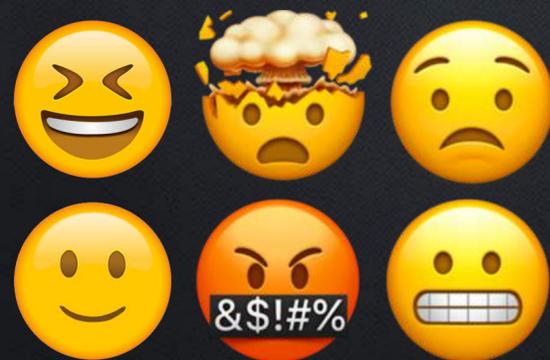




Software Engineering Conference Russia 2018

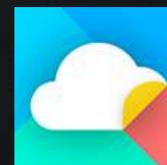
October 12-13
Moscow



Исследование
эмоциональных
откликов при чтении

Кирилл Улитин

Новые Облачные Технологии





joy: 0.00
sadness: 0.02
disgust: 0.44
contempt: 0.19
anger: 0.00
fear: 0.00
surprise: 0.20
valence: 0.00
engagement: 0.12



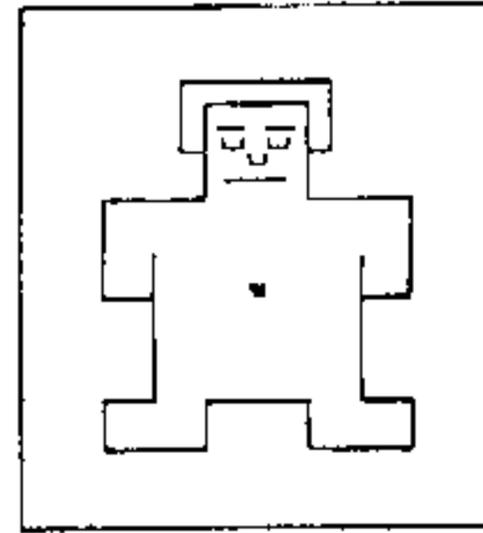
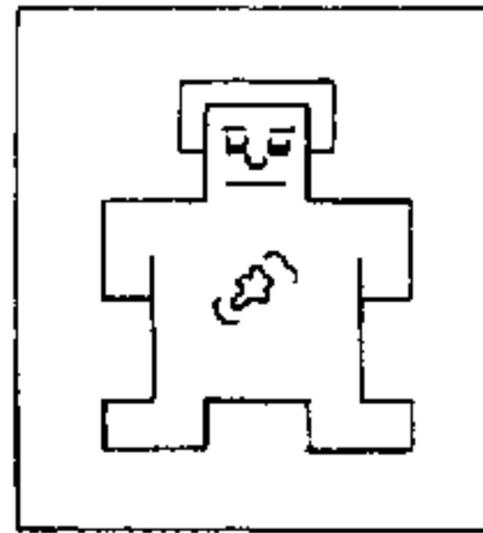
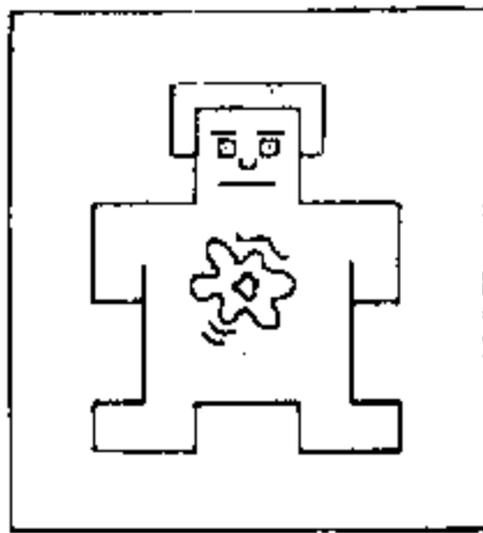
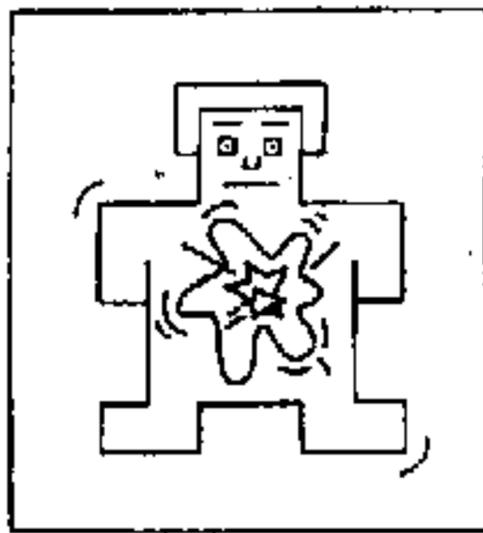
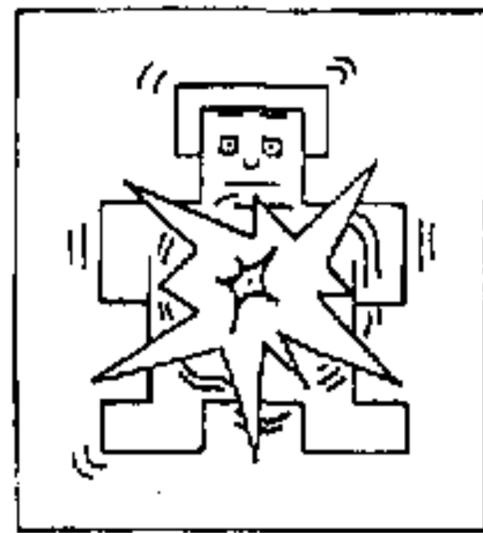
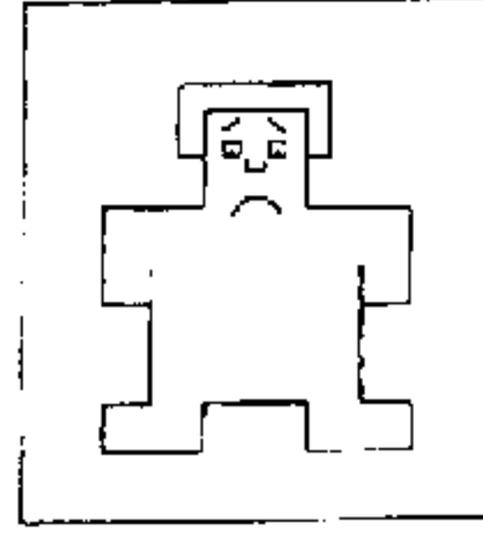
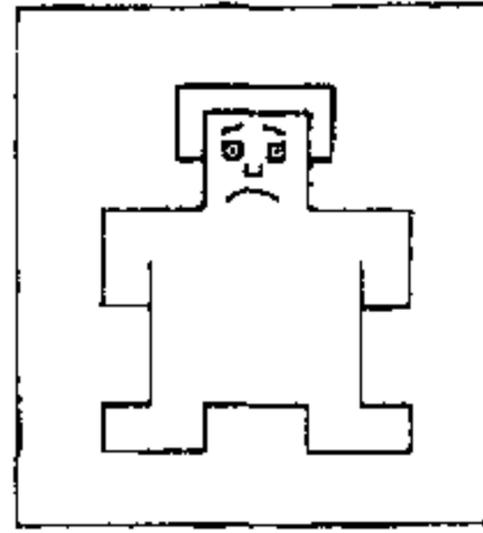
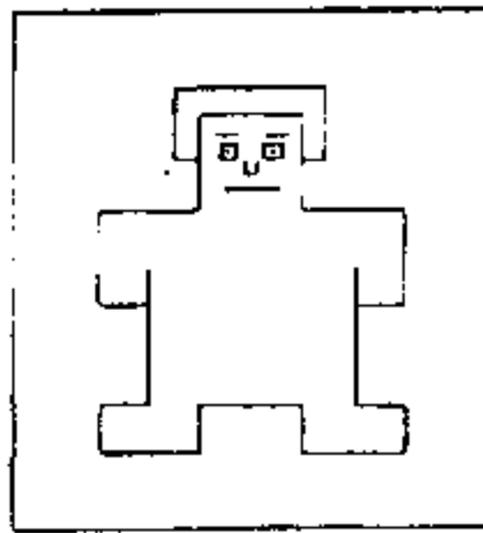
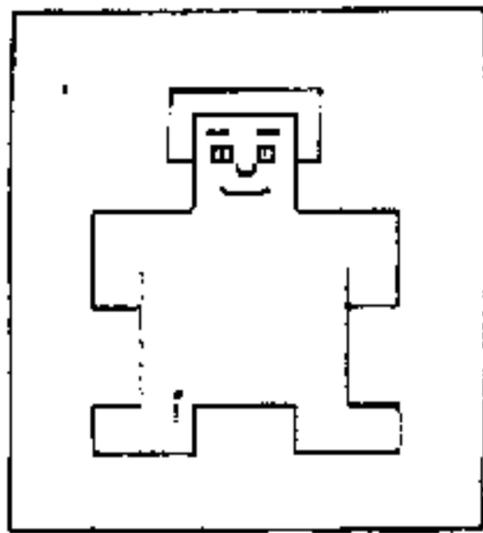
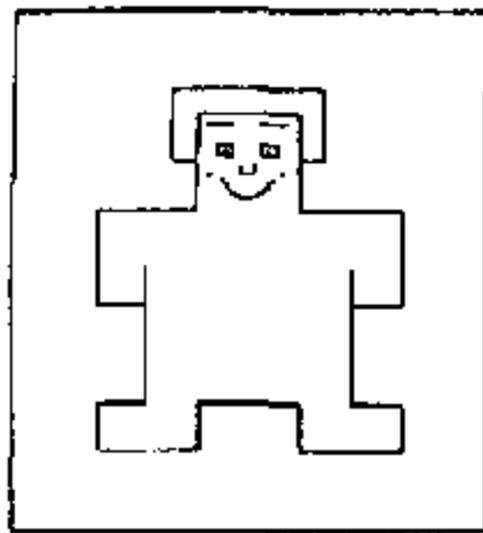
**KEEP
CALM
AND
TEST THE
HYPOTHESIS**

Можно ли применить алгоритм для распознавания эмоций по видео при чтении документов

