MISA LAB ONE REPORT

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Introduction

Bias field correction.

1. Brief description of the MICO algorithm

MICO (Multiplicative Intrinsic Component Optimization) is an energy minimization method for joint bias field estimation and segmentation of magnetic resonance (MR) images. The method utilizes the decomposition of MR images into two multiplicative intrinsic components, the true image that characterizes a physical property of the tissues and the bias field that accounts for the intensity inhomogeneity, and their respective spatial properties.

Bias field estimation and tissue segmentation are simultaneously achieved by an energy minimization process that optimize the estimates of the two multiplicative components. The bias field is iteratively optimized by using efficient matrix computations, which are verified to be numerically stable by matrix analysis.

The complete algorithm is given by:

1. Decomposition of MR images into multiplicative intrinsic components
   The MR image can be modelled as I(x) =b(x) +J(x)+n(x) where J(x) is the true image, b(x) is the bias field are considered the two intrinsic multiplicative components. These components are estimated using properties of each, namely the piecewise constant property of the true image J and the smoothly varying property of the bias field b.

2. Representation and Energy Formulation of the components
   To effectively use the properties of the bias field b and true image J, we need appropriate mathematical representation and description of the bias field and true image.

   The bias field is represented by a linear combination of a given set of smooth basis functions g1, ···, gM, which ensures the smoothly varying property of the bias field. The estimation of the bias field is performed by finding the optimal coefficients w1, ···, wM in the linear combination.
   The bias field is expressed $b(x) = \mathbf{w}^T G(x).$ as
   where w^T is the coefficient of the linear combinations.
   The true image J can be approximated by
   $J(x) = \sum_{i=1}^{N} c_i u_i(x).$ Where u_i is a vector of binary membership function of each region and constants, c_i.

Finally, energy formulation for multiplicative intrinsic component optimization is then given by

$$F_q(\mathbf{u}, \mathbf{c}, \mathbf{w}) = \int_{\Omega} \sum_{i=1}^{N} \left| I(x) - \mathbf{w}^T G(x) c_i \right|^2 u_i^q(x) dx.$$

Where the optimization of b and J can be achieved by minimizing the energy F with respect to u, c, and w. q is a fuzzifier (q>=1) in order to achieve fuzzy segmentation.

3. <u>Energy minimization</u>
The energy minimization can be achieved by alternately minimizing F_q(u, c, w) with respect to each of its variables given the other two fixed.

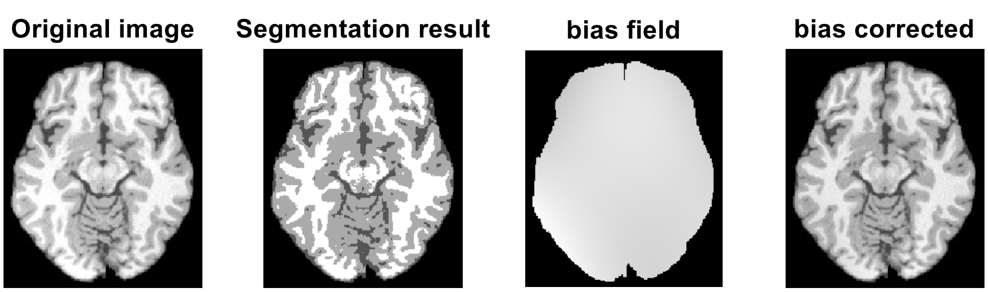
The minimization of the energy Fq(u, c, w) for q ≥ 1 as the following iteration process:
• Step 1. Initialize u and c;
• Step 2. Update b as ^b
• Step 3. Update c as ^c
• Step 4. Update u as ^u for the case q > 1 or for the case q = 1;
• Step 5. Check convergence criterion. If convergence has been reached or the iteration number
exceeds a prescribed maximum number, stop the iteration, otherwise, go to step 2.

During the iteration process, each of the three variables is updated with the other two variables computed in the previous iteration. Therefore, we only need to initialize two of the three variables, such as u and c in step 1 in the above iteration process. The convergence criterion used in step 5 is |c(n) − c(n − 1)| b ε, where c(n) is the vector c updated in step 3 at the n-th iteration, and ε is set to 0.001.

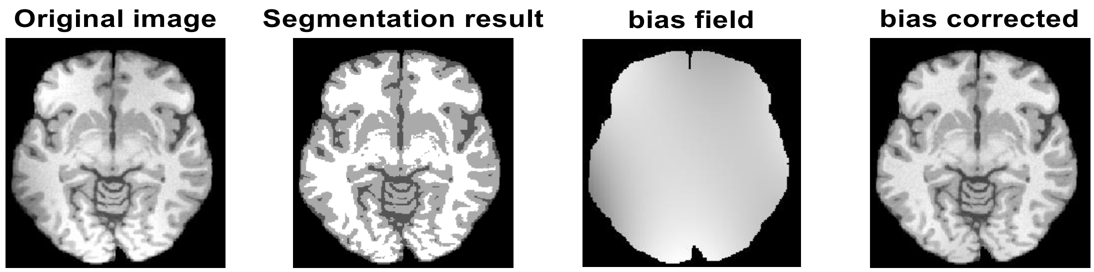
<u>Result and Discussion</u>

Image results before and after bias removal.

