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HEURISTICALLY IMPROVED BAYESIAN SEGMENTATION OF BRAIN MR IMAGES

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ABSTRACT
One of the major tasks or even the most prevalent task in medical image processing is image segmentation. Among them, brain MR images suffer from some difficulties such as intensity inhomogeneity of tissues, partial volume effect, noise and some other imaging artifacts and so their segmentation is more challenging. Therefore, brain MRI segmentation based on just gray values is prone to error. Hence involving problem specific heuristics and expert knowledge in designing segmentation algorithms seems to be useful. A two-phase segmentation algorithm based on Bayesian method is proposed in this paper. The Bayesian part uses the gray value in segmenting images and the segmented image is used as the input to the second phase to improve the misclassified pixels especially in borders between tissues. Similarity index is used to compare our algorithm with the well known method of Ashburner which has been implemented in Statistical Parametric Mapping (SPM) package. Brainweb as a simulated brain MRI dataset is used in evaluating the proposed algorithm. Results show that our algorithm performs well in comparison with the one implemented in SPM. It can be concluded that incorporating expert knowledge and problem specific heuristics improve segmentation result. The major advantage of proposed method is that one can update the knowledge base and incorporate new information into segmentation process by adding new rules.

Keywords: Magnetic Resonance Imaging (MRI); Segmentation; Bayesian classifier; Heuristics

INTRODUCTION
Image segmentation is the process of dividing an image into its constituent non-overlapping components (Khayati, Vafadust et al. 2008; Wang, Kong et al. 2008; Prakash, Singh et al. 2012; Loganathan and Kumaraswamy 2013; Nosrat, Karimi et al. 2013; Zeng, Han et al. 2014). This can be done in various forms such as labeling each pixel as a member pixel of each component which is a specific type of a wider research area known as classification. This labeling process relies mainly on gray value of pixels. Manual segmentation of images seems to be the first approach but it suffers from a few imperfections. First of all, it is highly time consuming and for large databases of images seems to be impossible. Furthermore, it is prone to personal errors and there is not enough confidence in its accuracy (Saha and Maulik 2014; Wang, Vachet et al. 2014). That is, the manually segmented versions of one specific image which is done by two different experts or by one expert in different times mostly are different. These are what we call them inter-rater and intra-rater inconsistency (Park, Kang et al. 2006; Zhuowen, Narr et al. 2008). Therefore, finding automatic methods for segmenting images appears to be mandatory (Kumar and Arthanariee 2014; Rajchl, Baxter et al. 2014; Valverde, Oliver et al. 2014).

Nowadays, Magnetic Resonance Imaging (MRI) is a prevalent way of realizing human brain and mostly is utilized in diagnostics and therapeutics. Potential of diagnosing and characterizing diseases using MR images make them suitable in developing new pharmacotherapeutic schemes (Yang, Zheng et al. 2005; Albert Huang, Abugharbieh et al. 2009; Varghese, Kumari et al. 2014). Segmentation is a major issue in processing and analyzing MR images which impress the final results of analysis. Automatic segmentation of brain MR Images into its main tissues remains an inextricable problem in domain of medical image processing. First of all, noise may change the gray value of pixels which uncertain the segmentation results. Moreover, inhomogeneity in MR Images changes the gray value of pixels belonging to one tissue gradually and thus complicates their segmentation. Furthermore, the limitation on image resolution leads to partial volume effect in which one voxel may include parts from more than one tissue. Other imaging artifacts such as calibration parameters also make segmentation of MR Images more complicated (Pham and Prince 1999; Brouwer, Hulshoff Pol et al. 2010; Maa, Tavaresa et al. 2010; Tohka, Dinov et al. 2010; Olfati, Tayeb et al. 2013; Agrawal and Sharma 2014).

In order to overcome above mentioned restrictions and designing powerful segmentation algorithms, the use of problem specific information and involving expert's knowledge (radiologists) seems to be beneficial (Tohka, Dinov et al. 2010; Maji and Paul 2014). In between the various methods used for brain MRI segmentation, the unsupervised Bayesian method has yielded acceptable results (Wells, Grimson et al. 1996; Broadhurst, Stough et al. 2006; Mahmood, Chodorowski et al. 2014). Therewith, rule based methods have been accepted as way of involving experts' knowledge in brain MRI segmentation (Pham and Prince 1999; Zhibin, Tianshuang et al. 2008).

This paper aims to design a heuristic segmentation algorithm based on Bayesian method. In the proposed algorithm, Bayesian method is used to initially segment brain MRI into three major tissues named as Cerebrospinal Fluid (CSF), Gray Matter (GM) and White Matter (WM). Afterward, a heuristically developed classifier which is designed to incorporate experts' knowledge into the problem is exploited to make corrections on fine details of brain MRI. Anatomical constraints of brain structures especially in borders between tissues and inconsistent adjacent voxels are used to extract brain model characteristics and finally extracting heuristic rules to improve the segmentation process. Important constraints such as inconveniency of distinct small tissue pieces and the need to annex them to the dominant neighbor tissue, integrity of cerebrospinal fluid (CSF) and cortex, impossibility of white matter and background pixels adjacency and etc are used as heuristic information in developing the algorithm.

