ITCS 5156: Project Proposal

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Primary Work Information

Title: ES1D: A Deep Network for EEG-Based Subject Identification

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Year: 2017

Conference/Journal Name: 2017 IEEE 17th International Conference on Bioinformatics and Bioengineering (BIBE)

Link: IEEE link

The Problem

- Unlabelled biometric information can be inferred from EEG data[2], especially when focusing on ERPs[4].
- Models might fail in recognizing significant patterns due to missing features in data.
- **Problem Statement:** The goal of this project is to contribute to the field of subject identification from EEG signals by replicating the ES1D model design and testing its ability to infer a subject's age.

Audio-visual stimuli	
Number of videos	18
Video content	Audio-Video
Video duration	65–393 s (M = 199 s)
Experiment information	
Number of participants	25 (23)
Number of males	14 (14)
Number of females	11 (9)
Age of participants	22–33 (M = 26.6, SD = 2.7)
Rating scales	Arousal, Valence, Dominance
Rating values	1–5
Recorded signals	14-channel 128 Hz EEG, 256 Hz ECG

Fig 1. DREAMER dataset[3] details

The Dataset

- Backup [dataset]() from Kaggle
- Access to the DREAMER dataset [3] has been requested

Why ES1D?

- Low cost and high accuracy
- Utilized lower-quality equipment, which implies the model handles noise well

Algorithm	Accuracy	(St Dev)	p-value
3-NN	0.8725	(0.04)	$9.36 \cdot 10^{-5}$
5-NN	0.8580	(0.04)	$3.57 \cdot 10^{-5}$
7-NN	0.8493	(0.05)	$2.54 \cdot 10^{-5}$
SVM-Linear	0.8879	(0.04)	$9.95 \cdot 10^{-5}$
SVM-Quadratic	0.5816	(0.07)	$2.66 \cdot 10^{-5}$
SVM-RBF	0.7498	(0.04)	$2.52 \cdot 10^{-5}$
Naive Bayes	0.6551	(0.08)	$2.62 \cdot 10^{-5}$
Proposed	**0.9401**	**(0.04)**	1

Fig 2. ES1D classification accuracy benchmarking[2]

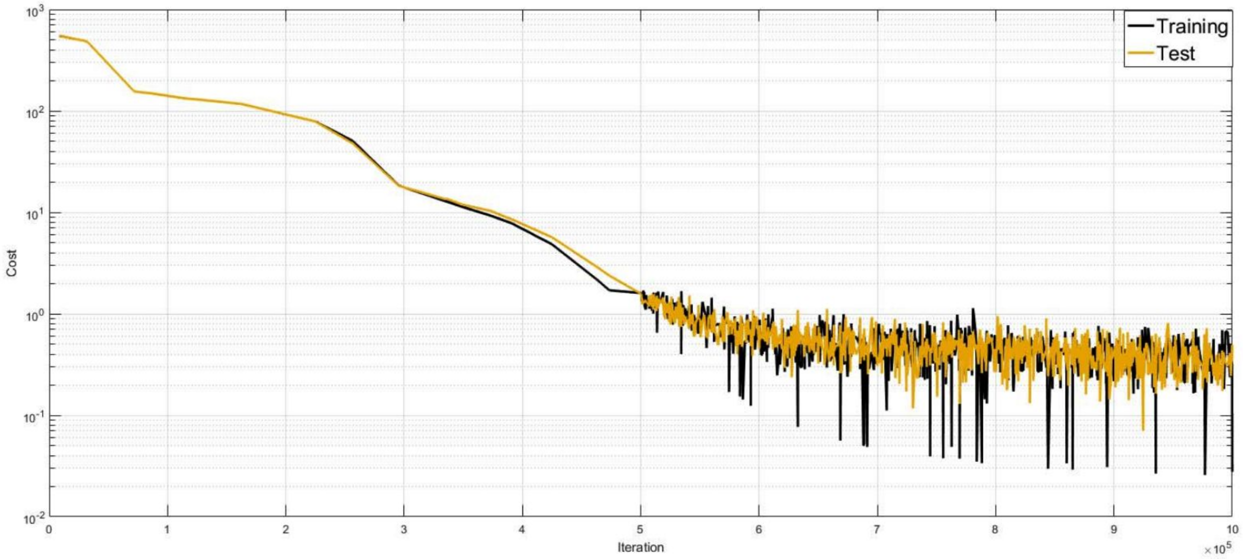

Fig 3. Test and training computation cost for ES1D[2]

How and why does ES1D work?

