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Combining Robust Expectation Maximization and Mean Shift Algorithms for Multiple Sclerosis Brain Segmentation

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Summary

- Introduction
- Method
- Validation
- Conclusions

Introduction

- Global methods
  - Use of the whole image information
  - **Expectation-Maximization (EM)**
  - Limit: little or none spatial information employed
- Local methods
  - Use of local information to create regions
  - **Mean Shift (MeS)**
  - Challenge: How to merge regions to obtain the final segmentation

Method

- Theory
  - Mean Shift (MeS)
  - Robust Expectation Maximization (REM)
- REMMeS

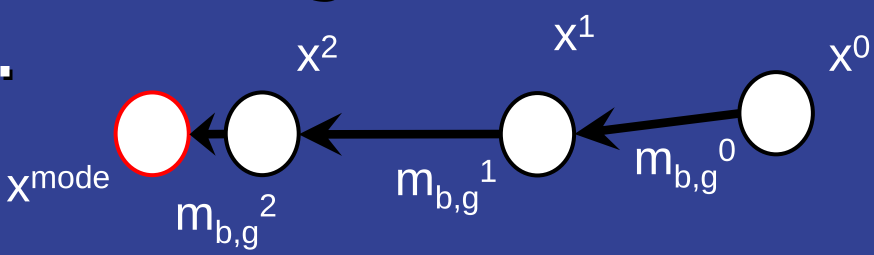
Mean Shift

- Non-parametric technique for probability density gradient estimation

$$m_{b,g}(x) = \frac{\sum_{i=1}^{n} x_i g\left(\left\|\frac{x-x_i}{b}\right\|^2\right)}{\sum_{i=1}^{n} g\left(\left\|\frac{x-x_i}{b}\right\|^2\right)} - x$$

d = dimension
b = bandwidth
k(x) = kernel profile
g(x)= -k'(x)
n = number of pixels

- A point x will arrive always to a point with $m_{b,g} \approx 0$, called mode. All points arriving to the same mode m will form a region.



Mean Shift for 3D images

- Clustering technique
  - d = m (number of MR sequences)
- Joint spatial-intensity domain
  - d = m + 3 (spatial dimensions)
  - Integration of spatial information

$$K_{b_s,b_r}(x) = K\left(\frac{x^s}{b_s}\right) K\left(\frac{x^r}{b_r}\right)$$

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Robust Expectation-Maximization

- 3-class Finite Multivariate Gaussian Mixture Model
- Modified Expectation-Maximization algorithm (mEM)
  - Trimmed Likelihood (Neikov et Al. 2006)

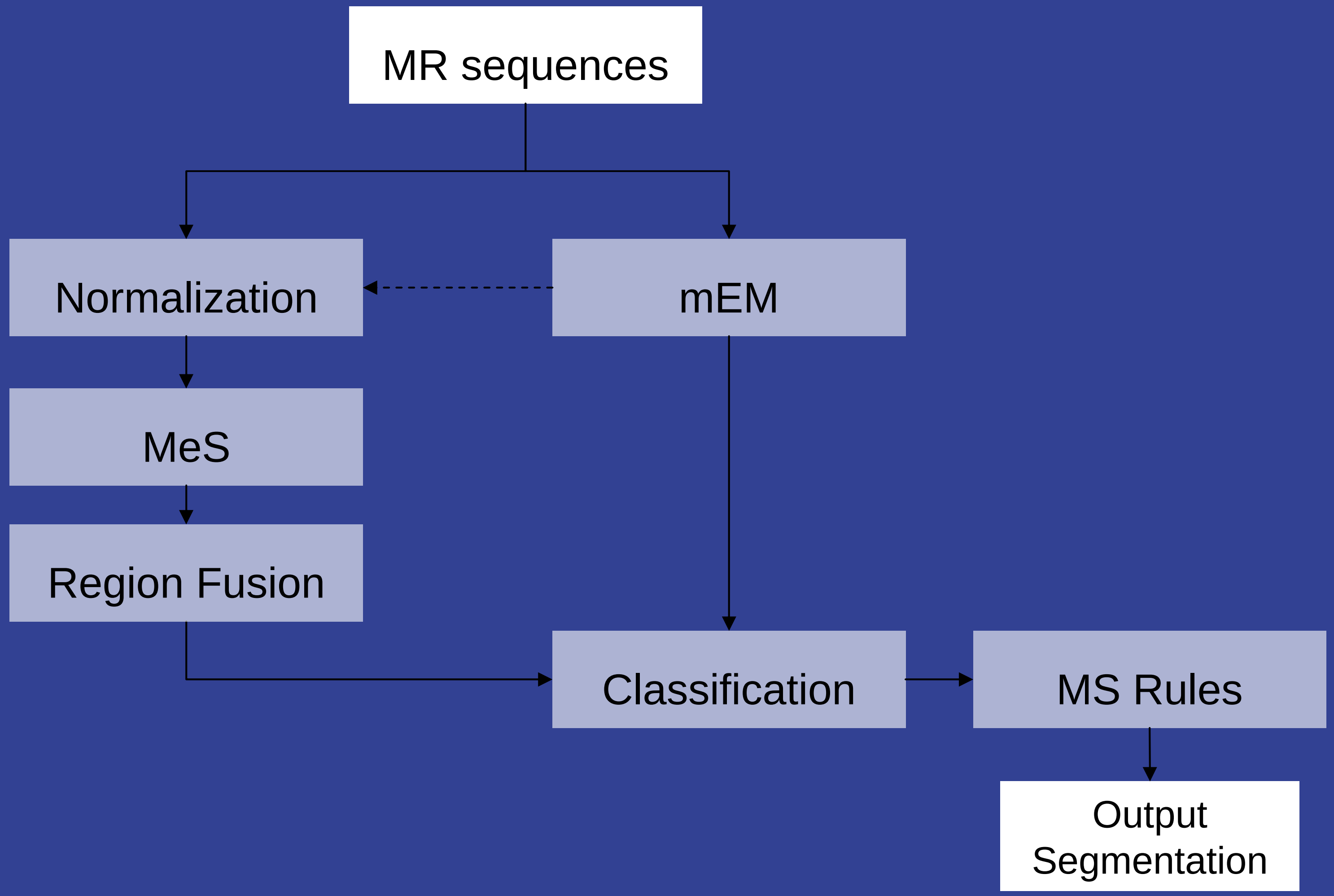
$$TL = \sum_{i=1}^{n-h} f(x_{\nu(i)};\Theta)$$

