Robust heart rate estimation using combined ECG and PPG signal processing

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Abstract. Heart rate variability (HRV) from recorded electrocardiograms (ECG) is a well-known diagnostic method for the assessment of autonomic nervous function of the heart, which is widely used to predict clinically relevant outcomes in the critical care setting, to risk stratify patients, and predict outcomes such as mortality. The morphological variations in the ECG waveform and the high degree of heterogeneity in the QRS complex often make it difficult to identify R waves, which may preclude the accurate analysis for HRV. Photoplethysmographic (PPG) signal can provide information about both the cardiovascular and respiratory systems and have extremely high degree of correlation with ECG during cardiac cycle. In this paper, we developed robust algorithm for high-resolution inter-beat waveform extraction using combined ECG and PPG analysis, which is highly needed for accurate HRV estimation. The simulation results showed high performance for inter-beat waveform detection in different cases that identifies missing/extra peaks in the QRS detection algorithm.

1. Introduction
Intensive Care Units (ICU) receive patients in critical condition, whose health state requires considerable attention and continuous monitoring from medical staff. Today, with modern computational-intensive biosensors, number and quality of physiological signals have significantly increased. Bedside monitors are intended for patient’s physiological measurements from diagnostic devices, converts the observable electric signals into digitalized waveforms and vital signs numerics, analyses them to track physiological state and sounds alarms at abnormalities [1]. Physiological variables such as heart rate, blood pressure, temperature, ventilation and brain activity are constantly monitored on-line. Due to the complex condition of critical patients and the huge amount of data, it can be hard for physicians to decide about the best procedure to provide them the best health care possible. The human factor can lead to errors in the decision-making process. Frequently, there is not enough time to analyse the situation because of stressful circumstances and furthermore, it is not possible to continuously analyse and memorize all the data.

This problem highlights the need for a more accurate and prevention-oriented health monitoring system, which will take care of a person’s physical health conditions at their earliest stage, through physical activity management, status monitoring, assessment as well as early notification in case of an emergency [2]. One of these key challenges is the autonomous ability to early diagnose and assess prognoses of developing pathologic conditions by an individual. Personalised health monitoring devices should be useful in early identification of medical conditions and facilitation of conventional clinical
diagnosis processes by analysing disease relevant data and providing intelligent diagnostic assessment and alert feedback, either to the patient or directly to clinicians.

Patients admitted to the ICU in general suffer from organ failure (single or multiple) or are at risk of such organ failure, which includes patients after major surgery and/or trauma. Heart rate variability (HRV) analysis is used to predict clinically relevant outcomes in the critical care setting, to risk stratify patients, and predict outcomes such as mortality and multiple organ dysfunction syndrome [3]. In the perioperative field, HRV allows observation of the specific frequencies resulting from the fluctuations and provides insight to autonomic nervous system (ANS) processes. Heart rate might therefore reflect general physiological performance and increased regularity of signals may represent a decomplexification through illness, based on the notion that complex physiological systems with several parallel regulatory mechanisms increase stability, and that stability is associated with complex patterns in time series like heart beats.

Heart rate variability is obtained by measuring the RR-intervals in electrocardiogram (ECG) recordings or inter-beat-intervals (IBI) from blood pressure signals [4]. Among them, ECG is considered as the common method to detect HRV signals since it provides a waveform, which makes it easier to exclude heartbeats not originating in the sinoatrial (SA) node. Clinical ECG recording commonly uses 12 leads for determination of the complex temporal dynamics of each cardiac cycle and graphical representation of the electrical activity of the heart. ECG recordings are, however, often imperfect. Common sources of noise are those generated by physiological processes, including electromyograph contamination, signal interference and respiration induced baseline drift, as well as those generated by non-physiological influences such as power line interference and electrode contact movement. In addition, morphological variations in the ECG waveform and the high degree of heterogeneity in the QRS complex often make it difficult to identify R waves, which may preclude the accurate determination of R-R intervals. These methodological problems inherent in the recording and analysis of ECG traces have motivated a search for alternatives.

![ECG and PPG waveforms](image)

Figure 1. Periodicity and correlation properties between ECG and PPG waveforms.

