THE ANDREW & ERNA VITERBI FACULTY OF ELECTRICAL ENGINEERING

SIPL
Signal and Image Processing Lab

TECHNION
Israel Institute of Technology

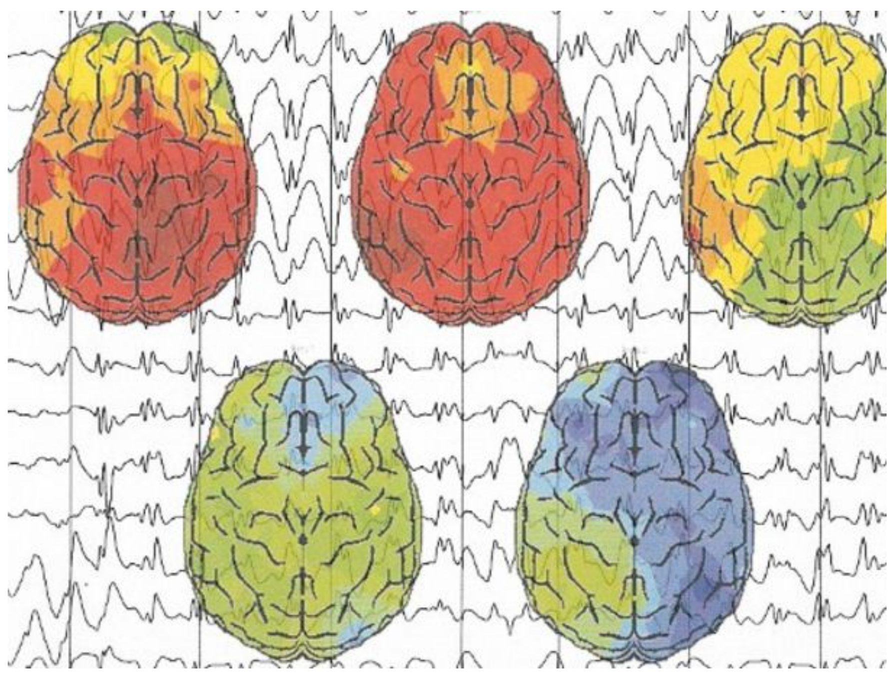
Work in Progress

Hyperbolic Representation Learning for EEG Signals

Yuval Mendelson & Daniel Bracha, Supervised by Ya-Wei Eileen Lin

Introduction

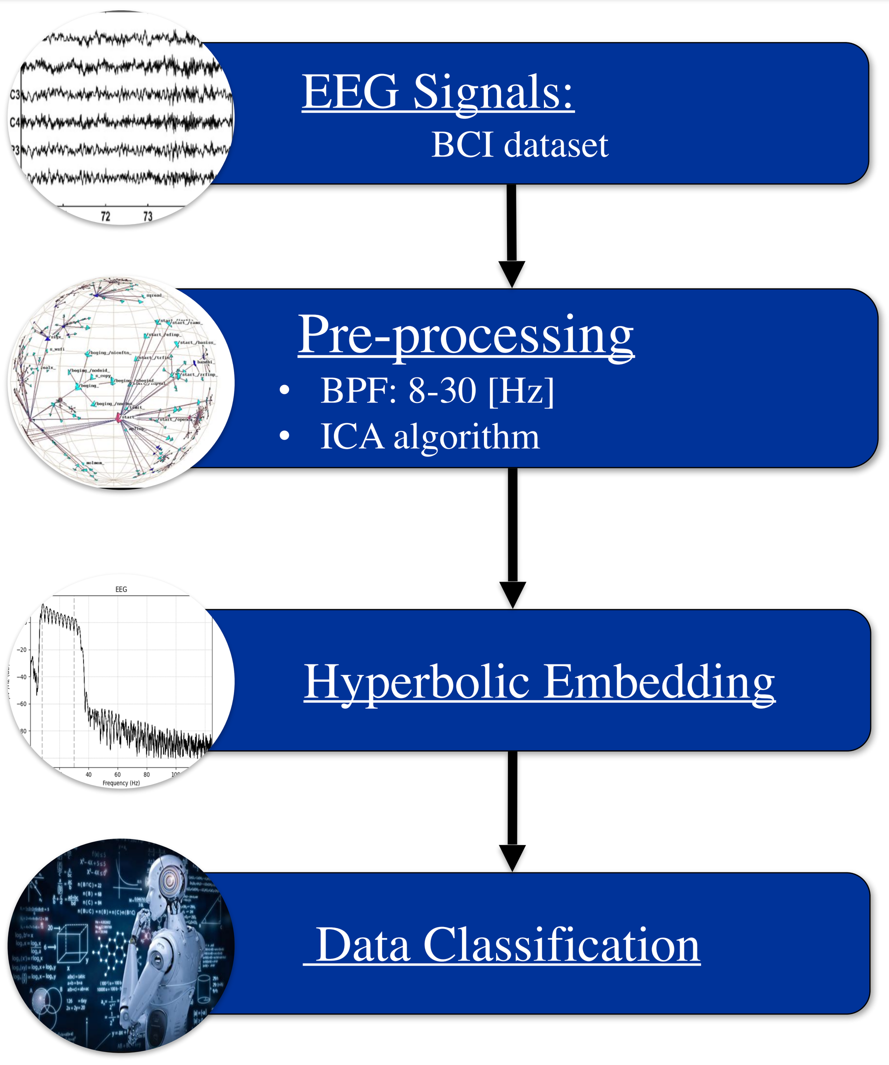
- EEG is an approach that records electrical signal of brain by electronic nodes
- The used EEG dataset is from 'BCI IV 2A competition', in which we analyze five patients performing 72 repetitions of four different movements
- Hyperbolic space is a type of Riemannian manifold with constant negative curvature
- One can utilize the hyperbolic representations for EEG task such as classification, due to the underlying hierarchical structure of the electronic nodes



