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Sensing Emotion through ECG Signals

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Outline

- Introduction to Automated Emotion Recognition - Methods and Results
- Publicly available AER Datasets
- Analyzing ECG Signals
- Data Collection Study: How you can help!



Automated Emotion Recognition

To develop an algorithm to monitor and identify emotions, we need three things:

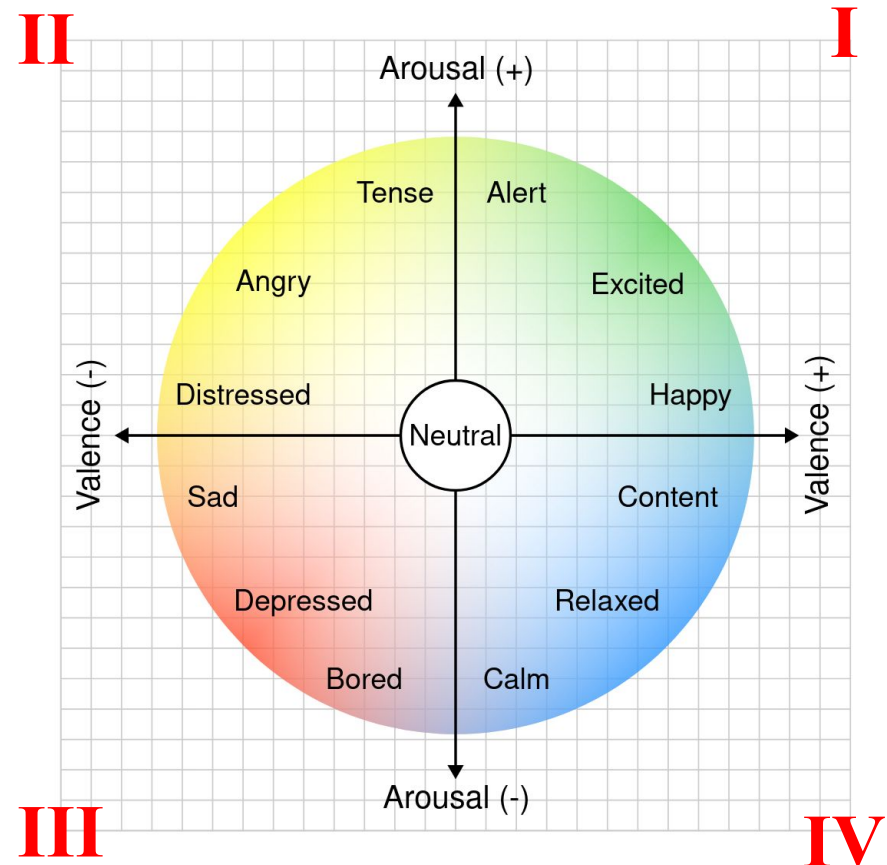
- A classification model (e.g. 6 basic human emotions)
- A method for ground truth assessments (e.g. “How are you feeling right now?”)
- A modality to monitor (e.g. Computer Vision, EKG, ECG, etc)



Emotion Classification

Dimensional Model of Human Emotion

- **Valence:** a characteristic of appeal or repulsion.
- **Arousal:** the state of being alert, awake and attentive
- **Dominance:** a sense of feeling in control (z-axis)