    - Ordering function

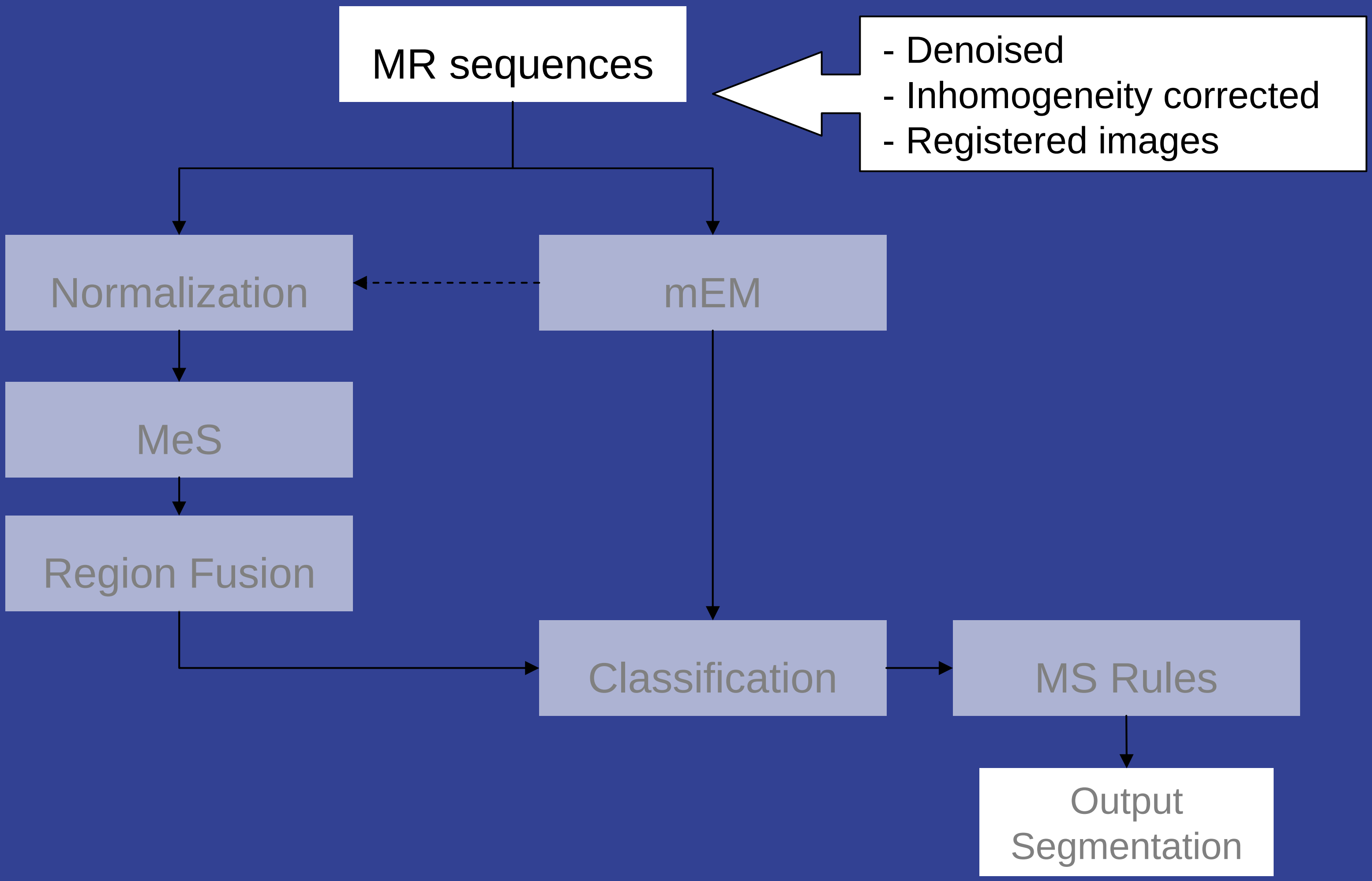
$$f(x_{\nu(1)};\Theta) \geq f(x_{\nu(2)};\Theta) \geq \ldots \geq f(x_{\nu(n)};\Theta)$$

  - In our experiments h=n/10

REMMeS


MR sequences
Normalization
mEM
MeS
Region Fusion
Classification
MS Rules
Output Segmentation

REMMeS


MR sequences
- Denoised
- Inhomogeneity corrected
- Registered images
Normalization
mEM
MeS
Region Fusion
Classification
MS Rules
Output Segmentation

