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Tissue classification in magnetic resonance images through the hybrid approach of Michigan and Pittsburg genetic algorithm

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ABSTRACT

Magnetic resonance system generates image data, where the contrast is dependent on various parameters like proton density (PD), spin lattice relaxation time (T1), spin–spin relaxation time (T2), chemical shift, flow effect, diffusion, and perfusion. There is a lot of variability in the intensity pattern in the magnetic resonance (MR) image data due to various reasons. For example a T2 weighted image of same patient can be generated by different pulse sequence (Spin Echo, Fast Spin Echo, Inversion recovery, etc.) or on different MR system (1T, 1.5T, 3T, system, etc.) or using different RF coil system. Hence, there is a need for an adaptive scheme for segmentation, which can be modified depending on the imaging scheme and nature of the MR images. This paper proposes a scheme to automatically generate fuzzy rules for MR image segmentation to classify tissue. The scheme is based on hybrid approach of two popular genetic algorithm based machine learning (GBML) techniques, Michigan and Pittsburg approach. The proposed method uses a training data set generated from manual segmented images with the help of an expert in magnetic resonance imaging (MRI). Features from image histogram and spatial neighbourhood of pixels have been used in fuzzy rules. The method is tested for classifying brain T2 weighted 2-D axial images acquired by different pulse sequences into three primary tissue types: white matter (WM), gray matter (GM), and cerebro spinal fluid (CSF). Results were matched with manual segmentation by experts. The performance of our scheme was comparable.

1. Introduction

Image segmentation requirement is important in all MR image analysis tools, used for diagnosis and for planning treatment. These image analysis tools analyze MR images of different contrast characteristics like: T1 weighted (T1), T2 weighted (T2), and proton density (PD). Different contrast images (like T1, T2, and PD) can be acquired using different pulse sequences, which are decided by radiologist, based on region of interest, patient history, type of coil or type of MR system [1,2]. There are variations in the intensity profile of histogram of particular contrast image say T2 weighted acquired using different pulse sequence, or different coil or MR system supplied by different vendor. The same is true for other contrast images also. The intensity/histogram pattern for same contrast image for the same subject under different scanning conditions may be similar, but there are intensity variations for same pixel in the acquired images. This is visible, in shift of peaks and valleys in the histogram. With these intensity variations under different acquisition conditions, it is difficult to obtain anatomical segmentation boundaries based on intensity threshold alone and needs an adaptive segmentation procedure.

Thresholding for MR image segmentation is the simplest approach. Extensive surveys discussing various aspects of threshold are reported in the literature [3,4]. Threshold selection algorithms have been compared with the help of experimental results on a set of real life images or on a set of histograms [5,6]. There are good examples, which show that separating object and background regions with the help of first order and second order statistics give good results for a large class of MR images [7]. Normally the threshold is applied on the intensity values only.

However, dynamic range of soft tissue contrast is widespread in MR images. Moreover the transition across boundaries is gradual, which poses special challenge for segmentation of anatomical boundaries. Also other problems encountered are due to potential sources of errors, such as image noise, intensity non-uniformity, and factors related to image weightings. Any algorithm for segmentation of MR images should adequately address these problems.

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Accurate segmentation of anatomical and pathological boundaries in the brain structures is necessary to improve clinical utility of MRI.

Soft computing techniques deal with partial truth or decision making with imprecision and uncertainty. These techniques use fuzzy logic, neural network and genetic algorithms, which can play an important role in developing MR image segmentation techniques [8]. Fuzzy rule [9] based systems are based on models, describing the behavior of the system to be constructed from a set of "examples" in the form of If... Then rules. Such constructions contain an uncertainty model of the type vagueness rather than randomness, and consequently they correspond to an explicit deterministic model even if it is not known. The segmentation of human brain images by fuzzy logic, neural network, evolutionary method [10–15] can produce results for specific problems. Reddick et al. [12] present an automated segmentation and classification scheme for multi-spectral MR images using artificial neural network. A knowledge based technique [16] is used for brain tumor segmentation. Genetic Algorithm (GA) based system is proposed for the prediction of future performance of individual stocks [17]. Shin and Kim illustrated to apply GA based approach for bankruptcy prediction modeling [18,19]. Knowledge based system generating handcrafted rules works well with the small number of variables, but fuzzy rules increase exponentially with the increase in the number of variables.

Fuzzy rule based classification techniques are reported in the literature [20]. These techniques use fuzzy matching techniques based on multivolume data set or fuzzy rule based on multi spectral data set for tissue classification [21–24]. One of the main drawbacks with multi-spectral and multivolume data set is to have a large number of images. This requires image data of the same slice of the same patient with different contrast (like T1 weighted, T2 weighted and PD weighted) to segment the MR image, which becomes difficult to obtain at times. Mehta et al. [13] proposed a hand crafted fuzzy rule based system to classify different tissue for T2 weighted brain MR images using two dimensional MR image data set. The method uses features from histogram and 2D spatial domain. These fuzzy rules, membership function, class boundaries, etc. are designed manually by analyzing 2-D MR image data. Although the resulting fuzzy rule based system (FRBS) gives good results, the whole process is not fully automatic. Also, the manual specifications are highly subjective.