Classification into 4 Quadrants

Ground Truth Assessments

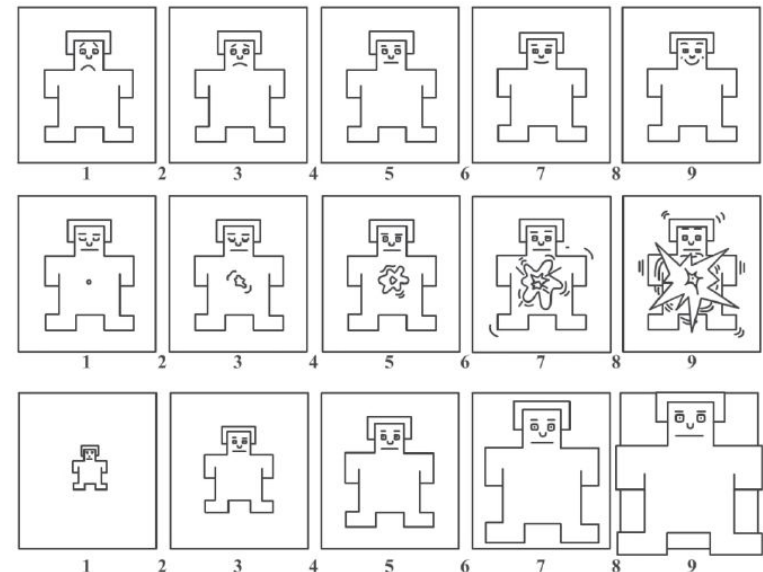
Semantic Differential

- 18 verbal bi-polar scales
(hot-cold, good-evil, etc)
- Literacy and fluency

	Factor 1 "Pleasure"	Factor 2 "Arousal"	Factor 3 "Dominance"
Unhappy-Happy	0.914	0.063	0.148
Annoyed-Pleased	0.883	0.068	0.158
Unsatisfied-Satisfied	0.868	0.144	0.114
Melancholic-Contented	0.725	0.095	0.056
Despairing-Hopeful	0.858	0.063	0.078
Bored-Relaxed	0.580	0.372	0.234
Relaxed-Stimulated	-0.211	0.774	0.052
Calm-Excited	-0.181	0.793	0.056
Sluggish-Frenzied	0.268	0.771	0.005
Dull-Jittery	-0.211	0.793	0.121
Sleepy-Wide awake	-0.046	0.810	0.047
Unaroused-Aroused	0.051	0.827	0.127
Controlled-Controlling	0.262	0.192	-0.673
Influenced-Influential	0.292	0.089	-0.618
Cared for-In control	-0.090	0.198	-0.626
Awed-Important	0.199	-0.040	-0.301
Submissive-Dominant	0.195	0.306	-0.695
Guided-Autonomous	0.161	-0.100	-0.479
Amount of variance accounted for:	24.6	23.12	12.18

Self Assessment Manikin (SAM)

- 3 Question Graphical Questionnaire to Assess:
 - Valence
 - Arousal
 - Dominance



How to Observe Emotions?

Expressive and behavioral, neurological and physiological



- Expressive / Behavioral:
 - Easy to recognize
 - Useful in public or covert surveillance (FACS)
 - Subject to deception



- Neurological / Physiological:
 - Very high correlation
 - Not subject to deception
 - Current applications limited to laboratory environments

Summary of AER Results and Trends

12 years of AER ML/DL Results show clear trends

Highest Predictive Value										Classification Accuracy	
	Model	Year	ECG	GSR	PPG	EMG	EOG	EMO	Arousal	Valence	
Koelstra	GNB	2012		X	X	X	X		0.53	0.61	
Valenza	SVM	2014	X						0.84	0.79	
Subramanian	SVM	2016	X	X				X	0.62	0.64	
Wiem	SVM	2017	X	X					0.64	0.65	
Udovicic	KNN	2017		X	X				0.68	0.66	
Santamaria-Granados	1D CNN	2019	X	Wearable Space					0.76	0.75	
Harper	CNN+LSTM	2022	X							0.9	
Hamad	PETSFCNN	2022	X							0.96	0.98
Sweeney-Fanelli	T-CNN	2024	X						0.99	0.97	

Improved upon CNN by retaining structural knowledge of the input data

Unimodal Emphasis

High Classification Accuracy



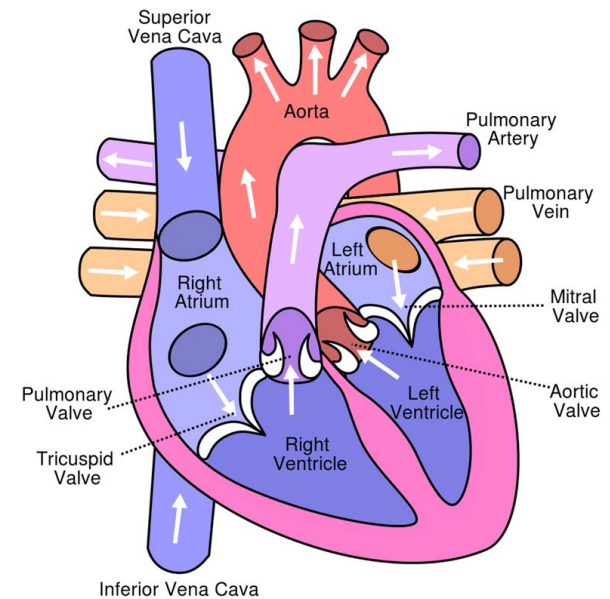
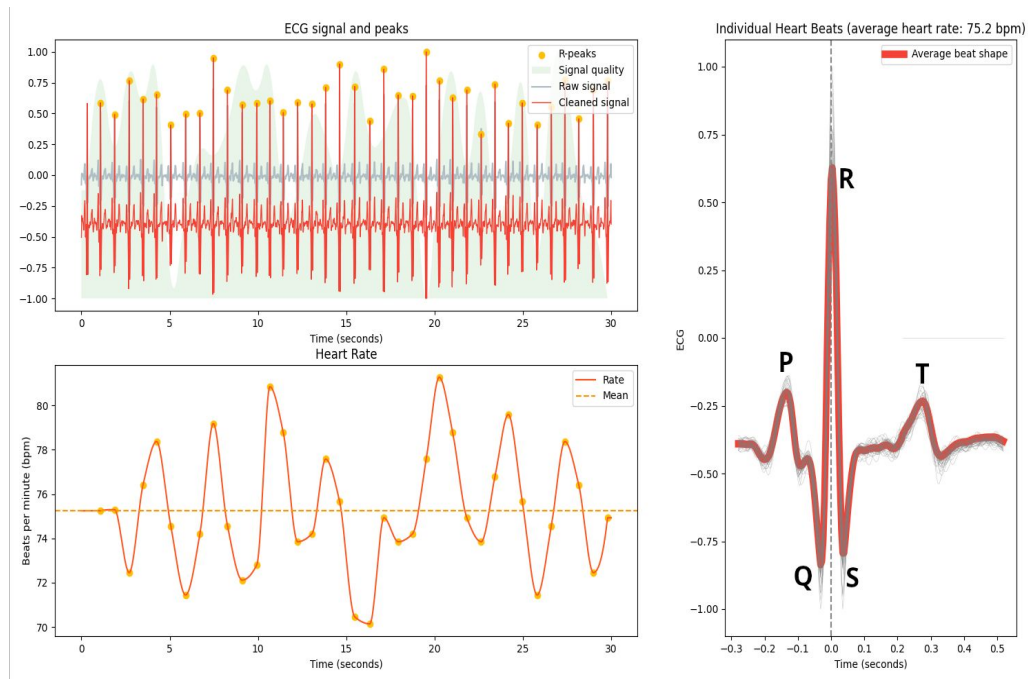
Publicly Available AER Datasets

