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The Quantitative and Qualitative Evaluation of Simultaneous Segmentation using Multiplicative Intrinsic Component Optimization in Brain MR Images

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Abstract: Segmentation of brain MR images is a major issue in medical image processing computations. In brain MR images, segmentation is caused by an inherent error which is called intensity in homogeneity. This is due to the existence of an overlap between different brain tissues which often causes false classification of tissues. This paper uses a new proposed method for segmentation and bias field correction simultaneously which is called Multiplicative Intrinsic Component Optimization (MICO). The proposed method, breaks down MR images into two components, one component characterizes a physical property of tissue and other inherent bias field that accounts for the intensity in homogeneity with spatial features. Then, via. energy minimization in an iterative process, the above components are optimized and consequently, segmentation and bias field correction was carried out, simultaneously. Qualitative assessment of MICO method was proved in terms of accuracy and robustness and showed high accuracy of about 90% for bias field correction and segmentation in three areas of the brain, especially in the area containing the Cerebrospinal Fluid (CSF).

INTRODUCTION

Most segmentation algorithms that are widely used are based on regioning and usually rely on in homogeneity of MR images intensity in that area. In most cases, due to an inherent factor that is strongly referred to as in homogeneity, segmentation is confronted with an error (Johnston *et al*., 1996). In brain MR images, due to the overlap between intensity ranges in different areas of the brain, such as GM, WM and CSF, we are always faced with intensity in homogeneity which can be seen for accumulation of energy in the areas mentioned and this is known as bias field. Therefore, for accurate segmentation of images, we require a method to estimate and correct the bias field. MICO method is an algorithm based on energy minimization via. optimization of the multiplicative intrinsic components of MR brain images which performs the segmentation and bias field correction simultaneously (Sled *et al*., 1998).

Generally, in MR brain images, it is assumed that it consists of two multiplicative intrinsic components. An intrinsic component used to determine the physical properties of the three main brain tissues that characterize spatial features of the tissues which is known as J(x). The second component is used to determine the characteristics of bias field to estimate and correct the intensity in homogeneities and is known as b. MICO method divides the brain MR images into the two components as mentioned above and performs simultaneous segmentation and bias field correction via optimization process. This is done by minimizing the energy in an iterative process in the areas of brain tissues which was originally proposed by Leemput *et al*. (1999).

More bias field correction algorithms have been proposed in the past two decades which are usually divided into two general classes: prospective methods (Styner *et al*., 2000; Ahamed *et al*., 2002; Li *et al*., 2008a, b; Likar *et al*., 2001; Vovk *et al*., 2007) and retrospective or revised methods (Vovk *et al*., 2007; Dawant *et al*., 1993; Li *et al*., 2011, 2014). Chan and Vese (2001) presented a method that estimates intensity inhomogeneity via a series of narrow strips with respect to selected points within each area of brain tissue. Another method called N3 was provided by Li *et al*. (2008a, b) based on the intensity histogram to correct the bias field. Pham and Prince introduced a method for segmentation and correction of bias field based on fuzzy algorithm called adaptive AFCM or FCM through which adaptive fuzzy algorithm and classification algorithm C or C-Means perform bias field correction and segmentation (Ahmed *et al*., 2002). The level set method algorithm was also presented by Ranfard (1994) which performed the simultaneous bias correction and segmentation operations. The aim of this study is to correct intensity in homogeneities on MR images and obtain the above mentioned regions of the brain via simultaneous segmentation and correct the bias field, especially the area containing the CSF which is used to measure cerebrospinal fluid and obtain the volume changes of this liquid on different days of the month and analyze its related diseases. The remaining part of this study is organized as follows:

MATERIALS AND METHODS

In this study, the proposed method is explained. The purpose of this study is to explain the bias field correction and segmentation method that perform bias correction and segmentation operations simultaneously. The main method or MICO is employed for simultaneous bias field correction and segmentation of three main areas of brain tissue and measurement of these areas to be used in medical applications. After obtaining the area and volume of brain tissues, quantitative analysis is performed using landmarks like jacquard, Dice, the accuracy of classification, etc., to evaluate the output of bias correction and MICO algorithm segmentation.

