**Heart-Rate Variability: A Potential Marker of Anesthetic Depth**

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**I. Abstract:**

This study investigates the feasibility of using heart-rate variability (HRV) parameters derived from electrocardiogram (ECG) to assess the anesthetic depth in patients undergoing surgery. Depth of anesthesia (DoA) is defined as the extent of central nervous system (CNS) depression due to an anesthetic agent [1]. Maintaining an appropriate depth of anesthesia is important for minimizing intraoperative complications and optimizing postoperative outcomes [2, 3]. While commercial electroencephalogram (EEG)-based DoA monitors have been developed, they have not been widely adopted into clinical practice, due to conflicting results on patient outcomes, high costs, and their inconvenience in the operating room [4]. As such, there has been growing interest in using alternative physiological signals, such as the ECG, to assess the DoA [5]. In this study, intraoperative vital signs data are selected from surgical cases in the *Vital Signs Database (VitalDB)* [6]. The ECG track data is then pre-processed, and HRV parameters are extracted to develop machine learning models to classify the DoA.

**II. Methodology:**

***Dataset****:* This study uses *VitalDB*, an open dataset containing high-resolution multi-parameter data from surgical cases at Seoul National University Hospital between August 2016 and June 2017 [6]. The release of the *VitalDB* dataset was intended to support machine learning research on intraoperative vital signs and biosignal analysis, aligning closely with the objectives of the current study.

***Case Selection****:* The case selected from the *VitalDB* dataset for inclusion in this study uses the following criteria:

* Presence of Tram-Rac 4A (SNUADC) monitoring device for the following track data:
  + *SNUADC/ECG\_II: ECG lead II*
* Presence of BIS VISTA monitoring device for the following track data:
  + *BIS/BIS: BIS index*
  + *BIS/SQI: Signal quality index*

***Labeling DoA****:* The bispectral index (BIS), derived from the EEG, is the most widely used marker of anesthetic depth in both clinical practice and research [7]. In studies of anesthetic depth, the index is commonly used to determine the level of sedation brought on by anesthesia [8, 9]. In this study, the BIS track data is used to classify the DoA as light (BIS 61-100), *moderate* (BIS 40-60), and *deep* (BIS 0-39) as shown in Table 2.1. Each BIS value is accompanied by a signal quality index (SQI) value, which provides a measure of its reliability regarding external interference and noise levels. Only BIS values associated with an SQI > 75 have been selected for analysis. The onset of these values are marked as BIS Events.

**Table 2.1:** Classification of Anesthetic Depth

|  |  |
| --- | --- |
| BIS Value | Anesthetic Depth |
| 0-39 | Deep anesthesia |
| 40-60 | Moderate anesthesia |
| 61-100 | Light anesthesia |

***Data Preprocessing:*** The ECG track data is first epoched into windows of 120 seconds, centered around each BIS event (±60 seconds from the onset of the BIS value). Bandpass filtering (1.0 Hz – 40.0 Hz) is then applied to the epochs (5th order Butterworth IIR filter) to reduce baseline wandering and signal interference. Following this, mean baseline correction is also applied. In order to remove epochs with flatlines (commonly due to ECG lead disconnection) and high-amplitude interference (commonly due to surgical instruments), amplitude thresholding is used. The peak-to-peak (PTP) amplitude of individual epochs is calculated, and epochs associated with a PTP beyond ±2.5 median absolute deviations (MAD) are dropped. Finally, a Hamilton segmenter algorithm is used to detect the R-peak location within each epoch [10]. The RR-interval (RRI) is then calculated for each epoch as the time difference between consecutive R-peaks, and the NN-interval (NNI) is obtained by dropping epochs that contain >2.5% RRIs that are ectopic or outliers. A visual representation of the pre-processing steps is shown in Figure 2.1.

**Figure 2.1:** ECG Pre-processing

A diagram of a flowchart

Description automatically generated

***Feature Extraction:*** The NNI is used to compute the power spectral density (PSD) of the HRV, as shown in Figure 2.2, and the following frequency-domain features are extracted from each epoch:

* The nLF (nomalized LF) and nHF (normalized HF) are calculated by taking the ratio between the LF power or HF power and their sum, where the LF component is defined as 40-150 mHz and the HF component is defined as 150-450 mHz.

* The LF:HF Ratio is calculated by taking the ratio between the LF power and the HF powers.

In addition, the time (in seconds) is also used as a feature.

**Figure 2.2:** PSD of Epoch 1

***A graph of a diagram

Description automatically generated***

***Machine Learning Models:*** Due to the large imbalance of datapoints in each DoA class *(light, moderate, deep*), the data is first balanced. The class with the fewest datapoints remains unchanged, while other classes are randomly resampled in order to achieve an approximately equal distribution of data points across all classes. Following this, the balanced data is split into testing (80%) and training (20%). The HRV features are then scaled with a standard scaler. In this study, a decision tree (DT) and a k-nearest-neighbors (KNN) model are developed to classify the depth of anesthesia. A grid search is then employed to optimize each model. The accuracy of each model is assessed and compared.

**III. Results:**

In this study, a DT and KNN model were developed to classify the DoA based on HRV parameters derived from ECG. After optimization, the DT model achieved an accuracy of 95.83%, while the KNN model achieved an accuracy of 86.67%. In both models, the *light* class had the highest accuracy (100% in DT and 94% in KNN). The accuracy for the *moderate* and *deep* classes were similar in the DT model at 94% and 95% respectively. Meanwhile, for the KNN model, the *moderate* class accuracy is higher at 87% than the *deep* class at 80%. The confusion matrices for these models are shown in Figure 3.1.

**Figure 3.1:** Confusion Matrices for DT and KNN

A chart of different colors

Description automatically generated A diagram of a color scheme

Description automatically generated with medium confidence

**IV. Conclusion**

Based on this preliminary study, HRV appears to be a promising indicator of anesthetic depth, with both machine learning models demonstrating acceptable accuracy. However, to assess the validity and generalizability of these models, a larger number of cases from diverse surgical settings and patient demographics should be analyzed. In addition, the conventional classification of anesthetic depth into *light*, *moderate*, and *deep* levels may be inadequate for certain surgical scenarios. Other machine learning models should also be explored. Moving forwards, larger-scale studies are necessary to validate these initial findings. This study hopes to inspire the development of an HRV-based index of anesthesia depth, offering a cost-effective and convenient alternative to existing EEG systems.

**V. References**

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