



Fuzzy Algorithms for Pattern Recognition in Medical Diagnosis

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Abstract

There has been increased interest in the development of fuzzy pattern recognition based medical imaging that contributes to solve the problems in early diagnosis and prognosis. In the context of medical imaging, uncertainties can be present at any point that can lead to serious inaccuracy with segmentation. There are several complementary and competing approaches to computer aided diagnosis, including fuzzy logic, neural networks and hybrid algorithms. To extract the interested structures, many researchers aim to develop fuzzy segmentation algorithms in medical data. Many fuzzy pattern recognition approaches have shown their effectiveness in medical diagnosis. This paper surveys the algorithmic methods of fuzzy pattern recognition for medical imaging.

Keywords: Fuzzy segmentation, Medical diagnosis, MRI.

Introduction

Medical diagnosis and prognosis problems are prime examples of decision making in the face of uncertainty. Dealing with uncertainties is a common problem in pattern recognition and the use of fuzzy set theory has given rise to a lot of new methods of pattern recognition for medical diagnosis. Fuzzy set theory plays a key in formalizing uncertainties for medical diagnosis and prognosis [Zadeh (1965), Bezdek (1981), Adlassing (1986), Sterimann (1997), Kuncheva *et al.* (1999), Steimann (2001)]. For the diagnosis and prognosis through the medical imaging, the supervised classification and unsupervised clustering are common pattern recognition techniques.

Clustering is guided by the medical knowledge that consists of medical descriptions and assertions. The two broad approaches to clustering are crisp and fuzzy clustering. In the medical application domain, there are usually imprecise conditions and therefore fuzzy methods seem to be more suitable than crisp one. The major groups of fuzzy methods are represented by fuzzy clustering, fuzzy rule-based, fuzzy pattern matching methods and

methods based on fuzzy relations. In fuzzy clustering, fuzzy *c*-means (FCM) clustering algorithms are the best known and most powerful methods used in cluster analysis in medical application. In the field of medical application, mining the medical images is the task of searching and retrieving the images and the use of pattern recognition methods for abstraction, indexing and retrieval of images is presented by Anatani *et al.* (2002). Uncertainties also affect image analysis and the most challenging problem in image analysis and pattern recognition research is segmentation [Souza *et al.* (2008), Hasanzadeh *et al.* (2008), Yang (2009)]. In medical image analysis, magnetic resonance (MR) image segmentation is the most popular imaging technique. The advantages of MRI are its high spatial resolution and soft-tissue contrast [Siyal *et al.* (2005)]. Bezdek *et al.* (1993) present a review of MR image segmentation techniques using pattern recognition. In general, pattern recognition studies have contributed to improve MR segmentation techniques. The main objective of medical image segmentation is to extract the

interested structures to some input features. It can be stated as the partition of an image into a number of non-overlapping regions, each with distinct properties. Various segmentation methods for MRI have been used to differentiate abnormal and normal tissues. One common difficulty in MR segmentation is the intensity inhomogeneity [Li *et al.* (2008)] and can be viewed as the task of clustering the pixels in the intensity space [Maulika *et al.* (2009)]. Intensity inhomogeneity refers to the variation of the same tissue over the image. It can be caused by imperfections in the RF coils or other factors relating to the acquisition sequences [Likar *et al.* (2001)]. Vovk *et al.* (2007) present a review of methods for correction of intensity inhomogeneity in MRI. Another important medical imaging modality that is used in diagnosis and prognosis is dermoscopy images and a review on the recent border detection methods in dermoscopy images is presented in Celebi *et al.* (2009).