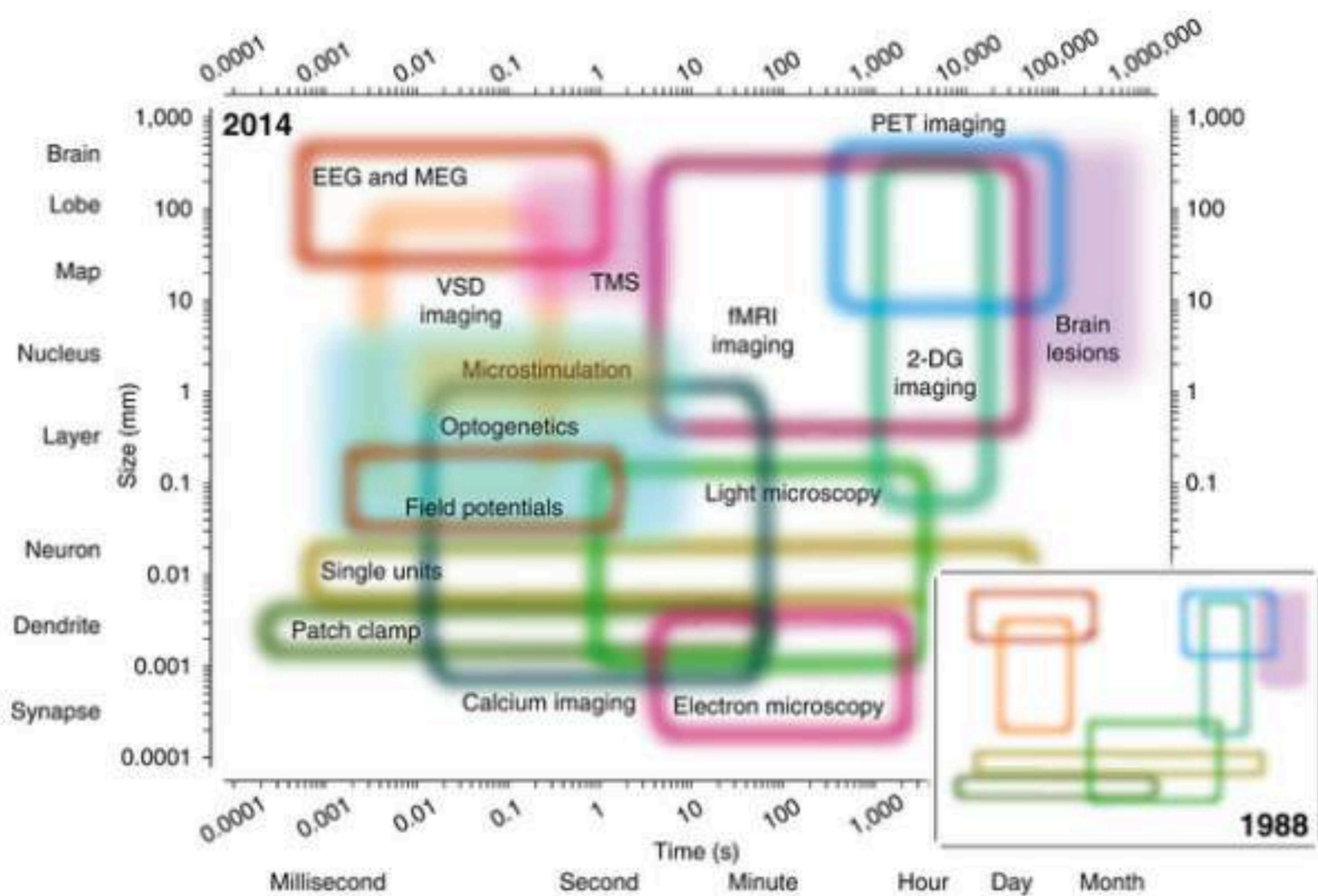
Насколько хорошо работает один из таких алгоритмов

