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Curvelet Transform Based Brain Tumor Classification Using Soft Computing Techniques

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Abstract:
In this project, a new method for Brain Tumor Classification using Probabilistic ANFIS Classifier is proposed. The conventional method for computerized tomography and magnetic resonance brain images classification and tumor detection is by human inspection. Operator assisted classification methods are impractical for large amounts of data and are also non reproducible. Computerized Tomography and Magnetic Resonance images contain a noise caused by operator performance which can lead to serious inaccuracies in classification. Various features such as local binary pattern (LBP) and law's texture features are extracted from brain MRI images. These feature set are trained and classified by using Support vector machine (SVM) and ANFIS (Adaptive neuro fuzzy interference system) Classifier. This algorithm is independent of the tumor type in terms of its pixels intensity. The proposed method gives fast and better recognition rate when compared to previous classifiers. The main advantage of this method is its high speed processing capability and low computational requirements.

Key words: *MRI/CT,multi model,neural network,gadolinium*

1. Introduction

Multiple sclerosis (MS) is a common disorder of the central nervous system characterized by focal inlammatory lesions of the white matter (WM) disseminated in time and space. Magnetic resonance imaging (MRI) is widely used to diagnos and monitors the activity of this disease because of its sensitivity to the focal WM lesions, which appear hyper-intense on T2-weighted MRI, and hence are commonly called T2w lesions. T1-weighted (T1w) scans obtained after injection of gadolinium- based contrast agents can help to identify a subset of MS lesions that are actively inlamed.[1] Contrary to T2w le-sions, the enhanced lesions are typically very small (Fig. 1).[2] The number and volume of enhancing lesions are important markers of disease activity as they are more sensitive than clinical markers, such as relapses. Because of their sensitivity and predictive value, quantification of gad-enhancing lesions has become an important outcome measure in the development of drugs (e.g., anti-inlammatory drugs) for MS. Gad-enhancing lesions are generally segmented manually. However, manual delineation and analysis of gad -enhancing le-sions is very time consuming and subject to intra- and inter- rater variability. As clinical trials in MS involve huge amount of data from different centers, it is desirable to have an automatic seg-mentation method that is robust to data obtained on multiple different scanners.

Unfortunately, automatic identification of enhancing lesions is very challenging. This is due, in part, to their variability in several aspects such as: texture and intensity [Fig. 1(d) and (i)], shape and size [Fig. 1(e) and (j)], and location across patients [Fig. 1(c) and (h)]. Furthermore, the majority of enhancing voxels are associated with nonlesional, normal structures [Fig. 1(b) and (g)]. 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 dificult and can lead to many false positives (FPs).

Existing methods for gad -enhancing lesion segmentation de-scribed in the literature are either not fully automatic [1], [2], or they depend on nonstandard MRI acquisition sequences [2], [3], or they need prior segmentation of T2w lesions in order to remove the false enhancements [3], [4]. Relying on prior T2w segmentation is not desirable for several reasons. Firstly, au-tomatic T2w lesion segmentation itself is a challenging task [5]–[9] and introduces undesirable delays in the identification of gad-enhancing lesions. Secondly, as enhancing lesions are typically small in size, small errors in localizing T2w lesions (even in the order of few pixels) may lead to missing an enhancing lesion.

2. Literature Survey

A number of segmentation methods have been proposed by other researchers to address the problem of T2w lesion seg-mentation. Leemput *et al*. [5] 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.* [6] combines the EM algorithm with template-driven segmentation, and partial volume effect correction to classify image pixels. Dugas–Phocion *et al.* [7] proposed adding a partial volume effect to the EM algorithm and using the Mahalanobis distance directly within the EM. Zijdenbos *et al.* [8] proposed a segmentation method based on a neural network classifier. In [9], 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 [6]–[8]. Therefore, these methods are limited in their ability to exploit contextual dependencies in the classification task. In [5] MRF is used to encode neighborhood relations through adapting an *Ising* model [11]. However, since observations are not

incorporated in the Ising model, it may lead to over- smoothing [12] which is specifically not desirable where the structures of interest may only have a few pixels, as is the case here. In [9], 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 en-hancing lesion detection. Miki *et al.* [1] 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. Bedel and Narayana [2] 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 luid (CSF) to eliminate enhanced areas caused by blood vessels inside CSF. The study by He and Narayana [3] also uses a special pulse sequence as in [2] to eliminate the false enhancements. Although it is a fully automatic approach, it requires prior segmentation of T2w lesions. Datta *et al.* [4] proposed an automatic technique for the identification of enhanced regions based on morphological operations. However, their technique also needs presegmentation of T2-w lesions in order to detect and remove non-lesion enhancements.

