Enhanced Representation and Learning of Magnetic Resonance Image Signatures in Multiple Sclerosis

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Outline

Introduction

Organization of Thesis

Longitudinal Intensity Normalization

MS Lesion Detection: Patient to Group Comparison

MS Lesion Detection: Probabilistic One Class Learning Approach

Summary and Perspectives
Outline

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Summary and Perspectives
Multiple Sclerosis (MS): MS is an acquired inflammatory and demyelinating disease which causes disabilities in young adults and is common in the northern hemisphere.

Figure: The demyelinated axons. Courtesy: http://www.nationalmssociety.org/
Introduction

Problems with MS:

- Cognition impairment, dizziness, vertigo and fatigue
- Walking (gait) difficulties
- Only state of the disease can be modified, not reversed

Figure: High regional prevalence of MS across the world. Courtesy: Pietrangelo 2015.
Introduction

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Figure: High regional prevalence of MS across the world. Courtesy: Pietrangelo 2015.
Introduction
Quest for Biomarkers

- Clinical symptoms not specific to MS
- Magnetic Resonance Images (MRI) for diagnosing MS
- McDonald Diagnostic Criteria [Polman et al. 2010] for MS based on MRI
- Non-invasive in nature
- High resolution images
- Does not use ionizing radiation like CT examination
- To monitor disease progression by number and size of MS lesions and atrophy
Figure: Top row: T1SE, T2-w, PD-w; Bottom row: FLAIR and T1-Gd
Introduction
MRI in MS

- To monitor disease progression in both: (1) longitudinal (patient-specific) and (2) Pool of patients (MS Patient Population)
- Need for MS lesion segmentation/detection frameworks
Introduction
MRI in MS

- To monitor disease progression in both: (1) longitudinal (patient-specific) and (2) Pool of patients (MS Patient Population)
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Issues with Brain MRI

- Large intra-class variance in brain tissue intensities and inter-class ambiguity between MS lesions and some tissue intensities
- MS Lesions don’t exhibit specific shape, size and characteristics
- Very few labeled data available
- Causes problem to segmentation/detection

State-of-the-art Methods

- Most of them based on parametric model
- Based on Heuristics
Motivation

- We propose MS Lesion Detection not Segmentation
- Segmentation $\Rightarrow$ crisp contours, Detection $\Rightarrow$ rough contours
Motivation

- We propose MS Lesion Detection not Segmentation
- Segmentation $\Rightarrow$ crisp contours, Detection $\Rightarrow$ rough contours

Figure: Segmentation vs detection comparison

- No clear consensus on segmentation
- Intra-/inter rater observations variability
- For MS, information about number of lesions (part of McDonald Diagnostic Criteria) and size of lesions (Total Lesion Load) is enough
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Summary and Perspectives
Organization of PhD Work

Components

Figure: Components of thesis work

I. MRI Serial Change Detection: Intensity Normalization
II. MS Lesions Detection, Voxel Based Statistical Patient to Group Comparison
III. MS Lesions Detection, Patch Based Learning One class Learning Approach
Outline

Introduction

Organization of Thesis

**Longitudinal Intensity Normalization**

MS Lesion Detection: Patient to Group Comparison

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Summary and Perspectives
PART I: Longitudinal Intensity Normalization

Motivation

- Monitoring the progression of MS

Figure: Courtesy: Alex Rovira et al. 2013.

- Longitudinal Studies which also involve Active Gd-Enhanced lesions
Problems with MRI

▶ Lack of standard intensity range unlike CT
▶ Conventional MRI are weighted images and not quantitative ones.
PART I: Longitudinal Intensity Normalization

Problems with MRI

▶ Lack of standard intensity range unlike CT
▶ Conventional MRI are weighted images and not quantitative ones.
▶ Remedy: *Intensity Correction*
PART I: Longitudinal Intensity Normalization

Problems with MRI

- Lack of standard intensity range unlike CT
- Conventional MRI are weighted images and not quantitative ones.
- Remedy: *Intensity Correction*

State-of-the-art Methods

- Nyul’s Method: Landmark based intensity standardization
- Hellier’s Method: Parametric mixture mapping
- Problem: MS Lesions get affected in intensity normalization
Pipeline

- Modeling of brain tissues in White Matter (WM), Gray Matter (GM) and Cerebrospinal fluid (CSF)
- Lesions are part of the outliers
- Gaussian Mixture Modeling (GMM) using $\gamma$- divergence
- Estimation of parameters of fixed and moving images
- Mapping of intensities

