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Diagnosis of MS Lesions on MRI Images

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Abstract: The increasing prevalence of MS as well as its early diagnosis requires precise imaging technique to diagnose MS. Among available imaging techniques, MRI is an effective diagnostic technique for its high sensitivity, lack of ionizing radiation and non-invasiveness. Since the diagnosis of MS and its classification depends on the skill of the physician, smart techniques can help the doctor in diagnosing and classifying. In this study, brain MRI data was classified into normal and MS or MS risk groups using wavelet transform, HMM and ML. The proposed technique generally involves training data collection, pre-processing, lesion segmentation and final detection. Data collection was based on existing valid databases such as Paden database. Pre-processing is an optional step, which will not be required if the images are of good quality. Second, lesions were segmented in the images. Image segmentation was the most important part of the study. The focus of this study was to provide a powerful technique against the noise for this phase. A number of MS candidates appeared. Next, MS lesions were distinguished from the candidates. MS lesions were ultimately detected by maximized standard function of maximum likelihood (ML).

Keywords: MS disease, MRI images, wavelet transform, hidden Markov model, maximum likelihood

1. INTRODUCTION

Multiple sclerosis (MS) is a common disease of the central nervous system (brain and spinal cord) causing white patches or plaques in the brain by destruction of myelin sheath. This destruction can impair the parts of the nervous system which are responsible for communication and result in symptoms and health problems. MS appears in several forms and its new symptoms occur either in recurrence stages (relapsing forms) or over time (intermittent forms). There is no known cure for MS. Existing treatments improve functions after each attack and prevent new attacks. Although the drugs prescribed to treat MS are modestly effective, they are followed by side effects and poorly tolerated. The life expectancy of people with MS is 5-10 years less than others. MS occurs usually in ages 20-50 years and in women twice as men. MRI images can predict MS progression. Recent studies suggest that MRI scans can well show MS progression if gray matter of the brain is not affected by the disease. In an attempt to find the cause of MS progression, new techniques were used to detect damages to brain gray cells. It was found that the patients whose MRI images showed abnormal black spots in the gray matter of their brains were more exposed to physical disabilities. These abnormal black spots imply high iron accumulation in the area. The promising results of MRI scans taken of people with MS can be used for advanced computations and techniques which can accurately calculate the visible damages, particularly in gray matter and predict the course of the disease more accurately. MRI-based calculations of gray matter damages can be used as an alternative symptom of progression. Purpose of this study is to provide a method based on image processing techniques (wavelet transform and HMM) for optimal detection of MS lesions, to overcome the problem of other works (removing lesions with noise), facilitate and accelerate the implementation. Many studies have focused on MS lesion detection in MRI images, each involving certain advantages and disadvantages. Borumand et al [1] used modulation of MRI images to analyze MS plaques. Yazdanabadi [2] considered multi-stage classification and analysis of lesions and determined acuteness of the detected areas. Mohsenzadeh [3] used a new hybrid median filter to overcome the problem of

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noise in MRI images. Mohamadi et al. [4] used kmeans, NG and SOM techniques for zoning and segmenting lesions. Bassem [5] classified the brain tissues by support vector machine on FLAIR images for segmentation of MS lesions. Grimaud and Lado [6, 7] reported other studies conducted in recent years. The present study presents a new technique for detection of suspicious MS lesions based on wavelet transform and HMM. In this study, HMM with a tree structure is used for extracting statistical properties of wavelet transform.

2. MATERIALS AND METHODS

Data collection is based on existing valid databases such as Paden database. Pre-processing is an optional step, which will not be required if the images are of good quality. Second, lesions are segmented in the images. Image segmentation is the most important part of the study. The focus of this study is to provide a powerful technique against noise for this phase. A number of MS candidate areas will appear. Next, MS areas are distinguished from the candidate areas. MS lesions are ultimately detected by maximized standard function of maximum likelihood (ML).

