Dynamic quantitative EEG signatures predict outcome in cardiac arrest

Edilberto Amorim, MD*; Mohammad Ghassemi, MPhil*; Jong W. Lee, MD, PhD; M. Brandon Westover, MD, PhD

Department of Neurology, Massachusetts General Hospital; Laboratory of Computational Physiology, Massachusetts Institute of Technology; Department of Neurology, Brigham and Women's Hospital.

INTRODUCTION

- Current prognostication strategies in cardiac arrest do not take full advantage of continuous measurement of neural networks' function provided by EEG
- We developed a pipeline that utilizes machine-learning methods and quantitative EEG (QEEG) features to provide continuous estimation of neurological recovery potential[1]

METHODS

- Retrospective
- Two academic centers in the U.S.
- Adult subjects
- First 48 hours of EEG recording from return of spontaneous circulation
- EEG: data streamed from Cz channel exclusively

QEEG features:
- Regularity
- Tsalis Entropy
- Alpha-to-Delta Ratio
- Subband Information Quantity (IQ)
- Voltage <10 uV

Poor outcome (at discharge):
- Cerebral Performance Category: 3-5

Statistical Analysis:
- Learning algorithm:
  10-fold cross validation resampling method
- Model performance:
  Logistic regression
  Area under ROC curve (AUC)
  Sensitivity and Specificity

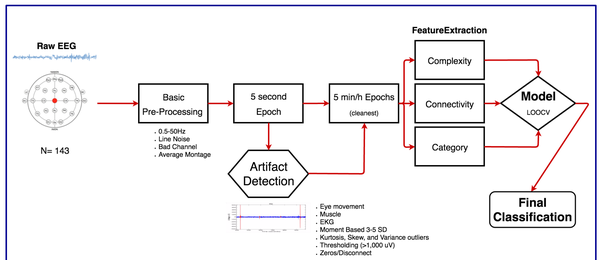

Figure 1: QEEG prognostication model pipeline

RESULTS

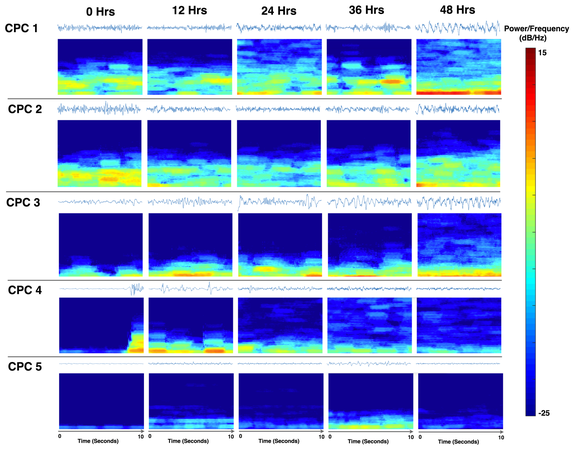

Figure 2: Illustration of EEG and spectrogram signatures evolution over 48 hours of five patients with distinct functional outcomes at discharge.

Table 1: Demographics

	CPC 1-2 N=37	CPC 3-5 N=106	Total N=143
Age* **(mean; SD)**	51.1 (19)	60.5 (18.5)	58.1 (19)
Female	37.8%	40.6%	39.2%
VF/VT*	64.9%	31.7%	39.2%