Испытывает ли человек при чтении эмоции, которые нельзя считать с лица

Можно ли использовать нейроинтерфейс для оценки эмоций



<https://www.ncbi.nlm.nih.gov/pubmed/7962581>

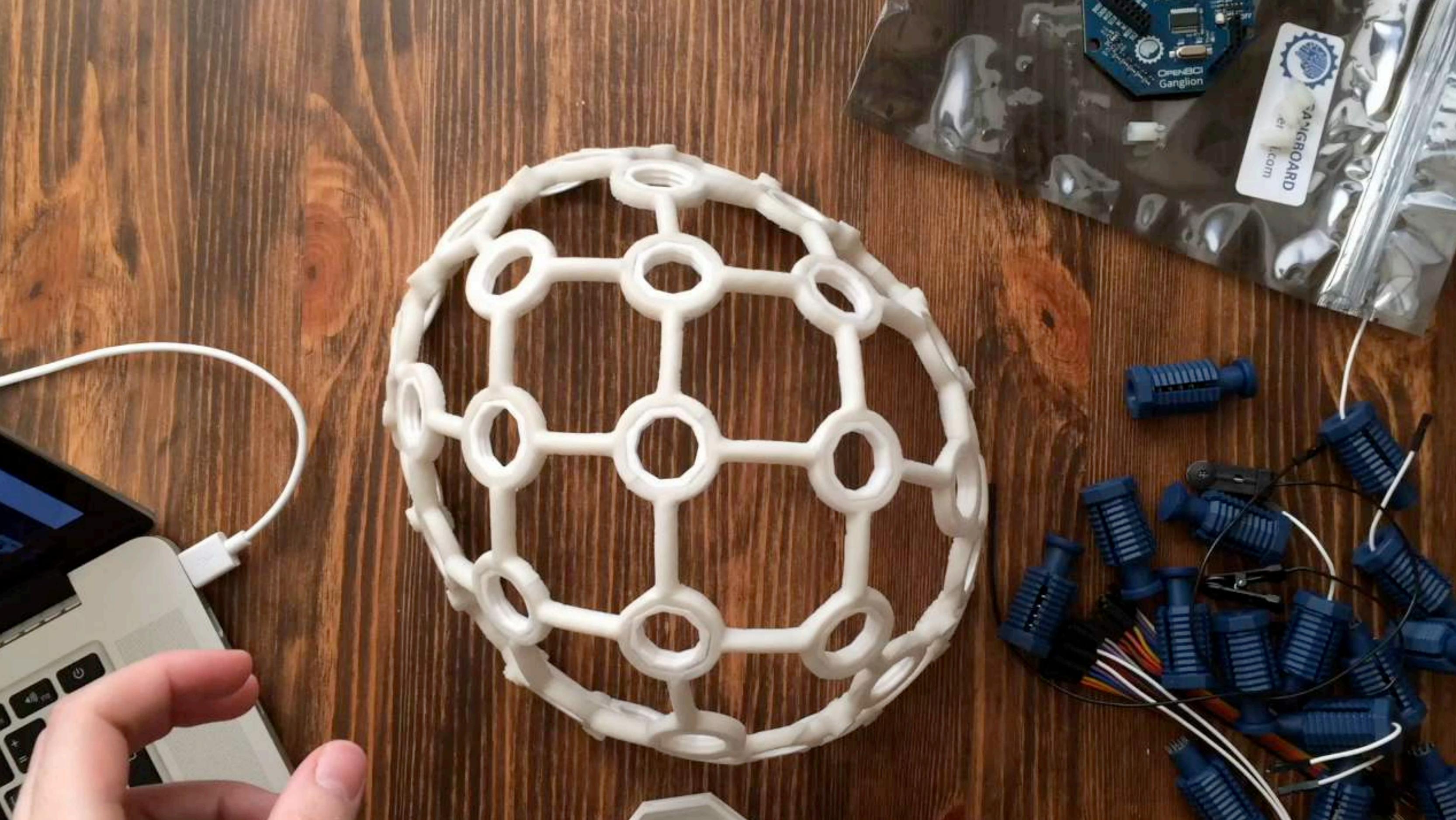




<http://neuro.chat/>





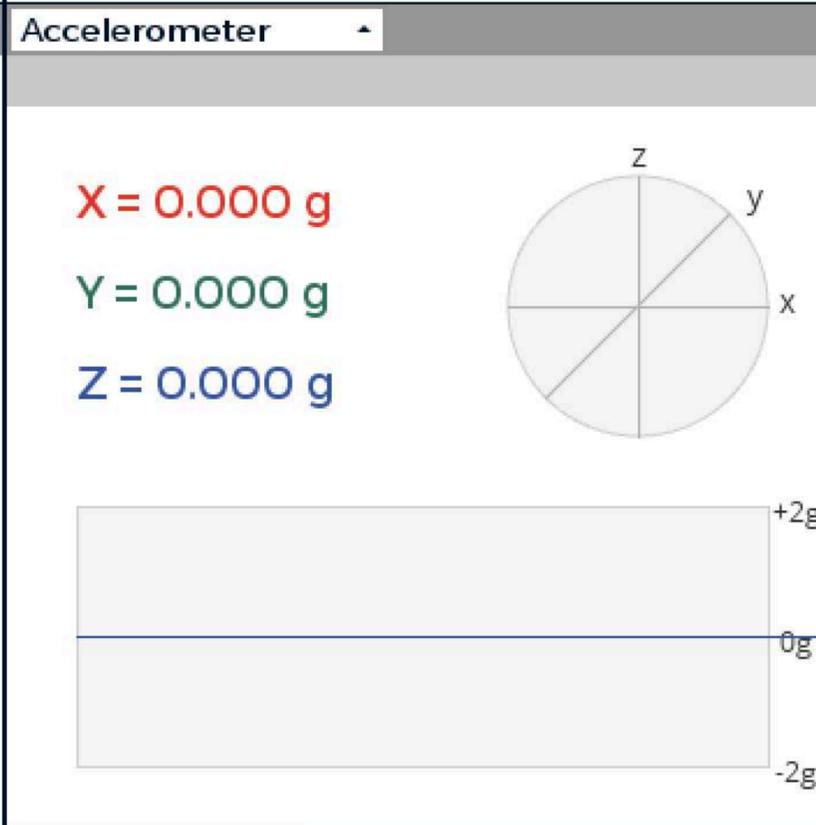
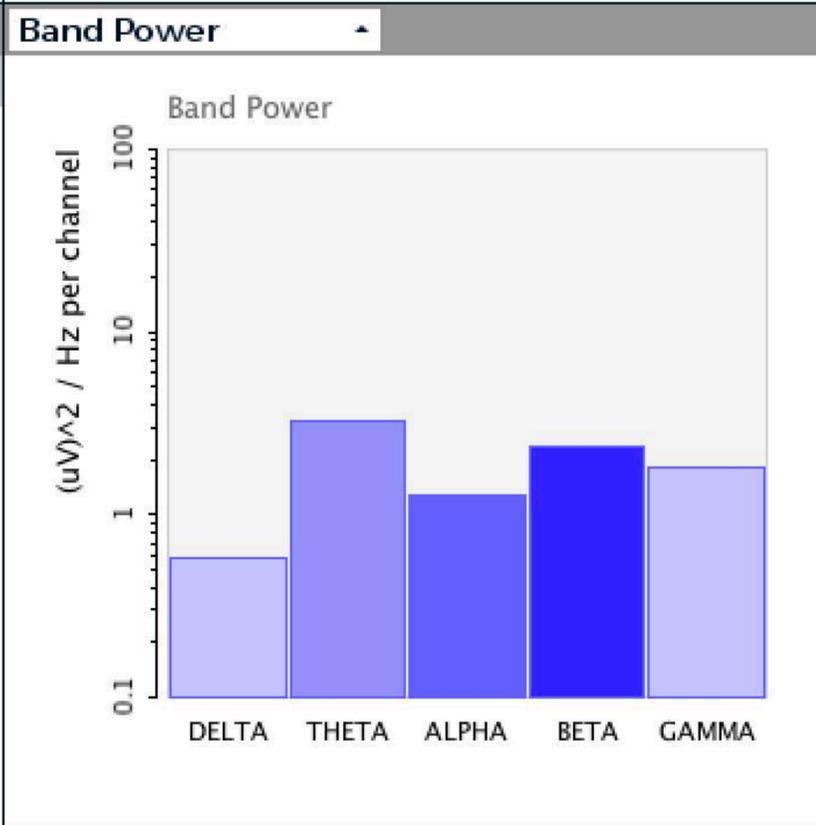
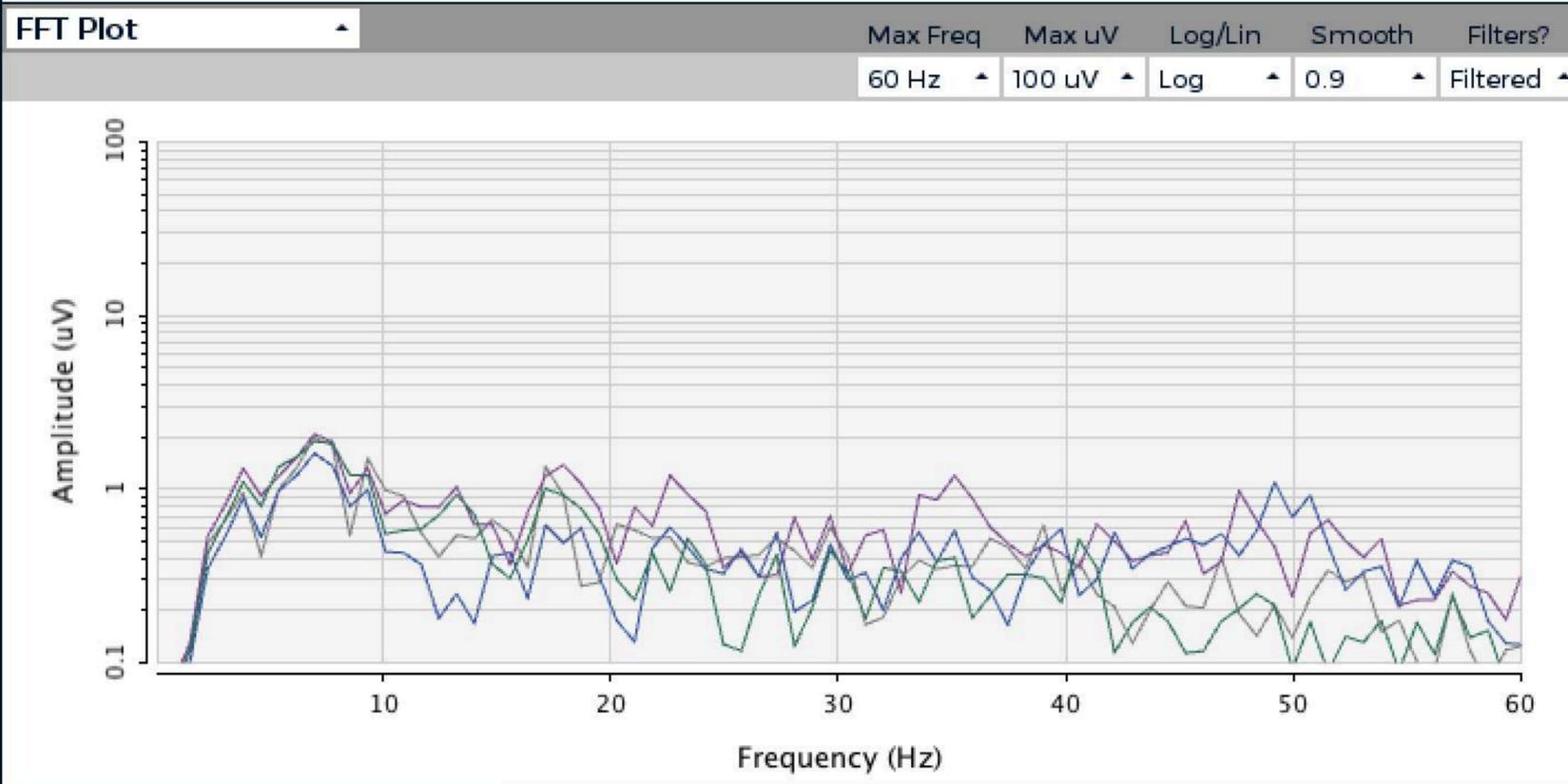
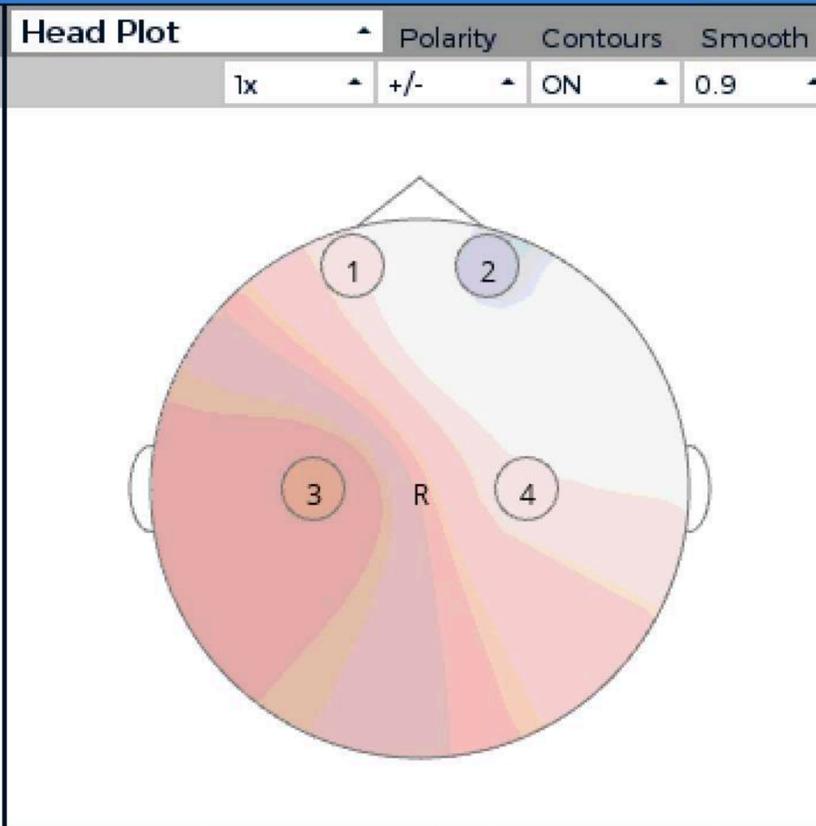
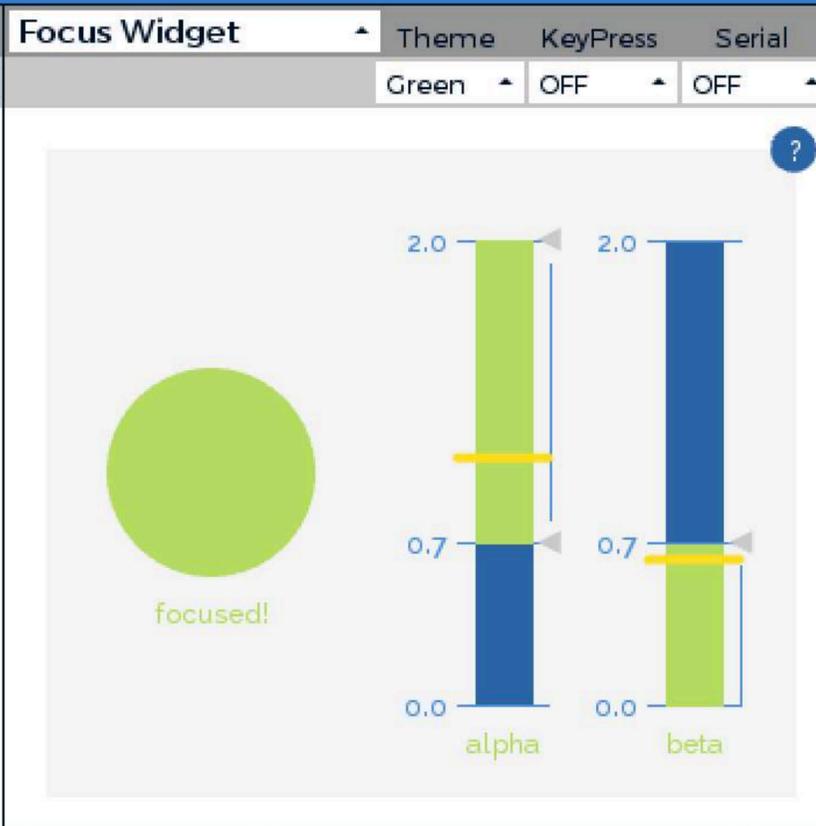
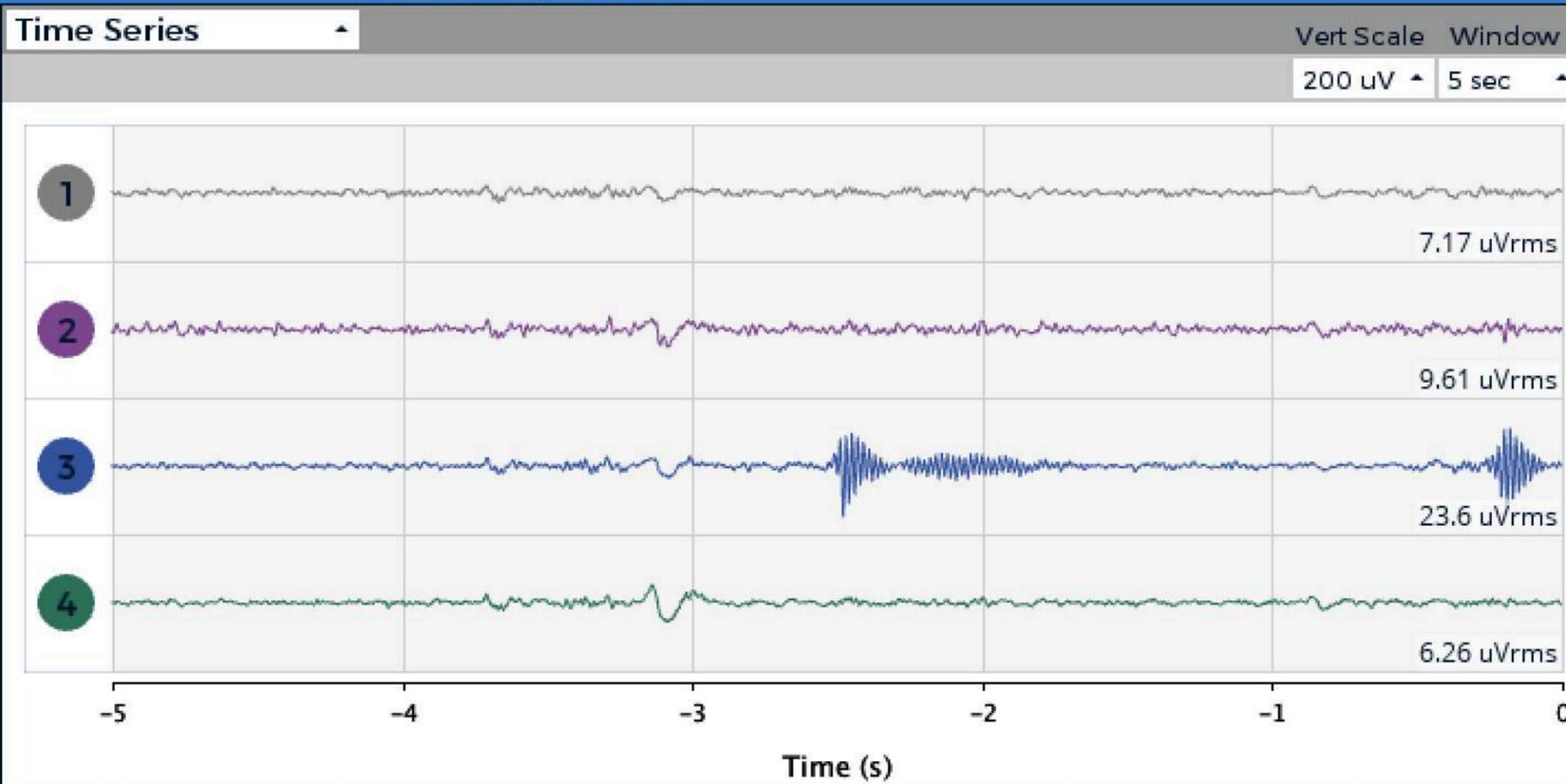


Start Data Stream

Notch 50Hz

BP Filt 5-50 Hz

Layout



Data stream stopped.

A Novel Emotion Elicitation Index Using Frontal Brain Asymmetry for Enhanced EEG-Based Emotion Recognition

Panagiotis C. Petrantonakis, *Student Member, IEEE*, and Leontios J. Hadjileontiadis, *Senior Member, IEEE*

Abstract—This paper aims at providing a novel EEG-based emotion recognition procedure based on the frontal brain asymmetry theory, an index (AsI), is introduced, in order to quantify the emotion elicitation procedure. This is accomplished by a multidimensional analysis between different EEG sites from the two hemispheres. The proposed approach was evaluated using (Fp1, Fp2, and F3/F4 10/20 sites) EEG recordings from healthy right-handed subjects. For the evaluation of the AsI, an extensive classification procedure using two feature-vector extraction techniques and six different classification scenarios in the frontal cortex was used. This resulted in classification results up to 94.40% for the user-dependent case and 94.40% for the user-independent case, demonstrating the efficacy of AsI as an index for the emotion recognition.

Index Terms—Emotion elicitation, electroencephalogram, frontal brain asymmetry, directed information.

