EEG Semantic Decoding using Deep Neural Networks

Juan Manuel Mayor Torres, Evgeny A. Stepanov & Giuseppe Riccardi

University of Trento - Department of Information Engineering and Computer Science

{juan.mayortorres,evgeny.stepanov,giuseppe.riccardi}@unitn.it

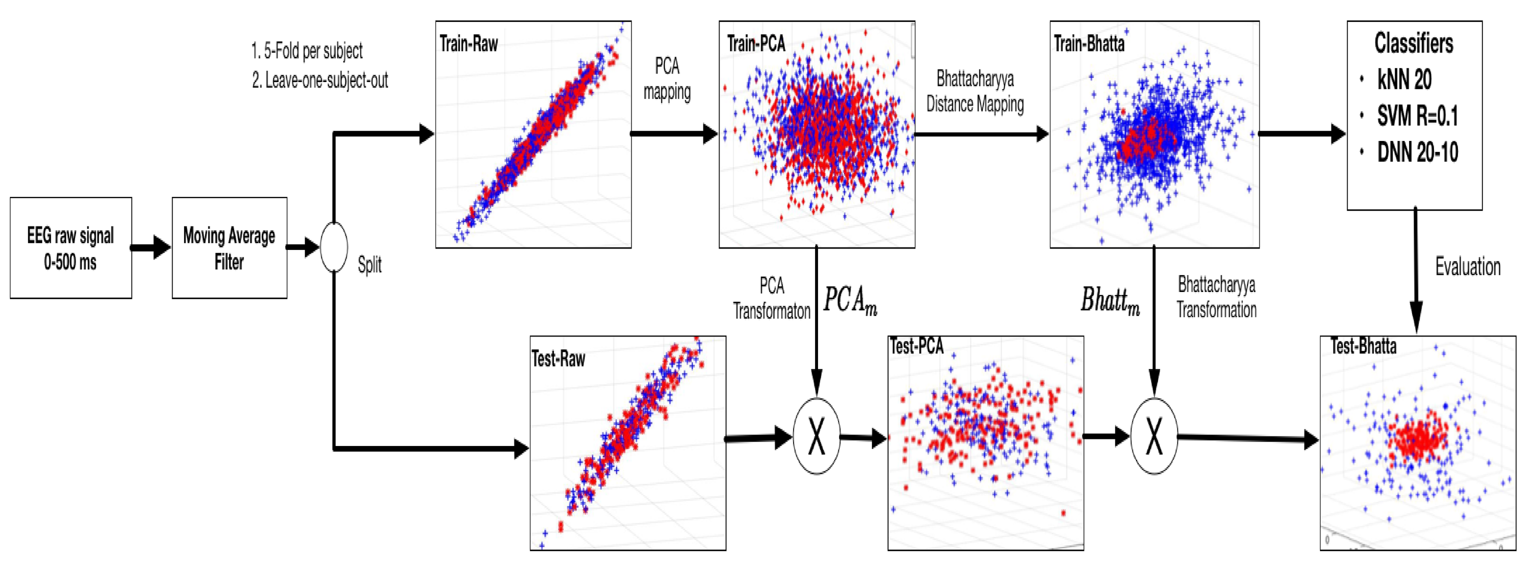
Background and Motivations

- Differences between conceptual representations are detectable in **early neural activations** [2];
  - Functional organization of concepts is reflected in neural responses [4];
  - e.g. Tools vs. Mammals;
- Incomplete understanding of the early activations associated with meaningful stimuli (pictorial, orthographic, or auditory), due to:
  - Low number of signal features in each trial
  - Limited number of training examples
  - High level of inter-subject variability
- Low inter-class separability (between **semantic neural responses**) is evident in:
  - Subject independent evaluation (Leave-One-Subject-Out)
  - Within subject evaluation (Leave-One-Trial-Out)