Several AER datasets which already include ECG and ground-truth correlations:

- ASCERTAIN: <https://ascertain-dataset.github.io/>
- DREAMER: <https://zenodo.org/record/546113>
- MANHOB-HCI: <https://mahnob-db.eu/hci-tagging/>

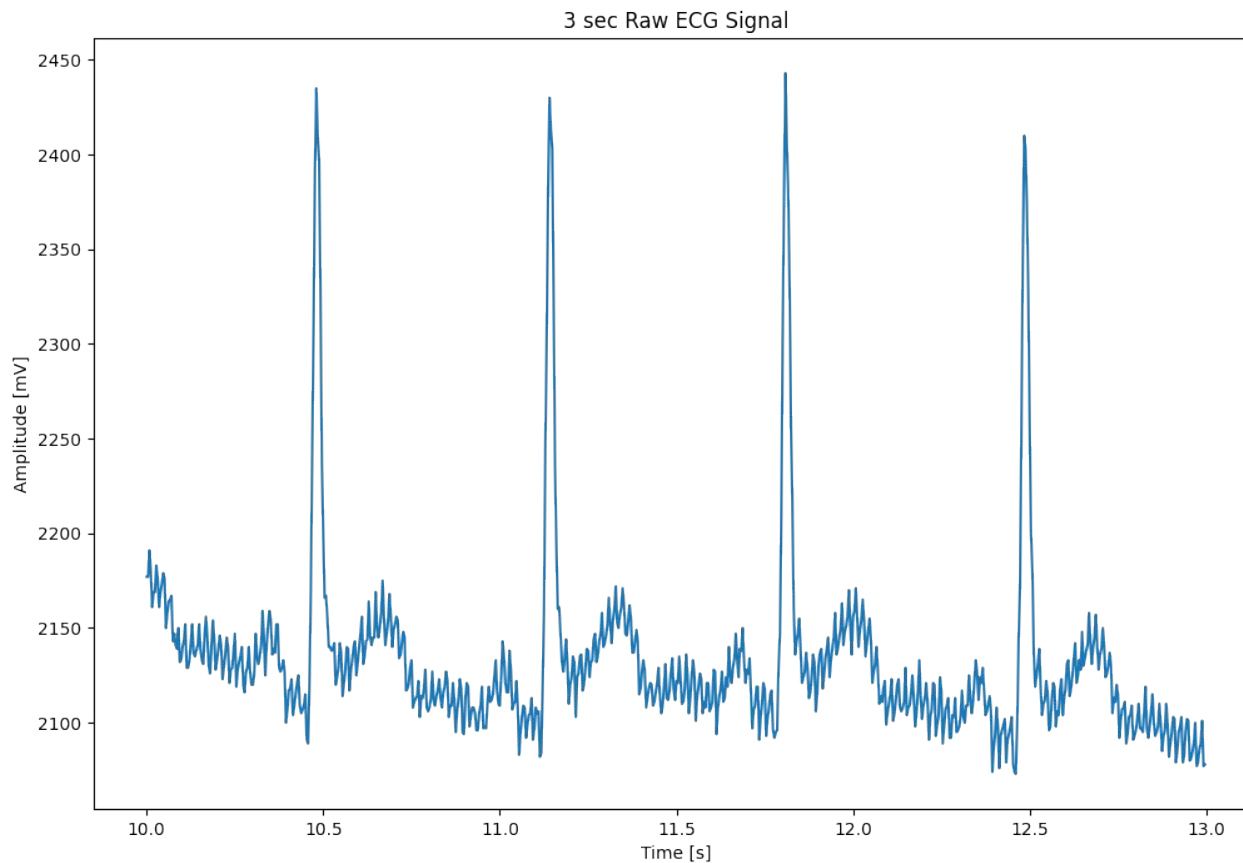
Components of an ECG Signal

- PQRST Complex
 - P-Wave: atrial depolarization
 - QRS Complex: ventricular depolarization (and atrial repolarization)
 - T-Wave: ventricular repolarization



Working with ECG Signals

- Raw ECG Signals are very noisy ... we can see the R-peak, but not much else



Working with ECG Signals

ECG signal filtering is a multistep process. A typical pipeline consists of:

- Removing baseline wander
- Removing powerline interference
- Isolating relevant ECG frequencies (specifically, removing EMG)

