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A SURVEY OF FUZZY RULE BASED IMAGE SEGMENTATION TECHNIQUES

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ABSTRACT

This paper describes the various fuzzy rule based techniques for image segmentation. Fuzzy rule based segmentation techniques can incorporate the domain expert knowledge and manipulate numerical as well as linguistic data. They are also capable of drawing partial inference using fuzzy IF-THEN rules. For these reasons they have been intensively applied in medical imaging. But these rules are application domain specific and it is very difficult to define the rules either manually or automatically so that the segmentation can be achieved successfully.

1 INTRODUCTION

Prewitt first stated that image segmentation should produce fuzzy regions [1]. Fuzzy image segmentation techniques are advantageous over classical methods as they are capable of handling imprecise data and they may be broadly classified in five classes [2]: fuzzy clustering, fuzzy rule, fuzzy geometry, fuzzy thresholding, and fuzzy integral. Initially fuzzy IF-THEN rules were extensively used in control engineering problems but now they are being increasingly applied in image segmentation. The advantages of the fuzzy rules based image segmentation over other methods are mainly [3] that humans can more easily understand the problems due to linguistic representation of numeric variables, it is computationally less expensive than fuzzy clustering methods, and it has the potential ability to integrate the domain expert knowledge. Generally fuzzy rule-based image segmentation has been applied in three types of images: light intensity (LI), magnetic resonance (MR), and computed tomography (CT) images and they are described in the sections 2, 3 and 4 respectively. Section 5 provides the conclusion.

2 FUZZY RULE BASED LI IMAGE SEGMENTATION

Chi and Yan utilized the fuzzy IF-THEN rules in the segmentation (separation of background and foreground pixels) of 256 gray scale geographic map images containing strings, streets, roads, boundaries etc. that are considered foreground pixels of the images [4-5]. Three features such as difference intensity (DI), local standard deviation (SD) and local contrast of darker pixel (CD) are used in segmentation. The input and output domains are divided into five fuzzy regions named as L2, L1, M, H1 & H2 and two fuzzy regions such as background & foreground respectively. Triangular membership functions shown are utilized for input regions. Fuzzy rules are generated by learning from examples. A pair of rules shown below is generated for each training sample.

IF DI is L1 AND SD is H1 AND CD is H2 THEN it is a foreground pixel
IF DI is H1 AND SD is M AND CD is L1 THEN it is a background pixel

To avoid repeated and conflict rules, the rules selected are supported by a large number of examples. If the centroid defuzzification value C_p<=0.5, the input pixel is categorized as background pixel otherwise it is categorized as foreground pixel. This system is faster than neural network techniques and superior to the adaptive thresholding techniques. It was found that some parts of characters are missed for standard triangular function [4]. This is because of selecting the shape and parameters of the membership functions was done intuitively. For this they used an automatic method using fuzzy C-means clustering (FCM) to determine the parameters of the membership functions. The shapes of the membership functions have been determined manually and heuristics rules are not used in this method.

3 FUZZY RULE BASED MR IMAGE SEGMENTATION

The fuzzy rule based MRI image segmentation methods may be broadly classified into two classes: Hybrid and conventional fuzzy rule based MRI segmentation.

3.1 HYBRID FUZZY RULE BASED MRI SEGMENTATION

Hybrid fuzzy rule based segmentation system consists of fuzzy rule based and FCM. Clustering is computational expensive and does not produce appropriate class alone due to inability of incorporating human expert knowledge [6]. For these reasons, a set of fuzzy rules is applied to classify the pixels/voxels. It is very difficult to define fuzzy rules that cover all pixels/voxels. So the classified pixels/voxels are used to initialize the cluster centers and FCM is used to classify the remaining unclassified pixels/voxels. Hybrid fuzzy rule based image segmentation systems are faster than clustering and are described in [3][6].