- 1,000,000 iterations, 150 random samples per iteration
- Learns specific spectral patterns from the EEG signals
- Adam for parameter optimization
- Tested against prior-knowledge defined feature sets

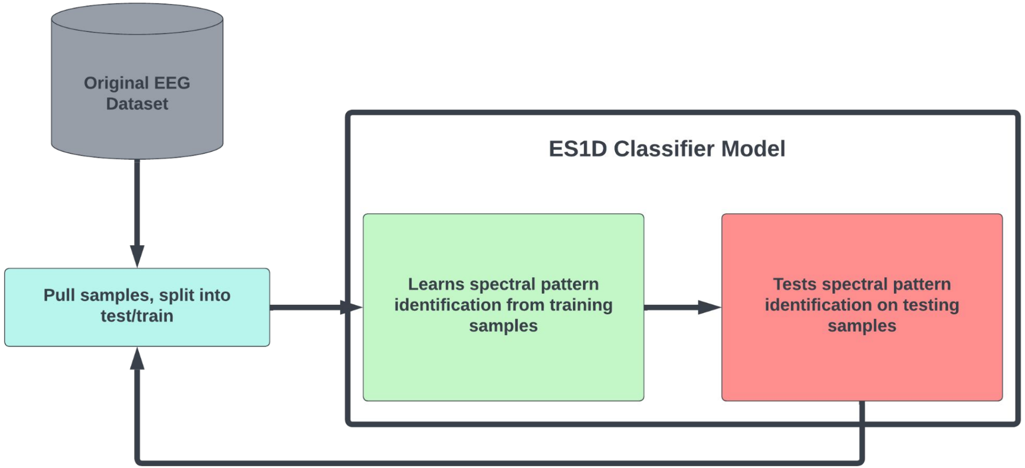

Fig 4. High-level overview of ES1D

Survey on related works (part 1)

CEREBRE[4]

- Contributed a (foundational) biometric information retrieval model from ERP analysis
- ES1D listed CEREBRE as one of its most important background papers
- Chosen for its review of biometric information retrieval potential in ERPs

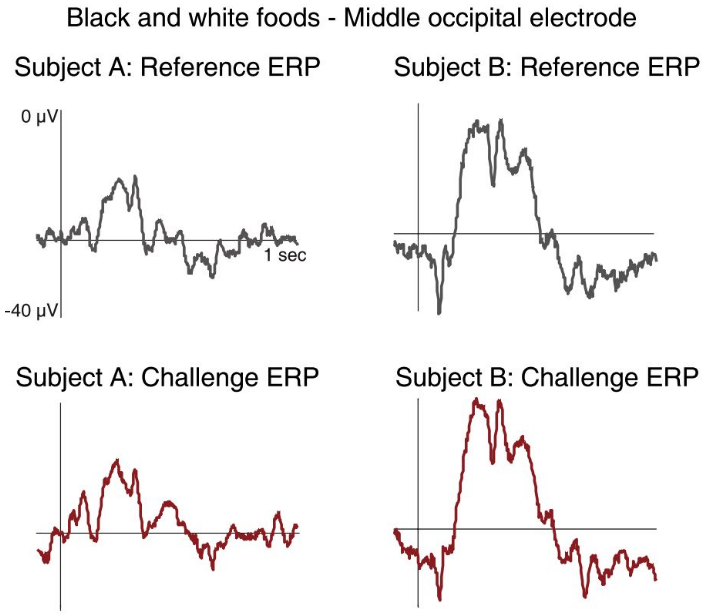

Fig 5. ERPs from two different subjects during identical stimuli exposure from CEREBRE [4]

Survey on related works (part 2)

Brainprint[1]

- Contributed another biometric information retrieval model from ERP analysis
- Introduced new metrics for evaluation of a classification method to account for the method's degradation
- Chosen because the data collection methods came from a limited number of electrodes on a lower-quality device, which implies that this model also handles noisy data well

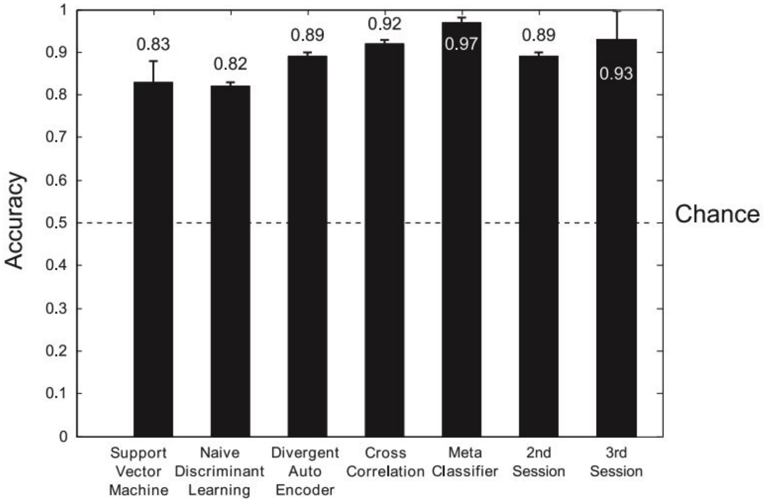

Fig 6. Classification accuracy benchmarking for different algorithms proposed in Brainprint[1]

Survey on related works (part 3)

Transformer Network[5]

