Smoothed ℓ^0(SL0) Based Burst Suppression Detection Method

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Introduction: Accurate automatic detection of burst suppression (characterized by a period of almost isoelectric) electroencephalographic (EEG) patterns is important in the field of brain monitoring as presence of BSP in EEG is an indicator of profound brain inactivation and deep unconsciousness [1]. Accurate automatic BSP detection can reduce the risk of over-sedation during surgery by giving early warning to the attending anesthesiologist.

Based on our experience, the NeuroSENSE monitor [2], which is currently one of the DOH monitors available, tends to overestimate suppressions as it is shown in Fig. 1. Our main motivation to do this work is addressing the overestimation of suppression detected by the NeuroSENSE monitor, especially for cases in which the amplitude of EEG signal is smaller than expected, e.g., in elderly patients with aging-induced modification of skull conductivity.

Method: We propose to use machine learning to develop a real-time algorithm to automatically detect BSPs in the EEG signals of patients under general anesthesia during surgery. We utilized a decision-tree based ensemble classification model for the BSP detection application. We use the RUSBoost technique [3] to train an ensemble classifier to address the problem of class imbalance in our application, as the non-suppression class instances greatly outnumber suppression class instances.
The smoothed ℓ^0(SL0) norm of a vector [4] is utilized to introduce new appropriate features for the BSP detection application. We propose SL0-based features in order to track the time-evolution of spatial properties of the EEG signal. We refer to the proposed algorithm as the *SL0-based BSP detection* method, emphasizing that the proposed BSP detection method successfully uses the SL0 norm of a vector for the BSP detection.

For the time-varying EEG signal denoted $\mathbf{S}(t)$, we consider the SL0 norm of EEG epochs $F_{\sigma_0}(\boldsymbol{S})$, which is an approximate of the ℓ^0norm of a vector, as a good candidate for suppression detection. The ℓ^0 norm of a vector is the number of its nonzero components. We also used several Spectral features in addition to the SL0-based features to design our classifier.

Results: We use an EEG database collected from adult patients of age 19 and older, presenting for an elective surgical procedure at Royal Columbian Hospital, New Westminster, BC, Canada, with American Society of Anesthesiologists' (ASA) physical status I to III, for which total intravenous anesthesia (TIVA) was deemed appropriate [6]. We employed a large and diverse amount of training data of 192 hours of EEG recordings over 90 subjects under surgery.

Our results show that the proposed automatic BSP detection method greatly outperforms the method in [1] as well as the method in [5] which is currently under use by the NeuroSENSE monitor, NeuroWave Systems Inc. [2] in terms of reducing false alarms and the overall classification accuracy. Our proposed method results in 38.74 minutes of false detections over 45.86 hours of test data that is substantially improved comparing to 60.64 [5] and 353.21 [1] minutes of false detections. In terms of true suppression detection, the proposed SL0-based algorithms performs similarly to the existing methods in [5] and [1]. Our method correctly detects 33.38 minutes of suppressions comparing to 34.74 and 33.64 minutes of suppression correctly detected by the first-order derivative-base [5] and local variance-based [1] methods.

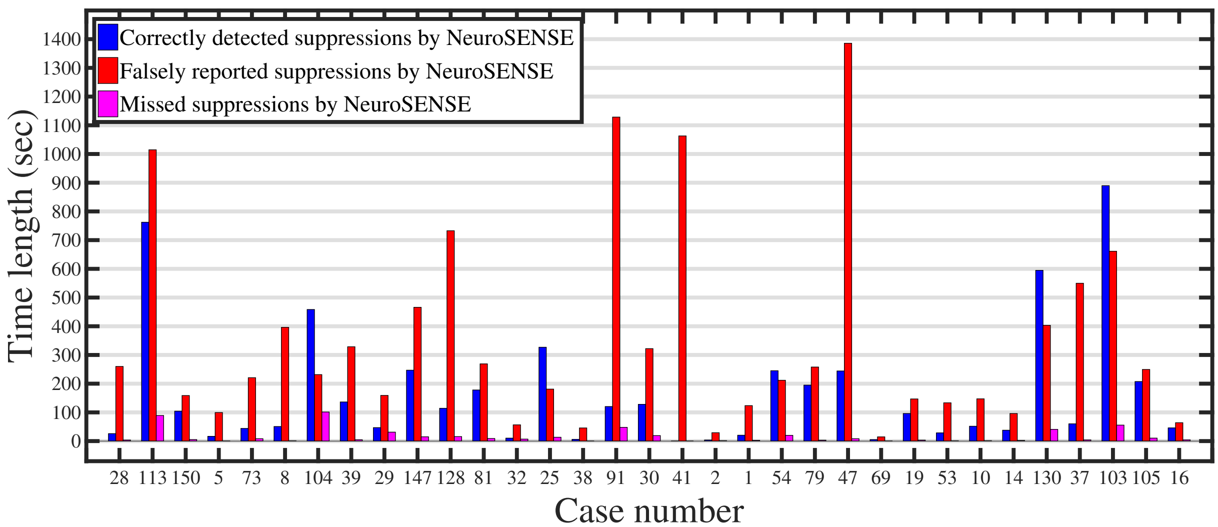

Fig. 1 The false alarm time length reported by NeuroSENSE monitors compared to the time length of accurately detected and missed suppressions for several selected cases.

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