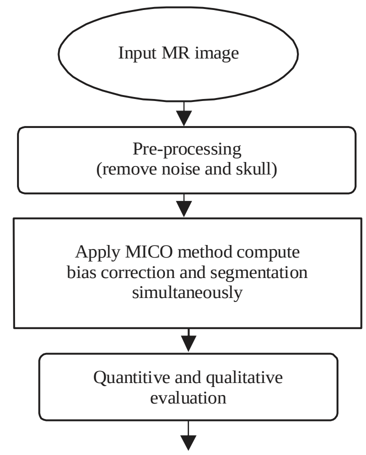

Fig. 1: Flowchart of the proposed method

The proposed method is as follows: Performing pre-processing to eliminate noise and skull. Implementation of the MICO method and obtaining bias and segmentation images. Doing qualitative analysis and obtaining analytical results. Figure 1 shows the flowchart of the steps mentioned above.

Multiplicative Intrinsic Component Optimization algorithm (MICO): As already mentioned, owing to intensity in homogeneities in different tissues, there is an overlap that leads to incorrect classification of tissues. Therefore, bias correction procedure leads to the elimination of intensity heterogeneity. MICO algorithm specifies true image of the physical characteristics of a tissue and its bias field intensity which is considered as intensity heterogeneity as well as the corresponding location features. In this algorithm, simultaneous bias field estimation and the image segmentation is obtained by an energy minimization process (Sled *et al*., 1998).

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 and four-dimensional tissues segmentation by setting the time and space. MICO algorithm can be applied to images with higher intensities like images with intensity of 7 Tesla, considering that these images has more complex profiles than the images of 1.5 and 3 Tesla. With the increasing number of major functions, a larger range of bias fields is approximated by a linear combination. These cases make the use of MICO algorithm in higher fields and other medical images with in homogeneities with high intensity possible.

Segmentation and bias field estimation method: As earlier mentioned, for a MR image. We have:

$$I(x) = b(x) * J(x) + n(x) \tag{1}$$

In this equation, J(x) is image intensity in voxel x and true. B(x) is image biased field and n(x) is noise added with an average of zero. It is assumed that, b has smooth changes. Real image J(x) defines the tissue feature in which the imaging is carried out and ideally, it takes a certain amount for a similar tissue. It is assumed that, J approximately has a constant value for all the pixels x in the i-th tissue. Thus, the bias field estimation and segmentation is considered as an energy minimization problem, the intrinsic component above estimation. To estimate the Image J, Piecewise Constant feature (PC) is employed and smooth changes feature of bias field is used for b. True image approximately with a fixed amount of Ci for i-th voxel x in the tissue can be marked through membership functions Ui. In ideal cases, it is assumed that each voxel contains only one type of tissue. In this case, the membership function will be binary Ui. However, it may be as a result of the impact of segmentation volume, particularly in relation to neighboring tissues, if it contains more than one tissue, in this case, membership functions would be in the form of fuzzy functions. If it is in binary mode, membership functions will be in the form of PC and if in fuzzy mode, it will be in the form of Piecewise Smooth (PS). By establishing limits on the bias field b and true image b, energy can be minimized. This energy is generally written as follows (Sled *et al*., 1998):

$$F(u, c, w) = \int \sum_{i=1}^{N} \left| I(x) - w^T G(x) C_i \right|^2 u_i(x) dx \tag{2}$$

This formula with the binary membership functions leads to hard segmentation. In order to obtain a result of smooth segmentation, fuzzy membership functions are employed. The MICO method performs segmentation and estimation of bias field by minimizing energy F(u, c, w) in two modes of the use of binary and fuzzy membership in relation to the limitations of b, J (Sled *et al*., 1998).

RESULTS AND DISCUSSION

In this study, 30 MR image strings for database used in Pezhvak Institute of Medical Imaging in Tabriz were used. All images have been developed in the T2 type and in the axial form and have a thickness of 5 mm with 1.5 Tesla scanners. First, images were applied to the MICO algorithm input. The algorithm simultaneously performs segmentation and bias field correction and leads to the creation of three component areas of brain tissue or WM, GM and CSF. Figure 2 shows the results of bias field correction and segmentation for a brain tissue as sample and separately for each algorithm.