![Diagram of Pipeline]

Parameters $\theta_{source}$
Parameters $\theta_{moving}$

Source Image
Moving Image

Intensity Normalization

Mapping (Linear Regression)
GMM Modeling of Normally Appearing Brain Tissue Intensities

The image intensities of a healthy brain with a 3-class GMM, where each Gaussian represents one of the brain tissues White Matter (WM), Gray Matter (GM) and Cerebrospinal fluid (CSF).

\[ f(x_i|\theta) = \sum_{k=1}^{3} \pi_k N(\mu_k, \Sigma_k) \]  

(1)
Brain Tissues Modeling

GMM Modeling of Normally Appearing Brain Tissue Intensities

The image intensities of a healthy brain with a 3-class GMM, where each Gaussian represents one of the brain tissues White Matter (WM), Gray Matter (GM) and Cerebrospinal fluid (CSF).

\[ f(x_i | \theta) = \sum_{k=1}^{3} \pi_k \mathcal{N}(\mu_k, \Sigma_k) \]  (1)

- Sensitive to outliers
**GMM using $\gamma$-divergence**

### $\gamma$-loss Function for the Normal Distribution

Consider the $\gamma$-loss function for the normal distribution with mean vector $\mu$ and covariance matrix $\Sigma$

\[
L_{\gamma}(\mu, \Sigma) = \left| \Sigma^{-\frac{\gamma}{2(1+\gamma)}} \right| \sum_{i=1}^{n} \exp \left( -\frac{\gamma}{2} (x_i - \mu)^T \Sigma^{-1} (x_i - \mu) \right)
\]  

(2)

*Notsu et.al. 2014*

### Significance of $\gamma$

- The bounded influence function of an estimator is an indicator of robustness to outliers
- The influence function for $\gamma$-divergence GMM is bounded whereas for regular GMM is unbounded
EM Algorithm

E-Step
Consider the $\gamma$-loss function for the normal distribution with mean vector $\mu$ and covariance matrix $\Sigma$

$$q_{ik} = \frac{\pi_k \exp \left( -\frac{\gamma}{2} (x_i - \mu_k)^T \Sigma_k^{-1} (x_i - \mu_k) \right)}{\sum_{k=1}^{K} \pi_l \exp \left( -\frac{\gamma}{2} (x_i - \mu_l)^T \Sigma_l^{-1} (x_i - \mu_l) \right)}$$  \hspace{1cm} (3)

M-Step

$$\mu_k = \frac{\sum_{i=1}^{n} q_{ik} x_i}{\sum_{i=1}^{n} q_{ik}}$$  \hspace{1cm} (4)

$$\Sigma_k = (1 + \gamma) \frac{\sum_{i=1}^{n} q_{ik} (x_i - \mu_k) (x_i - \mu_k)^T}{\sum_{i=1}^{n} q_{ik}}$$  \hspace{1cm} (5)

$$\pi_k = \frac{\sum_{i=1}^{n} q_{ik}}{\sum_{i=1}^{n} \sum_{l=1}^{K} q_{il}}$$  \hspace{1cm} (6)
Selection of Parameter $\gamma$

Let $K_\gamma$ be the number of clusters, the value of $\gamma$ which minimizes Akaike Information Criterion (AIC)

$$AIC_\gamma = -2 \sum_{i=1}^{n} \log f_\gamma(y_i|\theta) + 2 \left \{ K_\gamma \frac{p(p + 3)}{2} + K_\gamma - 1 \right \} \quad (7)$$
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$$AIC_\gamma = -2 \sum_{i=1}^{n} \log f_\gamma(y_i|\theta) + 2 \left\{ K_\gamma \frac{p(p+3)}{2} + K_\gamma - 1 \right\}$$

(7)

Figure: AIC vs $\gamma$ Plot
Obtain the means and covariances of tissues for the source and target images.

Choose a linear correction function such that \( g(x) = \sum_i \beta_i x_i \).

