EEG-based Classification of Bilingual Unspoken Speech using ANN

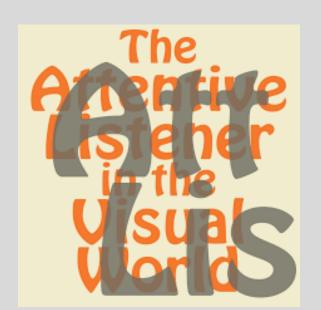
Advait Balaji, Aparajita Haldar, Keshav Patil, T Sai Ruthvik, CA Valliappan, Mayur Jartarkar and Veeky Baths



Cognitive Neuroscience Lab

Birla Institute of Technology and Sciences, Pilani, K.K Birla Goa Campus,





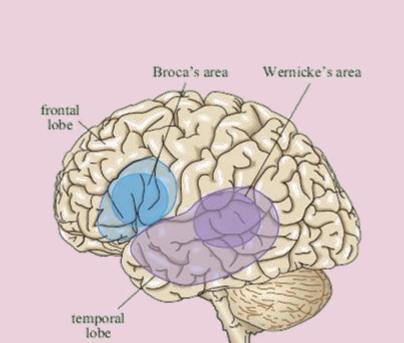
ABSTRACT

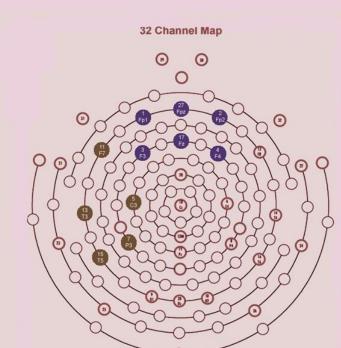
The ability to interpret unspoken or imagined speech through Electroencephalography (EEG) is of therapeutic interest for people suffering from speech disorders and 'locked-in' syndrome. It is also useful for brain-computer interface (BCI) techniques not involving articulatory actions. Previous work has involved using particular words in one chosen language and training classifiers in block or sequential mode to distinguish between them. Such studies have reported accuracies of 40-60% and are not ideal for practical implementation. Furthermore, in today's multilingual society, classifiers trained in one language alone might not always have the desired effect. To address this, we present a novel approach to improve accuracy of the current model by combining bilingual interpretation and decision making. We collect data from 5 subjects with Hindi and English as their primary and secondarylanguages respectively and ask them 20 'Yes'/'No' questions ('Haan'/'Na' in Hindi) in each language, with a response time of 10 seconds. We choose sensors present in regions importantto both language processing and decision making to supply inputs to Ensemble classifiers and Artificial Neural Networks (ANN) for prediction. Experimental results reveal an accuracyof 84.6% and 87.69% for decision and language classification respectively using ANN. The overall accuracy of bilingual speech was reported to be 75.38%.

METHODOLOGY

Data Acquisition and Experimental Setup

- In this study, we aim to recognize two words 'Yes' and 'No' in English and ('Haan'/'Na') in Hindi using EEG signals obtained from bilingual subjects. For this purpose, we use the Electrical Geodesics, Inc. (EGI) Clinical Geodesic EEG System 400, which is a 32 channel EEG headset for signal acquisition.
- The sensors of interest in this study are: F7, T7, P7, P3 and C3 for language classification and Fp1, FpZ, Fp2, F3, Fz, F4 for decision making. These sets of sensors are henceforth referred to as L sensors and D sensors respectively. Additionally, the complete set of 11 sensors (L+D) is also explored to find a pattern that gives the highest accuracy





phones. The subjects were presented with a Figure Bonsisted enfekte aftes and alle in the instrument of the consisted of the instrument of the in Questions were played out on a laptop and appeared in random order for different subjects to prevent preconceived or biased answers. After a particular question was played, subjects were asked to continuously think of either 'Yes' or 'No' for a response duration of 10 seconds.

