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BIAS FIELD ESTIMATION AND TISSUE SEGMENTATION IN MR BRAIN IMAGES USING MICO

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Abstract:

Due to the variations in the magnetic fields of the MRI machine. The bias field blurs images and causes intensity inhomogenities which reduces the performance of image such as segmentation and classification .A preprocessing step is required to correct the effect of bias field before making segmentation or classification is known as bias field correction. Tissue segmentation is a way for splitting an image into segments equivalent to distinct tissue classes. This paper intended a fresh energy minimisation process known as MICO (Multiplicative intrinsic component optimization) used to find out bias field and to segment the tissues of magnetic resonance brain images having benefit of the disintegration of magnetic resonance brain images into two components, particularly, true image, bias field and their relevant spatial properties. Finding bias field and segmenting of tissues are achieved at the same time by an energy minimisation process.

Keywords -- **MR brain images , Brain segmentation, Intensity inhomogeneity, Bias field estimation, Bias field correction**

1. INTRODUCTION:

One of the basic difficulties in medical image estimation is the image segmentation. In MR images the classifications faced by intensity inhomogenity which way the inherent artifact, displayed as intensity differences in the same tissue. Intensity articraft in MRI depends on several elements, specifically B0 and B1 field variations and particular interactions. Because of these intensity variations, there is occurrence of common difference between the ranges of distinct intensity ranges which leads to wrong classification. Other algorithm for image examination is image registration which also deceives variations in intensities. Therefore, we want to reduce the variations in intensities by estimating bias field before inspecting the MRI data.

After calculating the Bias field rectification is to be performed which does not leads variations in intensities of MR brain image and the bias corrected image is obtained by splitting the image by which the bias field is estimated . The K-means algorithm is not succeded in the presence of variations in intensites of the images. In these algorithms individual preprocessing step is to be computed to achieve bias field correction. Ion this method there is no requirement of preprocessing for intensity variations and then the bias field correction. This methods leads to a repeat process. This method makes a fresh proposal for finding out the bias field and segmentating the tissue using energy minimisation.

This method performs for both estimating bias field and segmentation of tissues in energy minimisation process to minimise components of an magnetic resonance brain image, bias field uses for differentiating the tissues and the true image is for finding physical properties the tissues. The process MICO is a rebousting process because of measure of energy in its variables.

2. LITERATURE SURVEW:

In Adaptive segmentation of magnetic resonance image data, Wells et al. finded a process depending on EM(expectation-maximization) algorithm for estimating the bias field and segmenting. Later this was made better by Guillemaud and Brady in finding out bias field of magnetic resonance images. However, the exception algorithm methods need good initialization either for estimating bias field or classification.It requires choices of belonging points for each class of tissues to execute initialization.These initializations which are immanent and frequently not bothering of correction of bias field automatically.

In this paper, we put forward a fresh approach for estimating the bias field and segmenting tissues by an energy minimisation. This method performs estimation of the bias field along with membership functions of tissues by energy minimisation method to minimize two multiplicative components of magnetic resonance image, bias field provides information about the variations in intensities and the true image provides the information of different properties of tissues.The spatial properties of these components completely reflects in their presentations and the proposed energy minimisation formulation. Our method, MICO (multiplicative intrinsic component optimization), is robust due to the relations of the energy function in each of its variables. The proposed MICO formulation can also be extended to 3D/4D segmentation with spatial/spatiotemporal regularization.

3. PROPOSED METHOD:

3.1PROCESS FLOW:

3.1.1 Decomposition of MR images into multiplicative intrinsic components

From process of being formed MR images, the mathematical equation of MR image $I(x)$ can written as

$$I(x) = b(x)\, j(x) + n(x) \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \quad (1)$$

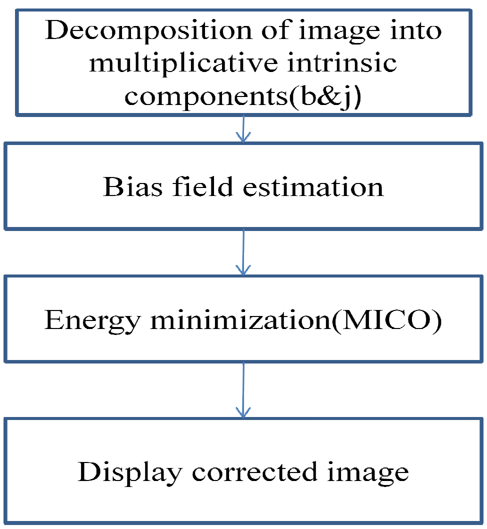

Fig 1: process flow for estimation and correction of bias field

we considered eq(1) as splitting of the magnetic brain image $I(x)$ into two intrinsic components, namely , b ,J and linear noise with no mean n. From this point of view, the approximate calculation of bias field and classification of tissues as energy minimisation situation of something neglizible splitting of the image $I(x)$ into intrinsic components namely b,J.We refer b , J are multiplicative components of the output magnetic resonance brain image $I(x)$. In this method , we inspect that image $I(x)$ as a function I: $\Omega\rightarrow$□on a same domain Ω. In the circumstances of vision of computer, an output image is divided similarly as shown in eq(1).