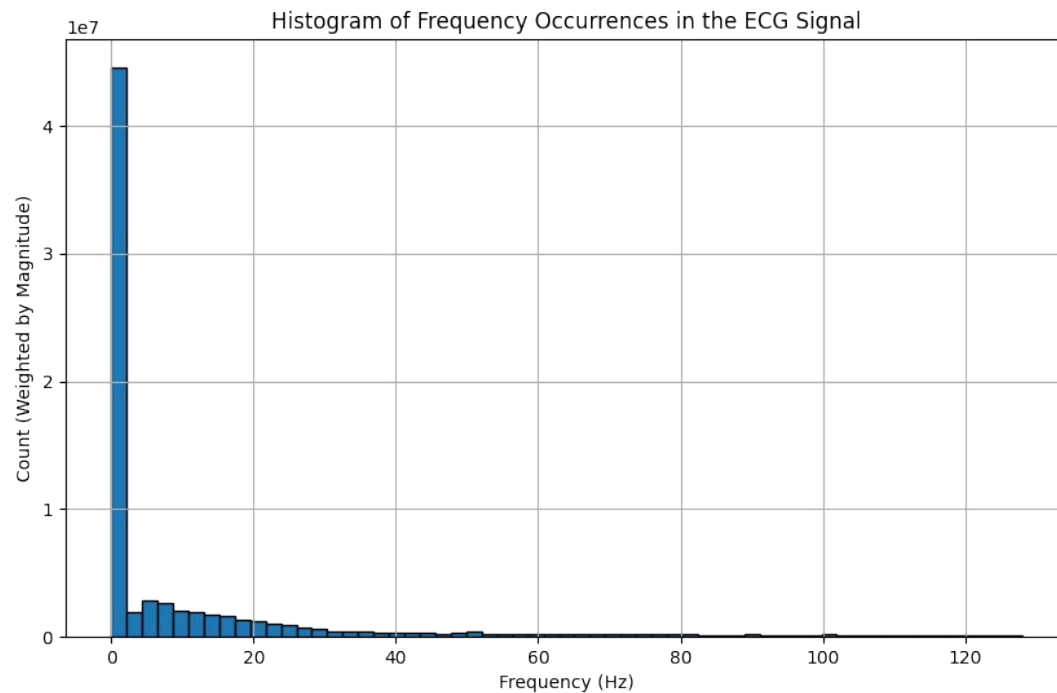
Other situations that come up frequently:

- Polarity inversion due to misplaced leads
- Signal quality rating



Knowing What To Filter Out

- Fast Fourier Transform (FFT) is used to analyze the frequencies within the signal
- We can plot the signal as a histogram showing how much each frequency range contributes to the signal data



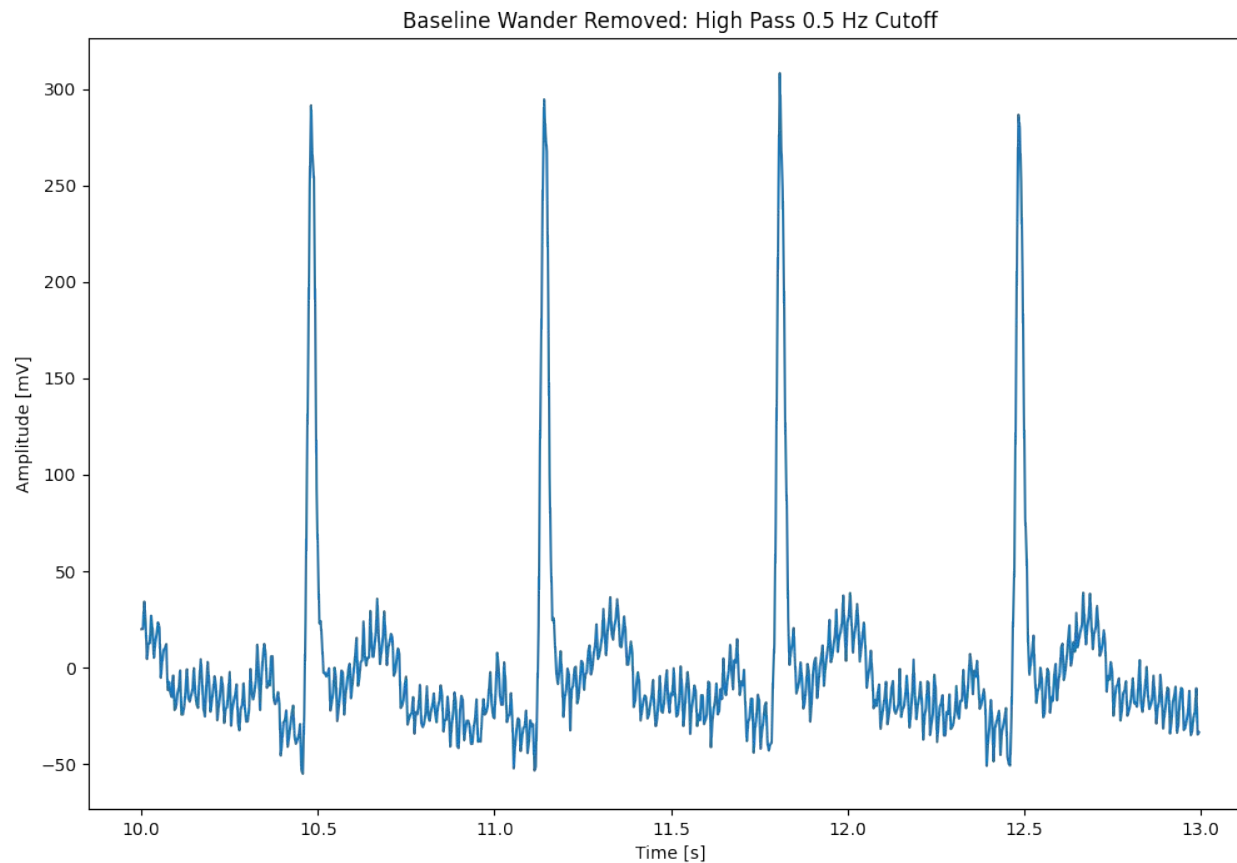
Baseline Wander

- Baseline drift caused by various things:
 - Body movement causing pads to change positions (even respiration)
 - Electrode contact issues (sweat, poor adhesion, etc)
 - Power supply or environment conditions
- Baseline levels tend to change over time, not a fixed offset in the signal
- Can be removed by high-pass filter to remove low-frequency (0.5 to 0.7 Hz) components



