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An Robust Algorithm for Segmenting Multiple Sclerosis from Magnetic Resonance Images

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ABSTRACT: Multiple Sclerosis (MS) is an autoimmune inflammatory disease that leads to lesions in the central nervous system. Magnetic Resonance Imaging (MRI) provide sufficient imaging contrast to visualize and detect MS lesions, particularly those in the white matter (WM). Medical image segmentation is an essential step for most consequent image analysis tasks. The proposed segmentation algorithm is composed of three stages: segmentation of the brain into regions using Fuzzy Particle Swarm Optimization (FPSO) in order to obtain the characterization of the different healthy tissues (White matter, grey matter and cerebrospinal fluid (CSF)). After the extraction of WM, atypical data (outliers) is eliminated using Fuzzy C-means algorithm, and finally, we introduce a Mamdani-type fuzzy model to extract MS lesions among all the absurd data. Although the FCM algorithm yields good results for segmenting noise free images, it fails to segment images corrupted by noise, atypical data (outliers) and other imaging artifact. The purpose of this study is to segment high dimensional data of WM lesions using Fuzzy Possibilistic C-means (FPCM). This approach is a generalized version of FCM algorithm. The objective of the work presented in this paper is to obtain an improved accuracy in segmentation of WM. Comparison results to the method of FPSOFCM showed that the defuzzification of the atypical data of the segmentation was 56.79 showing that the proposed FPSOFPCM outperformed the other method (FPSOFCM).

INTRODUCTION

Multiple sclerosis (MS) is an inflammatory, demyelinating and neurodegenerative disease of the central nervous system involving immune-mediated destruction of myelin and axonal damage that affects both white matter (WM) and gray matter (GM). MS is characterized by the formation of focal inflammatory lesions, also called plaques[1]. It may cause various potential symptoms, including visual problems[2], spasms[3], numbness[4], fatigue[5], among others. MS is typically diagnosed by the presenting symptoms, together with supporting neuroimaging methods, such as magnetic resonance imaging (MRI) to detect the damaged WM[6].

Both MS lesions and brain atrophy, are usually measured in-vivo from MRI by means of automatic or semi-automatic segmentation algorithms. The most frequent modalities to segment WM lesions include proton density-weighted (PD-w), FLAIR and T2-weighted (T2-w), this is because lesions appear hyper-intense in these sequences which makes them easier to detect[1]. However, WM lesions in MS can be detected with

standard MRI acquisition protocols without contrast injection. It has been shown that many features of lesions, such as volume T. Kalincik et al.[8] and location P. Sati et al.[9] are important biomarkers of MS, and can be used to detect disease on set or even track its progression. Therefore accurate segmentation of WM lesions is important in understanding the progression and prognosis of the disease. With T2-w MR imaging sequences, most lesions appear as bright regions in MR images, which is useful for automatic segmentation. Although manual delineations are considered as the gold standard, manually segmenting lesions from 3D images is tedious, time consuming, and often not reproducible. Therefore automated lesion segmentation from MRI is an active area of development in MS research[7].

In fact, robust and efficient segmentation of various tissues and structures in medical images is of crucial significance in many applications, such as the identification of brain pathologies fromMR images[10]. Actually, image segmentation is regarded a crucial stage in the image processing system that straight for efficiently guiding the clinicians in the process of medical diagnosis. In Moreover, related tasks such as position detection, primitive extraction, or pattern recognition all strongly dependent on the quality of the segmentation. The accurate segmentation of lesions in MRI is important for the accurate diagnosis, adequate treatment development and patient follow-up of the MS disease.

This paper is an extension of a previous work where we proposed a new automated segmentation method that detects the lesions of MS[11]. The previously published MS segmentation algorithm follows three stages: We initially segment the brain into different tissues classes, namely: WM, Grey Matter (GM) and Cerebrospinal Fluid (CSF) using Fuzzy Particle Swarm Optimization (FPSO) algorithm. Secondly, we use Fuzzy C-Means (FCM) algorithm to eliminate the atypical data of the white matter. And finally, a decision-making system that uses Mamdani-type fuzzy model is employed in order to ascertain whether a given voxel is an MS lesion or not[11]. However, we found that our method failed in accurately for segmentation of white matter lesions in MR images because the FCM algorithm yields good results for segmenting noise free images, it fails to segment images corrupted by noise, atypical data (outliers) and other imaging artifact.