3. THE PROPOSED TECHNIQUE FOR DETECTION OF MS LESIONS

3.1. Potential Lesions of the Image

Joint pixel likelihood of different classes is $f(x_r|c)$; $c = 1, 2, ..., N_c$. For segmentation of an image and detection of MS lesions, segmentation can be performed step by step based on a window with a certain size to check that the pixels of a window are assigned to a class. Notably, the window size can be very important. Accuracy will increase if windows with larger size are used for segmentation, because higher number of pixels is assessed and thus better data is acquired. However, there will be higher risk of pixels related to other classes. Although smaller window will lower this risk, the limited number of data will not provide enough accuracy of segmentation. In this study, the idea of dyadic blocks is used to implement segmentation windows. To do so, segmentation windows are recursively divided into four square sub-segments at any stage. This tree-like structure is shown in the figures below.

Note that i denotes the number of square sub-windows on each scale, and j is the scale index; $\rho(i)$ represents the parent window of the four secondary sub-windows. In segmentation of suspected MS lesions, it is crucial to have models of different tissues because it is difficult to achieve a perfect joint pixel likelihood. In this study, lesion segmentation is based on image field transform using wavelet, because this linear invertible transform provides elements which are more easier to model. Most available images, particularly gray images, have a structure in which wavelet transform provides precise segmentation. There are many statistical techniques to model the tissue structure; this study uses the hidden Markov model (HMM). The figure below shows the model extracted by HMM.

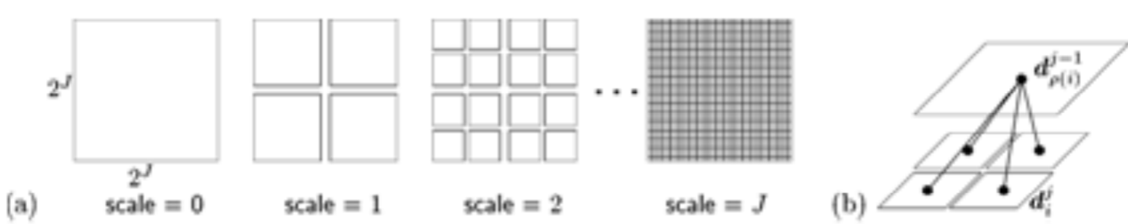

Figure 1: (a) tree structure of scale windows and (b) parent nodes and next generation

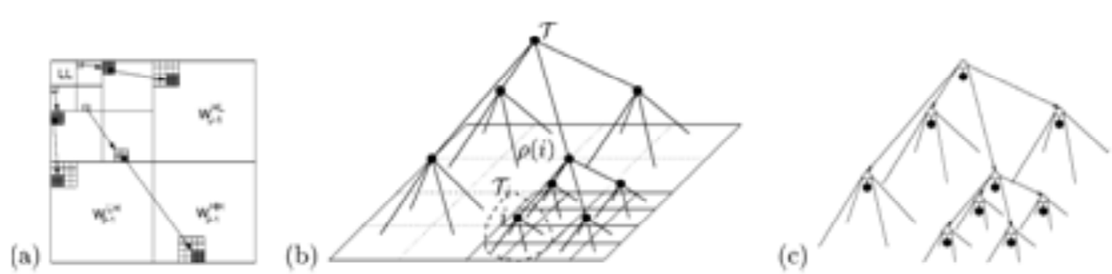

Figure 2: wavelet element dependence under different bands

Figure 2a shows wavelet element dependence at different scales in three samples. Figures 2b and 2c show the wavelet elements as black nodes and their connections with sub-segment elements for a sub-band. In Figure 2c, variable white nodes represent HMM state to control the Gaussian mixture model (GMM) of that node. Next, mixture model parameters are summed from variances of the double GMM and transient Markov probabilities in an M vector. Thus, HMM can serve as a large-scale model for approximation of almost all joint likelihoods of wavelet elements W, $f(w|M)$. For example, expectation maximization (EM) can be used to estimate HMM parameters. HMM is a tree with an interesting structure which can match the windows. Any sub-tree of a tree HMM is itself a tree HMM starting from i-th node which models the statistical behavior of wavelet elements of the d_i window. Therefore, likelihood of each window is considered as $f(d_i|M)$ in modelling the image. Now, the images can be segmented using this tool.