In the computational intelligence community, several hybrid approaches to pattern recognition have been made to attract the considerable attention in medical applications [John (2003), Herrera *et al.* (2005), Moussaoui (2006), Jabarajan *et al.* (2008), Punitha *et al.* (2008), Moein *et al.* (2008)]. One of the most common hybrid approaches is the integration of neural networks and fuzzy set theory known as neuro-fuzzy [Mitra *et al.* (2005)] and is increasingly applied to medical diagnosis. Tedorescu *et al.* [Tedorescu *et al.* (2000)] reviewed on report of research activities in fuzzy AI and medicine at USF CSE, including the fuzzy and neuro-fuzzy methods for medical diagnosis such as fuzzy clustering, fuzzy filtering, fuzzy image segmentation and fuzzy expert systems. It is found from the literature that integration of the individual Soft Computing tools help in designing hybrid systems which are more versatile and efficient compared to stand alone use of the tools [Ruspini *et al.* (1998), Pal (2003)]. Various Soft Computing methodologies and various applications in medicine between the years 2000 and 2008 are presented by Yardimci (2009).

In this paper, we provide an exclusive survey report of fuzzy approaches based on pattern

recognition for early diagnosis of disease. Rest of the paper is organized as follows: Section 2 focuses on the problems in medical diagnosis, concerning that certain problems have to be taken into account in every medical decision where they may have important and vital consequences for the patient. Section 3 and 4 presents the basic concept on segmentation and the MR image segmentation. The algorithmic methods on fuzzy pattern recognition for medical diagnosis are covered in Section 5. Finally, Section 6 concludes the paper.

Problems in Medical Diagnosis

Diagnosis and prognosis is the task of medical science. The most important problems in medical diagnosis and prognosis are [Adlassing (1986), Melek *et al.* (2009)]:

- (i) limited observation and subjectivity of the specialist,
- (ii) uncertainties and incompleteness in medical knowledge and
- (iii) poor time effect in diagnosis.

These difficulties have to be recognized during medical decision. A patient can have a set of symptoms which can attribute to several diseases and these symptoms need not be strictly numerical. In observing these symptoms, different doctors with different professional levels and clinical experience may have a case to make different diagnostic results, resulting in misdiagnosis. Also due to the unknown noise in acquisition process, the uncertainty is largely present in medical images. Thus, the use of computers in medical diagnosis and prognosis has become necessary with the increasing size and number of medical data. A large number of Computer Aided Diagnosis (CAD) has been employed in medical diagnosis and prognosis radiology for early diagnosis. Doi (2007) presents a historical review on Computer Aided Diagnosis (CAD) in medical imaging together with the current status and future potential of CAD environment.

To reduce deaths due to diseases requires early diagnosis and prognosis which requires an accurate and reliable diagnostic procedure. Pham *et al.*

(2009) applies a new meta-heuristic approach called Homogeneity Based Algorithm (HBA) that significantly increases the accuracy by using the concept of homogenous sets. Modern neurosurgery takes the advantages of magnetic resonance imaging (MRI) of the patient before the diagnosis procedure [Descoteaux *et al.* (2008)]. Several methods based on fuzzy approaches in pattern recognition for medical diagnosis have been developed and amongst them, fuzzy *c*-mean algorithm for MR image segmentation is widely used to analysis the medical image data.

Segmentation

In computer vision, segmentation refers to the process of partitioning a digital image into multiple segments which are actually sets of pixels. The goal of segmentation is to simplify and/or change the representation of an image into something that is more meaningful and easier to analyze. Image segmentation is typically used to locate objects and boundaries (lines, curves, etc.) in images. More precisely, image segmentation is the process of assigning a label to every pixel in an image such that pixels with the same label share certain visual characteristics.

The result of image segmentation is a set of segments that collectively cover the entire image, or a set of contours extracted from the image. Each of the pixels in a region is similar with respect to some characteristic or computed property, such as color, intensity, or texture. Adjacent regions are significantly different with respect to the same characteristic(s).

Some of the practical applications of image segmentation are:

- Medical Imaging
 - Locate tumors and other pathologies
 - Measure tissue volumes
 - Computer-guided surgery
 - Diagnosis
 - Treatment planning
 - Study of anatomical structure
- Locate objects in satellite images (roads, forests, etc.)

- Face recognition
- Fingerprint recognition
- Traffic control systems
- Brake light detection
- Machine vision

Several general-purpose algorithms and techniques have been developed for image segmentation.

