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Original Research Article

An automated ECG signal quality assessment method for unsupervised diagnostic systems

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ARTICLE INFO

Article history:

Received 23 July 2017

Received in revised form

14 October 2017

Accepted 18 October 2017

Available online xxx

Index Terms:

Signal quality assessment

Electrocardiogram

Baseline wander

Muscle artifacts

ABSTRACT

In this paper, the authors present an automated method for quality assessment of electrocardiogram (ECG) signal. Our proposed method not only detects and classifies the ECG noises but also localizes the ECG noises which can play a crucial role in extracting reliable clinical features for ECG analysis systems. The proposed method is based on three stages: Wavelet decomposition of ECG signal into sub-bands; simultaneous ECG signal and noise reconstruction; extraction of temporal features such as maximum absolute amplitude, zerocrossings, kurtosis and autocorrelation function for detection, localization and classification of ECG noises including flat line (FL), time-varying noise or pause (TVN), baseline wander (BW), abrupt change (AB), power line interference (PLI), muscle artifacts (MA) and additive white Gaussian noise (AWGN). The proposed method is tested and validated against manually annotated ECG signals corrupted with aforementioned noises taken from MIT-BIH arrhythmia database, Physionet challenge database, and real-time recorded ECG signals. Comparative detection and classification results depict the superior performance of the proposed method over state of art methods. Detection results show that our method can achieve an average sensitivity (Se), average specificity (Sp) and accuracy (A) of 99.61%, 98.51%, 99.49% respectively. Also, the method achieves a Se of 98.18%, and Sp of 94.97% for real-time recorded ECG signals. The method has an average timing error of 0.14 s in localizing the noise segments. Further, classification results demonstrate that the proposed method achieves an average sensitivity (Se), average positive predictivity (PP) and classification accuracy (A_c) of 98.53%, 98.89%, 97.50% respectively.

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1. Introduction

Q2 Recent advances in wearable healthcare monitoring devices have enabled early identification and treatment of the cardiovascular diseases through long-term continuous

monitoring [1]. Different low-complex algorithms are developed for QRS and arrhythmia detection, and for ECG denoising specifically for long-term ECG recordings [2–5]. In long-term recordings, ECG signal is often corrupted with different noises which include flat line (FL), time-varying noise or pause (TVN), baseline wander (BW), abrupt change

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<https://doi.org/10.1016/j.bbe.2017.10.002>

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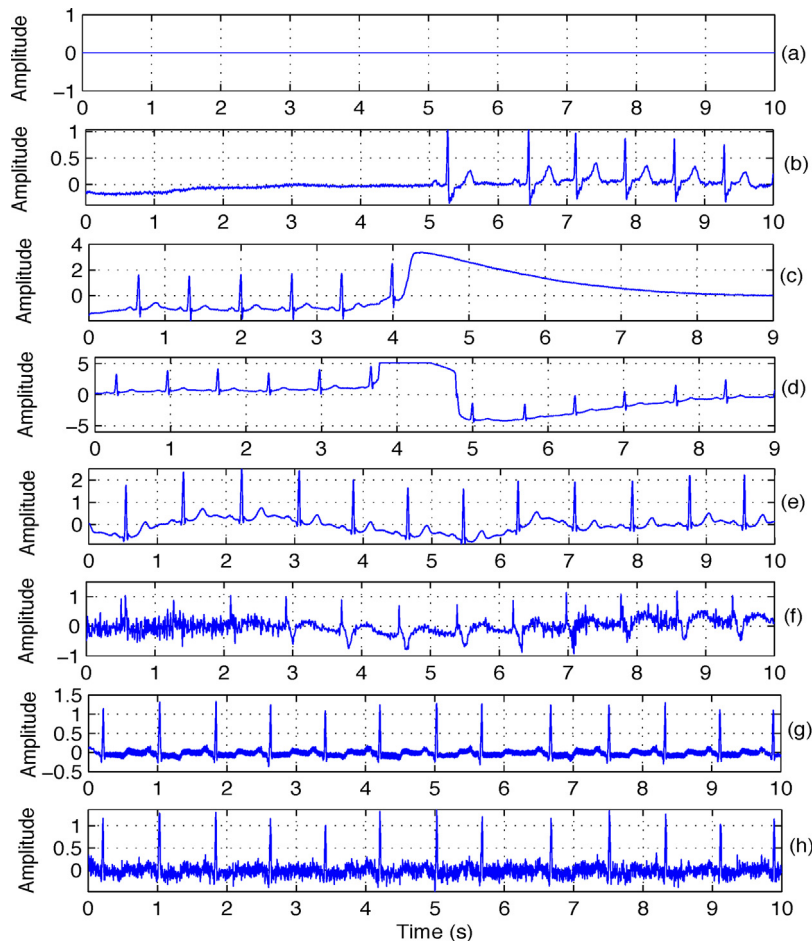


Fig. 1 – Illustrates various types of ECG noises: (a) Flat line taken from Physionet challenge database, (b) long pause in the ECG signal taken from MIT-BIH arrhythmia database (mitadb) record number 232, (c) ECG signal with device saturation (contains local FL) taken from mitadb record number 116, (d) ECG signal with abrupt change taken from mitadb record number 116, (e) ECG corrupted with baseline wanders taken from mitadb record number 111, (f) ECG corrupted with muscle artifacts taken from mitadb record number 104, and (g) ECG corrupted with synthetically generated PLI noise in mitadb record number 100 (h) ECG corrupted with synthetically added AWGN in mitadb record number 100.

(AB), power line interference (PLI), muscle artifacts (MA) and additive white Gaussian noise (AWGN) [6–12]. Snap shots of these ECG noises are shown in Fig. 1. It can be seen from Fig. 1 that local clinical features of the signal are completely masked by these noises. Therefore, assessment of clinical accessibility of ECG signals is a crucial step before accurate and precise data analysis, feature extraction, deterioration identification, alert generation and risk stratification [9]. Due to constrained computational resources and limited battery power, wearable devices demand less computationally complex automated method for detection, localization and classification of ECG noises.

1.1. Literature review of ECG signal quality assessment

Various signal quality assessment methods for ECG signal have been proposed in the literature. These quality assessment methods are broadly categorized into three groups: time and frequency domain feature-based methods, morphological event-based methods, signal decomposition-based methods.

In the morphological event-based quality assessment methods, QRS and fiducial point-based features such as RR interval [13–15], ratio of maximum to minimum RR interval [16], PQRST shape consistency [17,18], ratio of R-peak amplitude to noise-amplitude ratio [19,20], coherence of QRS complex [21] are extracted for assessing the quality of the ECG signals. However, detection of accurate R–R interval, QRS complex, fiducial points is quite challenging task due to time varying PQRST morphology in the ECG signal [22,23]. Hence, the performance of quality assessment methods based on these event detection deteriorates in the presence of irregular rhythms [23]. In time- and frequency-domain-based methods, various features such as energy-concavity index (ECI), correlation [24], higher-order moments and spectral energy [25], sub-bands power of distinct ECG components [25], correlation and diversity approach [26], modulation spectral signal representation [27], cross-covariance matrix of the ECG signals [28], linear prediction [29], correlation between original and reconstructed signal using kors matrix [30], maximum absolute amplitude [31], correlation-based regularity matrix [32],

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