Let a tree HMM be trained for each tissue class $c \in \{1, 2, ..., N_c\}$ based on M_c parameters; now, consider the wavelet transform state, $\tilde{w}$, of a test image, $\tilde{x}$, containing these tissues. The calculated multi-scale likelihood expressed for different windows will be based on each tree HMMs causing $f(\tilde{d}_i|M_c), c \in \{1, 2, ..., N_c\}$, for any dyadic image, d_i. By multi-scale likelihoods, the tested image segmentation can be easily performed based on maximum likelihood (ML) as $\hat{c}_i^{ML} = \arg c \in \{1, 2, ... N_c\}$. This segmentation results in a series with J members of different segmentations: $\hat{c}_i^{ML}, j = 0, 1, ..., J-1$. For detection of suspicious MS lesions, an image of the MS tissues is first selected to train tree HMMs. Figure 3 shows an example of this process. Then, a test image, as shown in Figure 4, is considered for segmentation using above mechanism by a tree structure of windows. Figure 5 shows the result of final segmentation for the last scale considered.

Figure 3: MS tissue

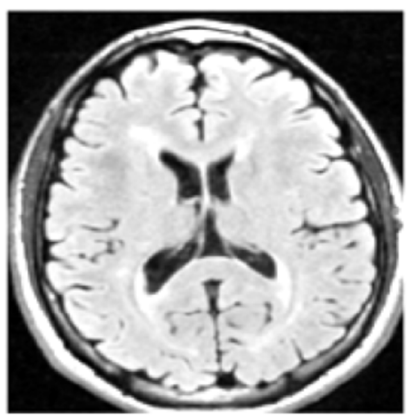

Figure 4: test image

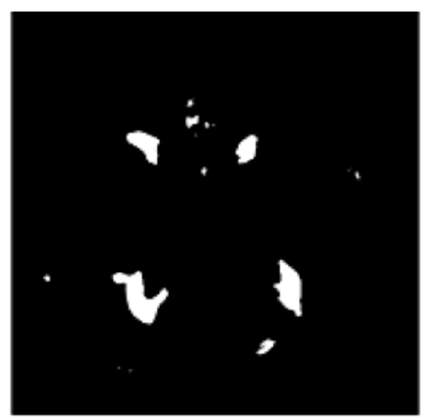

Figure 5: results of the proposed technique

Wavelet Transform and Dyadic Windowing

Wavelet transform is able to show certain important data of the image. This study focuses on the simplest type of wavelet transform based on Haar wavelet. Haar wavelet elements can be generated for an image by four two-dimensional wavelet filters including local leveler $h_{LL} = \frac{1}{2}\begin{pmatrix} 1 & 1 \\ 1 & 1 \end{pmatrix}$, horizontal edge detector $g_{LH} = \frac{1}{2}\begin{pmatrix} 1 & 1 \\ -1 & -1 \end{pmatrix}$, vertical detector $g_{HL} = \frac{1}{2}\begin{pmatrix} 1 & -1 \\ 1 & -1 \end{pmatrix}$ and diagonal edge detector $g_{HH} = \frac{1}{2}\begin{pmatrix} 1 & -1 \\ -1 & 1 \end{pmatrix}$.

To calculate the wavelet transform of a $2^J \times 2^J$ digital image (x), the matrix u is in the form of:

$$u_J[k, l] = x[k, l], \ 0 \le k, l \le 2^J - 1 \tag{1}$$

Then, the resulting matrix u_J is convolved by the expressed wavelet filters and other samples in both directions k

and l are removed. The resulting sub-band images are in the form of $u_{J-1}, w_{J-1}^{LH}, w_{J-1}^{HL}, w_{J-1}^{HH}$, each having a size of $2^{J-1} \times 2^{J-1}$. The results are set in a $2^J \times 2^J$ matrix as follows:

$$\begin{bmatrix} u_{J-1} & w_{J-1}^{HL} \\ w_{J-1}^{LH} & w_{J-1}^{HH} \end{bmatrix} \tag{2}$$

Then, filtering and downsampling continues on the image u_{j-1} for J iteration, u_j, $0 \le J \le J-1$.

Scaling coefficient matrix is the gradually leveled version of the original image u_J and the matrices of wavelet coefficients w_j^{LH}, w_j^{HL}, and w_j^{HH}, are the filtered high and band pass frequency, the detected horizontal and vertical edges and diagonal edges, respectively.