Mortality: 61.5%
* p<0.05

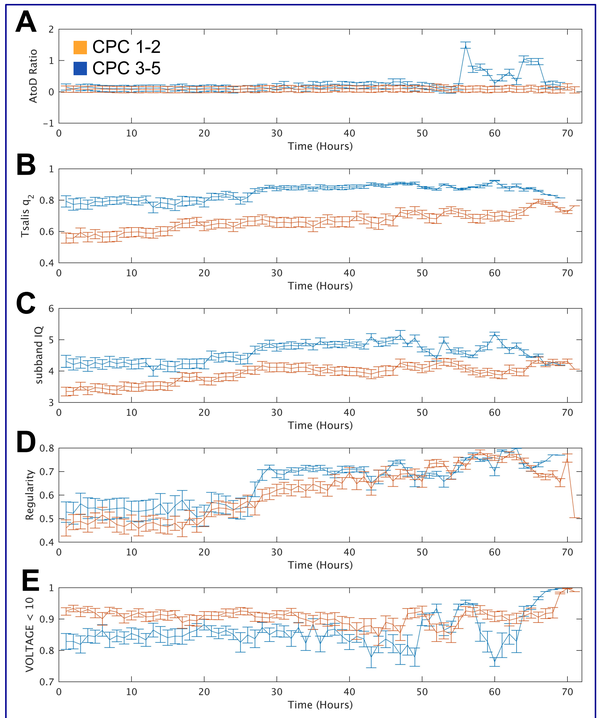

Figure 3: QEEG features trajectory with corresponding 95% confidence intervals by outcome group over 72h. **A:** Alpha-to-Delta Ratio; **B:** Tsalis Entropy; **C:** Subband IQ; **D:** Regularity; **E:** Voltage <10uV

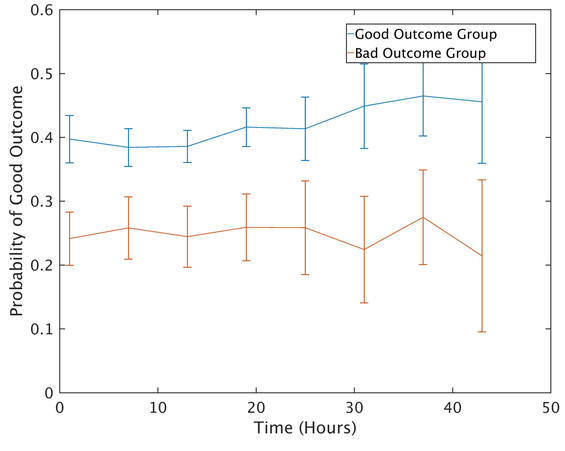

Figure 4: An adaptive prediction model demonstrated early separation of outcomes trajectories.

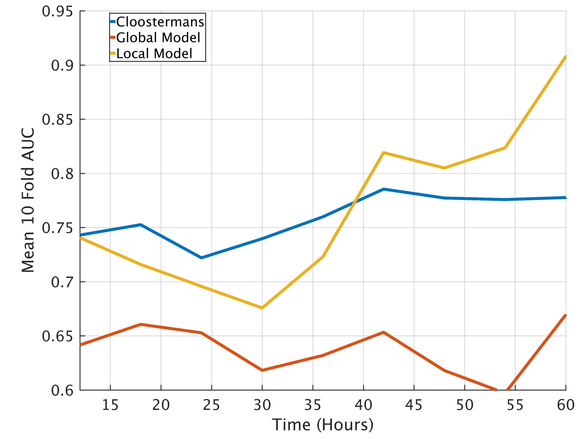

Figure 3: Superior outcome prediction performance was achieved by an adaptive model that recalibrates its prediction every 6 hours (local model). This approach outperformed methods that evaluate QEEG features change continuously (global or Cloostermans's model).[2]

- Our adaptive algorithm was able to identify outcome trajectory separation by 12 hours of recording ($p < 0.05$)
- Optimal performance was achieved at 36 hours (AUC 0.84) with FPR of 7% and sensitivity of 66% ($p < 0.0001$).

CONCLUSIONS

- Outcome prediction models in cardiac arrest that utilize QEEG should account for the dynamic changes of EEG patterns as a function of time
- Employment of machine-learning methods on QEEG analysis allows for early and robust outcome prediction in cardiac arrest

REFERENCES

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2. Tjepkema-Cloostermans MC, van Meulen FB, Meinsma G, van Putten MJ. A Cerebral Recovery Index (CRI) for early prognosis in patients after cardiac arrest. Critical care 2013;17:R252.

Contact: Ed Amorim, MD eamorim@mgh.harvard.edu
*These authors contributed equally to this work. Disclosures: none