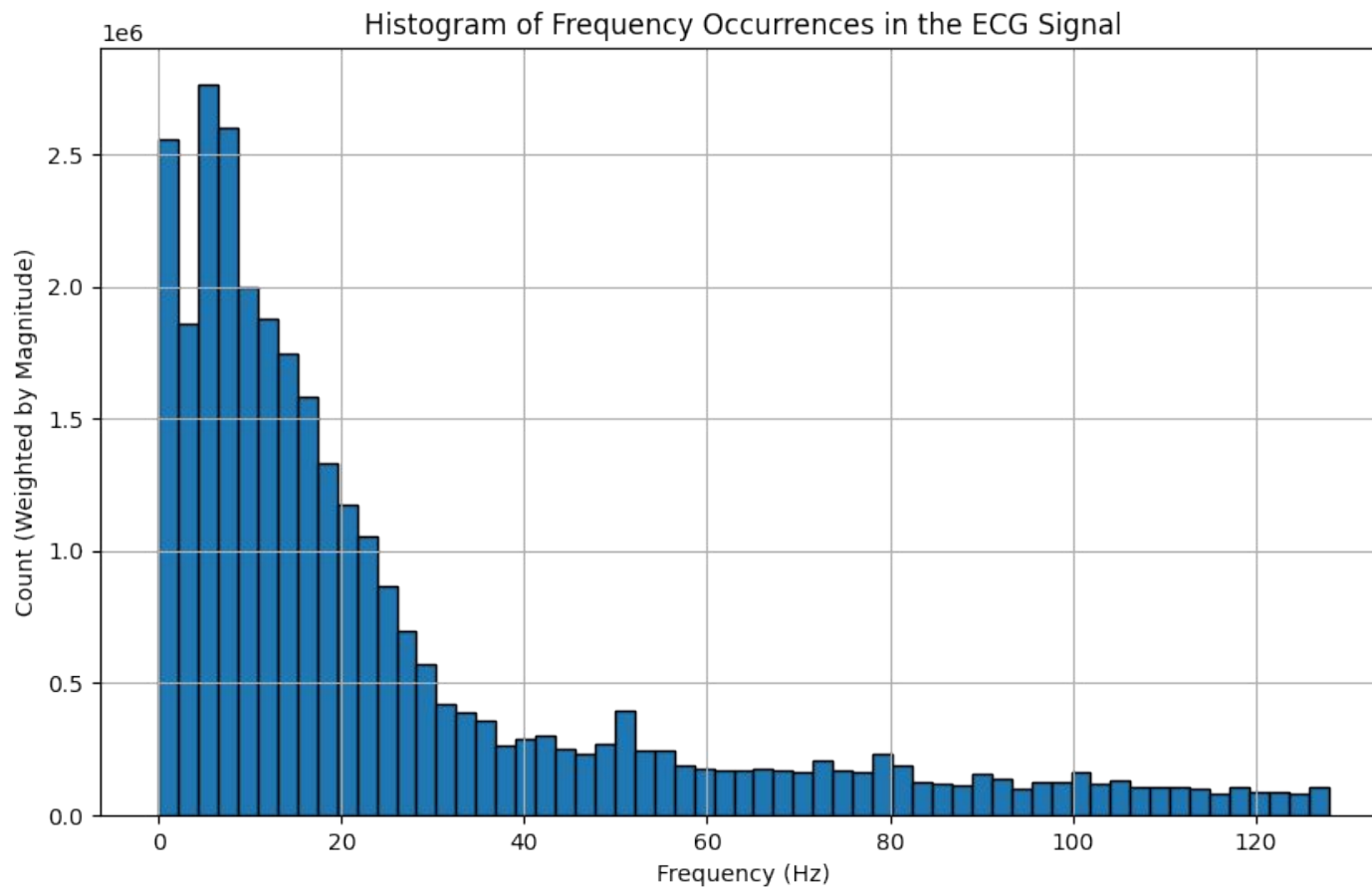
Baseline Wander

- High-pass butterworth filter with cutoff = 0.5 Hz
- Baseline is now 0, and the drift over time is eliminated