For example, the magnitude of the wavelet coefficient $w_{J-1}^{LH}[k,l], 0 \le k, l \le 2^{J-1}-1$ will be large if the 2 × 2 block window of the image involves horizontal edges, and vice versa. The 2 × 2 block window is written as:

$$\begin{bmatrix} x[2k,2l] & x[2k,2l+1] \\ x[2k+1,2l] & x[2k+1,2l+1] \end{bmatrix} \tag{3}$$

Iterative calculation for a Haar wavelet coefficient of a 2×2 block of an image results in a quad tree on wavelet coefficients in each sub-band. For dyadic windowing, iterative filtering is first done for the scale of zero and only LH band is examined. Then, the tree work will continue for more accuracy. In fact, each wavelet coefficient, such as $w_j^{LH}[k,l]$, analyzes the same areas of the original images that the four coefficients $w_{j+1}^{LH}[2k,2l]$, $w_{j+1}^{LH}[2k,2l+1]$, $w_{j+1}^{LH}[2k+1,2l]$, $w_{j+1}^{LH}[2k+1,2l+1]$ of the next sub-series do. Coefficients on a branch are called descendent from one node to the next and ancestor in the reverse direction. If the iterative filtering ends on the scale $j > 0$, there will be a large number of significant wavelet coefficients in each sub-band. Let W be the series of all wavelet coefficients; w^{LH}, w^{HL}, and w^{LH} are defined as the series of all coefficients in the sub-bands. The modeling framework presented in this study considers w_i as the realized random variable w_i and w as the realized random field of the wavelet W. Then, scale of the i-th factor is defined by $J(_{i)}$, in the quad tree of the considered sub-band. The parent ascendant nodes of i-th node are defined by $\rho_{(i)}$. $\mathcal{T}_i$ is defined as a sub tree of wavelet coefficients with the head node i including the coefficient w_i and its descendent.

There is a clear match between wavelet coefficients and dyadic windows based on two-dimensional Haar wavelet transform, which is obtained by iterative stepwise division of images to four segments. In fact, each $d_i^j s$ is obtained by dividing a square window at scale of j-1 to four sub-segments. Note that, all wavelet coefficients under the tree $\mathcal{T}_i$ starting from w_i are dependent on pixel values in d_i. To model each wavelet element W_i using HMM, a hidden state S_i, taking the value $m = S, L$, is considered for each wavelet element. This refers to the small and large variance. Likelihood of each wavelet element W_i is:

$$f(w_i) = \sum_{m=S,L} P_{S_i}(m)\, f(w_i \mid S_i = m) \tag{4}$$

$$f\left(w_i \mid S_i = m\right) = N\left(\mu_{i,m}, \sigma_{i,m}^2\right), \qquad P_{S_i}(S) + P_{S_i}(L) = 1 \tag{5}$$

Let small wavelet elements have low variance Gaussian likelihood and large wavelet elements have high variance Gaussian likelihood; they are modelled by these two likelihoods. To control the variance of these two Gaussian likelihoods in the model, durability of small and large wavelet elements is examined in the tree structure. For example, state transition probabilities $\varepsilon_{i,m'}^{\rho(i),m}$ for m, $m' = S, L$ represent small or large W_i based on small or large upstream node $W_{\rho(i)}$ for two hidden states $\{S_{\rho(i)}, S_i\}$. For any i, a state transition probability matrix is defined as follows:

$$f\left(w_i \middle| S_i = m\right) = N\left(\mu_{i,m}, \sigma_{i,m}^2\right), \qquad P_{S_i}(S) + P_{S_i}(L) = 1 \tag{6}$$

As the focus of this study is gray images, $\varepsilon_{i,S}^{\rho(i),S}$ and $\varepsilon_{i,L}^{\rho(i),L}$ are large for their durability.

Tree HMM for Wavelet Elements

A complete wavelet transform consists of three sub-bands with tree parallel quad trees. For example, i-th node in LH, HL and HH of the quad tree corresponds to the same dyadic window d_i in the image.

