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

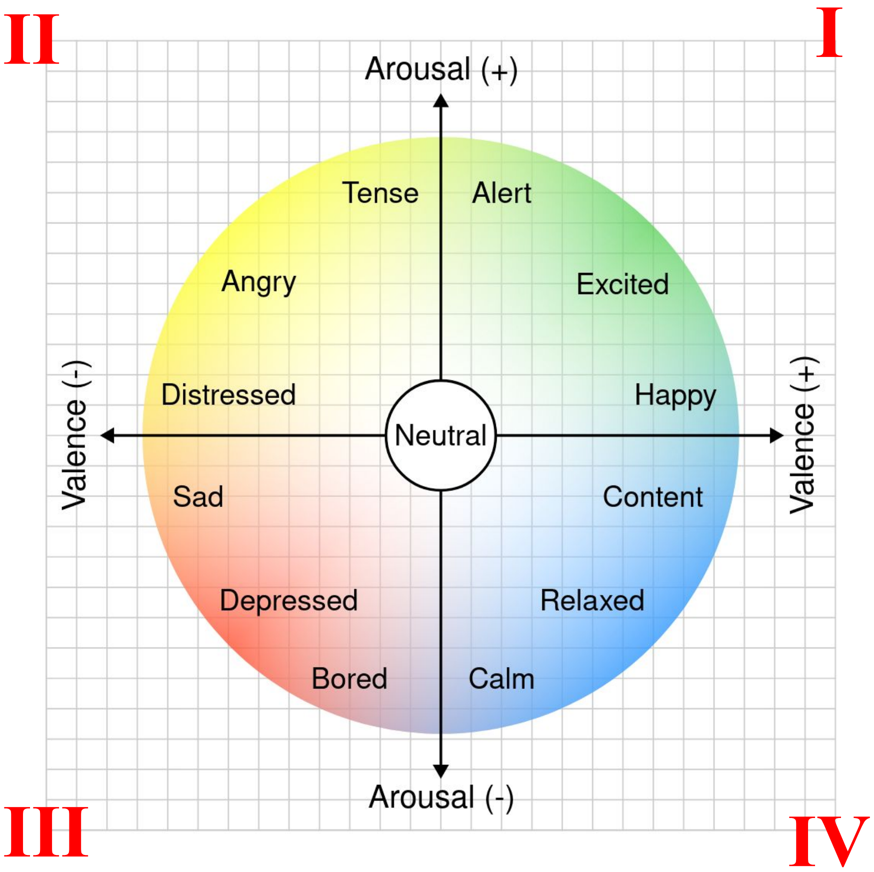
To develop an algorithm to monitor and identify emotions, we need three things:

- 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

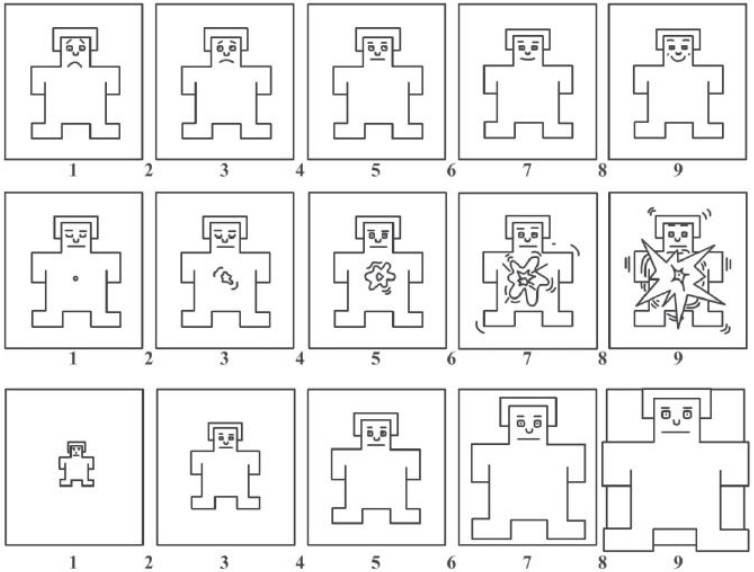
Semantic Differential

- 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 Accuray	
	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						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

