Hybrid Clustering and Logistic Regression for Multi-Modal Brain Tumor Segmentation

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Abstract. Tumor is an abnormal tissue type, therefore it is hard to be identified by some classical classification methods. It was tried to find a non-linear decision boundary to classify tumor and edema by a joint approach of hybrid clustering and logistic regression.

Keywords: Sparse dictionary learning, K-means clustering, Logistic Regression

1 Introduction

Classifying tumor is challenging as it represents a collection of some abnormal tissue types which results in not enough labeled training dataset to "learn" about the different characteristics of an unseen tumor. In this situation, clustering would be a viable approach, as it divides a given dataset into a number of sub-groups without requiring the labeled training dataset. While the more classical clustering methods such as k-means and Expectation Maximization (EM) produce good clustering result, they just divide a given dataset into a number of sub-groups, such that there is no "learning" process involved that a learned knowledge can be applied to an unseen dataset.

Sparse dictionary learning [1, 2] has been applied to a number of wide range of disciplines such as signal reconstruction for medical image acquisition [3], image denoising [4], object recognition [5], and medical image segmentation [6]. By representing a given dataset by a combination of some learned dictionary's basis vector sets, the dataset can be clustered. This approach, often referred as sparse coding, was applied for object recognition [7, 8] and multi-modal medical image segmentation [9].

It was noticed that edema is already quite well classified by this method, whereas tumor is not. There are different types of tumor in the dataset, therefore there is no clear pattern in the images of different modalities for tumor. Logistic regression was applied to find a non-linear decision boundary to classify these different types of tumors from a more normal tissues.This is combined with volume-wise k-means clustering method to segment a cluster of tumor-like region.

2 Methods

2.1 Segmentation of Edema by Sparse Coding

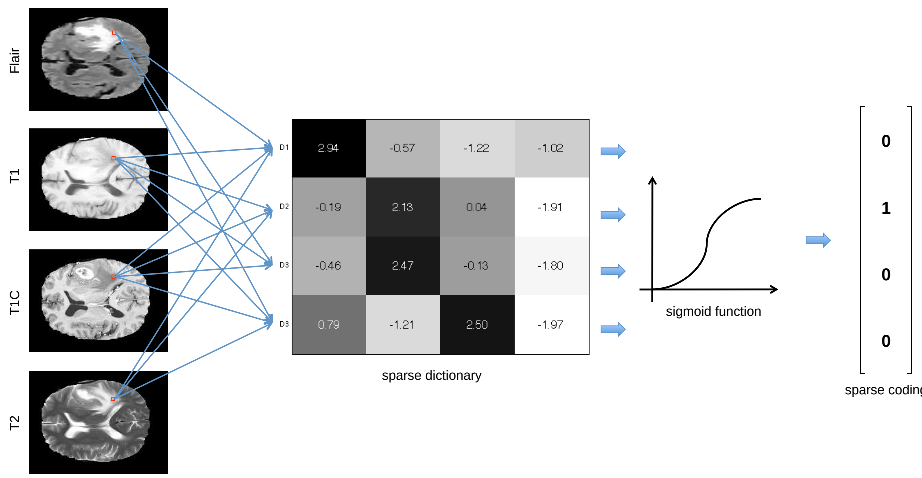

Fig. 1. Sparse coding of a slice in a volume with its multi-modal MR images by a 4×4 size sparse dictionary.

A sparse dictionary for the behavior of the image intensities in the given multiple image modalities (Flair, T1, T1C, and T2) is learned by a sparse autoencoder [10, 11]. The 4×4 sparse basis dictionary is shown in Fig. 1, where each column represents a dictionary entry. The image intensities in a pixel position of different image modalities are convolved with each of the dictionary entry, where the values become a binary digit after being applied a logistic sigmoid function.

Different combinations of dictionary entries represent the characteristics of different tissue types, which results in different binary digit numbers. $15(= 2^4 \quad 1)$ different types of tissue characteristics can be captured by sparse coding with a dictionary of 4×4 size. The hyper-parameters in sparse dictionary learning, such as the size of the dictionary and the sparsity constraints, are chosen by cross-validation.

