Modern Methods and Tools for Human Biosignal Analysis

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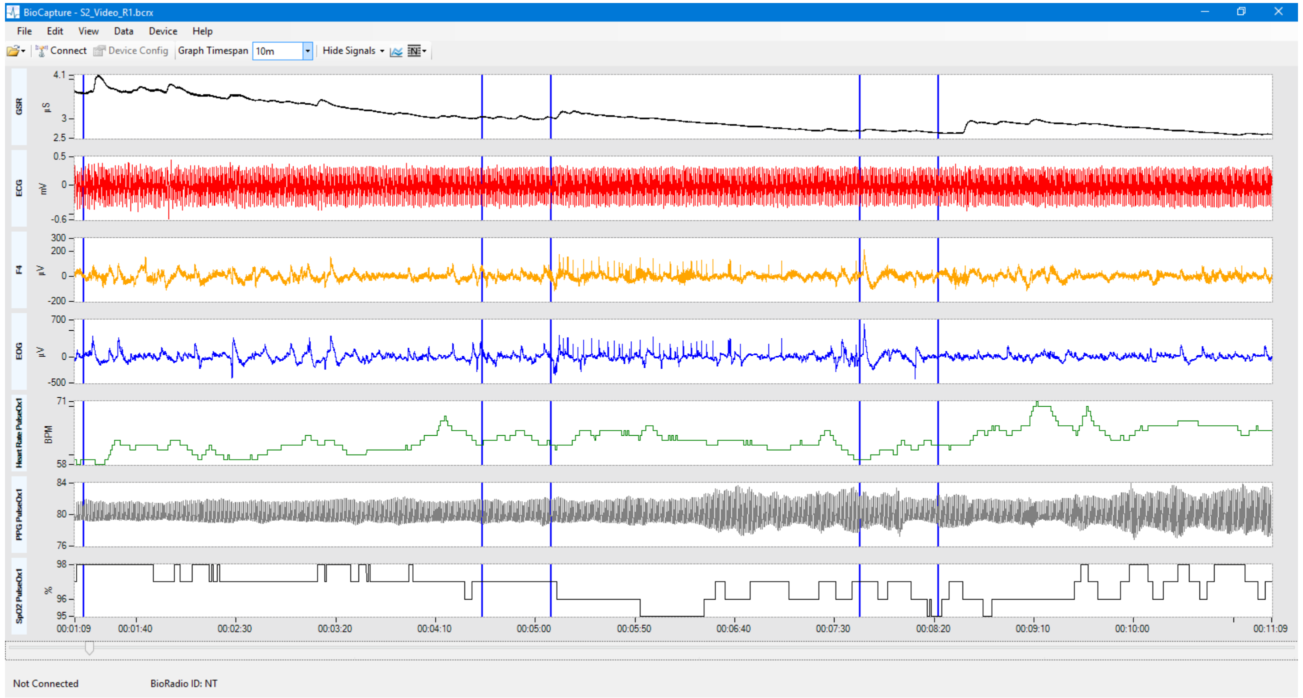
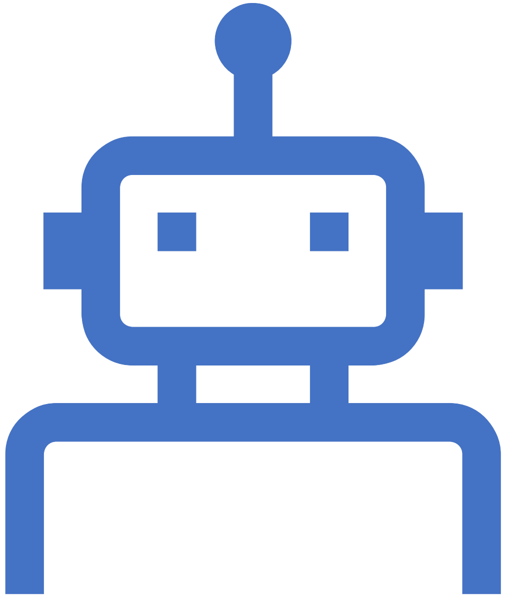
What is a Biosignal?

- The term *biosignal* refers to any signal that can be measured from living organisms.
- Biosignals can be classified as:
    - Bioelectrical signals (signals that originate in nerves and muscles), electrical conductance (e.g. Galvanic skin response),
    - Bioimpedance signals,
    - Bioacoustic signals,
    - Bio-optical signals (e.g. blood-oxygen saturation based on reflection or pulse rate by the change in skin color)



How are biosignals useful?

- Medical applications, e.g. heart rate, blood oxygen levels
- Sleep studies (Polysomnography)
- Affective computing, recognizing human emotion based on physiological variations.
- Human-Computer Interaction, e.g. Affect-aware Virtual Reality

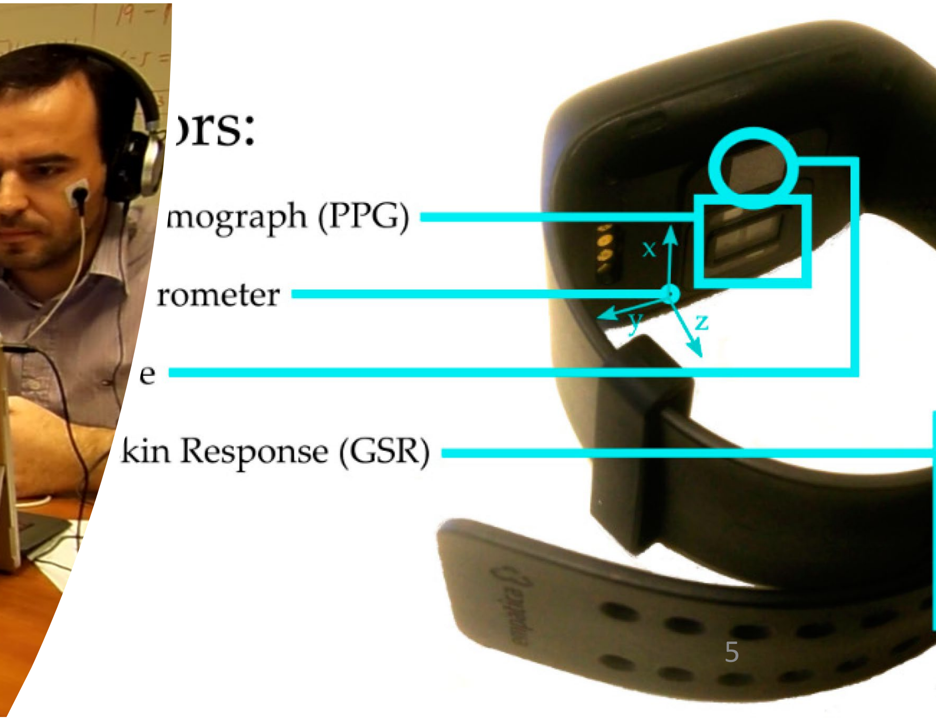


Common types of Biosignals

- *Brain activity*: Electroencephalogram (EEG) and Near-infrared spectroscopy (NIRS)
- *Electrical activity of muscles*: Electromyogram (EMG) and Electrooculogram (EOG)
- *Heart activity*: Heart rate (HR), and Electrocardiogram (ECG)
- *Electrodermal Activity* (EDA), also known as skin conductance, or Galvanic Skin Response (GSR)
- *Air flow* in and out of lungs, *Breathing effort* and rate
- The *level of oxygen* in the blood (Oximetry-PPG)

How are Biosignals collected?

Invasive or non-invasive devices can be used



Case Study 1: Peripheral Biosignal Analysis for Emotion Recognition

How are you doing?

- Humans can recognize emotional state
  - Facial expression
  - Appearance, Movement
  - Voice inflection

- Ekman and Friesen conducted research starting in the late 1960s involving facial expression as an indicator of six universal emotions: happiness, sadness, anger, fear, surprise, disgust, interest.

- Concept of **affective computing** described by Rosalind Picard in 1995 incorporates emotion as an input to automated systems.

Beyond Human Senses

- Signals non-detectable by humans known to provide additional information regarding emotional state
- Galvanic Skin Response (Electrodermal Activity) is an example – key signal used during the administration of a lie detector test
- Technological developments have lowered the cost of monitoring physiological signals
  - *Consumer*: heart rate, movement (acceleration)
  - *Research*: brain/muscle/heart electrical activity, respiration

A bit of Biology

- Detectable emotional responses have origins in “fight or flight”
- Body attempts to stay in steady state – homeostatis
- When stressed physiological changes occur in preparation for action

✓ Heart rate increases

✓ Restricted peripheral blood flow

✓ Sweat glands express

✓ Hormones are released

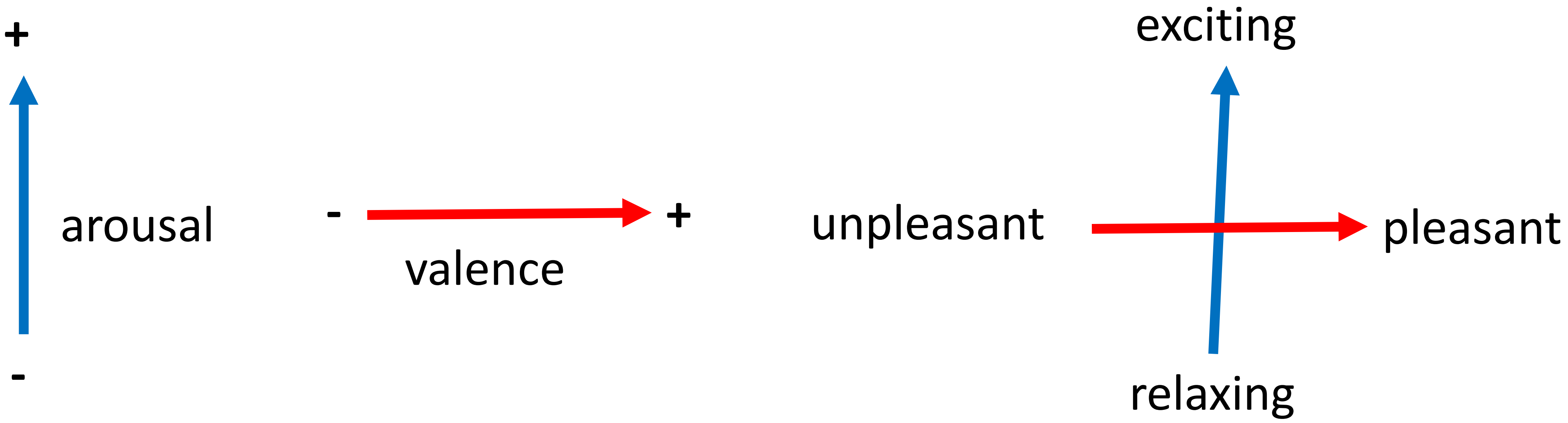
Autonomic Nervous System	
<u>Parasympathetic</u> Maintenance Low arousal	<u>Sympathetic</u> Prepare to act High arousal

Emotional Response Classification

"How does that make you feel?"

