Open Technology: The Free EEG 32 project: Tensor Flow Models and Complexity Metrics.

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Abstract

Open Technology, for wearables with just in time manufacturing is illustrated with the Free EEG 32 project, with open source hardware and software fulfilled with Seeed Studios, and Mouser as the vendors. The product illustrates the use of 32 EEG channels for M.L based learning of 32 dimensional data streams for the classification, with deep learning of meditative states, quantified as spectral power ratios, differential spectral power ratios and identification of the various bardos, and biofeedback mechanisms. Inspired by the MUSE headset, soundscape engineering is used as feedback on meditation coherence and bird chirps indicate transcendental success factor thresholds, illustrated with the Transcendental Meditation (™) system of Maharishi Mahesh Yogi.

A theoretical framework for the complexity of deep learning models, training set estimation and external validity measurements is described, with tensor decomposition for the deep learning network.

Keywords: ™, EEG based hardware, 32 channels, Free EEG 32, Seeed studio, gerber, just in time, on-demand, drop-shipping, D-Commerce, portals, MUSE headband, FFT, Chaos analysis, deep learning.

1. **INTRODUCTION**

1.1 Problem Definition.

1. The Free EEG 32 is open technology and can be fulfilled in open source on demand using the Seeed Studio, integrating pcb making, component sourcing, 3DP and assembly, all under one roof, and drop shipped by a logistics system, using Amazon e-commerce solutions for retailing.
2. Software is developed for Transcendental meditation using 32D r-cnn based deep learning for classification of meditative states.
3. Soundscape engineering as aural feedback on meditative coherence.
4. Bird chirp using bone conduction speakers for coherence factors > thresholds. A stochastic playback for > 6 chirps.

1.2 Background.

Nomenclature of EEG points

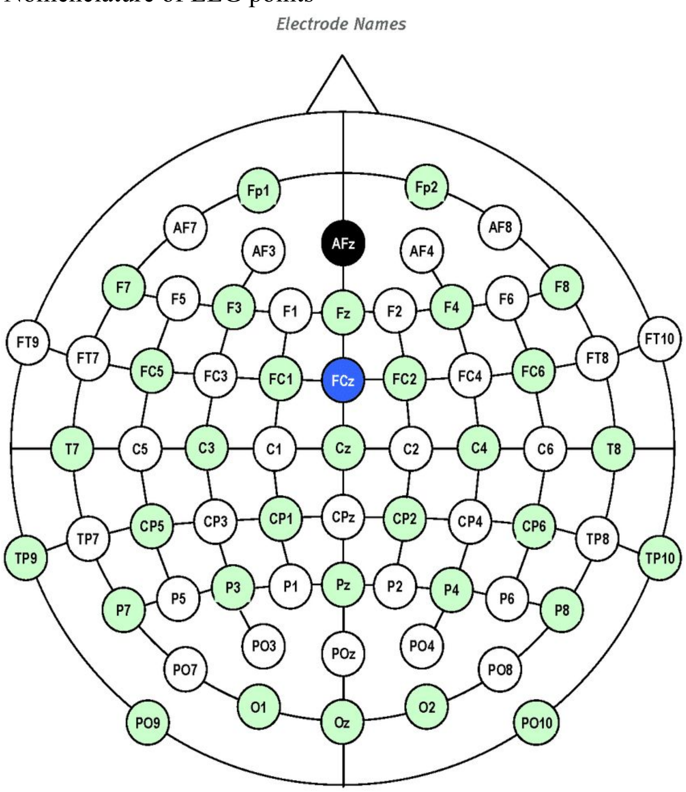

FIGURE 1: EEG ELECTRODE LAYOUT (Rupasov et al., 2012)[1,2]

32 channel recording and the Free EEG 32 movement.(Hackster.io, n.d.)

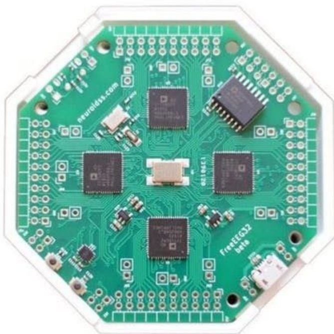

FIGURE 1: FREE EEG 32 PRODUCT IMAGE (HACKSTER.IO)

An ARM M-7, based MCU, with four ADC processors for 32 channels. “AD7771 analog-to-digital converters (eight channels each), with up to 128kSPS simultaneous sampling, up to eight programmable gain, 107dB dynamic range (@ 32kSPS), and onboard SAR (successive-approximation-register) ADC for diagnostics. The board also packs separate USB ports for power and data and an SD card slot for data storage.” “which boasts 32-channel, 24-bit, sigma-delta, simultaneous sampling for scientists and hackers looking for research-grade equipment without the high costs.” The software, by NeuroIDSS is available open source on github.(Hackster.io, n.d.; neuroidss, n.d.-a) The pcb layout files are indicated below and available on the github
repository for download as gerber or kicad files.

