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Robust heart rate estimation from multimodal physiological signals using beat signal quality index based majority voting fusion method

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A R T I C L E   I N F O

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A B S T R A C T

In this paper, we present a new beat signal quality index (SQI) based majority voting fusion algorithm for robust heart rate (HR) estimation from multimodal physiological signals, namely, cardiovascular and non-cardiovascular signals. A novel statistical and probabilistic based beat SQI assessment method has been developed for voting fusion. Modified slope sum function and Teager-Kaiser energy operator method has been used for beat detection in electrocardiogram (ECG) and non-cardiovascular signals. The performance of majority voting fusion method in beat detection has been evaluated on PhysioNet/CinC Challenge-2014 public training dataset and has achieved overall score of 94.93%. The performance of the algorithm has been tested on PhysioNet/CinC Challenge-2014 hidden test set and MIT-BIH Polysomnographic dataset and it has achieved scores of 90.89% and 99.77% respectively. The proposed method has improved average rMSE of HR estimate from 15.54 bpm to 0.24 bpm for noisy ECG signals and from 11.68 bpm to 0.84 bpm for noisy ECG and noisy ABP signals of PhysioNet/CinC Challenge-2014 public training database. The majority voting fusion method has yielded HR estimate with average rMSE of 1.80 bpm, when both ECG (avg. rMSE of 4.58 bpm) and ABP (avg. rMSE of 3.96 bpm) signals of MIT-BIH Polysomnographic dataset are noisy. The use of multimodal signals in fusion has increased the accuracy of HR estimates in noisy ECG and ABP signals. The majority voting fusion algorithm based on beat SQI has enabled effective and reliable use of non-cardiovascular signals in robust HR estimation from multimodal physiological signals, even when both ECG and ABP signals are noisy.

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1. Introduction

Multimodal physiological signals, namely, cardiovascular and non-cardiovascular (NC) signals are continuously recorded in intensive care unit (ICU) to monitor health parameters of patients. The accuracy of measurement of vital health parameters like heart rate, blood pressure, respiration rate etc. is important for proper treatment, medication and health care of critically ill ICU patients. HR can be directly estimated from cardiovascular signals that are related with functioning of heart such as ECG [1] and ABP. However, ECG and ABP are sometimes contaminated or may be missing due to measurement errors arising from sensor displacement, muscle movement, or electrical interference leading to inaccurate HR estimation and false alarms in ICU.

Activities of heart generate strong electrical field, which introduces ECG R-peak artifacts in NC signals namely, Electroencephalogram (EEG), Electro-oculogram (EOG) and Electromyogram (EMG) [2]. These physiological signals hence contain redundant information of heart rate. Noises created by various sources of measurement errors do not affect multimodal signals in the same way. So, these signals can be considered to be independent to a certain extent. Therefore, the R-peak artifacts present in NC signals can be used to increase the accuracy of estimation of heart rate by fusion of these NC signals with cardiovascular signals. Many studies have been carried out in the past on detection of ECG artifacts in EEG, EOG and EMG signals and their removal [3–5].

Though ECG artifacts often contaminate the NC signals, their presence is inconsistent [6]. Signal quality index, therefore, plays a vital role in fusion of NC signals with the cardiovascular signals. Several studies have been carried out on signal quality assessment. Ikaro Silva et al. proposed a SQI estimation method based on adaptive filtering of all available signal channels from multichannel waveform records [7]. Zong et al. have used fuzzy logic approach to assess ABP signal quality [8]. Q. Li. et al. used signal quality indices for robust HR estimation [9]. G. D. Clifford et al. used support vector machine (SVM) and multilayer perceptron artificial neural network classifiers to identify quality of ECG and evaluated their performance using seven SQIs individually and different com-

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binations of the SQIs on modified PhysioNet/CinC Challenge-2011 challenge dataset [10]. Joachim Behar et al. used SVM classifier to evaluate performance of seven SQIs individually and their different combinations on a variety of arrhythmias [11]. We have developed a novel SQI assessment method that is based on combination of statistical measure and rhythm of heart beats.

Data fusion plays very important role in robust parameters extraction for supporting clinical decisions of ICU patients [12]. Robust heart beat detection from multimodal physiological signals, is a recently explored area of research. Lars Johannesen et al. proposed a robust heart beat detection method by fusing multimodal signals using voting technique [13]. They have used modified versions of U3 detector for beat detections in ECG, EEG and EOG signals and the detector used for EEG and EOG signals was trained with initial annotations obtained from voting of cardiovascular signals. They have assigned predetermined fixed lower weights to SV, EEG and EOG signals as compared to weights of ECG and ABP signals in voting, irrespective of quality of signal. Jongmin Yu et al. also proposed a heart beat detection method from multimodal physiological signals using voting fusion technique [14]. They have used adaptive filters in cascade for detection of ECG artifacts in NC signals. Three candidate locations of heart beat; one from ECG, one from other group of cardiovascular signals (BP, SV, and SpO_2), and one from NC signals have been merged through voting for majority. In the method proposed by Gieraltowski et al., four annotation sets, two sets from ECG signals (gqrs, RS slope and amplitude), one set from ABP signal and one set from NC signals were joined sequentially in following order: ECG, ABP, and EEG, EOG, EMG to obtain final annotation set. A signal is rejected, if annotations detected are less than $1/6^{th}$ of total beat annotations [15].