MR Image Segmentation

The principle of magnetic resonance imaging (MRI) was discovered in the late 1940s [Base (2004)] and has become more powerful and useful because of its ability to measure spatial distribution between the anatomical structures of biological tissue [Awate *et al.* (2007), Tyagi *et al.* (2009)] compared to other medical imaging modalities. MRI is a medical imaging technique that uses nuclear magnetic resonance of protons to produce proton density images. The image pixel value can be considered as subsets of parameters including the time constants characterization T1 (magnetization vector along with longitudinal axis) and T2 (transverse component) and proton density (that has distinct value). By changing the effect of these meters, MR images can differentiate the structures obtained from the same anatomical positions. In diagnosis and prognosis using magnetic resonance imaging (MRI), segmentation is often required to extract the interested and meaningful structure on MR data and is considered as an important basic operation for meaningful analysis and interpretation of acquired images. Segmentation subdivides an image into its constituent regions or objects that have similar properties to produce anatomical structures and the quality of any image interpretation depends on it [Chabrier *et al.* (2006)]. MR image segmentation using pattern recognition methods plays a vital role for early diagnosis by detecting the abnormal changes in tissues and organs. As the image segmentation is fundamentally a clustering problems, the techniques based on fuzzy clustering plays a vital role in MRI to analyze the patient's data (determine the exact location of an organ) and was introduced by Bezdek and for the first time Hall *et al.* (1992) applied this in brain

tissue to give visual representation of the original data. Any improvement in segmentation methods can lead to important impacts on MR image processing technique. Image segmentation of structures from MRI can be applied in the study of many disorders and allows 3D visualization of human tissues and quantitative analysis of tissue volume diagnosis. In neurosurgery, accurate segmentation of MR images into different tissues is characterized by voxel (location of each measurement in 3D image) intensities. Intensity inhomogeneity can also occur in segmenting MRI data. Fuzzy clustering techniques can be applied to identify homogeneous clusters of points in feature space and label each cluster as a different region. The image segmentation techniques based on fuzzy homogeneity can be extended to color images [Yeong *et al.* (2005), Chaabane *et al.* (2009)]. Sowmya *et al.* (2009), explains the soft computing color image segmentation techniques such as fuzzy *c*-means (FCM), possibilistic *c*-means algorithm (PCM) and neural networks. In medical applications, due to the restrictions imposed by image acquisition, human-computer interaction segmentation method is necessary to check the accuracy produced by the automated segmentation. Olabarriaga *et al.* (2001), present a review on human-computer interactive methods for the segmentation of medical images.

Fuzzy Pattern Recognition for Medical Diagnosis

Development of the methods for fuzzy pattern recognition is constantly increasing for medical diagnosis and prognosis. One of the most likely applicable fields of fuzzy set theory which Zadeh himself described was medical diagnosis [Steimann (1997), Seising (2006)] and since then several methods based on fuzzy knowledge and information has been developed to detect the diseases at its early stage. Fuzzy set theory provides a number of suitable properties for pattern recognition diagnostic system due to its ability to deal with uncertainties, vagueness and incompleteness in medical diagnosis and prognosis. It can be used to represent fuzzy objects (both linguistic and/or set of variables) and fuzzy logic (reasoning methods). Torres *et al.* (2006) present

a review on the current applications of fuzzy logic in medicine and bioinformatics. The main reasons for the application of fuzzy set theory in pattern recognition are: (i) its way of representation in linguistic approach with excellent formulation of input feature, (ii) representation of missing or incomplete knowledge as a degree of membership and (iii) its capability of drawing approximate inferences. Fuzzy set theory help to transfer a qualitative evaluation of the medical data into the algorithmic structure and the focus of this paper is on algorithmic methods for pattern recognition based on fuzzy set theory. Baraldi *et al.* (1999a, 1999b) present a survey on fuzzy clustering algorithms for pattern recognition. Literature survey shows that many fuzzy clustering algorithms aim to model fuzzy (i.e., ambiguous) unsupervised (unlabeled) patterns efficiently and is widely used for segmentation of MRI in brain tissue. Following are the some of the fuzzy clustering techniques.