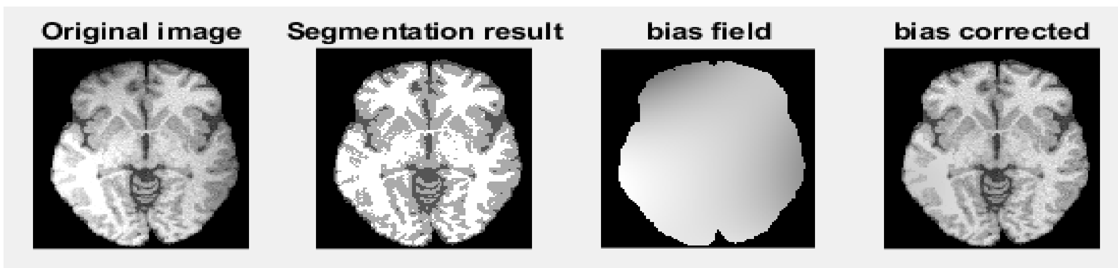
➢ brainweb59.tif



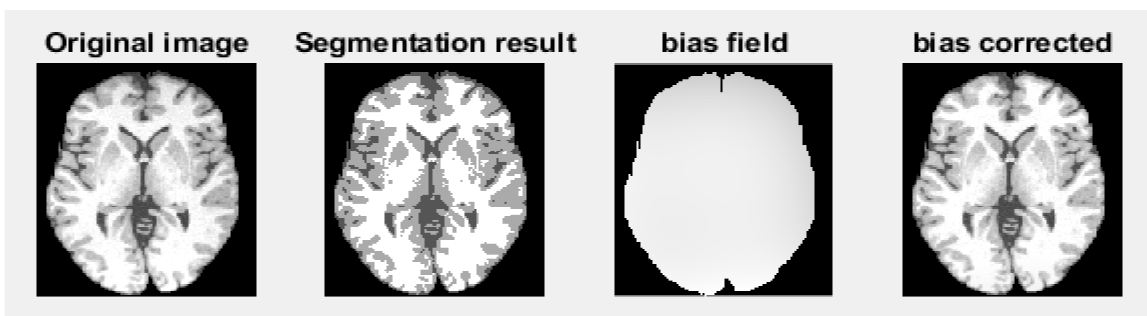
➢ Brainweb64.tif



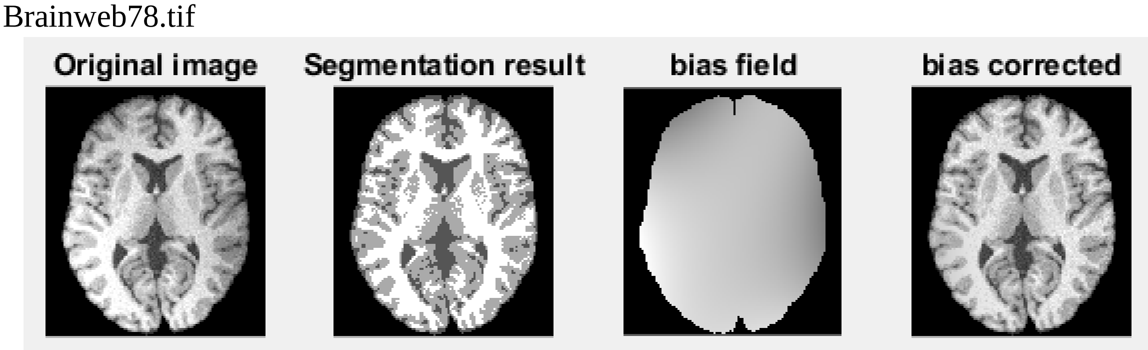
➢ Brainweb67.tif



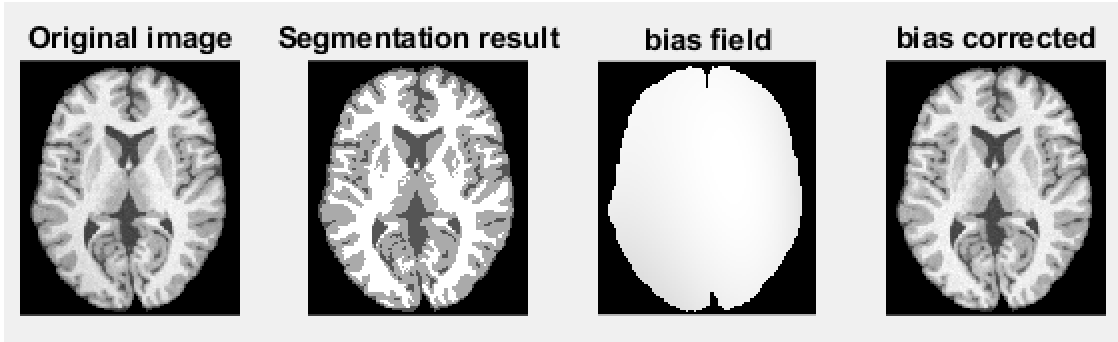
➢ Brainweb72.tif



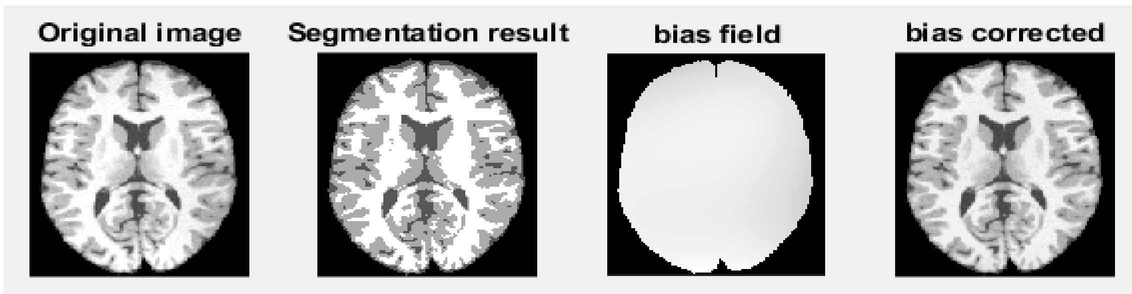
➢ Brainweb78.tif



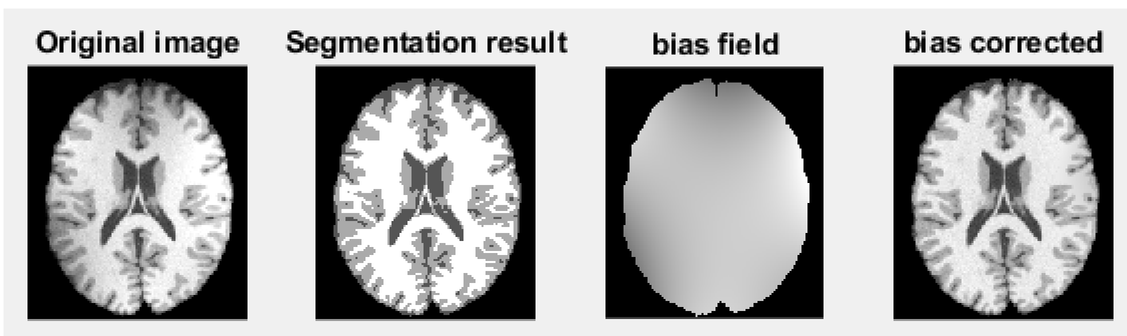
➢ Brainweb79.tif



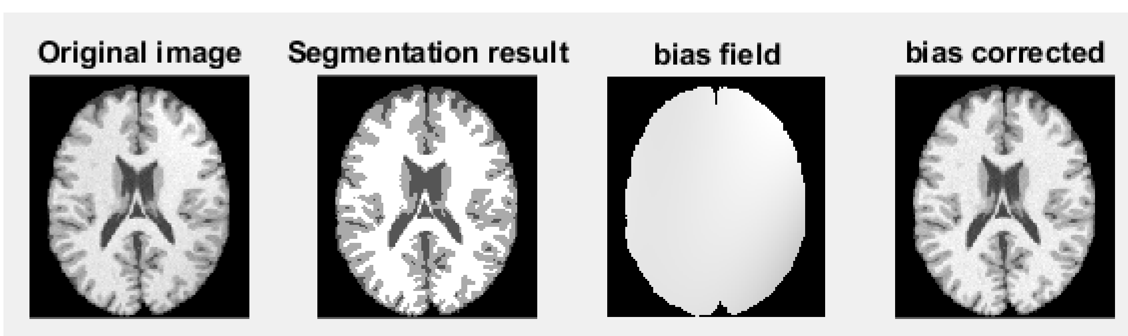
➢Brainweb83.tif



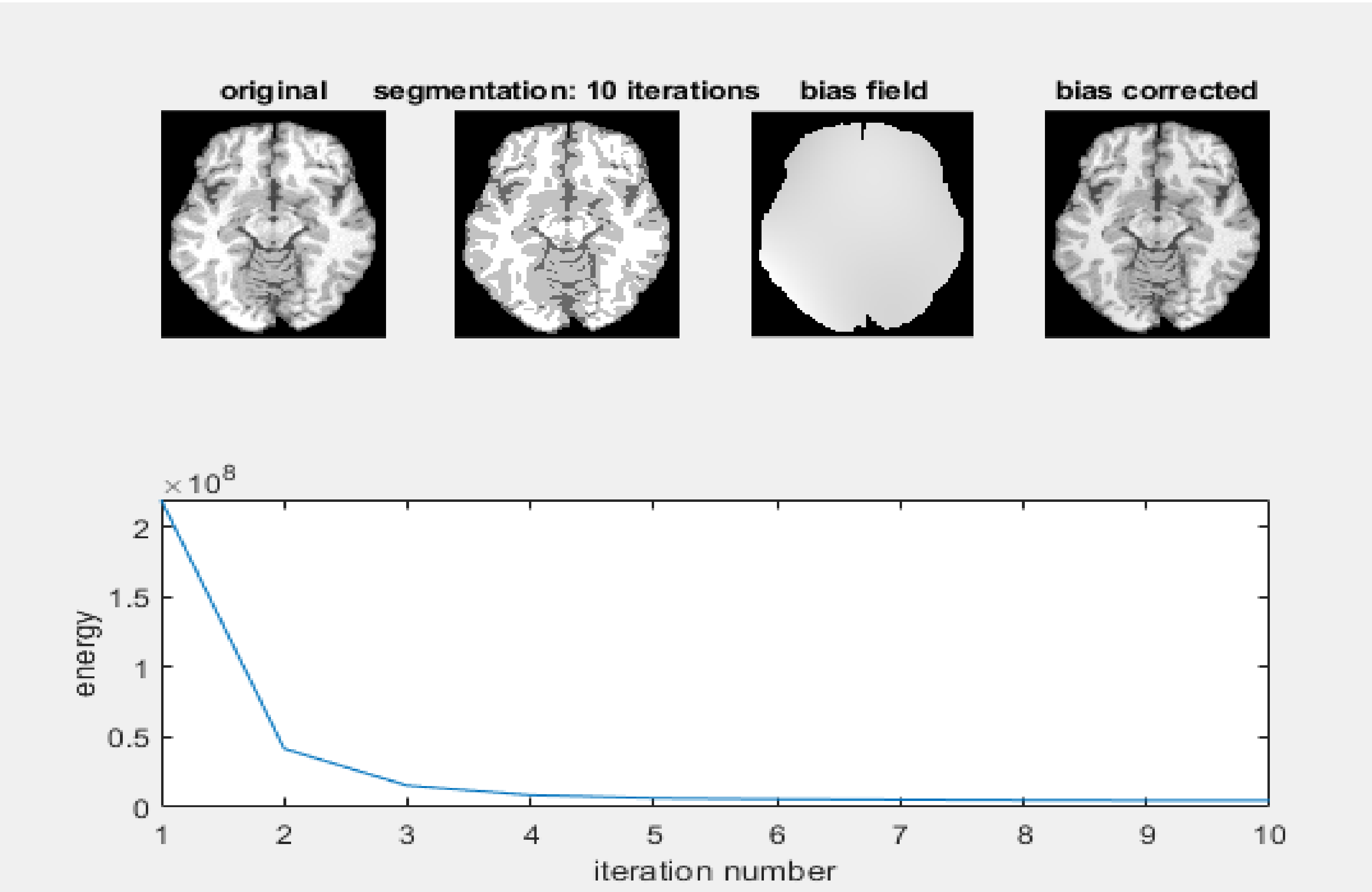
➢Brainweb90.tif



➢Brainweb91.tif