Johnson et al. [16], Thomas De Cooman et al. [17], Quang Ding et al. [18] and Marcus Vollmer [19] have carried out studies on robust heart beat detection using only cardiovascular signals. The focus of all the earlier studies, except proposed by Q. Li et al., was on robust heart beats detection, using either cardiovascular signals or multimodal physiological signals. Q. Li et al. proposed a robust HR estimation method based on signal quality indices, Kalman filtering and data fusion using ECG and ABP signals from MIMIC-II database [9].

In this paper, we present a new majority voting fusion method based on novel beat SQI for robust heart rate estimation from fusion of cardiovascular and NC signals. We have also used modified version of our previous slope sum function (SSF) and Teager-Kaiser Energy (TKE) method for beat detection [20], which is referred to as modified SSF-TKE method.

This paper is organized as follows: In Section 2, a layout of the proposed work is given, which is followed by detailed description of beat SQI algorithm and majority voting fusion method. The performance evaluation of the methods on standard datasets and comparison with other studies is reported in Section 3. Discussion is presented in Section 4. The final Section 5 gives conclusion of the study.

2. Materials and methods

2.1. Databases

PhysioNet is a standard research resource of complex physiological signals. The performance of proposed beat SQI method has been tested on set-a of PhysioNet/CinC Challenge-2011 training database [21]. The dataset is a collection of 1000 standard 12-lead ECG recordings (leads I, II, III, aVR, aVL, aVF, V1, V2, V3, V4, V5, and V6) each of 10 s duration. The signals are sampled at 500 Hz with 16-bit resolution. The dataset contains 773 acceptable records, 225 unacceptable records and 2 indeterminate records (which are not considered for evaluation).

PhysioNet/CinC Challenge-2014 training dataset (set-p) [22] and extended training dataset (set-p2) [23], together known as public training set containing 200 records of human adults, has been used to evaluate the performance of the beat SQI based voting fusion method. The proposed algorithm is also tested on revised hidden test data set of PhysioNet/CinC Challenge- 2014 containing 200 records. Each record has simultaneously recorded four to eight signals of 10 min each or occasionally of shorter duration. The sampling frequency of signals in public training set is either 250 Hz or 360 Hz whereas signals in the test dataset have been sampled at rates between 120 Hz and 1000 Hz. *Reference beat annotations* of records of the training dataset have also been given.

The performance of beat SQI based voting fusion method has also been evaluated on MIT-BIH Polysomnographic (PSG) database [24]. This database contains multiple physiological signals of 16 adult males during sleep. It has 18 records of four to seven-channel Polysomnographic recordings of 80 h. Each record contains an ECG, invasive blood pressure, an EEG and respiration signals of up to duration of 6.5 h. Some signals include an EOG signal and an EMG signal (from the chin). The signals are digitized at a sampling rate of 250 Hz with 12-bit resolution.

PhysioNet/CinC Challenge-2011 training set-a database, PhysioNet/CinC Challenge-2014 public training dataset, PhysioNet/CinC Challenge-2014 hidden test dataset and MIT-BIH Polysomnographic (PSG) database are denoted as DB1, DB2, DB3 and DB4 respectively.

The proposed robust HR estimation method involves following four steps: 1) R-peak detection in ECG, ABP signals and R-peak artifacts detection in NC signals, 2) Estimation of beat SQIs of signals, 3) Fusion of heart beats using beat SQI based majority voting fusion method and 4) Robust HR estimation from fused heart beats. The layout of proposed work is given in Fig. 1.

2.2. R-peak detection in multimodal physiological signals

The accuracy of heart rate estimation depends on accuracy of R-peak detection in the signals. QRS complex is the most distinct and visible morphological feature of ECG. However, ECG signals are sometimes contaminated by different sources of noise. These artifacts often have similar shape as QRS complex, which makes QRS detection difficult. Hence preprocessing of signals is necessary to reduce the noise and enhance QRS complexes for proper beat detection.

2.2.1. Preprocessing

Most of the energy of QRS complex in ECG lies between frequency range of 3 Hz–40 Hz. In modified SSF-TKE method, we have applied first order Butterworth filter of 5–40 Hz to suppress high frequency noise and remove base line wander for R-peak detection in ECG.

ECG artifacts appear as poorly formed QRS complex with diminished amplitude in NC signals, but usually with steep slopes and temporal duration similar to those of ECG QRS complex. We have applied first order Butterworth filter of different frequency ranges to enhance the ECG artifacts and suppress base signal in NC signals. Optimal beat detection in EEG, EOG and EMG signals has been achieved with Butterworth filter of frequency ranges of 5–55 Hz, 10–25 Hz and 5–15 Hz respectively.

2.2.2. R-peak detection in multimodal signals

An open source QRS detection algorithm ‘gqrs’ has been used for R-peak detection in ECG signals [25]. We have also used modified SSF-TKE method for R-peak detection in ECG signal.

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