ASCS: Automated Sleep Classifier System

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Abstract

The ASCS prototype is comprised of a battery-powered sensor device for recording EEG (electrical-brain- activity) signals and a machine learning algorithm for classifying and organizing gathered data in a research-friendly format. The ASCS is a low cost alternative to similar EEG recording devices with greater potential for accuracy than non-EEG-based sleep classifying devices like FitBit or Apple Watch.

Austin (Electronics concentration) designed, programmed, and tested the battery-powered ASCS sensor device printed circuit board (PCB). The goal of the design is to prepare low-voltage EEG signals for digitization, provide the necessary storage for a night's worth of data, and stay running for at least 10 hours.

Brandon (AI/ML concentration) implemented a fully trained algorithm that's capable of classifying sleep EEG data. Additionally, he analyzed the output data from the device and formatted it to seamlessly implement into the algorithm.

Parker Parmacek (Energy concentration) developed a charging system for devices like the ASCS sensor as his Capstone Project.

Background

Sleep health science is an important field of study for improving quality of life. One way scientists identify irregularities and harmful patterns in sleep is through electrical brain activity, the recording of which is called electroencephalography (EEG). The highest quality EEG recordings are usually done in sleep study labs with expensive equipment that can cause discomfort for patients, and the results from these studies are difficult to interpret without professional training. More commercially accessible devices that measure sleep do so with less accurate methods than EEG and are usually incapable of producing the kind of digital data researchers could analyze with sophisticated programs or share for further study.

Acknowledgements

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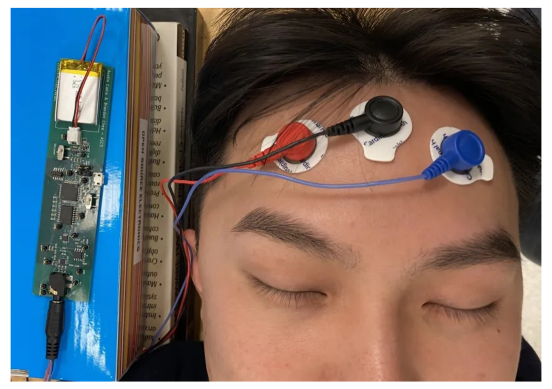
- Prof. John Lund: Device development & soldering expertise
- Reza Afshari: Soldering tools and assistance
- Prof. Todd Morton: Sensor device code development
- Prof. Junaid Khan: Advising

Methodology

Hardware & Software: Electrodes → Filters & Amplifiers → Microcontroller Analog to Digital Converter → Machine Learning Algorithm →

Signals & Data: Brain Activity | Noisy Signal (~100µV) | Signal (~1V, 1-35Hz) | Sampled Signal (fs = ~500Hz) | Formatted Data and Sleep Stages