I. INTRODUCTION

HUMAN machine interaction (HMI) has attracted attention in the last decade as machines have influenced our lives in many aspects, such as work, profession, and entertainment. It has been argued that machines could understand a person's affect and become more intuitive, smoother, and more user-friendly. A new approach in the HMI area known as Affective Computing (AC). AC is the research field that designs systems and devices that can recognize human emotions and would serve as a bridge between machines with the ability of acting emotionally.

Emotion recognition is the first step towards the mentioned ultimate endeavor of AC. In order to achieve this, many approaches have been proposed, such as facial expressions [2], [3], speech [4], heart rate variability, the autonomous nervous system (ANS) (e.g., galvanic skin response) [6], [7] or even

Psychophysiology, 40 (2003), 838–848. Blackwell Publishing Inc. Printed in the USA.
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DOI: 10.1111/1469-8986.00121

EARLY CAREER AWARD

Clarifying the emotive functions of asymmetrical frontal cortical activity

EDDIE HARMON-JONES
Department of Psychology, University of Exeter

Abstract

Asymmetrical activity over the frontal cortex is associated with different motivations. Explanations of the functions of positive affect and/or approach motivation, positive affect and/or withdrawal motivation, as only positive (negative) affect, and withdrawal motivation. Consequently, this research is unique in that it examines the valence, motivational direction, and motivational content of the emotion of anger, a negative emotion. It is argued that frontal cortical activity is due to asymmetrical activity in the frontal cortex, as discussed.

Descriptors: Emotion, Motivation

 **frontiers**
in Neuroscience

METHODS
published: 02 October 2015
doi: 10.3389/fnins.2015.00354



CrossMark

Musical neurofeedback for treating depression in elderly people

Rafael Ramirez^{1*}, Manel Palencia-Lefler², Sergio Giraldo¹ and Zacharias Vamvakousis¹

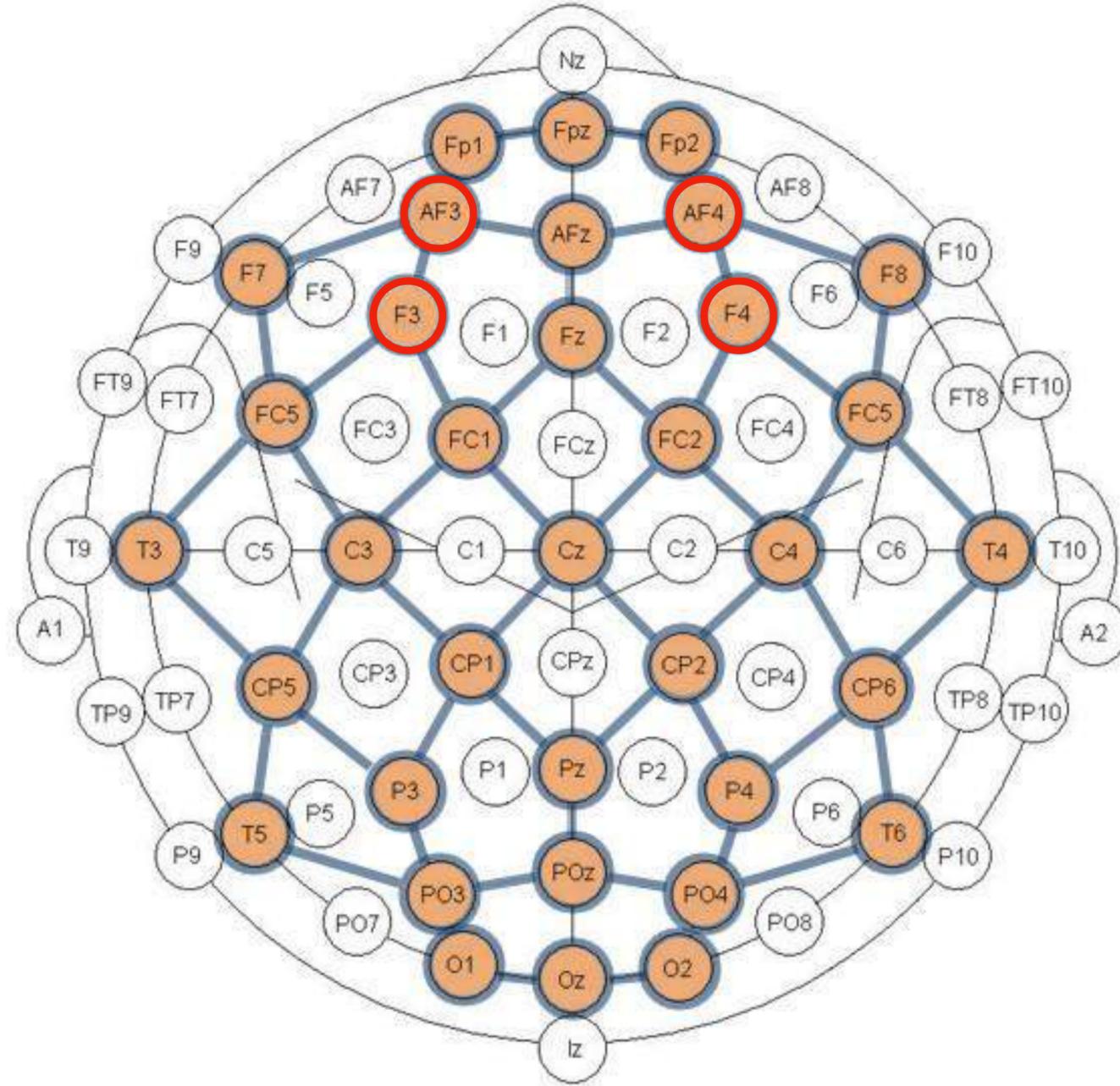
¹ Department of Information and Communication Technologies, Universitat Pompeu Fabra, Barcelona, Spain, ² Department of Communication, Universitat Pompeu Fabra, Barcelona, Spain

$$\text{Arousal} = (\beta_{F3} + \beta_{F4} + \beta_{AF3} + \beta_{AF4}) / (\alpha_{F3} + \alpha_{F4} + \alpha_{AF3} + \alpha_{AF4})$$

$$\text{Valence} = \alpha_{F4} - \alpha_{F3}$$

Ultracortex Mark IV

Node Locations (35 total)



Based on the internationally accepted **10-20 System** for electrode placement in the context of EEG research

Arousal

Activation



Pleasant

Valence

Unpleasant



Deactivation

Study	Stimuli	#Chan.	Method Description	Emotion states	Accuracy	Pattern Study
[4]	IAPS, IADS	3	Power of alpha and beta, then PCA, 5 subjects, classification with FDA	Valence and arousal	Valence: 92.3%, arousal: 92.3%	×
[5]	IAPS	2	Amplitudes of four frequency bands, 17 subjects, evaluated KNN, Bagging	Valence (12), arousal (12) and dominance (12)	Valence: 74%, arousal: 74%, and dominance: 75%	×
[6]	Video	62	Wavelet features of alpha, beta and gamma, 20 subjects, classification with KNN and LDA	disgust, happy, surprise, fear and neutral	83.26%	×
[7]	Music	24	Power spectral density and asymmetry features of five frequency bands, 26 subjects, evaluated SVM	Joy, anger, sadness, and pleasure	82.29%	✓
[8]	IAPS	8	Spectral power features, 11 subjects, KNN	Positive, negative and neutral	85%	×
[9]	IAPS	4	Asymmetry index of alpha and beta power, 16 subjects, SVM	Four quadrants of the valence-arousal space	94.4% (subject-dependent), 62.58% (subject-independent)	×
[10]	Video	32	Spectral power features of five frequency bands, 32 subjects, Gaussian naive Bayes classifier	Valence (2), arousal (2) and liking (2)	Valence: 57.6%, arousal: 62% and liking: 55.4%	×
[11]	Music	14	Time-frequency (TF) analysis, 9 subjects, KNN, QDA and SVM	Like and dislike	86.52%	✓
[12]	Video	32	Power spectral density features of five frequency bands, modality fusion with eye track, 24 subjects, SVM	Valence (3) and arousal (3)	Valence: 68.5%, arousal: 76.4%	×
[13]	Video	62	Power spectrum features, wavelet features, nonlinear dynamical features, 6 subjects, SVM	Positive and negative	87.53%	✓
[14]	IAPS	64	Higher Order Crossings, Higher Order Spectra and Hilbert-Huang Spectrum features, 16 subjects, QDA	Happy, curious, angry, sad, quiet	36.8%	✓