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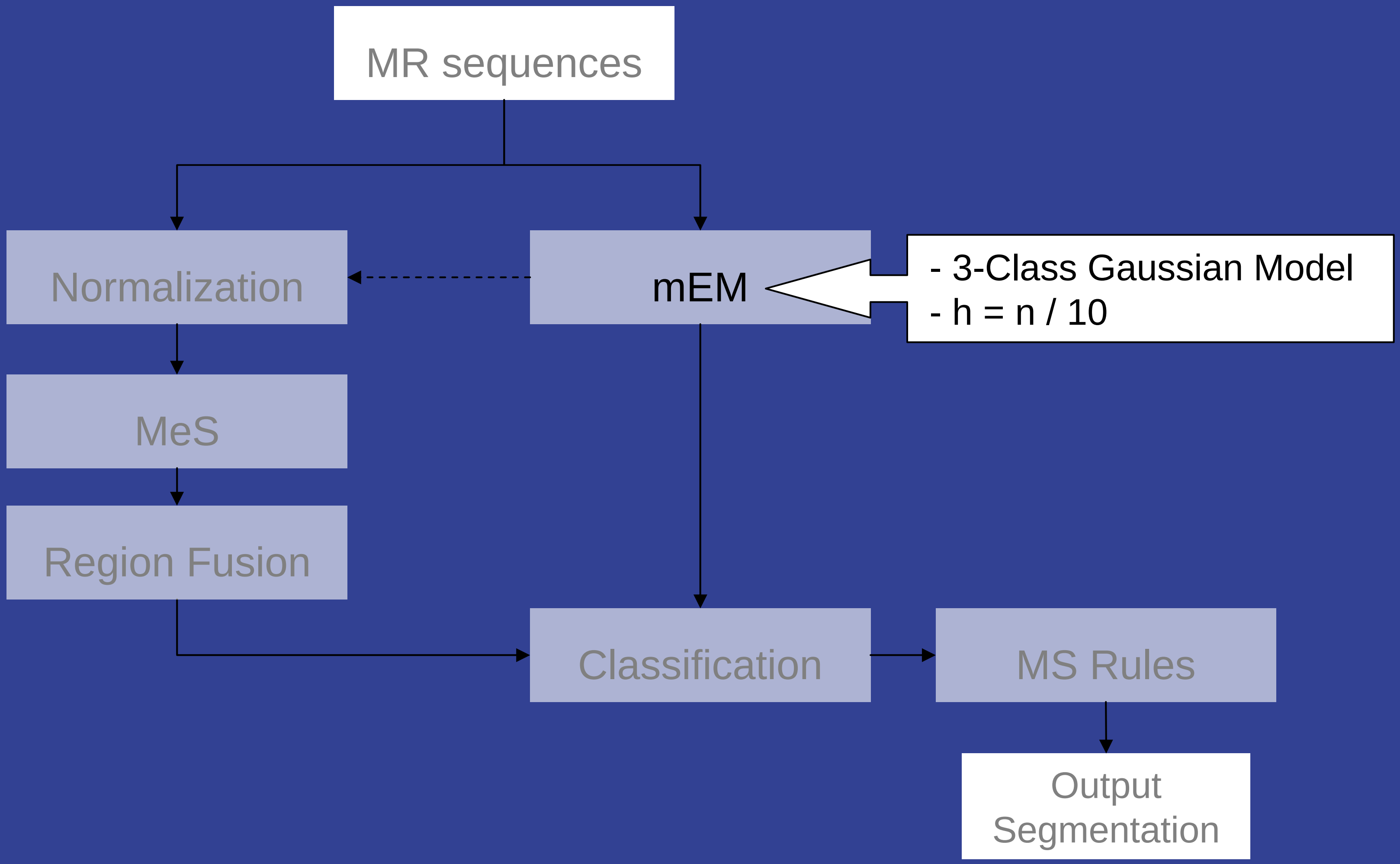
REMMeS



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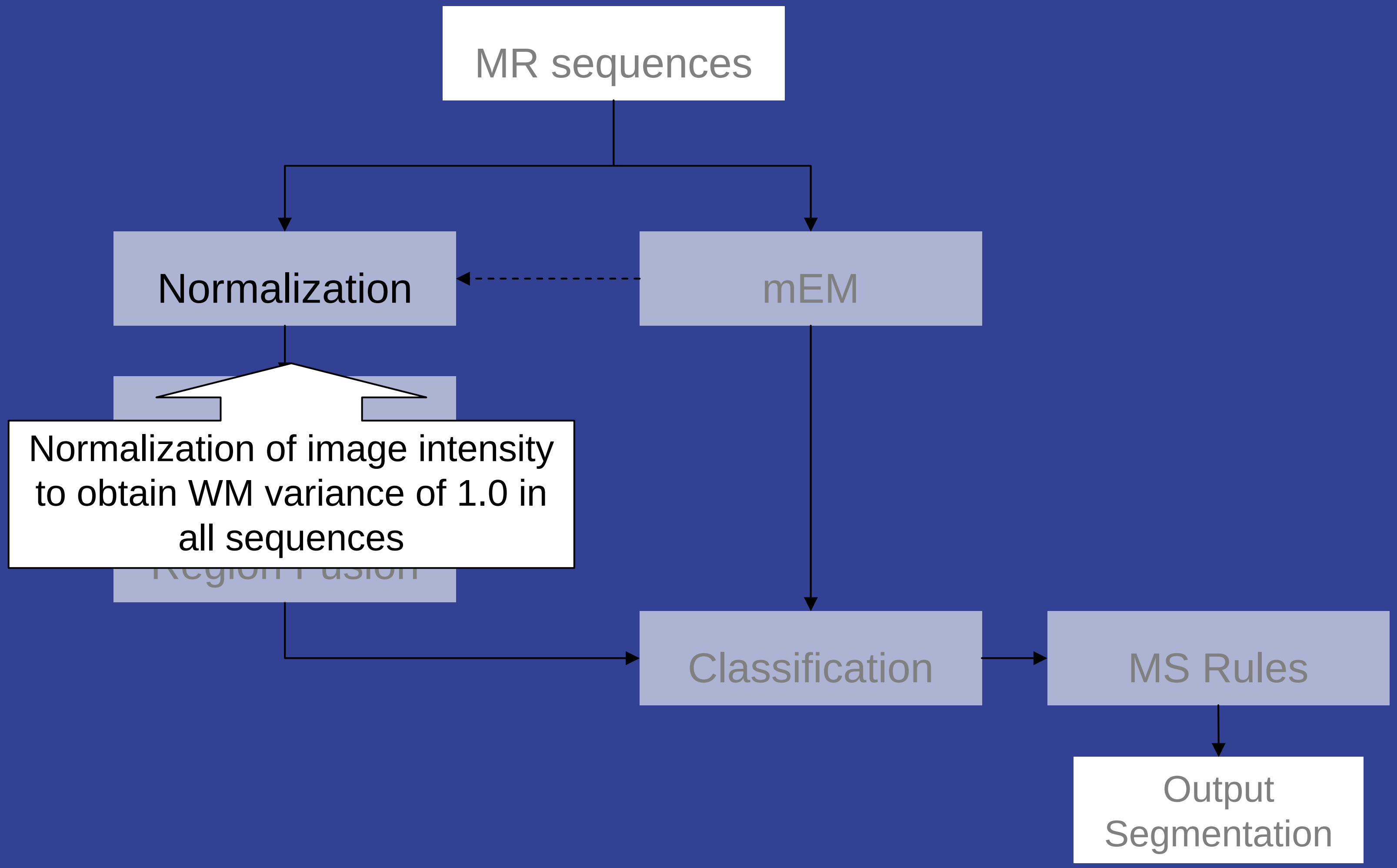
REMMeS



