Sedation Prediction using EEG Spectrogram in ICU Patients

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NEUROLOGY

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Introduction

1. Both over- and under-sedation are common in ICU patients, which can lead to longer ICU stay, more adverse events and eventually poorer clinical outcomes [1].
2. Various clinical sedation assessment tools have been designed to monitor sedation levels in the ICU with interference with the patient and limited time resolution [2].
3. To overcome these disadvantages, brain monitors that track electroencephalogram (EEG) features have been proposed as a real-time alternative to clinical assessments [3].
4. Existing monitors have been tested almost exclusively in the surgical setting, without being optimized for use in ICU patients with higher illness variability.
5. Existing monitors extract various hand-crafted EEG features from both time and/or frequency domains, predict a noisy sedation level for each EEG segment and then smooth them to get a stable index [4].

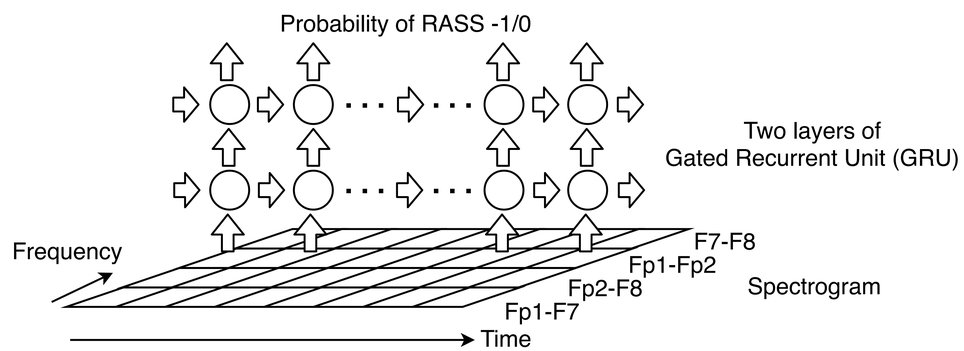
Dataset

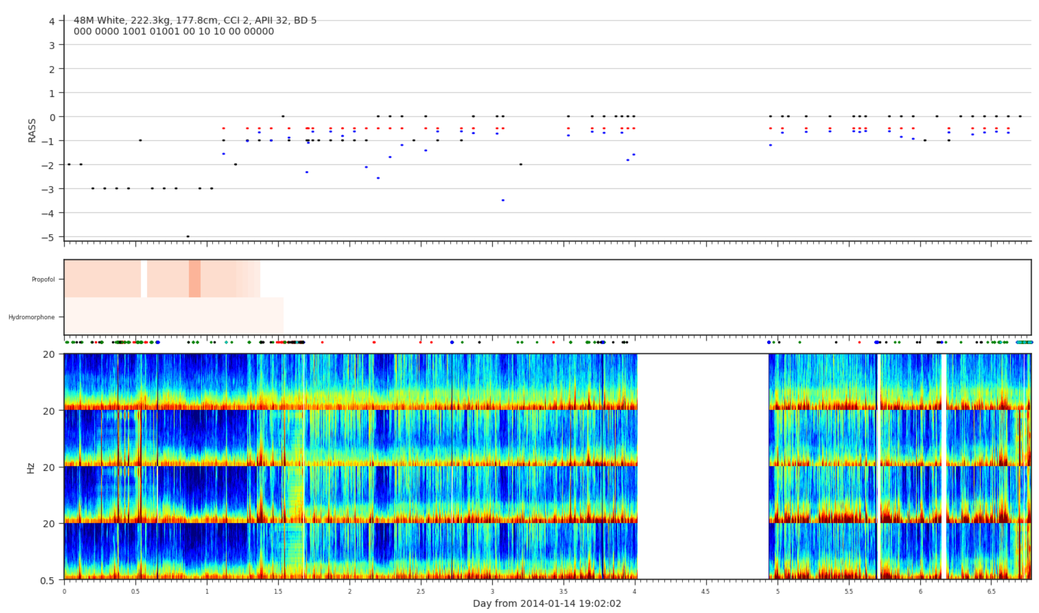
Characteristic	Median (IQR)
#Patient	154
Age (year)	60 (51 – 75)
Sex	F 49 (32%); M 105 (68%)
Race	White 135; Black 9; Asian 2; Unknown 8
BMI (kg/m2)	29 (23 – 35)
Days in ICU	12 (7 – 19)
APACHE-II	22 (15 – 28)
CCI	3 (2 – 4)
Sepsis	22 (14%)
ARF	92 (60%)
Surgery	31 (20%)
Cardiac	10 (6%)
Liver or renal failure	35 (23%)

Table 1: Patient characteristics (Approved by MGH IRB)

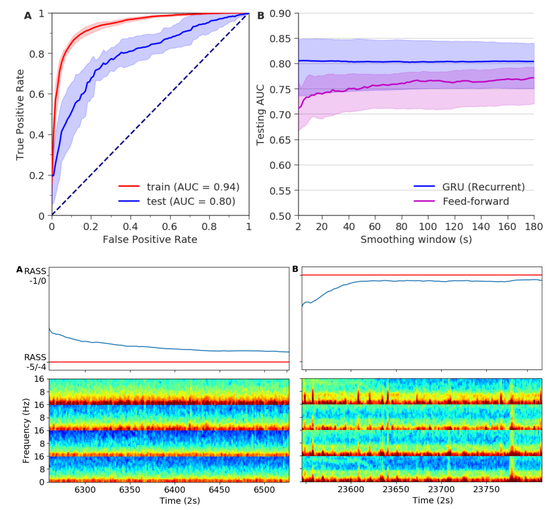
Methods

1. **Reference sedation levels** Richmond Agitation Sedation Scale (RASS) is assessed every 2 hours. We consider only assessments with RASS -5/-4 (deeply sedated) vs. -1/0 (not sedated).
2. **EEG** 10min before each RASS assessment; Fs 250Hz at Fp1-F7, Fp2-F8, Fp1-Fp2 and F7-F8; bandpass between 0.5Hz and 16Hz; multitaper spectrogram estimation with 2 Hz resolution.
3. **Artifact removal** amplitude >500uV; or spectrum is spuriously staircase-like, indicating non-physiologic artifacts from ICU machines. About 10% of the data is removed.
4. **Classification** 2-layer GRU with 32 hidden nodes [5]. 10-fold cross validation.





Results



Discussion

1. **Robustness** The ability of the GRU to learn and appropriately forget temporal context makes it possible to ignore minor perturbations and hence more robust to artifacts.
2. **Smoothing** This model obtains an average testing AUC at 0.8 without any additional feature extraction or smoothing. A feed-forward model followed by smoothing obtains lower AUC, where smoothing leads to stable estimates of sedation levels while creating a response delay. In contrast, the RNN model achieves both low-variance estimates of sedation level and short delay time.

Future Works

1. Ordinal regression to use all RASS levels.
2. Using waveforms instead of the spectrogram.
3. Personalized calibration.

Conclusion

Reliable sedation monitoring in ICU patients can be achieved using a recurrent neural network trained end-to-end from EEG spectrograms. The sedation level predictions are stable (low variance) without ad hoc smoothing.

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Reference

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