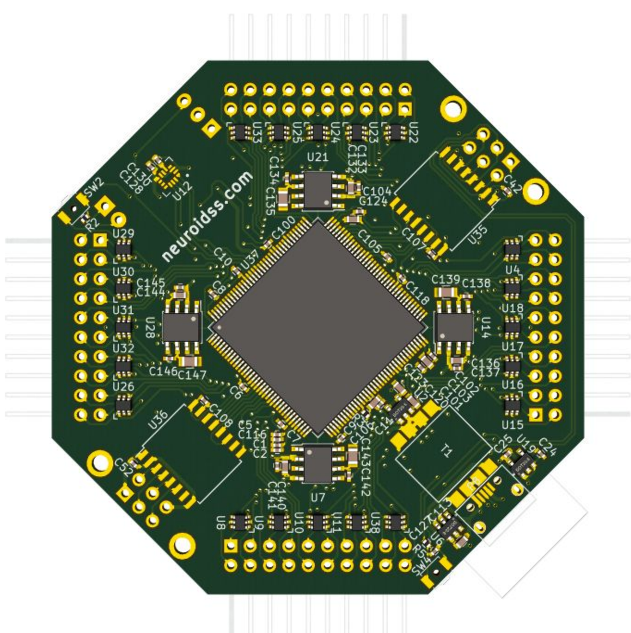

FIGURE 3: FREE EEG 32 PCB IMAGE TOP (HACKSTER.IO)

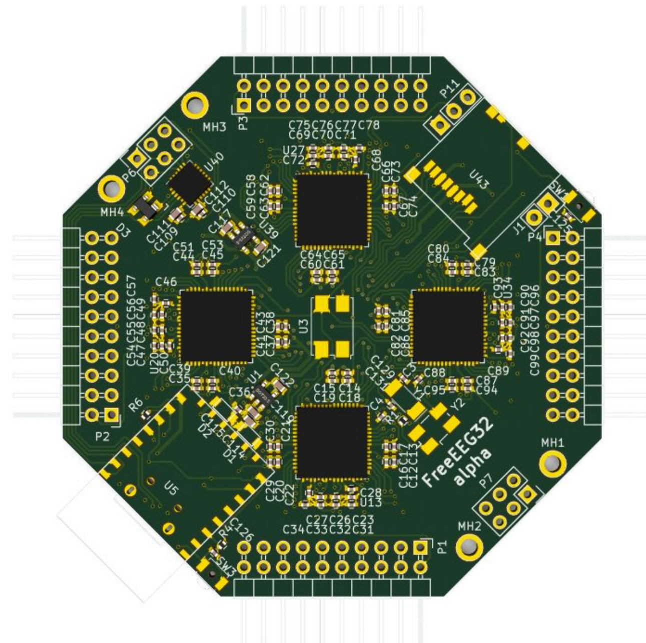

FIGURE 3: FREE EEG 32 PCB IMAGE BOTTOM (HACKSTER.IO)

Bill Of Materials. [BOM.]