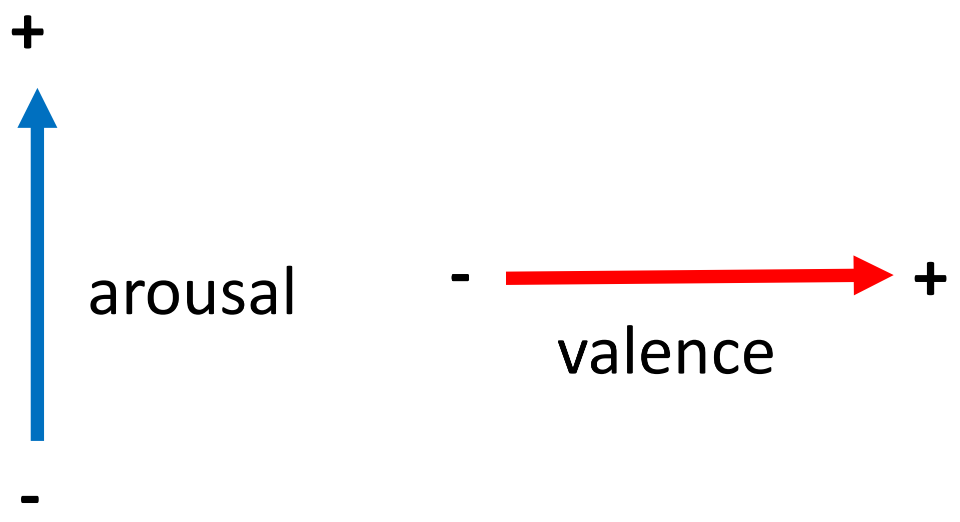
Emotional Response Classification

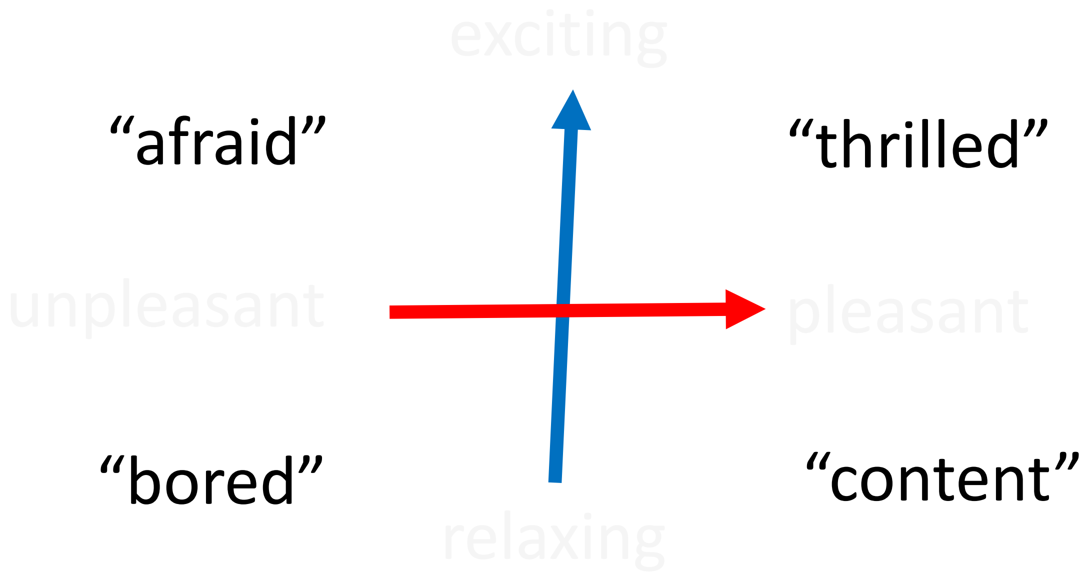
"How does that make you feel?"



Emotional Response Classification

“How does that make you feel?”





Experimental Design and Data Collection

Tools: BioRadio

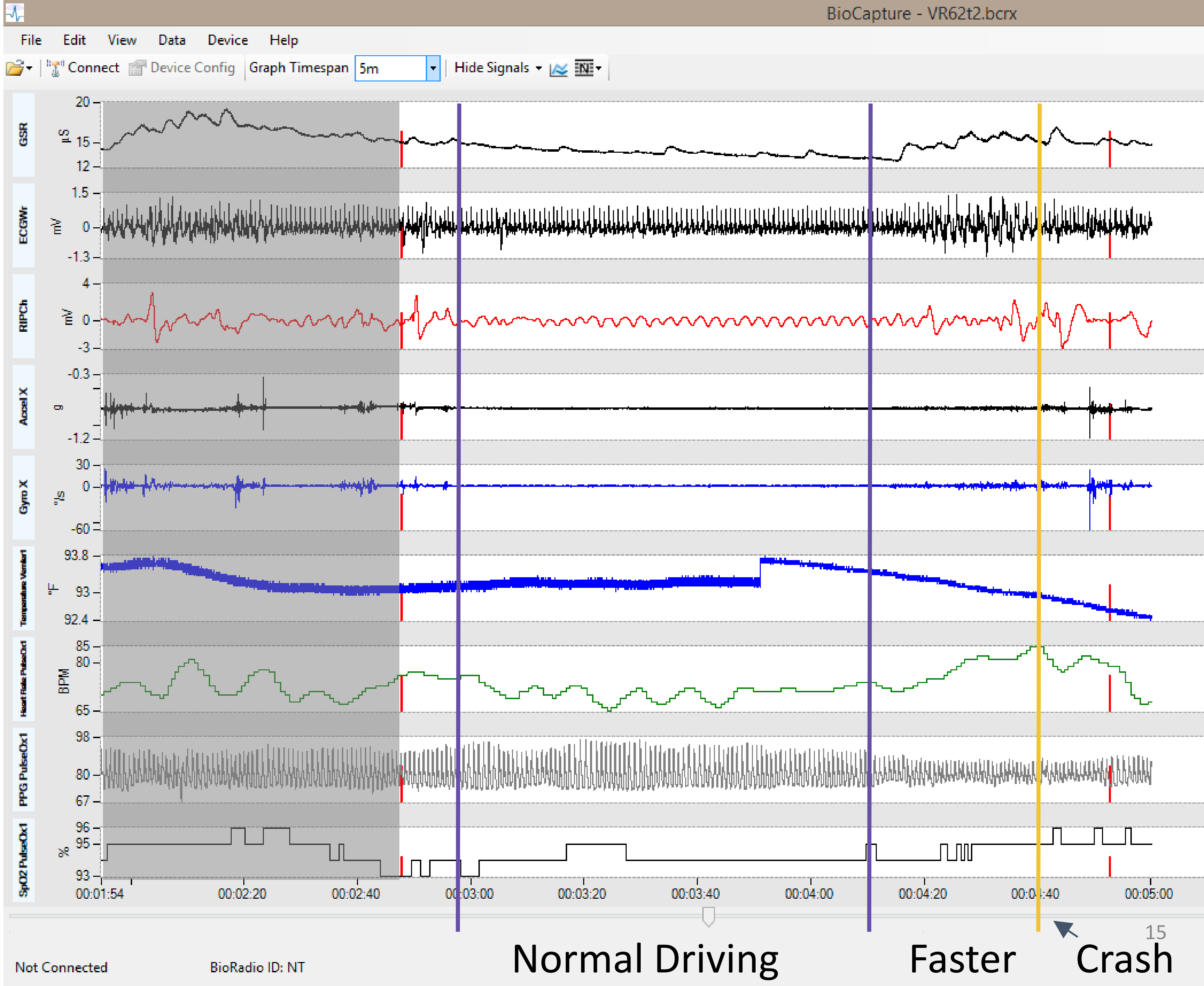
- Physiological Data Collection
- Electrical Activity - 4/8 configurable inputs
    - Heart - electrocardiography (ECG)
    - Muscle - electromyography (EMG)
    - Eye Movement - electrooculography (EOG)
    - Brain - electroencephalography (EEG)
    - Skin Response - electrodermal activity (EDA aka GSR)
    - Breath - respiratory inductance plethysmography (RIP)
- Motion - 6-axis accelerometer, triaxial linear acceleration and angular velocity
- Auxiliary Inputs - Surface Temperature, Photoplethysmogram (PPG), Heart Rate (optical), and Oxygen Saturation (SpO_2)

Early Work
VR Test Run

"Leisurely" lap

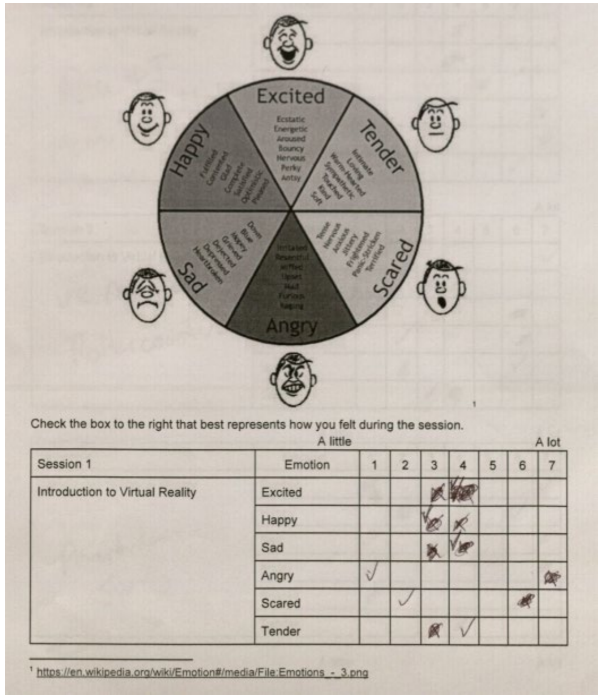
faster lap

unexpected wreck



Classification Labels – Keep it Simple!

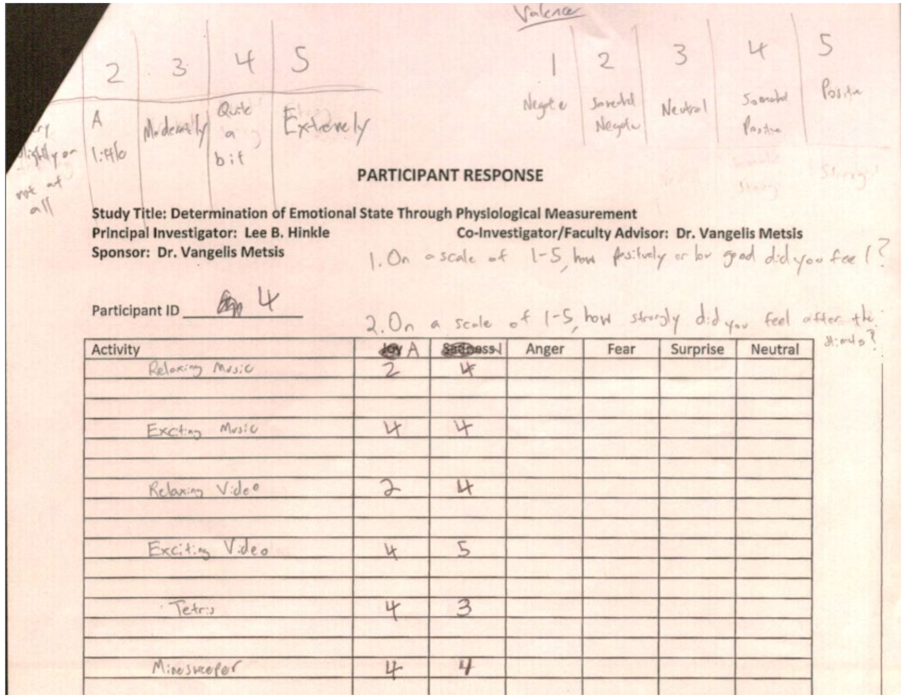
Preliminary testing showed it was very difficult to self-classify experience



Check the box to the right that best represents how you felt during the session.

