

Prediction of Cardiac Arrest Recovery by Analysis of the EEG and ECG Jonah Bois¹, Jessica Feltovich¹, Jake Malobicky¹, Katie McFarland¹, Yasmine Sleiman¹

Background

Post-anoxic coma after resuscitation from cardiac arrest is due to the occurred 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]. A CPC score of 1 would mean that the patient had full recovery of all neurological function, while a score of 5 would mean death. Accurate prognosis of a patient's neurological recovery is vital for helping physicians in determining future treatment plans and resource allocations.

Mission Statement

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

Project Planning



Gantt Chart: Tracks weekly progression of iNeuroCardia's project.

Customer Need		Metric	Ideal \		
Accurate Prognosis		CPC Ranking	1-5 (Comp Ran		
Algorithm Training		True Positive Rate (TPR)	> 80		
Risk of Harm		False Positive Rate (FPR)	< 5		
Output Replicability		Physician Feedback (1-5 Rating)	5/		
Algorithm Efficiency		Time to Produce Output	Real-		
Compatibility		Ability to connect with ICU devices/wearables	At least 4 simultar		
User Friendliness		End-User Training Time	<1+		
Reasonable Cost		Licensure	\$18,000 -		
House of Quality: Ranks our product along wit benchmarks based on their application to ea and metric.					
Manufacturing Design					
	1 1/2 2 1				

Design Inputs

License	1-Year Individual	1-Year Site (4	1-Yea
		EEG Machines)	EEG N
Price	~\$10,000	~\$18,000	~\$

Mentors: Dr. Stephen Helms-Tillery¹, Dr. Leonidas lasemidis^{1,2} ¹School of Biological and Health Systems Engineering, Arizona State University ²Department of Translational Neuroscience, Neurology and Neurosurgery, Barrow Neurological Institute, Phoenix, AZ

Device Concept and Design







We will develop a software module for analysis of the EEG and ECG signals from cardiac arrest (CA) patients using linear (Fourier-based and autoregressive modelbased) and nonlinear (entropy) measures of dynamics over hours following CA. The performance of the thus derived features for categorizing CA patients in agreement with the CPC scale will be assessed by Linear Discriminant Analysis (LDA), a common machine learning technique for data classification and dimensionality reduction [3]. A LDA classifier cross-validated with k=5-folds will classify between a good and poor outcome from post-anoxic coma using our extracted features from the linear and nonlinear methods of analysis. K-fold cross-validation randomly splits the data into k subgroups, using one of the k subgroups as test data, with each subgroup being used once as the test set over k iterations. A k-fold crossvalidated model produces k sensitivity and specificity results, which are then averaged to estimate the device's overall performance.





Product Specifications

CPC Score	Outcome		Variables	Values
1	Good Neurological Function		Sampling Frequency	500 Hz
5	Death		Butterworth High Pass Cutoff	0.1 Hz
Key Band Frequenci Theta	es	Value 4 – 8 Hz	Comb Filter	25 Hz intervals (until 200 Hz)
Alpha		8–12 Hz	Class/Pathway	Class II/510k

Value olete CPC nge) 0%

5%

Time

devices neously

Hour

\$24,000

n 5 other ch need

ar Site (10 Machines) 24,000

Figure 2: 10-minute segment of high pass and comb filtered EEG signal, which is then band-pass filtered from 4-12 Hz.

Figure 4: Average approximate entropy values in bipolar channels T3-T5 for patients in two different outcome groups. This was computed over 10 second segments for each hour.



Figure 5: Initial product architecture displaying input and output relationships based on our developed technical models. This shows the process from raw data input, to analysis techniques, and to the results that will be provided by the final product.

Band Powe

Shannon E

Power Spec

Fourier Tra

Larger Shannon entropy values correlate well with more disorder in brain activity, indicative of parallel multi-processing and healthy cognitive function [4,5].

Design Status and Future Work

The FFT-based methods of analysis are in the final stage of development (integration with the main code to start producing) massive results over time per patient). The autoregressive modelbased methods of analysis are in the stage of testing with simulation data. The nonlinear methods of analysis are also in the testing phase. We have just begun exploring the integration of the machine learning part of the design.



We would like to thank our collaborators at Barrow Neurological Institute, Dr. Leonidas Iasemidis and Alexander Nicholas, for their guidance and support during this project. Another thank you goes out to our faculty mentor, Dr. Stephen Helms-Tillery, for providing additional input and expertise.





Product Architecture

er:
$$P_{band} = \int_{f_1}^{f_2} PSD(f) df$$

entropy: $H(x) = -\int_{-\infty}^{\infty} p(x) \cdot \log_2[p(x)] dx$
extral Density: $PSD(f) = |X(f)|^2$
ensform: $X(f) = \int_{-\infty}^{\infty} x(t)e^{-j2\pi ft} dt$

Acknowledgements

References

Scan here to view the references utilized.