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.

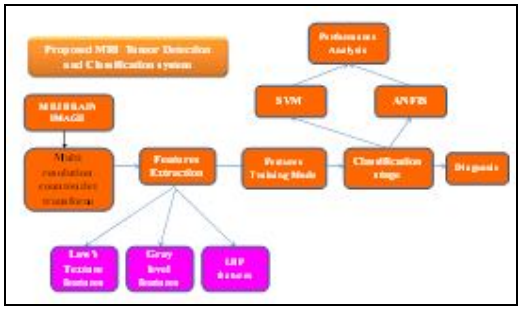

Figure 1

3.2. Feature Extraction

3.2.1. Haralick' texture features:

The most commonly used measures of texture, in particular of random texture, are the statistical measures proposed by Haralick. Unlike Laws' texture energy measures, some of Haralick's measures may not be directly related to the intersecting structures, spiculaions, and node-like patterns of architectural distortion, but they may provide useful information regarding the statistical properties of the given ROI or image. Haralick's texture measures are based upon the moments of a joint probability density function (PDF) that is estimated using the joint occurrence or co-occurrence of gray levels, known as the gray-level co-occurrence matrix (GCM), and may be computed for various directions and distances. GCMs were computed with unit pixel distance for the angles of 0 , 45 , 90 , and 135.

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. pro-posed a multiscale 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 multiscale 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 a image feature descriptor.

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. A set of gray-level-based descriptors taking this information into account were derived from homogenized images considering only a small pixel region centered on the described pixel.These features are

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

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

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

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

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

3.2.4.ANFIS Design

A multilayer ANFIS, 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 ANFIS 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. This choice was grounded on the fact of interpreting ANFIS output as posterior probabilities.

4. Simulation Results

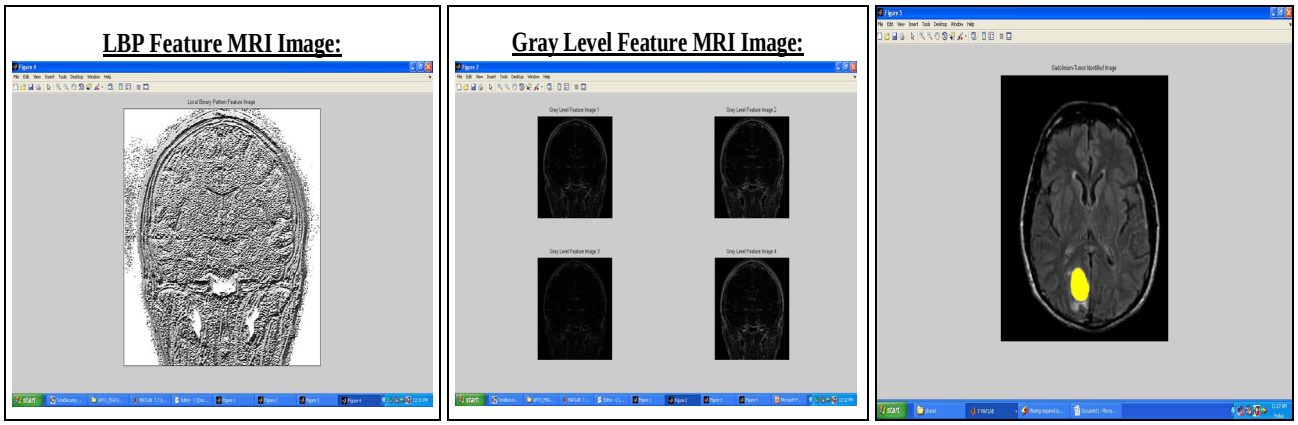

Figure 2, 3, 4

Performance Evaluation Parameters	Existing (SVM)	Proposed (ANFIS)
Sensitivity	0.8210	0.723995
Specificity	0.8672	0.999852
Positive Predictive Value	0.9102	0.990623
Negative Predictive Value	0.9327	0.994135
Accuracy	0.9528	0.994080

Table 1: ComparisonResults

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