Wearable Space

Improved upon CNN by retaining structural knowledge of the input data

Unimodal Emphasis

High Classification Accuracy

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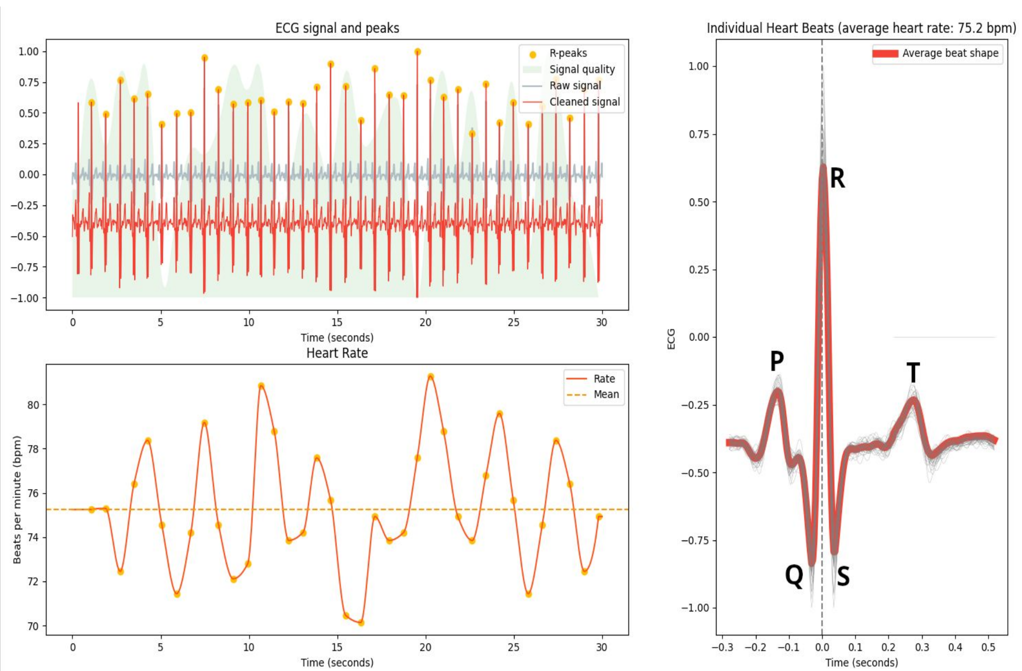
Publicly Available AER Datasets

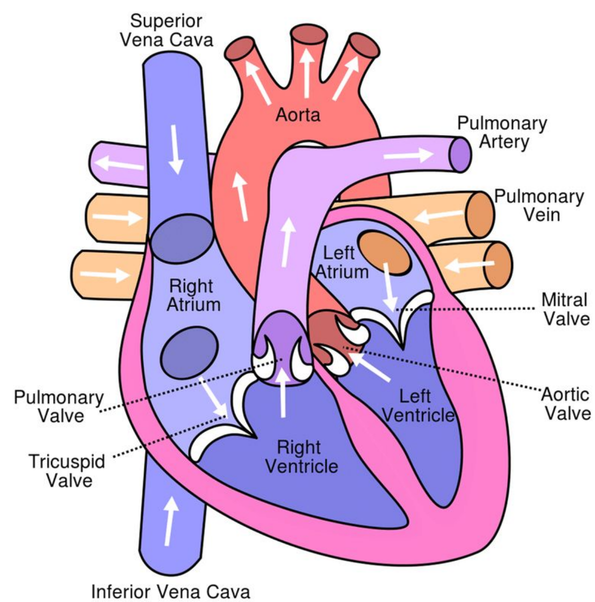
Several AER datasets which already include ECG and ground-truth correlations:

- 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

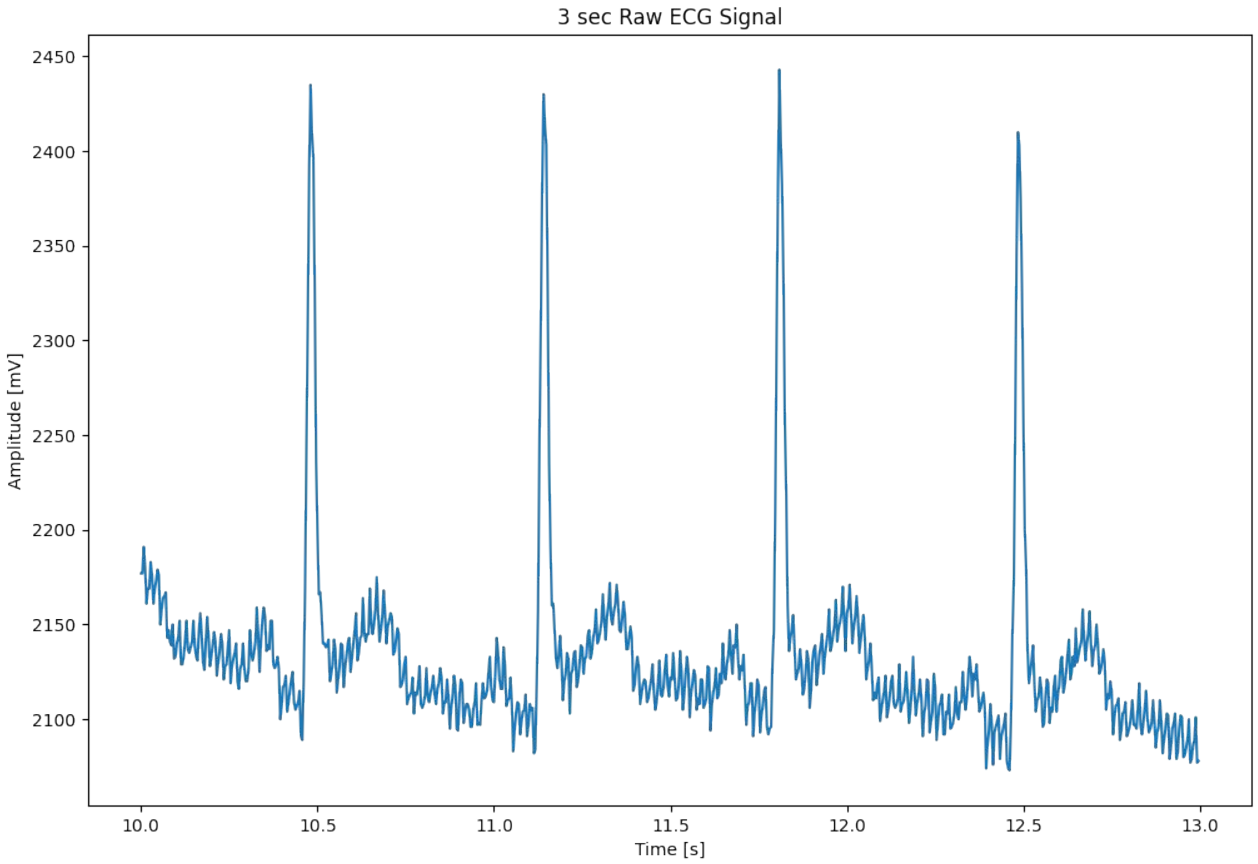
- PQRST Complex
  - P-Wave: atrial depolarization
  - QRS Complex: ventricular depolarization (and atrial repolarization)
  - T-Wave: ventricular repolarization





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:

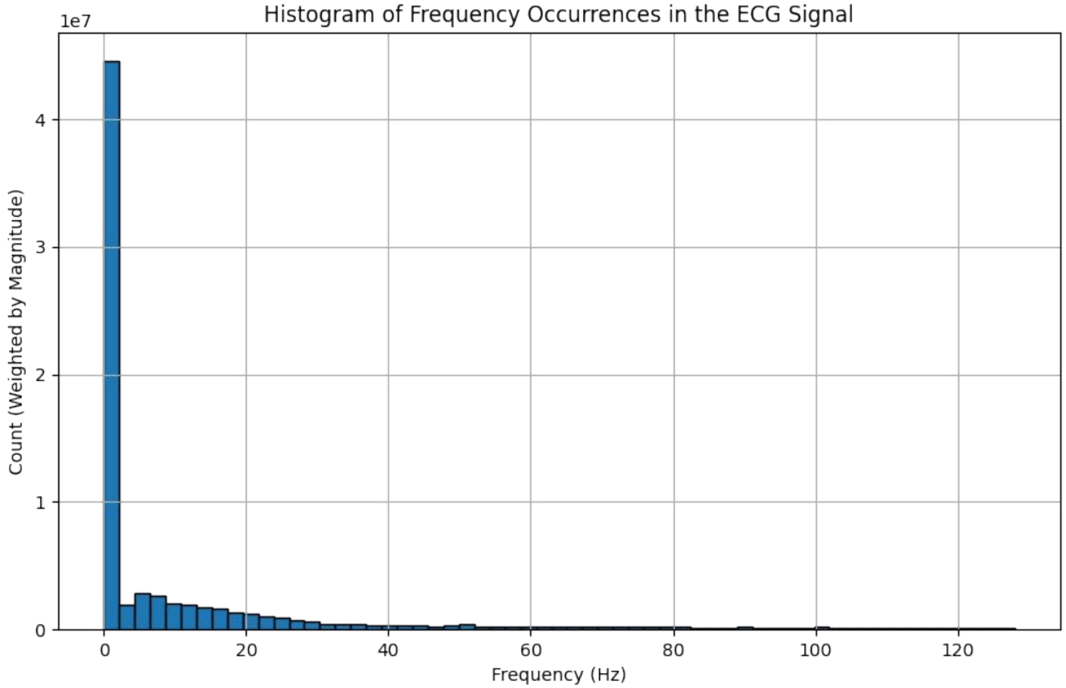
- Removing baseline wander
- Removing powerline interference
- Isolating relevant ECG frequencies (specifically, removing EMG)