Accuracy

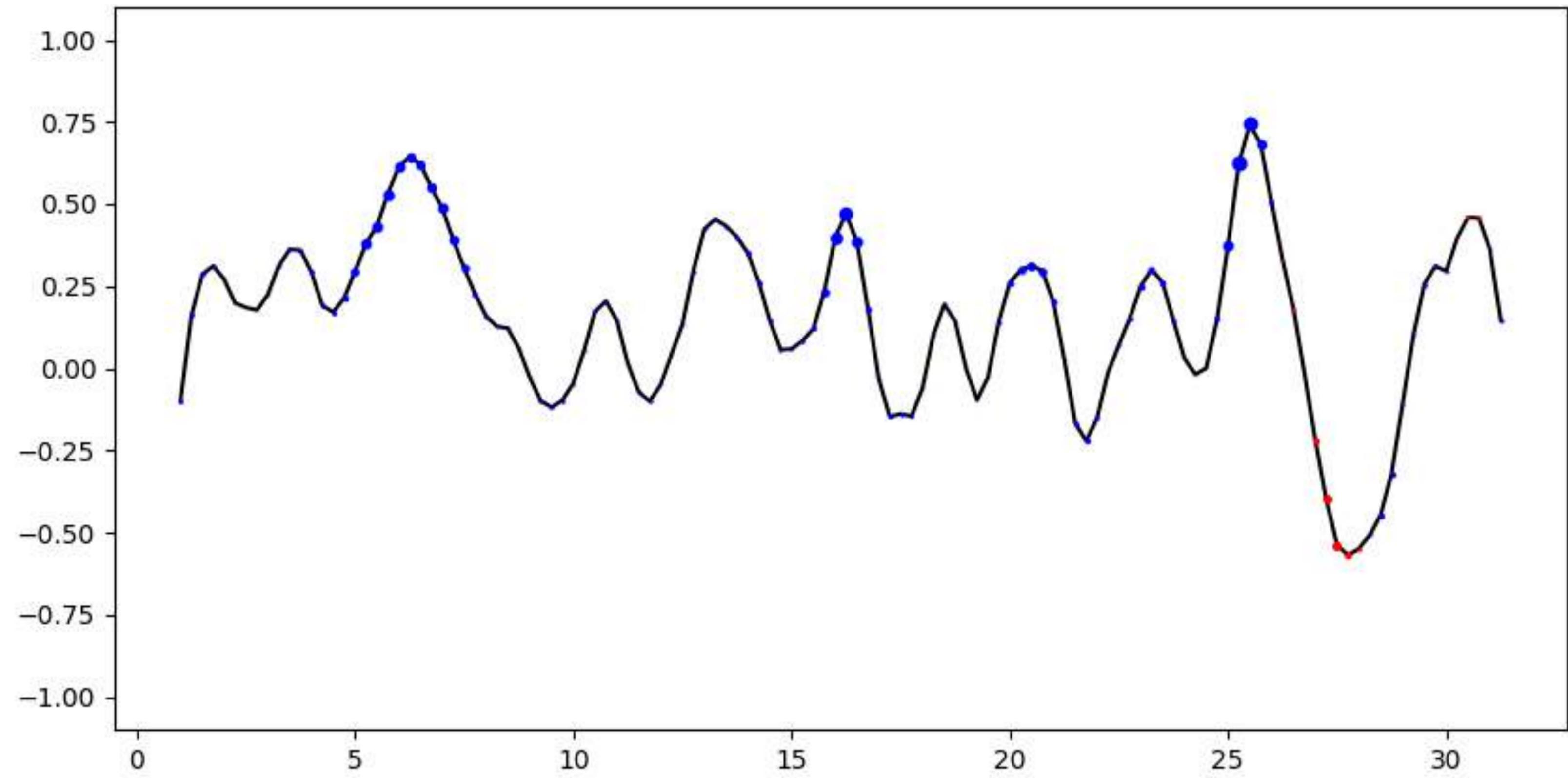
Valence: 92.3%,
arousal: 92.3%

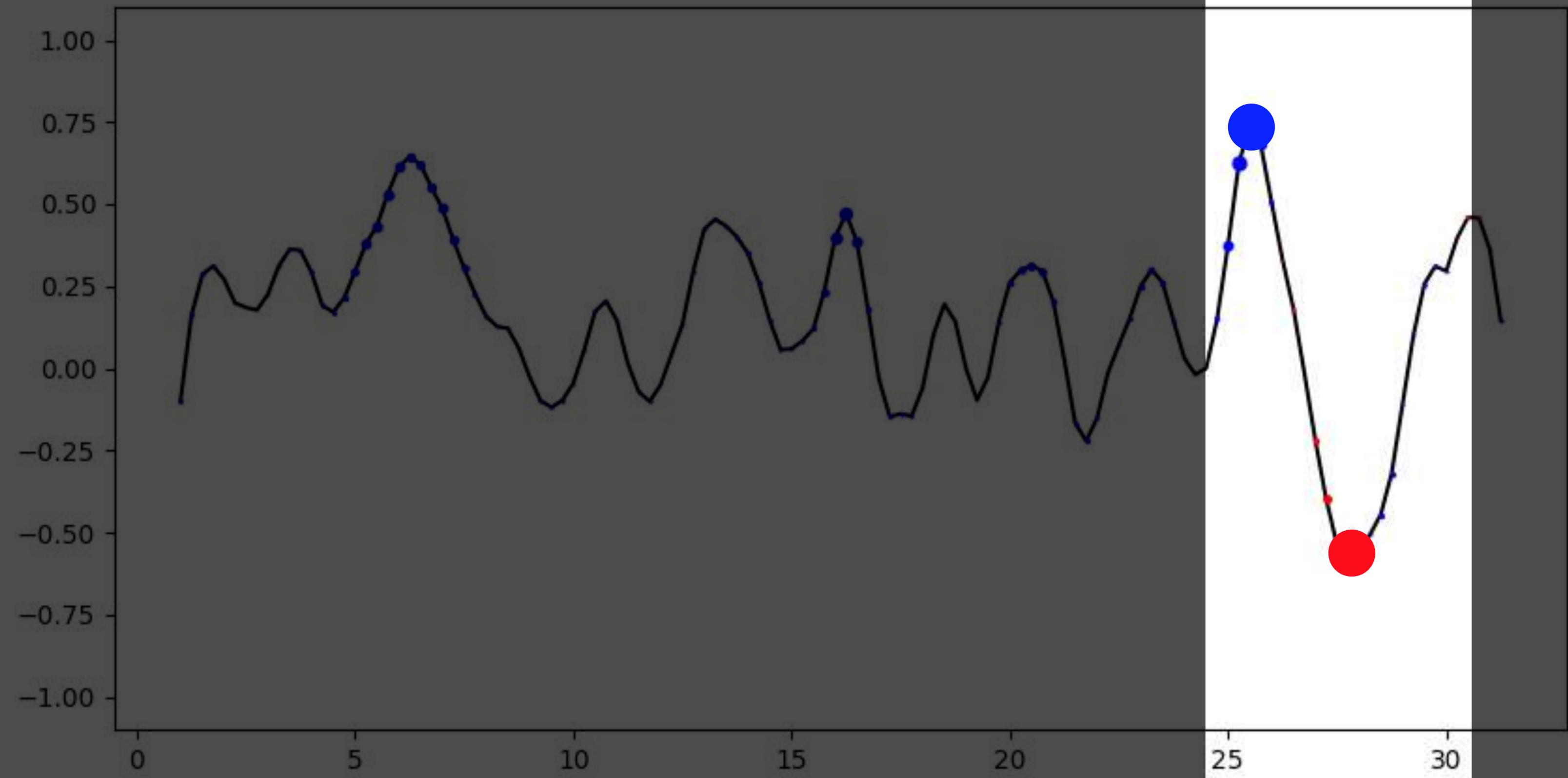
Valence: 74%,
arousal: 74%, and
dominance: 75%

83.26%

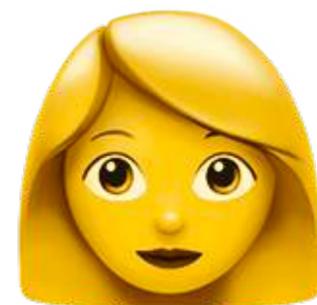
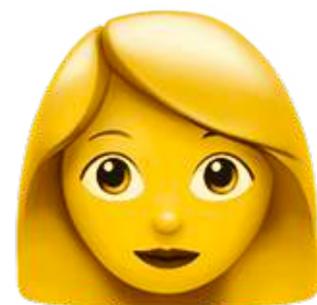
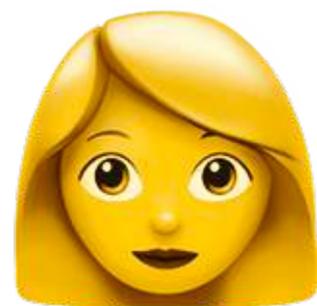
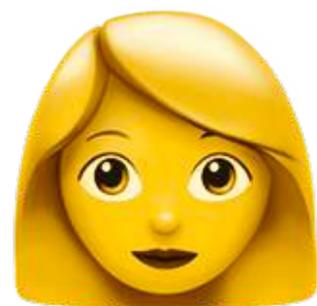
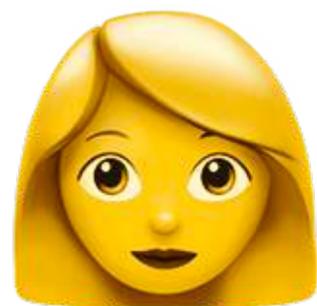
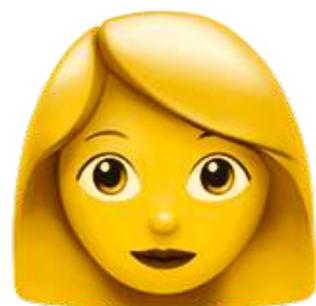
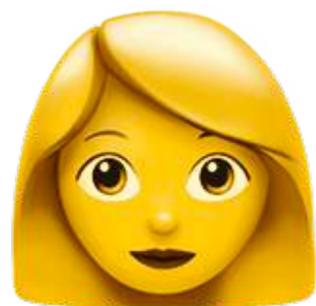
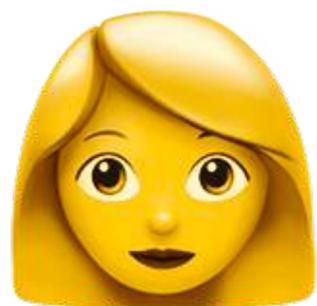
82.29%

85%









Подготовка

1

Просмотр ролика

2

Интервью

3

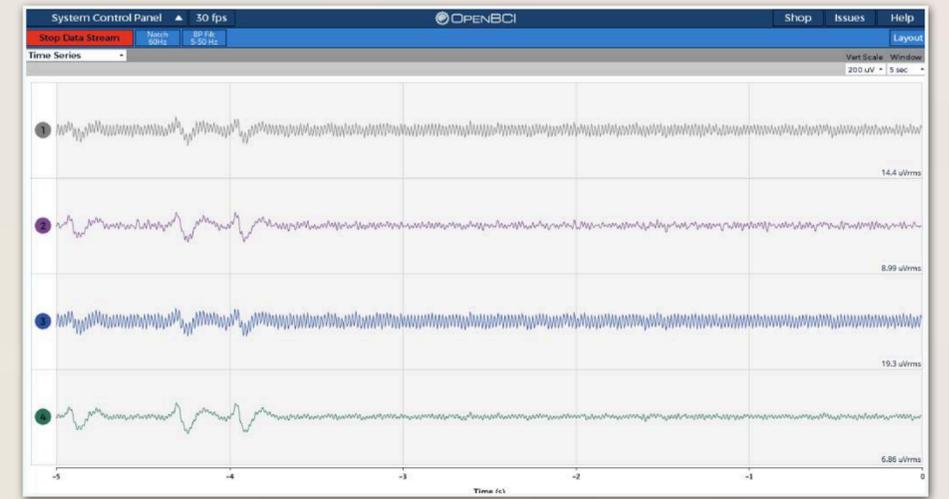
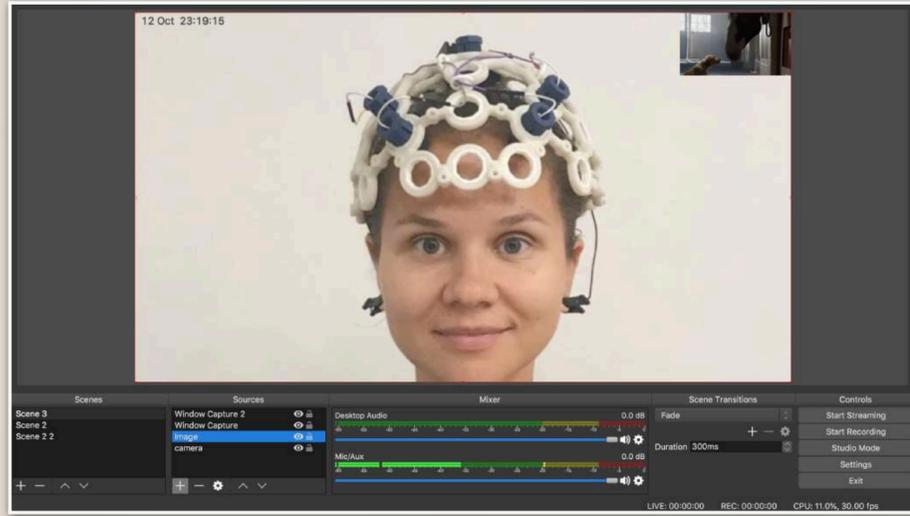
Video

10s

Text Video

10s





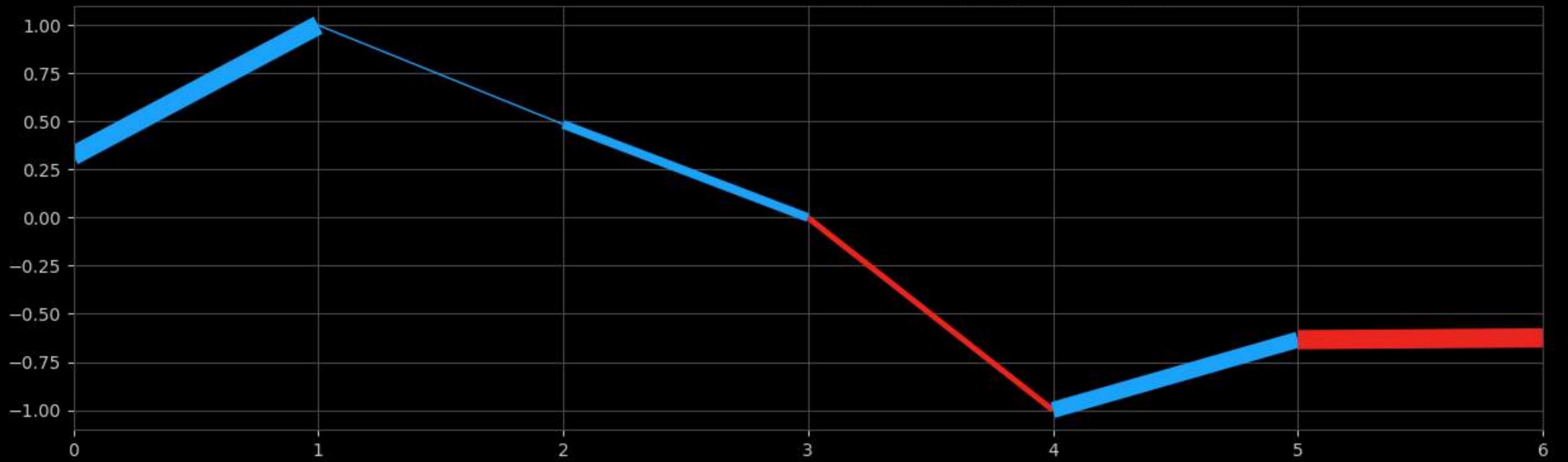
A Collection Python EEG (+ ECG) Analysis Utilities for OpenBCI and Muse <http://autodidacts.io>

eeg
openbci
ecg
muse
python
data-visualization
data-analysis
neuroscience

86 commits
1 branch
0 releases
4 contributors

Branch: master
New pull request
Create new file
Upload files
Find file
Clone or download

curiosity Add support for Muse data recorded with LSL (Lab Streaming Layer)		Latest commit d6b04a6 on 19 Jun 2017
data	added sample data	3 years ago
plots	Added sample plots	3 years ago
.gitignore	Update	3 years ago
EEGrunt.py	Add support for muse data recorded with Lab Streaming Layer	a year ago
README.md	Update README to mention new ECG analysis functions (and add link to ...	2 years ago
analyze_channel.py	Add support for Muse data recorded with LSL (Lab Streaming Layer)	a year ago
analyze_data.py	Add support for Muse data recorded with LSL (Lab Streaming Layer)	a year ago
analyze_ecg_channel.py	deCamelCase hrv window length var	2 years ago
analyze_ecg_data.py	deCamelCase hrv window length var	2 years ago