Session 1	Emotion	1	2	3	4	5	6	7
		A little						A lot
Introduction to Virtual Reality	Excited							
	Happy							
	Sad							
	Angry	✓						
	Scared		✓					
	Tender				✓			

[1] https://en.wikipedia.org/wiki/Emotion#/media/File:Emotions_-_3.png



Valence

2 3 4 5
A little, Moderately, Quite a bit, Extremely

1 2 3 4 5
Negative, Somewhat Negative, Neutral, Somewhat Positive, Positive

PARTICIPANT RESPONSE

Study Title: Determination of Emotional State Through Physiological Measurement
Principal Investigator: Lee B. Hinkle
Co-Investigator/Faculty Advisor: Dr. Vangelis Metsis
Sponsor: Dr. Vangelis Metsis

1. On a scale of 1-5, how positively or how good did you feel?

2. On a scale of 1-5, how strongly did you feel after the stimulus?

Participant ID 4

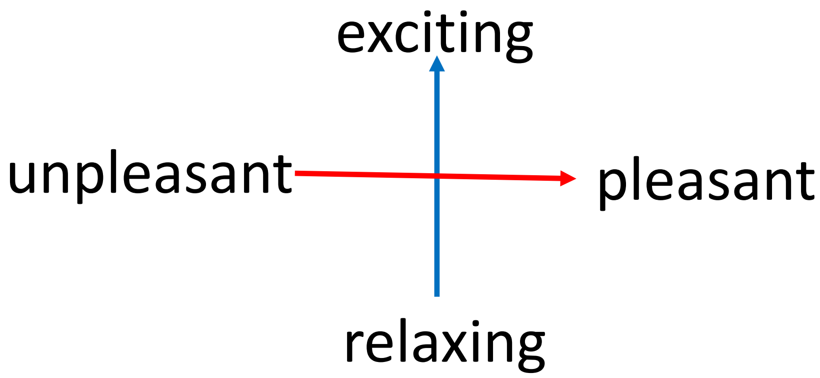
Activity	A	V	Anger	Fear	Surprise	Neutral
Relaxing Music	2	4				
Exciting Music	4	4				
Relaxing Video	2	4				
Exciting Video	4	5				
Tetris	4	3				
Minesweeper	4	4				

Classification Labels

Subject Self-Reporting
- Too difficult to remove headset - must be oral
- Simplified version of arousal valence model used

After each session:
Question 1: “Did you find this movie exciting, relaxing, or neutral?”
Question 2: “Did you find this movie pleasant, unpleasant, or neutral?”

(1,-1) stressed	(1,0)	(1,1) excited
(0,-1)	(0,0)	(0,1)
(-1,-1) bored	(-1,0)	(-1,1) relaxed



Sensor Setup

- Headset with headphones and Xbox game controller

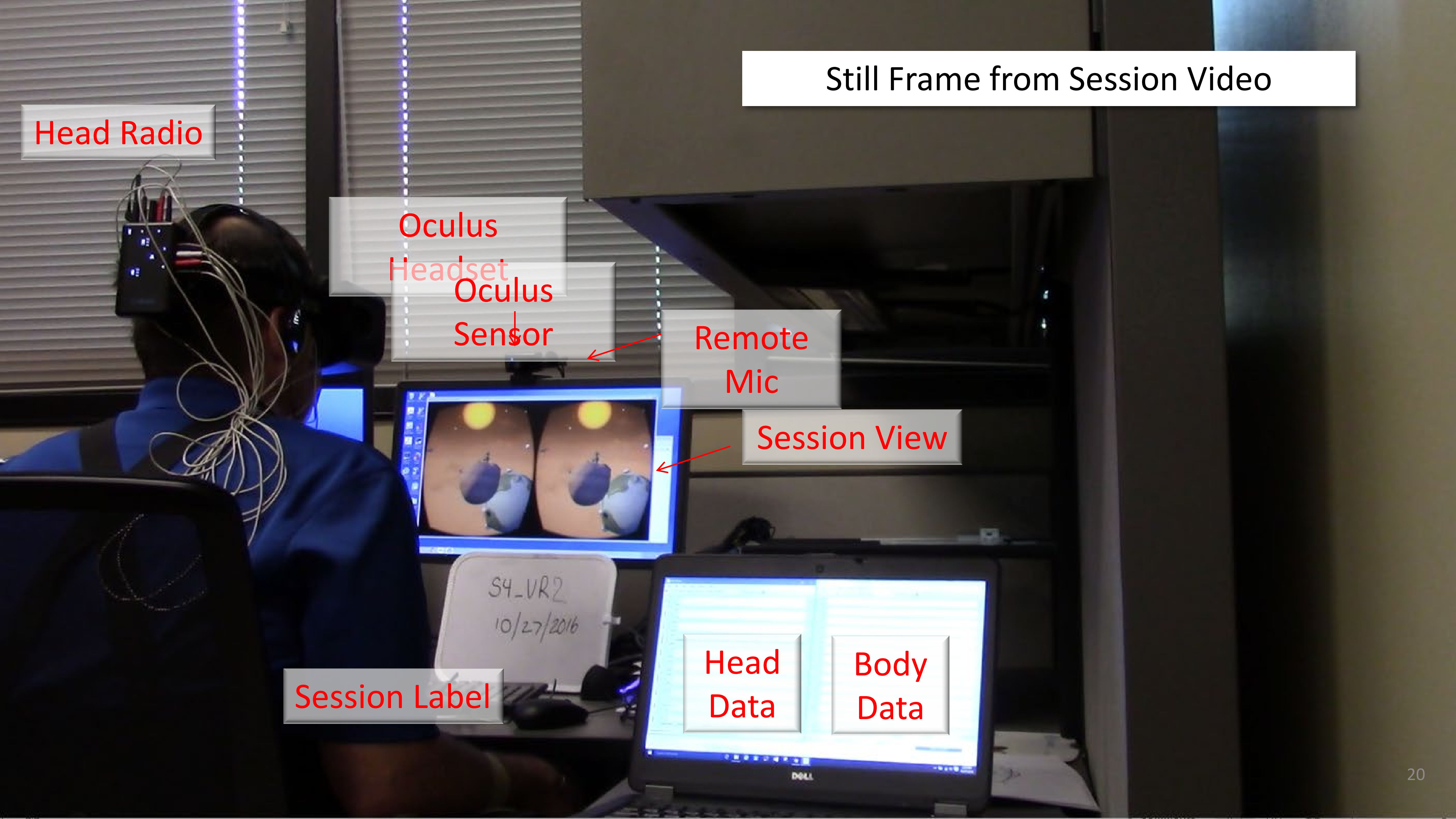
- Head Radio (in back)
  - EEG/EOG/EMG(smile)

- Body Radio (in Support Belt)
  - ECG/GSR/PulseOx
  - Chest & Abdomen Respiration

Sensor List 24 total channels

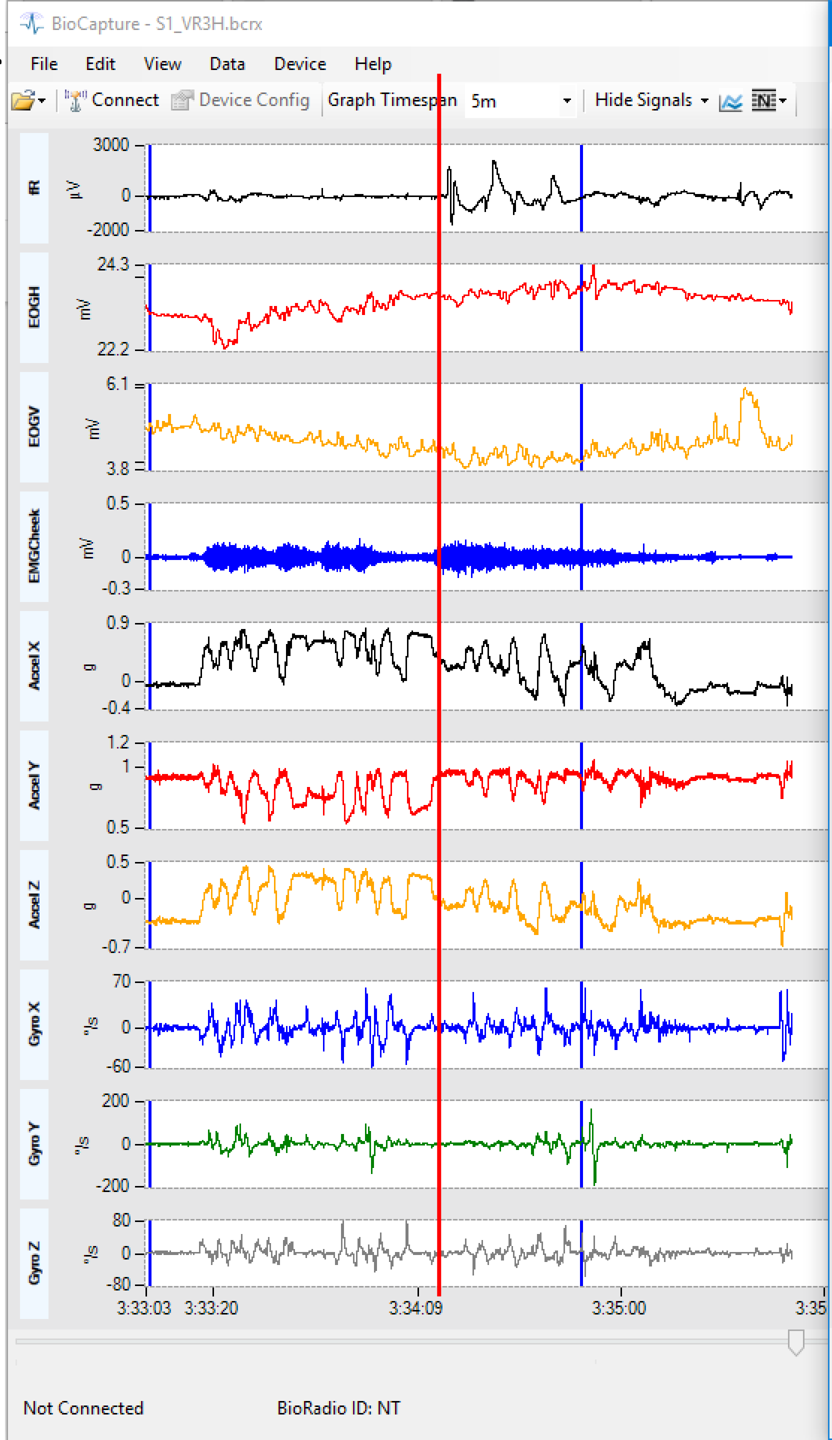
Radio	Signal	Sensor Location	Qty
H_Ch1	EEG f4	High right forehead	1
H_Ch2	EOG - Horizontal	Outside of eyes	1
H_Ch3	EOG - Vertical	Above and below right eye	1
H_Ch4	EMG – Zygomaticus “smile” muscle	Right cheek	1
H_int	Accel XYZ, Gyro XYZ	Rear of head	6
B_Ch1	GSR (Electrodermal Activity)	Right index and pointer finger	1
B_Ch2	ECG	Left and right wrists	1
B_Ch3	Chest Respiration (RIP)	Chest strap	1
B_Ch4	Abdomen Respiration (RIP)	Stomach strap	1
B_Aux	Peripheral Temperature	Right pinkie finger	1
B_Aux	Heart Rate via PulseOx	Right ring finger	1
B_Aux	Blood Volume (PPG) via PulseOx	Right ring finger	1
B_Aux	Blood Oxygen (SpO2) via PulseOx	Right ring finger	1
B_int	Accel XYZ, Gyro XYZ	Right waist	6