The coefficients \( \beta_i \) are estimated to minimize the following cost function:
\[
\sum_{l=1}^{n} (g(\mu_{\text{source},k}) - \mu_{\text{target},k})^2
\]

\( g(x) \) is the transformation function which maps intensity of the moving image with respect to the source image.
Lesion Change Detection

Image at T0 -> Intensity Normalization -> Voxel-to-Voxel Comparison (Subtraction) -> Otsu Thresholding -> Lesion Change Detection & Interpretation
Dataset

- Dataset 1: 18 patients with 4 time points (center 1)
- Dataset 2: 40 patients with 3 time points (3 different centers)
- MRI Modalities: T1-w MPRAGE, T2-w and FLAIR
- The volume size for T1-w MPRAGE and FLAIR: $256 \times 256 \times 160$; voxel size: $1 \times 1 \times 1 \ mm^3$
- For T2-w, the volume size is $256 \times 256 \times 44$ and voxel size is $1 \times 1 \times 3 \ mm^3$
- For Gd, a T1-w volume without contrast agent (pre-contrast) and T1-w Gd-enhanced (post-contrast)
- Volume size: $256 \times 256 \times 44$; voxel size: $1 \times 1 \times 3 \ mm^3$
Preprocessing Pipeline

Denoising (Coupe et al. 2008), Bias Field Correction (Tustison et al. 2009), Registration (Commowick et al. 2012) and Skull Stripping (Smith et al. 2002)

Figure: Pre-processing Pipeline.
Experimental Setup

- Experiment 1: Longitudinal intensity normalization between image at first time point and subsequent time points
- Experiment 2: Longitudinal lesion detection
- Experiment 3: Intensity normalization for T1-gd image between pre-post contrast image
- Experiment 4: Active Gd Enhanced lesion detection
## Qualitative Evaluation

### Difference Image

<table>
<thead>
<tr>
<th></th>
<th>$t_0$</th>
<th>$t_3$</th>
<th>$t_0-t_3$</th>
<th>$t_0-t_3$ (Aligned)</th>
</tr>
</thead>
<tbody>
<tr>
<td>T1w MPRAGE</td>
<td><img src="image1" alt="T1w MPRAGE $t_0$" /></td>
<td><img src="image2" alt="T1w MPRAGE $t_3$" /></td>
<td><img src="image3" alt="T1w MPRAGE $t_0-t_3$" /></td>
<td><img src="image4" alt="T1w MPRAGE $t_0-t_3$ (Aligned)" /></td>
</tr>
<tr>
<td>T2w</td>
<td><img src="image5" alt="T2w $t_0$" /></td>
<td><img src="image6" alt="T2w $t_3$" /></td>
<td><img src="image7" alt="T2w $t_0-t_3$" /></td>
<td><img src="image8" alt="T2w $t_0-t_3$ (Aligned)" /></td>
</tr>
<tr>
<td>FLAIR</td>
<td><img src="image9" alt="FLAIR $t_0$" /></td>
<td><img src="image10" alt="FLAIR $t_3$" /></td>
<td><img src="image11" alt="FLAIR $t_0-t_3$" /></td>
<td><img src="image12" alt="FLAIR $t_0-t_3$ (Aligned)" /></td>
</tr>
</tbody>
</table>
Qualitative Evaluation
Lesion Detection
Performance Evaluation

1. $\chi^2$ distance ($\chi^2_{x,y} = \frac{1}{2} \sum \frac{(x_i-y_i)^2}{x_i+y_i}$) for histogram alignment

2. Lesion Detection: The lesion is said to be detected if $\frac{R_c \cap R_{GT}}{R_{GT}} \geq \varphi$ where $R_c$, $R_{GT}$ and $\varphi$ are respectively the candidate region in the image, the ground truth and a threshold

3. Regions are labeled using connected component labeling

4. The precision and recall of lesion detection averaged across the patients for various overlap thresholds $\varphi$

5. ROC-AUC from Precision Vs (1-Recall) plots using various $\varphi$
Chi-squared distance analysis

Table: Chi-squared distance analysis for histogram matching for dataset 1.

<table>
<thead>
<tr>
<th>Modality</th>
<th>Before Normalization</th>
<th>After Normalization</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Proposed</td>
</tr>
<tr>
<td>T1-w</td>
<td>0.56 (±0.03)</td>
<td>0.18 (±0.045)</td>
</tr>
<tr>
<td>T2-w</td>
<td>0.62 (±0.029)</td>
<td>0.28 (±0.037)</td>
</tr>
<tr>
<td>FLAIR</td>
<td>0.56 (±0.027)</td>
<td>0.32 (±0.038)</td>
</tr>
</tbody>
</table>

Table: Chi-squared distance analysis for histogram matching for dataset 2.