Photoplethysmography (PPG) is one on the most popular technologies in the last decade for monitoring of the physiological conditions of a patient, and, because it is an non-invasive method, PPG has been largely applied to personal portable devices and pulse oximetry due to its convenience and capacity to perform continuous readings. Commonly, it includes an optical sensor that emits light onto the skin, receives the transmitted or reflected light and measures local blood volume changes at each cardiac cycle by considering the difference of light absorption rate in the photodiode through the tissue. In addition, the signal can provide information about both the cardiovascular and respiratory systems. The vast viability of the utilization and easiness of the patient’s physiological data acquisition characterize this method. The relationship between volume and pressure in vessels leads to similar morphology between PPG signals and arterial blood pressure signals. With respect to common
characteristics of ECG and PPG signals, current research studies demonstrated an extremely high degree of correlation between these signals during cardiac cycle [5]. Thus, both ECG and PPG signals can be used to determine an HRV signal for ANS monitoring or estimation the respiratory rate for patient [6]. The first common property of these two signals that you can immediately notice from the observation of their waveforms is their periodicity or, in other words, the repetition of the one form over time (figure 1). In some papers, results of correlation analysis between PPG pulse intervals PP and HRV calculation using RR pulse intervals (ECG), confirms these claims about the high level of correlation in terms of mentioned parameters between these two signals, indicating the possibility of joint signal processing for heart rate monitoring [7].

2. Materials and methods
Heart rate variability can be used as a window into the cardiorespiratory control system and as a tool for examining the fluctuations of the sympathetic and parasympathetic arms of the ANS but interpretation of the results depends on the conditions under which the recording was obtained and the length of the recording itself. The heart rate may be increased by slow acting sympathetic activity or decreased by fast acting parasympathetic (vagal) activity. The balance between the effects of the sympathetic and parasympathetic systems, the two opposite acting branches of the autonomic nervous system, is referred to as the sympathovagal balance and the reflected in the beat-to-beat changes of the cardiac cycle [8]. Conventionally, heart rate variability analyses are performed using R–R interval time series obtained from continuous electrocardiographic (ECG) recording by detecting each QRS complex. Normal-to-normal (N–N) interval time series contain only R–R intervals resulting from sinus node depolarizations.

HRV can be analyzed by different methods, which are usually categorized as time-domain methods, frequency-domain methods, and methods based on the non-linear dynamics of HR. Time-domain method is the simplest method to perform, various statistical parameters can be calculated include the mean NN interval, the mean heart rate, the difference between the longest and shortest NN interval, the standard deviation of N–N beats, rMSSD as the square root of the mean squared differences of the successive N–N interval and pNN50 as the percentage of differences between adjacent N–N intervals that are by more than 50 ms.

In frequency domain methods, various spectral methods are used for the analysis of RR intervalogram. Since RR intervals in time series are non-stationary and they are spaced unevenly, it needs to make re-sampling. The Lomb-Scargle periodogram can overcome this weakness and it can estimate the PSD directly from irregularly sampled RR interval series without resampling. The most common classifications for HRV spectrum are: very low frequency (VLF: 0.003-0.04Hz), low frequency (LF: 0.04-0.15Hz) and high frequency (HF: 0.15-0.4Hz). The ratio of LF to HF appears to be a sensitive measure of the autonomic nervous system’s (ANS) response to a sudden change in cardiovascular control and this ratio represents an evaluation of the ANS balance. In addition to conventional time and frequency-domain HR variability analysis, there are other methods based on the non-linear system theory and beat-to-beat dynamics. Non-linear analyses include return maps, such as Poincaré plots, fractal scaling analysis (DFA analysis), different complexity measures (e.g., Lyaponov exponent, correlation dimension), and approximate entropy, for instance. The clinical utility of these non-linear HR variability analyses has been tested in various sets of R–R interval data.

Among the techniques used in its evaluation, the heart rate variability (HRV) has arising as a simple and non-invasive measure of the autonomic impulses, representing one of the most promising quantitative markers of the autonomic balance. The HRV describes the oscillations in the interval between consecutive heart beats (RR interval), as well as the oscillations between consecutive instantaneous heart rates. It is a measure that can be used to assess the ANS modulation under physiological conditions, such as wakefulness and sleep conditions, different body positions, physical training and pathological conditions. Changes in the HRV patterns provide a sensible and advanced indicator of health involvements [9].
The heart rate variability signal is usually obtained from an ECG recording that is captured over a certain period of time. A complete analysis of an ECG consists of, first, detecting beat positions, and, then, delineating the waves that form each beat. In order to obtain HRV parameters from ECG signals, interpolation, R wave detection and generating the R-R interval signals should be performed. In the literature, many proposals can be found that yield good results, both in beat detection and waves delineation \[10, 11\]. There are algorithms that achieve a rate of success greater than 99.5% in beat detection. Besides, recent technical advances have made possible to achieve low execution times (even real-time) or to eliminate the need for specific hardware. Most of these proposals are based on single-channel detection, in some cases applied independently to two channels of the ECG. This can make these systems sensitive to interference, noise or bad contact between the electrodes and the patient’s skin, since signal degradation can cause detection problems. Such problems can increase the number of false positives (artifacts erroneously detected as beats) and temporal errors (mismatches between detected and actual positions of beats), thus worsening the performance given by ECG delineation algorithms.

