Development and Validation of an Artifact Rejection Method for use in a Cardio-Respiratory Coherence Monitor

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Background: Previously, our team developed a nociception detection algorithm, to detect and quantify stress responses exhibited by the body in reaction to a noxious stimulus during general anesthesia [1]. This algorithm quantifies the coherence between respiratory sinus arrhythmia and respiratory frequency, providing a single feedback variable (NI) indicating the nociceptive state of the patient; a high NI is indicative of increased nociception. Short artifacts in either heart rate (HR) or respiratory rate (RR) distort the NI value for over one minute, due to the delay introduced by filtering [2], invalidating the signal for an unacceptably long period for real-time clinical use.

The aim of this work is to implement and validate an approach for a) predicting heart rate when artifacts are detected, b) removing capnography-zeroing artifacts, while maintaining the coherence and limiting the effect on the NI, and c) establishing a signal quality index (SQI), ranging from 0 (unusable) to 100 (uncompromised), as a measure of signal reliability during real-time clinical use.

Methods: A real-time auto-regressive HR prediction function was developed to predict missing or replace incorrect HR data (see example in Figure 1). Auto-regressive modeling can capture the frequency content of the signal and was expected to maintain coherence. The prediction accuracy was optimized using previously recorded anesthetic cases [2], leading to a 20th order model with an identification signal of 150 samples, or 30 seconds. Artifact-free data were used to evaluate the effect of HR prediction on the calculated NI values; at each second of data, artifact-free NI were calculated for the next minute, and 4 NI values were calculated using 1 to 6 seconds of predicted HR. These predicted NI values were compared to the artifact-free NI to evaluate the accuracy of predicted NI values (NI error) and explore possible indicators of large NI errors. To mitigate the effects of capnography zeroing artifacts, compromised data segments were replaced by the average of the three previous breaths.

Results: NI errors were calculated for 64 cases corresponding to 99.6 hours of anesthetic data. HR prediction lengths, and predicted NI values, were determined to be the strongest predictors of the NI error (see Figure 1). They were therefore used to define the SQI. For a 1 second prediction, the error remains below 15 for any predicted NI, while for a 6 second prediction it exceeds 30 for high predicted NI values. An NI error of 30 was established as the maximum tolerance before the data is no longer deemed to be of acceptable quality, and the SQI is set to zero until new valid data are acquired.

Conclusion: The HR prediction algorithm and respiratory interpolation successfully mitigated the effect of artifacts, improving the overall response of the CRC algorithm by reducing NI signal distortion when artifacts are present. This will allow for real-time operation of the NI in the OR. Future steps include validation and verification of the algorithm and the SQI during general anesthesia.

References: [1] Conf Proc IEEE Eng Med Biol Soc.;2012:3813-6. [2] J Clin Monit Comput. 2013;27(5):551-60

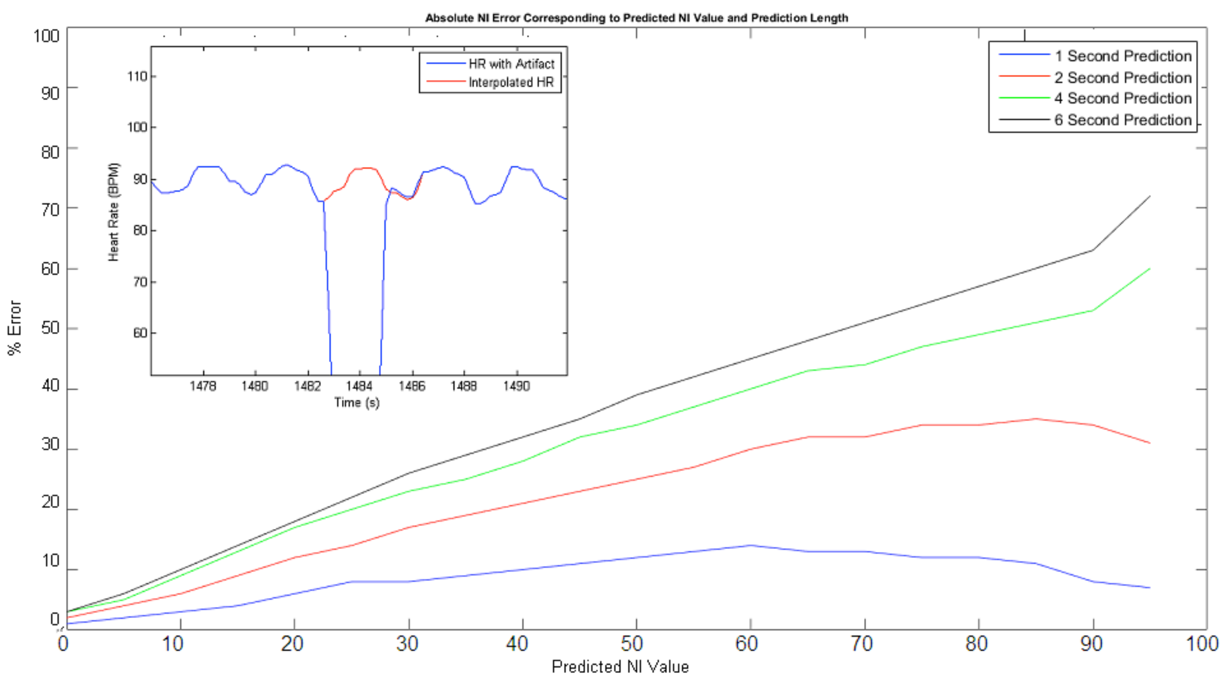

Figure 1: Nociception Index (NI) error for varying HR prediction lengths. Data are split by the length of predicted HR samples used in the NI computation. Predicted NI values were sorted into bins, in increments of 5, and the NI error (predicted NI - artifact-free NI) distribution of each bin was evaluated. These plots represent the 99^{th} percentile error of each bin. The inset subplot shows an example of an episode of heart rate artifact, which was substituted with a predicted heart rate.