Clustering-based Unsupervised Brain MRI Segmentation

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INTRODUCTION

Background

- Semantic and lesion/tumor segmentation of brain magnetic resonance imaging (MRI) has many uses in research and clinical applications.
- Annotation of brain MRI is traditionally done by radiologists with specialized skills.
- Supervised methods are not applicable due to difficulty in collecting large, high-quality labels.

Previous Work

- Generative models trained purely on healthy brain images (AnoVAEGAN). [1]
- K-means with feature vectors from 3D CNNs to segment lung cancer in pathology images. [2]
- Unsupervised encoder learning for natural image segmentation (IIC, MoCo). [3, 4]

Data

- **Human Connectome Project (HCP)** public database. [5]
- Data of **99** subjects were processed and used.

Oracle and baseline

- Oracle data comes from **FreeSurfer** segmentation results, labels ranging from **0** to **14175**. [6]
- **114** labels that are actually presented in the 99 subjects are reclassified into 5 categories: **Brain Mask**, **Deep Grey Matter**, **Grey Matter**, **White Matter**, and **Cerebrospinal fluid (CSF)**. [7]
- Baseline comes from the **mean-shift** algorithm. [8]

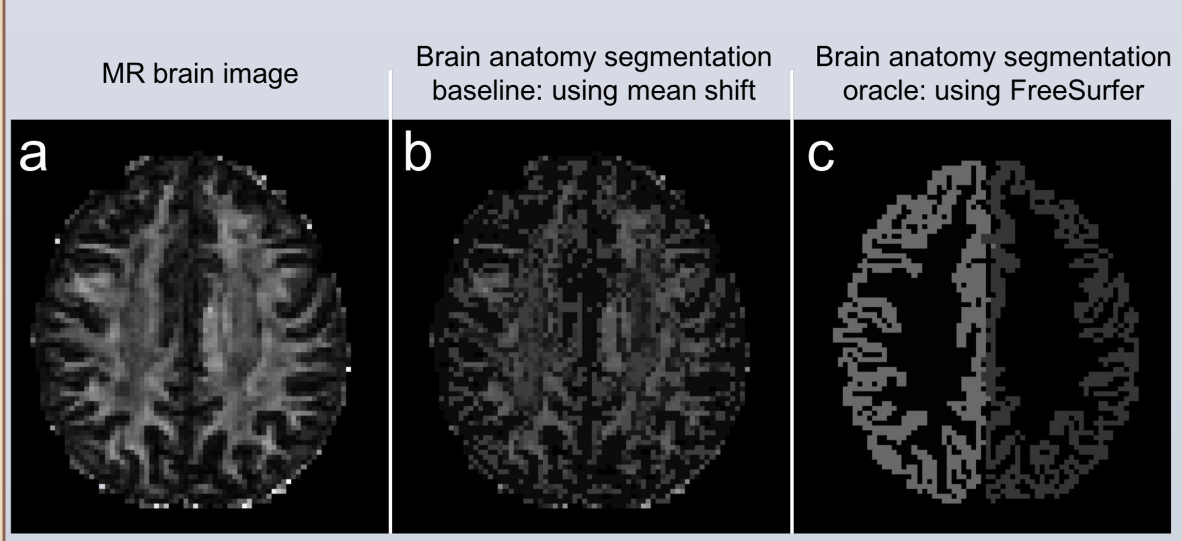


Figure 1. Example of a brain MR image (a), and segmentations results using the mean shift algorithm as baseline (b) and the FreeSurfer as oracle (c).