The method using adapting fuzzy rules for segmenting the brain tissue into six classes: white matter (WM), gray matter (GM), cerebro-spinal fluid (CSF), pathology, skull tissues and background is described in [6]. In this method 105 axial brain slices, 5 mm thick from 15 persons (39 normal slices from 8 persons and 66 abnormal slices from 7 patients) are used for experimental purposes. Relative voxel intensities of T1, T2 and PD weighted intensity images are used as feature. The shapes of the membership functions are triangular and trapezoidal. The parameters of the membership functions (a1, a2, b1, b2, b3, b4, b5 and b6) are calculated by determining the turning points (peaks, valleys or the starting point of the histogram) of intensity histograms of T1, T2 and PD images using a training set consisting of 6 normal & 4 abnormal slices and suggestions of expert radiologists. The PD histogram of the patient with brain tumor become like the PD histogram for abnormal slice due to the change of properties of gray and white matter. The turning points of this histogram are obscure and difficult to select. They used an edge detection technique in order to sharpen the boundary between gray & white matter utilizing a suitable threshold to detect the peaks. The initial value of threshold is chosen as 5 and increased by 5 until two peaks are found. If peaks are not found, two peaks are assumed at 1/3 and 2/3 of the region between b1 and b2. The Set-A, Set-B, Set-C, Set-D, Set-E, and Set-F are defined from the membership functions. A set of the following fuzzy rules are defined heuristically.

IF voxel in T1 in Set-E AND voxel in T2 in Set-F THEN voxel is CSF
IF voxel in PD is Set-C AND voxel in T1 in Set-A THEN voxel is White matter
IF voxel in PD is Set-D AND voxel in T1 in Set-A AND NOT (voxel in T2 is Set-F AND voxel in T1 is Set-E) THEN voxel is Gray matter
IF voxel in T1 is Set-B AND voxel in T2 is Set-F THEN voxel is Pathology
IF voxel in T1 is Set-B AND NOT (voxel in T2 is Set-F) THEN voxel is Other
IF PD voxel intensity < b1 AND T2 voxel intensity < c1 THEN voxel is Bcakground

Rules adapt themselves for each slice during processing. After classification using fuzzy rules the unclassified voxels and isolated voxels for each class are assigned the membership values with the average membership values of their neighbors and zero respectively. Finally the voxel membership values are normalized (0 to 1). The incorrect classified voxels (voxels whose membership value <= 0.80) are classified using semi-supervised clustering algorithm [7]. The correctly classified voxels are used as training set for the clustering algorithm. This system is faster than FCM. Rules are generated based on turning points of the histograms that are not sufficient enough to distinguish the brain tissues containing a significant amount of overlapping voxels. The threshold and approximate peaks (when there are no peaks in the PD histogram) are chosen empirically.

Another hybrid fuzzy rule based brain MR image segmentation method, which separates WM, GM, CSF and CMV lesion from the brain is described in [3]. In this method a set of T1, T2 & PD weighted images containing 12 normal images and 3 abnormal images with lesions are used for experimental purposes. Preprocessing step consists of two sub-steps: Image registration and selection of region of interest (ROI). Image registration makes the same pixel coordinates for the same pixels contained in two different images by the method of shifting of coordinates. Intracranial region of the brain is selected as ROI. The shapes of the membership functions are identified perceptually. Three different types of tissue such as WM, GM and CSF were identified for T2 images. T2 image as well as its edges that are determined by Cohen's edge detection method [8] are classified into five classes WM, GM, CSF, WM-GM and GM-CSF using standard FCM algorithm. The mean intensities (μ_i) and variance (σ_i) of ith class are used to calculate the parameters of the membership function for ith class. The PD weighted image and its edge values are given to FCM, which classifies them into four classes. The class containing highest pixel intensity is discarded in order to eliminate the high edge values on the boundary of the brain. The techniques used to generate the membership function for PD weighted images are same as T2 weighted images. For PD weighted abnormal images contain periventricular hyperintensity which have higher pixel intensities in brighter class than other pixels in the same class. So another membership function for PD weighted abnormal image is generated. A membership function is used to represent the closeness of a pixel from the center of the brain as the ventricle is considered a major connected CSF areas adjacent to the center of the brain. This membership function is used to discover the periventricular hyperintensity, which represents the lesions of the PD weighted images. Two groups of fuzzy rules have been developed. First and the second group are used to segment the T2 weighted images and to recognize the CMV lesions respectively. The first group is shown below.