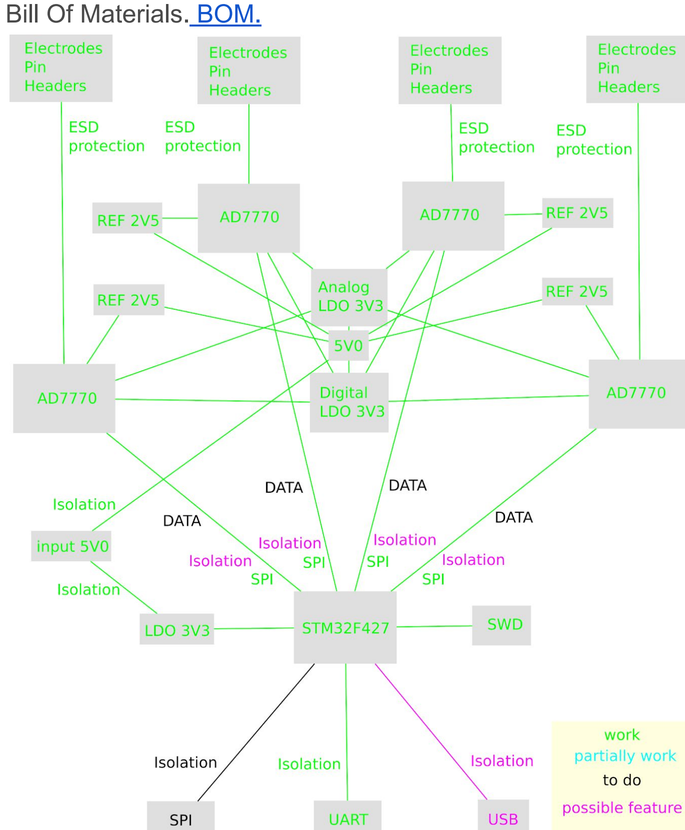

FIGURE 4: PSYCHOPY PROTOCOLS ILLUSTRATED IN THIS BLOCK DIAGRAM.

2. MATERIALS AND METHODS

2.1 SeeeD studio for Just In Time Fulfilment.

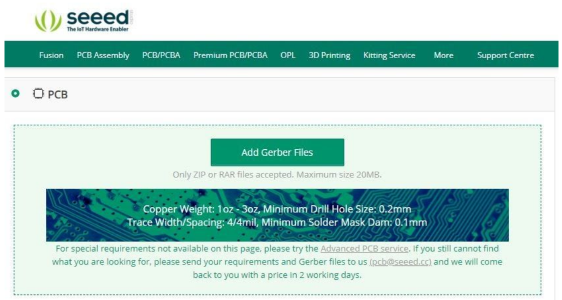

FIGURE 5: SCREENSHOT OF SEEEDSTUDIO FUSION PORTAL FOR JUST IN TIME MANUFACTURING ON DEMAND

Seeed Fusion PCB and assembly with 3DP as an example of a fulfilment service.(Fusion PCB Manufacturing & Prototype PCB Assembly - Seeed Studio, n.d.) (Bheemaiah Corporation does not endorse this service, available to the reader at his or her discretion.)

Alpha 1.5(neuroidss, n.d.-b) (neuroidss, n.d.-b)[3]uses psychopy, the UML is described below.(Home — PsychoPy v3.0, n.d.-a) "PsychoPy[4,5] is an free cross-platform package allowing you run a wide range of in the behavioral sciences (neuroscience, psychology, psychophysics, linguistics...) This is a community project. Users have all the source code. Users are the developers. Users support each other. Alongside open-source, we're strongly supporters of Open Science, and we'll try to encourage and facilitate that wherever we can!"(Home — PsychoPy v3.0, n.d.-b)[1]

2.2 Network Architecture and Classification Alphabet [S]

We define six states of quantification of the TM coherence and six thresholds of bird chirps [BC]. For a 32 channel EEG dataset E, we define a map to a charegory in [S] and [BS], as ->([S],[BS]) for each E in [E], the training set, we define a similar test set, [Et]. We use a CNN and a R-CNN architecture which is 32D, for the classification task. This is proposed as future work in clinical studies for data collection. (Thomas et al., 2018)[4] describe a 32D CNN network, with tensorflow, for the classification of EEG data, for Interictal Epileptiform Event Detection. Defined as an event stream, they convert, [E], the 32D data stream to a feature space [F] and use an SVM for an event stream data mining. The figure below reproduced from the publication summarizes the architecture.

Lyapunov Exponents for a monotonicity on a quantitative measure [S] and {BS}[6] describes a matlab program for estimating lyapunov exponents for a 1D waveform.[7,8]

The traditional phenomenological model of networks of neurons, leads to a signal processing model, of waveforms, [9] with a synchronization aspect to computation, leading to the use of coherence as a definition in a monotonicity in [S], a quantitative measure of meditation coherence and bird song triggers.
A newer model as a quantitative measure is in the modeling of the fluctuations and the chaos as a dynamical system aspect, leading to a monotonicity definition in lyapunov coefficients, chaos theory and ergodicity definitions and fluctuation analysis, leading to a generic stability theory and invariants in defining metrics.