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

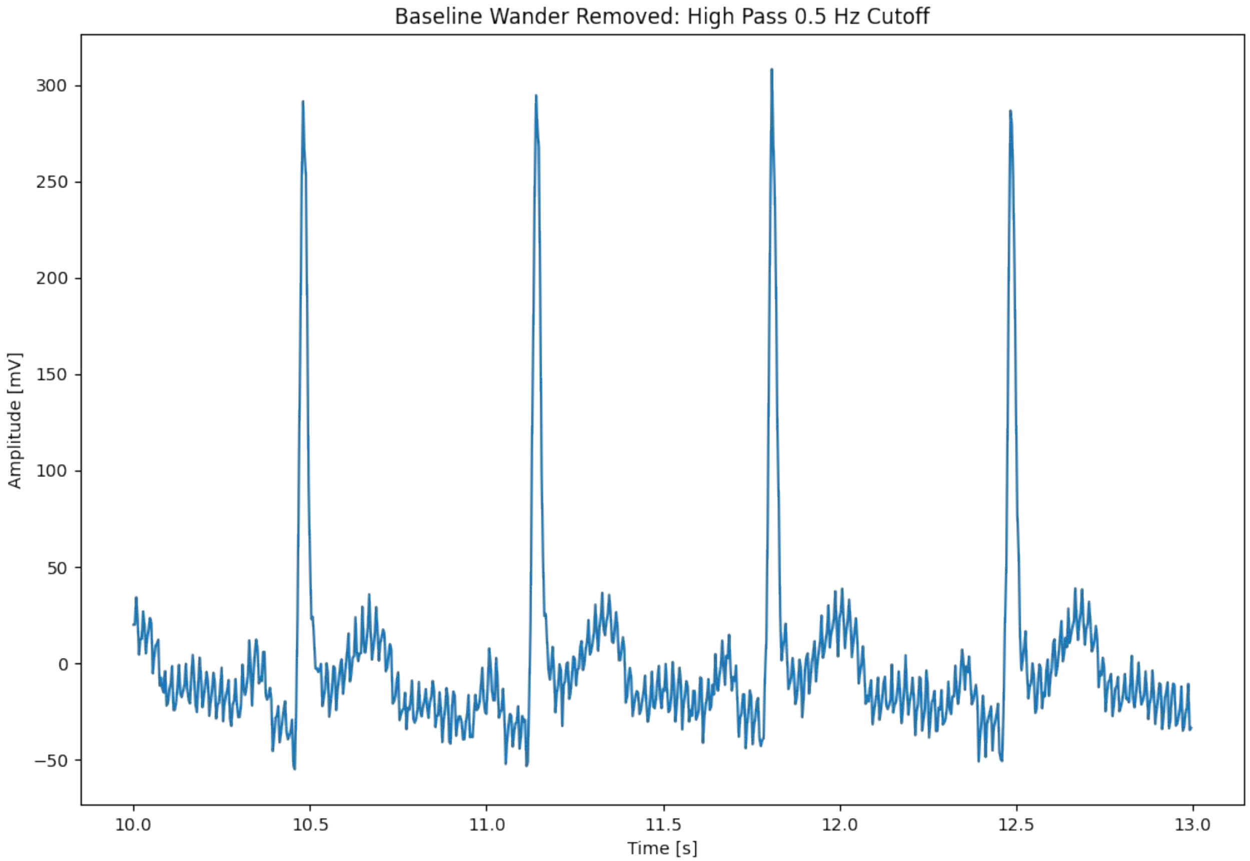


Baseline Wander

- 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

