# Brain MR Image Segmentation via Adaptive Distribution


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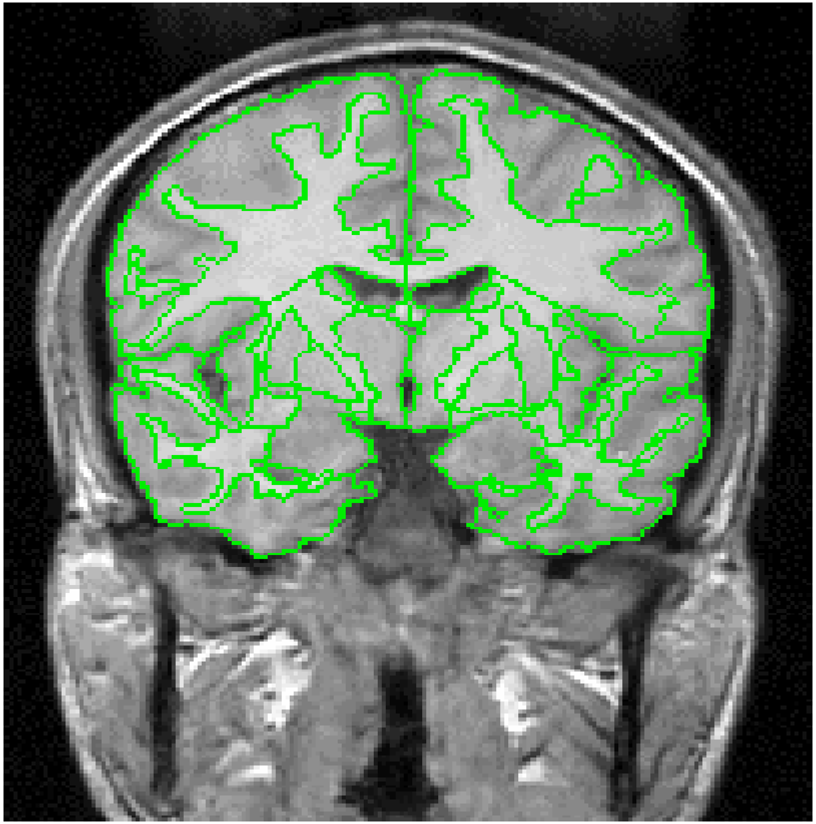
# Brain MR Image Segmentation

Brain Tissues are usually partitioned into two types: Gray Matter and White Matter, excluding CSF.



# Applications of MR Image Segmentation

1. **Support f(functional)MRI Aalyses**

   Neurons, the operation units of brains, are located in gray matter.

   Locating functional responsive regions of active neurons to experiments.

2. **Volumetric Study of Brain Development and Diseases**

   Gray matter volume loss in the frontal lobe of schizophrenia patients.

   Growth rates of myelination process with white matters.

# MR Image Segmentation Procedure

1. **Preprocessing**

   Removing non-brain voxels (after accurate registration)