TABLE I

THE DIFFERENT PARAMETERS OF THE IMPLEMENTED CNN NETWORK

Parameter	Values
Number of convolutional layers	1
Number of convolutional filters	32
Dimension convolutional filters	1×5
Number of pooling layers	1
Number of fully connected layers	1
Number of hidden layer neurons	3000
Activation function	ReLU (Rectified Linear Unit)
Pooling block size	2×2
Dropout probability	0.5
Optimizer	Adam optimizer
Learning rate	10^{-4}
Training termination criteria	Until the validation error saturates

FIGURE 6: PERCENTAGE OF PAPERS THAT SHOULD BE FORMATTED CORRECTLY

2.3 Bag of Words in EEG analysis.

The MUSE headset uses museio, for OSC messages, from bluetooth channels, in this paper we propose using "Word Messages" instead of the sound based OSC format.
We define a data structure of a Bag of Words as an object representation, and consider these word streams, collected in

semiotics as a bag, and a sorting filter called the “HAT filter”, for active sorting of the words.

Words are sorted and processed, to indicate a coherence measure, using the following set.
CT = (correlation, fluctuation, chaotic, deep learning)
We define the alphabet [S] and [TG] on these 1D streams described as word streams and classified into semiotics of words in a bag of words.

2.4 Word encoding from 1D signals.

Words can always be expressed as JSON.
A word consists of an arbitrary sequence of an alphabet, say [A] is a word W and [W] a sentence S and [S] a paragraph.
Thus natural language as semiotics provides a description or a word cloud, represented as a bag of word, bag of bags and the cloud consisting of bags of words.
The word cloud is analogous to a point cloud, from which the 1D data can be reconstructed, should the analysis use tools, beyond the semiotics of the filters used.

2.5 Filters for correlation.

Correlation between words, is by a word2vec mapping to a prime representation and analysis of correlations between words, for sorting and processing in homology measures. Filters for this form procedural data mining in semantic interpretations of 1D streams in discrete language as events.
2.6 Filters for fluctuation analysis.
([10]) describes Detrended Fluctuation Analysis (DFA) on 1D data, leading to a word cloud with DFA feature spaces, on reconstruction of the waveform from the word cloud, decreasing fluctuation and recursion in self similarity are future topics of research.

2.6 Filters for chaotic analysis.

([11])reports EEG Wavelet Entropy decreased during MBSR , ([12])is a study in complexity indices of EEG streams from Zen meditators with higher beta and theta to alpha levels and decreasing complexity as coherence. ([13])indicates dimensionality complexity (DCx) measures of Sahaja Yoga, indicating in increased beta and theta waves and increased coherence and decreased complexity.([14])describes Fuzzy Kernel least square SVM classification on wavelet feature spaces, on openBCI data.[15]

Complexity measures, on 32D streams, as an application of CT and the HAT filter, include complexity dimensionality and wavelet , amongst many other classifiers and semantic maps for word, sentence and paragraph semantic boundaries in the word cloud and the classification to ([S], BC]).

2.7 Conv32D CNN and R-CNN

The proposed Tensor Decompositions are:

[16] describes a CP-Tensor Decomposition.
for a three layer CNN network, extended to 32D vectors.
Addition of recursion leads to R-CNN topologies.

2.8 VC Dimension and RC Dimensionality for the DNN model.

tf.keras.layers.Conv1D

```
tf.keras.layers.Conv1D(
       filters,  kernel_size,  strides=1,
padding='valid',
data_format='channels_last',
            dilation_rate=1,   groups=1,
activation=None, use_bias=True,
    kernel_initializer='glorot_uniform',
bias_initializer='zeros',
                kernel_regularizer=None,
bias_regularizer=None,
activity_regularizer=None,
                 kernel_constraint=None,
bias_constraint=None, **kwargs
)
```
[17]

Using an alphabet of six consciousness states and bird chirps, ([S], {BC]), we use a convolutional classifier, Conv32D net as a classifier with 12 outputs, ([S], [BC]). We consider defining the VC dimensionality and approximate a training set of EEG data, of size 10*VC-dimension.

3. CONCLUSION

To conclude, a model of open source hardware, software and research technology is defined, with the Free EEG 32 adopted with TensorFlow to the study of ™ meditation for the design of an app, providing a meditator feedback on the state of meditation, with an added set of bird chirps to define a higher degree of coherence.

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