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Analysis of electrocardiographic signals to assess heart rate variability under surgical context: a methodological proposal

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Abstract—**This manuscript presents a methodological proposal for computing heart rate variability (HRV), specifically designed for analysing physiological signals in surgical patients. The method involves ECG signal processing, tachogram computation, and HRV feature analysis. Results show strong correlation (0.99) and low mean absolute error (0.0069 mV) between pre-processed ECG signals and reference. Artifacts notably affect certain HRV features, but the proposed method achieves high precision, recall, and AUROC curve (0.96) in distinguishing normal from artifact-laden tachograms. Overall, the proposed methodology offers a comprehensive and efficient processing approach for obtaining high-quality tachograms from ECG signals.**

Index Terms—**anaesthesia, digital signal processing, electrocardiographic signals, heart rate variability, surgery, tachogram.**

I. INTRODUCTION

Heart rate variability (HRV) assessment, crucial for analysing the autonomic nervous system's intricacies, provides insights into cardiovascular health [1]. Electrocardiographic (ECG) signals are commonly utilized for HRV computation [1]. Notably, HRV analysis is vital in surgical settings, predicting mortality and morbidity post non-lethal cardiac ischemia [2]. A systematic review explored HRV's predictive role in intra and postoperative complications [2]. For example, the low-to-high-frequency ratio predicts intraoperative hypotension during spinal anaesthesia, while total power of low frequency predicts hypotension under general anaesthesia [3]. HRV holds promise in surgical contexts for outcome prediction and understanding surgeon stress. Nonetheless, further high-quality comparative studies are required to comprehensively grasp its potential and standardize its application [4].

HRV analysis necessitates multiple processing techniques, with high-quality ECG segment selection being crucial due to noise sensitivity [5]. Various approaches, including Machine Learning (ML) model training [6], [7], [8] have been proposed to select segment quality, thereby increasing the complexity in the solution of this issue. Previous studies emphasize the importance of accurate RR interval acquisition and processing for HRV analysis [9]. Proper R-peak detection, from ECG signal filtering to QRS complex acquisition, is essential. Despite some studies using the Pan-Tompkins method for R-peak detection [10], others apply multiple filters to improve data quality and obtain precise RR intervals [11]. However, many studies lack detailed data preprocessing methodologies [12]. No single algorithm is optimal for R-peak detection under various conditions or artifacts. Additionally, HRV artifacts post-tachogram (TCG) obtaining, such as extra beats, missed beats, ectopic beats, and outliers [11] [13], are often overlooked [14].

Based on existing literature and identified gaps, this manuscript shows a methodological approach proposed to consolidate previously developed procedures into a series of steps for HRV analysis. Specifically designed for analysing physiological signals in surgical patients, this method begins with ECG signal processing, advances to TCG computation, and concludes with HRV feature analysis.

II. METHODS

For this study, ECG recordings from the VitalDB database [15] were sampled at 500 Hz, involving 30 colorectal surgery patients (16 females, 14 males) aged 20 to 90 years with normal cardiac and pulmonary function and ASA-score=1 (American Society of Anaesthesiologists). Patients with diabetes and hypertension were excluded. The proposed methodology is outlined as follows:

1. Selection of good-quality segments: The algorithm described in [16] was utilized for selecting high-quality ECG segments. Analysis was performed in 60-second windows, computing features such as maximum and minimum values and the number of zero-crossings in nonoverlapping five-second windows. Thresholds were applied to assess segment quality, resulting in 510 segments included as analytical sources for this study.

2. ECG Filtering: A Notch filter was applied to eliminate undesirable frequencies associated with electrical network noise (60 Hz, according to VitalDB). The Butterworth filter, configured as a fourth-order filter with a cut-off frequency of 0.8 Hz, effectively removed low frequencies associated with

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respiration, movement, or impedance mismatch between electrode and skin [17]. Additionally, high-frequency noise was smoothed using Wavelet transform with the biorthogonal 3.5 mother wavelet and two levels of decomposition [18].

3. R-wave segmentation: To highlight the QRS complex, a third-order Butterworth bandpass filter ranging from 5 to 20 Hz was applied [10]. Various algorithms for R-peak estimation, including *Christov, WQRS, Engzee, SWT, Hamilton, Pan Tompkins,* and *Two-average* detectors, were evaluated using the *Detectors* library in Python [19]. The selection criterion was based on the average signal amplitudes at detected R-peak positions, with the algorithm yielding the highest average value chosen. Despite its computational intensity, precise R-peak detection is vital for accurate HRV analysis [20]. Given that R-peak detection may be slightly offset or different ECG waveforms may be detected as R-waves, the peak-corrector function from the *wfdb* library for Python was employed [21]. This function smooths the signal with a moving average filter and adjusts detected peaks to coincide with local maxima of the smoothed signal.