Qualitative results: The MICO algorithm works well to decompose the MRI images to its intrinsic components through energy minimization and thus can bias correct the images very well.



The Result shown in the above figure is bias field correction and segmentation using MICO algorithm with energy minimization techniques. The figure shows Original image, Bias image corrected, Segmentation image and energy Minimization histogram from left to right respectively.

Quantitative comparisons: The MICO uses energy minimization techniques and can clearly understand from the above figure. The energy was very high initially as shown in the above and gradually goes down as number of iteration increases.

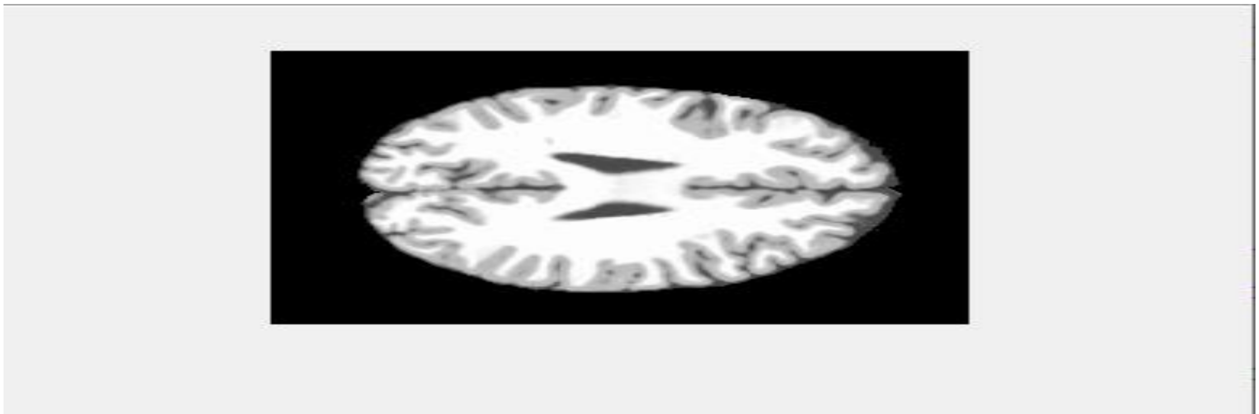
Applying parameters found in 2D for one brain Volume of 3D Image.

To segment and to make bias field correction for brain volume in 3D, we have done the following steps.

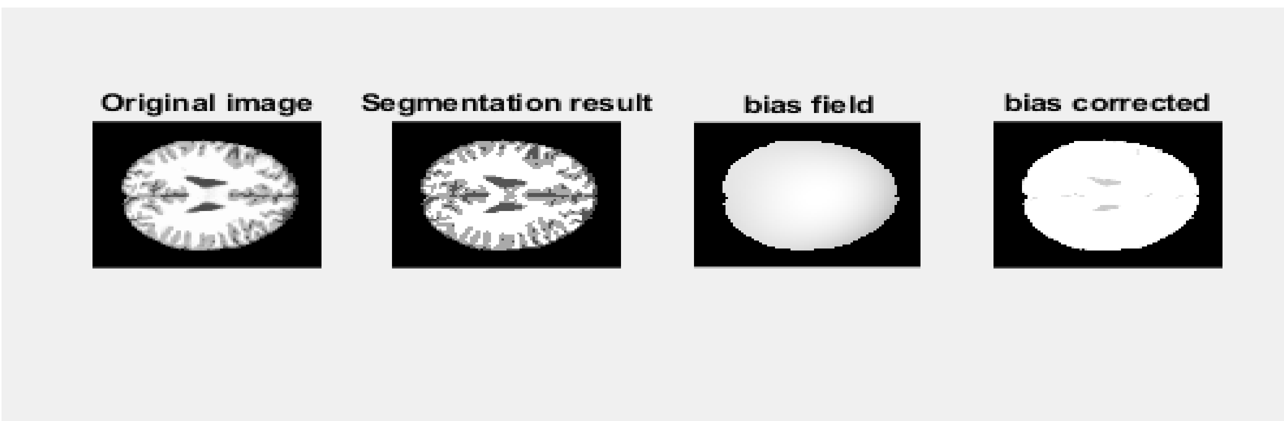
- Read the Nifti file of brain in 3D

- Extracting one slice from 3D image or technically, It is 2D image
- Checking the slice using visualization tool(ITK SNAP)
- Performing Segmentation and bias field correction.