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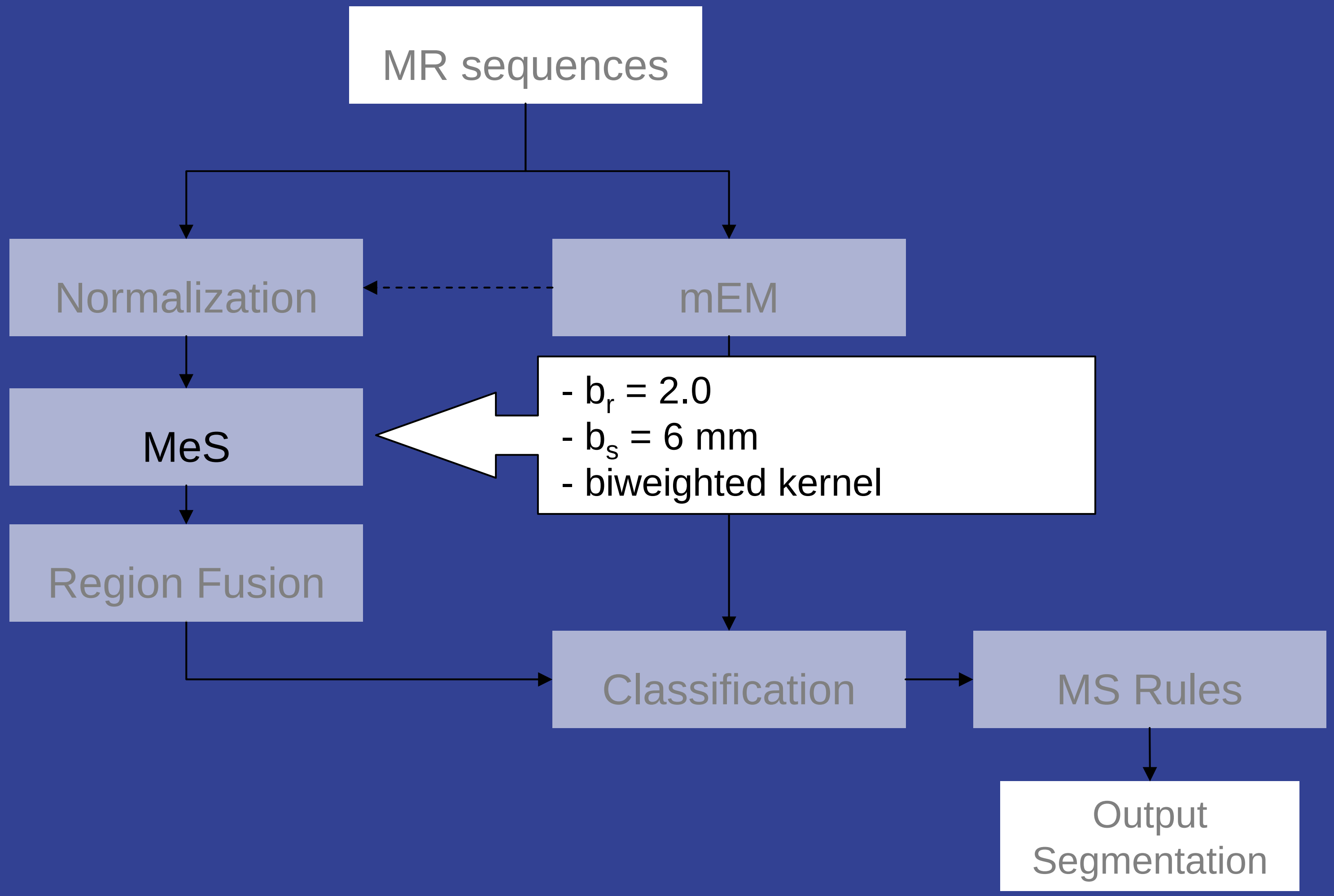
REMMeS