The three sub-bands of wavelet transforms in this case are statistically independent. A full M representing the tree HMM of wavelet elements of an image involves three tree HMMs characterized as $M = \{\theta^{LH}, \theta^{HL}, \theta^{HH}\}$. Thus, the tree HMM is a parametric tree model to describe joint likelihood of wavelet elements. For independent sub-bands, we can write:

$$f(w|M) = f(w^{LH}|\theta^{LH}) f(w^{HL}|\theta^{HL}) f(w^{HH}|\theta^{HH}) \tag{7}$$

Calculation of Multi-scale Likelihood

By a series, M, of tree HMM parameters and wavelet transform of the test image, $\tilde{w}$, calculation of the likelihood $f\left(\tilde{w} \middle| M\right)$ is straightforward. Therefore, likelihood can be calculated for all dyadic windows of the image simultaneously in an upward swipe through the tree structure. First, likelihood of a sub-tree, $\mathcal{T}_i$, of wavelet elements starting from a node, w_i, of one of the sub-bands is calculated. Let this sub-band contain tree HMM parameters θ; by upward swipe of the quad tree to the node i, the conditional likelihood, $\beta_i(m) = f(\mathcal{T}_i|S_i = m, \theta)$, is derived. Thus, likelihood of elements in $\mathcal{T}_i$ can be calculated as follows:

$$f\left(T_i \middle| \theta\right) = \sum_{m=S,L} \beta_i(m)\, p(S_i = m|\theta) \tag{8}$$

Wavelet elements of the square window d_i include three segments $\mathcal{T}_i^{LH}$, $\mathcal{T}_i^{HL}$, $\mathcal{T}_i^{HH}$. Using three upward swipes of tree HMM, the likelihood $f(\mathcal{T}_i|\theta)$ is easily calculated for each sub-tree. Assuming independent sub-band, we have:

$$f(d_i|M) = f(\mathcal{T}_i^{LH}|\theta^{LH})\, f(\mathcal{T}_i^{HL}|\theta^{HL})\, f(\mathcal{T}_i^{HH}|\theta^{HH}) \tag{9}$$

Using the above equation, likelihoods can be calculated for each tissue model of each square dyadic window.

Figure 6: Block diagram of the proposed lesion detection technique

3.2. Results of Software Simulations

For simulations, MS-related MRI database contains images of MS masses derived from Paden database. This section evaluates the accuracy of detected suspicious MS lesions. The goal is to compare the proposed technique with the results of MS detection on MRI images by the expert.

- Similarity index (SI): $SI = 2 * \frac{A \cap B}{A + B}$

- Intersection-to-union ratio: $R = \frac{A \cup B}{A \cap B}$

where *A* and *B* represent MS images extracted by the expert and by the computer. SI is used here for evaluation of results.

Table 1
Results of software simulations

Result	*Sample/number of samples*
100%	98/model images
92%	52/test images
96%	150/total images

As the results show, the proposed technique could detect all simple cases (model) and 92% of complex samples (tests) where suspicious lesions cannot be easily detected. The total rate of detection was 96%.

4. EVALUATION AND COMPARISON OF SIMILAR TECHNIQUES AND THE PROPOSED TECHNIQUE

In recent works, authors have focused on improved detection of brain lesions, particularly MS lesions, which is relatively difficult. They have used several algorithms including the technique used in other studies [6, 7], along with HMM [8] which achieved relatively good results. However, there have been difficulties in setting edges; therefore, they use different techniques to solve this problem and perform the segmentation based on edges. However, it is likely to ignore different lesions for labeling. Literature review shows that k-means offline/online, NG and SOM algorithms are useful for unsupervised processes for segmentation of brain MRI and differentiation of brain tissues. They can be used as a convenient and efficient tool to provide doctors with additional auxiliary images to increase accuracy, reduce diagnosis and treatment time, and facilitate this process. In the near future, they can pave the way for automatic and reliable processes of diagnosis and treatment. By comparing the detection technique of MS lesions on MRI images using image processing and artificial neural networks (ANNs) with other studies, it can be concluded that image processing algorithms and ANNs can provide acceptable results for correct detection of MS lesions. Bassem [10] used SVM algorithm for classification phase. They provided their images from different sources; nevertheless, they could detect 95% of lesions correctly. Mohammad Khanlu et al used fractal analysis for classification phase and extracted 92% of lesions correctly in input images to the algorithm. As this technique detected MS lesions on MRI images using image processing and ANNs, image processing was also used for segmentation. However, output of this phase included both MS lesions and artifact areas which are not lesions. For classification by a back-propagation ANN, many artifacts can be isolated from MS lesions. Although 96% of lesions appeared in the image, several artifacts also appeared in the output. The number of artifacts can be reduced by increasing the number of neurons in the hidden layer of ANN and training the network by higher number of images. In cases evaluated by the proposed technique, ~84% lesions were detected on average, which is acceptable for doctors. The detected lesions included acute (55%), average (35%) and weak (10%) lesions. Moreover, 96% of cases were detected correctly. This technique can be used to evaluate MS lesions to facilitate and accelerate the lesion detection and segmentation processes. Finally, the proposed technique outperformed other detection techniques. Using HMM, wavelet transform and maximum likelihood, this technique provides higher accuracy for detection of lesions.