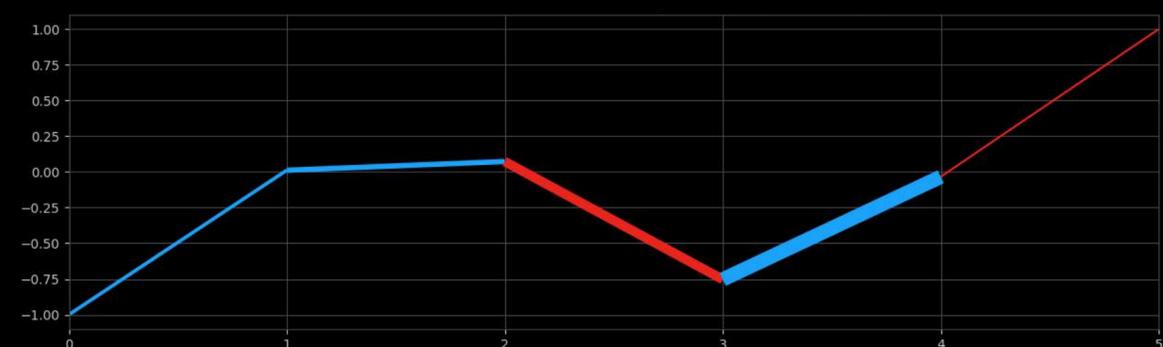
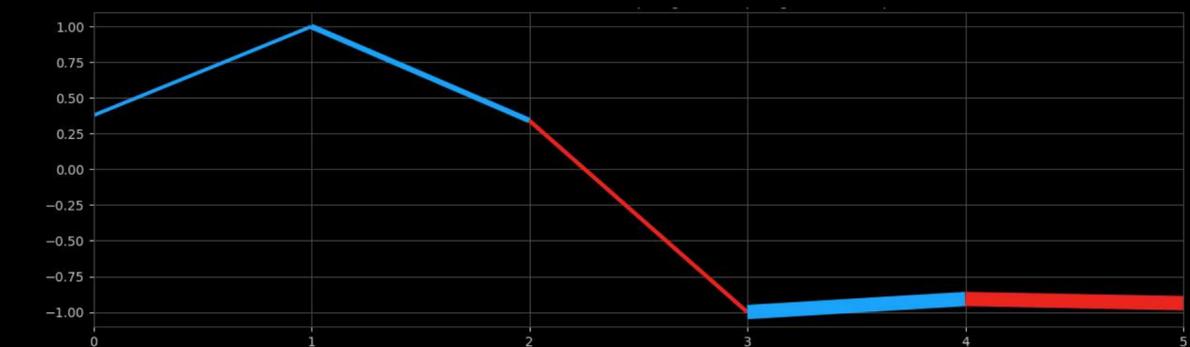
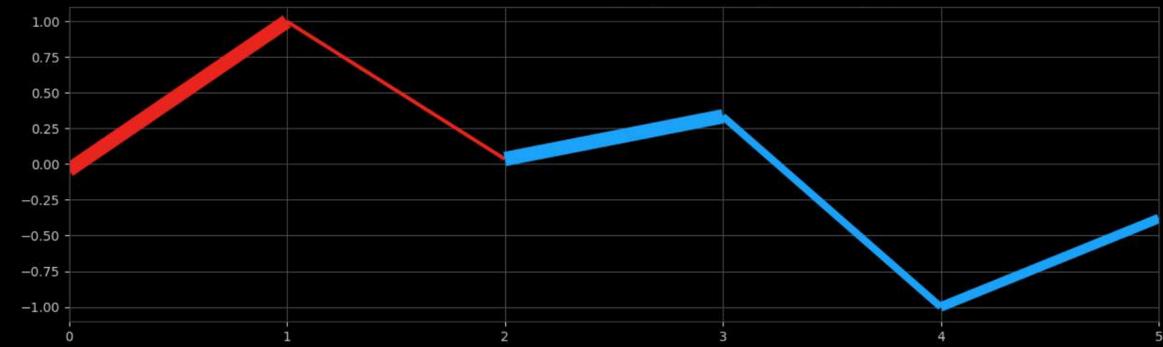
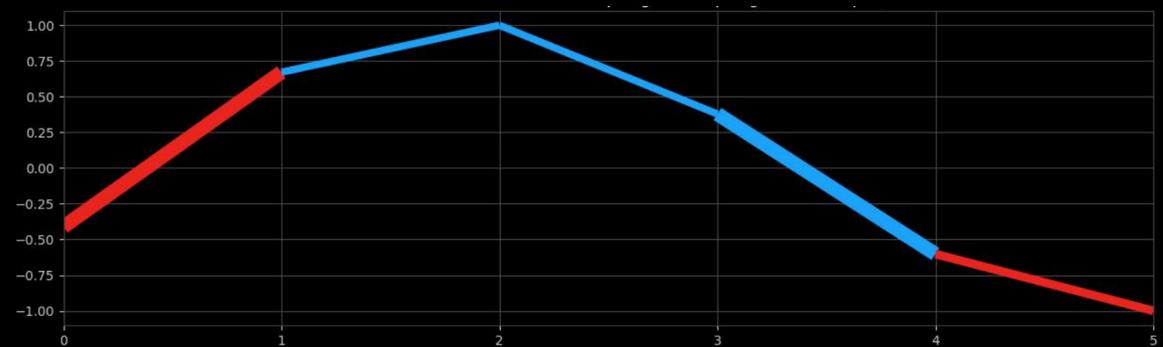
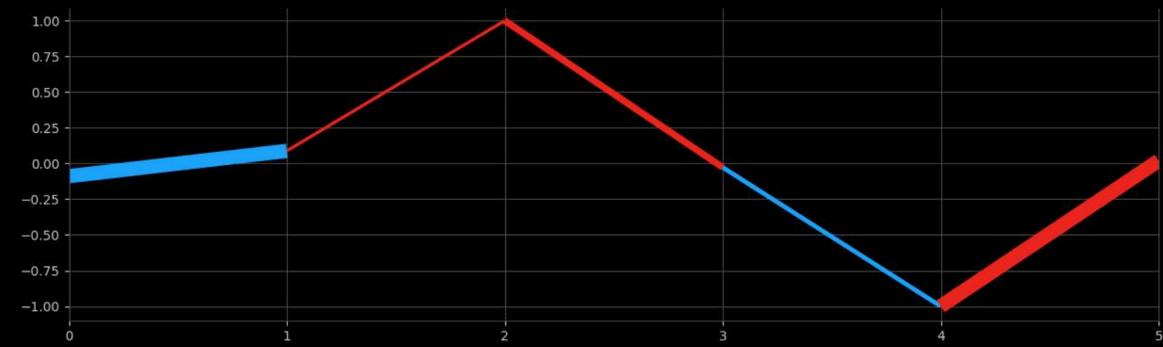
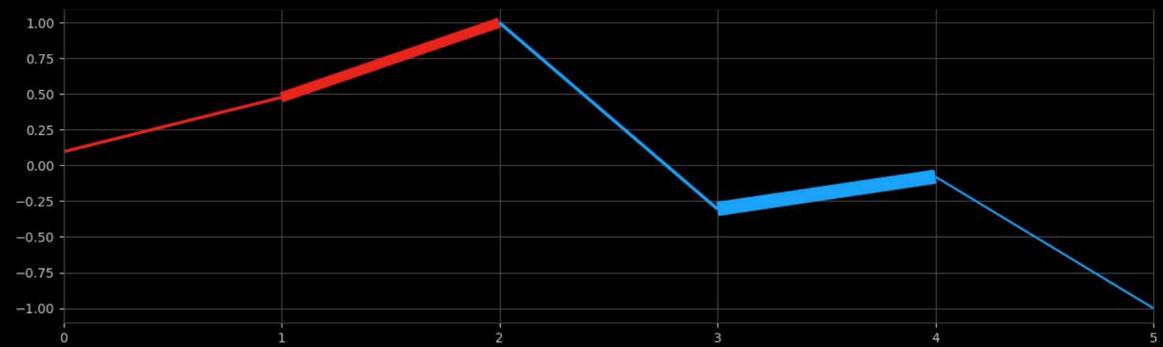
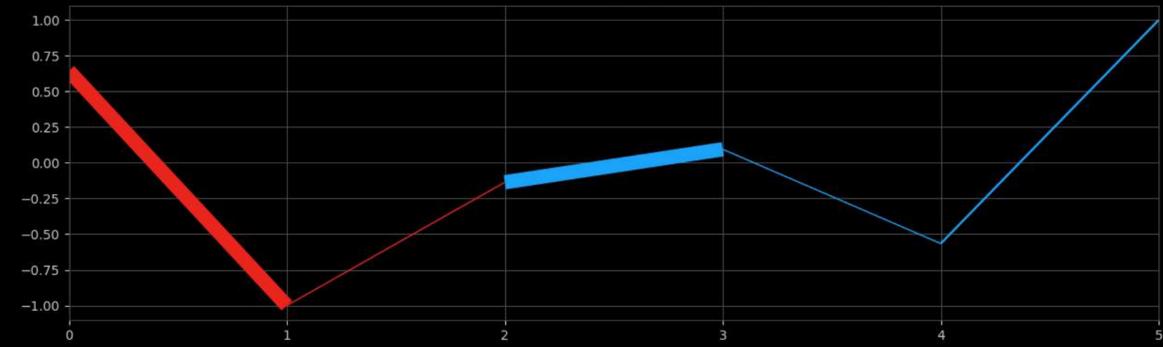
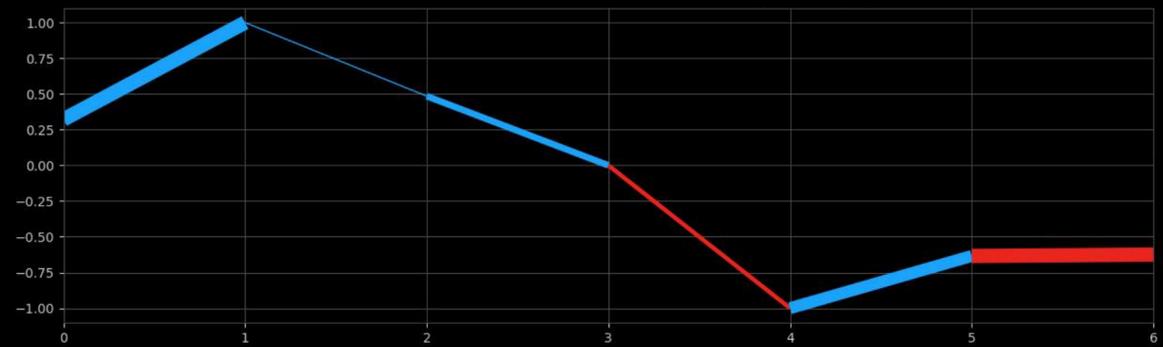
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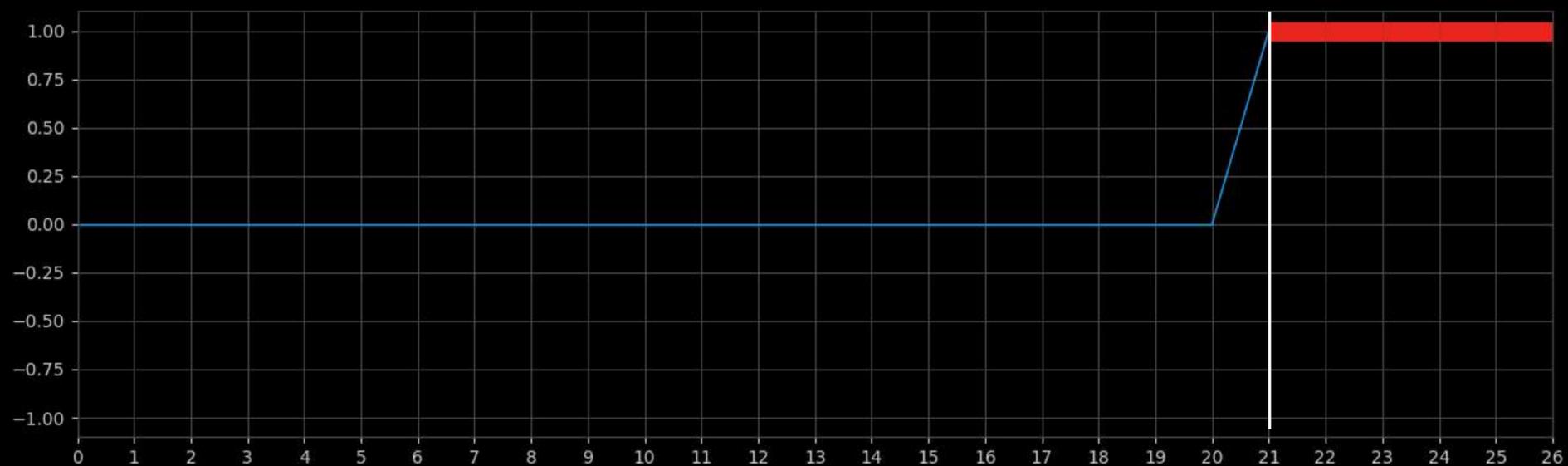
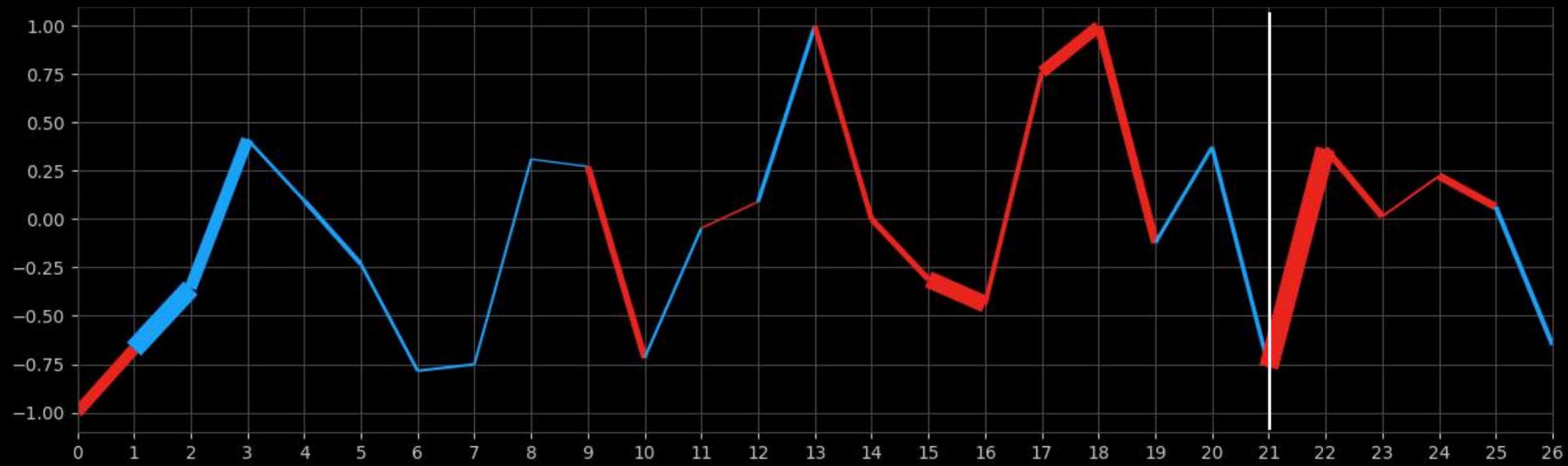
2

