Prediction of Cardiac Arrest Recovery by Analysis of the EEG and ECG

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Background

Post-anoxic coma after resuscitation from cardiac arrest (CA) is due to a temporary lack of oxygen to the brain. Only 20% to 30% of all patients survive after the first 24 hours of being in the coma state [1]. The outcomes of this condition range from full neurological recovery to different degrees of neurological disability quantified by the Cerebral Performance Category (CPC) scale [2]. This score is determined by using a 19-channel scalp EEG system along with one ECG channel to collect data from adult ICU comatose patients after return of spontaneous circulation following CA. The data collected is analyzed in real-time with generalized partial directed coherence plots (GPDC). Accurate prognosis of a patient's neurological recovery is vital for guiding physicians in determining future treatment plans and resource allocations.

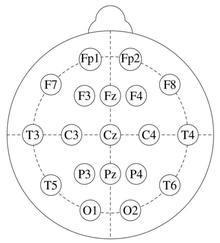

Figure 1: A standard 10-20, 19 channel scalp EEG montage [3]

Data was provided by the George B. Moody PhysioNet Challenge and collected by the International Cardiac Arrest REsearch (I-CARE) consortium from seven academic hospitals in the U.S. and Europe. EEG was monitored up to 72 hours post-ROSC, with varying duration/start-times between patients. The dataset also included patient age, sex, location of CA, time between CA and ROSC, presence or absence ventricular fibrillation, and targeted temperature management.

Mission Statement

We strive to provide accurate prognosis for post-cardiac arrest patients to receive a better life-sustaining treatment.

Product Specifications

CPC Score	Outcome
1	Full Neurological Function
5	Death

Variables	Values
Sampling Frequency	500 Hz
Butterworth High Pass Cutoff	0.1 Hz
Comb Filter	25 Hz intervals (until 200 Hz)

Scan here to view the complete list of product specifications.

Prototype

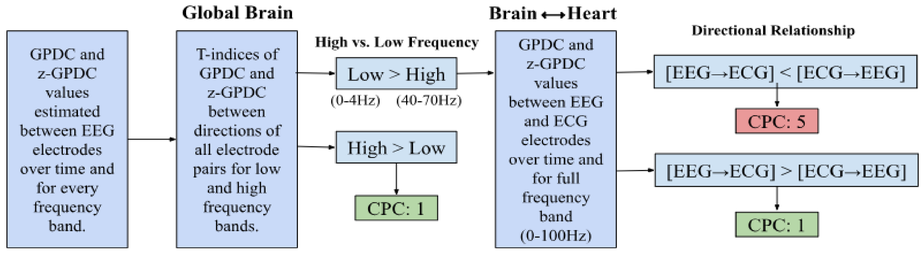

Figure 2: Flow diagram displaying the steps taken in the algorithm to determine a patient prognosis. These steps include the analysis of the GPDC, T-GPDC, and TZ-GPDC values and the respective evaluation criteria.

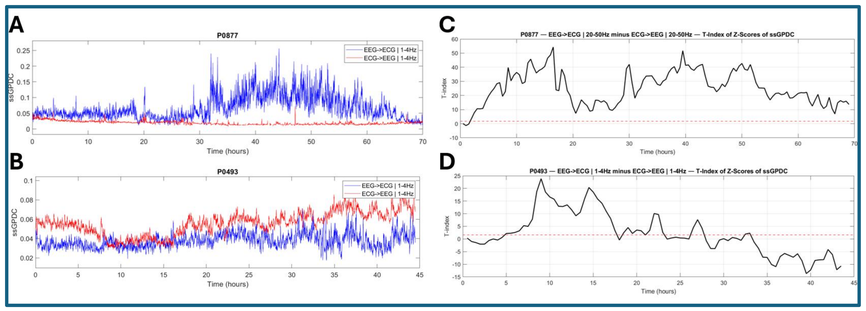

Figure 3: GPDC profiles between Brain and Heart averaged over low frequencies (A) per directional flow of information and their T-index profile (C) for a patient with good outcome (CPC=1), and for a patient with poor outcome (CPC=5) in (B) and (D), respectively.

