Vipul Kashyap (ID# 304-453-114)
Jerry Li (ID# 804-487-244)
CS 188 - Computational Methods for Medical Imaging

Brain Segmentation (Skull Stripping) - Literature Review

Brain segmentation, or skull stripping, refers to the process of isolating the brain from other structures in a medical image of the brain. This usually involves the removal of the skull and any other non-brain tissue from the image, such as the dura and scalp. It is often done as a pre-processing step as it is improves the speed and accuracy of many brain image analysis/processing algorithms, such as coregistration and tissue segmentation, while also decreasing algorithm complexity (Roy 2015). Skull stripped images have become a standard preliminary step for many brain image processing tools.

Skull stripping is very commonly done on magnetic resonance (MR) images and so we will be focusing our research on MR images. More specifically, we will be working with axial views of the brain taken using the fluid-attenuated inversion recovery (FLAIR) pulse sequence. The images primarily contain brain tissue surrounded by the scalp, skull, and dura tissue.

Although manually processing the images is arguably the most accurate approach to skull stripping, it is time intensive and does not scale for large projects involving hundreds of patients and large number of slices for each patient (Hwang 2011). Our goal is to use machine learning to develop a tool that is able to segment the brain tissue in MR images with reasonably high accuracy and speed.

There are several state-of-the-art methods currently developed for skull stripping. The Brain Extraction tool is a fast method that utilizes a sphere in the center of gravity and continuously deforms it until it expands to encompass the surface of the brain (Kleesiek 2016). Another common method is Hybrid Watershed Algorithm that finds the outline of the brain using edge detection, but tends to do poorly when faced with images containing brain tumors. A more recent approach is the Robust Learning-Based Brain Extraction (ROBEX), where voxels on the brain boundary are detected using random forests (Butman 2017).

Many of these techniques mentioned required tuning of several numerical parameters depending on the dataset in order to achieve the best results. However, in an research paper published in 2016 by Kleesiek et al., they used deep learning architecture in order to successfully extract the brain from several different modalities of images with minimal (or even no) need for parameter turning. In particular, they trained 3D deep convolutional neural networks that can automatically learn the important features in the dataset from training, and used them to able to extract the brains from various types of scans with impressive accuracy (Kleesiek 2016). Their mean Dice score, which is a common measure of accuracy for these sort of tasks, was 95.12, which outperforms many of other techniques mentioned above.

For our project, we will be doing something similar to the approach presented by Kleesiek, with some modifications. In particular, we will also be stripping the ventricles in the center of the brain from the image. We will be using the OsiriX software to manually prepare the training data we will use. By selecting the brain sections with the program, we can export a binary mask of the image. Finally, we will train our dataset with a convolutional network written using the Tensorflow framework, and test its accuracy.

Works Cited

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