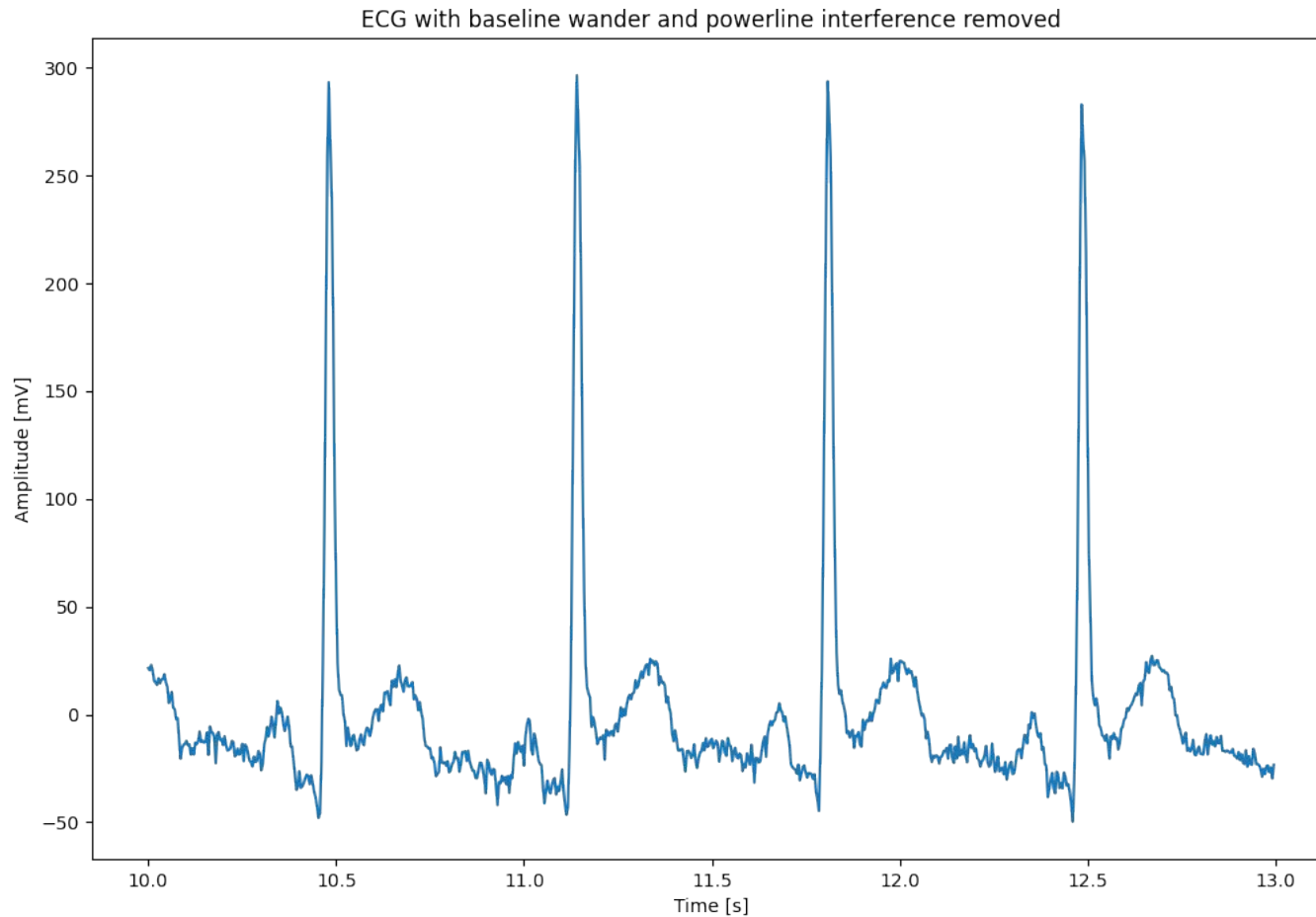
Revisit Frequency Domain ...

- We just took out some low-frequency noise, let's see how much that impacted the frequency distribution ...



