

Skull Stripping for MRI: a deep neural network approach

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Abstract—In this work, we developed a deep Convolutional Neural Network(CNN) scheme to perform brain skull stripping on Magnetic Resonance Image(MRI). We analyzed previous works on machine learning including ensembled learning and linear models. By conducting series of experiments, we find weaknesses of popular machine models, like linear models and ensembled learning methods on poor scalability and strong assumption on structure of images. In order to reduce above problems, we propose a CNN approach to reach a higher scalability that can generalize to and visual accuracy.

Index Terms—Medical Imaging, Machine Learning, Skull Stripping, MRI

I. INTRODUCTION

Computer aided diagnosis based on medical images from MRI(magnetic resonance image) has gained ubiquitous usage for its noninvasive, nondestructive, flexible properties[2]. With the help of FLAIR(Fluid-attenuated inversion recovery), Diffusion-weighted(DW) MRI, people can get an anatomical structure of human soft tissues with high resolution. Especially to satisfy the demand for interior and exterior structure of brain structures, MRI can produce cross-sectional images from different angles, for example, top-down, side-to-side and front-to-back: however, having slices from different angles give a lot of challenges in stripping those tissues which people are interested in, from xtra-cranial or non-brain tissues that has nothing to do with brain diseases such as Alzheimers disease, aneurysm in the brain, arteriovenous malformation-cerebral and Cushings disease and etc[1].

As a preliminary step for further analysis, brain segmentation, i.e. skull stripping, needs both speed and accuracy in practice, which should be considered in any algorithms proposed. By Kalavathi et al. [2], they can be classified into five categories: mathematical morphology-based methods, intensity-based methods, deformable surface-based methods, atlas-based methods, and hybrid methods. However, as we further reviewed on state-of-arts that are vaguely described in hybrid methods, we believe machine learning-based methods should also have its own place in brain segmentation. Machine learning is a broad concept that include many interesting algorithms that we would like to implement and experiment on. For example, Butman introduced a robust machine learning method that detects the brain boundary by random forest[2].

As random forest has high expressive power on voxels of brain boundary, this method can reach an high accuracy robustly. Popular methods like deep learning can also applied. For example, Kleesiek et al.[8] used non-parametric 3D Convolutional Neural Network(CNN) to learn important features and reach the highest Dice score among all the methods we have reviewed. However, as a parametric algorithm, GMM also has its place in brain segmentation. For example, Yunjie et al. developed a skull stripping method with an adaptive gauss mixture model and a 3D mathematical morphology method. The GMM is used to classify brain tissues and to estimate the bias field in the brain tissues [5]. These methods, along with well-implemented libraries such as sklearn[6], Tensorflow[7], are readily available for our use.

Our contribution in this work is as following:

- We conduct a series of experiments on previous works of machine learning based skull stripping, including ensembled learning like random forest and linear models like SVM. Then we analyze their weaknesses.
- To solve problems of previous works, we adopt Convolution Neural Network(CNN) in a scheme similar to autoencoder.
- We manually labelled a range of MRI images. As previous sklearn-based works focus heavily on structure of image(pixel color, position and color of surrounding pixel), we labeled various MRI examples that previous models would fail.

II. PROBLEM FORMULATION

Problem Definition

We formulate our problem in the following way: given an image as matrix X , we can view it as a sum of skull matrix S and stripped matrix X' , with dimension w and h , as such

$$S_{ij} = \begin{cases} X_{ij} & \text{if it is skull} \\ 0 & \text{otherwise} \end{cases}$$

and

$$X'_{ij} = \begin{cases} 0 & \text{if it is skull} \\ X_{ij} & \text{otherwise} \end{cases}$$

and X'_{ij} should be an output of our program. What we want is to optimize the following objective:

$$J(X') = \alpha |X_{ij} - X'_{ij}|_2 + |S_{ij} - X'_{ij}|_2$$

where α is a hyperparameter that can regularize the loss function and prevent overfitting. In this case, because brain stripping is a preprocessing step, we tend to penalize more to keep original brain structure the same, so we need a higher α .

Then there are many ways to solve the problem, both in terms of discriminative models and generative models. For all the baseline models in this paper, one can calculate

$$P(S_{ij} = 0 | i, j, X_{ij}, \{X_{mn}\}_{d((m,n),(i,j)) < \varepsilon})$$

where d is a self-defined distance metric and ε is a predefined patch size. From an input data perspective, there are three major popular methods

- pixel-based. Choosing $\varepsilon = 0$ and only select features based on itself.
- patch-based. This method is the most popular for its scalability, by which one can choose distance to be Euclidean distance or Manhattan distance and tune a self-defined ε as a hyperparameter.
- image-based. One simply feeds the whole image in. Larger ε usually requires more computational power, but CNN method proposed in section IV will be image-based.

and latter experiments will show the difference on choosing features and ε .

Data Preparation

TODO

III. BASELINE MODEL

IV. CNN MODEL

V. DISCUSSION AND FUTURE WORK

REFERENCES

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