Final Project Proposal – BME 51100 – Fall 2021

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1. What is the scientific question/biomedical/clinical application you will address and why is it important?
Magnetic Resonance Imaging (MRI) data are crucial for clinical studies and research. The structural information of human head helps in different fields of research such as Transcranial Magnetic Stimulation (TMS), Transcranial Direct Current Stimulation (tDCS), brain tumor detection, uncertainty quantification analysis, etc. However, for these applications and research purpose, MRI images less than 3T resolution are of little use since the tissue boundaries become uncertain in the images. On the other hand, acquiring large number of higher resolution images (3T, 5T, 7T) are significantly expensive. Hence, a large database is often necessary for population-based studies, which is often quite impossible to gather from a single machine, environment, or race of people. **Hence, we aim to develop a workflow to generate synthetic segmented MRI images for a single environment**, which will help in population-based analysis and machine learning algorithms. Although generating 3D synthetic human head models is computationally quite expensive, we aim to work with a single slice of MRI scans in this project.

2. What data you will use and where it will come from? Briefly describe the dataset.
The database that we want to study is from Wu-Minn Human Connectome Project [https://www.humanconnectome.org/study/hcp-young-adult/document/1200-subjects-data-release]. There are 1206 healthy young adult participants (1113 with structural MR scans) collected in 2012-2015. In addition to 3T MR scans, 184 subjects have multi modal 7T MRI scan data and 95 subjects also have some resting-state MEG (rMEG) and/or task MEG (tMEG) data available. **For our analysis purpose, we will roughly use 800 3T/7T structural T1w and T2w healthy MRI scans.**

3. Formulation of the scientific question in signal processing problem terms, and how success will be evaluated.
The steps proposed for the synthetic data generation are proposed as follows-

- **Step 1**: generate segmented head-models of the MRI images with different tissue types [Atlas based segmentation- using tools like Freesurfer/SPM]
- **Step 2**: generate voxelized head-models of the segmented head-tissues.
- **Step 3**: Choose a single slice (i.e. Middle sagital/coronal slice of the head models across different subjects) use the chosen voxelized (pixelized) slices to train a Generative Adversarial Network (GAN) to generate synthetic slices.
- **Step 4**: After training GAN, generate thousands of synthetic samples and post-process them. This step involves different image processing techniques (i.e. noise removal, artifacts removal, quantization etc.)
- **Step 5**: Compare the data quality between synthetic data and ground truth data. This step involves comparing pixel distribution across different tissues, similarity check, statistical inference, etc.
- **Evaluation:**
  - Quality of the data during voxelization at step 2. The size of the grid will play an important factor in the data quality.
  - Evaluating GAN at step 3 using Inception/ FID scores.
  - Evaluating synthetic data at step 5 using statistical inference and descriptive statistics.

4. What approaches (signal processing techniques) will you try?
The MRI scans will be first segmented based on Atlas based data found in Freesurfer/ SPM database. The steps involve intensity uni formation of the raw data, skull segmentation, tissue type segmentation using Gaussian mixture models. The GAN will be implemented using deep neural network (most probably StyleGAN/DCGAN for its recent great success in generating synthetic images). The post-generation processing involves removing artifacts, tissue type quantization based on histogram data analysis, continuous tissue line segment. The final step involves how the generated data looks like. This involves statistical inference with the null assumption that the generated data and the ground truth data are same. It is assumed that the p-value will be very high. Hence, we cannot reject null hypothesis. Hence, a high p-value is our target. Since, once we have trained the GAN, we can generate as high number of data as we want. Hence, we can simply skip explicit modeling and use the permutation trick.

5.Describe two project objectives/aims that outline the extent of implementation for your project to earn an "A" grade for content; similarly describe what you would complete to earn a "B" grade.
The main bottleneck of this project is training a GAN network. Unlike traditional neural network training, this type of network involves two different networks (generator and discriminator) trained simultaneously and reaching an equilibrium. Most of the time, the training fails to reach equilibrium, or even if it reaches equilibrium, the generated data looks the same

(a copy of a single image). The problems of mode failures is quite extensive in these type of training. Besides, the human head models require a specific shape and style. For example, GM should not be inside WM, CSF should be outside the GM. Above CSF, there should be skulls and scalp. Hence, training a GAN maintaining all of these restrictions is a quite challenge. Hence, completing this step (**step 3**) may be considered for a ‘B’ grade. And completing up to **step 5** *(the post processing and statistical inference)* may be considered for ‘A’ grade.

6. Any other relevant issues, literature, and factors influencing feasibility.

The post-processing step (step 4) requires significant image processing techniques. Hence, it might happen that post-processing is not quite optimal. The generation of virtual head models is quite time consuming. But luckily, we have already generated virtual head models for a significant number of subjects.