METHODS

Data preprocessing

1. Image normalization
2. Artifact correction
3. Coregistration between different contrasts
4. MRI physical model fitting (DTI) [9]

(64 contrasts-> 4 contrasts as below)

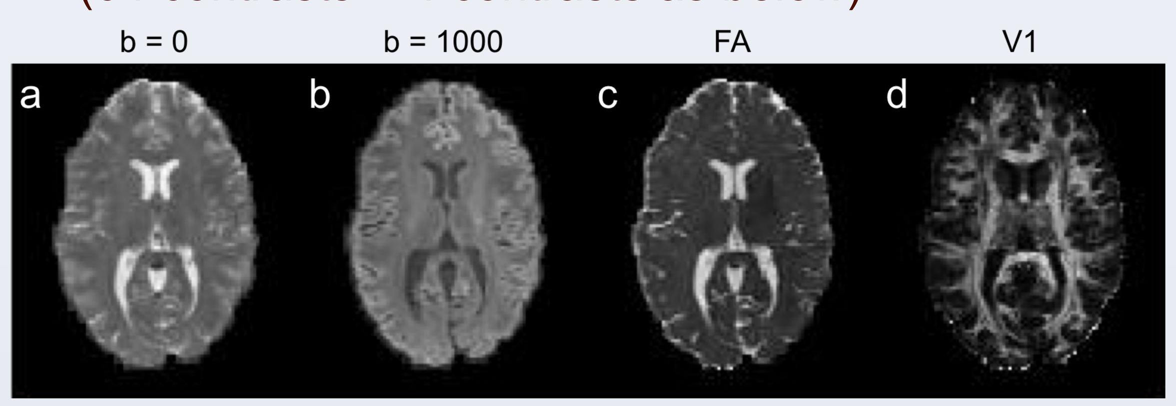
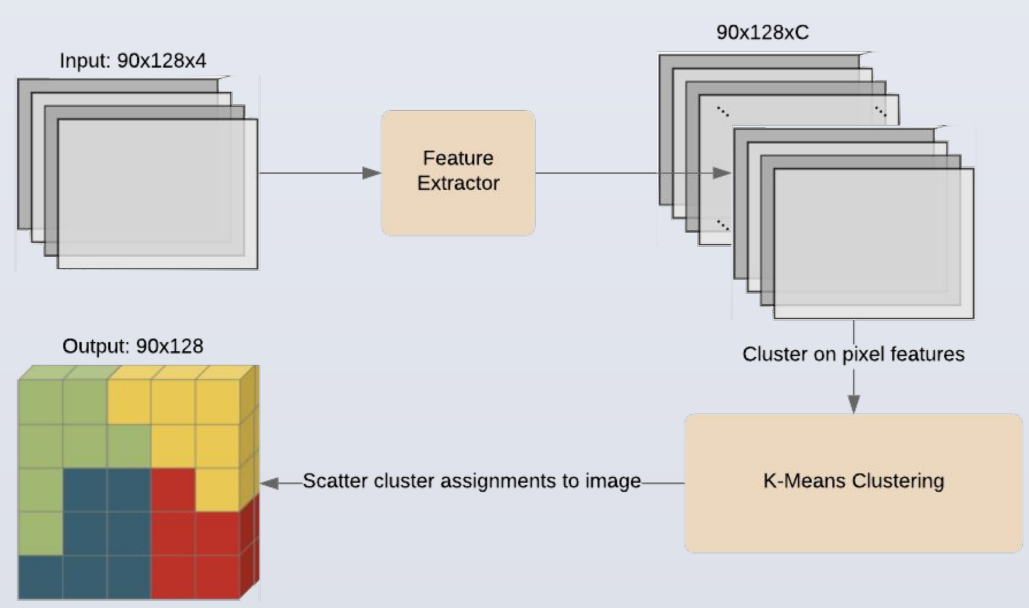
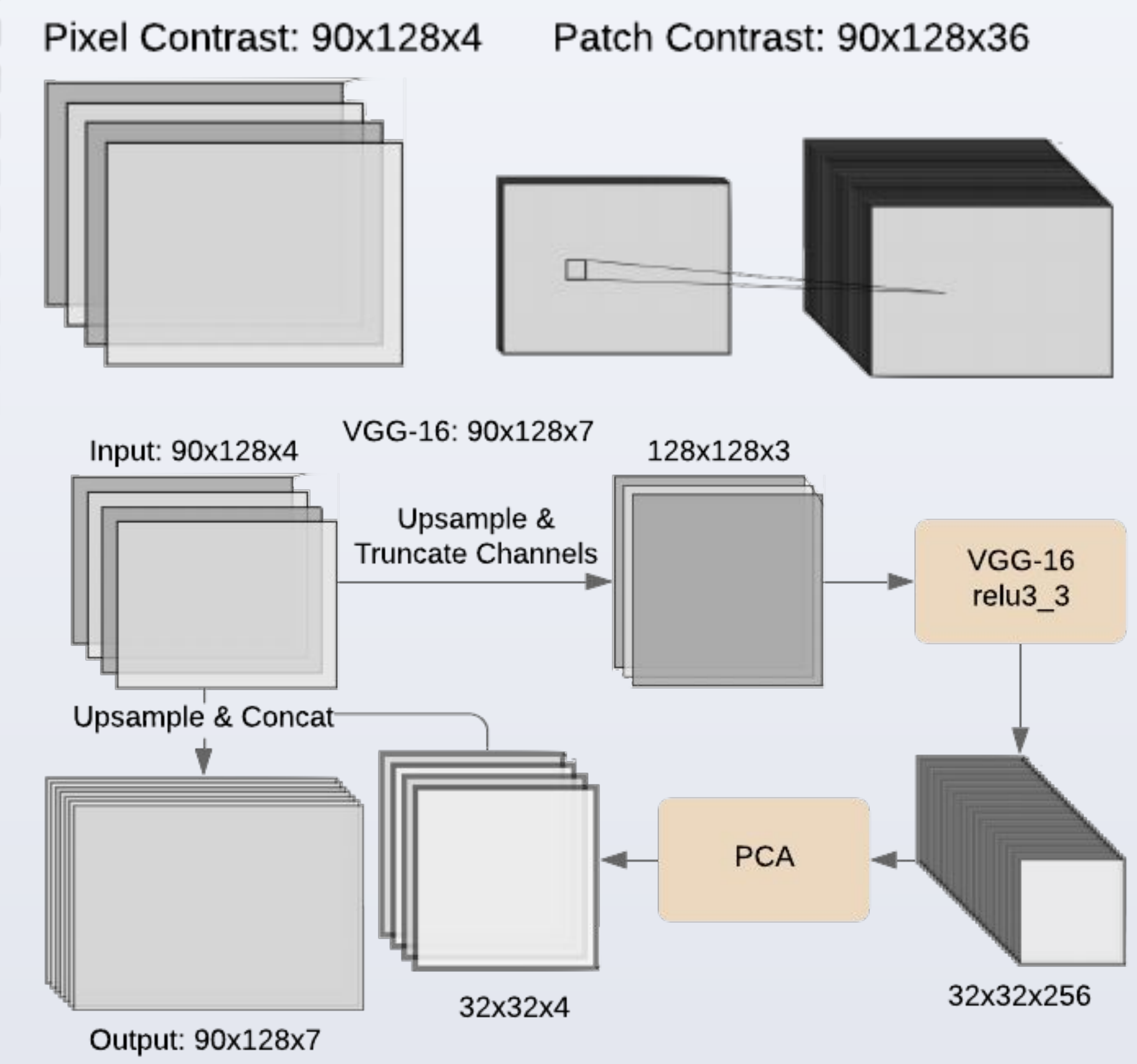