<table>
<thead>
<tr>
<th>Modality</th>
<th>Before Normalization</th>
<th>After Normalization</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Proposed</td>
</tr>
<tr>
<td>T1-w</td>
<td>0.3 (±0.08)</td>
<td>0.16 (±0.062)</td>
</tr>
<tr>
<td>T2-w</td>
<td>0.45 (±0.039)</td>
<td>0.26 (±0.027)</td>
</tr>
<tr>
<td>FLAIR</td>
<td>0.58 (±0.031)</td>
<td>0.30 (±0.048)</td>
</tr>
</tbody>
</table>
Lesion Detection Evaluation

Figure: ROC-AUC for dataset 1.

Proposed Method (AUC = 0.72)
Nyul (AUC = 0.60)
Hellier (AUC = 0.58)
Lesion Detection Evaluation

Figure: ROC-AUC for dataset 2.
Qualitative Evaluation
Active Gd-Enhanced Lesions Detection in T1-w-Gd Image
## Chi-squared distance analysis

<table>
<thead>
<tr>
<th>Dataset 1</th>
<th>Before Normalization</th>
<th>Method</th>
<th>After Normalization</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>0.34(±0.06)</td>
<td>Nyul</td>
<td>0.29(±0.01)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Proposed</td>
<td><strong>0.12(±0.06)</strong></td>
</tr>
<tr>
<td></td>
<td></td>
<td>Hellier</td>
<td>0.22(±0.03)</td>
</tr>
</tbody>
</table>

**Table:** Chi-squared distance analysis for histogram matching for T1-w Gd dataset 1.
Lesion Detection Evaluation

Figure: ROC-AUC for dataset T1-w-Gd.

- **Proposed Method (AUC = 0.71)**
- **Nyul (AUC = 0.51)**
- **Hellier (AUC = 0.54)**
A good tool for detecting lesions in longitudinal studies

- Allows for better patient-adapted therapeutic strategies
- Better method compared to Nyul and Hellier method
- Fast (15 minutes for 3 volumes) on 3.8 GB RAM, Intel Core i7 2.40GHz, with 8 cores machine
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Longitudinal Intensity Normalization

MS Lesion Detection: Patient to Group Comparison

MS Lesion Detection: Probabilistic One Class Learning Approach

Summary and Perspectives
In clinical trials, MS lesion detection is carried out manually.

It is time consuming, costly, and prone to inter- and intra-observer variability.
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It is time consuming, costly, and prone to inter- and intra-observer variability.

Remedy: *MS Lesion Detection Framework*
PART II: MS Lesion Detection
Patient to Group Comparison

- In clinical trials, MS lesion detection is carried out manually
- It is time consuming, costly, and prone to inter- and intra-observer variability
- Remedy: *MS Lesion Detection Framework*
- Intensity correction followed by computation of statistical differences between a patient and atlas
Atlas construction for the characterization of pathologies

Controls T1-w, T2-w and FLAIR

Atlas construction

Statistical Multi-Channel Atlases

Intensity Normalization

Registration and Comparison

Patient Image
Statistical Comparison

Mahalanobis distance between patient vector $x_q$ and mean of control population $\bar{X}$; difference statistic between $x_q$ and $\mathcal{N}(\bar{X}, \Sigma_x)$

$$d^2(x_q) = (x_q - \bar{X})^T \Sigma_x^{-1} (x_q - \bar{X})$$  \hspace{1cm} (8)

$d^2$ will vary between 0 and $+\infty$
Mahalanobis distance between patient vector \( x_q \) and mean of control population \( \bar{X} \); difference statistic between \( x_q \) and \( \mathcal{N}(\bar{X}, \Sigma_X) \)

\[
d^2(x_q) = (x_q - \bar{X})^T \Sigma_X^{-1} (x_q - \bar{X})
\] (8)

\( d^2 \) will vary between 0 and \(+\infty\)

Test statistics on \( d^2 \):

- p-value: statistic \( T = \frac{M(M-h)}{h(M^2-1)} d^2 \) follows a Fisher distribution with parameters \( h \) and \( M - h \): \( T \sim F(h, M - h) \)

\[
p(x_q) = 1 - F_{h,M-h} \left( \frac{M(M-h)}{h(M^2-1)} d^2(x_q) \right)
\] (9)

where \( F_{h,M-h} \) is the cumulative distribution function of a Fisher distribution with parameters \( h \) and \( M - h \)