This paper proposes a genetic algorithm based supervised learning method to automatically generate fuzzy rule to classify different tissue for MR brain images. An improved evolutionary learning algorithm for fuzzy rules has been designed for this purpose. By applying the proposed learning scheme, rule sets can be generated for different image scanning conditions using appropriate training data sets. Integrated sets of the rules will have the ability to analyze different types of MR images. In this paper, we report use of this learning technique with T2 weighted axial brain image data set from two different pulse sequences. The rule set works well in segmenting the 2-D MR image into three tissue types: white matter (WM), gray matter (GM), and cerebro spinal fluid (CSF).

This paper is organized as follows: Section 2 discusses the algorithm and feature analysis. Section 3 presents algorithm of learning system, which is a hybrid approach of Pittsburg and Michigan, and its applications to generate rule set through GBML for tissue segmentation. Section 4 presents fuzzy rules generated and comparison of manual tissue classification with proposed classification approach. Section 5 gives conclusion.

2. Algorithm and feature analysis

The method works in two phases: knowledge engine (KE) for rule generations using pattern of changes and classification phase for identifying the different tissue. The knowledge engine is a learning system that generates rule set from patient image data and classification phase uses the same rule set to classify tissue into WM, GM, CSF. Here rule set is generated automatically for MR brain image segmentation, which adaptively changes with the addition/alteration of new training data set. New data addition may be from new MR system or new pulse sequence. The learning method is based on hybrid of two popular approaches of genetic algorithm based machine learning techniques (GBML) namely Michigan and Pittsburg approach. The generated rule set is tested on MR axial T2 weighted brain images data set. Two types of pulse sequences Spin Echo (SE) and Fast Spin Echo (FSE) are used to generate T2 weighted axial image data set used to test the algorithm. It is working reasonably well to classify brain image data into three main tissue types' WM, GM, and CSF and error with respect to manual segmentation is found to be 1.1% minimum and 10.5% maximum in different trials.

2.1. Fuzzy features

The good features selection plays an important role for successful segmentation in 2-D MR images. Several such features like intensity, shape, and positional properties have been suggested in the literature [24,25]. All these have advantages and disadvantages. None of them are general enough to account for all the type of changes in the MR brain data. In the paper [13], fuzzy features are discussed in a hand crafted fuzzy rule based system. We used six features: histogram intensity (His_Inten), slope along the histogram (His_slope), prototype location with respect to intensity value (His_Loc), distance of the pixel intensity from prototype (His_GLS), Intensity Consistency over Spatial Neighbourhood (Neigh_Inten), Spatial Consistency of Histogram Slope (Neigh_Slope). In the present paper for evolutionary learning system, four features are selected out of six to reduce complexity and the number of rules for classification. These are His_Inten, His_slope, Intensity Consistency over Spatial Neighbourhood (Neigh_Inten), Spatial Consistency of Histogram Slope (Neigh_Slope). Each input feature has three fuzzy sets representing the linguistic description *low*, *medium*, *high*. Here the GBML classification system using these fuzzy features will classify the tissue type as WM, GM, or CSF.

3. Learning system

The design of a learning fuzzy rule set can be formulated as a search problem [26]. Here input is training data set and definition of attribute set. Training data can be expressed as m real vectors $X_A = (x_{A1}, x_{A2}, \ldots, x_{An})$, where $A = 1, 2, \ldots, m$ and n is the number of attributes in pattern space defined as $[0, 1]^n$.

The training data depicts input numerical values with output conditions. Input attributes are defined as fuzzy set (fuzzy gradient) with membership function. The fuzzy set can be 3, 5, or 7 between 0 and unity. The membership functions can be rt.triangular, lt.triangular, Triangular, Sigmoid Gaussian or others. Here in the experiment the axial MR data set with four attributes are considered. These are from 1-D histogram of the MR image and spatial neigbouring pixels attributes. Each feature is divided into three fuzzy subsets low, medium and high with one do not care condition. The membership function, which can be trained also, is fixed triangular here. Thus with four attributes total number of fuzzy if–then rules for segmentation is $(3+1)^4$. It is impossible to use all rules in segmentation system. If the number of attributes or levels in fuzzy gradient is increased the fuzzy rules will increase exponentially. Moreover the number of fuzzy set is discrete. It is non-differential. Keeping these problems in consideration genetic algorithm is the ideal choice here for optimizing fuzzy rules. Genetic algorithms are commonly used evolutionary algo-