Figure 2. One representative example of preprocessed images from the HCP dataset (a: averaged b=0 image, b: averaged b=1000 image, c/d: FA /V1 maps derived from all b=1000 images).

Segmentation pipeline



Feature Extraction



Evaluation

Segmentation label matching with the Hungarian method:

1. Cost matrix calculation between labels
2. Linear assignment to find a permutation [10]

Segmentation Accuracy Evaluation:

1. Pixel accuracy: (TP + TN)/(TP + TN + FP + FN)
2. Sørensen-Dice coefficient (Dice score)

RESULTS

Different patch sizes for feature extraction

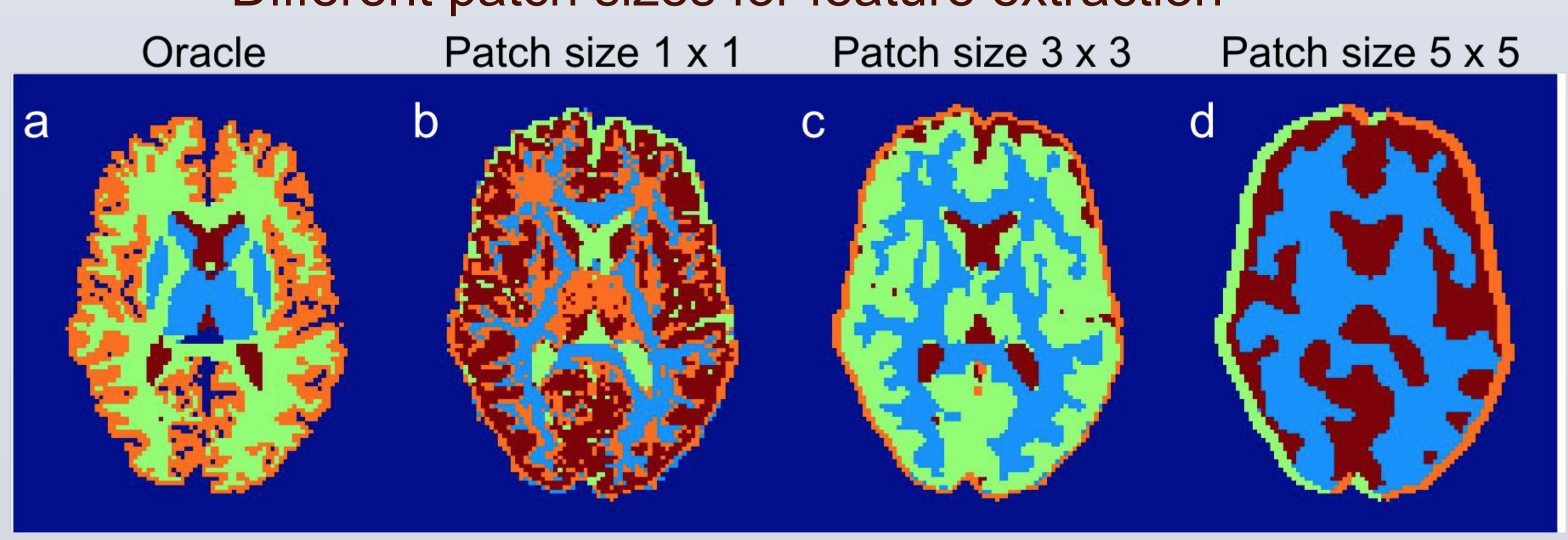
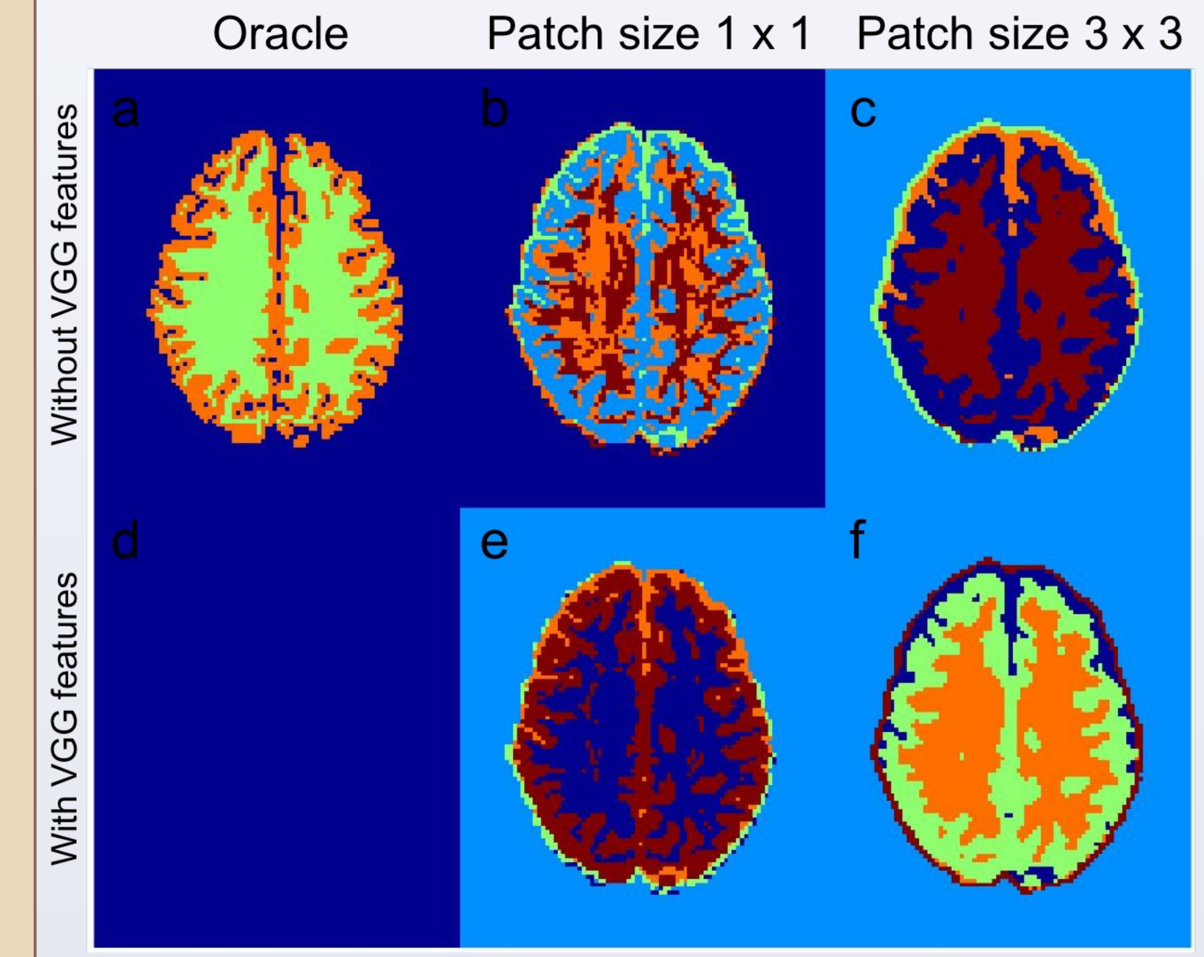