IF pixel in T2 is Dark THEN pixel is White Matter
IF pixel in T2 is Grey THEN pixel is Grey Matter
IF pixel in T2 is Bright THEN pixel is CSF

Second group shown below is formulated by splitting the last rule of the first group into three new rules that discriminate CSF and CMV lesions.

IF pixel in T2 is Dark THEN pixel is White Matter
IF pixel in T2 is Grey THEN pixel is Grey Matter

IF pixel in T2 is Bright AND pixel in PD is Dark-Grey
THEN pixel is CSF
IF pixel in T2 is Bright AND pixel in PD is Very Bright
AND pixel is not close to the ventricle
THEN pixel is CSF
IF pixel in T2 is Bright AND pixel in PD is Very Bright
AND pixel is close to the ventricle
THEN pixel is CMV lesion

All pixels are classified using the rules described above. The pixels whose membership values are less than 0.5 and the pixel having two maximum membership values are declared as unclassified pixels. The initial value of each cluster center is derived from the average value of each respective classified class. All unclassified pixels are classified using FCM. If the number of classified pixels in CMV lesion is very small (from 10 to 20), they are reclassified as CSF. This system is 10 to 20 times faster than FCM and gives better result for abnormal images containing lesions. The structures of the membership functions have been defined according to the knowledge of medical experts.

3.2 CONVENTIONAL FUZZY RULE BASED MRI SEGMENTATION

Conventional fuzzy rule based segmentation uses only fuzzy rules to segment the MR image. Sasaki et. al. introduced such a fuzzy rule based method to segment the menisci region from MR images [9]. Five T1 weighted images (three normal and two injured knees), each contains 60 separate 1.5 mm thick slices are used in the experiments. The knowledge used to generate the fuzzy rules is : voxel intensities of cartilage regions are high, the menisci region lies in between the thigh and shinbone, the cartilage regions are adjacent to the center of the gravity of the knees, the menisci are automatically located near the cartilage, and the voxel intensities of the menisci regions are coherent . Two different sets of fuzzy rules are developed as the segmentation is performed in two stages. In first the candidate region of the menisci are segmented whereas the menisci are extracted from the candidate region in the second stage. Candidate region can be defined as the region between the cartilages as menisci are always located between the cartilages. A set of voxels represented by straight contiguous two dimensional data(x,z) is called unit(x,z). Two types of units such as unit A and unit B are defined to segment the candidate region. Unit A contains the candidate region while unit B does not contain any candidate region voxels. From the knowledge, 1, 2 and 3, the following rules are defined functions in order to segment the candidate region.

IF d is small AND n is large THEN degree of belonging to unit A is large
IF d is large AND n is small THEN degree of belonging to unit B is large

Where d and n denote distance of the interested unit from the center, and the number of disparity of voxel intensity on a unit respectively. The membership functions for distance and disparity to measure the values of linguistic variables, small and large are defined intuitively. The degree of belonging to unit A and B are calculated using equations: gradeA=w1 udsmall(d)+w2 unlarge(n) and gradeB=w1 unlarge(d)+w2 unsmall(n) where w1 and w2 are weights. The unit is classified into unit A if gradeA > gradeB, otherwise the unit is classified into unit B. From knowledge 4 and 5, two membership functions uc & ui, and the following two fuzzy rules are derived to segment the menisci from the candidate region.