   Inter-slice intensity normalization

2. **Bias field (biased intensity) correction**

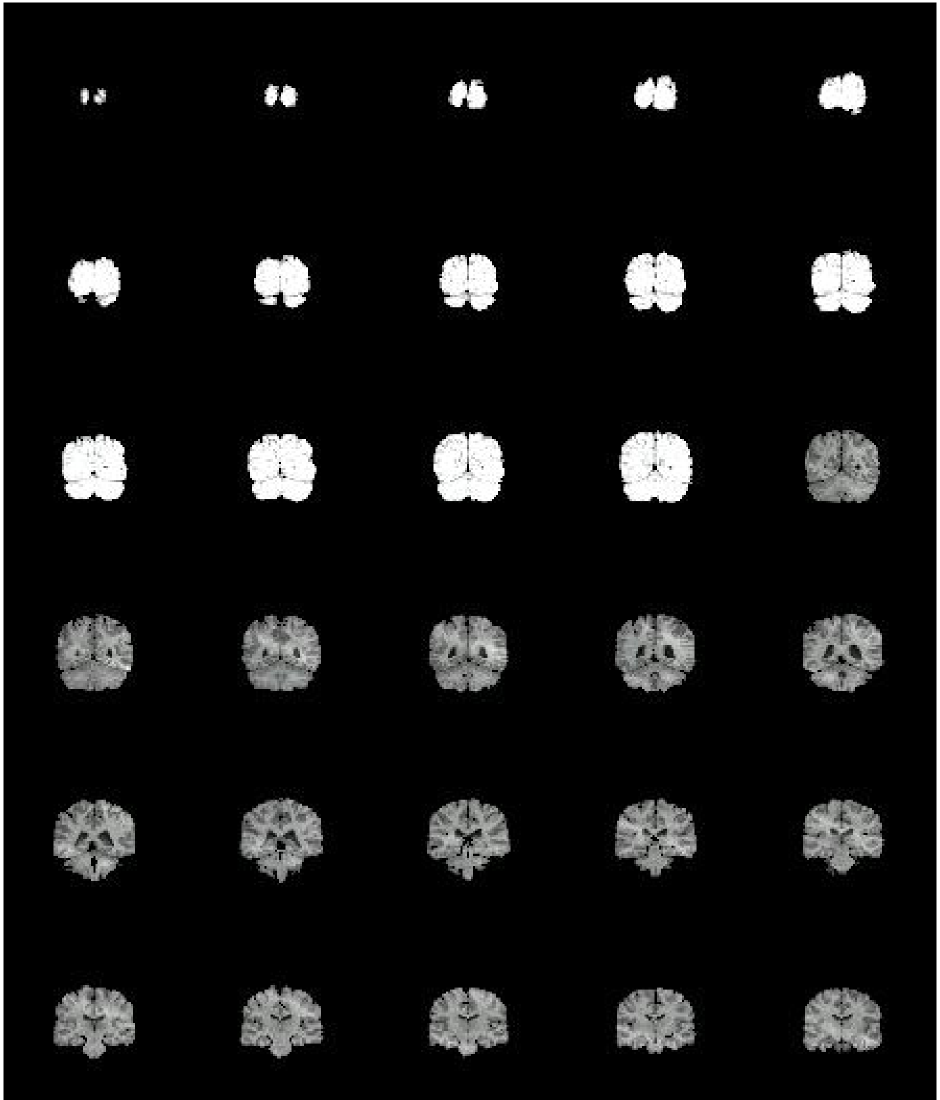
   Nonparametric intensity non-uniformity normalization (N3), Sled *et al*. (2000)