Lesion segmentation plays an important role in the diagnosis and follow-up of multiple sclerosis (MS). This task is very time-consuming and subject to intra- and inter-rater variability. In this paper, we present an improved tool for automated MS lesion segmentation. Our approach is based on three main steps, initial brain tissue segmentation according to the gray matter (GM), WM, and cerebrospinal fluid (CSF) performed using the algorithm Fuzzy Particle Swarm Optimization (FPSO). This is followed by a second step where the lesions are segmented as outliers to the normal apparent WM brain tissue using a Fuzzy Possibilistic C-means (FPCM) algorithm and decision-making system that uses Mamdani-type fuzzy model.

The remaining of this paper is organized as, follows; related works are presented in Section 2. The proposed algorithm of automatic MS lesion detection and its various steps are highlighted in is described I and Section 3. Section 4 reports the experimental results. Finally, conclusion and future work are summarized in section 6.

RELATED WORK

There are several methodologies available to detect MS from MR images. The degree to which the disease has affected can be known by estimating the volume of MS lesion through MR imaging and this helps in planning the treatment. Udupa, J.K. et al[12] have proposed a new system with which MS lesions can be segmented from dual-echo fast spin echo MRI and the computation of MS lesion volume can be eventually performed.

Many automated lesion segmentation methods have been proposed in the past decade[18]. There are usually two broad categories of segmentations, supervised and unsupervised. Unsupervised lesion segmentation methods rely on intensity models of brain tissue, where image voxels containing high intensities in FLAIR images are modeled as outliers[19-20] based on the intensity distributions. The outlier voxels then become potential candidates for lesions. Eventually the segmentation can be refined by a simple thresholding technique[21-23]. Alternatively, Bayesian models such as mixtures of Gaussians[24-26] or Student's t mixture models[27] can be applied on the intensity distributions of potential lesions and normal tissues. Optimal segmentation is then achieved via an expectation-maximization algorithm. Additional information about intensity distributions and expected locations of normal

tissues via a collection of healthy subjects[28] can be included to determine the lesions more accurately. Local intensity information can alsobe included via Markov random field to obtain a smooth segmentation[29]. Ying Wu et al[13] have dealt with an automatic segmentation scheme that segments and classifies MS lesions into three sub-kinds from T2-w and contrast-enhanced T1-w brain images of 12 MR scans. On the other hand, S. Sivagowri, et al[14] have presented an automatic method for segmenting MS lesions from MR images. It uses a governed-classifier, namely, support vector machine (SVM) for differentiating the blocks that lie in MS lesion regions and non-MS lesion regions using textural features.

Supervised lesion segmentation methods make use of atlases or templates, which typically consist of multi-contrast MR images and their manually delineated lesions. As seen in the ISBI-2015 lesion segmentation challenge[30], supervised methods have become more popular and are usually superior to unsupervised ones, with four out of top five methods being supervised. These methods learn the transformation from the MR image intensities to lesion labels (or memberships) on atlases, and then the learnt transformation is applied onto a new unseen MR image to generate its lesion labels. For instance, logistic regression[31-32] and SVM[33] have been used in lesion classification, where features include voxel-wise intensities from multi-contrast images and the classification task requires to label an image voxel as lesion or non-lesion. Instead of using voxel-wise intensities, patches have been shown to be a robust and useful feature[34]. As such, random forests[35-37] and k-nearest neighbors[38] based algorithms have used patches and other features, computed at a particular voxel, to predict the label of that voxel. Dictionary based methods[39-41], use image patches from atlases to learn a patch dictionary that can sufficiently describe potential lesion and non-lesion patches. For a new unseen patch, similar patches are found from the dictionary and combined with similarity-based weighting. In the proposed methodology by Colm Elliott et al[16], mutual fragmentation is performed on the sequential scans for carrying out a temporarily reliable tissue segmentation that produces lesions.

