be computed from ECG measurements with minimum or without motion artifacts by averaging a few cycles of ECGs. The presence of motion artifacts can be checked by investigating signal power of the accelerometer: $P_{acc} = \frac{1}{N}\sum_{n=1}^{N}\sqrt{a_x(n)^2 + a_y(n)^2 + a_z(n)^2}$. If $P_{acc} < \eta_{motion}$, then the N ECG measurements are regarded as artifact free, where the threshold value η_{motion} is to be determined in an empirical way. Now, the QRS template is generated by searching the peak(R) and minimum points (Q and S) nearby the the peak location. We illustrate an example in Fig.3. With the QRS template, we formulate the detection

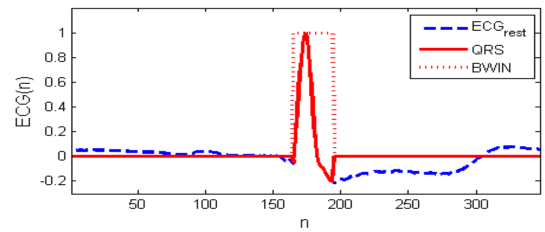

Fig. 3. The QRS complex template (solid line) and binary window (dotted line). The binary window (BWIN) will be used to extract QRS complex from ECGs

problem to the TDOA (time-difference of arrival) problem in speech signal processing. Amongst many TDOA algorithms using multiple channels, the cross-correlation methods is selected to find the time-difference because of its implementation simplicity and low complexity. The generalized cross-correlation with phase transform (GCC-PHAT) was introduced in [12], and widely used for robust detection of speech signals [13, 14]. Now, the detection problem in (1) can be expressed as

$$x_t(n) = s(n), \qquad x(n) = \gamma s(n-\tau) + v(n), \tag{6}$$

where $x_t(n)$ is the QRS template, and $x(n)$ is the denoised ECG measurements which are sampled during exercise. Computing the cross-correlation of these two vectors in the frequency domain requires $\mathcal{O}(N)$ multiplications comparing the time domain complexity $\mathcal{O}(N^2)$:

$$G_{x_t x}(\omega) = X_t(\omega) \cdot X^*(\omega) \tag{7}$$

where $X_t(\omega)$ and $X(\omega)$ are the Fourier transform of $\vec{x}_t$ and $\vec{x}$ respectively, and $X(\omega)^*$ denotes complex conjugate of $X(\omega)$. Using the inverse Fourier transform operator $\mathcal{F}^{-1}$ with weight-function $\psi(\omega)$,

$$\vec{r}_{x_t x} = \mathcal{F}^{-1}\left\{\psi(\omega)\hat{G}_{x_t x}(\omega)\right\}, \tag{8}$$

the time domain cross-correlation is obtained. Selecting the weight-function $\psi(\omega)$, we choose the phase transform (PHAT) which is defined as

$$\psi(\omega) = \frac{1}{|X_t(\omega) \cdot X^*(\omega)|}, \tag{9}$$

which normalizes each frequency bin of cross-correlation to generate a sharp peak in the time domain. Thus, the GCC-PHAT output can be $r_{x_t x}(n) = \delta(n - \tau)$. Investigating the maximum point over $\vec{r}_{x_t x}$ as $\hat{\tau} = \arg\max_\tau r_{x_t x}(n)$. The GCC-PHAT filtering can be summarized as below

$$\hat{\tau} = \arg \underset{\tau}{\text{maximize}}\ \mathcal{F}^{-1}\left\{\frac{X_t(\omega)\cdot X^*(\omega)}{|X_t(\omega)\cdot X^*(\omega)|}\right\}, \qquad (10)$$

where $\hat{\tau}$ indicates the location where the QRS template $s(n)$ is placed on the ECG measurement $x(n)$. With the location estimate, the delayed version of QRS template $\hat{x}$ is generated by shift operation to find the signal gain γ in (1) which can be found by solving minimization problem: $\text{minimize}_\gamma\ ||\vec{x} - \gamma\hat{x}||_2^2$. By defining expectation of the error function $\mathbb{E}[\vec{e}] = \mathbb{E}[||\vec{x} - \gamma\hat{x}||_2^2]$, we can solve the minimization problem by partial derivatives: $\frac{\partial}{\partial\gamma}\vec{e} = 0$ which is equivalent to $2\gamma\hat{x}^T\hat{x} - 2\vec{x}^T\hat{x} = 0$, and we compute $\hat{\gamma} = \frac{\vec{x}^T\hat{x}}{\hat{x}^T\hat{x}}$. Now, we find all the unknown parameter of (1), so that QRS detection is possible from the corrupted ECG measurement.

