
Multiple Sclerosis Lesion Segmentation in MRI Images

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Abstract

Medical Imaging is an emerging field that can help workload for medical professionals and increase outcomes for afflicted individuals. Our focus is on comparing classification techniques for Multiple Sclerosis lesions in order to find the most successful techniques. We also attempt to combine some techniques to improve detection success. Our results confirm the standard that Random Forest typically provides the best results, but that there are other options useful in segmenting lesions. Interestingly, Random Forest also tends to classify quicker than other algorithms, particularly when compared to SVM. This makes it the most practical in terms of accuracy and speed.

1 Introduction

Multiple Sclerosis is a debilitating disease that affects the brain and spinal cord. Technically, MS is an autoimmune disease; the immune system attacks parts of the body, in this case, the protective covering of nerve fibers. If occurrences are bad enough, the nerves can build up scar tissue, which impedes nerve conduction. This scar tissue is what we refer to as lesions.

One of the most shocking aspects of Multiple Sclerosis is that it primarily affects individuals between the ages of 15 and 40. Women are also twice as likely to be affected by MS. Early detection is key to managing symptoms and controlling disease outcomes. Affected individuals can use exercise, cool temperatures and a balanced diet to help treat symptoms.

To detect Multiple Sclerosis lesions, scans are made of patient brains. Medical professionals analyze these scans, looking for signs of MS. These manual segmentation techniques have several drawbacks, not least among them the time input required by the medical professionals. Manual

segmentation also has a high rate of error; only 70% of lesions are properly detected [CITATION NEEDED]. Automatic segmentation techniques hope to improve these.

One of the main challenges of automatic segmentation is the low lesion volume in patient brain matter. Typically, only a small percentage of the patients brain has lesions, which can make detecting them difficult. This also poses a problem when gathering positive examples of the lesion. The positive to negative ratio is much lower than in many other segmentation problem spaces. Further, since most patients have very little lesion tissue, over classification can be a problem with automated segmentation. If a healthy brain is scanned and processed, ideally, we would show no lesions. In practice, this is can be very difficult.

1.1 Related Work

Segmentation of Lesions in MRI images is an active area of research. The 3 main objectives are:

1. Extracting features that can differentiate healthy tissues from scar tissues,
2. Selecting the most relevant features that help achieve the task, and
3. Improving the performance of the classification.

1.1.1 Review of Segmentation Methods

In MS lesion segmentation, the typical features are the intensity of each voxel in different modality images. Additionally, some methods like [1], combined K-NN based on intensities with a template-driven segmentation method to reduce false positives. Others like the method presented in [6] used the probability of a voxel belonging to tissue class with help of an atlas. Intensity of the six neighbor voxels can be added to feature vector of a point which has been used with an ANN in [5]. In [3], they used up to 255 features derived from applying different filters on images, and then with the help of principal component analysis (PCA), data is transformed to new orthogonal coordinates so the first column covers the greatest variance between data; hence, a simple thresholding on the first component of PCA can classify lesions. In [2], random decision forest (RDF) is used with local (like intensity) and context-rich (will be discussed later) features. RDF has the advantage of automatically selecting the best features over other methods.

1.1.2 Exploring Combinations [PLEASE GIVE YOUR COMMENTS ON THIS PART]

Lots of methods have been employed for lesion segmentation as mentioned before but no valid comparison is done to measure performance of different classifiers using different features. In this project we aim to compare various algorithm's efficiencies on the same data and feature sets to explore their properties in lesion segmentation. We use Support Vector Machine (SVM), Neural Networks, K-Nearest Neighbors, Random Forest, Markov Random Field, and Logistic Regression as classifiers. For features, we use Haar-Like, image filters, LM filters, entropy, gaussian based, and atlas. In a broad sense, we tried to extract all possible features to see how the well-known classifiers operate based on them.

2 Feature Detection

Image analysis aims at reducing information to a subset that is relevant to the task in hand. Information reduction often happens gradually with information being reduced until the desired result is extracted from the data. [4] The first level of reduction computes local features that are assumed to pertain to objects of interest.

2.1 Context (Haar-Like Features)

In the detection phase of the Viola-Jones object detection framework [?], a window of the target size is moved over the input image, and for each subsection of the image the Haar-like feature is calculated. This difference is then compared to a learned threshold that separates non-objects from objects. Because such a Haar-like feature is only a weak learner or classifier (its detection quality is

slightly better than random guessing) a large number of Haar-like features are necessary to describe an object with sufficient accuracy.