A. Automated segmentation - Methods for automatic segmenting the MR images with fuzzy clustering is a general pattern recognition technique. Fuzzy methods for automatic segmentations can be applied in set of images with a variety of diagnosis. Several research groups have developed semi-automated/fully-automated segmentation that can produce good results for a specific problem and contribute to diagnosis and prognosis such as: segmentation of human brain MRI using fuzzy clustering [Hatta *et al.* (2000), Barra *et al.* (2001), Amini (2004)], tissue in hand MR Image using fuzzy *c*-means [Tripolti *et al.* (2007)], automatic approach of brain MRI by combining 3D segmentation and SVM classification [Akselrod Ballin *et al.* (2006)], cardiac MRI using unsupervised clustering techniques [Lynch *et al.* (2006)], tissue in calf and thigh MR Image [Attar (2006)], articular cartilage in the knee using voxel classification approach [Folkesson *et al.* (2007)]. Hatta *et al.* (2000) developed a fully automated segmentation by a three step technique in sequential image segmentation procedure. Barra *et al.* (2001) also developed a fully automated segmentation by a three step technique based on information fusion. In a sequential image segmentation procedure

voxels are successively added to existing regions when the voxels meet certain criteria. The whole brain consisting of gray matter and white matter is attempted to segment by fuzzy information granulation and can be adapted in finding the thresholds (Th_1 and Th_2) of the intensity histogram of human brain MR volume. The intensity histograms are treated as the information and the peaks as the granules and are applied in 50 different human's brain MR volume classifying into one of the two histogram models. Finally it is attempted to decompose the obtained whole brain using knowledge-based representation. In the fusion technique, first it is attempted to model the information by extracting the information from MRI, then according to the redundancy of the previously modeled information it is aggregated in the second step and is called fusion process. Finally it takes a decision or defuzzification for the segmentation of cerebral structures and is successfully applied in 14 T1-weighted MR images. Evanthia E. Tripolti *et al.* proposed a fully-automated method of four stages based on the segmentation of MRI using a fuzzy *c*-mean schema and was successfully applied to a dataset of 504 MR images from 25 rheumatoid arthritis patients. Knowledge-based methods combined with fuzzy clustering based on features related to the image intensity and position of pixels are appropriate for automatically segmentation of MR images and can make unsupervised algorithms with segmentation for medical diagnosis more powerful. Various unsupervised algorithms for MRI segmentation have been developed [Tao (2002), Wismuller *et al.* (2004)]. Multiresolution image segmentation is also an approach to unsupervised algorithms that is automatically segmentation of MRI and is the combination of pyramidal image segmentation and fuzzy clustering [Rezaee *et al.* (2000), Mali *et al.* (2006)].

B. Fuzzy Learning Vector Quantization (FLVQ) - Model selections for medical diagnosis and prognosis have been increasingly in attention in improving the accuracy of medical diagnosis [Wismuller *et al.* (2004), Mangiameli *et al.* (2004), Hung *et al.* (2008), Mendonca *et al.* (2009)]. Model-based fault diagnosis methods based on fuzzy clustering, SOM, neural gas network attempt