Goals

- Extract meaningful and useful features from EEG signals
- Learn the underlying hierarchical structure of the EEG signals
- Implement the hyperbolic representation with Lorentz model and the equivalent Poincare model
- Visualize the obtained hyperbolic embeddings
- Classify and compare the results from different patients

Diagram



Hyperbolic Geometry

Hyperbolic space is a non-Euclidean space with a negative constant sectional curvature and an underlying geometry that describes tree-like data with small distortion

- Special properties:
  - Exponential growth with geodesic path
  - Riemannian operations
  - Hierarchy by nature

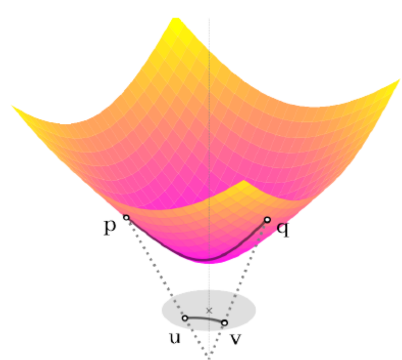
Two models of the hyperbolic space are used:

- Poincaré model: the geodesic distance is defined by

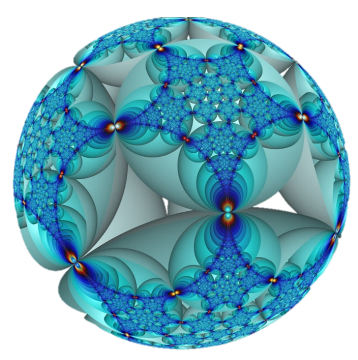
$$d_p(x,\ y) = arcosh\left(1 + 2\frac{\|x-y\|^2}{\left(1-\|x\|^2\right)\left(1-\|y\|^2\right)}\right)$$