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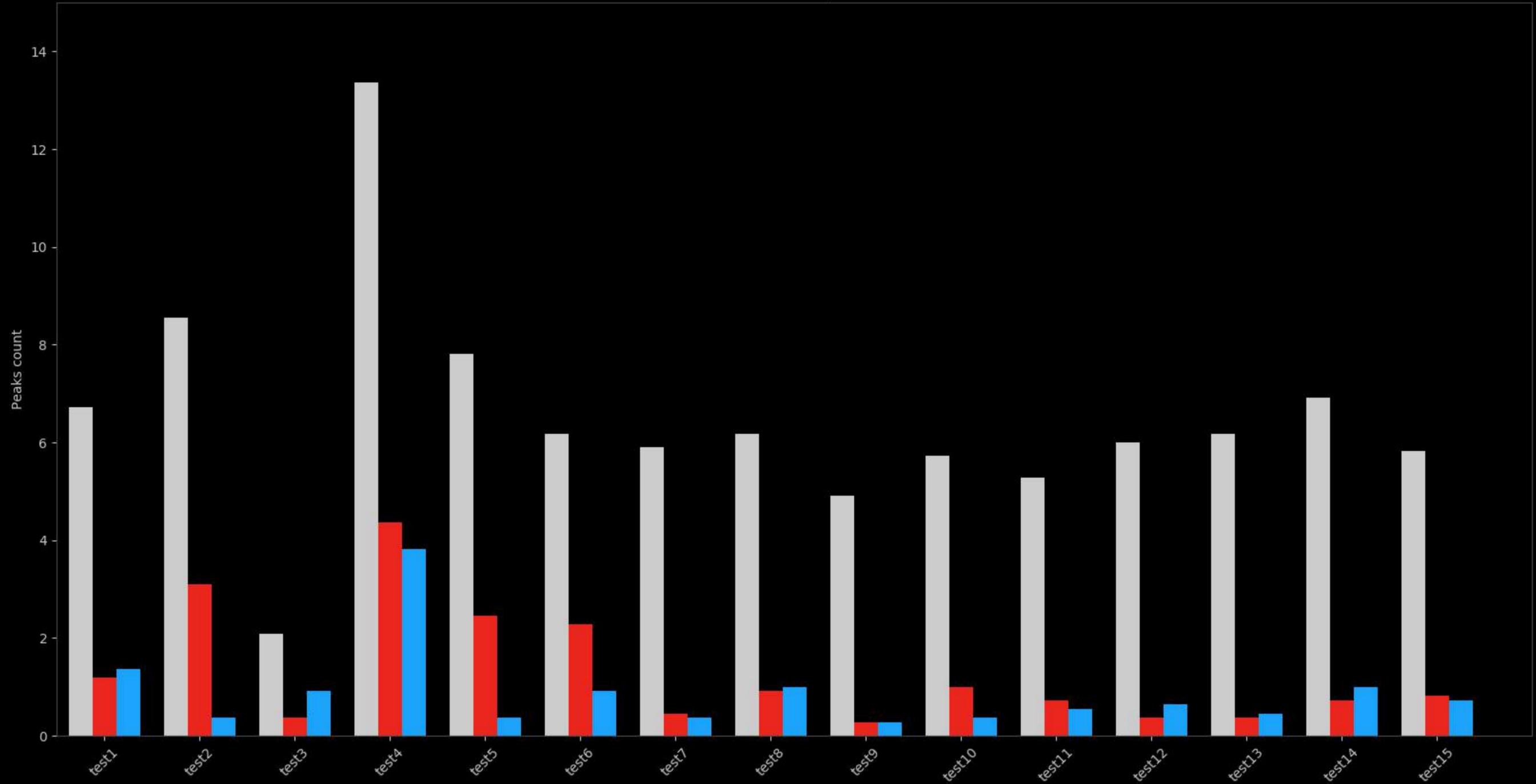
Bestclipstube



На **к**онец



Peaks count by tests



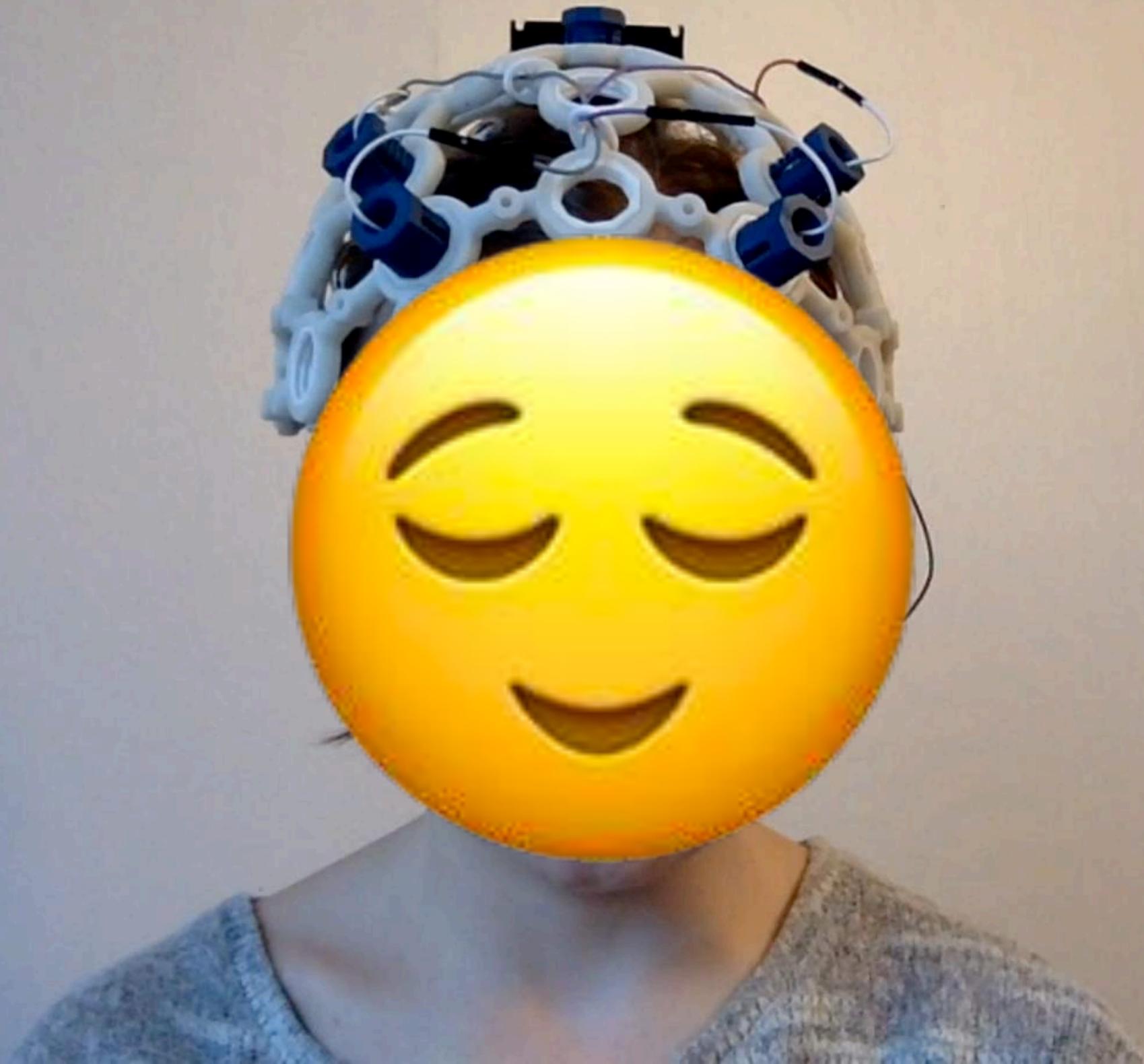
	% случаев когда эмоция верно определена алгоритмом по изображению	% случаев когда менялось выражение лица	% случаев когда эмоция верно определена экспертно по ЭЭГ	% случаев когда респондент неверно описал свои эмоции
Вместе	28%	51%	86%	17%