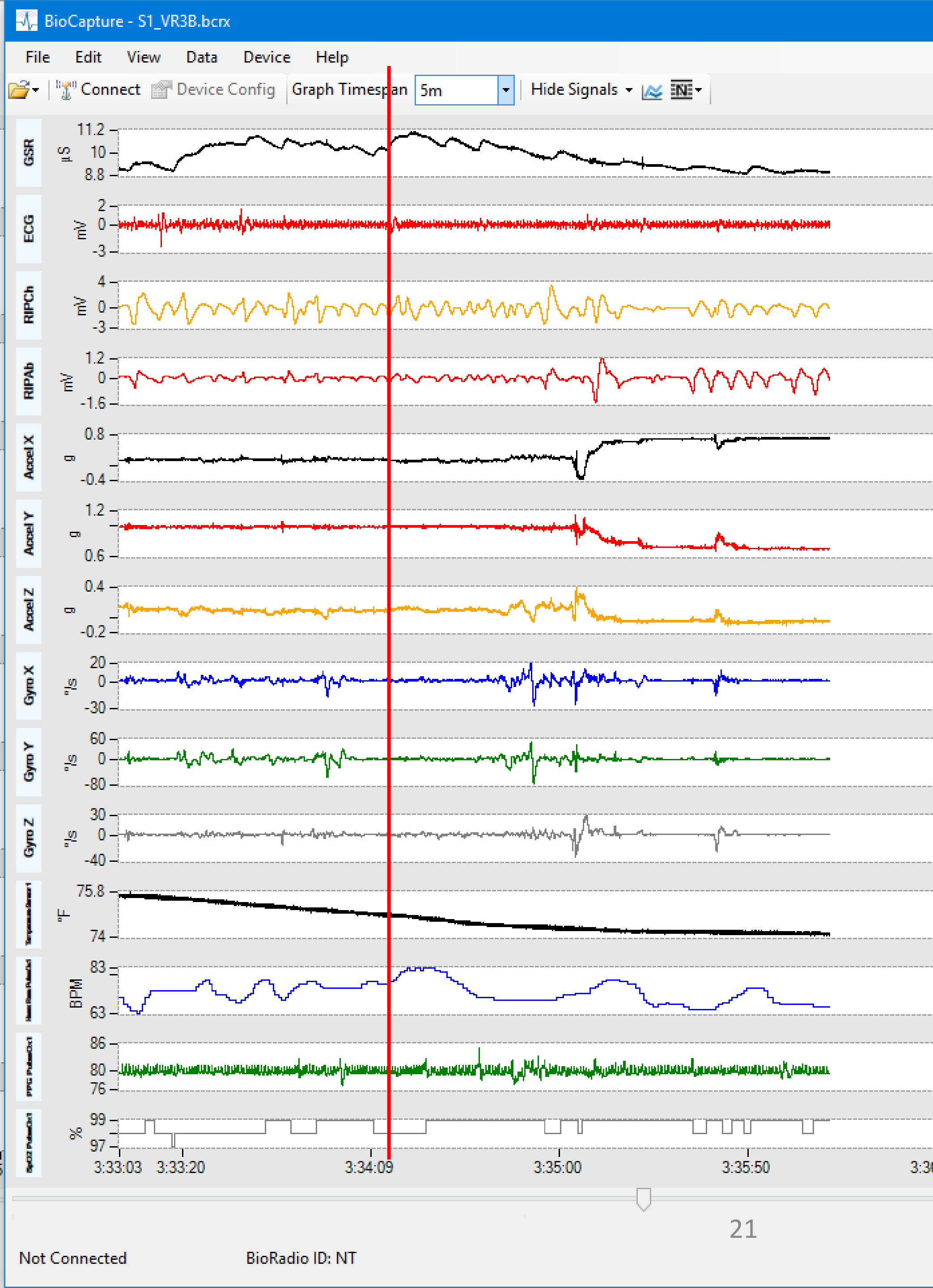
Still Frame from Session Video



Quick Visual Analysis of Pendulum Swing Video Signals in BioCapture

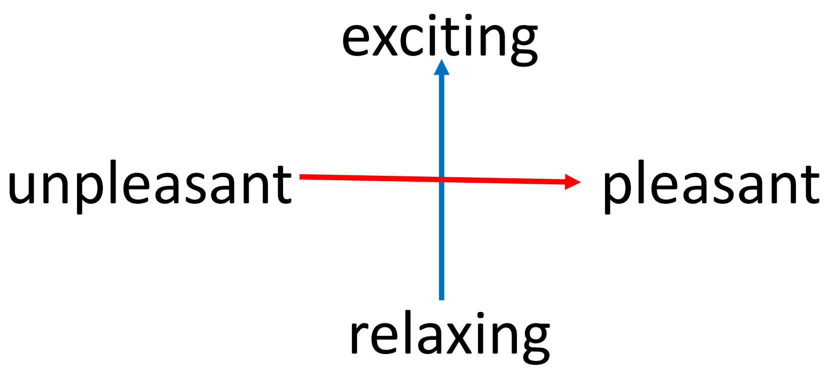
	A	B	C	
1		MVI_004	Real Time	
2			S1_VR3H	S
3	Start H	0:17:05	3:29:41 AM	
4	Start B	0:17:21		3
5	Start of Rollercoaster [Mark]	0:17:41	3:30:15 AM	
6	Start of Drop	0:18:19	3:30:53 AM	
7	Stop Rollercoaster	0:19:31	3:32:05 AM	
8	Start Standing	0:20:03	3:32:37 AM	
9	Finish Standing	0:20:14	3:32:48 AM	
10	Jump into Unknown [Mark]	0:20:30	3:33:04 AM	
11	Pushed in VR	0:21:40	3:34:14 AM	
12	Jump into Unknown Finish	0:22:10	3:34:44 AM	
13	Ending [Mark]	0:22:16	3:34:50 AM	
14				
15	NOTE: All this done in BioCapture - need to confirm increase prec			





Classification Results

- Subject Self-Reported data for 11 segments
- Skewed toward pleasant and exciting
- No unpleasant relaxing e.g. “bored” results



Total Responses for 5 Subjects

Introduction to Virtual Reality Demo

		3
		1
		1

The Rose and I Movie

	1	1
	1	2

Rollercoaster 3D Movie

1	1	3

Pendulum Swing 3D Movie

	1	4

In Cell Game

	1	2
	1	1

Lost Movie

1	1	
	2	1

Dream Deck Demo: Overall

	3	
	1	1

Dream Deck Demo: City Scene (Height)

	1	1
	1	1
		1

Dream Deck Demo: Alien (Creepy)

		1
1	3	

Dream Deck Demo: Dinosaur (Scary)

2	1	1
	1	

Lucky's Tale Game

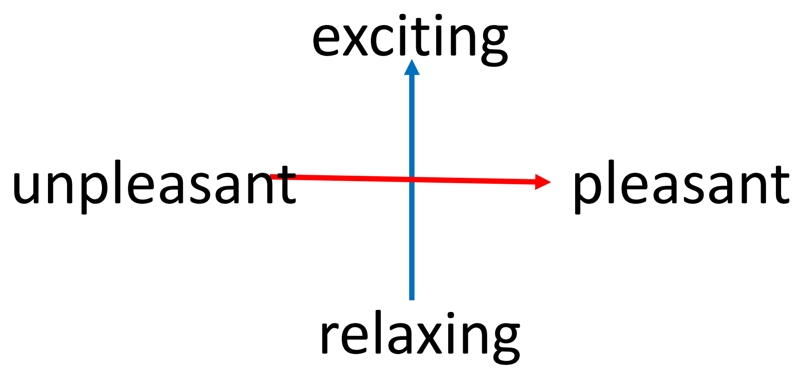
		2
1	1	1

All subjects, all sessions

4	9	17
2	11	7
0	1	4

Classification Results

- Subject Self-Reported data for 11 segments
- Skewed toward pleasant and exciting
- No unpleasant relaxing e.g. “bored” results



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		3
		1
		1

The Rose and I Movie

	1	1
	1	2

Rollercoaster 3D Movie

1	1	3

Pendulum Swing 3D Movie

	1	4

In Cell Game

	1	2
	1	1

Lost Movie

1	1	
	2	1

Dream Deck Demo: Overall

	3	
	1	1

Dream Deck Demo: City Scene (Height)

	1	1
	1	1
		1

Dream Deck Demo: Alien (Creepy)

		1
1	3	

Dream Deck Demo: Dinosaur (Scary)

2	1	1
	1	

Lucky's Tale Game

		2
1	1	1

All subjects, all sessions

4	9	17
2	11	7
0	1	4

S15VR23

344817x29 table

	1 fR	2 EOGH	3 EOGV	4 EMGCheek	5 AccelX	6 AccelY	7 AccelZ	8 GyroX	9 GyroY	10 GyroZ	11 GSR	12 ECG	13 RIPCh	14 RIPAb	15 AccelXB	16 AccelYB	17 AccelZB	18 GyroXB	19 GyroYB
1	-0.0087	0.0234	0.0040	-0.0083	-0.0654	0.9619	-0.2239	-0.0610	-0.3662	1.0986	7.0151	0.0035	0.0014	-0.0040	0.7947	0.5400	-0.2546	1.2207	0
2	-0.0087	0.0234	0.0040	-0.0083	-0.0706	0.9573	-0.2249	0	-0.4272	1.0376	7.0151	0.0035	[illegible]	[illegible]	0.7949	0.5405	-0.2454	1.0986	0.0610
3	-0.0087	0.0234	0.0040	-0.0083	-0.0647	0.9575	-0.2231	-0.1831	-0.5493	0.9766	7.0151	0.0035	0.0014	-0.0040	0.8015	0.5322	-0.2549	1.1597	0
4	-0.0087	0.0234	0.0040	-0.0083	-0.0674	0.9631	-0.2275	-0.1831	-0.6104	1.0376	7.0151	0.0035	0.0014	-0.0040	0.7959	0.5352	-0.2517	1.1597	-0.0610
5	-0.0087	0.0234	0.0040	-0.0083	-0.0684	0.9578	-0.2195	-0.1221	-0.6104	1.1597	7.0151	0.0035	0.0014	-0.0040	0.7964	0.5371	-0.2517	1.0986	0
6	-0.0087	0.0234	0.0040	-0.0083	-0.0657	0.9546	-0.2244	-0.1831	-0.4883	[illegible]	[illegible]	[illegible]	0.0014	-0.0040	0.7930	0.5400	-0.2512	1.0986	0
7	-0.0087	0.0234	0.0040	-0.0083	-0.0664	0.9636	-0.2236	-0.2441	-0.5493	1.2817	7.0151	0.0035	0.0014	-0.0040	0.7937	0.5374	-0.2488	1.1597	0.0610
8	-0.0087	0.0234	0.0040	-0.0083	-0.0681	0.9590	-0.2354	-0.4272	-0.4272	1.3428	7.0124	0.0035	0.0014	-0.0040	0.7947	0.5376	-0.2410	1.2817	0.0610
9	-0.0087	0.0234	0.0040	-0.0083	-0.0698	0.9641	-0.2295	-0.5493	-0.4272	1.6479	[illegible]	[illegible]	[illegible]	[illegible]	0.7991	0.5317	-0.2439	1.2817	0.1831
10	-0.0087	0.0234	0.0040	-0.0083	-0.0662	0.9629	-0.2246	-0.4883	-0.4883	1.6479	7.0124	[illegible]	[illegible]	-0.0040	0.7932	0.5388	-0.2451	1.2207	0.1221
11	-0.0087	0.0234	0.0040	-0.0083	-0.0625	0.9614	-0.2246	-0.6714	-0.4272	1.7090	7.0124	0.0035	0.0014	-0.0040	0.8032	0.5371	-0.2456	1.2817	0.0610
12	-0.0087	0.0234	0.0040	-0.0083	-0.0654	0.9578	-0.2219	-0.7324	-0.4272	1.8921	7.0124	0.0035	0.0014	-0.0040	0.8003	0.5381	-0.2463	1.2207	0.1221
13	-0.0087	0.0234	0.0040	-0.0083	-0.0664	0.9568	-0.2224	-0.8545	-0.3662	2.0142	7.0124	[illegible]	[illegible]	-0.0040	0.8020	0.5388	-0.2427	1.2207	0
14	-0.0087	0.0234	0.0040	-0.0083	-0.0632	0.9551	-0.2266	-0.9155	-0.4272	2.1973	7.0124	[illegible]	[illegible]	-0.0040	0.7971	0.5369	-0.2439	1.2207	-0.0610
15	-0.0087	0.0234	0.0040	-0.0083	-0.0608	0.9587	-0.2129	-0.6714	-0.4883	2.2583	7.0124	[illegible]	0.0014	-0.0040	0.7998	0.5305	-0.2446	1.2817	-0.1221
16	-0.0087	0.0234	0.0040	-0.0083	-0.0659	0.9592	-0.2241	-0.6714	-0.4272	2.2583	7.0050	0.0036	0.0014	-0.0040	0.7983	0.5366	-0.2417	1.1597	-0.1221
17	-0.0087	0.0234	0.0040	-0.0083	-0.0657	0.9600	-0.2231	-0.7324	-0.4272	2.4414	7.0050	0.0037	0.0014	-0.0040	0.7947	0.5393	-0.2468	1.2207	-0.2441
18	-0.0087	0.0234	0.0040	-0.0083	-0.0630	0.9565	-0.2205	-0.6104	-0.4272	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	-0.2488	1.2207	-0.3052
19	-0.0087	0.0234	0.0040	-0.0083	-0.0635	0.9578	-0.2183	-0.4883	-0.3662	2.4414	[illegible]	[illegible]	[illegible]	[illegible]	0.7954	0.5344	-0.2461	1.2207	-0.3662
20	-0.0087	0.0234	0.0040	-0.0083	-0.0598	0.9614	-0.2234	-0.4272	-0.4272	2.4414	7.0050	0.0037	0.0014	-0.0040	0.7959	0.5364	-0.2512	1.2817	-0.3662
21	-0.0087	0.0234	0.0040	-0.0083	-0.0637	0.9541	-0.2283	-0.3052	-0.2441	2.5635	7.0050	[illegible]	[illegible]	[illegible]	0.7888	0.5352	-0.2522	1.0986	-0.0610
22	-0.0087	0.0234	0.0040	-0.0083	-0.0559	0.9563	-0.2207	-0.3052	-0.3662	2.5024	[illegible]	[illegible]	[illegible]	[illegible]	0.7905	0.5398	-0.2385	1.0986	-0.3052
23	-0.0087	0.0234	0.0040	-0.0083	-0.0593	0.9575	-0.2246	-0.3662	-0.3662	2.5024	7.0050	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	1.2207	-0.4272
24	-0.0087	0.0234	0.0040	-0.0083	-0.0623	0.9587	-0.2178	-0.3052	-0.4272	2.3804	7.0101	0.0037	0.0014	-0.0040	0.7883	0.5308	-0.2468	1.3428	-0.3052
25	-0.0087	0.0234	0.0040	-0.0083	-0.0574	0.9563	-0.2168	-0.3662	-0.2441	2.3193	7.0101	0.0037	0.0014	-0.0040	0.7908	0.5354	-0.2427	1.4038	-0.3052