Considering that the twelve-lead circuitry was used for the signal acquisition in electrocardiograph, and the multilead analysis of QRS complex would be resistant to presence of noise from the sources like electrode motion and electromyographic (EMG), some researchers tried to detect QRS complex on two or more leads. The work \[12\] applied the vote based fusion strategy for the multilead fusion after detecting QRS complex in multichannel ECG recordings. This method achieved a high precision but relative lower sensitivity. To overcome this problem, we developed a robust method for inter-beat signal extraction combining both multichannel ECG and PPG auxiliary signals. A block diagram of the proposed algorithm is depicted in figure 2.

The single-channel detection algorithm is based on well-known Pan-Tompkins method \[10\]. Briefly, it consists in adapting the single-channel Pan-Tompkins detection algorithm to the different leads of a multichannel ECG recording, to overcome the limitations when detecting beats due to high level of noise existing in the recordings, the missing of some part of the ECG signals, or the impossibility to use adequate preprocessing methods that improve the quality of the original signal. Firstly, the ECG signal was filtered by a cascade of a lower-pass filter and a high-pass filter. The bandpass filter reduces the influence of muscle noise, 60 Hz interference, baseline wander, and T-wave interference. The desirable passband to maximize the QRS energy is approximately 5-15 Hz. After filtering, the signal is differentiated to provide the QRS complex slope information with using low-complexity five-point derivative filter. After differentiation, the signal is squared point by point. This makes all data points positive and does nonlinear amplification of the output of the derivative emphasizing the higher frequencies (i.e., predominantly the ECG frequencies). Finally, the moving-window integration of the squared signal was calculated and used as the auxiliary signal. The purpose of moving-window integration is to obtain waveform feature information in addition to the slope of the R wave. The QRS complex corresponds to the rising edge of the auxiliary signal. So it can be identified by thresholding the amplitude of the auxiliary signal. Generally, the width of the window should be approximately the same as the widest possible QRS complex. If the window is too wide, the integration waveform will merge the -QRS and T complexes together. If it is too narrow, some QRS complexes will produce several peaks in the integration waveform. These can cause difficulty in subsequent QRS detection processes. To improve successful detection rate the width of the window was suggested 150 ms, which is determined empirically in \[10\]. If there was no QRS complex detected during a specific interval, the process of searchback was performed and the maximal peak between the two given thresholds during the interval was treated as the QRS complex. Furthermore, the neighbouring peaks whose interval was
smaller than 360 ms was checked in order to remove the high T wave which would be misclassified as the QRS complex.

![Filtered and SSF PPG signal.](image)

**Figure 3.** Filtered and SSF PPG signal.

Although the QRS complex detector may produce some false positives (falsely detected QRS complex) or false negatives (missed QRS complex) on the single lead, this problem can be solved by the combining multi-lead detection. After detecting the QRS complex on each single ECG lead, we used following strategy to validate the QRS complexes. Firstly, the detected QRS complexes auxiliary signal is binarized and summarized for all available leads. Then, the generalized waveform is analysed by fusion window with width of 150 ms for searching first detected QRS complex. If the value of generalized signal is higher than the half of number of available leads, the QRS complex is detected. The first QRS complex out of current window is treated as a new candidate for new QRS complex and compared with threshold again. This procedure is continued until all QRS complexes were assigned.

For the PPG recordings, a neighbouring peak searching method was used to derive the peak events from the amplitude of the filtered PPG signals [13] and then the intervals between the successive detected peaks (PPIs) were calculated for HRV analysis. All of the RR- and PP- intervalogram time series underwent an initial automated editing process before a careful manual editing was performed by visual inspection. So far, different types of algorithms have been developed in order to detect the maximum of each PPG pulse. This information is of great performance for the determination and calculation of various parameters and values such as: peak-to-peak intervals variation, frequency of the pulse signal, amplitude of each pulse, etc. One of these algorithms is Zong’s algorithm, which is consisted of three main steps: filtering, sum slope function (SSF) calculation and delineation.

Since PPG sensor uses ambient light, there are disturbances and noises that make PPG signal poor. This deterioration can be greater due to noise that occurs as a result of motion artifacts. In order to eliminate this flaw, PPG signal is processed in parallel with ECG. In order to improve signal quality, a high pass baseline filter with a cut-off frequency of 0.5 Hz has been applied. Besides, a low pass filter has been used with a cut-off frequency of 5 Hz for the smoothing PPG signals, because it may be affected by high frequency interference. Second step includes calculation for sum slope function, the purpose of this metric is to increase and emphasize the rise of PPG pulse and remove the rest of the wave by setting to zero values [14]. Finally, for performing delineation process a sliding window is used to search for local peak in auxiliary SSF signal (figure 3), which size is defined empirically and was 150 ms corresponding QRS detection algorithm.