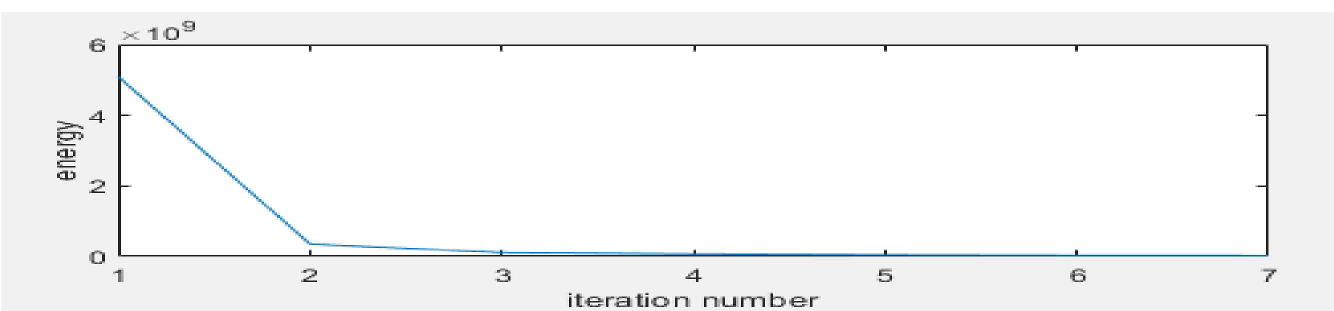
The following figure shows the slice taken from the 3D brain image.



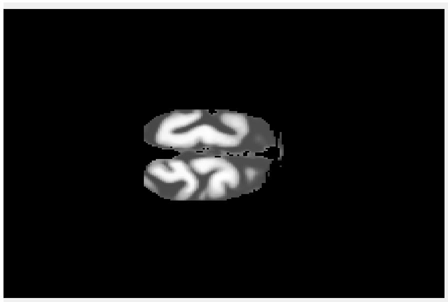
After tuning the parameters from 2D image, we got the following result of segmentation and bias correction (qualitative result), but the result for bias corrected is distorted.

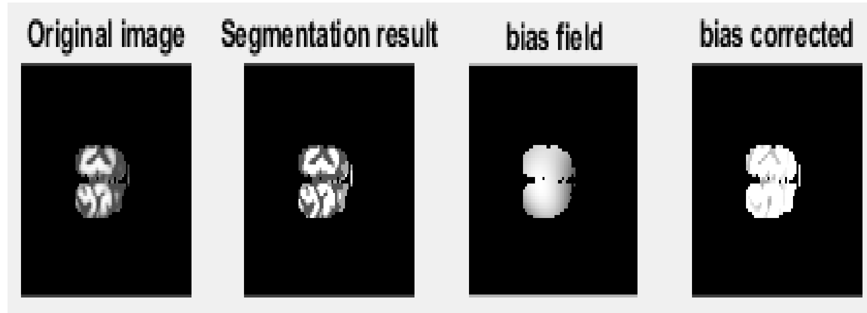


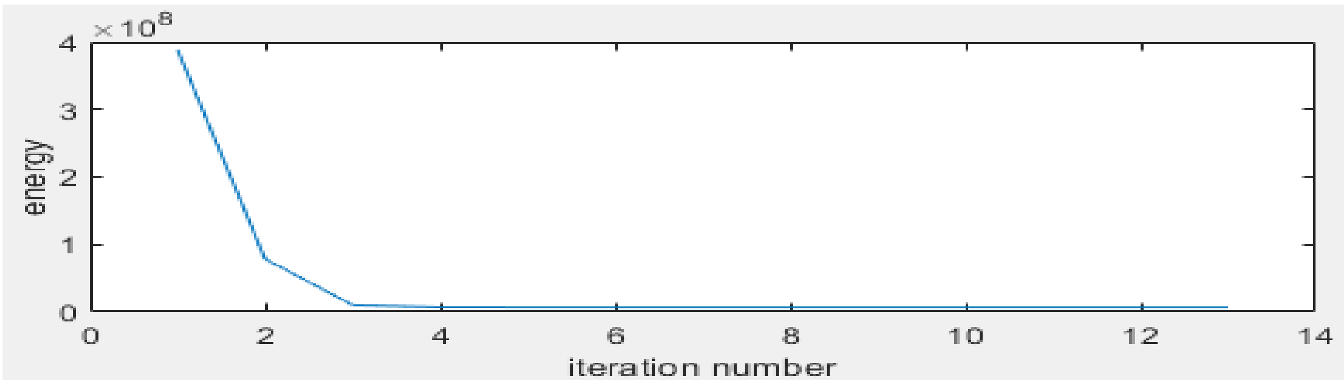
The following figure is Energy minimization histogram result that we got from 7 iteration.