Raw Data: S15VR23.mat

Subjects 1-5, Session VR2 & 3

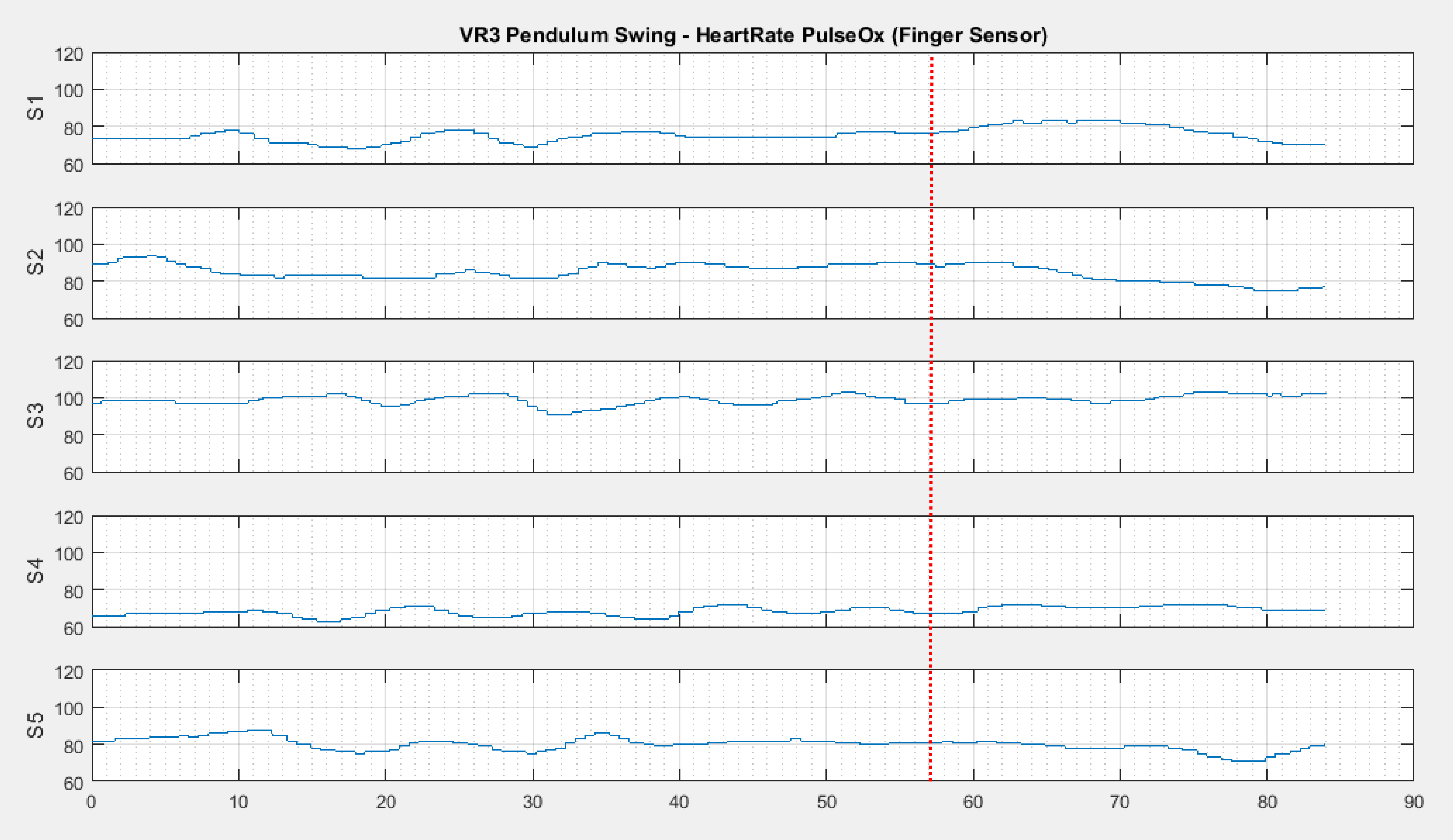
29 Columns

- 24 time based signals
- 5 classification labels
  - Subject
  - Session
  - Segment
  - Arousal
  - Valence

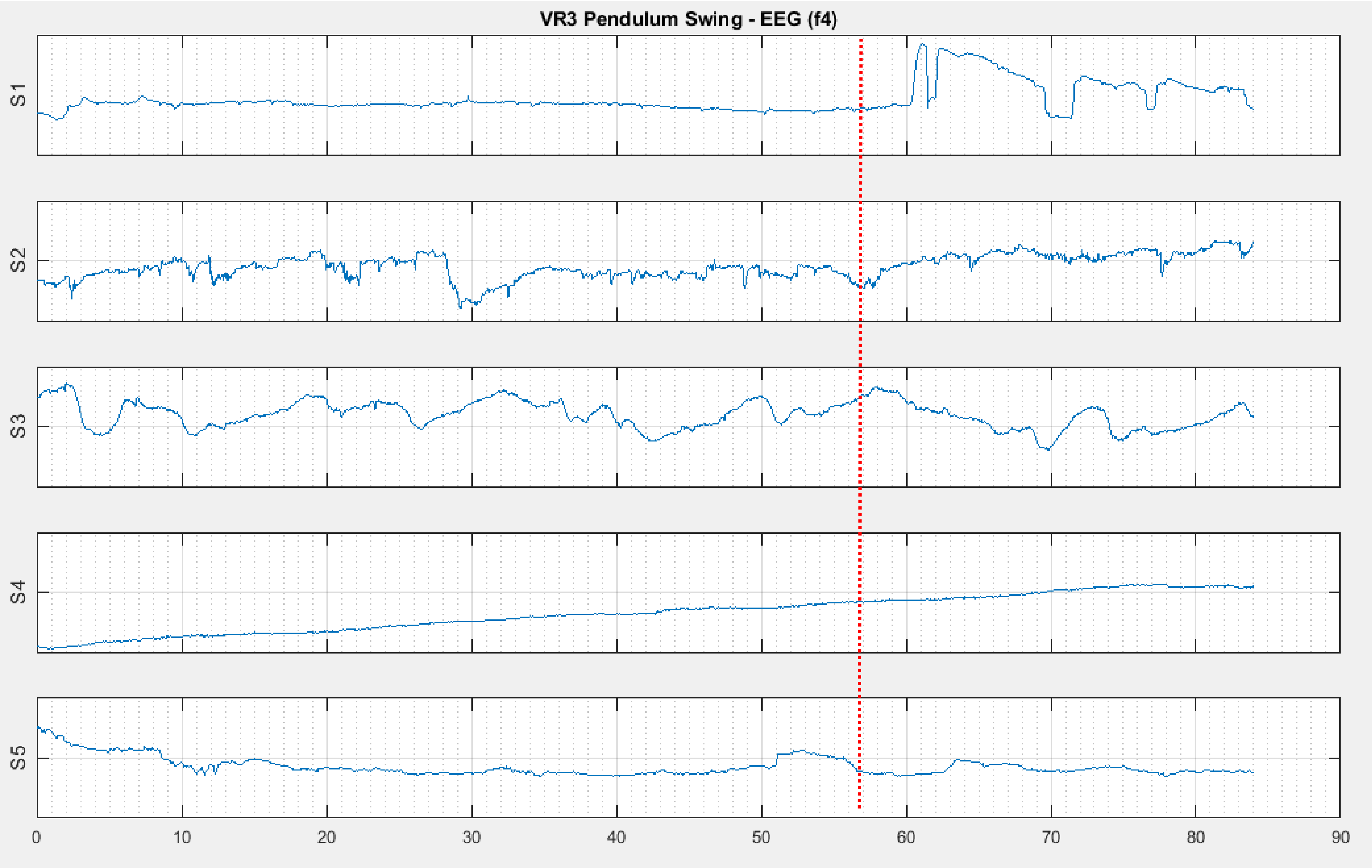
344817 Rows @ 250Hz Sample Rate

- 23 minutes total
- 4m 35s per Subject
- each Segment 90s
  - Rose and I, Rollercoaster, Swing