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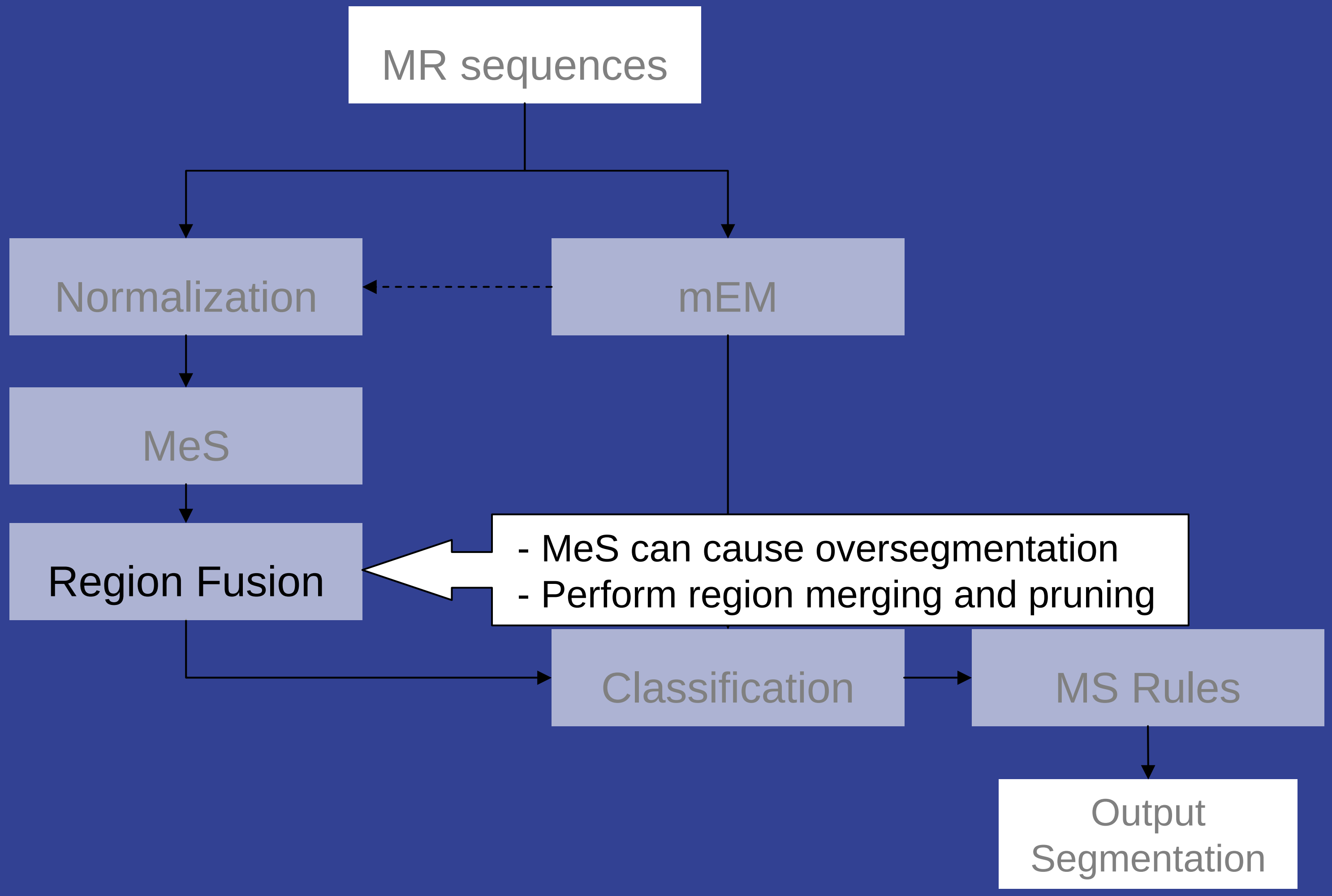
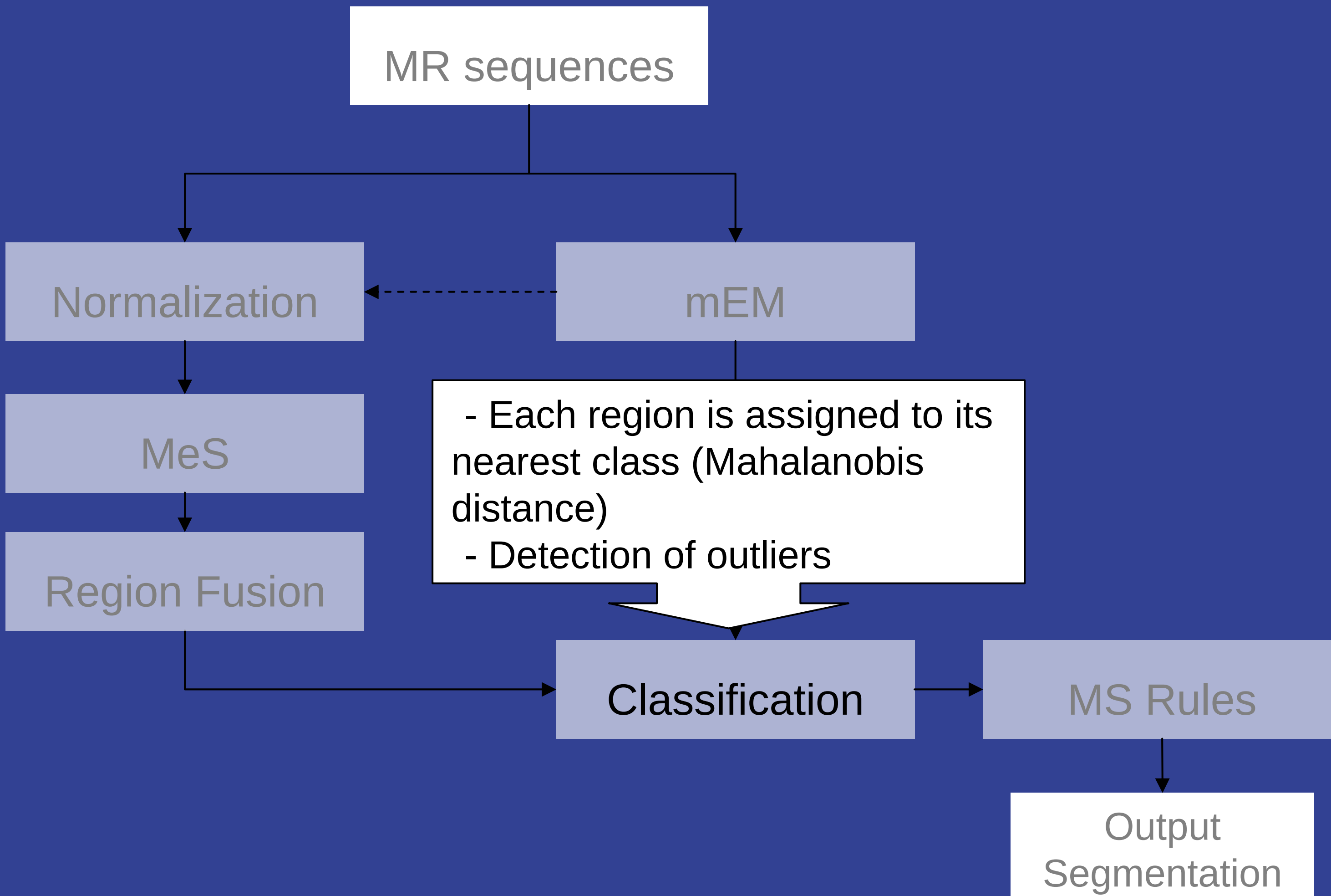
REMMeS