In Fig. 2, the energy curve has been plotted against the number of repetitions which clearly demonstrates the energy minimization process by MICO algorithm in an iterative process. In this section, to compare the results obtained and quantitative assessment of the results of the proposed algorithm, two other cases were considered. First, segmentation is done for the original input image manually and then by Otsu's multiple thresholding algorithm (Samson *et al*., 2000). The aim of this method is to compare the output results of MICO method with other methods such as level set (Ranfard, 1994) which has no internal procedures to correct the bias field and consequently, the segmentation of brain regions will be faced with errors.

Figure 3 shows the results of segmentation obtained from MICO algorithm bias correction method. This chart shows the percentage of segmentation pixels relative to each of the algorithms separately on each

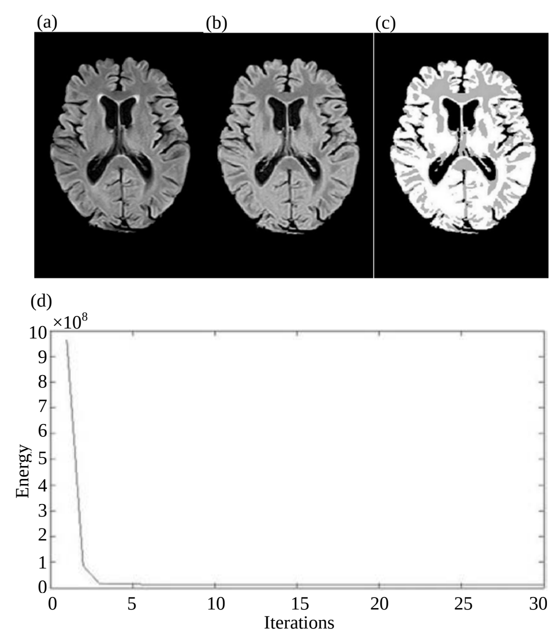

Fig. 2(a-d): Results of bias field correction and segmentation using MICO algorithm, (a) Original image, (b) Bias image corrected, (c) Segmentation image and (d) energy minimization histogram

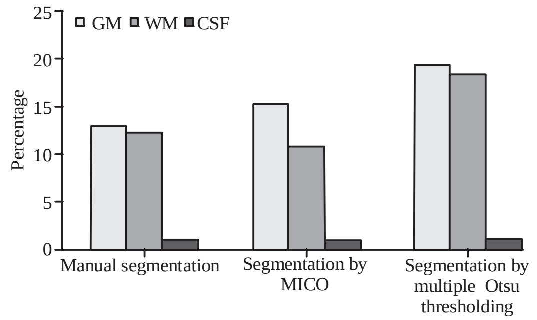

Fig. 3: The results of MICO algorithm segmentation

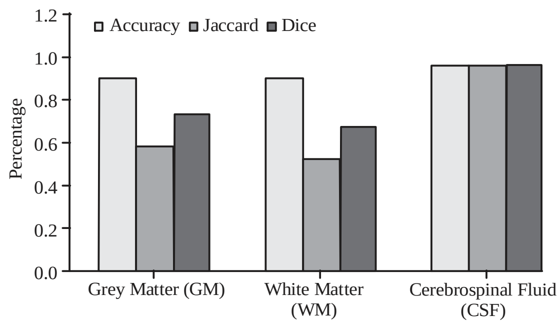

Fig. 4: Quantitative results of indexes for MICO algorithm

of the 3-dimensional areas of brain tissue and for all images. For quantitative evaluation of the results, there is need to use a series of important indicators for the quantitative analysis of images that include: Jacquard index, Dice, the accuracy of classification, false positive rate, false negative rate, true positive rate or Sensitivity index (S), true negative rate or features index (SP):

$$\text{Jaccard}(A, B) = \left|\frac{A \cap B}{A \cup B}\right|, \text{Dice}(A, B) = \frac{2|A \cap B|}{|A|+|B|} \tag{3}$$

$$\text{Accuracy} = (TP+TN)/(TP+FP+FN+TN) \tag{4}$$

$$SP = \frac{TN}{TN+FP}, S = \frac{TN}{TP+FN} \tag{5}$$

$$FPR = \frac{FP}{TP+FN}, FNR = \frac{FN}{TP+FN} \tag{6}$$

The results of quantitative analysis of indicators are presented in Table 1-3 for the three-dimensional areas of brain tissue or WM, GM and the CSF. After quantitative evaluation by the criteria listed above, the results are displayed in Fig. 4. The results are for all three regions and three main indices are shown for brevity.