- False Discovery Rate (FDR) Correction [Benjamini et al.1995]
Dataset

- Dataset 1: 16 (center 1)
- Dataset 2: 40 (3 different centers)
- 20 controls for atlas construction
- MRI Modalities: T1-w MPRAGE, T2-w and FLAIR
- The volume size for T1-w MPRAGE and FLAIR: $256 \times 256 \times 160$; voxel size: $1 \times 1 \times 1 \ mm^3$
- For T2-w, the volume size is $256 \times 256 \times 44$ and voxel size is $1 \times 1 \times 3 \ mm^3$
Preprocessing Pipeline

- Atlas construction for each sequence from controls
- Patient to atlas registration
Experimental Setup

- Experiment 1: MS Lesion detection on each of T1-MPRAGE, T2-w and FLAIR with and without intensity normalization
- Experiment 2: MS Lesion detection on composite vector image formed by T1-MPRAGE, T2-w and FLAIR with and without intensity normalization
Figure: Top row: from left to right, a slice of MRI from T2-w Sequence from dataset 1, corresponding ground truth (red). Bottom row: from left to right, MSL detection (green) obtained by without and with intensity normalization.
Figure: Top row: from left to right, a slice of MRI from composite vector image from dataset 1, corresponding ground truth (red). Bottom row: from left to right, MSL detection (green) obtained by without and with intensity normalization.
**Criterion for Lesion Detection:** The lesion is said to be detected if \( \frac{|R_c \cap R_{GT}|}{R_{GT}} \geq \varphi \) where \( R_c \), \( R_{GT} \) and \( \varphi \) are respectively the candidate region in the image, the ground truth and a threshold.

- The precision and recall of lesion detection averaged across the patients for various overlap thresholds.
- ROC-AUC from Precision vs (1-Recall) plot using various \( \varphi \).
Quantitative Results I

Figure: ROC-AUC for dataset 1 without intensity normalization.
Quantitative Results II

Figure: ROC-AUC for dataset 1 with intensity normalization.
Figure: **ROC-AUC for dataset 2 without intensity normalization.**
Quantitative Results IV

Figure: ROC-AUC for dataset 2 with intensity normalization.
Outline

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MS Lesion Detection: Probabilistic One Class Learning Approach

Summary and Perspectives
Objective: Propose an automatic framework for MSL Detection based on multichannel MRI patch based information

Motivation

▶ State-of-the-art machine learning algorithms: SVM [Vapnik et al.1995], Logistic Regression[Zhang et al.2002], NN...

▶ Works well in practice when training examples in classes are balanced

▶ If not?
Objective: Propose an automatic framework for MSL Detection based on multichannel MRI patch based information

Motivation

- State-of-the-art machine learning algorithms: SVM [Vapnik et al. 1995], Logistic Regression [Zhang et al. 2002], NN...

- Works well in practice when training examples in classes are balanced

- If not?

- Class Imbalance $\Rightarrow$ under-/over-fitting of the Classifier [Chawala 2005]

- Class imbalance between NABT and MS lesion patches
Motivation

- A common fix: A higher misclassification penalty on the minority class

Figure: Toy example of SVM for balanced and unbalanced classes, Courtesy: www.scikit-learn.org.
When does a common fix work well?

▶ When there is enough variation in the minority class (we are aware of extreme training examples)
▶ Is it the case in context of MS Lesion detection?
▶ No
▶ Owing to no specific shape, size and nature of MS Lesions
▶ Remedy: MS Lesion detection based on one class learning
Motivation

- When does a common fix work well?
- When there is enough variation in the minority class (we are aware of extreme training examples)

Remedy:
- MS Lesion detection based on one class learning
Motivation

- When does a common fix work well?
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- Is it the case in context of MS Lesion detection?

Remedy: MS Lesion detection based on one class learning
Motivation

- When does a common fix work well?
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When does a common fix work well?
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Owing to no specific shape, size and nature of MS Lesions
Remedy: *MS Lesion detection based on one class learning*
Methodology

- Classify Normal Appearing Brain Tissues (NABT) and MSL based upon bag of words features.
- A probabilistic classifier can recognize MSL as a novel class, trained only on NABT.

Figure: Framework for MSL Detection: Training Phase
Figure: Framework for MSL Detection: Testing Phase
Selection of NABT patches from border of super-voxels using SLIC (Achanta et al. 2012.)

Figure: Super-voxels using SLIC on control subject on FLAIR sequence.