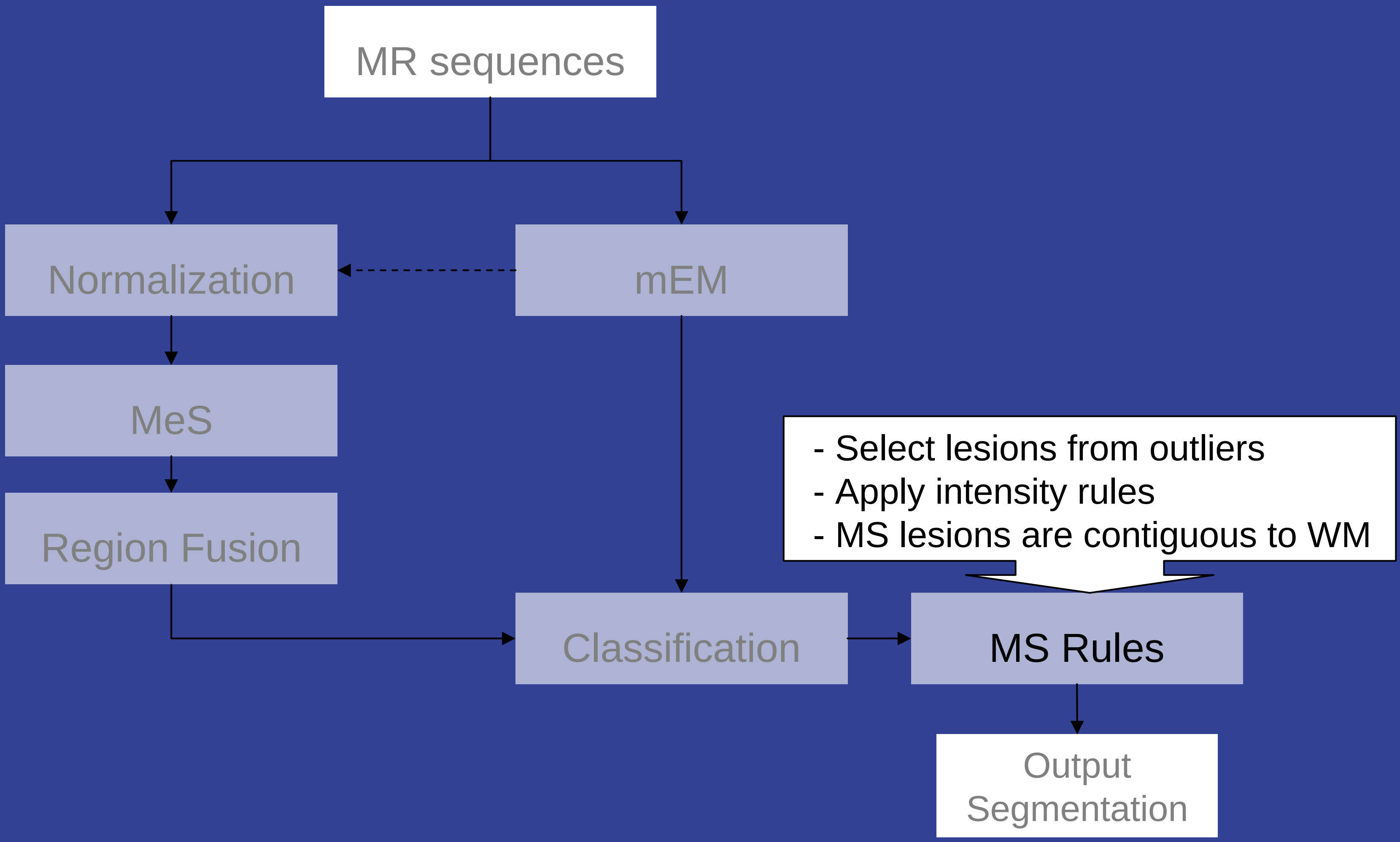


REMMeS

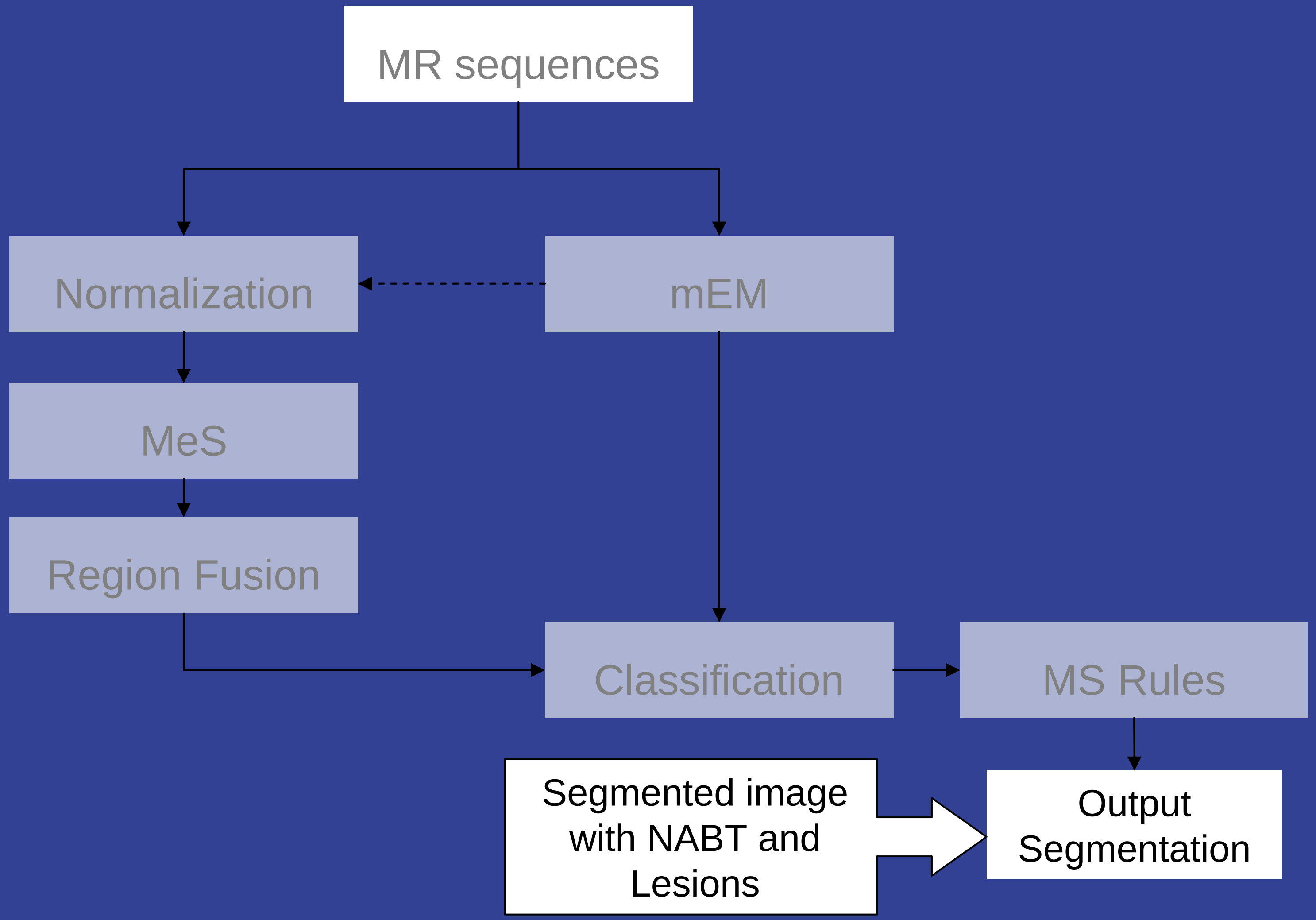


MR sequences
Normalization
mEM
MeS
Region Fusion
- Each region is assigned to its nearest class (Mahalanobis distance)
- Detection of outliers
Classification
MS Rules
Output Segmentation

REMMeS


MR sequences
Normalization
mEM
MeS
Region Fusion
Classification
- Select lesions from outliers
- Apply intensity rules
- MS lesions are contiguous to WM
MS Rules
Output Segmentation

REMMeS


MR sequences
Normalization
mEM
MeS
Region Fusion
Classification
MS Rules
Segmented image with NABT and Lesions
Output Segmentation

Validation : Methods

- Four similar approaches :
  A. Proposed algorithm
  B. As A. but replacing mEM with the classical EM
  C. No MeS regions, each voxel is independently classified with the mEM.
  D. As C. but replacing mEM with the classical EM

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Validation: Data

- Synthetic images (T1-w, T2-w and PD-w)
  - MS brain with moderate lesion load from Brainweb
  - 3% noise (n)
  - 0%, 20% and 40% of inhomogeneity (rf)
- Real images (T1-w, T2-w and PD-w)
  - 7 patients
  - Denoised, inhomogeneity correction, normalized in the stereotaxic space, Skull-stripped.
  - Lesions were manually segmented by an expert.