Table 1: Values of indexes for GM region with MICO algorithm

Sequence	Jaccard	Dice	Accuracy	FPR	FNR	TPR	TNR
1	0.7764	0.8741	0.9443	0.0393	0.1145	0.8855	0.9607
2	0.7738	0.8725	0.9323	0.0546	0.1052	0.8948	0.9454
3	0.7320	0.8452	0.9337	0.0590	0.0954	0.9046	0.9410
4	0.5223	0.6862	0.8811	0.0806	0.2900	0.7100	0.9194
5	0.6099	0.7577	0.9116	0.0610	0.2163	0.7837	0.9390
6	0.5892	0.7415	0.9177	0.0546	0.2341	0.7659	0.9454
7	0.6734	0.8048	0.9374	0.0442	0.1637	0.8363	0.9558
8	0.6141	0.7609	0.9275	0.0586	0.1600	0.8400	0.9414
9	0.5341	0.6963	0.9063	0.0754	0.2100	0.7900	0.9246
10	0.6013	0.7510	0.8947	0.0805	0.2046	0.7954	0.9195

Table 2: Values of indexes for WM region with MICO algorithm

Sequence	Jaccard	Dice	Accuracy	FPR	FNR	TPR	TNR
1	0.5625	0.7200	0.9126	0.0540	0.2709	0.7291	0.9460
2	0.3188	0.4834	0.8853	0.0685	0.4992	0.5008	0.9315
3	0.3981	0.5695	0.8669	0.0780	0.4327	0.5673	0.9220
4	0.6332	0.7754	0.9164	0.0564	0.2061	0.7939	0.9436
5	0.5870	0.7398	0.8998	0.0665	0.2454	0.7546	0.9355
6	0.5443	0.7049	0.8855	0.0781	0.2719	0.7281	0.9219
7	0.6174	0.7634	0.9203	0.0499	0.2287	0.7713	0.5010
8	0.5610	0.7188	0.9019	0.0585	0.2844	0.7156	0.9415
9	0.5564	0.7150	0.9183	0.0392	0.3209	0.6791	0.9608
10	0.5512	0.7106	0.9056	0.0618	0.2676	0.7324	0.9382

Table 3: Values of indexes for CSF region with MICO algorithm

Sequence	Jaccard	Dice	Accuracy	FPR	FNR	TPR	TNR
1	0.9946	0.9973	0.9964	0.0111	0.0199	1	0.9889
2	0.9949	0.9975	0.9965	0.0113	0.0211	1	0.9887
3	0.9937	0.9958	0.9958	0.0120	0.0279	1	0.9880
4	1.0000	1.0000	1.0000	0.2020	0.0000	1	1.000
5	1.0000	1.0000	1.0000	0.0000	0.0000	1	1.000
6	0.9971	0.9986	0.9979	0.0075	0.0186	1	0.9925
7	0.9972	0.9986	0.9980	0.0067	0.0000	1	0.9933
8	0.9975	0.9988	0.9981	0.0077	0.0000	1	0.9923
9	1.0000	1.0000	1.0000	0.0000	0.0144	1	1.000
10	0.9974	0.9987	0.9981	0.0063	0.0000	1	0.9937

CONCLUSION

In this study, the proposed method was applied to actual MR images and quantitative and qualitative analysis was conducted on 3-dimensional areas of brain tissue in a process of bias field correction and segmentation. By software implementation, the results measured for each tissue were provided. In conjunction with the MICO algorithm, according to the results, it was concluded that this algorithm in the area of CSF has better segmentation results. Regarding the results of the bias field correction with respect to the quantitative tables obtained from the indicators, it can be concluded that the bias correction output using MICO algorithm has better results and is more accurate and this is due to bias correction routine power using MICO algorithm, especially in the area containing CSF which showed high accuracy of 0.9. In addition, when we use bias correction output of the algorithm above as the main input of other algorithms such as Otsu's multiple thres holding, it improves significantly the results of their segmentation which will be the subject of future research.

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