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ANFIS based Automated System for the Detection of Gadolinium Lesions in Brain MRI

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Abstract

Multiple sclerosis (MS) is a chronic disease that affects different parts of the central nervous system at different points of time. The central nervous system is made up of the brain and spinal cord. MS is an auto-immune disorder of the central nervous system characterized by the presence of Gadolinium lesions. In this paper, an intelligent technique is proposed for the automatic segmentation of Gadolinium lesions from the brain Magnetic Resonance Imaging (MRI) of MS patients. Since, manual interpretation of the lesions based on visual examination by radiologist/physician may lead to erroneous diagnosis when a large number of MRIs are analyzed; we propose an automated intelligent classification system. The proposed technique uses a trained classifier, Adaptive Neuro Fuzzy Interference System (ANFIS) to discriminate between the regions of MS lesions and non-MS lesion regions mainly based on the textural features. The proposed method consists of three stages, namely, pre-processing, feature extraction and classification. The classifier's goal is to classify subjects as normal and abnormal brain MRI. The main contribution of the proposed technique described in this paper is the use of textural features like Gray level co-occurrence features, Local binary pattern features, Gray level based features, Histogram and Wavelet features to detect Gadolinium lesions in a fully automated approach that does not rely on manually delineating the lesions. The obtained results exhibit a sensitivity of 72% and maximum accuracy of 99% which assures that the proposed method would be viable for use in clinical practice for the detection of Gadolinium lesions in brain MRI of MS affected patients.

Keywords: *MRI/CT, Multiple Sclerosis, Multi-Modal, ANFIS, Neural Network, Gadolinium.*

1. Introduction

Multiple sclerosis (MS) is an auto immune disease of the central nervous system. MS affects different parts of the central nervous system and it can affect the functioning of many parts of the body, i.e., when the immune system attacks tissues in the central nervous system, the messages the brain sends get interrupted. It may result in a variety of symptoms from blurred vision to severe muscle weakness and degradation, depending on the affected regions of the brain. To better understand this disease and to quantify its evolution, magnetic resonance imaging (MRI) is increasingly used nowadays. Manual delineation of MS lesions in MR images by human expert is time-consuming, subjective and prone to inter-expert variability. Therefore, automatic segmentation is needed as an alternative to manual segmentation. However, the progression of the MS lesions shows considerable variability and MS lesions present temporal changes in shape, location, and area between patients and even for the same patient, which renders the automatic segmentation of MS lesions a challenging problem. This is due, in part, to their variability in several aspects such as: texture and intensity, shape and size, and location across patients.

Furthermore, the majority of enhancing voxels are associated with non-lesional, normal structures. Most of these are blood vessels, but certain areas of healthy brain tissues also normally enhance. Moreover, noise in MRI may also produce enhancement similar to that of MS lesions. This makes the problem very difficult and can lead to many false positives (FPs). Existing methods for gadolinium lesion segmentation are not fully automatic.

In this paper, we propose a technique that uses textural features to describe the blocks of each MRI slice along with other features. The technique applies the classification process on slices of each sectional view of the brain MRI independently. For each sectional view, a trained classifier is used to discriminate between the blocks and detect the blocks that potentially include MS lesions mainly based on the textural features with aid of the other features. The blocks classification is used to provide an initial coarse segmentation of the MRI slices. The textural-based classifier is built using Adaptive Neuro Fuzzy Interference Systems (ANFIS), one of the widely used supervised learning algorithms that have be utilized successfully in many applications.

2. Literature Survey

A number of segmentation methods have been proposed by other researchers to address the problem of T2w lesion segmentation. Leemput *et al* [1] proposed a generative method by means of Expectation Maximization (EM) to detect lesions as outliers from the intensity distributions of healthy tissues. The method proposed by Wei et al combines the EM algorithm with template-driven segmentation, and partial volume effect correction to classify image pixels. In [2], Dugas–Phocion *et al* proposed adding a partial volume effect to the EM algorithm and using the Mahalanobis distance directly within the EM. Zijdenbos *et al* [3] proposed a segmentation method based on a neural network classifier. In spatial decision forests were used for automatic lesion detection by incorporating long range contextual features. These automatic T2w lesion segmentation methods typically perform pixel-wise classifications. Therefore, these methods are limited in their ability to exploit contextual dependencies in the classification task. In MRF is used to encode neighborhood relations through adapting an Ising model. However, since observations are not incorporated in the Ising model, it may lead to over-smoothing which is specifically not desirable where the structures of interest may only have a few pixels, as is the case here. Although contextual features are extracted from the observations, labels interactions are not considered.