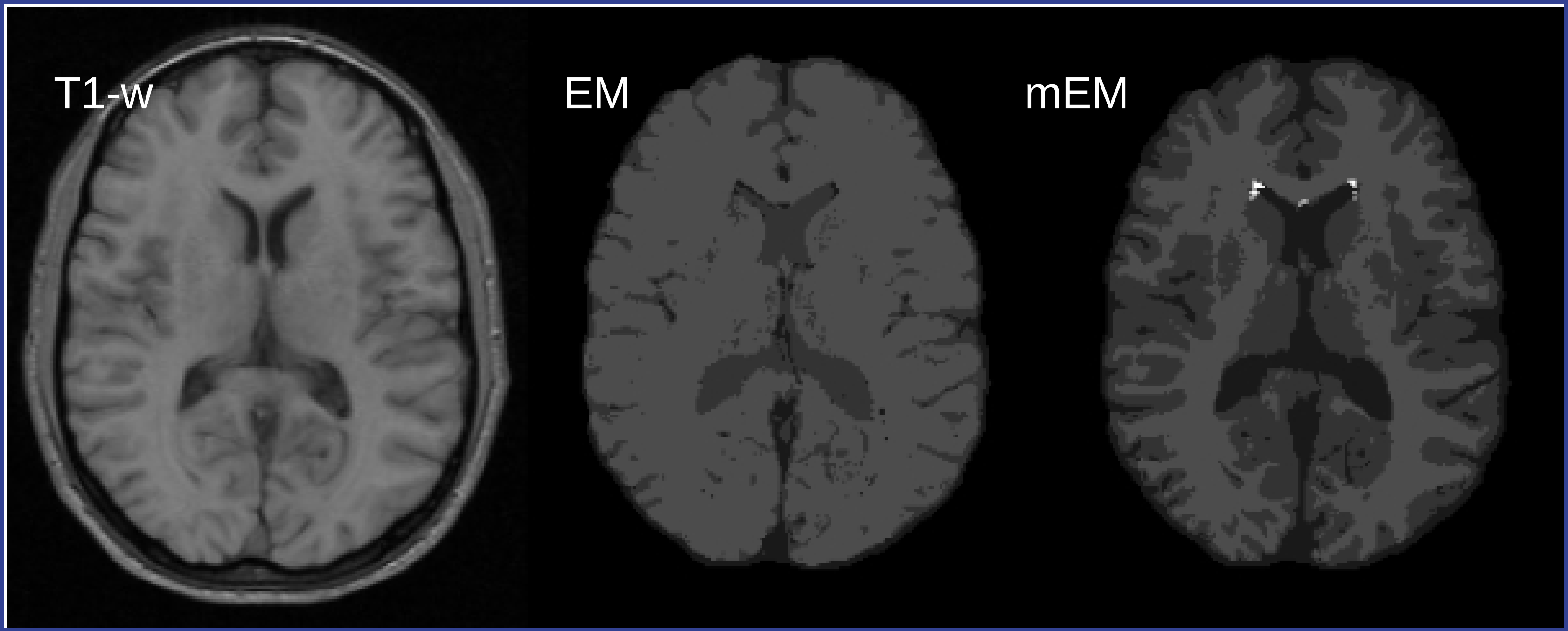
Results

	BW n3rf0	BW n3rf20	BW n3rf40	Average Real
D	0,79	0.80	0.78	-
C	0,72	0.77	0.41	0.52 ± 0.07
B	**0,87**	0.84	**0.79**	-
A	**0,87**	**0.85**	0.63	$\mathbf{0.55 \pm 0.05}$

- Brainweb noise 3% and 0% inhomogeneity:
  - Rousseau et al., ISBI'08: 0.63
  - Freifeld et al., ISBI' 07: 0.77
  - Van-Leemput, TMI'01: 0.80
  - Our method: 0.87