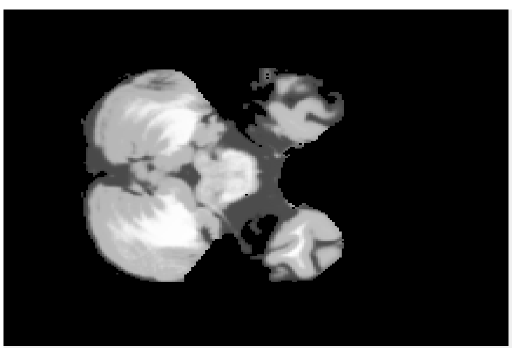
Second slice taken from the 3D image: Segmentation and biased correction (blurred)

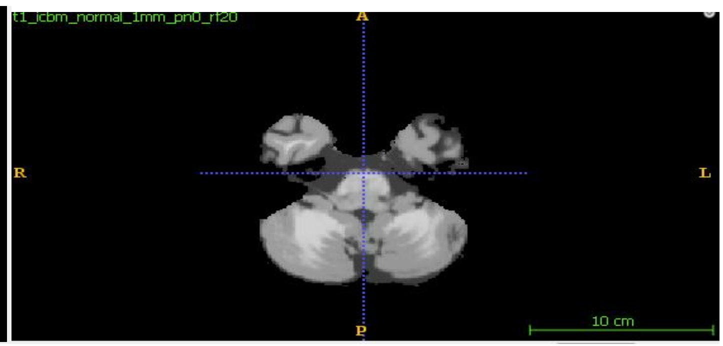




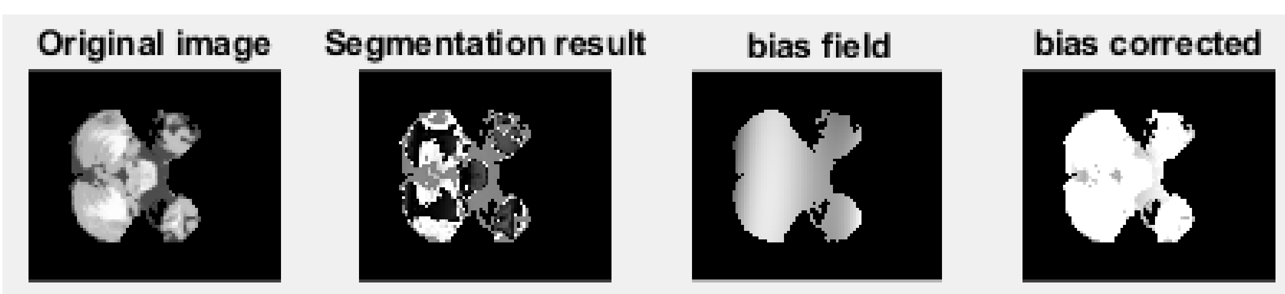


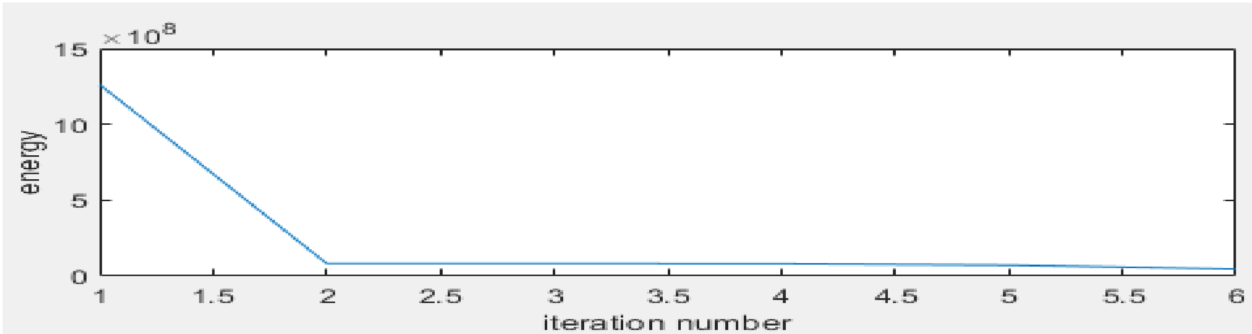
The third slice taken from the 3D Images with tuning of iteration and q parameters.



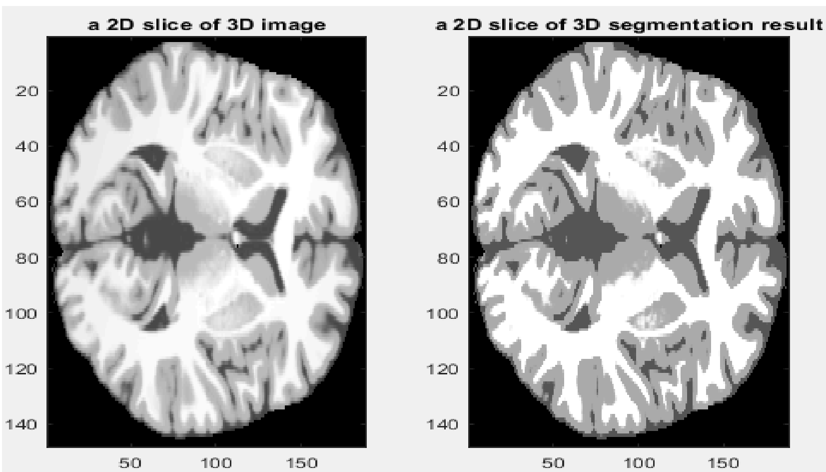


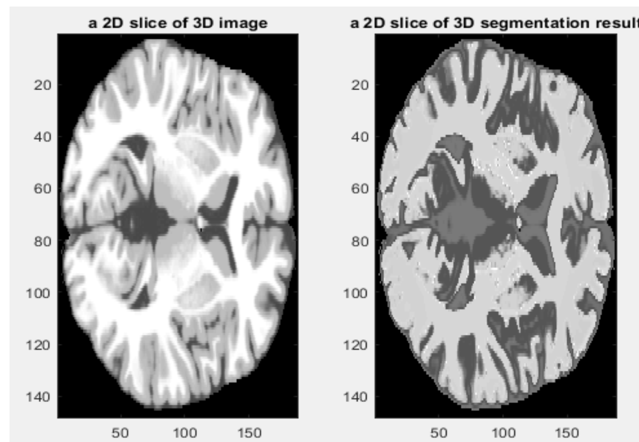
Segmentation and bias field correction simultaneously after we got from 14 iterations (quantitative and qualitative result).

