Conditional Random Fields for Brain Tissue Segmentation

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Introduction

We propose the first of its kind, **fully conditional random field** (CRF)[1] based framework for **structural-MRI-image analysis**

As a proof of concept, we applied a CRF based framework to the **brain tissue segmentation task** for MRI images.

We applied our approach to standard brain image repository data sets, and prove that it can **generalize across datasets**

Motivation

Atlas based approaches can **fail to capture the morphological changes** that could result from brain diseases such as brain cancer or Alzheimer's.

Probabilistic approaches are much better suited to this task due to their ability to generalize to novel situations and handle noise.

Experimental Methodology

Our experiments were designed to answer the following questions:

Q1: How does the CRF-based approach compare against atlas based MRI-image analysis methods?

Q2: How does the CRF-based approach compare against atlas free MRI-image analysis methods?

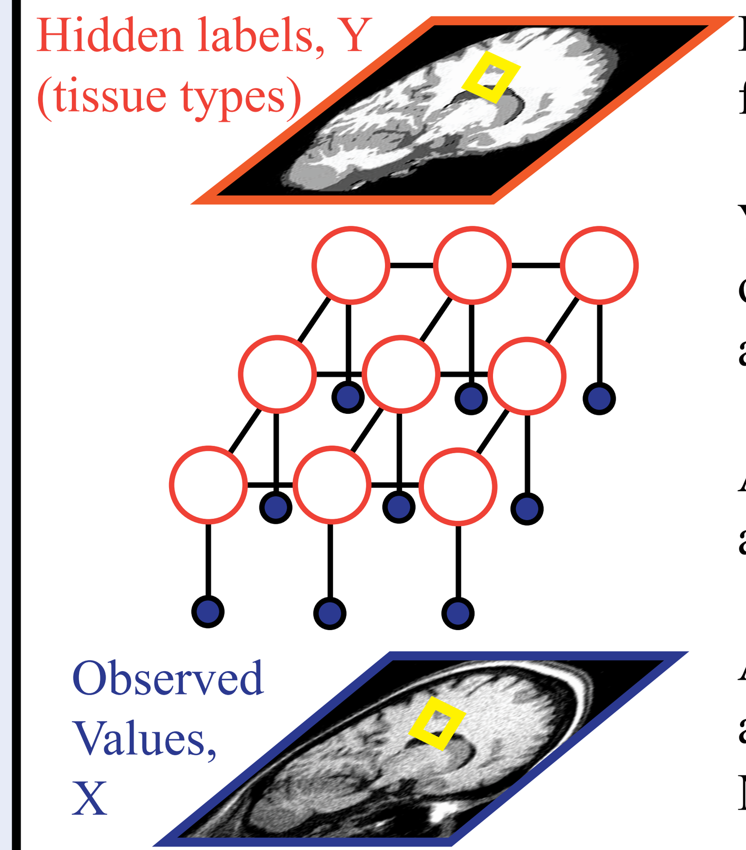
Q3: How does the CRF based approach generalize across different data sets?

Manually segmented brain MRIs were acquired from the Internet Brain Segmentation Repository(IBSR)[2]

Results were compared against Voxel-Based Morphometry (VBM8)[3] , SPM8 New Segment (SPM8+)[4], and FAST[5]

Segmentation Framework

CRF Setup



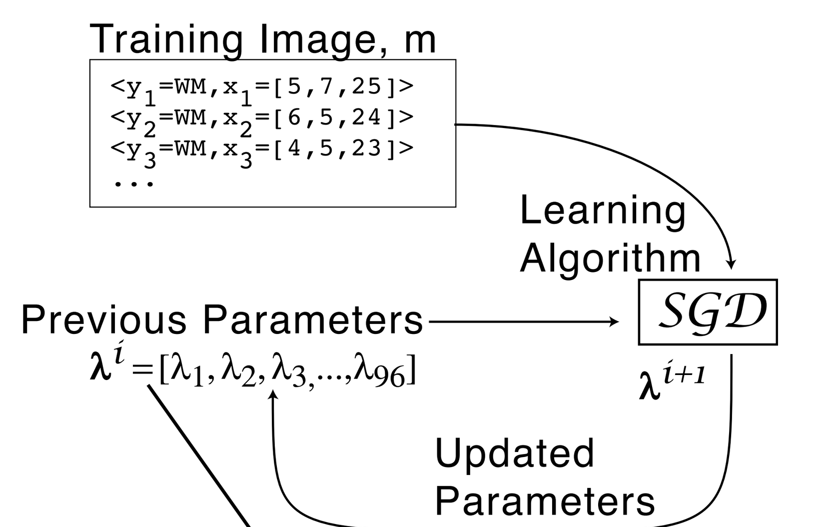
Infers a set of hidden labels, **Y**, from a set of observed values, **X**