METHODOLOGY

Preprocessing and Feature Extraction

- Raw data obtained from the EGI Geodesic headset was filtered using Net Station Digital 60/50 Hz notch filter to obtain data between 0-40 Hz. The data was segmented to extract values appearing only during the 10 second response time
- The bin_power method in the PyEEG package was used to transform the data using a Fast Fourier Transform (FFT) into the frequency domain. The result was split into five bands (α , β , γ , δ and θ) depending on the frequencies. Only α , β and γ bands were considered as viable features for training the classifiers. infants. A window size of 250, shifting right by one in each iteration, was considered and the powers for all three bands were calculated over the entire duration of 10 seconds. Average power of α , β and γ bands over 2251 windows is calculated.

$$\{\alpha_{\mathbf{k},\mathbf{j}},\beta_{\mathbf{k},\mathbf{j}},\gamma_{\mathbf{k},\mathbf{j}}\} = \sum_{\mathbf{i}=0}^{250} \{\alpha_{\mathbf{i}},\beta_{\mathbf{i}},\gamma_{\mathbf{i}}\} \div 250$$

$$\{\alpha_{\mathbf{a}vg,\mathbf{j}},\beta_{\mathbf{a}vg,\mathbf{j}},\gamma_{\mathbf{a}vg,\mathbf{j}}\} = \sum_{\mathbf{k}=0}^{150} \{\alpha_{\mathbf{k},\mathbf{j}},\beta_{\mathbf{k},\mathbf{j}},\gamma_{\mathbf{k},\mathbf{j}}\} \div 2251$$
Flow Chart

$$\{\alpha_{\mathbf{a}vg,\mathbf{j}},\beta_{\mathbf{a}vg,\mathbf{j}},\gamma_{\mathbf{a}vg,\mathbf{j}}\} = \sum_{\mathbf{k}=0}^{1500} \{\alpha_{\mathbf{k},\mathbf{j}},\beta_{\mathbf{k},\mathbf{j}},\gamma_{\mathbf{k},\mathbf{j}}\} \div 2251$$
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$$\{\alpha_{\mathbf{k},\mathbf{j}},\beta_{\mathbf{k},\mathbf{j}},\gamma_{\mathbf{k},\mathbf{j}}\} \div 250$$
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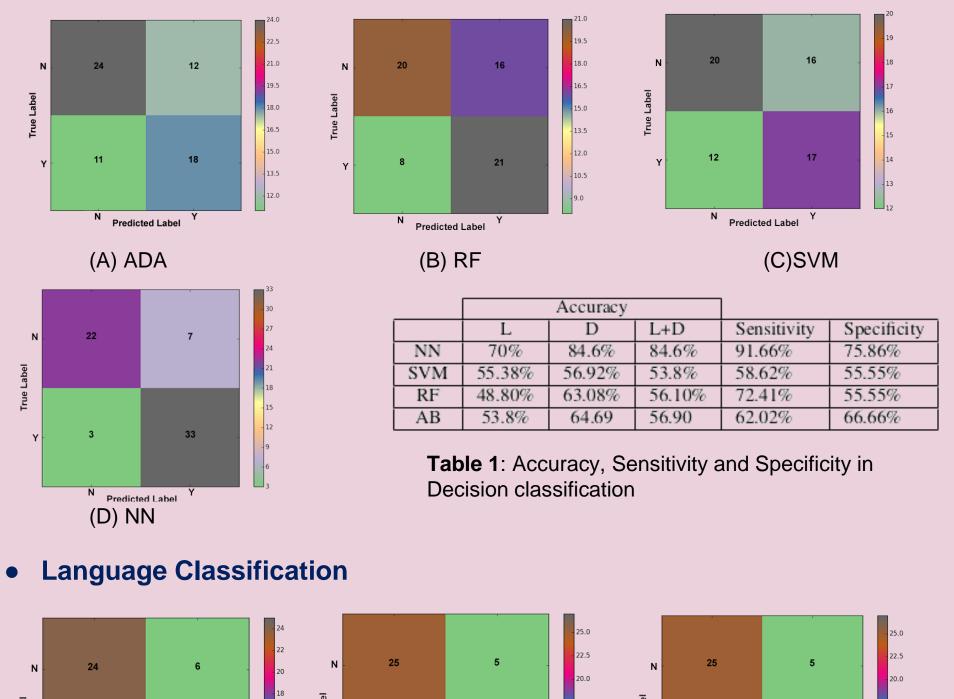
Figure 3. Flow chart of the methodology process