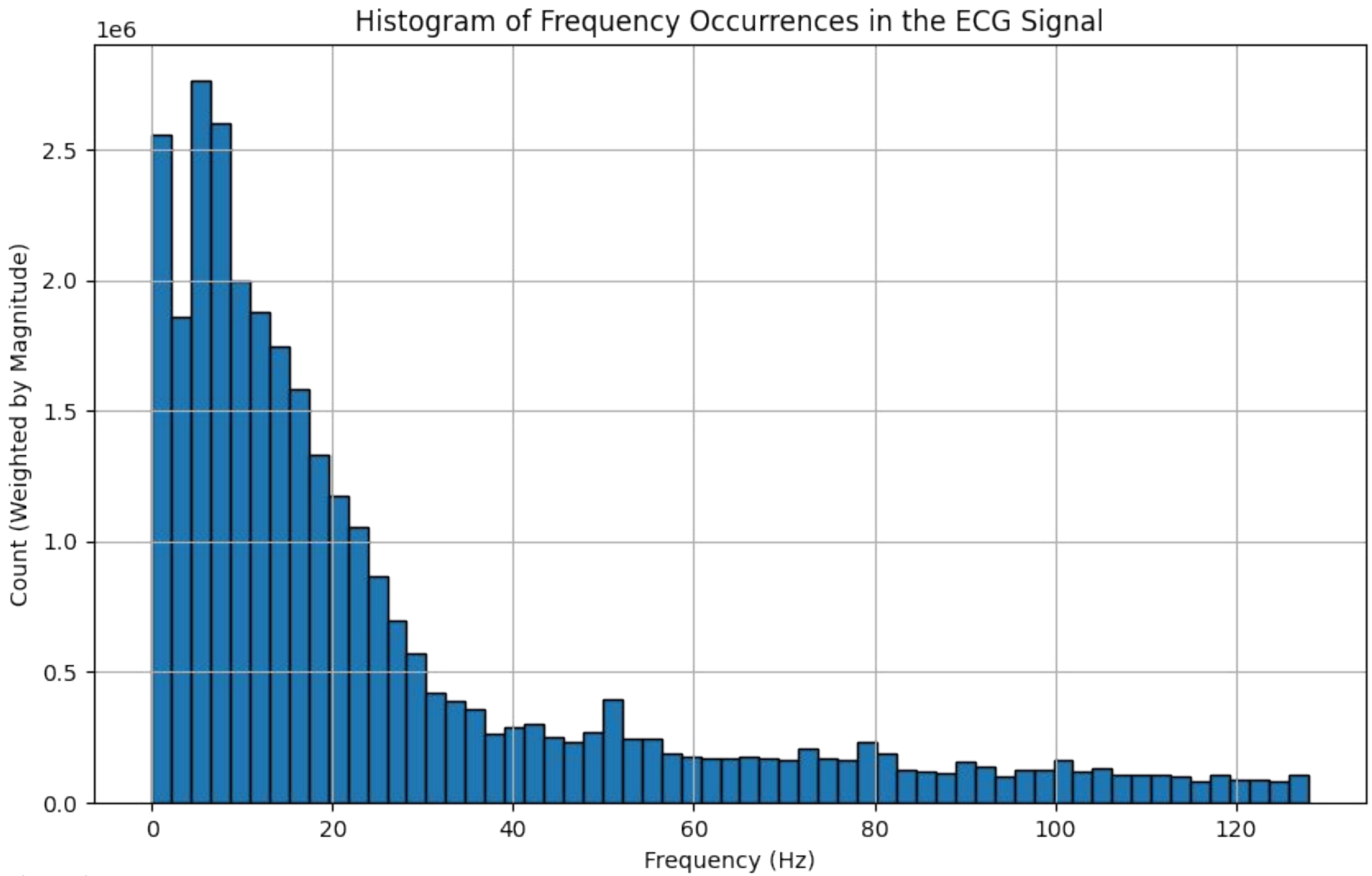
Baseline Wander

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



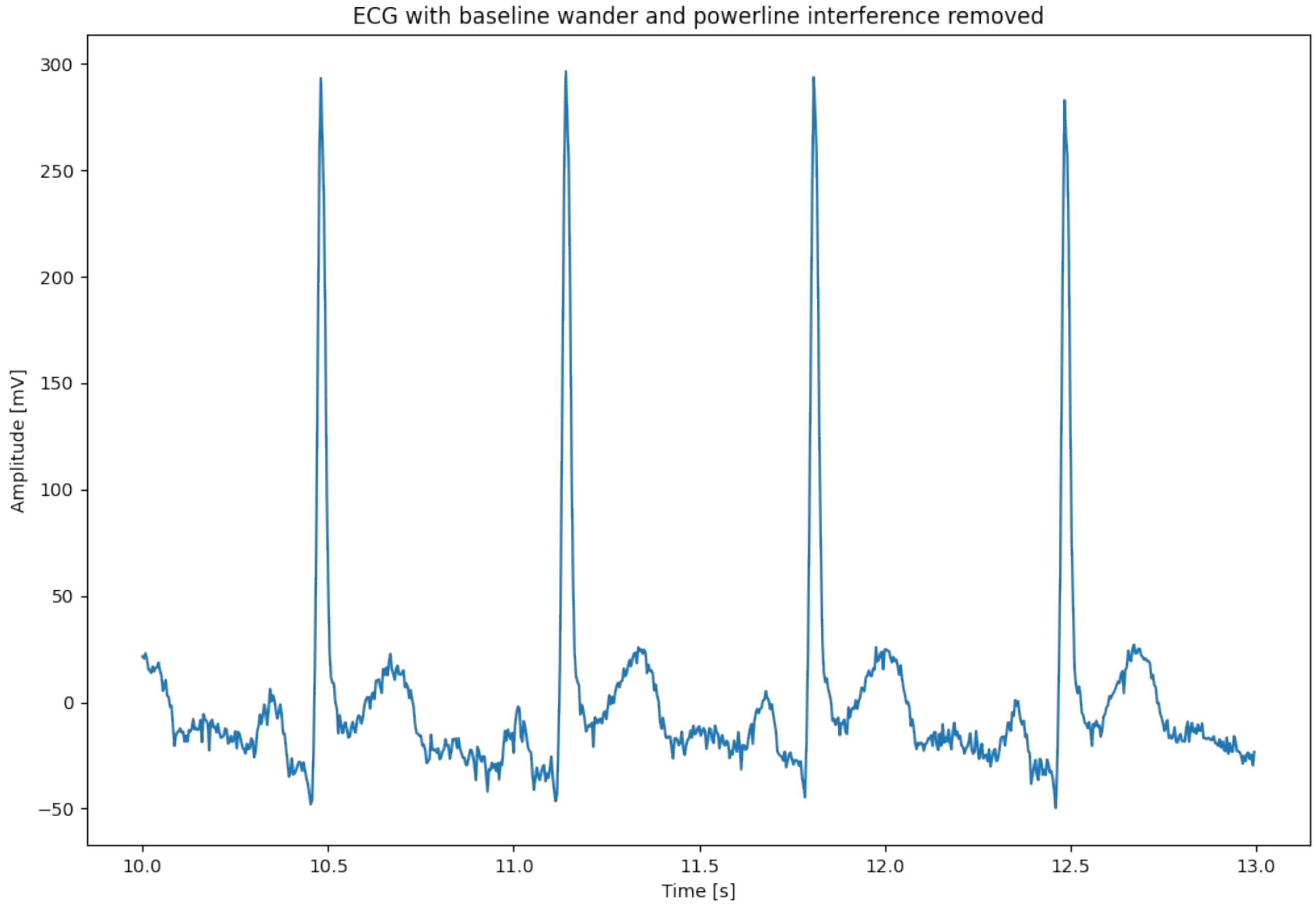