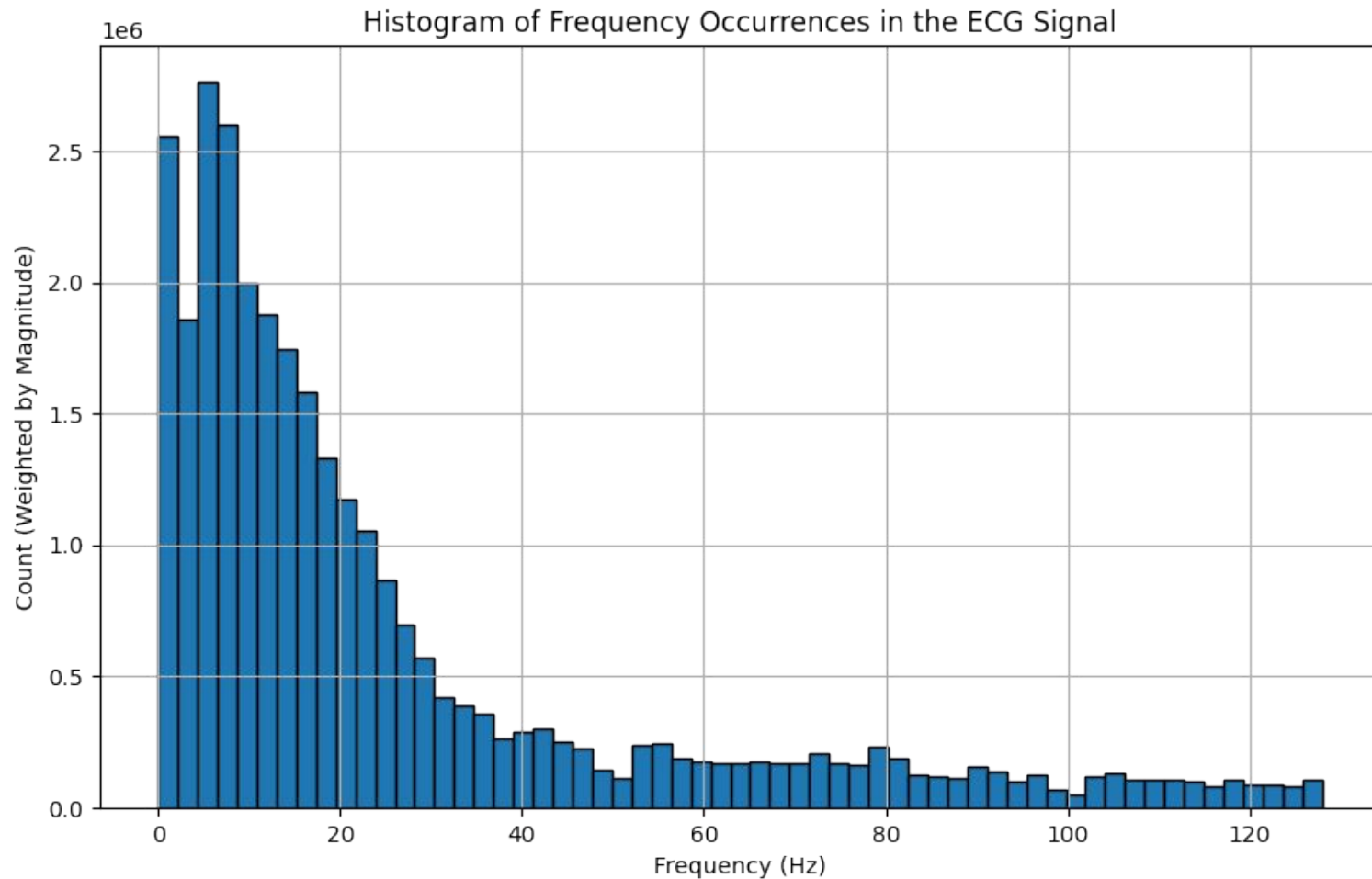
Powerline Interference

- Bandpass Filter to remove 50Hz Frequency Noise (or 60 Hz)



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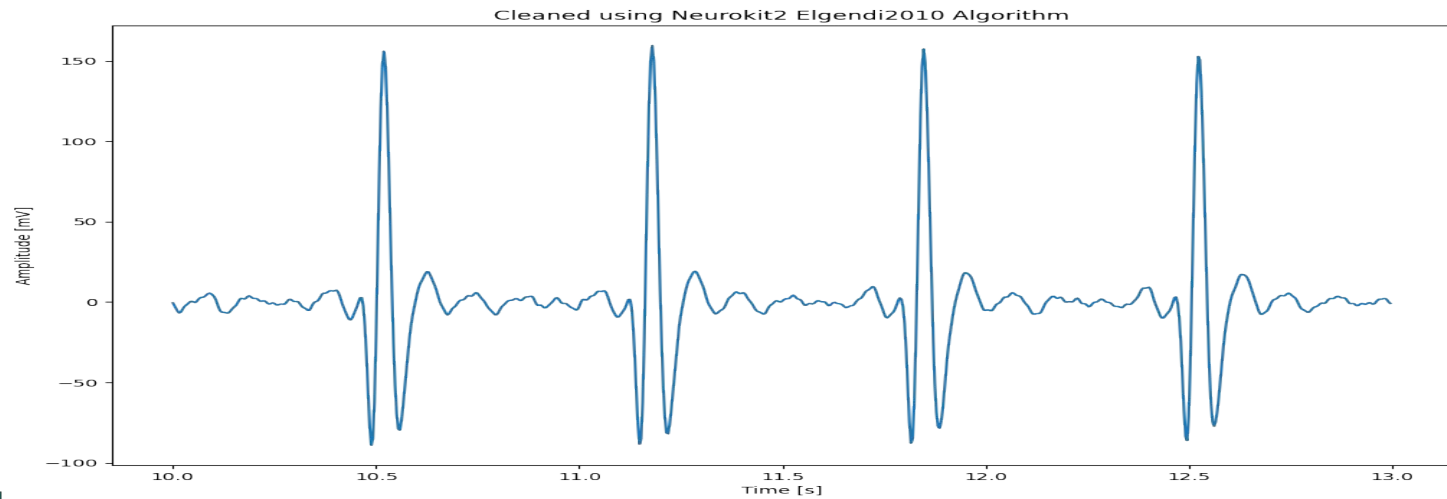
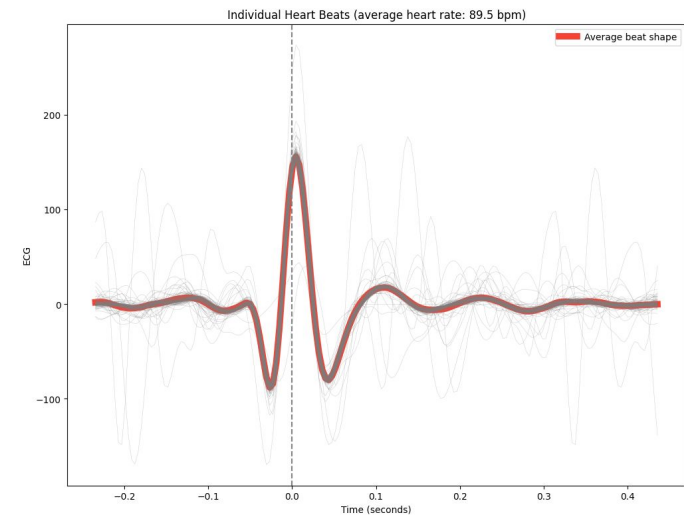
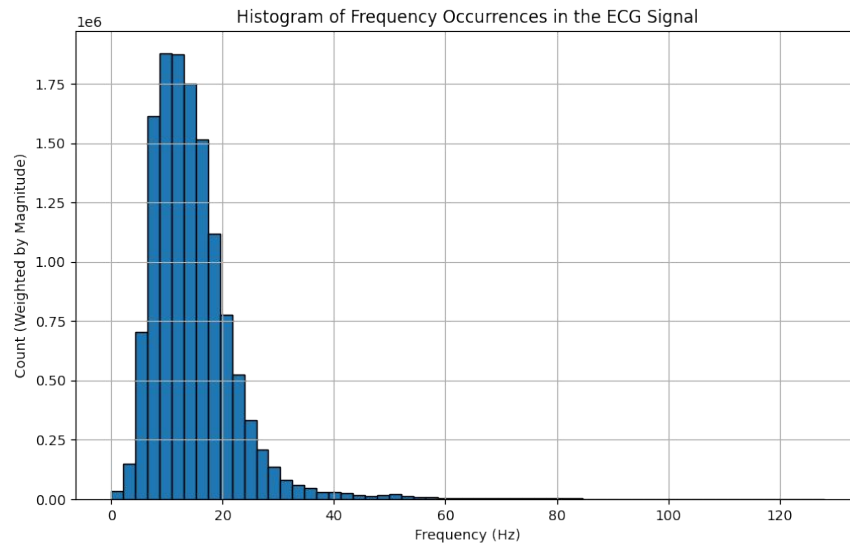
What frequencies do we really want?