RESULTS

Comparative Analysis of different Machine Learning Classifiers

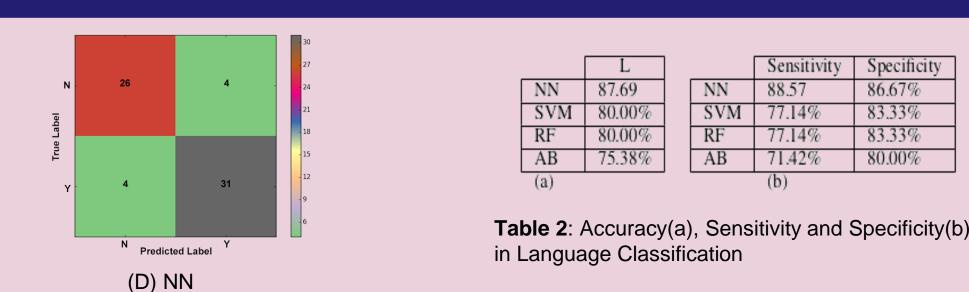
• Decision Classification

(A) ADA

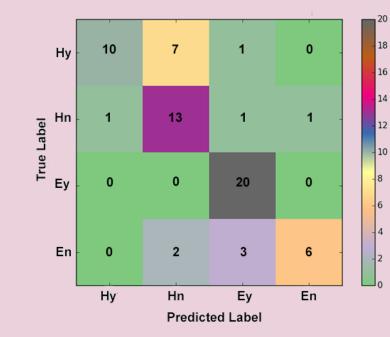


(C)SVM

RESULTS



• Language and Decision Classification



Improvement over previously published studies

This Work	2 in each language(4), 5, 6 for Decision(D)and 5 for Language(L) and 11 for D +L	D - 84.6% L - 87.69% Total - 75.3%
Salama et al. [6]	2, 7, 1	Offline 56% Online 57%
Torres-Garcia et al. [3]	5, 21, 16	20%
Porbadnigk et al. [12]	5, 21, 16	45.5%
Calliess [11]	5, 23, 16	49%
Wester and Shultz [10]	5, 21, 16	42%
STUDY	WORDS, SUBJECTS, ELECTRODES	ACCURACY

Table 3: Parameters and criteria for arrhythmia classification.

CONCLUSIONS

- We present a novel automated method of data acquisition using a TCP between the device and acquisition software that reduces eyeblink/motion artifacts leading to better feature extraction.
- We use a rolling mean method to obtain averaged powers of the α, β and γ bands by splitting the time series data into windows of 250 data points leading to better data representation per time point.
- In a novel finding, we are able to classify semantically similar words 'Yes'/'No' and 'Haan'/'Na'(in unspoken speech) in two different languages (English and Hindi) at a high accuracy of 75.38% and classify decision and language at an accuracy of 84.6% and 87.69% respectively using **Artificial Neural Networks.**
- These findings are a great improvement over previous findings in the same domain. This could be used for real-time devices.

REFERENCES

- 1. M. D'Zmura, S. Deng, T. Lappas, S. Thorpe and R. Srinivasan Toward EEG sensing of imagined speech, International Conference on Human-Computer Interaction. Springer Berlin Heidelberg, 2009.
- 2. K. Brigham and B. V. K. V. Kumar. Imagined Speech Classification with EEG Signals for Silent Communication: A Preliminary Investigation into Synthetic Telepathy. Bioinformatics and Biomedical Engineering (iCBBE), 2010. 4 th International Conference on, Chengdu, 2010.
- 3. Torres-Garcia Alejandro Antonio, Reyes-Garcia Carlos Alberto and Villasennor-Pineda Luis. Toward a silent speech interface based on unspoken speech., The 5 th International Joint Conference on Biomedical **Engineering Systems and Technologies, 2012.**
- 4. K. Amarasinghe, D. Wijayasekara, M. Manic. EEG based brain activity monitoring using Artificial Neural Networks. The 7 th International Conference on Human System Interactions (HSI),2014.

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