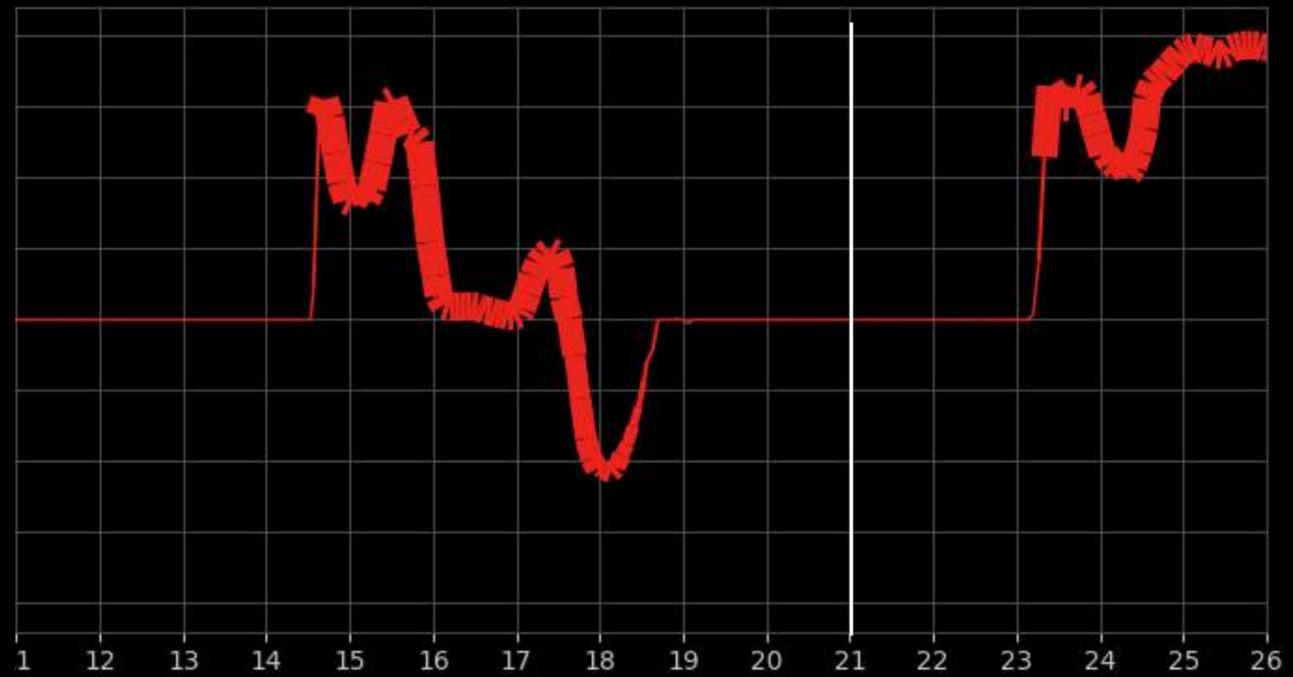
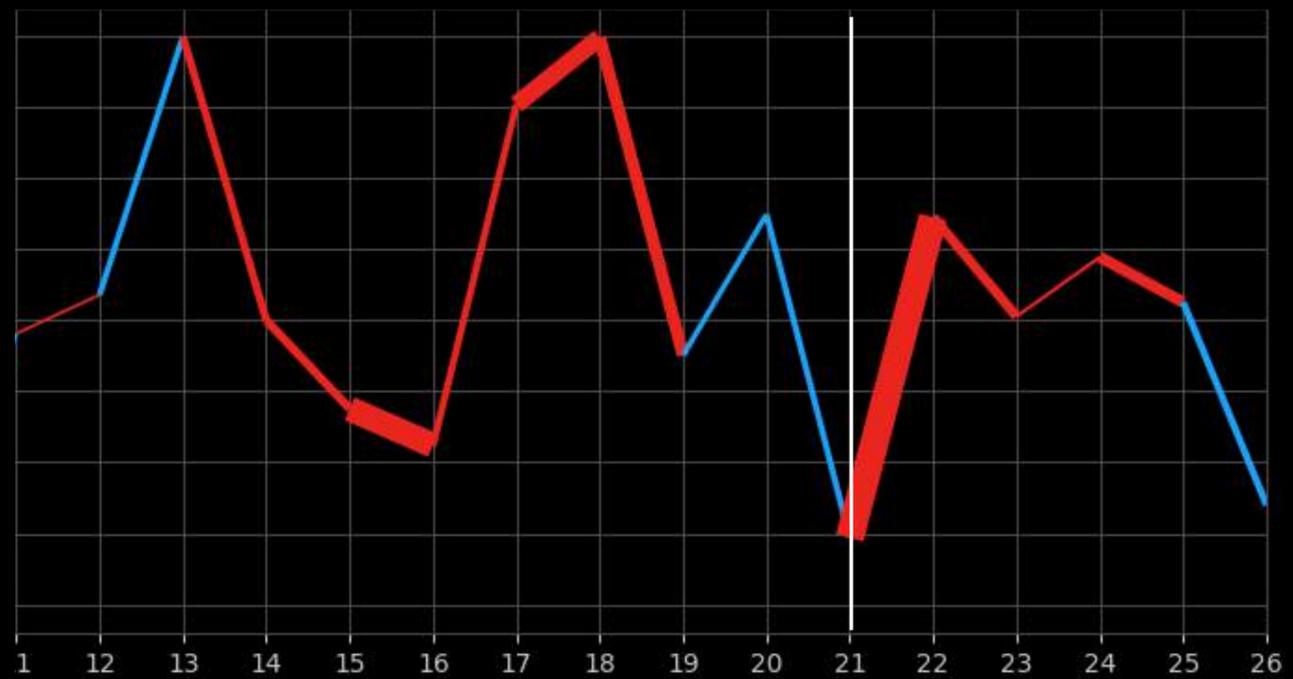
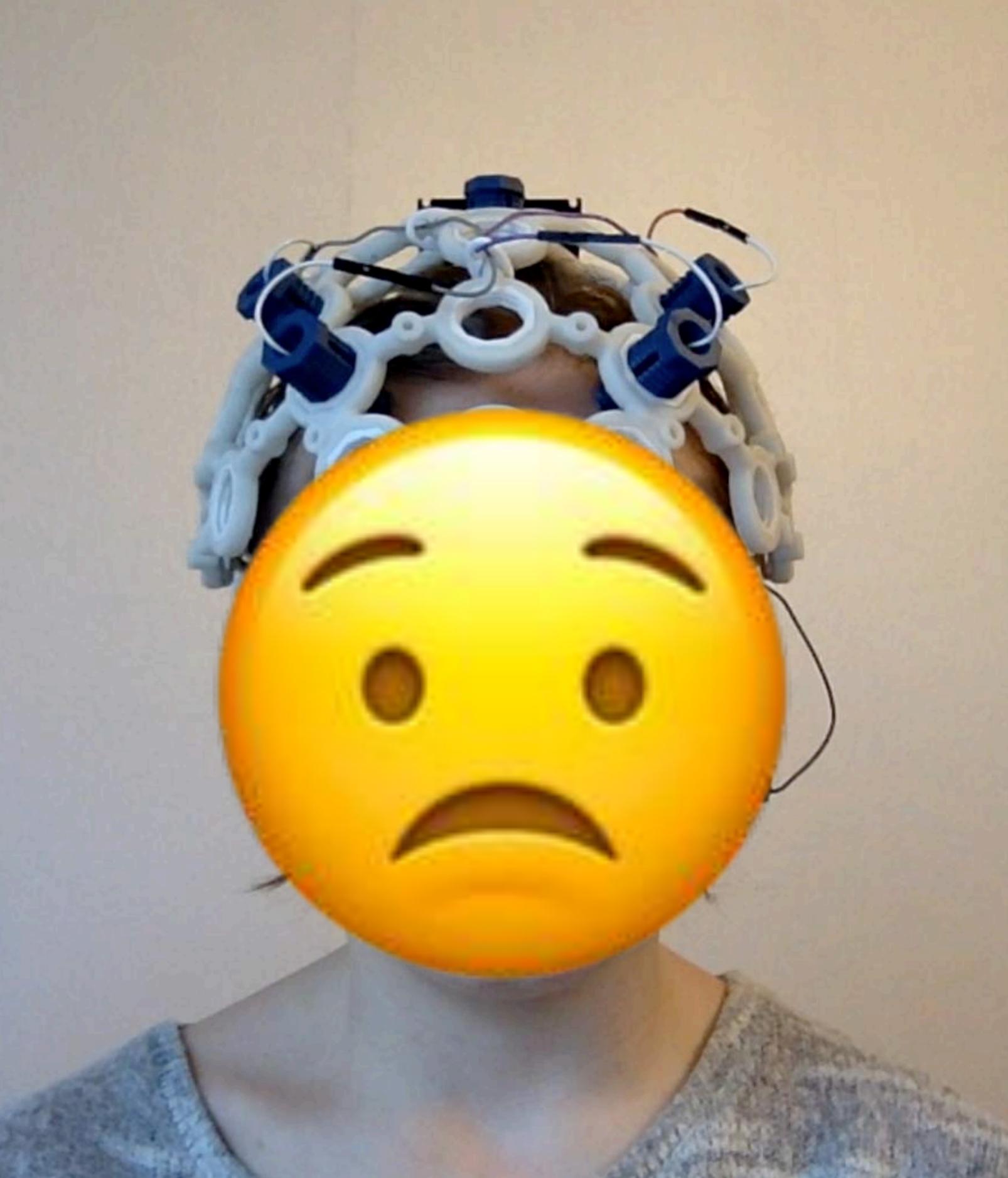
***12 респондентов 180 роликов**

	% случаев когда эмоция верно определена алгоритмом по изображению	% случаев когда менялось выражение лица	% случаев когда эмоция верно определена экспертно по ЭЭГ	% случаев когда респондент неверно описал свои эмоции
Вместе	28%	51%	86%	17%
Видео	45%	80%	98%	13%
Текст	20%	32%	80%	16%

30 Sep 15:05:46







Ошибки алгоритма распознавания эмоций

Затянутое наступление эмоции (больше 3-5 секунд)

Очень короткая эмоция меньше 1 секунды (смущение, испуг, подавленные эмоции)

Ошибки в определении (напряжение, удивление вместо страха, радость вместо смущения)

Насколько хорошо работает один из алгоритмов

Можно ли применить алгоритм для распознавания эмоций по видео при чтении документов

Испытывает ли человек при чтении эмоции, которые нельзя считать с лица

Можно ли использовать нейроинтерфейс для оценки эмоций

45% для видео, 20% для текста (для использованной выборки)

При чтении текста эмоции на лице проявляются только в момент развязок, а в остальное время остаются нейтральными.

При просмотре роликов люди более активно выражают эмоции на лице 80%, чем при чтении текста 32%

Да

ЭЭГ дает высокую точность при оценке эмоций (98% / 80% видео/текст)



Спасибо!
Вопросы?

- Кирилл Улитин
- kirill@ulitin.ru
- ulitin.ru