Revisit Frequency Domain …

- 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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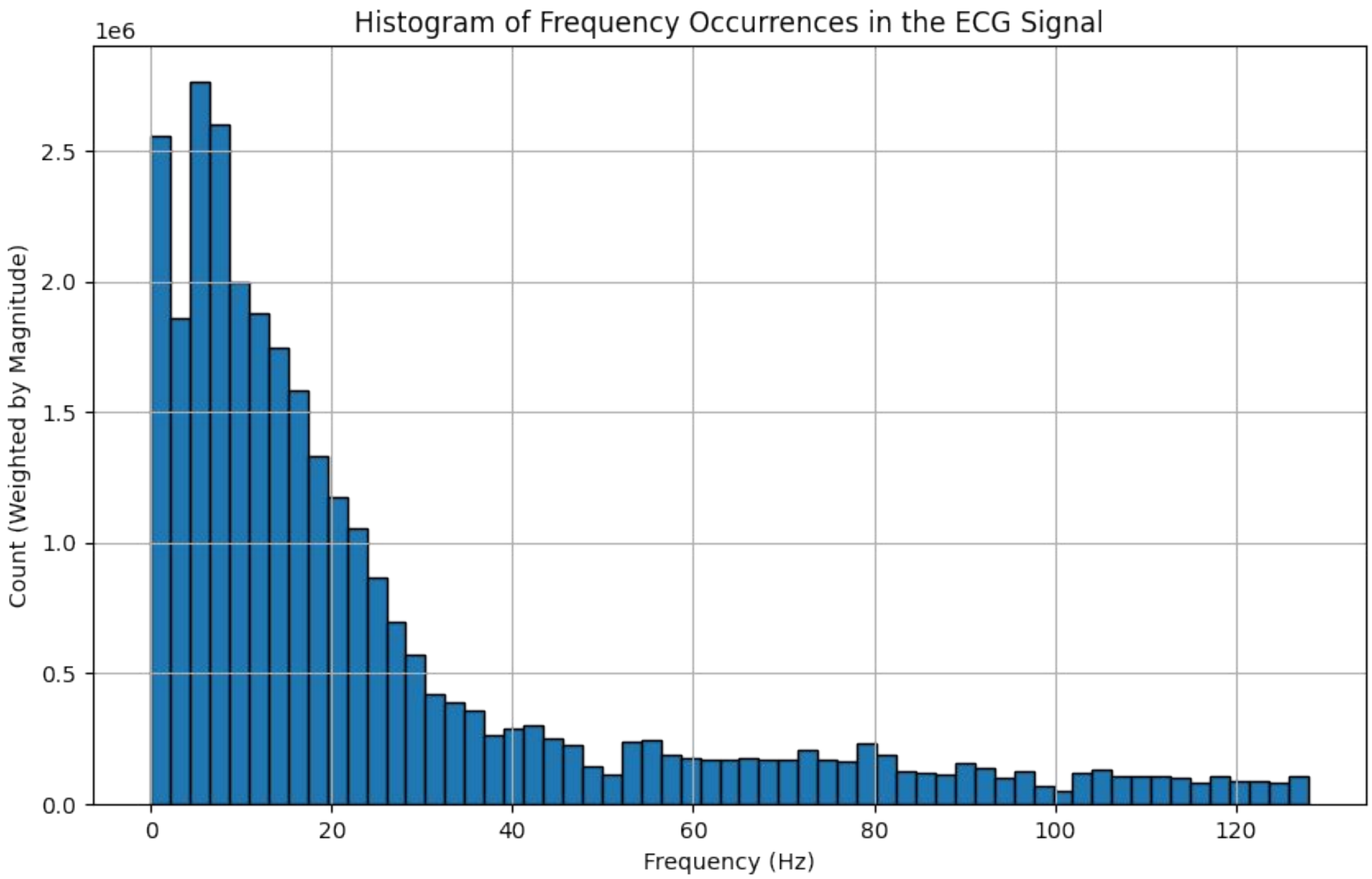
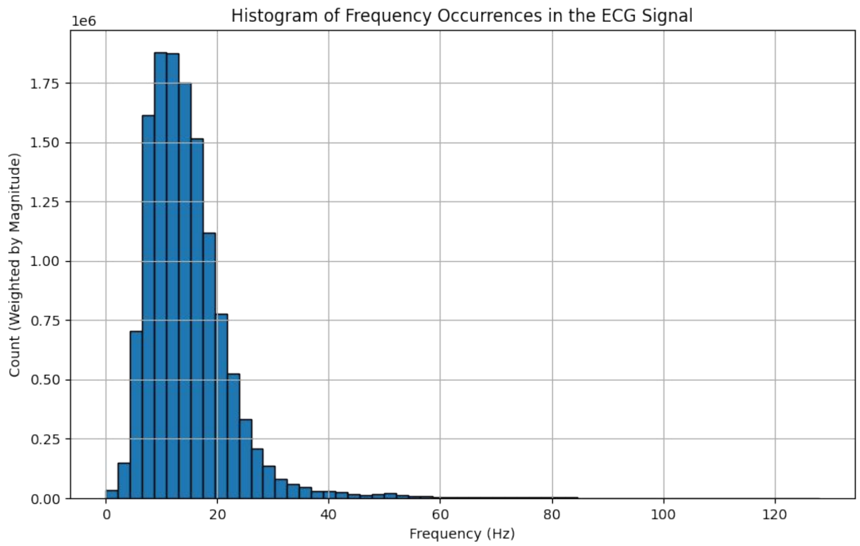


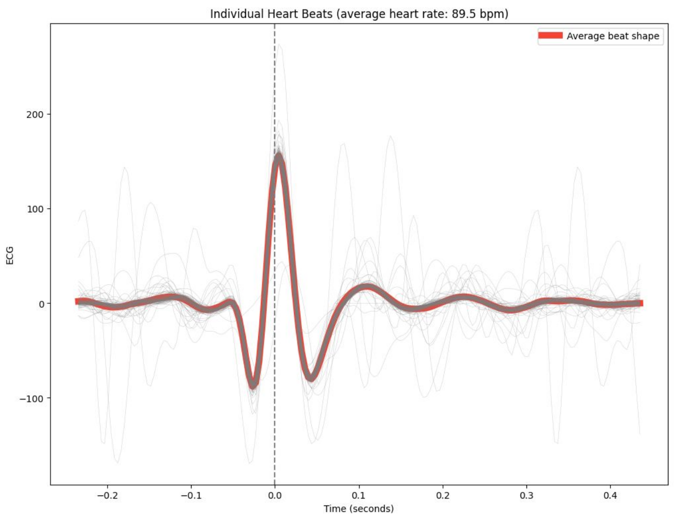
What frequencies do we really want?