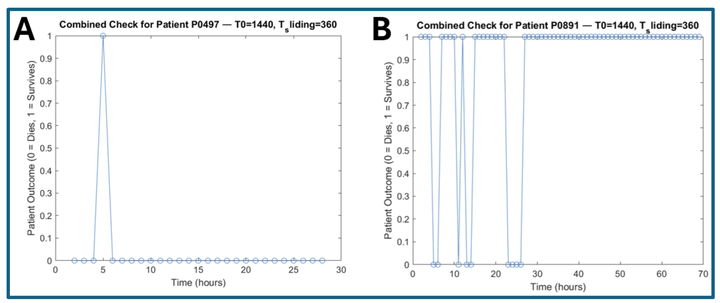

Figure 4: Algorithm outputs over time for patients with (A) good outcome and (B) poor outcome generated through MATLAB using a sliding window of 4 hours.

Technical Model

$$\textbf{Fourier Transform: } X(f) = \int_{-\infty}^{\infty} x(t)e^{-j2\pi ft}dt$$

Generalized Partial Directed Coherence (GPDC) is a linear, scale-independent measure of directed connectivity in the frequency domain [4] used to analyze how different brain regions influence each other across channels and frequency bands related to specific brain functions. These GPDC profiles are also statistically (z-scored) normalized with respect to the first hour, per direction, in each pair of time series (referred to as z-GPDC). The difference between the two directions in the GPDC and z-GPDC profiles is quantified by the statistical distance of their mean values provided by the t-test, which we have called T-index of GPDC and z-GPDC, respectively.

Verification Results

Linear Discriminant Analysis (LDA) is a common machine learning technique for data classification and dimensionality [5]. We developed an LDA classifier, cross-validated with k=5 folds, to classify between a good and poor outcome. Data from 25 patients with known CPC scores and EEG/ECG recordings with minimal artifacts were analyzed. Each fold had 5 patients as the testing dataset and the remaining 20 as the training dataset. Each patient in the testing dataset was assigned a 0 or 1 according to the algorithm's prognosis (see **Figure 4**). This procedure was repeated 5 times until all patients were included in the 5 testing datasets. The ROC curve (see **Figure 5**) was also generated to optimize the performance of the algorithm with respect to the T_0. The sensitivity of the algorithm was maximized with T_0=4 hours.

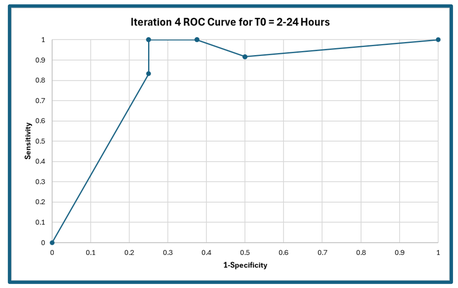

Figure 5: Example Receiver Operating Characteristic (ROC) curve, revealing the sensitivity and specificity within each time reference window (T_0).

Sliding Window (T_0) = 4 Hours	
True Positive	13 Patients
True Negative	9 Patients
False Positive	3 Patients
False Negative	0 Patients
Positive Predictive Value (PPV)	13/16 = 81.25%
Negative Predictive Value (NPV)	9/9 = 100%
Sensitivity	13/13 = 100%
Specificity	9/12 = 75%
Accuracy	88%

Design Status and Future Work

The next steps of our product allow for an effortless user experience by advancing the graphical user interface. Also, we will seek to increase the algorithm's specificity while maintaining its high sensitivity. In doing so, the algorithm can then be applied in real-time with ICU devices. Regulatory steps would involve following those of a Class II software device and 510K pathway.

Acknowledgements

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References

Scan here to view the references utilized.