Methodology

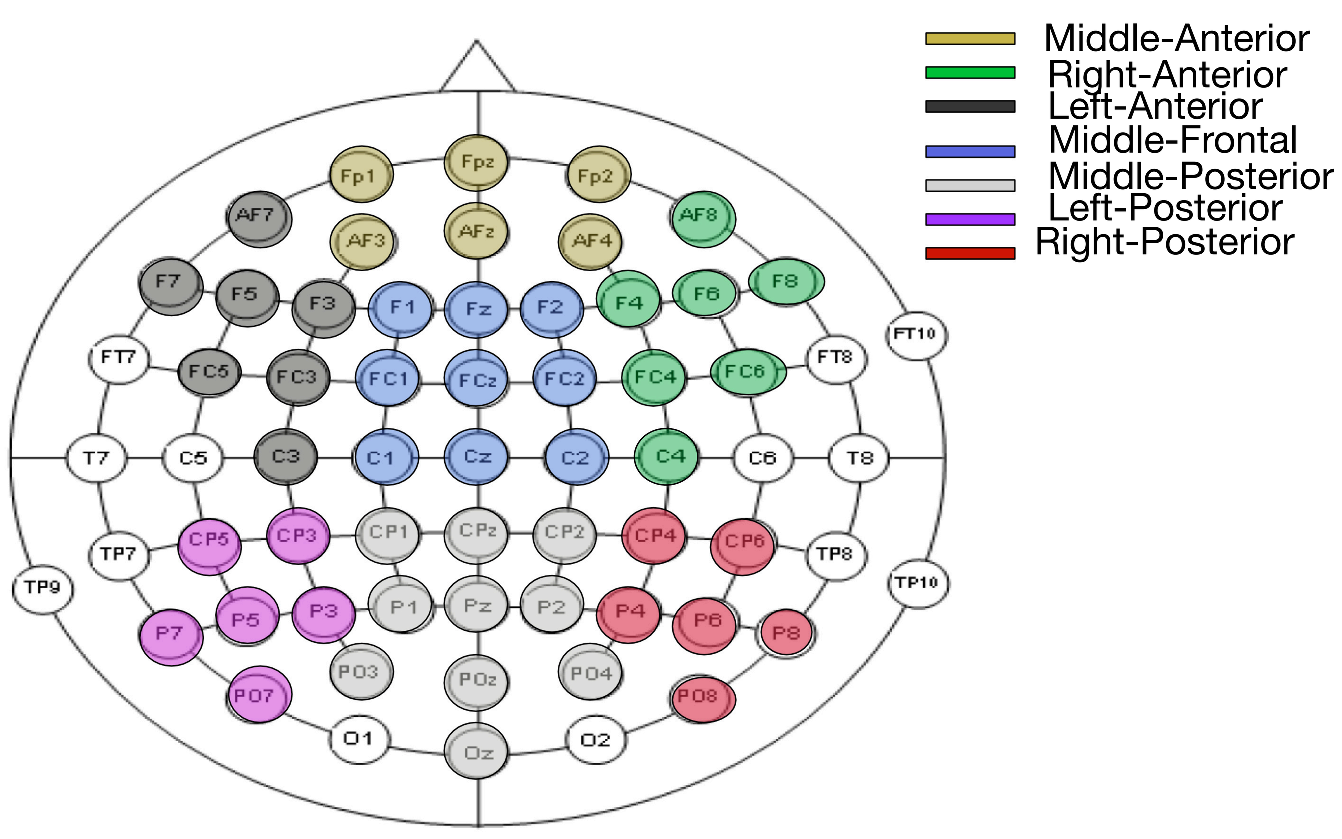
1. Semantic class recognition using early neural responses
2. Region-Of-Interest (ROI) based training and evaluation
   - 7 critical ROIs
3. Signal Pre-processing [3]:
   - Moving Average Filter
   - Principal Component Analysis (PCA);
   - Bhattacharyya Distance;
4. Feature Selection:
   - 20 top ranked features with respect to PCA and Bhattacharyya Distance criterion
5. Machine Learning Algorithms:
   - K-Nearest Neighbors (kNN-20);
   - Support Vector Machines (SVM) with Radial Basis Function (RBF) kernel (R=0.1);
   - Deep Neural Network (DNN):
     - 20 input unis, 10 hidden units, 2 output units;
     - NN unit is a ***Restricted Boltzmann Machine*** (RBM)
     - Pre-training using auto-encoder scheme and *unsupervised Contrastive Divergence* of 100 iterations [1], using a $\epsilon_{CD} = 0.1$;
     - 2500 iterations of fine-tuning back-propagation training with a learning rate $\epsilon_{fine} = 0.01$;
6. Evaluation Scenarios:
   - Cross-Subject: ***Leave-One-Subject-Out*** (LOSO)
   - Within-Subject: ***Leave-One-Trial-Out*** (LOTO)
   - Within-Subject: ***5-Fold per subject*** (5-Fold Cross-Validation)

Pipeline



Semantic decoding pipeline and its corresponding subcomponents. The training and test distribution evolves through each new feature space (PCA and Bhattacharyya), obtaining concentric separation regions at the end of the entire process