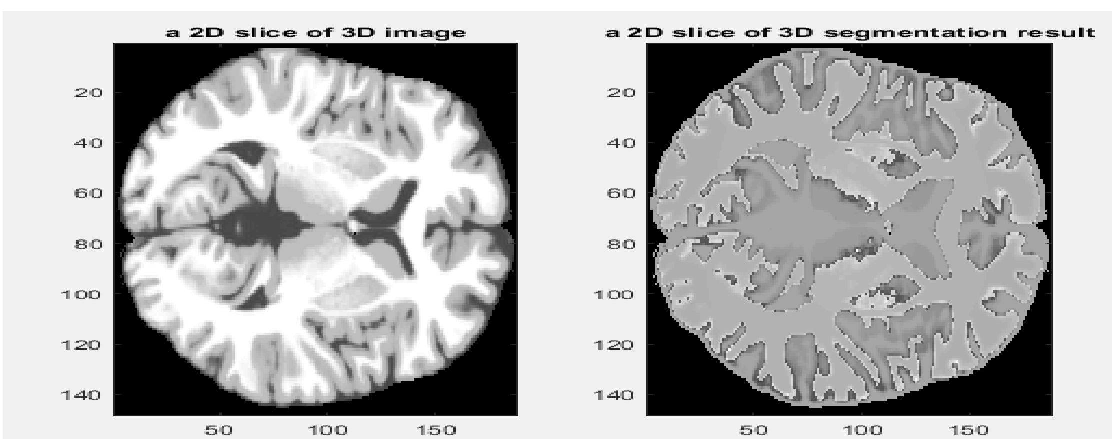




By directly tuning the Mico 3D parameters, we go the following slice segmentation results, particularly with tuning of fuzzifier(q) and number of iterations. The result below shows slice in 3D and image and Segmentation.







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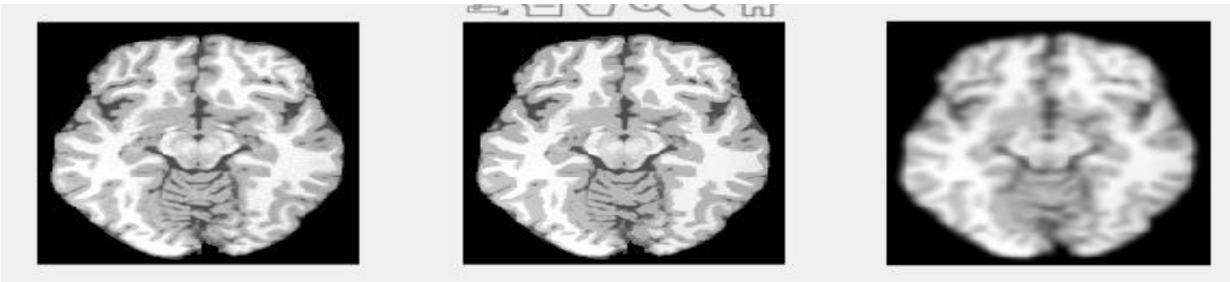
Noise Suppression

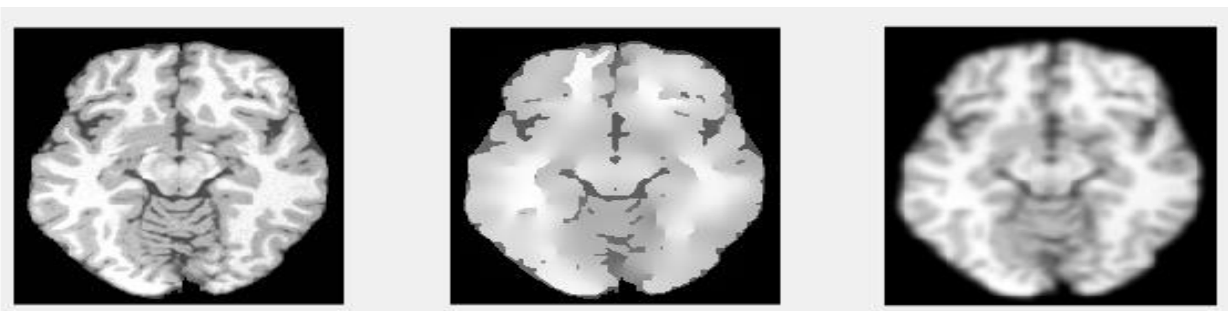
Effect of parameters: Original Img ; Anisotropic Diffusion : Blurred image

Effect of Kappa

- num_iter = 100; delta_t = 0.25; kappa = 5; option = 1;

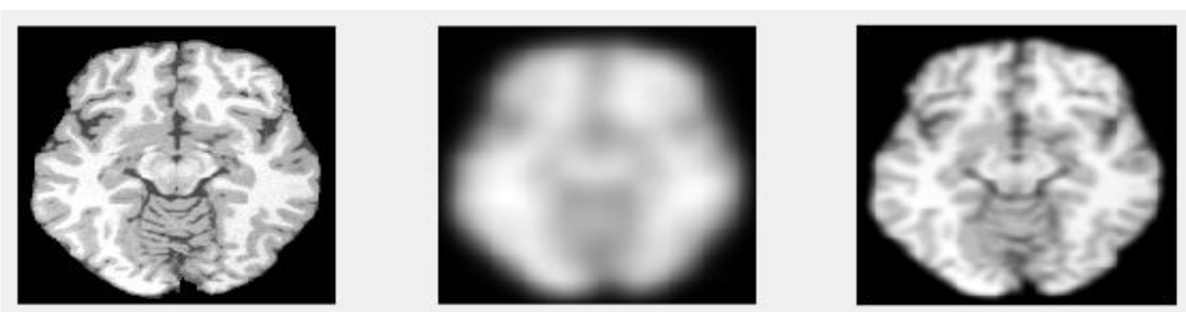


- num_iter = 100; delta_t = 0.25; kappa = 20; option = 1;