Y is **conditionally independent** of the rest of the data given **X** and its neighborhood

Avoids label bias and assumptions of the structure of **X**

Avoids independence assumptions necessary for Markov random fields(MRF)

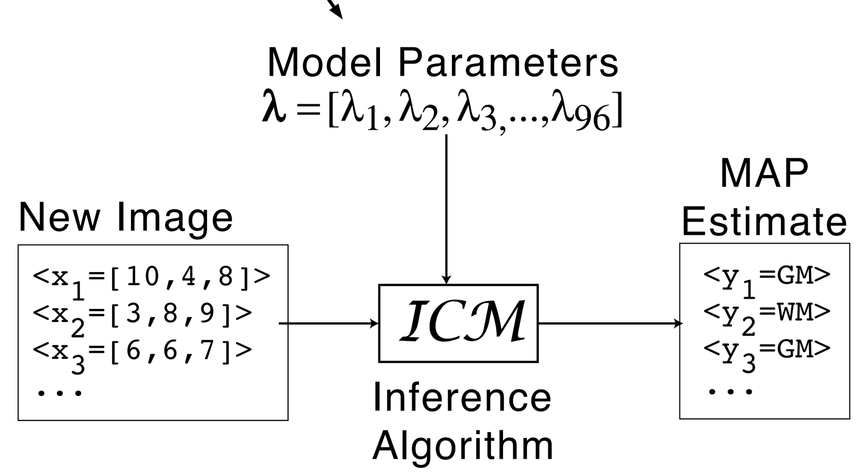
Training



Training learns the set of feature weights or parameters which give the model best performance

We used **stochastic gradient descent** with loopy belief propagation

Inference

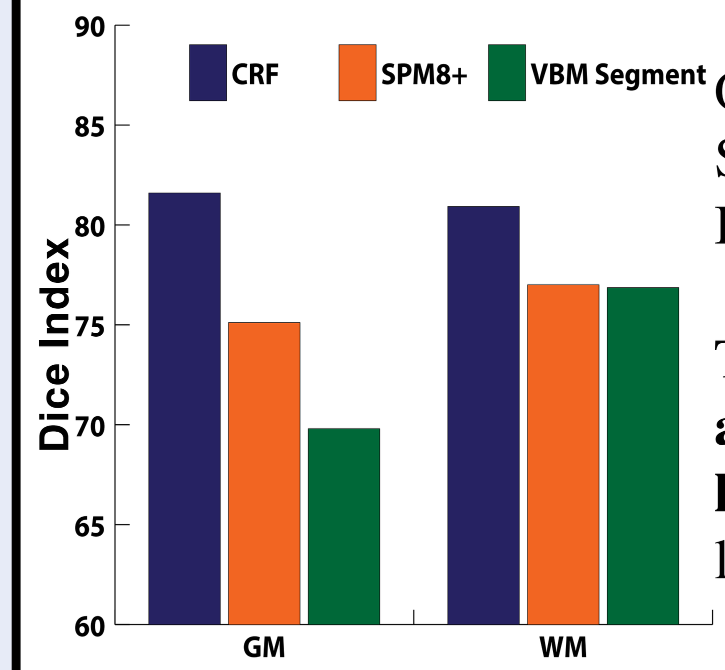


Inference uses learned parameters to find the most likely label configuration for a novel (non-segmented) image

We used **iterated conditional modes** with restarts

Results

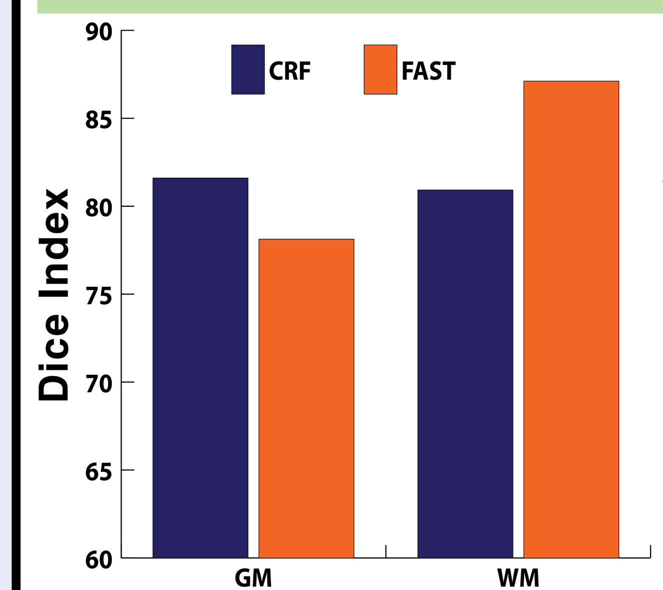
Q1: CRFs outperform atlas-based methods



Outperforms SPM8 New Segment and VBM8 on the IBSRV2.0 dataset

The CRF based approach **avoids strict prior knowledge** and information loss from image warping