Data Visualization – Pendulum Swing Heart Rate



Data Visualization – Pendulum Swing EEG



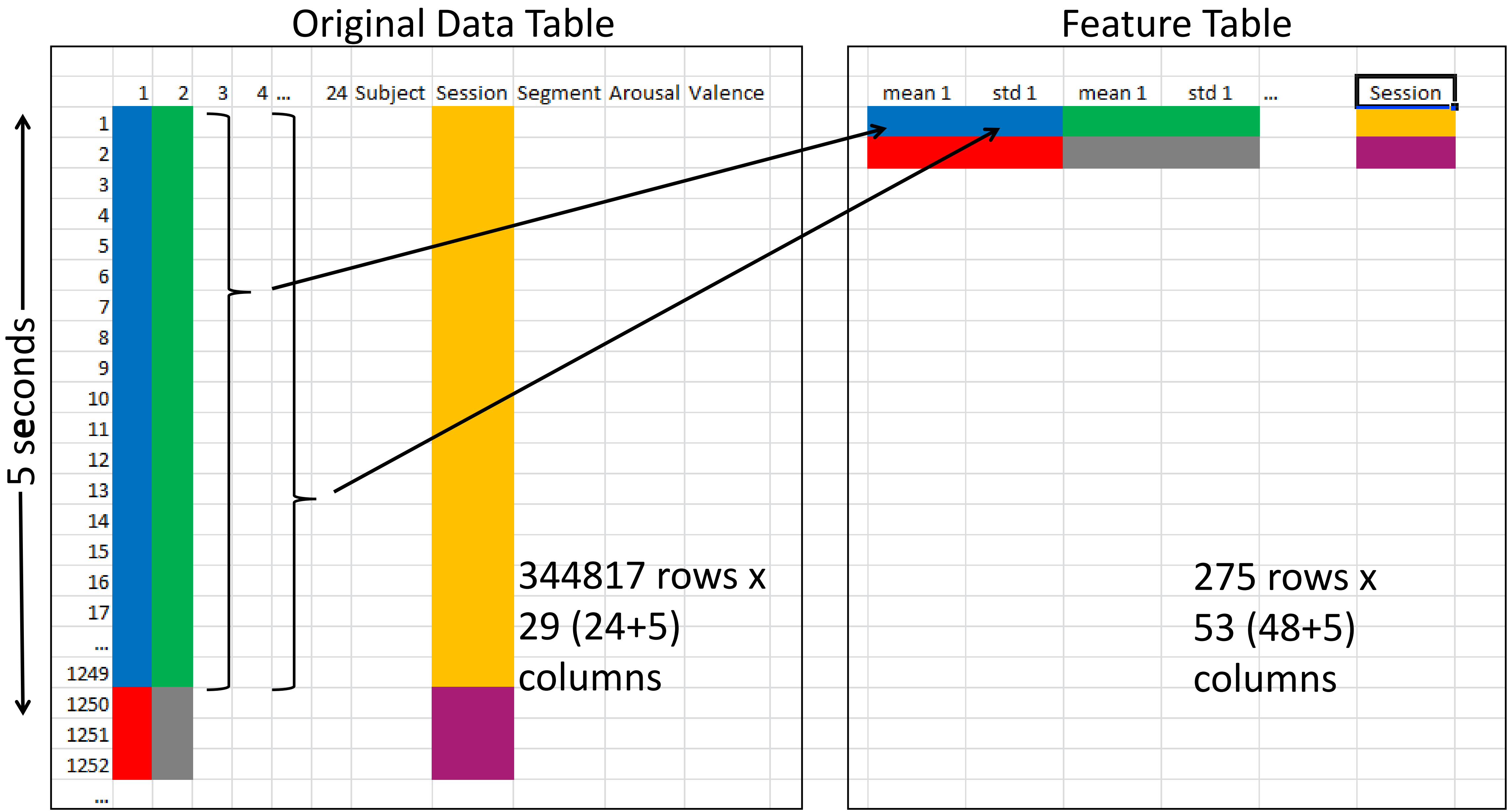
Data Preparation

"Data scientists, according to interviews and expert estimates, spend from 50 percent to 80 percent of their time mired in this more mundane labor of collecting and preparing unruly digital data, before it can be explored for useful nuggets."

For Big-Data Scientists, 'Janitor Work' Is Key Hurdle to Insights New York Times August 18, 2014

See also http://blog.revolutionanalytics.com/2014/08/data-cleaning-is-a-critical-part-of-the-data-science-process.html

Simple Segmentation and Feature Extraction



V0.028

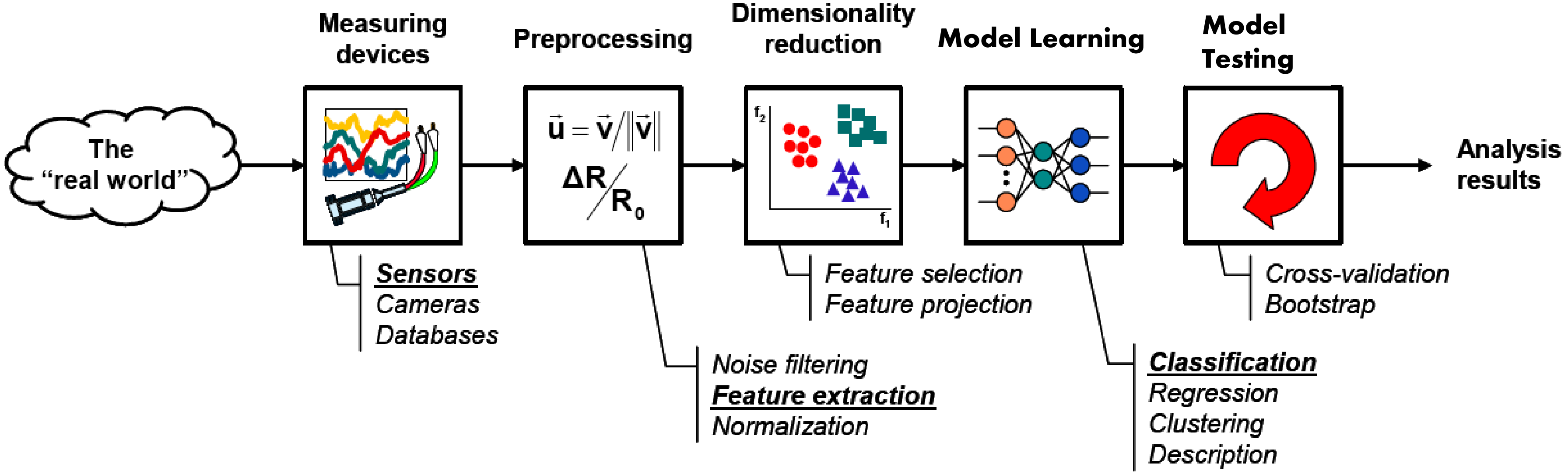
More Complex Feature Extraction

- General-purpose signal properties
  - Time domain
  - Frequency domain
  - Other signal properties
- Caveat: these are all hand-engineered features.
- Python TSFRESH library
  https://tsfresh.readthedocs.io/en/latest/text/list_of_features.html

nF.	Feature name
1	Average
2	Standard deviation
3-8	PSD- peaks frequency
9-14	PSD-peaks amplitude
15	Energy
16	Zero crossing rate
17	Energy entropy
18	Spectral centroid
19	Spectral spread
20	Spectral entropy
21	Spectral Rolloff point
22-26	MODWT- Energy of Wavelet coefficients
27-31	MODWT- Percentage of Energy of Wavelet coefficients
32-36	MODWT- Standard deviation of Wavelet coefficients
37-41	MODWT- Mean of Wavelet coefficients
42	Tsallis entropy
43	Renyi entropy
44	Shannon entropy
45-54	RSP of subbands
55	RSP- Slow wave bands-spectral bands Delta
56	RSP- Slow wave bands-spectral bands Theta
57	RSP- Slow wave bands-spectral bands Alpha
58-72	Harmonic parameters
73	Hjorth parameters– Activity
74	Hjorth parameters– Mobility
75	Hjorth parameters– Complexity
76	Skewness
77	Kurtosis
78-87	Autoregressive parameters
88-90	Percentile 25, 50, 75

Table XIV
LIST OF EXTRACTED FEATURES WITH THEIR RELEVANT NUMBERS.

The Learning Process (traditional Machine Learning)



The Learning Process (Deep Learning)

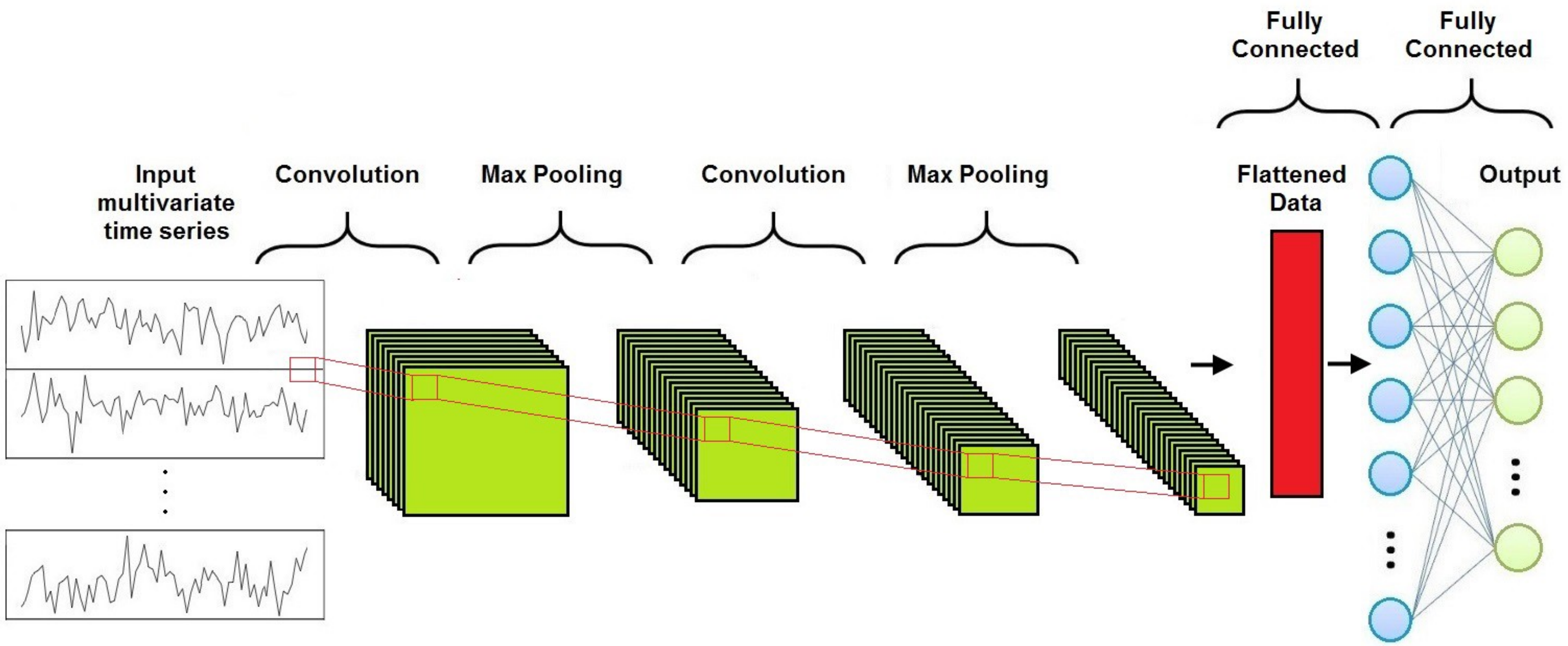


Image credit: Marco Del Pra
https://towardsdatascience.com/time-series-classification-with-deep-learning-d238f0147d6f

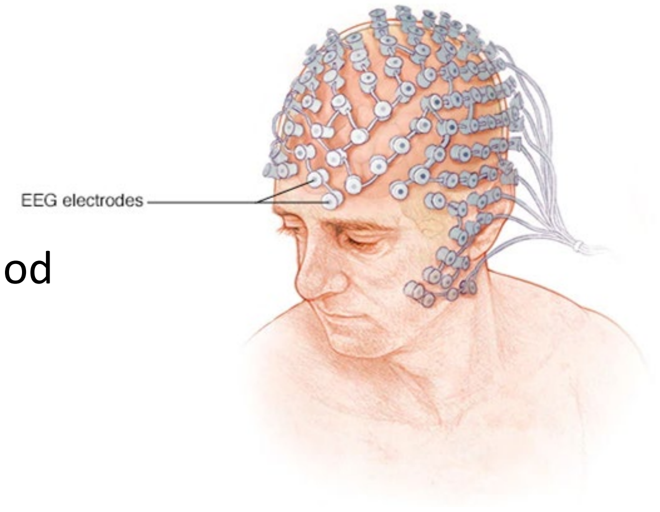
Case Study 2:
EEG Biosignal Analysis

What is EEG?

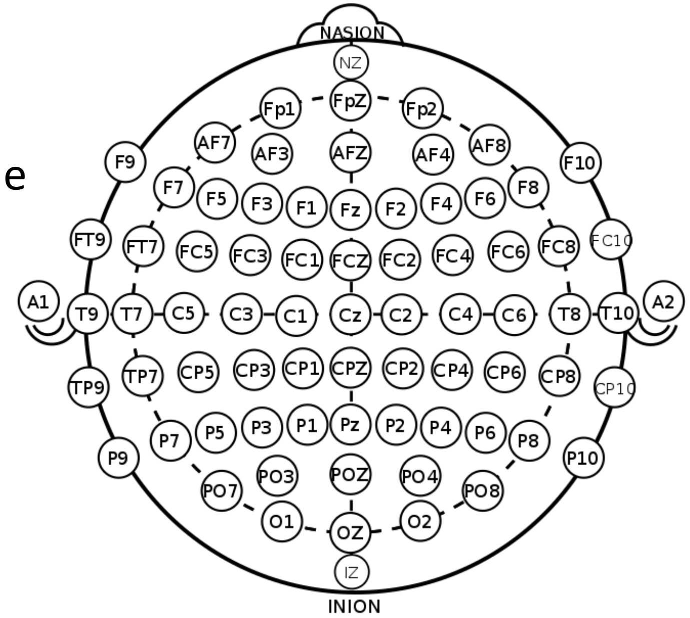
❖ Electroencephalography (EEG) is an electrophysiological monitoring method to record electrical activities of the brain.