- num_iter = 100; delta_t = 0.25; kappa = 100; option = 1

;

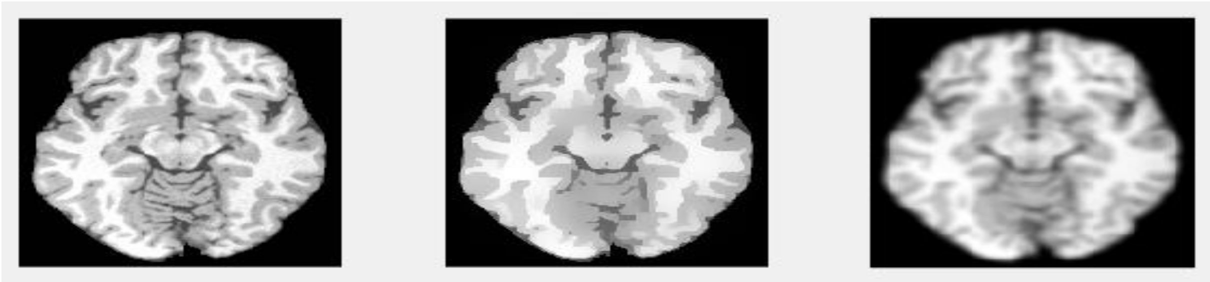


kappa controls conduction as a function of gradient. If kappa is low small intensity gradients can block conduction and hence diffusion across step edges. A large value reduces the influence of intensity gradients on conduction and results in a very blurred image. As Kappa increases, the details in the MR image are reduced.

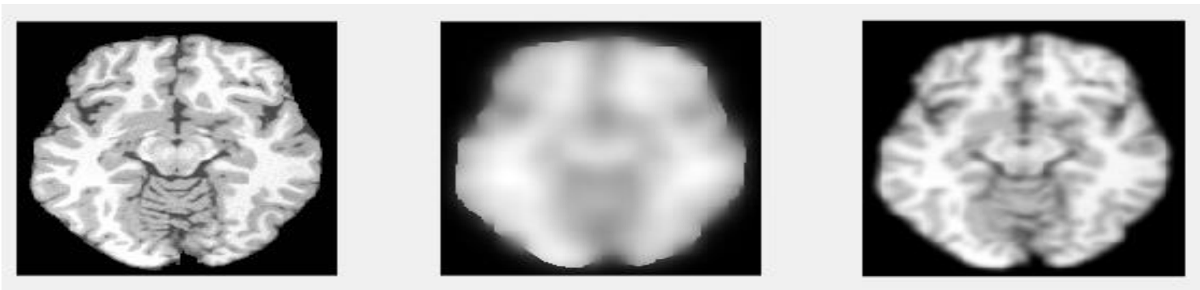
Option

Diffusion equation 1 favours high contrast edges over low contrast ones. While Diffusion equation 2 favors wide regions over smaller ones.

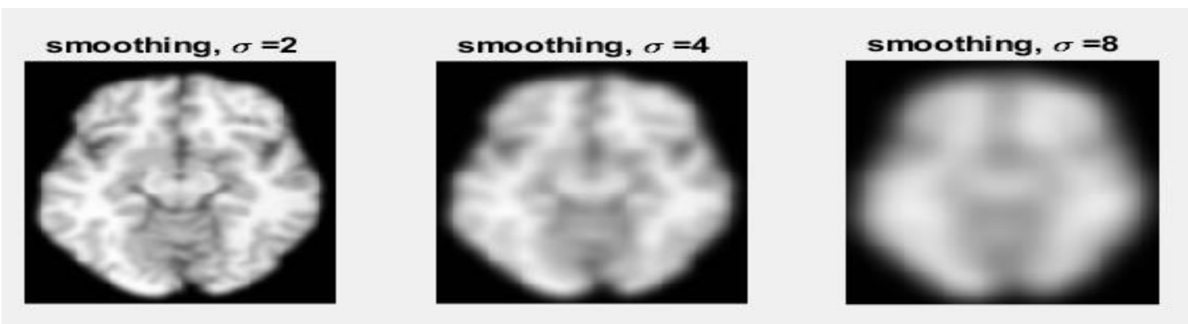
num_iter = 100; delta_t = 0.25; kappa = 5; option = 2;



num_iter = 100; delta_t = 0.25; kappa = 25; option = 2;



Isotropic smoothing (Gaussian Smoothing)



Qualitatively, we can clearly see that anisotropic diffusion performs much better at denoising without loss of much finer details than isotropic smoothing techniques such as a Gaussian smoothing. The figure above shows a Gaussian smoothing of MR image with sigma 2,4 and 8.

Conclusion

Generally, the most important advantages and innovations offered by this algorithm are, segmenting and estimating the bias field simultaneously in an energy minimization process and thus optimization of two multiplicative intrinsic components estimations of an MR image. MICO relationship can be developed for 3-dimensional (3D).
Performing pre-processing to eliminate noise, Implementation of the MICO method, obtaining bias and segmentation images with qualitative and quantitative analysis are the main task done in this lab session.