in grouping image pixels based on the similarity of their intensity profile in time and the model based on bootstrap methods attempt to select feature weights based on fuzzy methods. Various models for medical diagnosis have been described in the literature [Mangiameli *et al.* (2004)]. Neural net models for medical diagnosis and prognosis have been increasingly studied for many years. A widely and successfully used neural paradigm for finding prototypes is the self organizing map (SOM). Concerning the major problems of self organizing map (SOM), the generalized Kohonen's competitive learning (GKCL)-based algorithms (KCL, fuzzy KCL (FKCL), fuzzy soft KCL (FSKCL)) and the learning vector quantization (LVQ)-based algorithms (LVQ, fuzzy LVQ (FLVQ), fuzzy soft LVQ (FSLVQ)) have been developed to improve performance and usability [Kim *et al.* (2001), Wu *et al.* (2003), Lin *et al.* (2003), Bezdek *et al.* (2005), Filippi *et al.* (2006), Yang *et al.* (2007)]. Learning vector quantization (LVQ) is a simplest case for self organizing map (SOM). Mingoti *et al.* (2006) present a comparison of SOM neural network, fuzzy *c*-mean, *k*-means and hierarchical clustering algorithms. The comparison found that fuzzy *c*-mean clustering algorithm performed well in all situations than any other algorithms. LVQ attempts to update only the winning prototype, generalization of LVQ-fuzzy is developed to updates all the *c*-prototypes with the learning rule. Lin *et al.* (2003) proposed a generalized Kohonen's competitive learning (GKCL) for MR image segmentation called fuzzy KCL (FKCL) and fuzzy soft KCL (FSKCL) and is successfully applied to two actual ophthalmology cases. Amongst the GKCL-based algorithms, FSKCL is the most robust to outlying lesions and can easily interfere by a biased set of learning rates. However GKCL algorithm has some limitations as they are highly sensitive in selecting the MRI data set in fixed pixel and may affect the number of iteration. Fuzzy learning vector quantization (FLVQ) can reduce this sensitivity of parameters. It provides a subsequent link between batch FCM and LVQ and also overcomes the problems in LVQ. This was first discussed by Huntsberger and Ajjimarangsee in the year 1990. The FLVQ

is more suitable than GKCL-based algorithms in comparison and gained a successful batch clustering algorithm that is applied in MRI. Further, another modified batch clustering learning method called fuzzy-soft learning vector quantization (FSLVQ) is proposed in Wu *et al.* (2003) and produce better performance than the FLVQ in comparison but it is tested with numerical data only. Based on this, Yang *et al.* (2007) proposed the FSLVQ segmentation technique with MRI and it works well on Alzheimer disease (AD) MRI. The tested results of the FSLVQ are compared with the other LVQ-based and GKCL-based algorithms and the comparison found that the FSLVQ is more robust and suitable. Further, Yang *et al.* (2008) proposed fuzzy-soft competitive learning algorithm (FS-CLA) which is modified from FSLVQ by incorporating a fuzzy relaxation technique using fuzzy membership functions as a kernel type of neighborhood interaction function. The modified algorithm FS-CLA is successfully applied in MRI segmentation to reduce medical image noise effects with learning mechanisms.

C. Fuzzy noise reduction model - The fundamental problem in image analysis is the unknown noise that persists always in the image analysis and the intensity inhomogeneity which is caused by limitations in imaging devices. For years several methods are proposed to reduce the noise from image and the correction of intensity inhomogeneity such as: fuzzy *c*-means with adaptive spatial information [Pham (2001), Liew *et al.* (2003), Chuang *et al.* (2006)], suppressed fuzzy *c*-means to MRI segmentation [Hung *et al.* (2006)], fuzzy filter with adaptive noise [Schulte *et al.* (2007), Souza *et al.* (2008)], segmentation for bias/retrospective correction of images [Ahmed *et al.* (2002), Madabhushi *et al.* (2006), Vovk *et al.* (2006)], multicontext fuzzy clustering (MCFC) of MRI brain tissues [Zhu *et al.* (2003)], robust segmentation techniques [Cinque (2004), Shen *et al.* (2005), Cai *et al.* (2007), Yang *et al.* (2008), Cao *et al.* (2008), Kannan (2008), Yang *et al.* (2008), Yang *et al.* (2009)]. The FCM objective function of image does not include any spatial interaction between observations and thus the membership functions may be sensitive to noise. One approach for reducing this sensitivity is post