4. Calculation of TCG: TCG was calculated with the time difference between the corresponding identified R-peaks, for each ECG segment. Each time difference between two adjacent R-peaks is presented as one value in the TCG. Typically, when obtaining the TCG, four common types of artifacts are identified: extra beats, missed beats, ectopic beats, and outliers. These artifacts, manifested as peaks of higher amplitude, should be removed to avoid affecting subsequent analyses [22]. Artifact detection was based on the median of the TCG (M-TCG).

Extra beats are identified when both their corresponding data and one of their adjacent data in the TCG are below M-TCG, and the sum of these values is close to M-TCG. To correct the presence of an extra beat, one of the two data points was removed, and the other was replaced by their sum.

Missed beats are distinguished because their corresponding value is approximately double M-TCG. For detection, time lapses greater than 1.5 times M-TCG were considered. Then, for correction, following [22], data detected as missed beats were replaced by two values corresponding to half of each.

The correction of ectopic beats and outliers was based on [22]. In the subsequent explanation, the term "outlier" may encompass both ectopic beats and outliers. Differences between successive values of the TCG were computed to create the drr series. Subsequently, a threshold (U1) was calculated by multiplying the interquartile range of the drr series by a constant factor of 5.2. Then, the values of the drr series were divided by U1, and absolute values were taken; values greater than one were associated with outliers. Since the TCG does not follow a normal distribution, some outliers may go undetected, prompting a second evaluation. In this step, the M-TCG was subtracted from the TCG, generating the mrr series, where each value was multiplied by two, if and only if, it was less than zero. The interquartile range of the mrr series was then determined and multiplied by 5.2 to obtain a threshold (U2). The values of mrr were divided by U2, and absolute values were taken; values greater than one were associated with outliers. This entire process should be executed using sets of consecutive peaks; 45 non-overlapping peaks are recommended for optimal results [22].

Outliers were replaced by interpolation using a decision tree regression model. The model was trained on the dataset, excluding outlier values. Once trained, the model was used to predict missing values in the TCG, substituting outlier values.

5 Evaluation: To evaluate the methodology, several metrics were applied to the ECG signals, TCG calculation, and HRV analysis. Mean absolute error (MAE) and Pearson correlation coefficient were used to assess ECG signals. These metrics were applied to three signal types: a reference signal, the reference signal contaminated with randomly generated noise of varying frequencies, and the processed contaminated signal using the proposed methodology.

500 TCG segments were examined, some randomly tainted with a single outlier (ectopic beat, missed beat, or extra beat), chosen at random. Post TCG correction, outlier-detected segments were labelled "1", while those without were "0". Using these labels, a confusion matrix gauged effectiveness to detect atypical beats, estimating sensitivity, accuracy, precision, F1-score, specificity, Cohen kappa score, and AUC-ROC.

For HRV assessment, 44 features in the time, frequency, nonlinear, and geometric domains were extracted from reference TCGs, contaminated with three different artifacts (extra, missed, ectopic), and corrected with the proposed methodology. This analysis aimed to assess the impact of TCG artifacts on the HRV features. Features were extracted using *hrv-analysis* [23] and *NeuroKit* [24] libraries. The ten most and least relevant features were then selected by the Mutual Information (MI) method from the *Sklearn library* [25].

III. RESULTS AND ANALYSIS

The assessment of ECG processing revealed a correlation coefficient of 0.99 and a MAE of 0.0069 mV for the processed signal compared to the reference signal. For the contaminated signal, metrics indicated a correlation coefficient of 0.87 and a MAE of 0.0500 mV. Analysis of the confusion matrix for distinguishing normal and atypical beats yielded a Cohen's kappa score of 0.91, precision, and F1-score of 0.95, and accuracy, recall, and AUC-ROC curve of 0.96. In [26], a deep convolutional autoencoder was implemented to eliminate various types of noise, thus improving the overall quality of the ECG signal. Processed signals showed an MAE of 0.0055 mV and a correlation coefficient of 0.85 compared to the reference signals, while contaminated signals displayed an MAE of 0.0130 mV and a correlation coefficient of 0.65 when compared to the same reference. These findings reinforce the effectiveness of the proposed methodology in processing ECG segments. In [27], the relationship between ECG noise and heartbeat detection was studied for clean ECG signals and simulated signals with different noises. The results showed a recall exceeding 0.98 in R-peak detection for clean signals and with noisy signals exhibited a minimum recall of 0.65. The evaluation of the proposed methodology in TCG processing suggests this methodology can accurately identify atypical beats (ectopic, extra, and missing) and effectively distinguish an atypical beat from a normal one, crucial for TCG correction. In contrast to previous approaches utilizing ML classification models for selecting high-quality ECG segments [6], [7], [8], the proposed methodology employs a statistical signal analysis algorithm with low computational cost.