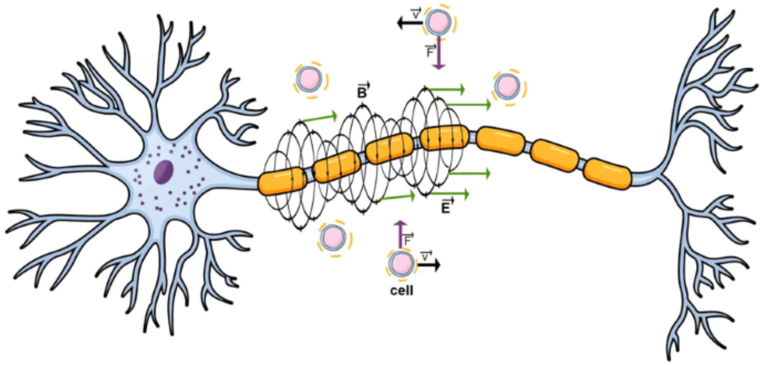
❖ It is typically noninvasive, with the electrodes placed along the scalp.

❖ EEG measures voltage fluctuations resulting from ionic current within the neurons of the brain.



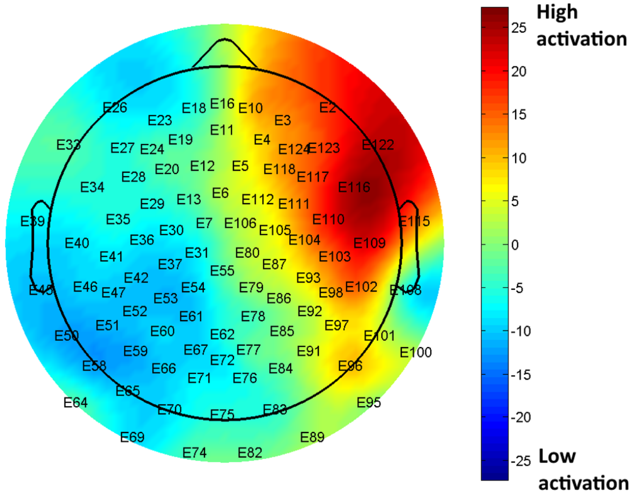
Epileptic spike and wave discharges monitored with EEG





EEG Advantages

- The greatest advantages of EEG is its high temporal resolution. EEG can determine the relative strengths and positions of electrical activity in different brain regions.
- Does not require the head/body to be fixed.
- Lightweight, portable.
- Affordable.
- Easy to use.



EEG

fMRI / PET

MEG

EEG usage

- For medical use, EEG is one of the main diagnostic tests for epilepsy. And it might also be helpful for diagnosing or treating the following disorders:
  - Brain tumor
  - Brain damage from head injury
  - Stroke
  - Sleep disorders
  - Brain dysfunction
  - Test of brain death in comatose patients
  - Test drug effects, Etc...

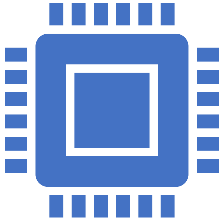
- For research use, EEG, and the related study of ERPs are used extensively in neuroscience, cognitive science, cognitive psychology, neurolinguistics and psychophysiological research, etc.

- Machine learning techniques have been used on EEG data and have shown high levels of success in classifying mental states (Relaxed, Neutral, Concentrating), mental emotional states (Negative, Neutral, Positive), Brain computer interfaces (BCI), etc.

Challenges of EEG Processing

- Low signal-to-noise ratio (SNR). Easy to be affected by environment noise.
- Non-stationary. Statistics vary across time.
- High inter-subject variability. Physiological differences between individuals.
- A Variety of data recording settings. Different stimuli, sampling rates, number of channels.
- Require domain experts to add labels. Time consuming, data shortage.
- Domain approaches are used to pre-process data.

Is there hope for successful EEG analysis?

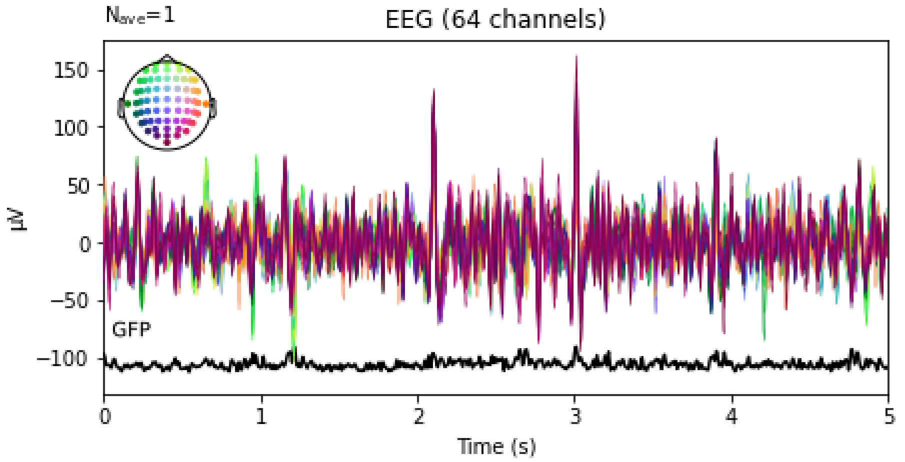


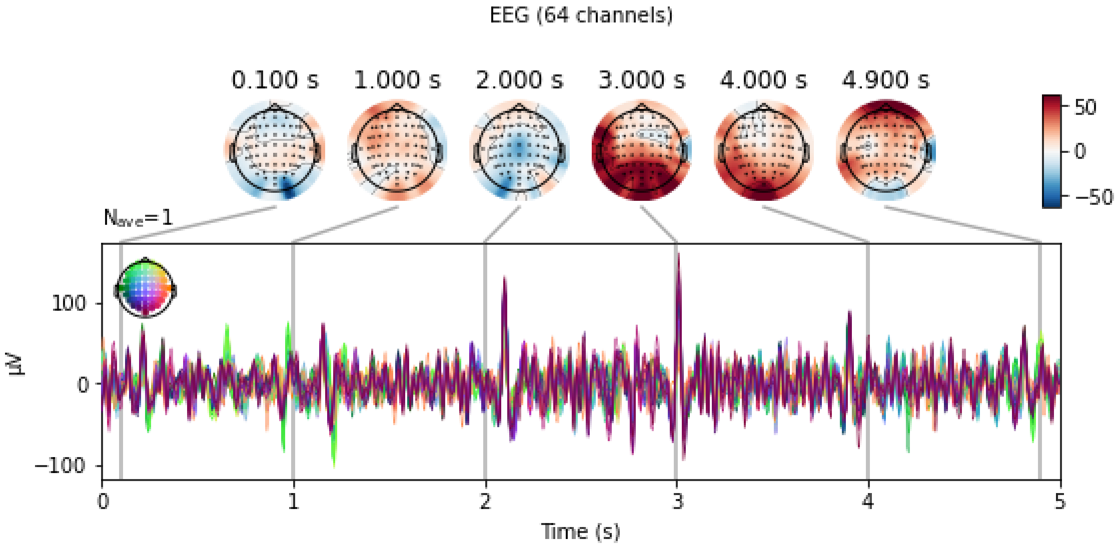
Deep learning (DL) could significantly simplify processing pipelines by allowing automatic end-to-end learning of preprocessing, feature extraction and classification modules, it potentially can reach competitive performance on the target task.

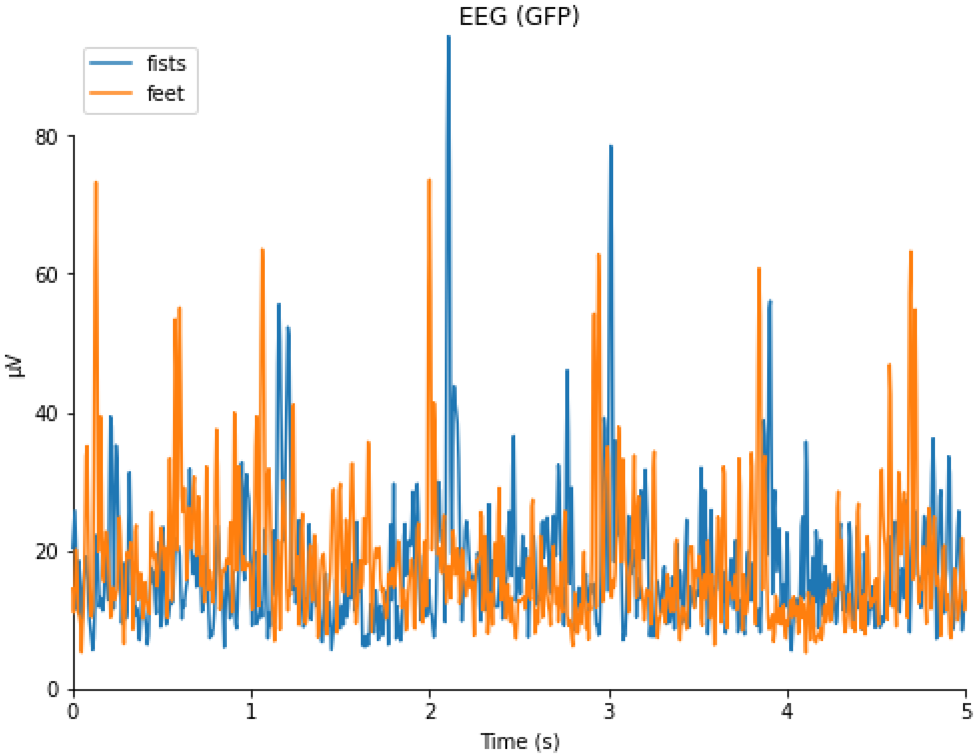
Deep learning as a data driven approach, it requires a large amount of data to generate considerable results comparing to traditional methods.

Many deep learning techniques have been used to improve EEG data classification accuracy but few of them tackle the issue to solve the data shortage problem in this field.

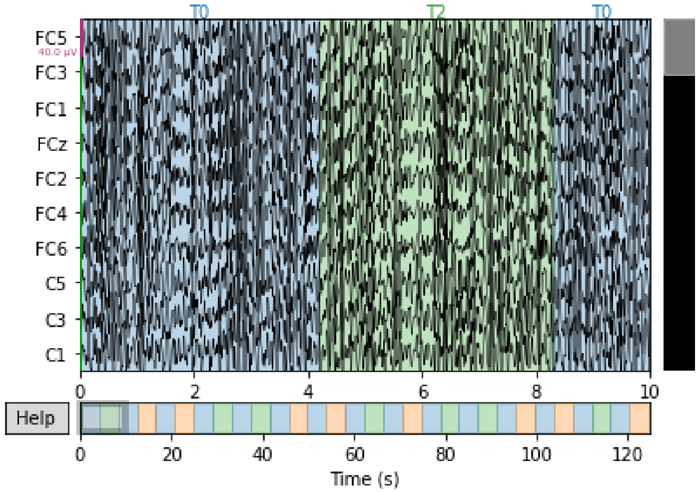
Visualizations



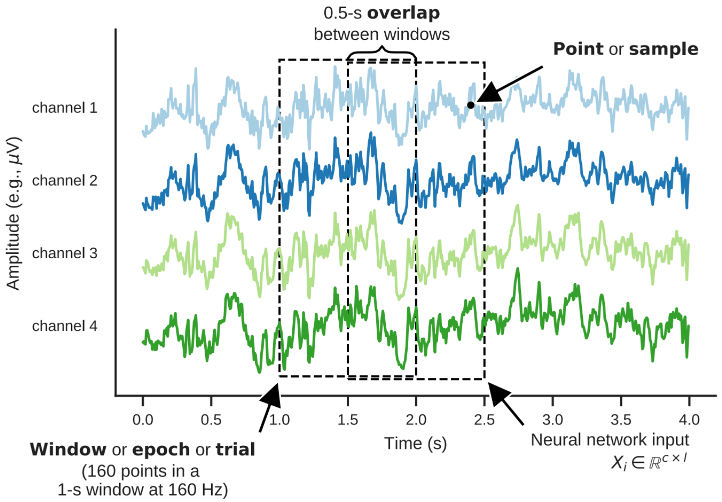




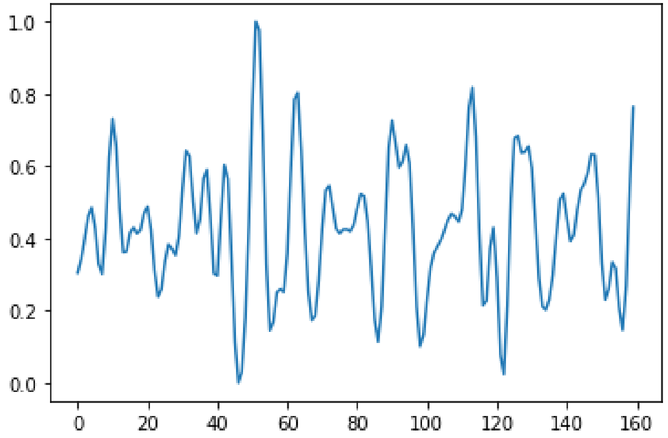
Common preprocessing steps



Concatenate raw data



Segment data



Amplify each channel signal and normalize to 0-1

Methodology

Classify with **traditional machine learning** models

Feature extractor:

e.g. Common spatial pattern (CSP)