Figure 3. One representative segmentation results using FreeSurfer (a), and K-means with different patch sizes (b-d). For the choice of the patch sizes, there is a trade-off between the noise level and the details. The result is too noisy with patch size 1 (b), and too many details are lost with patch size 5 (d).

	Grey matter	White matter	Deep grey matter	CSF	Brain mask	Pixel accuracy
Patch size = 1 x 1	0.78 ± 0.09	**0.79** ± **0.04**	0.05 ± 0.08	0.22 ± 0.26	0.94 ± 0.01	0.84 ± 0.04
Patch size = 3 x 3	**0.80** ± **0.10**	0.75 ± 0.09	0.03 ± 0.06	0.20 ± 0.28	0.94 ± 0.01	0.84 ± 0.04
Patch size = 5 x 5	0.74 ± 0.15	0.67 ± 0.14	0.01 ± 0.04	0.16 ± 0.27	0.93 ± 0.01	0.81 ± 0.05
Patch size = 3 x 3 with features from pretrained VGG	**0.80** ± **0.10**	0.74 ± 0.11	0.02 ± 0.05	0.20 ± 0.28	0.92 ± 0.03	0.83 ± 0.05

Table 1. Dice scores of five different classes and pixel accuracy with different segmentation settings.

RESULTS (continued)



ANALYSIS

- Increasing the patch size trades off detail in segmentation in favor of being more robust against noise.
- Including features from pretrained VGG network reduces misclassification. [11]
- The proposed method works well in classifying grey and white matter, and poorly in classifying CSF and deep grey matter.

FUTURE WORK

- Explore more feature extraction methods
- Leverage other quantitative metrics for evaluation

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