- Eliminate as much EMG Signal Interference as possible (muscle activation: 20Hz to 500Hz)
- Read about ECG Signals:
 - P-Waves are typically between 0.5Hz and 10Hz
 - QRS-Complex typically lies between 10Hz and 40Hz
 - T-Waves are typically between 1Hz and 7Hz

So we have some options ... (switch to code on play around....)



Final, Cleaned Signal



On-Campus Study for Emotion Recognition

How you can help!



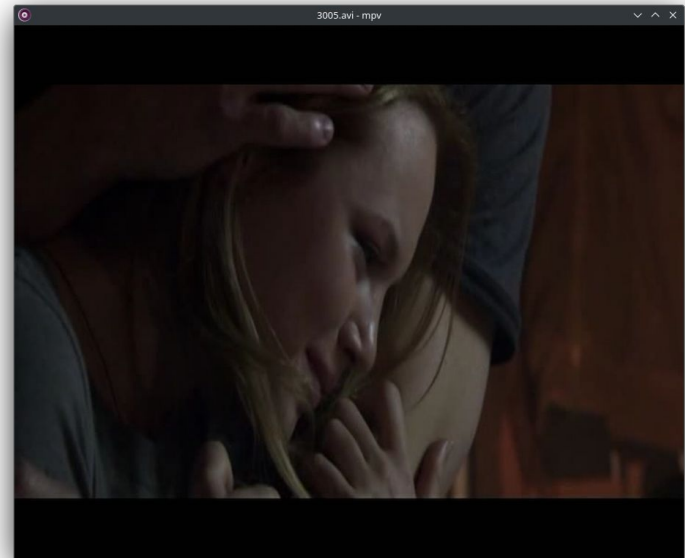
Data Collection / Human-Participant Study

- **Why:** Only two datasets still readily accessible for AER research: ASCERTAIN and DREAMER. Additional data needed for training and model optimization
- **How:** IRB approved at Feb 21 2024 session.
- **Goal:** 50 participants with ECG, PPG, and GSR signal recording, in-lab with controlled affective stimulus.
- **Outcomes:**
 - *CUADS*: CU Affects Data Set
 - *CUADSw*: CU Affects Data Set for Wearables
 - Open Source research tools (data API and mobile app)



Data Collection Materials and Methods

- Shimmer Sensing ECG “Wearable” Sensors
- Emotibit PPG + GSR Sensor
- Watch video clips, and complete a SAM survey for each



Get Involved

- **When:** before you're all too stressed about finals
- **What do you have to do?**
 - Show up
 - Spend 45 minutes watching video clips
- **Important to know:**
 - There'll be scheduled breaks, and you can leave anytime for any reason
- **Qualifying / Disqualifying factors:**
 - Qualifying: be a human, capable of feeling emotions.
 - Disqualifying: individuals prone to emotional dysregulation



Questions?

Links From These Slides:

Source Code + Sample ECG:

https://github.com/cutimcsf/ee502_ecg_guestlecture

AER Datasets:

- ASCERTAIN: <https://ascertain-dataset.github.io/>
- DREAMER: <https://zenodo.org/record/546113>
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