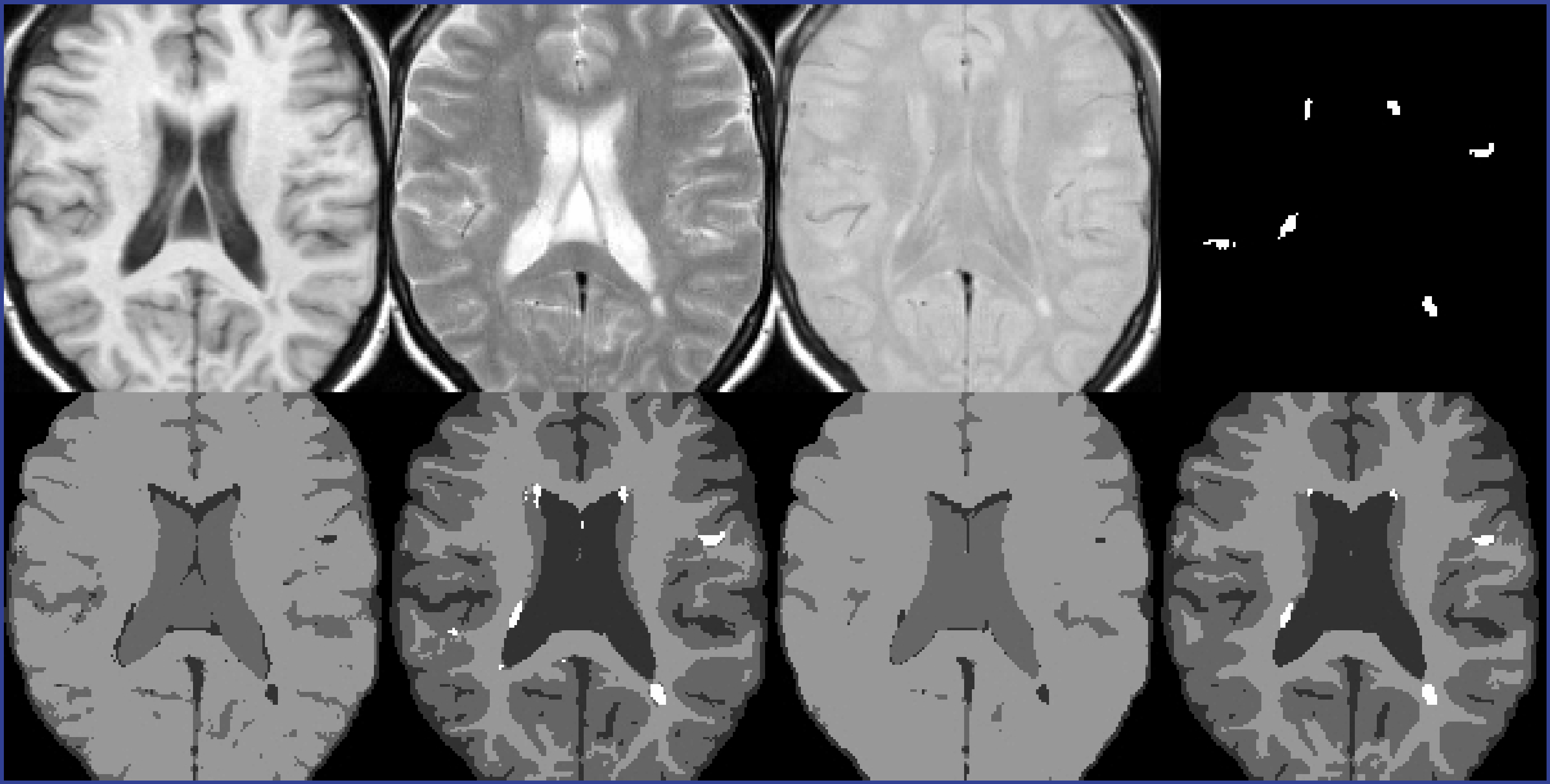
Results

- Example of classification with mEM vs. classical EM



Results

T1-w T2-w PD-w Lesions



D. EM C. mEM B. EMMeS A. REMMeS

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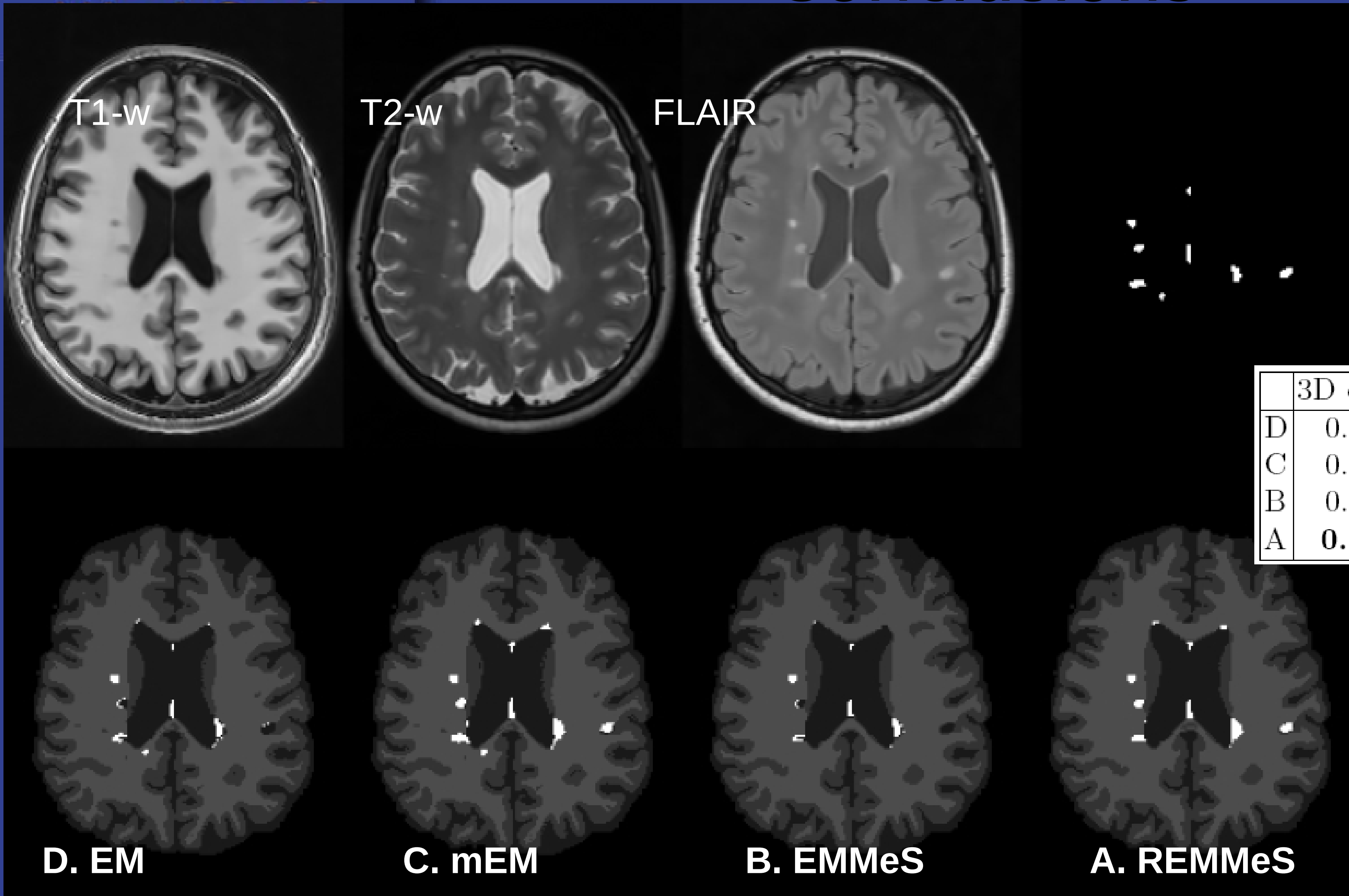
Conclusions

- Presented new method combining global and local information
  - Importance of robust Expectation-Maximization
  - MeS will keep the information of the contours
- Future works:
  - Reduce the execution time
  - Automatic adjustement MeS parameters
  - Improve validation (more experts, more methods)

Conclusions



	3D data
D	0.49
C	0.66
B	0.43
A	**0.67**

Thank you very much for your attention

Supported by Arsep