An output or output image I(x) can break into smaller parts as I = RS with two component (R) Reflectance image and (S) illumination image.Calculation of these images from an output image was the most important drawback in vision of computer. Many methods have put forward to rough calculation of the images from that of an orginal image based on distinct assumptions of these images. In this , we have considered b as bias field and J as true image as components of an output magnetic resonance brain images. We put forward a narrative method for calculating these components from output magnetic resonance brain image.

The method put forward is distinct from those methods for finding out the fraction of radiant energy that is reflected from a surface and lighting images in method computervision. In point of, the finding multiplicative intrinsic images are undetermined problem because not having the sufficient information concerning the non familiar images Reflectance image and illumination image.If we does'nt knowabout the usage of finding out b and J of the output magnetic resonance brain image I is an unresolved problem.

The method of solving the problem is splitting of the MR brain image I into components b , J in respective with the spatial properties which are used in finding the formulas of this method.

3.2. 2 Bias field estimation:

By efficient use of of b and properties we need suitable mathematical presentation their discription. In our process,bias field is presented by a one-dimensional which is the combination basis functions g1,...,gM, which smoothness property of bias field. In the approach of MICO to 1.5 T and 3 T magnetic resonance image data consumes the basic functions of first degree are 20 polynomials. The finding of bias field is obtained by finding optimal coefficients w1,.., wM in the one-dimensional combination $b(x) = \Sigma\, k^{M}=1^{wkgk}$. w = (w1, …, wM)^T represents the coloumn vector for coefficients w1, …, wM where $(\cdot)^T$ is inverse operator. The basic functions g1(x), .., gM(x) are presented by a function G(x) = (g1(x), …, gM(x))^T. Thus, bias field is represented as

$$b(x)=W^T G(x)\ldots\ldots\ldots\ldots\ldots(2)$$

The above representationis used for energy minimisation method for finding out the bias field.The piecewise constant is approximately the true image property which is specified precisely as follows. We considered that image area Ω consists of N different types of tissues. J(x) is roughly a constant c_i for x in i-th tissue. Replace with Ω_i the place where the i-th tissue is seen. Each place or region (tissue) Ω_i can be presented by its members function u_i. In the most suitable situation where every volume element consists of only single tissue type, the members function u_i is a binary members function, with ui(x) = 1 for $x \in \Omega_i$ and ui= 0 for $x \notin \Omega_i$.

In actuality, one volume element may consist much tissues types due to incomplete volume effect, specially at the action of interfacing neighboring tissues. In this condition , the N tissues are presented by fuzzy members function ui(x) that takes values 0 and 1 and fulfill $\Sigma\, i^N = 1^{ui\,(x)} = 1$. The fuzzy member function $u_i(x)$ value can be understand as percentage of i-th tissue in the volume element x. Such members functions u1, …., uN is presented by a vector in column form as u = (u1,…, uN)^T, whereas T is inverse operator.

The member functions and constants, and true image is given by

$J(x) = \sum_{i=1}^{n} ci u_i(x)$…………(4)

In this condition the members functions are two functions, function in eq(4) is the piecewise function, as J(x) = ci for x $\in \Omega i = \{x: u_i(x) = 1\}$. The binary members functions u_1, .., u_N represents difficult classification result, and corresponding places Ω_1,........, Ω_N forms a division of image domain area Ω, such that $\cup_i^N =1^{\Omega i} = \Omega$ & $\Omega_i \cap \Omega_j = \emptyset$.Basically, fuzzy members functions u1, …, uN consists of values 0 and 1 represent a easy classification result .Depending on eq (1), we put forward an energy minimisation method for finding out of occurring of bias field and segmenting of tissues. The result for tissue classification is specified by the members function u = (u1, …, uN). The bias field b which is estimated is accustomed to create corrected bias field image, which is calculated as I/b.