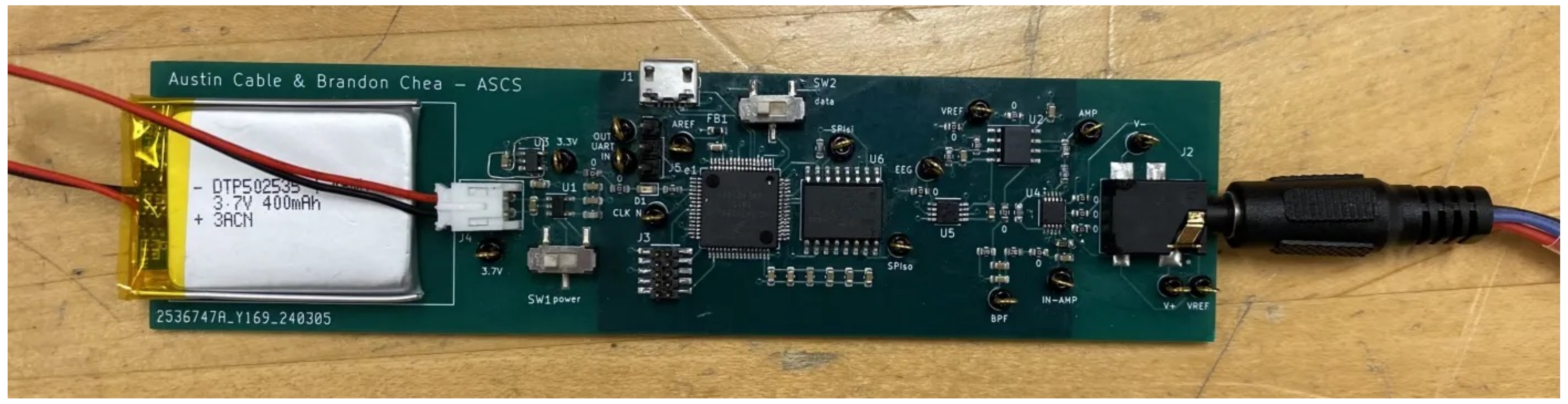
Hardware

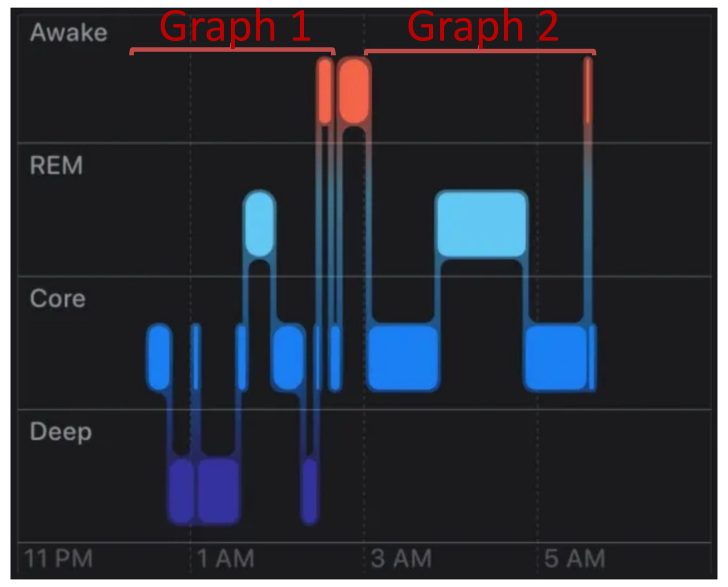
- Microcontroller Unit (MCU): NXP KL26
  - 16-bit SAR Analog to Digital Converter
- External Flash Memory (64MB)
- High quality In-Amp and Op-Amp
- Battery and power circuitry
- Connectors, switches, LED