The visualization of the 15 different tissue types identified by the sparse coding is shown in Fig. 2 with the ground truth of edema and tumor for the slice. It is noticeable that edema is already quite well classified by the bright blue region where it contains a region of a tumor as well. The segmentation performance for edema by sparse coding in F1-score $(2 \cdot (precision \cdot recall)/(precision + recall))$ on 10 cross-validation set was 0.54, which outperformed the other methods tried for edema segmentation (logistic regression: 0.246, neural network[1]: 0.14).

[1] neural network classification on image intensities of each voxel in the

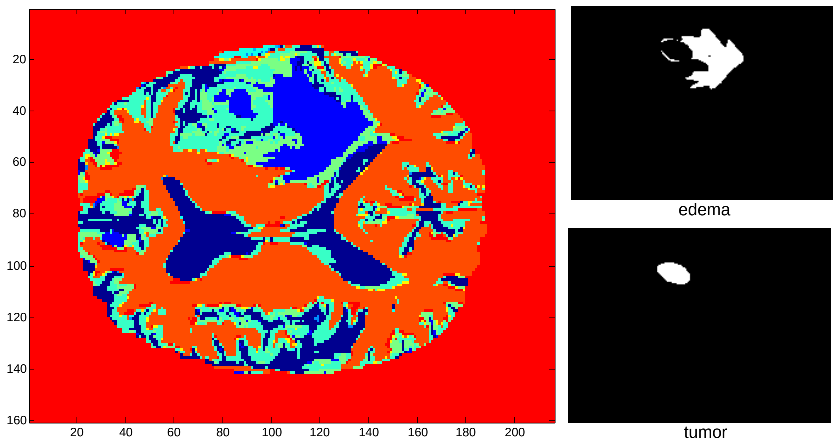

Fig. 2. Tissue type clustering result of an image slice by sparse coding with 4×4 size dictionary.

2.2 Segmentation of Tumor by Logistic Regression and K-means Clustering

Whereas edema was well classified by the sparse coding, tumor was not, probably because tumor is a highly heterogeneous tissue type or just an abnormal region. In the training dataset, tumor in some volumes were well observed by Flair images, whereas in some other volume it was better observed by T1-Contrast images, but no obvious pattern could be found unlike the other tissue types or edema. Therefore, it was tried to find a non-linear decision boundary to separate these "abnormal" tumor from a more "normal" tissue types with logistic regression. Logistic regression models the conditional probability of given feature $\mathbf{x}$ belonging to a class $y \in \{0, 1\}$ as the logistic sigmoid function $(1/(1+e^{\mathbf{x}}))$. Second order polynomial feature with two combination of the four image modalities were used

$$\mathbf{x} = \{x_1x_2, x_1^2x_2, x_1x_2^2, x_1^2x_2^2, x_1x_3, \cdots, x_1^2x_4^2, x_3x_4, x_3^2x_4, x_3x_4^2, x_3^2x_4^2\}$$

, where x_1, x_2, x_3, x_4 represent the image intensities of each image modality. The F1-score for tumor classification with this method was 0.246 on a cross-validation dataset with 10 volumes, outperforming the other classification methods for tumor classification (sparse coding: 0.0031, neural network: 0.0001).

Another insight for the tumor segmentation was, that a tumor is usually surrounded by an edema. Consequently, if the region found by the logistic regression is inside the already segmented edema region, it is regarded as well classified. When the region segmented by logistic regression is outside of the edema region, and then it is regarded as segmentation failure. In this case, a multi-modal k-means clustering was applied to capture a cluster of a region within edema but has a different characteristic than edema.

3 Results

The average segmentation performance evaluated are shown in Table 1. No human input is required during the segmentation process, and the average segmentation time for a single patient volume was about 1.8 minutes.

Table 1. Performance evaluation results

Av.Dist.1	Av.Dist.2	Dice.1	Dice.2	Haus.1	Haus.2	Cohen's	Sens.1	Sens.2	Spec.1	Spec.2
6.526	15.478	0.391	0.3	37.883	94.282	0.144	0.511	0.416	0.992	0.995

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