acquisition image filtering but it can result in image degradation. Various methods of fuzzy filtering in reducing the adaptive noise for medical images and digital color images have been developed. Souza *et al.* (2008) introduced a scaled-based filtering method called generalized scaled (*g*-scaled regions) and it becomes a powerful technique for filtering noise in medical image. However it is limited to that region during evaluation. Another popular approach for reducing noise and correction of intensity inhomogeneity is the FCM clustering algorithm with adaptive spatial. The FCM clustering algorithm with spatial information allows spatial interaction between pixels that can reduce the noise and can formulate the intensity inhomogeneity due to bias field. The spatial information incorporates the neighborhood membership function of each pixel on the center pixel of interest during classification. Many researchers have applied various techniques for spatial/bias information with segmentation and it is found that FCM with spatial information performed better than other techniques. Liew *et al.* (2003) proposed a FCM clustering algorithm (ASFCM) both for adaptive spatial and correction of intensity inhomogeneity and is successfully applied in 3D MR images and the real MRI. If the spatial function is in non-homogeneous region then the neighborhood membership function of each voxel on the center voxel is suppressed otherwise the influence of the neighborhood voxels on incorporates into the membership function for clustering computation. The fuzzy clustering with spatial information is also applied in bio-image segmentation in Pham (2008). By combining the fuzzy *c*-means and the spatial information, the inherent difficulty that present in many bio-imaging due to the background pixels that have same values as those belongs to the object are modeled. It is found from the literature that the FCM clustering segmentation algorithm with spatial information is applied for reducing noise that contain in images and correction of intensity inhomogeneity and also performed good results for a specific problem. Literature survey showed that, the important task in all the applications of the image segmentation is to identify the homogeneous cluster of pixels in the intensity space. Started from 1996, several

promising and new methods to reduce this task in MR images have been developed such as high frequency maximization, information minimization. Another popular method for identifying the region of interest from MRI is maximum intensity projection (MIP). Hata *et al.* (2009) proposed fuzzy MIP to visualize the region of interest for 3D MRI.

Other approaches have been proposed in various literatures to increase the robustness of the FCM clustering algorithm to noise reduction and the correction of intensity inhomogeneity. Yang *et al.* (2008) proposed a Gaussian kernel-based fuzzy *c*-means algorithm with a spatial bias correction and as reported it has more efficiency and robustness comparing to FCM and other variations of FCM. By adopting a weight function for the prototype equation, robust fuzzy clustering algorithms based on image segmentation methods

modified the other FCM such that the sensitivity to noise becomes less [Yang (2004)]. Various approaches to robust clustering for segmentation have been proposed in the literature. One approach to robust clustering is the mean shift based clustering [Comanniciu *et al.* (2002), Wu *et al.* (2007), Lorenzo *et al.* (2009)] and the quality of the output is controlled by the kernel density functions.

A comparison on some of the algorithmic approaches for MR imaging using fuzzy techniques is summarized in Table1(a) and Table1(b). It is seen from the tables that all the approaches are successfully applied in particular type of patient problems and contribute to the early diagnosis and prognosis. However these approaches have some limitations as they require further research across different types of problems.

Table1(a): Comparison of algorithmic approaches for MR imaging using fuzzy techniques

Reference	Algorithm	Purpose	Advantages	Limitations
Souza <i>et al.</i> 2008	Generalized scale-based filtering (gD method)	Image filtering	Considerable gain in terms of AUC(Area Under Curve) values over NCD (Nonlinear Complex Diffusion) and bD (b-scale based Diffusion) processes	The evaluation of scale-values and the filtering for the gD method is done once at the beginning which if done iteratively can improve the performance of the gD
Siyal <i>et al.</i> 2005	Modified FCM	Image segmentation	Performs correction of intensity inhomogeneity and can be applied at an early stage in an automated data analysis before a tissue model is available	Limited to segmentation of one-channel MR data
Kanan 2008	Fuzzy Membership C-Means (FMCMs)	Image segmentation	Performs better than FCM in segmentation of the multi-MRI data	The FMCMs has been tested with only the training data sets and further testing needs with real data sets
Yang <i>et al.</i> 2007	Fuzzy Soft LVQ (FSLVQ)	Image segmentation	FSLVQ is more robust and suitable than other LVQ-based and GKCL-based algorithms in comparison	Quality of the segmentation depends on the starting learning rates and parameter selection
Hung <i>et al.</i> 2006	Modified Suppressed FCM(MSFCM)	Image segmentation	More accurate results and better detection of abnormal tissue than SFCM	The number of iteration and CPU time is slightly larger than SFCM
Yang <i>et al.</i> 2008	Gaussian Kernel based FCM (GKFCM)	Image segmentation	GKFCM is more efficient and robust with good parameter learning scheme in comparison with FCM and its variations	For the case of Gaussian noise of 10% level, KFCM _{S₂} has better result than GKFCM