Even though there have been many studies for T2w lesion detection, only a few have investigated the problem of enhancing lesion detection. Miki *et al* [4] proposed using fuzzy connectivity to delineate enhancing lesions. Their approach is not fully automatic, as it requires human confirmation after each enhanced area is found by the algorithm.

The study by He and Narayana [5] also uses a special pulse sequence as in to eliminate the false enhancements. Although it is a fully automatic approach, it requires prior segmentation of T2w lesions. Datta *et al* [6] proposed an automatic technique for the identification of enhanced regions based on morphological operations. However, their technique also needs pre segmentation of T2-w lesions in order to detect and remove non-lesion enhancements.

Bedell and Narayana [7] suggested using a special pulse sequence which increases the contrast between blood signal enhancement and lesion enhancement. In addition to the need for a special pulse sequence, this algorithm also requires user inputs for initial seed placement for detection of cerebro-spinal fluid (CSF) to eliminate enhanced areas caused by blood vessels inside CSF.

3. Proposed System Model

3.1 Preprocessing

Preprocessing is used to remove the noises from the MRI Brain image. It is also used to convert heterogeneous image in to homogeneous image. Anisotropic diffusion filter is used in MRI Brain image preprocessing. Brain images are prone to be affected by noise in digital imaging which can occur during image transmission and digitization. In the resultant image the neighboring pixels represent additional samples of the same value as the reference pixel, i.e. they represent the same feature. At edges, this is clearly not true, and blurring of features results. In this paper, we have used Anisotropic diffusion filtering to perform de-noising and image smoothing. Here, the neighboring pixels are ranked according to brightness (intensity) and the median value becomes the new value for the central pixel. Anisotropic diffusion filters can do an excellent job of rejecting certain types of noise, in particular, shot or impulse noise in which some individual pixels have extreme values. In anisotropic diffusion filtering operation, the pixel values in the neighborhood window are ranked according to intensity, and the middle value (the median) becomes the output value for the pixel under evaluation.

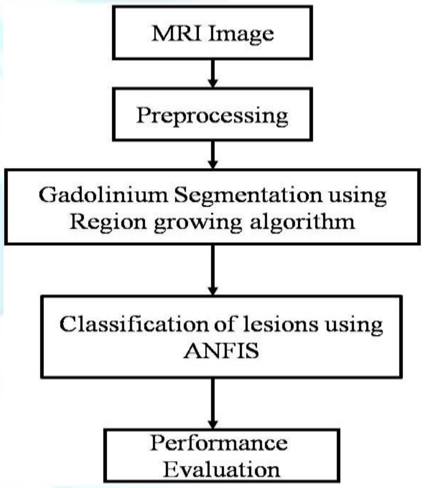


Fig. 1 Flow graph of proposed method.

3.2 Feature Extraction

3.2.1 GLCM features

The gray-level co-occurrence matrix (GLCM) is a statistical method that considers the spatial relationship of pixels, hence it is also known as the gray-level spatial dependence matrix. To identify texture in an image, we model texture as a two dimensional array gray level variation. This array is called Gray Level co-occurrence matrix. GLCM features are calculated in four directions which are 0°, 45°, 90°, 145° and four distances (1,2,3,4). Five statistical measures such as correlation, energy, entropy, homogeneity and sum of square variance are computed based on GLCM. The size of GLCM is determined by number of gray level in an image. For each of the formula: G is the number of gray level used. The matrix element $P(i,j \mid \Delta x,\Delta y)$ is the relative frequency with two pixels separated by pixel distance $(\Delta x,\Delta y)$, which occur within a given neighborhood, one with intensity i and other with intensity j.

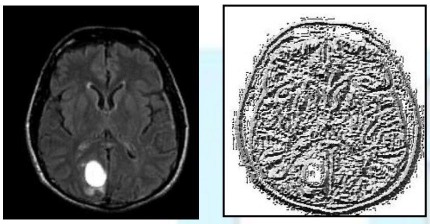
A gray level co-occurrence matrix (GLCM) contains information about the positions of pixels having similar gray level values. A GLCM P[i,j] is defined by first specifying a displacement vector d = (dx,dy) and counting all pairs of pixels separated by d having gray levels i and j.

3.2.2 Local Binary Pattern (LBP)

The local binary pattern (LBP) feature has emerged as a silver lining in the field of texture classification and retrieval. Ojala *et al* proposed LBPs, which are converted to a rotational in-variant version for texture classification. Various extensions of the LBP, such as LBP variance with global matching, dominant LBPs, completed LBPs, joint distribution of local patterns with Gaussian mixtures, etc., are proposed for rotational invariant texture classification.