5. CONCLUSION

This study addressed the detection of MS lesions on MRI images. Data collection was based on existing valid databases such as Paden database. MS lesions were ultimately detected by maximum standard function of maximum likelihood (ML). The purpose of this study was to evaluate the classification of data resulting from brain MRI into two groups, normal and MS/MS risk, using wavelet transform, HMM and maximum likelihood. The detected lesions included acute (55%), average (35%) and weak (10%) lesions. Moreover, 96% of cases were detected correctly. The results showed that the proposed technique outperformed other techniques of lesion detection.

References

[1] Akmal A. Younis, Bassem A. Abdullah, Pradip M Pattany, and Efrat Saraf-Lavi. *Multiple Sclerosis Lesion Segmentation in Multi-Channel MRIs using Texturalbased SVMs.* s.l.: Journal of the Digital Imaging, 2011.

[2] Bassem A. Abdullah, Akmal A. Younis, Pradip M. Pattany, and Efrat Saraf-Lavi. *Textural based SVM for MS Lesion Segmentation in FLAIR MRIs* USA: Open Journal of Medical Imaging, 2011.

[3] Bassem A. Abdullah, Akmal A. Younis, and Nigel John. *Multi-Sectional Views Textural based SVM for MS Lesion Segmentation in Multi-Channels MRIs.* USA: The Open Biomedical Engineering Journal, Dec. 2011.

[4] F. Fazekas, F. Barkhof, M. Filippi, R I Grossman, D. KB Li, W. I. McDonald, H. F. McFarland, D. W. Paty, J. H. Simon, J. S. Wolinsky, and D. H. Miller *The Contribution of Magnetic Resonance Imaging to the Diagnosis of Multiple Sclerosis.*. s.l.: Neurology, 1999.

[5] Y. Miki, M.A. van Buchem, R.I. Grossman. *Multiple sclerosis lesion quantifiction using fuzzyconnectedness principles.* J.K. Udupa, L. Wei, S. Samarasekera, s.l.: IEEE Trans. Med. Imag, 1997, Vol. 598.

[6] A. P. Zijdenbos, R. Forghani, and A. C. Evans. *Automatic "pipeline" Analysis of 3-D MRI Data for Clinical Trials: Application to Multiple Sclerosis".* s.l.: IEEE Transactions on Medical Imaging, 2002.

[7] Khadem, Mohammad Shajib. Göteborg, *MRI Brain image segmentation using graph cuts.* Sweden: Master of Science Thesis, 2010.

[8] R. Khayati, M. Vafadust, F. Towhidkhah, and S. M. Nabavi. *Fully Automatic Segmentation of Multiple Sclerosis Lesions in Brain MR FLAIR Images using Adaptive Mixtures method and Markov Random Field Model.* s.l.: Computers in Biology and Medecine, 2008.

[9] A. O. Boudraa, S MR Dehakb, Y. M. Zhu, C. Pachai, Y. G. Bao, and J. Grimaud. *Automated Segmentation of Multiple Sclerosis Lesions in Multispectral MR.* USA: Computers in Biology and Medecine, 2000.

[10] K. V. Leemput, *Quantitative Analysis of Signal Abnormalities in MR Imaging for Multiple Sclerosis and Creutzfeldt-Jakob Disease.* PhD Thesis. s.l.: Katholieke Universiteit Leuven, 2001.