Signals contaminated with artifacts degrade the signal morphology. In [26], the impact of ECG noise on heartbeat detection was investigated, showing a recall of 0.98 for clean signals compared to a minimum recall of 0.65 for noisy signals. This underscores the importance of ECG signal processing for accurate R-peak detection, crucial for generating high-quality TCGs. Evaluation of the proposed methodology yielded a Cohen kappa score of 0.91; precision, specificity and F1-score of 0.95; and recall, accuracy and AUC-ROC performance of 0.96, indicating its ability to identify atypical beats effectively, essential for TCG correction. Unlike previous studies utilizing specific algorithms like Hamilton or Pan Tompkins for R-peak detection [11], [13], the proposed methodology concurrently evaluates various algorithms to identify the most effective one. Additionally, in TCG generation, a limitation observed in some studies [11], [13] is addressed by identifying artifacts such as extra beats, missed beats, ectopic beats, and outliers, with the aim of TCG processing.

Remarkable changes were observed in seven time-domain and three nonlinear features extracted from the TCG compared to those from the reference TCG (Table I). Conversely, two frequency-domain, three nonlinear, four time-domain, and one geometric feature showed less relevance.

TABLE I
SET OF THE TOP FIVE MOST RELEVANT TCG-FEATURES

Feature_MI	Missed beats	Extra beats	Ectopic beats	Reference
CVSD_1.11	0.18 ± 0.03	0.16 ± 0.11	0.06 ± 0.01	0.02 ± 0.03
SD1_1.07	28.32 ± 4.46	24.0 ± 13.34	9.46 ± 1.94	3.48 ± 5.39
SVD-entropy _1.06	0.42 ± 0.04	0.38 ± 0.13	0.19 ± 0.03	0.08 ± 0.09
std of HR_0.98	4.97 ± 1.51	28.46 ± 15.83	3.36 ± 1.89	2.17 ± 2.13
Range of NNI_0.91	949.34 ± 221.69	665.05 ± 137.42	377.55 ± 90.08	112.64 ± 116.57
SET OF THE FIVE LEAST RELEVANT TCG-FEATURES				
Triangular index_0.04	4.85 ± 3.13	7.61 ± 6.15	5.08 ± 2.21	4.86 ± 3.11
Rényi entropy_0.07	3.59 ± 0.26	3.86 ± 0.41	3.67 ± 0.23	3.59 ± 0.26
Shannon entropy_0.07	5.18 ± 0.37	5.57 ± 0.58	5.29 ± 0.33	5.18 ± 0.38
Median of NNI_0.11	888.65 ± 189.64	797.81 ± 208.8	945.2 ± 210.86	882.27 ± 190.27

In [14], the authors analysed the influence of ectopic beats on HRV features such as SDNN, LF/HF ratio, Sample entropy (SampEn), and SampEn based on threshold. However, other types of artifacts and potentially relevant HRV features were not explored. In the evaluation of HRV features in this study, variations were observed when comparing contaminated TCGs with respect to the reference ones and those processed using the proposed methodology. Notable changes were observed in features such as NNI range and RMSSD. This is reflected in the feature ranking provided by MI analysis, highlighting these features as the most representative for discriminating between reference TCGs and those contaminated with different types of artifacts. Features minimally affected by noise were median of NNI, mean of NNI, and Shannon entropy. MI analysis similarly indicated that these features are less representative for discriminating between reference TCGs and those contaminated with different types of artifacts. This analysis underscores the importance of processing TCGs for conducting HRV analysis affected by various types of artifacts.

IV. CONCLUSION

The proposed methodology offers a comprehensive and efficient processing option, capable of obtaining high-quality TCGs from ECG signals, which holds promise for future research in various health fields. Features utilized in HRV analysis were considered to evaluate TCG correction, revealing significant dispersion from the mean in various features like Coefficient of variation of successive differences (CVSD) and SD1; this is an indicative of substantial variability within the dataset, common in medical contexts due to factors such as individual differences, outliers, or the complexity of physiological processes. For future studies, this methodology will be employed to assess how heart rate responds to different environments, drugs, and body positions, aiming to deepen our understanding of heart physiology through HRV analysis.

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