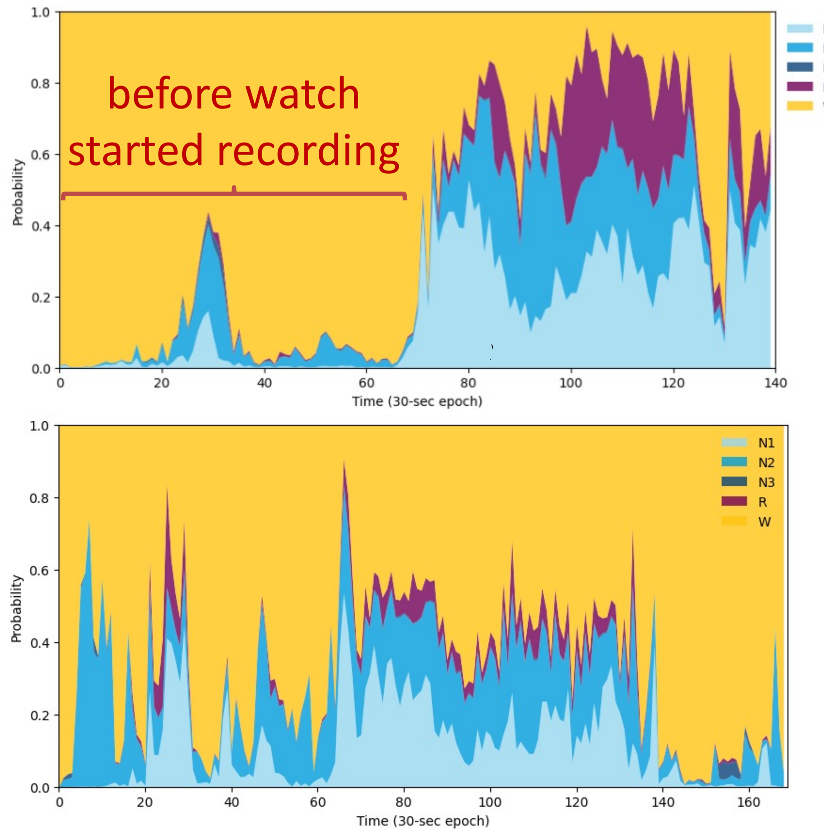
Software

- MCU programmed in C
  - uC/OS-III real time operating system
- Classification Algorithm
  - Written in Python
  - Trained on sleep databases
  - Libraries: YASA and SleePyCo (Sleep-classification), and MNE (EEG)

Results







Apple Watch graph (left) of sleep stages vs YASA interpretation (right) of ASCS sensor device data from the same night of sleep.

- Sensor device prototype capable of recording and storing EEG signal data for at least 9 hours of sleep on a full battery charge
  - Low cost (~$60)
  - No heat or sound
- Algorithm that processes, classifies, and formats sensor data
  - Outputs research-friendly .edf files

Challenges and Future Direction

Current Problems

- Transmitting data via USB (connecting both halves)
- Noise levels on EEG signal from filters and amplifiers
- Accuracy of classifying data from sensor device

Temporary Workarounds

- Recording device data with Logic Analyzer
- Additional layer of filtering by disconnecting device sections

Future Work

- Data transmission via USB
- Improve amplification and filtering of input signal
- Reduce size of printed circuit board
- Higher quality electrodes for improved signal quality
- Casing and on-board electrodes for wearability
- Algorithm accuracy refinements
- Add intuitive algorithm user interface

	N1	N2	N3	R	W
epoch					
0	0.006490	0.001413	0.000014	0.000620	0.991463
1	0.008722	0.001827	0.000708	0.000530	0.988212
2	0.001949	0.001123	0.000103	0.000189	0.996636
3	0.002168	0.001222	0.000049	0.000007	0.996554
4	0.001745	0.000900	0.000030	0.000011	0.997314
...	...	...	...	...	...
135	0.345501	0.067010	0.000312	0.109238	0.477940
136	0.335724	0.111635	0.001463	0.203814	0.347364
137	0.417680	0.051762	0.000754	0.200650	0.329154
138	0.381248	0.046219	0.000602	0.110797	0.461133
139	0.444271	0.100598	0.001142	0.131740	0.322249

140 rows × 5 columns

The numbers in the table better quantify the data shown in the graph to the left. It shows the likelihood of the various stages at the specified epoch.

References

S. Lee, Y. Yu, S. Back, H. Seo, and K. Lee, "SleePyCo: Automatic sleep scoring with feature pyramid and contrastive learning," Expert Systems with Applications, vol. 240, p. 122551, 2024. doi: 10.1016/j.eswa.2023.122551.

R. Vallat and M. P. Walker, "An open-source, high-performance tool for automated sleep staging," Elife, vol. 10, 2021. doi: 10.7554/eLife.70092.

Muhammad Sheeraz, W. Saadeh, and Muhammad, "A Wearable EEG Acquisition Device With Flexible Silver Ink Screen Printed Dry Sensors," May 2023, doi: https://doi.org/10.1109/iscas46773.2023.10181812.

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Capstone Project

Electrical & Computer Engineering Program