In this paper, section 2 explains the method used, Subsection 2.1 interprets Bayesian method and subsection 2.2 describes the second heuristic part of the algorithm. In section 3 the simulation results are described and compared with the segmentation method implemented in SPM (Ashburner and Friston 2005). Finally section 4 discusses the achieved results.

METHODOLOGY

Proposed algorithm uses Bayesian classifier as the core method. The heuristic classifier at the second stage of algorithm makes final decision about the labels of each voxel based on the results of Bayesian algorithm. Gaussian Bayes classifier is used in proposed method and the expectation maximization (EM) is the method is used in maximizing likelihood probability of tissues. The iterative EM method assigns a posteriori probability to each voxel and according to the Bayesian classifier; class with maximum posteriori probability is the winning class that the voxel belongs to. Section 2.1 describes this method in more details.
After this initial classification of pixels, a heuristic classifier is used to finalize the segmentation algorithm. It uses the expert knowledge to improve the previously segmented image by Bayesian classifier. This knowledge is extracted and implemented in the form of tuning rules.

Bayesian method

Bayesian classifier is an unsupervised classifier designed based on Bayes' probability formula (equation 1).

$$p(w|x) = \frac{p(x|w) \quad p(w)}{p(x)}\text{, where } p(x) \neq 0 \qquad (1)$$

In which $p(w)$ is the priori probability of class w, $p(x|w)$ is the likelihood probability, $p(x)$ is the probability of gray value x and $p(w|x)$ is the posterior probability which makes the final classification. Each gray value x is classified as a member of class w if the posterior probability of it is highest in between all other classes. $p(x)$ is constant for all the classes and so the classification result is independent of it.

It has been shown that the distribution of gray values in all the tissues is normal and the *expectation maximization (EM)* is used for calculating these likelihood probabilities (Dempster, Laird et al. 1977; McLachlan and Krishnan 1997). It is constituted of two iterative steps, *Expectation* and *Maximization*. In *expectation step (E-Step)* given the current estimate of distribution parameters, the conditional posteriori probability of w is calculated using Equation (1). In *maximization step (M-Step)* based on the last classification performed in *expectation step (E-Step)*, it calculates new values of distribution parameters as well as a priori probability.

Given the normal distribution of intensities for each of brain tissues, there are two steps as follow:

E-Step:

$$p(w_i|x_j) = \frac{G(x_j,\mu_i^m,\sigma_i^m).p(w_i)^m}{\sum_k G(x_j,\mu_k^m,\sigma_k^m).p(w_k)^m} \qquad (2)$$

M-Step:

$$\mu_i^{m+1} = \frac{\sum_j x_j.p(w_i|x_j)}{\sum_j p(w_i|x_j)} \qquad (3)$$

$$(\sigma_i^{m+1})^2 = \frac{\sum_j (x_j-\mu_i^{m+1})^2.p(w_i|x_j)}{\sum_j p(w_i|x_j)} \qquad (4)$$

$$p(w_i)^{m+1} = \frac{\sum_j p(w_i|x_j)}{\sum_i \sum_j p(w_i|x_j)} \qquad (5)$$

E-Step aims to calculate the posteriori probabilities based on current estimate of distribution parameters and *M-Step* recalculates distribution parameters based on new posteriori probability. This iterative algorithm runs until converges. The convergence criterion is a minimum value for Mean Square Error (MSE) or a specified number of iterations.
The proposed method uses EM for maximizing likelihood in Bayesian classifier and at the end of this phase the classification result yields the segmented MR image.

Heuristic method

Herein, the heuristic classifier at second phase of the algorithm uses the Bayesian segmented image to improve it in subtle parts of borders between tissues (Cordón, Herrera et al. 2001). EM generated Gaussian probability distribution functions of gray values in each tissue are used to segment them based on the Bayesian method. 8-neighbors of each pixel are considered as neighboring system. Connected pixels of the same type constitute an object. Left/Right and Up/Down edges of neighboring rectangle are considered as opposite sides and accordingly, objects of each pair as opposite objects. The following rules are the most important heuristic rules ~~are~~ used in the algorithm.