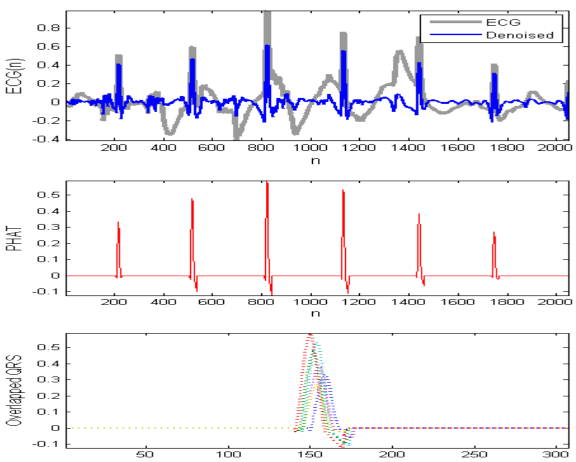

Fig. 4. Detection results during jogging (HR = 110 bpm).

3. EXPERIMENTS

For experiment, we select OP Innovations' TrueSense Exploration Kit [15] which includes all the required components for the proposed system. The sensor kit is equipped with dry-electrode pairs (512Hz sampling), a tri-axis accelerometer (8-32Hz sampling per channel), a memory module for storage, and ZigBee communication capability. We place the sensor assembly on the location between V1 and V2 of the subject's chest using a chest strap. For seamless detection, signal framing and windowing techniques are used with 50% overlap with the neighboring frames. ECG measurements are processed by N = 128 (250ms), and we first remove motion artifact using the methods in Subsection 2.3. Fig.4 and 5 illustrate the QRS detection snapshots. The first slots of the figures show ECGs with motion artifacts (bold-gray lines) and the result of artifact cancellation (thin-solid lines). The

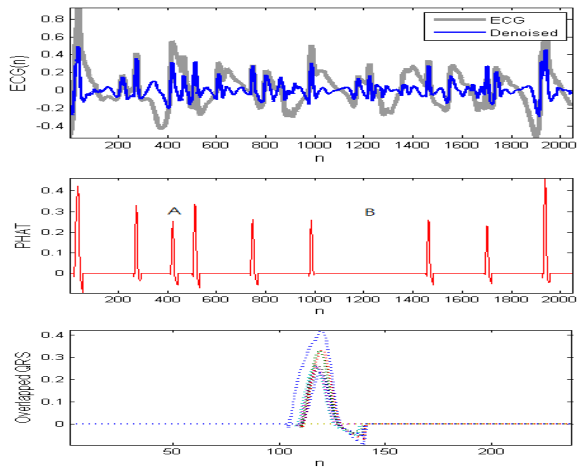

Fig. 5. Challenging case during running (HR = 129 bpm).

second slots present the QRS detection results after GCC-PHAT filtering and QRS complex thresholding. The thresholding is performed considered two factors: the QRS gain γ and distortion. We define the QRS distortion as $\zeta(\hat{s}, \gamma\vec{s}) = ||\hat{s} - \gamma\vec{s}||^2/||\gamma\vec{s}||^2$, where $\hat{s}$ is the detected QRS complex, and $\vec{s}$ is the QRS template. If $\gamma > 0.5$ and $\zeta(\hat{s}, \gamma\vec{s}) < 0.5$, then we take $\hat{s}$ and vice versa. The second slot of Fig.5 shows a false detection (A) and a miss (B). The correction of the false and miss detections is possible by tracking back the location on the ECGs using heart rate information. The third slots overlap the detected QRS complexes. We note here the number of dictionary clusters found by the ISI which are used to remove the motion artifacts: 26-28 for walking, 10-12 for jogging, and 8-9 clusters for running.

4. DISCUSSION AND CONCLUSION

The proposed QRS detection method consists of artifact reduction using dictionary learning and QRS complex detection using GCC-PHAT filtering. The dictionary based artifact cancellation shows high efficiency in which comes from the robust representation of the artifact influence on the ECG measurements. We propose the GCC-PHAT filter to detect QRS complexes by formulating a TDOA estimation problem as in source localization. Both the methods require low computational complexities comparing to similar family of algorithms which is suitable for portable systems. Motion and gait recognition can be realized using the trained acceleration dictionary with a clustering method. The dynamic effect of exercise to heart rate changes can investigated by adding the recognition. By augmenting arrhythmia case to the QRS templates, detection of normal and abnormal QRS complexes are possible using the same approaches presented in Section 2. Due to the limit of space, we focus on introducing the new approaches, and the result of quantitative research will appear on future publications.

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