In order to provide an accurate and reliable HRV parameter calculation, the conventional techniques require uninterrupted series of RR intervals (inter-beat waveform). Peak detection errors are arised when the detection algorithm misses a beat due to arrhythmic events or faulty sensors or detects one where is none and ectopic beats often determined abrupt changes in the RR interval time series that can lead to substantial deviations of HRV indices. All HRV parameters are calculated on ‘normal-to-normal’ (NN) inter-beat intervals (or NN intervals) caused by normal heart contractions paced by sinus node depolarization. Before computing the beat to beat metrics, it is important to have an outlier removal
process that identifies missing/extra peaks in the QRS detection algorithm outputs and PPG beat-to-beat algorithm outputs. Ignoring peaks from ECG recording causes abnormal beat durations that would lead to inaccurate results. In order to decrease false detection in evaluation of inter-beat intervals we can analyse PPG waveform due to their spatial correlation and periodicity. Thus, sum slope function of PPG signal is used to eliminate abnormal RR intervals which are arising with electrical artefacts and arrhythmia from ECG recording. Any ECG peak that changed the beat duration more than 20% was labelled an outlier. After removing these abnormal ECG peaks, missing/extra peaks in the PPG signal were identified by correlating each ECG peak with a peak in the PPG signal. A PPG peak was correlated with an ECG peak if it is within time proximity of the ECG peak. When a PPG peak cannot be identified or too many peaks are identified within the time proximity of an ECG peak, these were identified as outliers. The abnormal beat durations that these missing/extra PPG beats would cause are ignored as outliers during metrics calculations.

The proposed robust method for HRV analysis was implemented and evaluated with databases from the openly accessible database (PhysioNet). This database encompasses high resolution physiologic waveforms (such as ECG, blood pressures, plethysmograms, respirations) that were obtained from adult patients and different morphologies such as baseline fluctuations, low and varying amplitudes and irregular heart rhythms. The multichannel algorithm for QRS detection from ECG recordings was evaluated on the St. Petersburg Institute of Cardiological Technics 12-lead Arrhythmia Dataset, which contains 75-half-hour recordings collected from 32 patients (17 men and 15 women) aged between 18 and 80 (mean age 58), suffering from diverse heart conditions [15]. ECG were obtained using 12-lead device and digitized at 257 samples per second. The performance of proposed method for inter-beat waveform evaluation using combined ECG and PPG analysis was evaluated using a benchmark dataset called the CapnoBase [16]. The dataset is composed of multiple physiological signals recorded from 29 children and 13 adults. The PPG signals were recorded at a sampling frequency of 300 Hz for 8 min. All of the data processing were performed using MATLAB® (Mathworks, Natick, MA, USA). The available raw ECG and PPG signals are sampled at the rates of 257 Hz and 300 Hz, respectively. Therefore, before performing HRV analysis it was essential to resample the inter-beat intervalogram from these high rates to baseline sampling rate which is equalled 1000 Hz, extracted simultaneously from both ECG and PPG signals.

The performance of the QRS complex detection algorithm for multilead ECG recordings was measured by classical parameter set: sensitivity (Se), precision (+P) and detection error rate (DER). P. If the margin between a detected QRS complex and annotated beat was smaller than 150ms, which was suggested by the standard of ANSI/AAMI EC57m this QRS complex was treated as the TP (true positive). Otherwise, it was treated as the FP (false positive). The simulation results show that the proposed multichannel algorithm for QRS detection was achieved the lowest DER (0.56 %), sensitivity (99.12 %) and RMS RR interval error = 74.5 ms. Other tests which are performed with using dataset CapnoBase have shown that using combination of PPG and ECG waveform analysis allows to improve determination for RR intervalogram while reducing error by ∆ RMS RR interval error = 93.2 ms in single-lead case.

3. Conclusion
Heart rate variability (HRV) signal is a popular noninvasive marker of the autonomic nervous system, extensively obtained from ECG and PPG signals. With respect to common characteristics of ECG and PPG signals, an extremely high degree of correlation between these signals is demonstrated. The first common property of these two signals that you can immediately notice and to identify their similarities and mutual correlation. In addition to periodicity, also as a common feature that can be highlighted are time intervals between two peaks (two adjacent pulses) in PPG or ECG signal. Comparing HRV calculation using PPG pulse intervals PP and HRV calculation using RR pulse intervals (ECG), confirms these claims about the high level of correlation in terms of mentioned parameters between these two signals. The robust method for HRV analysis which is based on combined ECG and PPG signal processing was proposed in this work. The simulation results showed high performance for inter-beat waveform detection in different cases. Future work will focus on creating own database contains a high-
resolution physiological signals collection and processing of different types of body signals for the purpose of reliable analysis of patients in the case of intensive care.

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