The LBP operator on facial expression analysis and recognition is successful. Xi Li *et al* proposed a multi scale heat-kernel-based face representation as heat kernels is known to perform well in characterizing the topological structural information of face appearance. Furthermore, the LBP descriptor is incorporated into multi scale heat-kernel face representation for the purpose of capturing texture information of the face appearance.

The MRI image is divided into several regions from which the LBP feature distributions are extracted and concatenated into an enhanced feature vector to be used as an image feature descriptor. The source brain image and its LBP feature image are shown in Figure 2.



(a) (b)

Fig. 2 (a) Source brain MR image, (b) Local binary pattern feature MR image obtained using proposed method.

3.2.3 Gray Level based features

Since blood vessels are always darker than their surroundings, features based on describing gray-level variation in the surroundings of candidate pixels seem a good choice. Based on this, a set of gray level based descriptors were derived from homogenized images considering only a small pixel region centered on the described pixel. These features are given as follows,

$$F_1(x,y)= I_H (x,y) - \min \{I_H (s,t)\} \quad (1)$$

$$F_2(x,y)= \max \{I_H (s,t)\} - I_H (x,y) \quad (2)$$

$$F_3(x,y)= I_H (x,y) - \text{mean} \{I_H (s,t)\} \quad (3)$$

$$F_4(x,y)= \text{std}\{I_H (s,t)\} \quad (4)$$

$$F_5(x,y)= I_H (x,y) \quad (5)$$

The gray level features were extracted for the source image (Figure 2a) and are illustrated in Figure 3.

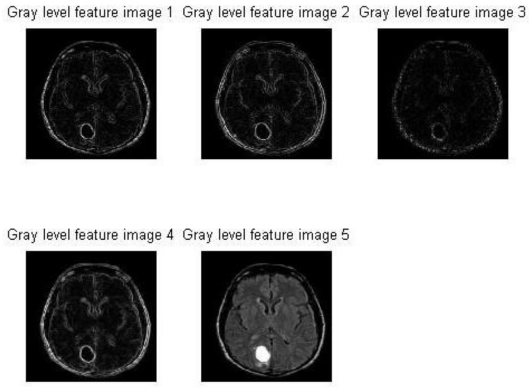


Fig. 3 Gray level based feature extracted MR image simulated using MATLAB.

3.2.4 Wavelet features

The gray-scale histogram of an image represents the distribution of the pixels in the image over the gray-level scale. It can be visualised as if each pixel is placed in a bin corresponding to the colour intensity of that pixel. All of the pixels in each bin are then added up and displayed on a graph. The frequencies of all the intensity levels can be seen, and the image can be analysed based on this graph.

The histogram is a key tool in image processing. It is one of the most useful techniques in gathering information about an image. It is especially useful in viewing the contrast of an image. If the grey-levels are concentrated near a certain level the image is low contrast. Likewise if they are well spread out, it defines a high contrast image.

3.2.5 ANFIS architecture

A multilayer feed forward adaptive network, consisting of an input layer, three hidden layers and an output layer, is adopted in this paper. The input layer is composed by a number of neurons equal to the dimension of the feature vector (nine neurons). Regarding the hidden layers, several topologies with different numbers of neurons were tested. A number of three hidden layers, each containing 15 neurons, provided optimal configuration. The output layer contains a single neuron and is attached, as the remainder units, to a nonlinear logistic sigmoid activation function, so its output ranges between 0 and 1. For the training of the network, there is a forward pass and a

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backward pass. The forward pass propagates the input vector through the network layer by layer. In the backward pass, the error is sent back through the network in a similar manner to back propagation.

4. SIMULATION AND RESULTS

To analyze the performance of the proposed algorithm to detect the Gadolinium lesions, the images obtained using the proposed methodology is compared with its corresponding ground truth images. The performance of the proposed technique is analyzed with the following parameters:

- Sensitivity [Se = TP / (TP +FN)]
- Specificity [Sp = TN / (TN +FP)]
- Positive predictive value [Ppv = TP / (TP+FP)]
- Negative predictive value [Npv =TN / (TN+FN)]
- Accuracy [Acc = (TP + TN) / (TP+FN+TN+FP)]

The parameters, Se and Sp define the ratio of well-classified lesion and non-lesion pixels, respectively. Ppv is the ratio of pixels classified as lesions that have been correctly classified. Npv is the ratio of pixels classified as background pixels that are correctly classified. Lastly, Acc is the ratio of total well-detected and classified Gadolinium lesion pixels. All these parameters help in defining the performance of our proposed technique as explained in the previous sections and are tabulated in Table 1.