Machine learning Method:

K Nearest Neighbors, Linear SVM, RBF SVM, Gaussian Process, Decision Tree,

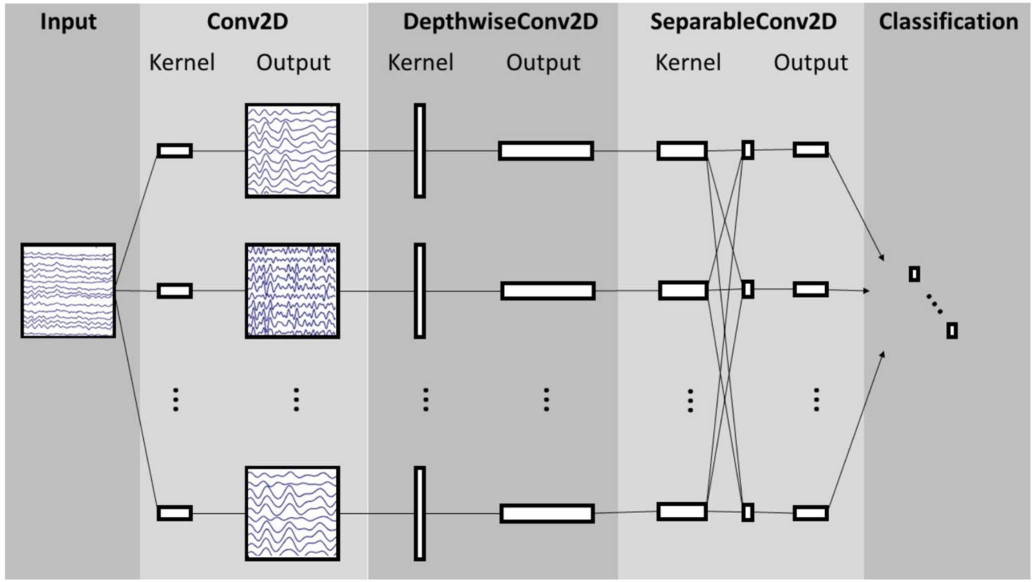
Random Forest, AdaBoost, Naive Bayes, Logistic Regression,

LinearDiscriminantAnalysis, QuadraticDiscriminantAnalysis, etc.

Training method: sklearn.Pipeline(CSP + MLModel)

Methodology

Classify with **deep convolutional neural networks**



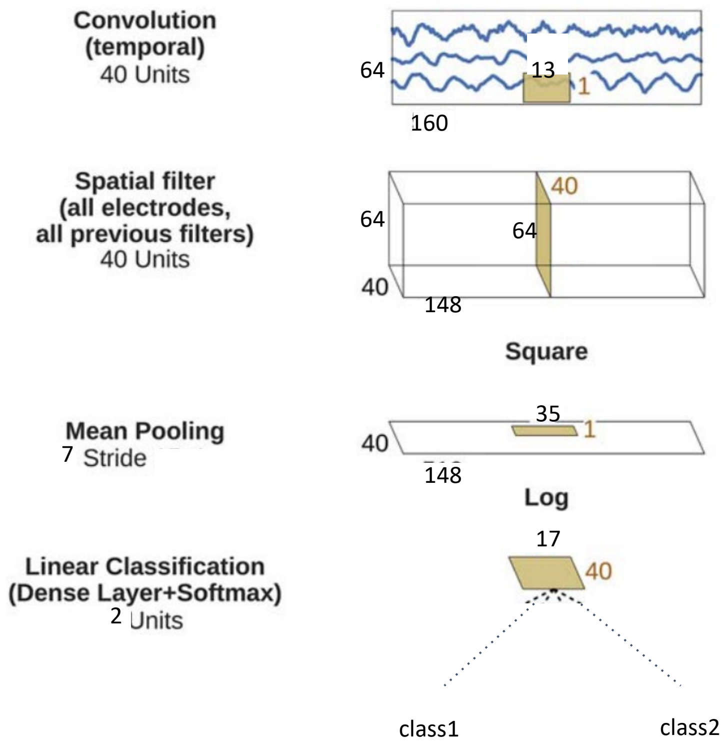
EEGNet

Layer (type)	Output Shape	Param #
input_2 (InputLayer)	[(None, 1, 64, 160)]	0
conv2d_2 (Conv2D)	(None, 8, 64, 160)	256
batch_normalization_1 (Batch	(None, 8, 64, 160)	32
depthwise_conv2d (DepthwiseC	(None, 16, 1, 160)	1024
batch_normalization_2 (Batch	(None, 16, 1, 160)	64
activation_3 (Activation)	(None, 16, 1, 160)	0
average_pooling2d_1 (Average	(None, 16, 1, 40)	0
dropout_1 (Dropout)	(None, 16, 1, 40)	0
separable_conv2d (SeparableC	(None, 16, 1, 40)	512
batch_normalization_3 (Batch	(None, 16, 1, 40)	64
activation_4 (Activation)	(None, 16, 1, 40)	0
average_pooling2d_2 (Average	(None, 16, 1, 5)	0
dropout_2 (Dropout)	(None, 16, 1, 5)	0
flatten (Flatten)	(None, 80)	0
dense (Dense)	(None, 2)	162
softmax (Activation)	(None, 2)	0

Lawhern, Vernon J., et al. "EEGNet: a compact convolutional neural network for EEG-based brain–computer interfaces." Journal of neural engineering 15.5 (2018): 056013.

Methodology

Classify with **deep convolutional neural networks**



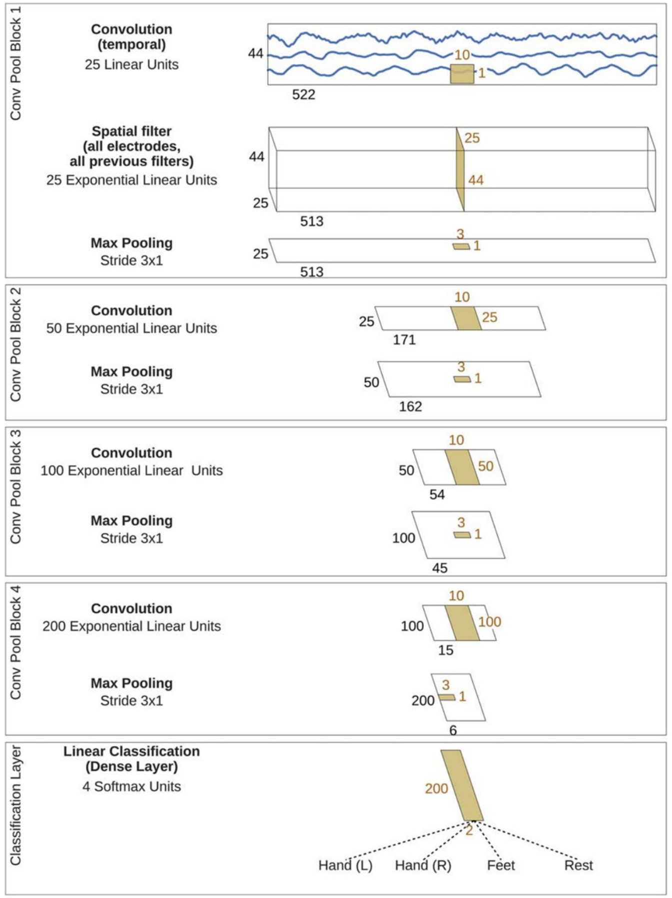
ShallowConvNet

Layer (type)	Output Shape	Param #
input_1 (InputLayer)	[(None, 1, 64, 160)]	0
conv2d (Conv2D)	(None, 40, 64, 148)	560
conv2d_1 (Conv2D)	(None, 40, 1, 148)	102400
batch_normalization (BatchNo	(None, 40, 1, 148)	160
activation (Activation)	(None, 40, 1, 148)	0
average_pooling2d (AveragePo	(None, 40, 1, 17)	0
activation_1 (Activation)	(None, 40, 1, 17)	0
dropout (Dropout)	(None, 40, 1, 17)	0
flatten (Flatten)	(None, 680)	0
dense (Dense)	(None, 2)	1362
activation_2 (Activation)	(None, 2)	0

Schirrmeister, Robin Tibor, et al. "Deep learning with convolutional neural networks for EEG decoding and visualization." Human brain mapping 38.11 (2017): 5391-5420.

Methodology

Classify with **deep convolutional neural networks**



DeepConvNet

Layer (type)	Output Shape	Param #
input_3 (InputLayer)	[(None, 1, 64, 160)]	0
conv2d_3 (Conv2D)	(None, 25, 64, 156)	150
conv2d_4 (Conv2D)	(None, 25, 1, 156)	40025
batch_normalization_4 (Batch	(None, 25, 1, 156)	100
activation_5 (Activation)	(None, 25, 1, 156)	0
max_pooling2d (MaxPooling2D)	(None, 25, 1, 78)	0
dropout_3 (Dropout)	(None, 25, 1, 78)	0
conv2d_5 (Conv2D)	(None, 50, 1, 74)	6300
batch_normalization_5 (Batch	(None, 50, 1, 74)	200
activation_6 (Activation)	(None, 50, 1, 74)	0
max_pooling2d_1 (MaxPooling2	(None, 50, 1, 37)	0
dropout_4 (Dropout)	(None, 50, 1, 37)	0
conv2d_6 (Conv2D)	(None, 100, 1, 33)	25100
batch_normalization_6 (Batch	(None, 100, 1, 33)	400
activation_7 (Activation)	(None, 100, 1, 33)	0
max_pooling2d_2 (MaxPooling2	(None, 100, 1, 16)	0
dropout_5 (Dropout)	(None, 100, 1, 16)	0
conv2d_7 (Conv2D)	(None, 200, 1, 12)	100200
batch_normalization_7 (Batch	(None, 200, 1, 12)	800
activation_8 (Activation)	(None, 200, 1, 12)	0
max_pooling2d_3 (MaxPooling2	(None, 200, 1, 6)	0
dropout_6 (Dropout)	(None, 200, 1, 6)	0
flatten_1 (Flatten)	(None, 1200)	0
dense_1 (Dense)	(None, 2)	2402
activation_9 (Activation)	(None, 2)	0

Schirrmeister, Robin Tibor, et al. "Deep learning with convolutional neural networks for EEG decoding and visualization." Human brain mapping 38.11 (2017): 5391-5420.

Practical examples with source code

- Visit the shared Google Drive folder: https://drive.google.com/drive/folders/1-GSnRyWCjodfnnkeiY5mu9pDLxAdAs2p?usp=sharing

OR

- GitHub repository: https://github.com/imics-lab/biosignal_analysis_tutorials