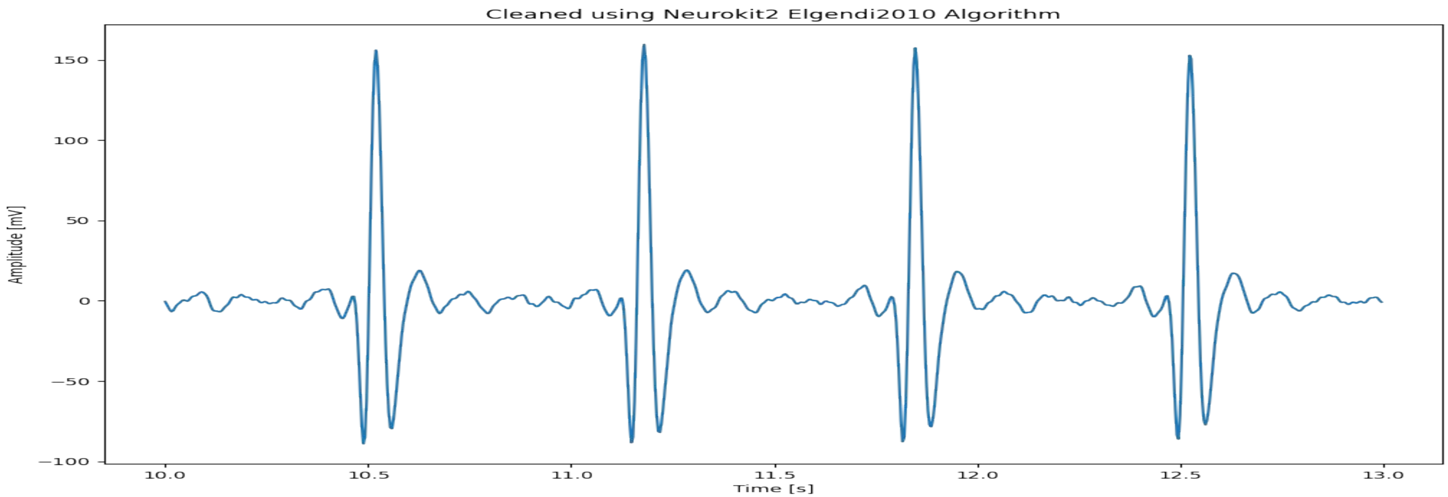
- Eliminate as much EMG Signal Interference as possible (muscle activation: 20Hz to 500Hz)
- Read about ECG Signals:
  - P-Waves are typically between 0.5Hz and 10Hz
  - QRS-Complex typically lies between 10Hz and 40Hz
  - T-Waves are typically between 1Hz and 7Hz

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

Final, Cleaned Signal







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On-Campus Study for Emotion Recognition

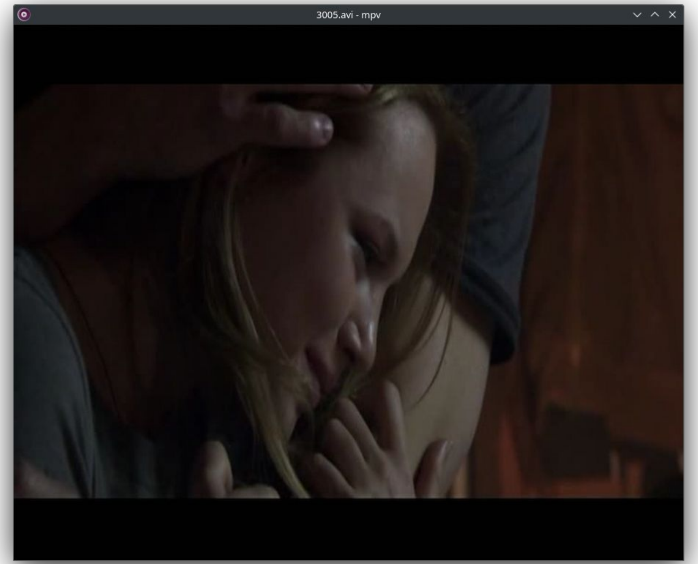
How you can help!

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

Neurokit2:

GitHub: https://github.com/neuropsychology/NeuroKit

Home: https://neuropsychology.github.io/NeuroKit

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