- Contributed another deep learning model for age and gender classification
- Focus was not ERP specific
- Provided a detailed review on EEG classification methods
- Chosen because its datasets align closely with the project’s goal and the lack of ERP focus highlights the biometric information retrieval potential from EEG signals in general

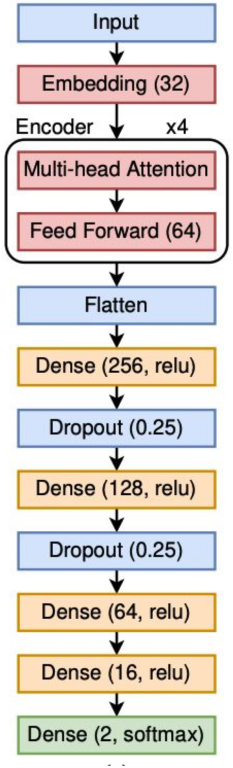

Fig 7. Transformer Network age/gender classification model architecture[5]

Reproductions from ES1D

- Planning to recreate the ES1D classification model
- If the DREAMER dataset[3] is used, preprocessing methods will be replicated from ES1D as closely as possible
- Classification will be applied to gender, rather than age, as this label is included in the DREAMER dataset as well

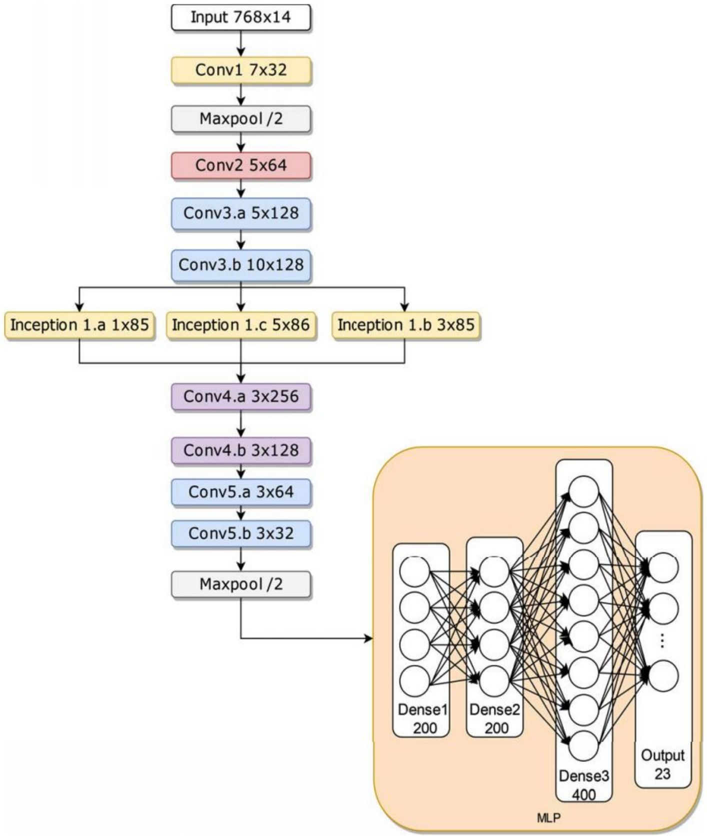

Fig 8. ES1D Model Architecture [2]

Timeline (from what I know so far)

Due Date	**Goal Description**
09/19	Finalize dataset to test ES1D model design on
09/24	Complete the preprocessing steps so that new data works for ES1D
09/29	Rough replication of the ES1D model
10/03	Model refinement
10/10	Finish the report and presentation

What I hope to learn

- More about deep learning model architecture design
- What information is contained in ERPs
- How to tune a deep learning model
- How to deal with the frustrations of finding usable, public datasets

References

[1] Armstrong, B. C., Ruiz-Blondet, M. V., Khalifian, N., Kurtz, K. J., Jin, Z., and Laszlo, S. Brainprint: Assessing the uniqueness, collectability, and permanence of a novel method for erp biometrics. Neurocomputing 166 (2015), 59–67.

[2] Arnau-Gonzalez, P., Katsigiannis, S., Ramzan, N., Tolson, D., and Arevalillo-Herrez, M. Es1d: A deep network for eeg-based subject identification. In 2017 IEEE 17th International Conference on Bioinformatics and Bioengineering (BIBE) (2017), pp. 81–85.

[3] Katsigiannis, S., and Ramzan, N. Dreamer: A database for emotion recognition through eeg and ecg signals from wireless low-cost off-the-shelf devices. IEEE Journal of Biomedical and Health Informatics 22, 1 (2018), 98–107.

[4] Ruiz-Blondet, M. V., Jin, Z., and Laszlo, S. Cerebre: A novel method for very high accuracy event-related potential biometric identification. IEEE Transactions on Information Forensics and Security 11, 7 (2016), 1618–1629.

[5] Siddhad, G., Gupta, A., Dogra, D. P., and Roy, P. P. Efficacy of transformer networks for classification of raw eeg data, 2022.