- Extraction of a feature vector from intensities of patches on multi-channel MRI
- Dimensionality reduction using PCA
Let $\mathcal{Y} = \{-1(\text{NABT}), +1(\text{MSL})\}$

Compute class-posterior probability $p(y|x)$ [Quinn et al. 2014, Sugiyama et al. 2010]

Estimate $p(y = i|x)$ for each $i \in \mathcal{Y}$ by $q(y = i|x, \theta_i) = \theta_i^T \phi(x)$

The analytical solution for $\theta_i$: $\hat{\theta}_i = (\Phi^T \Phi + \rho I_B)^{-1} \Phi \pi_i$

$\rho \uparrow$ sensitivity towards outliers $\downarrow$
The conditional probability of MS Lesions $p(y = +1|x, \theta)$ with $q(y = +1|x, \theta_{+1}) = 1 - \theta_{-1}^T \phi(x)$ can be expressed as

$$q(y = +1|x, \theta_{+1}) = 1 - q(y = -1|x, \theta_{-1})$$ (10)

Testing is performed as a full search (placing a patch at every voxel) which in turn generates probability map.

Aggregation of probability score is done by weighted Gaussian smoothing [Reddy et al.2012].

Multi-level Ostu thresholding to obtain detection mask [Ng et al.2004]
Methodology

Testing
Dataset

- Dataset 1: 16 (center 1)
- Dataset 2: 40 (3 different centers)
- 20 controls for NABT patches
- MRI Modalities: T1-w MPRAGE, T2-w and FLAIR
- The volume size for T1-w MPRAGE and FLAIR: $256 \times 256 \times 160$; voxel size: $1 \times 1 \times 1 \ mm^3$
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Preprocessing Pipeline

- **T1-w MPRAGE**
  - Denoise
  - Bias Field Correction
  - Source Image
- **T2-w**
  - Denoise
  - Bias Field Correction
  - Registration
- **FLAIR**
  - Denoise
  - Bias Field Correction
  - Registration
- **Skull Stripping**
Experimental Setup

- Patch size: $3 \times 3 \times 3$
- Calibration of parameters on 2 MS patients which were excluded in test dataset
- The regularization parameter $\rho$ from $10^{-3:1:2}$
- Comparison with 1-Class SVM (Scholkopf et al. 2001) & Minimum Covariance Determinant (MCD) estimator (Rousseeuw et al. 1999)
- In 1-Class SVM, $\nu$ from $2 \times 10^{-4:1:1}$
- For MCD, the concentration of outliers selected from 5% to 40%
- Evaluation on both datasets with and without intensity normalization
Figure: A slice of FLAIR with lesion detection in axial mode, top row: a slice of FLAIR, same slice overlayed with ground truth (red), detections (green) obtained by OCSVM; Bottom row: from left to right, detection obtained by MCD and proposed method.
Figure: A slice of FLAIR with lesion detection in axial mode, top row: a slice of FLAIR, same slice overlayed with ground truth (red), detections (green) obtained by OCSVM; Bottom row: from left to right, detection obtained by MCD and proposed method.
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- The precision and recall of lesion detection averaged across the patients for various overlap thresholds.
- ROC-AUC from Precision vs (1-Recall) plot using various \( \varphi \).
Figure: ROC-AUC for dataset 1 without intensity normalization.
Figure: ROC-AUC for dataset 1 with intensity normalization.
Figure: ROC-AUC for dataset 2 without intensity normalization.
Quantitative Results IV

Figure: ROC-AUC for dataset 2 with intensity normalization.
Conclusion: PART III

- Our method achieves better performance compared to benchmark methods: OCSVM and MCD.
- Generic in nature and can be extended to ischemic strokes, tumor.
- Works well on multi-center databases
- Time complexity for (1) proposed method: $O(n^3)$ (2) OCSVM: $O(dn^3)$
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Summary and Perspectives
Summary

- Introduced the robust longitudinal intensity normalization method based on $\gamma$-divergence GMM
  

- A group to patient statistical comparisons based at voxel level is simple MSL detection method but achieve very high performance
  

- MSL detection based on one class learning approach is effective and fast
  

- Intensity normalization helps in increased MSL detection
Future Work

- Intensity Normalization Method can be improved:
  1. Using other parameters like covariance
  2. Exploiting multi-sequence information
- MSL detection based on Patient to Group comparison can be extended to statistical comparison of patches using kernel methods.
- For MSL detection using one class learning
  - Inclusion of other sequences i.e. MTR and DTI
  - Effect of different patch size on performance
  - Incorporation of selective search technique instead of sliding-window
Thanks!

Thank You All !!