Table 1: Performance evaluation of the proposed Gadolinium lesion segmentation method

Images	**Se**	**Sp**	**Ppv**	**Npv**	**Acc**
1	0.9987	0.9992	0.9811	0.9972	0.9963
2	0.9977	0.9954	0.9934	0.9999	0.9952
3	0.9877	0.9936	0.9383	0.9979	0.9935
Average*	0.9947	0.99607	0.97093	0.99833	0.9950

Se=Sensitivity; Sp= Specificity; Ppv= Positive Predictive Value; Npv=Negative Predictive Value; Acc=Accuracy.
*the average value is calculated for a set of 3 images considered.

The entire algorithm was developed based on MATLAB and the code takes 36 seconds per image on an average to run on a 2.1 GHz Intel Pentium Core i3 machine with 2GB RAM.

The original (source) images considered for our experiment, ground truth images of the same (manually segmented images by a physiologist) and lesion segmented images by our proposed method are depicted in Figure 4.

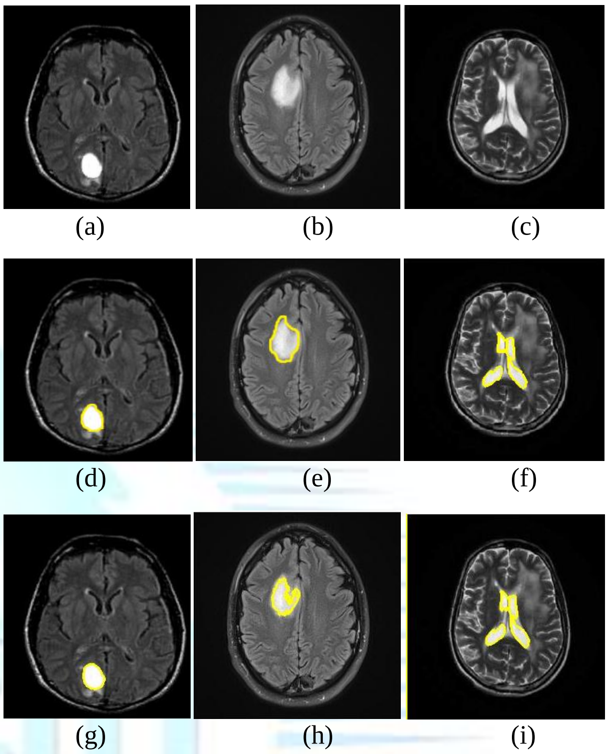

Fig. 4 (a-c) Source images, (d-f) Ground truth images, and (g-i) Gadolinium lesion identified images using proposed method.

The performance of our proposed algorithm using ANFIS is compared with SVM technique and is tabulated in Table 2. The same is graphically illustrated in Figure 5. The experimental results prove that the accuracy rate and sensitivity of proposed methodology to be higher compared with other conventional methods.

Table 2: Comparison of the values of various parameters obtained using ANFIS with SVM (better results are obtained for ANFIS methodology)

Methodology	**Se**	**Sp**	**Ppv**	**Npv**	**Acc**
SVM	0.72399	0.5071	0.93203	0.98951	0.9883
ANFIS	0.9947	0.99607	0.97093	0.99833	0.9950

Se=Sensitivity; Sp= Specificity; Ppv= Positive Predictive Value; Npv=Negative Predictive Value; Acc=Accuracy.
*only average values are tabulated.

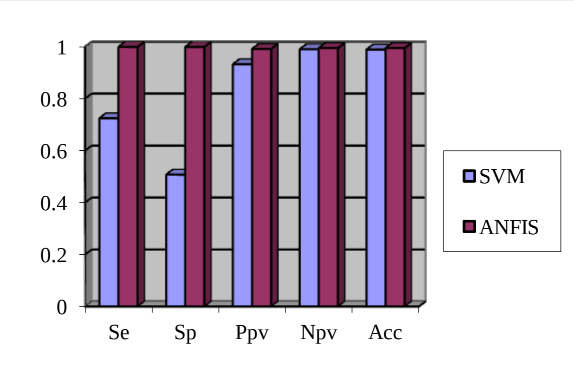

Fig. 5 Graphical representation of performance comparison of proposed method (ANFIS) with SVM.

5. CONCLUSION

The method employed in this paper has given better performance and proved to be an efficient classification model for classification problems with different dimensionality and different lesion sizes. The automated system has been developed for the classification of Gadolinium lesion into malignant and benign pattern with the aim of supporting radiologists in visual diagnosis. This paper has investigated a classification of brain MRI images using GLCM, LBP and many more features. The maximum accuracy rate of Gadolinium lesion classification by ANFIS (Adaptive Neuro Fuzzy Interference Systems) is 99%. For future work, GLCM features combined with various other features will be implemented using ANFIS to improve the results in classification of Gadolinium lesions of brain MR images. Using proper feature selection, the classification accuracy may be further improved efficiently.

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