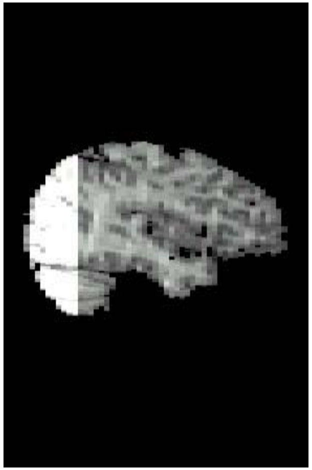
3. **Statistical classification**

   modulus-transformation modeling plus EM

4. **Post-smoothing via Markov random fields**

# Interslice Intensity Non-uniformity

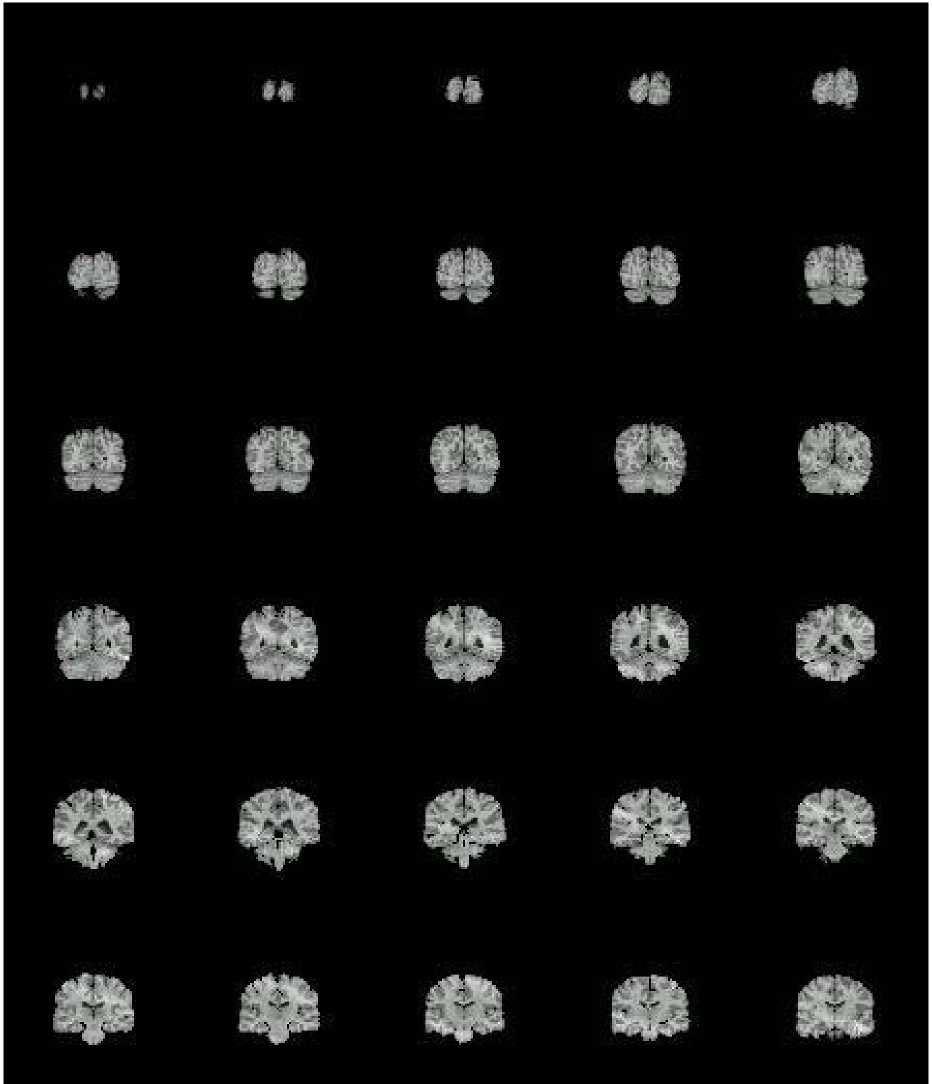


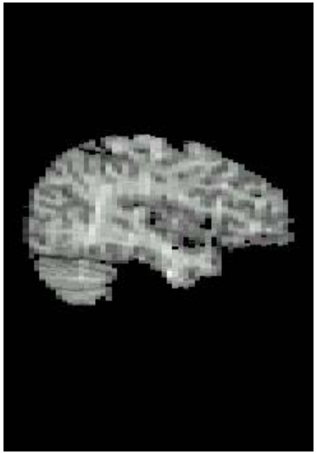


Up: Sagittal view of the data (biased at back)

Left: Coronal image series (from back to front)

# Corrected Images





Left: Coronal image series from back to front

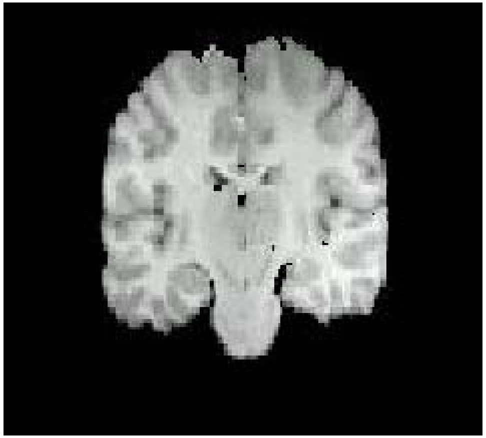
Up: Sagittal view of the same data

# Bias Field (Inhomogeneity)

•nonparametric *intensity* non-uniformity normalization (N3); Sled et al. 1998[1]
•ranked high in accuracy, precision, stability among six bias correction algorithms[2]

Biased Image

Bias-corrected Image



• Sled *et al*. A nonparametric method for automatic correction of intensity nonuniformity in MRI data. 1998, *IEEE Trans. Med. Imag*. 17: 87-97.
•Arnold *et al*. Qualitative and quantitative evaluation of six algorithms for correcting intensity nonuniformity effects. 2001. NeuroImage 13: 931-943.

# Modulus Transformation Modeling for Tissue Intensity

$$p(y \mid k) = p(y^{(\lambda_k)} \mid k) \cdot \left| y \right|^{\lambda_k - 1}$$

$$= G(y^{(\lambda_k)} \mid \mu_k, \sigma_k^2) \cdot \left| y \right|^{\lambda_k - 1}$$

***y*: tissue intensity**

***p*(*y*|*k*): intensity distribution of k*th* voxel type**

$\mu_k$, $\sigma_k^2$, $\lambda_k$: **parameters for k*th* voxel type**

# Mixture Distribution of Modulus Model

**Observed histogram is an adaptive mixture of *K* distributions:**

$$p(y) = \sum_{k=1}^{K} w_k \cdot G(y^{(\lambda_k)} \mid \mu_k, \sigma_k^2) \cdot |y|^{\lambda_k - 1}$$

**Unknown parameters:** $\omega_k$, $\mu_k$, $\sigma_k^2$, $\lambda_k$

# Validation of Segmentation Methods

- There is no ground true segmentation, and manual segmentation results by two or more experts are taken as gold-standard reference.