IF voxel is anatomically adjacent to the cartilage THEN the degree of menisci voxel for uc is high
IF the intensity of the voxel is same as coherent intensity of the menisci voxel THEN the degree for ui is high

The total degree, gradeM=w3uc(i)+w4ui(m) where w3 and w4 are the weights. If gradeM > T, the voxel is classified as menisci voxels where T is the threshold. This method can successfully identify the tears. The rules have been defined based on anatomical position and coherent intensity of the menisci voxels. The structure of the membership function is defined from the knowledge of the expert. The parameters used in membership function are taken from the MR device parameters.

4 FUZZY RULE BASED CT IMAGE SEGMENTATION

A fuzzy rule based automatic segmentation of intrathoracic airway trees on CT image has been described in [10]. Five canine data sets, each contains 40 slices of 3mm thick are scanned from five anesthetized dogs. 40 slices, 8 per data set are randomly selected and their airways are perceptually determined by an expert in order to determine the training and test sets. Segmentation consists of the following five steps: separation of lungs from the volumetric data set, definition of primary airway tree, preprocessing of all individual image slices, fuzzy rule based identification of airways in all image slices, and construction of airway tree using 3-D connectivity. The techniques used for steps 1, 2, and 3 are described in [10-11]. Primary airway tree contains the major branches of the tree and is defined as the 3-D connected components of the image voxels below a threshold, which is formed by 3-D seeded region growing approach. The main task of preprocessing step is to identify the background and all possible locations of airways and vessels for each slice. The pixels (55 to 110 gray level intensities) are considered background pixels. The voxels darker and brighter than background are treated as candidate airways and vessels respectively. The anatomical information used to determine the airways is: airways are generally dark, airways are encompassed by airways wall, and airways are near to airway vessels. The following three features are defined according to a region adjacency graph properties [12].

- BRIGHTNESS: Uses minimum and maximum grey level regions to represent the airways and vessels candidate regions respectively.
- ADJACENCY: Represents the grey level of the brightest adjacent region.
- DEGREE OF WALL EXISTENCE: It determines the existence of the wall. The degree of wall existence is determined by the ratio of the total number of concentric rays possessed dark-bright-dark profile and the total number of concentric rays directed from the center of the candidate region.

The membership functions for BRIGHTNESS, ADJACENCY and DEGREE_OF_WALL _EXISTENCE including their linguistic variables are determined perceptually. The parameters of the membership function are determined from a manually tracking training set containing eight randomly selected slices of a single volumetric data set. The conflicts arisen among membership functions are solved manually in order to get optimum classification results. The rule banks are developed for the segmentation. For example, a rule of the rule bank,

IF BRIGHTNESS is LOW AND ADJACENCY is LOW AND DEGREE_OF_WALL_EXISTENCE is HIGH THEN region is airway with MEDIUM confidence

Centroid defuzzification is applied to get numerical confidence level for each region, which indicates the possibility that the region belongs to airway. Airway tree named C-tree is constructed by stacking of all the regions whose airway confidence level is more than 73% utilizing shape based interpolation along z-axis. From C- tree, A tree and B-tree are created. A-tree is defined as a 3-D connected region and subset of C-tree, which contains the airway-tree root. B-tree is the combination of A-tree and disconnected airway tree branches of C-tree that contains above threshold volume. This method has constructed three trees: A-tree, B-tree and C-tree and is not fully automatic.

5 CONCLUSION

This paper describes some of the existing fuzzy rule based image segmentation techniques. The most difficult task of fuzzy image segmentation is to determine the shape and parameters of the membership functions. Some of the methods have calculated the parameters of the membership functions automatically but all of the methods have applied the predefined structures of the membership functions. It has been seen from the literature that fuzzy rule based image segmentation techniques seem promising but they are very much application specific and very difficult to define and select fuzzy rules that cover all voxels/pixels. Fuzzy rule based techniques are capable of incorporating expert knowledge, processing the linguistic variables and drawing partial inferences.

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