- Lorentz model: the geodesic distance is defined by

$$d_l(x,\ y) = arcosh\left(x_0y_0 - \sum_{i=1}^{n} x_iy_i\right)$$

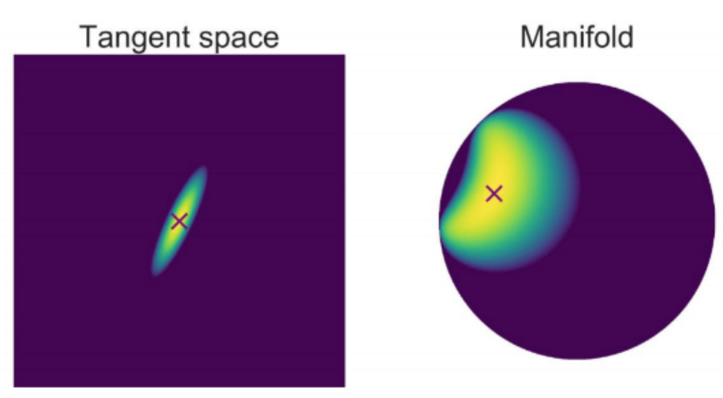


Lorentz model



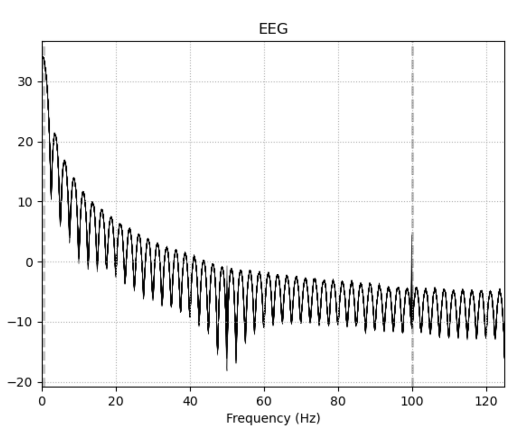
Poincaré ball

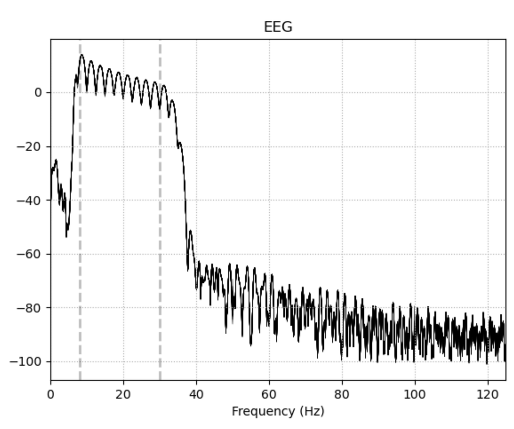
- Poincaré model is better for visualization while Lorentz model is more stable for its Riemannian operations
- Hyperbolic Gaussian introduces a sampling method on the hyperbolic space such that one can sample from this hyperbolic probability distribution



Pre-processing

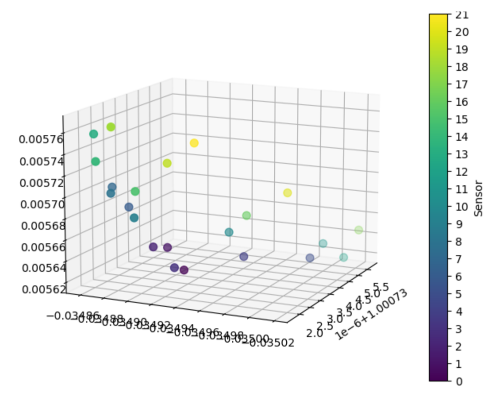
- Implement a BPF at 8-30 [Hz] using Hamming window
- Apply ICA algorithm to the EEG dataset
- Slice the dataset and group them into different movements



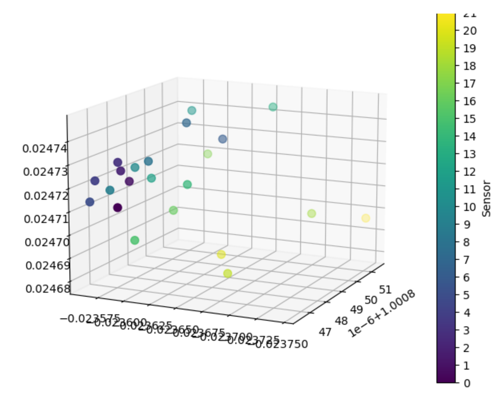


Results

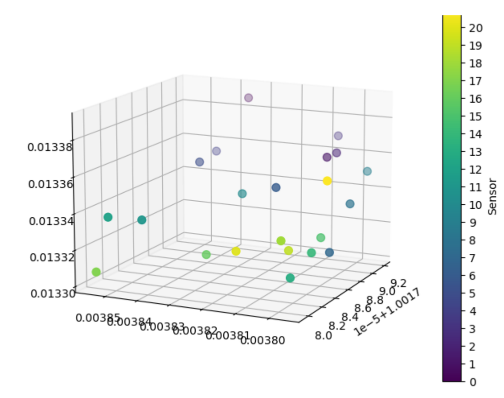
- The obtained embeddings of EEG signal from each patient are learned with hyperbolic Gaussian in the framework of MLP and ADAM optimization
- The visual results of the 3D hyperbolic embedding from patient 9 are presented in the following:



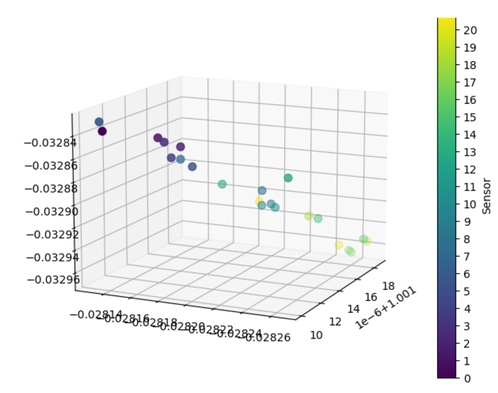
Patient num. 9
leg movement - filtered



Patient num. 9
tongue movement - filtered

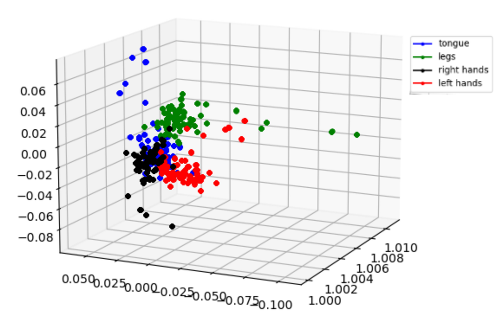


Patient num. 9
Left hand movement - filtered

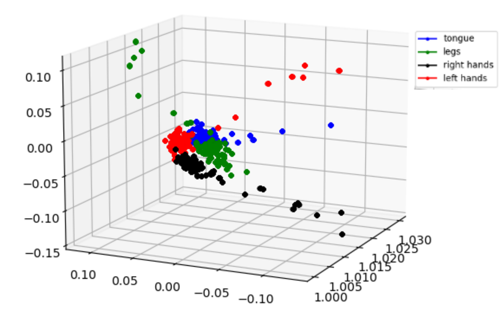


Patient num. 9
right hand movement - filtered

- The visualization of all the movements from patient 9 with and without filter:

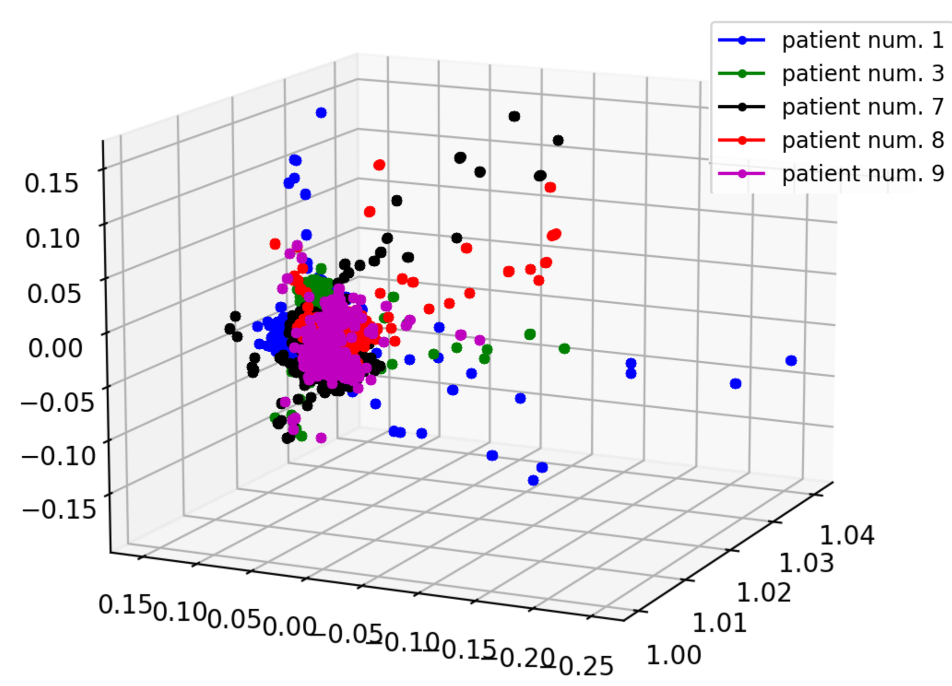


Patient num. 9 unfiltered



Patient num. 9 filtered

- The visualization of all five patients:



Conclusions

- Hyperbolic representation can well present the EEG data in our experiment
- Different patients locate around the same area in the hyperbolic space
- Our next step is to design a measure to evaluate the obtained embeddings

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