- Internet Brain Segmentation Repository (IBSR)

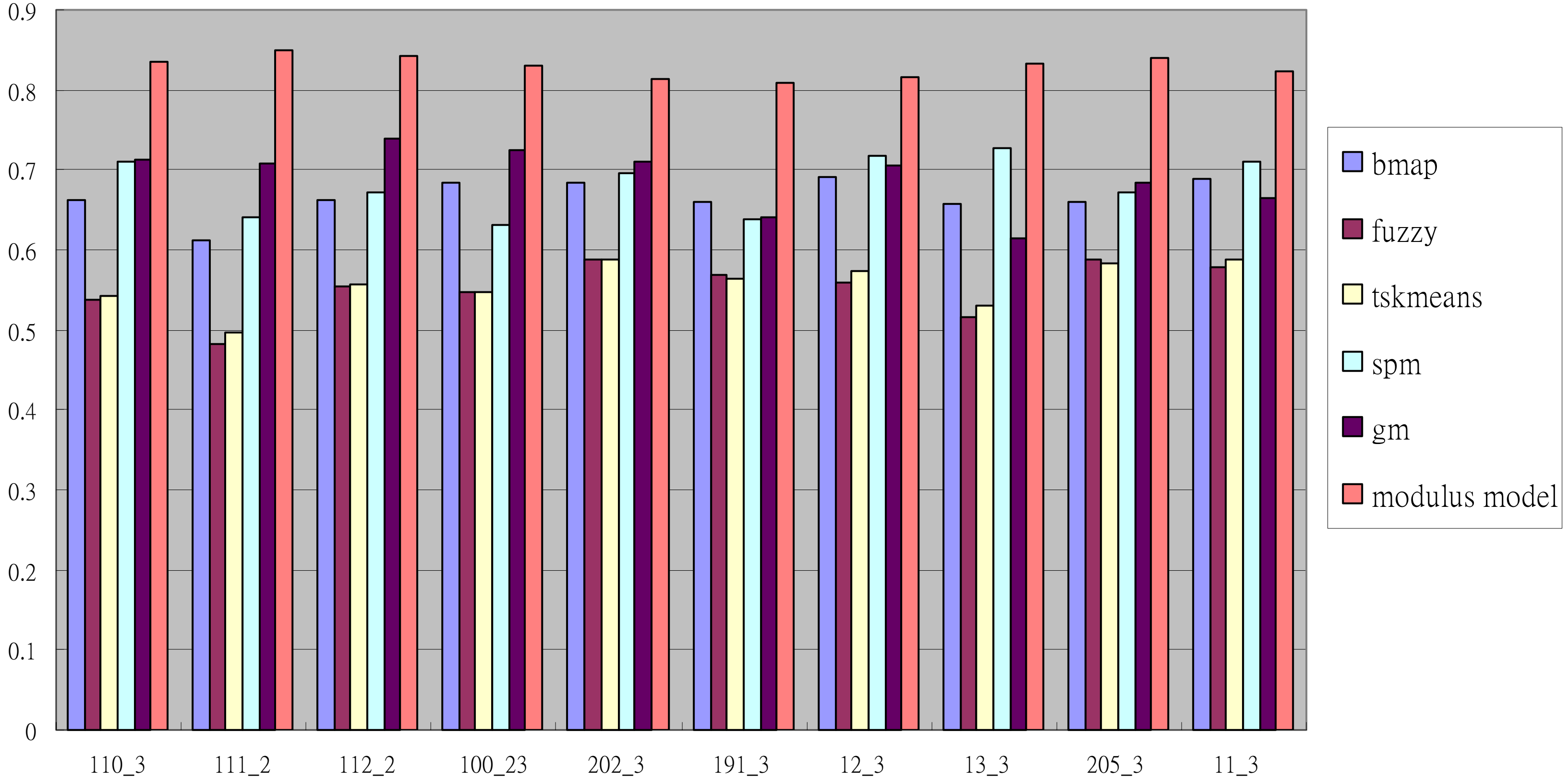
  http://www.cma.mgh.harvard.edu/ibsr

  20 data sets: 10 biased and 10 unbiased (incl. manual ref.)

- Calculate Jaccard similarity index between computed segmentation and manual segmentation.