3.2.3 Energy minimisation

Energy minimisation could accomplished by an alternative minimizing F_q(u, c, w) concerning variables specified by fixing the other . The optimization of F_q(u, c, w) concerning each variable is shown below

Optimization of c

For constant w & u = (u1, …., uN)^T, energy function F(u, c, w) can be decreased by concerning c variable . It is simple to indicate F(u, c, w) which is minimised by c=ĉ=($\hat{c}_1$,…, $\hat{c}_N$)^T with

$$\hat{C}_i=\frac{\int_\Omega I(x)b(x) \cup_i^q(x)dx}{\int_\Omega b(x)*b(x) \cup_i^q(x)dx}, \text{ i=1, N…… (5)}$$

I. Optimization of w and finding out the bias field

For constant valus of c and u, we decrease energy function F (u, c, w) by concerning w variable . This is accomplished by work out the equation $\frac{\partial F}{\partial w}$=0. It's simple to prove that

$$\frac{\partial F}{\partial w}=-2v+2Aw$$

Where v is M-dimensional vector in the column form is given by

$v=\int_\Omega G(x)I(x)(\sum_{i=1}^{N} c_i \cup_i^q(x))$ dx…… (6)

Where A is matix with same no.of rows and same no.of columns

$A=\int_\Omega G(x)G^T(\sum_{i=1}^{N} c_i{*}c_i \cup_i^q(x))$dx:….(7)

The equation $\frac{\partial F}{\partial w}$=0 is conveyed as a one-dimensional equation:Aw =v.From these we can estimate the biase field equation as

b^(x)= ŵ^{T}G(x).

It is indicated that A matrix is not a singular matrix. Therefore,from eq(7), the vector ŵ is clearly expressed as

$$\hat{w} = (\int_\Omega G(x)G^T (\sum_{i=1}^{N} c_i{*}c_i \cup_i^q(x))\, dx)^{-1}\int_\Omega G(x)I(x)\, (\sum_{i=1}^{N} c_i \cup_i^q(x))\, dx \text{… (8)}$$

The ideal vector ŵ is given by eq(8), the bias field estimation equation is represented as follows

b^(x) = ŵ ^{T}G (x) …….. (9)

III.Optimization of u

For the minimization of u, we considered the circumstance as q >1. For constant values of c and w, we decrease the energy function F (u, c, w) dependent on the constraints that u ∈ U. It indicates F (u, c, w) is minimised at u = Û= ($\hat{U}_1$, $\hat{U}_N$)^T, given by

$$\hat{U}_i(x)=(\frac{(\delta i(x))}{\sum_{i=1}^{N}(\delta j(x))})^{1/1-q}, \text{ i=1,…..,N………(10)}$$

Where,

$$\delta_i(x) = (I(x)-w^T G(x)c_i)^2$$

For q = 1, it indicates that Û is given by

$$\hat{U}_i(x)=\begin{cases} 1, & i=i_{min}(x); \\ 0, & i\neq i_{min}(x). \end{cases}$$

Where $i_{min}(x) = \text{argmin}\{\delta_i(I(x))\}$.

4. RESULTS

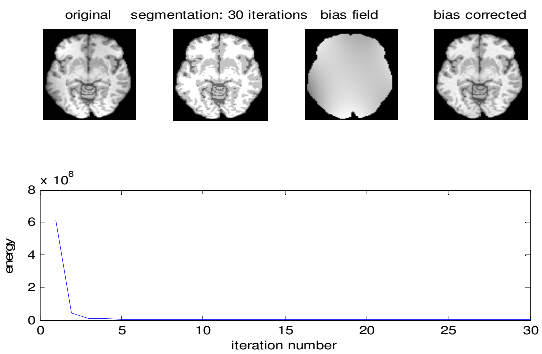

Fig 2.During initialization

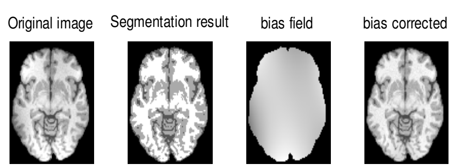

Fig 3. Bias corrected image

This method was broadly tested not only the synthetic data but also on real magnetis resonance image data. In above figures the fig2&3 shows experimental results for synthetic and real magnetic resonance(MR) brain image and also some images with huge intensity variations

5. CONCLUSION AND FUTURE SCOPE:

The method MICO(multiplicative intrinsic component optimization), for estimating bias field and segmentating magnetic resonance brain images in energy minimisation formulation is robust, efficient and accurate than the existing method. This method can also be applied successfully to 1.5T and 3T MR images .

This MICO formulation needs to be extended to 3D/4D tissue segmentation with spatial/spatiotemporal regularization.

6. REFERENCES:

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