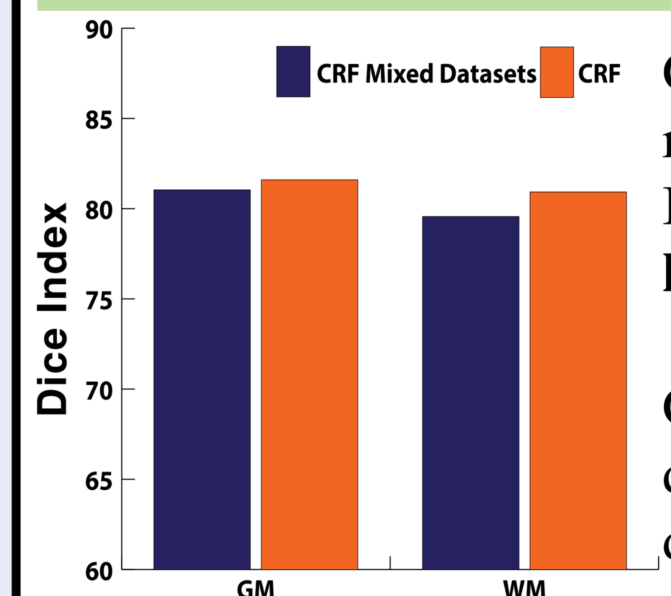
Q2: CRFs comparable to probablistic methods



CRFs perform better on gray matter, while FAST performs better on white matter

Compared to FAST, we **employ very little domain knowledge** or engineered features

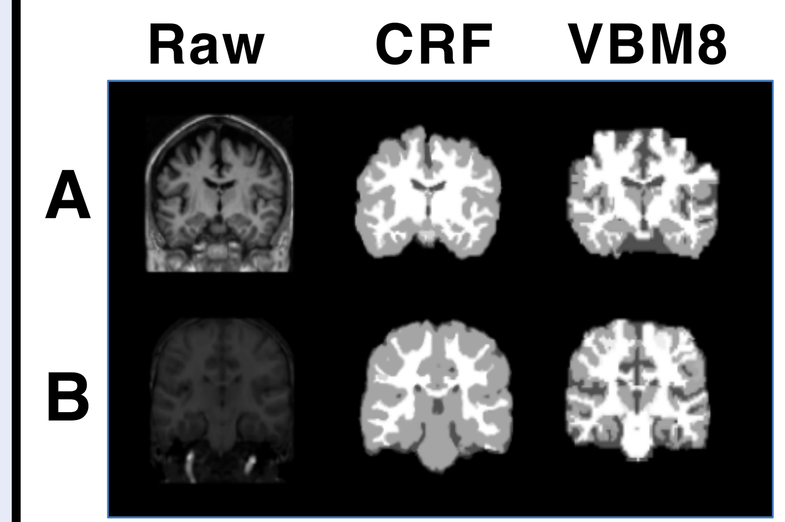
Q3: CRFs generalize well across data sets



Can apply learning from low-resolution IBSRV1.0 data to IBSRV2.0 data **with almost no loss**

CRFs are learning general qualities of tissue types, not data-specific qualities

Conclusion



Where CRFs do well (A) and poorly (B) compared to an atlas based method

This is the first work on **employing CRFs on per voxel based analysis for MRI images**. Results were superior to that of atlas based methods while being comparable to the state-of-the-art MRF based method.

When compared to the MRF method, **we employ no domain engineered features**. We also demonstrated that the resulting classifier allowed for generalization across multiple resolution images.

Future Work

As a next step we hope to apply the CRF framework to other MRI analysis problems. We hope to see if our method can perform atlas free anatomical segmentation. Using the results of the image analysis for prediction of events such as onset of Alzheimer's is another future possibility. The real impact of automatic segmentation can be realized by combining their output with powerful classifiers.

Acknowledgments

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Literature cited

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