- If “neighbors are WM”, then “new center is WM”
- If “neighbors are GM”, then “new center is GM”
- If “neighbors are CSF”, then “new center is CSF”
- If “neighbors are WM”, then “new center is not a CSF”
- If “neighbors are CSF”, then “new center is not a WM”
- If “old center is WM” AND “number of new objects is more than old ones”, then “new center is WM”
- If “old center is GM” AND “number of new objects is more than old ones”, then “new center is GM”
- If “old center is CSF” AND “number of new objects is more than old ones”, then “new center is CSF”
- If “neighbors have opposite separated WM objects”, then “new center is WM”
- If “neighbors have opposite separated GM objects”, then “new center is GM”
- If “neighbors have opposite separated CSF objects”, then “new center is CSF”

RESULTS AND DISCUSSION

Proposed method is tested on 30 simulated MR images of Brainweb and also on 30 real MR images of ADNI. The gold standard is the manually segmented version of these images. To evaluate the algorithm on each image, the sensitivity and specificity of all three tissues and similarity index (Wolda 1981) are used as the evaluation measures. These measures are defined in equations 6 and 7.

$$sensitivity = \frac{TP}{TP+FN} \qquad (6)$$

$$specificity = \frac{TN}{TN+FP} \qquad (7)$$

In which, TP stands for “True Positive”, TN stands for “True Negative”, FP stands for “False Positive” and FN stands for “False Negative” rates.
Average sensitivity and specificity of the segmented images for all three tissues are evaluated in both simulated and real groups. Table 1 shows the resulted sensitivity and specificity measures in simulated Brainweb images.

Table 1 Sensitivity & Specificity for simulated MRI tissues

Tissue	CSF	Gray Matter	White Matter
Sensitivity	79.8	91.2	89.45
Specificity	81.4	90.75	87.4

Average similarity index achieved in simulated images is 83.4% for SPM and 92.45% for proposed one. This can be shown in Figure 1.

Better segmentation achieved in our algorithm is visually manifest (e.g. in areas indicated by rectangles in Figure 1). This can be a visual reason for higher similarity index of our algorithm.

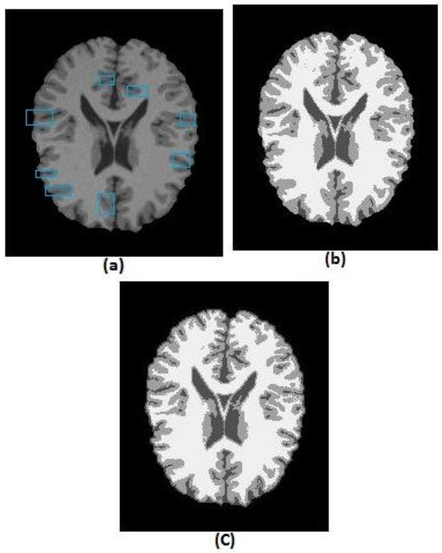

Figure 1. Brain Web sample image (a) Original Simulated Image; (b) Segmented by SPM; (c) Segmented by proposed algorithm

In a similar way, Table 2 reveals the resulted sensitivity and specificity measures in real images.

Table 2 Sensitivity & Specificity for real MRI tissues

Tissue	CSF	Gray Matter	White Matter
Sensitivity	81.65	94.5	88.2
Specificity	80.55	92.7	88

In a similar manner, average similarity index achieved in real images is 80.8% for SPM and 91.75% for proposed one. This can be shown in Figure 2.

Accordingly, better segmentation achieved in proposed algorithm is visually manifest (e.g. in areas indicated by rectangles in Figure 2) which express the higher similarity index of our algorithm.

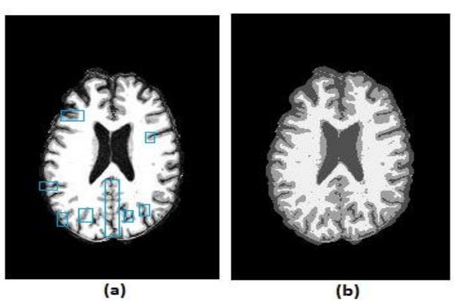

Figure 2. ADNI sample image (a) Original real Image; (b) Segmented by SPM; (c) Segmented by our algorithm

Both experiments show that using proposed algorithm can increase the accuracy of segmentation with respect to the Ashburner's one implemented in SPM. This can be because of using problem specific information and expert knowledge in improving segmentation results.
Figure 3 indicate the resulted similarity indexes for both groups of images using SPM and the proposed method.

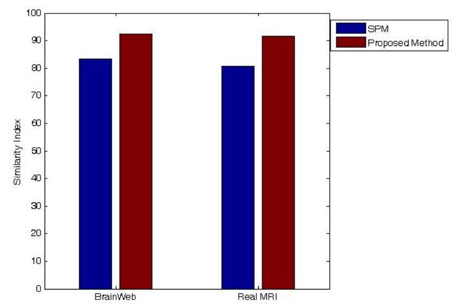

Figure 3. Resulted Similarity Index for both groups of images

CONCLUSION

Proposed method uses problem specific information and expert knowledge in segmenting Brain MR Images. This information enables it to make some improvements on misclassified voxels especially in border areas. The major advantage of using heuristic rules in ameliorating segmentation results is its flexibility in incorporating new knowledge into the algorithm. This can be done by simply updating the rules in the knowledge base.
As a suggestion for future work, it seems that using 3D MR images and 3D neighboring system can improve the segmentation power of the algorithm. This improvement is the result of using adjacent slices in configuring the neighboring system.

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