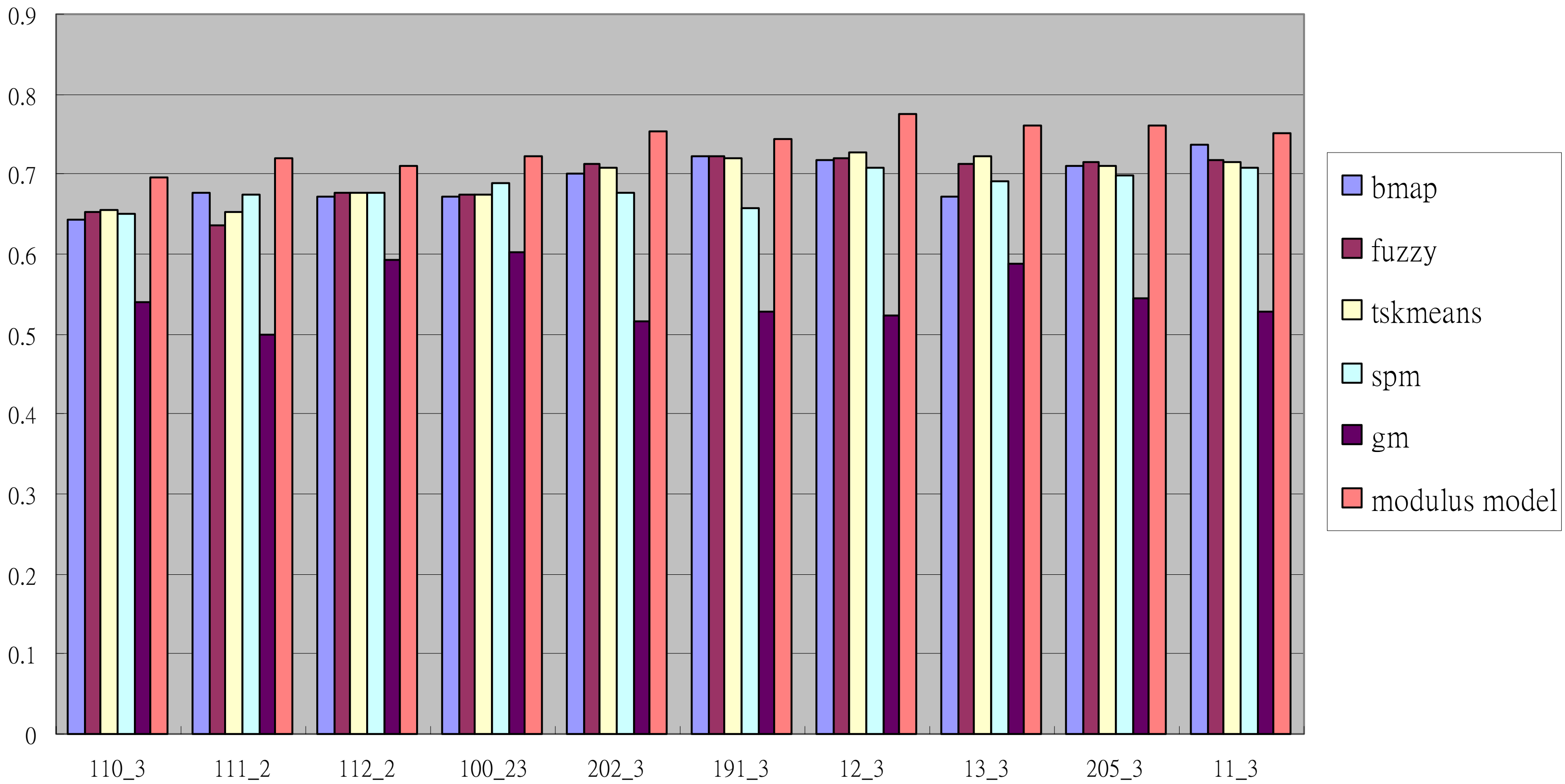
$$J = \frac{|S_1 \cap S_2|}{|S_1 \cup S_2|}$$

# Comparison of Gray Matter Segmentation with Un-biased Data Sets




The Jaccard indices of bmap, fuzzy and ts-k-means are available from IBSR.

# Comparison of White Matter Segmentation with Un-biased Data Sets




The Jaccard indices of bmap, fuzzy and ts-k-means are available from IBSR.

# For the Workshop

- Do research only with scientifically meaningful problems.
- Make research findings that shall be scientifically useful.
- Do not do statistical mathematical studies for existing methods and procedures, unless it is enlightening and unexpectedly new.
- Science can only progress with new/original findings, we have greater expectations for better research findings from our younger generation in the near future.