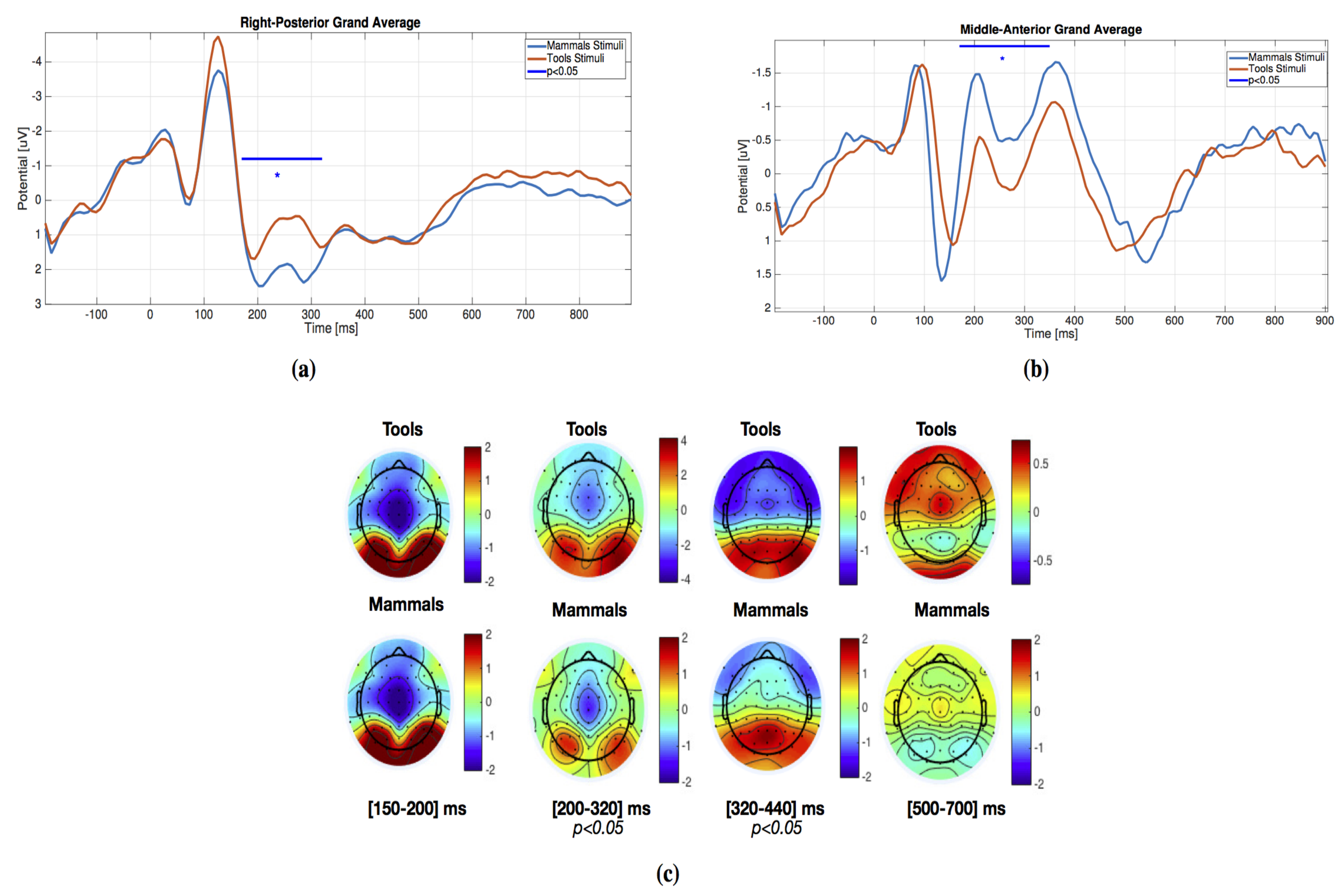
Channels per Region of Interest



Data Set [5]

- **Subjects**: **7** healthy **Italian** speakers (5 male and 2 female,mean age $\mu = 29$)
- **Task**: name animal and tool objects presented in normalized grey-scale photographs
- **Stimuli**: (photographs)
  - 30 land-mammals
  - 30 work-tools
- **Procedure**:
  - Random order per participant;
  - 180 trials per class (360 in total)

Experimental Results



(a) (b) (c)

- **Time plots** for right-posterior (a) and middle anterior (b) regions:
  - significant region between $[150 - 320]$ ms;
  - consistent with early visual processes hypothesized to follow early neural responses [4];
- **Scalp plot** (c)
  - significant activations around posterior and middle-posterior regions;
  - significant activations especially for P1 and N2 ranges;

Average Accuracies per Evaluation Setting

Modalities	LOSO			5-Fold per subject			LOTO per subject		
ROIs	**kNN-20**	**SVM R=0.1**	**DNN 20-10**	**kNN-20**	**SVM R=0.1**	**DNN 20-10**	**kNN-20**	**SVM R=0.1**	**DNN 20-10**
Middle-frontal	0.535	0.567	0.731	0.401	0.699	0.782	0.232	0.544	0.687
Left-Anterior	0.532	0.651	0.746	0.443	0.631	0.771	0.351	0.561	0.715
Right-Anterior	0.510	0.583	0.730	0.467	0.681	0.789	0.421	0.589	0.688
Middle-Anterior	0.545	0.657	0.721	0.378	0.674	0.797	0.444	0.621	0.734
Middle-Posterior	0.578	0.527	***0.752***	0.452	0.731	***0.824***	0.501	0.666	0.751
Left-Posterior	0.612	0.611	0.744	0.534	0.743	***0.834***	0.411	0.642	***0.633***
Right-Posterior	0.624	0.626	***0.758***	0.452	0.761	***0.853***	0.455	0.611	***0.624***
Average	0.562	0.603	**0.740**	0.447	0.703	**0.807**	0.402	0.605	**0.691**
All-ROI$_s$	0.601	0.633	**0.751**	0.527	0.718	**0.838**	0.565	0.673	**0.744**

- ***Bold-Italics***: values are significant with T-test and $p < 0.05$
- High performance considering only $[0 - 500]$ ms ranges;

Conclusions

- A novel pipeline for semantic decoding;
- Outperforms state-of-the-art results;
  - Support for the semantic-decoding process embedded in neural responses;
- Motivation for using Deep Learning for the task;

References

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