Table1 (b): Comparison of algorithmic approaches for MR images using fuzzy techniques

Reference	Algorithm	Purpose	Advantages	Limitations
Hata <i>et al.</i> 2009	Fuzzy Maximum Intensity Projection (FMIP)	Image segmentation	FMIP corrects the intensity distortion of whole images by using decay function and the FMIP with appropriate fuzzy segmentation is useful for establishing 3D rendering techniques with low cost for huge medical image datasets	Applicability is restricted to endorrhachis in MRI
Yang <i>et al.</i> 2009	Robust fuzzy clustering	Noisy image segmentation	Suitable for noisy image segmentation	Needs more mathematical analysis of the penalty terms in the modified algorithm
Yang <i>et al.</i> 2008	Modified Deterministic Annealing Algorithm (DA-RS)	Noisy image segmentation	Can be applied to fuzzy or probabilistic clustering algorithm and kernel based algorithm	Due to the computation of spatial information DA-RS needs more execution time than other DA type algorithms
Chuang 2006 [19]	FCM with bias estimation	Noisy image segmentation	Suitable for noisy image segmentation with both single and multiple feature data with spatial information	Applicability is restricted to the image data with spatial information
Shen <i>et al.</i> 2005	Improved FCM (IFCM)	Noisy image segmentation	IFCM performs better than the traditional FCM	Sensitive to algorithmic parameter value selection
Hata <i>et al.</i> 2000	Automated method based on fuzzy logic	Automatic segmentation	Can identify the whole brain from MR volumes with high accuracy	Segmentation is restricted in RCH (Right Cerebral Hemisphere), LCH (Left Cerebral Hemisphere), CB (Cerebellum), BS (Brain Stem) portions
Barra <i>et al.</i> 2001	Automated method using information fusion	Automatic segmentation	Less sensitive to individual variability of the structure morphology than model-based techniques	Not very encouraging results with images on areas where borders of structures are badly contrasted
Tripolti 2007	Automated method using FCM	Automatic segmentation	Results in high detection and quantification compared to manual segmentation	Reduction of false positives and detection of old and acute inflammation is not addressed

Conclusion

To understand the disease process at its early stage, it is important to perform quantitative analysis in addition to qualitative evaluation of the medical data. Medical imaging process plays a vital role in early diagnosis. Applying fuzzy pattern recognition diagnosis methods in medical imaging can solve the problems in traditional methods.

Various researchers have attempted to introduce different algorithmic approaches for fuzzy pattern recognition that can contribute to the medical diagnosis and prognosis and also for further development of new methods. All the approaches are successfully applied in particular problems. In broad sense, fuzzy pattern recognition with an application to medical diagnosis for recognizing the disease in early stage is a challenging research

area from both theory and practical point of view. This paper presents an exclusive survey of some of the algorithmic approaches on fuzzy pattern recognition methods with segmentation of MRI imaging such as: automated segmentation, FLVQ (fuzzy learning vector quantization) and noise reduction model. All the approaches have success on particular types of patient problems but need further research across different types of problems. As medical images contain uncertainties

and there are difficulties in classification of image into homogeneous regions, more of research is needed to be conducted in fuzzy pattern recognition based techniques before all the problems of medical diagnosis and prognosis are recognized and solved.

Further it seems that the efficiency of the existing standard algorithms for cluster analysis in medical diagnosis can further be improved by applying other hybrid soft computing techniques.

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