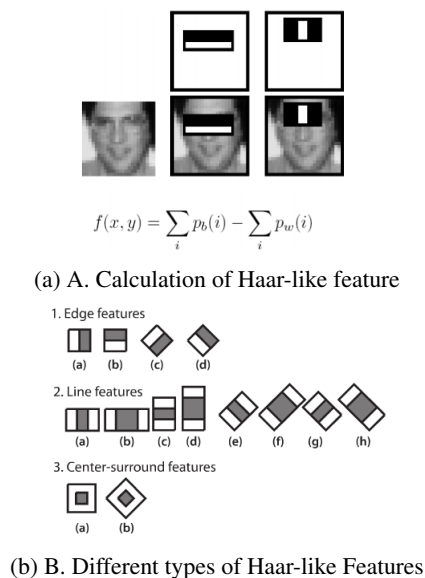


Figure 1: Haar-Like Features

2.2 Image Filters

Filtering is a technique used for modifying or enhancing an image. It can be used to emphasize certain features or remove other features in an image. In image processing filters are mainly used to suppress either the high frequencies in the image, i.e. smoothing the image, or the low frequencies, i.e. enhancing or detecting edges in the image. We extract the features through Linear filtering of the MRI image using convolution.

2.2.1 Leung-Malik (LM) Filter Bank

We use the filter bank provided by the Visual Geometry Group at the University of Oxford [1] to obtain a set of features. The LM set is a multi scale, multi orientation filter bank with 48 filters. It consists of first and second derivatives of Gaussians at 6 orientations and 3 scales making a total of 36; 8 Laplacian of Gaussian (LOG) filters; and 4 Gaussians. The filters occur at the basic scales $\sigma = \sqrt{2}, 2, 2\sqrt{2}, 4$. The Gaussians occur at the four basic scales while the 8 LOG filters occur at σ and 3σ .

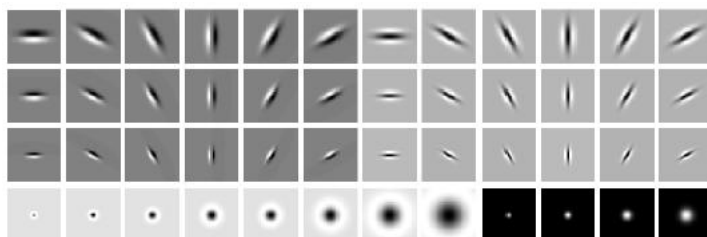


Figure 2: The LM filter bank has a mix of edge, bar and spot filters at multiple scales and orientations. It has a total of 48 filters

2.3 Entropy & Gaussian based Features)

2.4 Atlas Features

All the features need to explained briefly with good images.

3 Classifiers

Reasons for using each classification method. Brief description about them. No need for images here I guess.

3.1 Support Vector Machines

3.2 Neural Networks

3.3 k-Nearest Neighbours

3.4 Random Forests

reason for using random forest instead of a single decision tree: decision trees are known to suffer from overfitting, so it is better to have a forest and ensemble many decision tree. based on [2]

3.5 Markov Random Fields

The basic principle of Markov Random Field is to treat the input image as a graph in which each voxel is a node and all the neighboring voxels are interconnected. In the case of foreground segmentation, two spatial nodes of foreground and background are added to the graph and edges between voxels. Each pair of nodes are assigned a weight equal to the probability that a given voxel belongs to either foreground or background. The aim of this algorithm is to use a graph-cut to divide graph into two classes subject to the condition that combination of cutted edges is minimum. The advantage of this method is considering neighbors probabilities as a feature. In this project, we trained a random forest (which claimed to be the best algorithm for lesion segmentation) and used it to obtain initial probabilities of each voxel belonging to lesion. Then, MRF is applied based on the constructed graph.

3.6 Logistic Regression

4 Experiment Design

Pipeline Diagram is required here

4.1 Validation Measures

False Positive, false negative, etc. Why Dice is preferred?

4.1.1 Dice Score

4.1.2 Accuracy

4.1.3 Sensitivity

4.1.4 Detections

4.2 Training and Test Data

BrainWeb and Miccai Challenge Data. Explain how sampling is done on data to train the classifier.

5 Results

Lots of Images! Table with comparative results. Explanation for why we get these results.

Classifier	Dice Score	Accuracy	Sensitivity	Detection
SVM	0	0	0	0
Neural Networks	0	0	0	0
k-Nearest Neighbours	0	0	0	0
Random Forest	0	0	0	0
MRF with RF	0	0	0	0
Logistic Regression	0	0	0	0

5.1 State of the art results

The best results for segmenting MS lesions reported until now comes from random forest algorithm explained in [2]. Their proposed method contains of 30 separated decision trees with maximum depth of 20; each tree has a lower bound for information gain which stops it from further growing. They used two types of features, local features which are intensities and context-rich features which combine intensity of a single voxel with distant regions. This method is tested on MICCAI grand challenge 2008 and they got a dice score of 39.39 ± 18.4 . This result comes from doing a 3-fold cross-validation, meaning model is trained on two different brains and tested on the third one and the procedure repeats for three times.

The important thing they revealed about MS lesion segmentation task is its need of having as more comprehensive training set as possible. They demonstrated that classifier with their selected features cannot detect lesions in locations which are not represented in training data.

5.2 Discussion

Detailed analysis of the results we get from different results

6 Conclusion

7 Acknowledgements

8 References

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