Class-based methods[17-19], modeled the lesions as an independent class to be extracted. In[36], a combination of intensity-based k-nearest neighbor classification (k-nn) and a template-driven segmentation (TDS) was designed to segment different types of brain tissue. Lesions were modeled as one of the expected tissue types, and the class parameters were obtained through a supervised voxel sampling scheme on two randomly selected scans. Since the manual training step is highly data-dependent, it is expected to be conducted for each study or data set. A summary of the aforementioned techniques is given in Table 1.

Table 1: Comparison of MS lesion segmentation methods

Author	Method	Sequences	Evaluation
Udupa et al.[12]	Fuzzy Connectedness Principles	T1-w, T2-w and PD-w	NA
Wu et al.[13]	KNN	T1-w, T2-w and PD-w	Spe=0.53 Sen=0.80
Prastwa et al.[17]	Bayesian classification	T1-w, T2-w and FLAIR	Spe=0.99 Sen=0.03
Zhang et al.[19]	SWE+KNN	MS image	Spe=0.99 Sen=0.96
Souplet et al.[21]	EM	T1-w, T2-w and FLAIR	Spe=0.99 Sen=0.26
Jain et al.[23]	MSmetrix	3D T1-w 3D FLAIR	Sen=0.57 Pre=0.83
Strumia et al.[25]	Geometric Brain Model	T1-w, T2- w and FLAIR	Spe=0.56 Sen=0.70
Dworkin et al.[32]	CV	T1-w, T2-w, PD-w and FLAIR	NA
Maier et al.[35]	ET	T1-w, T2- w and FLAIR	NA
Deshpande et al.[41]	Sparse Representations and Adaptive Dictionary Learning,	T1-w MPRAGE, T2-w, PD and FLAIR	Sen=0.60

PROPOSED APPROACH

In this study, we use information from T1- w, T2-w and proton density-weighted (PD) images. This is motivated by the fact that T1-w, T2-w and PD images contain information about WM

lesions[42]. The proposed approach makes use of both unsupervised reasoning offered by a-two step segmentation method as well as an approach that mimics expert reasoning in order to identify whether a potential voxel is a lesion or not. An optimization based approach involves initial identification of the WM class from each of the MR modality using a Fuzzy Particle Swarm Optimization (FPSO) algorithm assuming that the voxels can be WM, GM or CSF as hypothesized in[42]. The focus on WM is also rooted to related clinical studies[43-44], which indicated that the infringement predominantly inflammatory present in the WM is likely in relate with the mechanisms of degeneration and achievement where the measurement of the load lesional provides insights about the degree of progress of the WM in the course of the disease[11]. Second, following the argumentation highlighted by Ait-Ali et al.[45], WM tissue is often pervaded by atypical data, which often weakens the detection of lesions. Therefore, discarding the negative effect of atypical data becomes necessary. Lesion or not, a fuzzy like reasoning that imitates expert reasoning which gathers global information regarding image contrast as well as the signal type before making such decision[11]. Figure 1 shows the proposed workflow for the segmentation of MS lesions. The initial images are noisy, the inhomogeneities are corrected and all images are registered in the same space. Details of the different phases are provided in the subsequent subsections.

Segmentation of the brain by Fuzzy particle swarm optimization algorithm

Brain MRI segmentation is an essential task in many clinical applications because it influences the outcome of the entire medical analysis pipeline. This is because subsequent processing steps rely on accurate segmentation of anatomical regions. For instance, MRI segmentation is commonly used for measuring and visualizing different brain structures, for delineating lesions, for analyzing brain development, and for image-guided interventions and surgical planning. This diversity of image processing applications has led to development of various segmentation techniques with variable accuracies and degrees of complexity. In this study, the segmentation of the brain tissues into different segments, namely: WM, GM and CSF is a key step in our approach. For this purpose, an optimization-based approach using Fuzzy Particle Swarm Optimization algorithm has been adopted in our approach. This is motivated by its simplicity, ability to deal with high dimensional datasets, as well as its proven efficiency in similar other segmentation tasks as pointed out in [46-47]. The application of Fuzzy Particle Swarm Optimization (FPSO) approach for clustering in our case yields three distinct classes corresponding to WM, GM and CSF. The outcome of this segmentation serves as the basis for implementing lesion-handling based strategies.

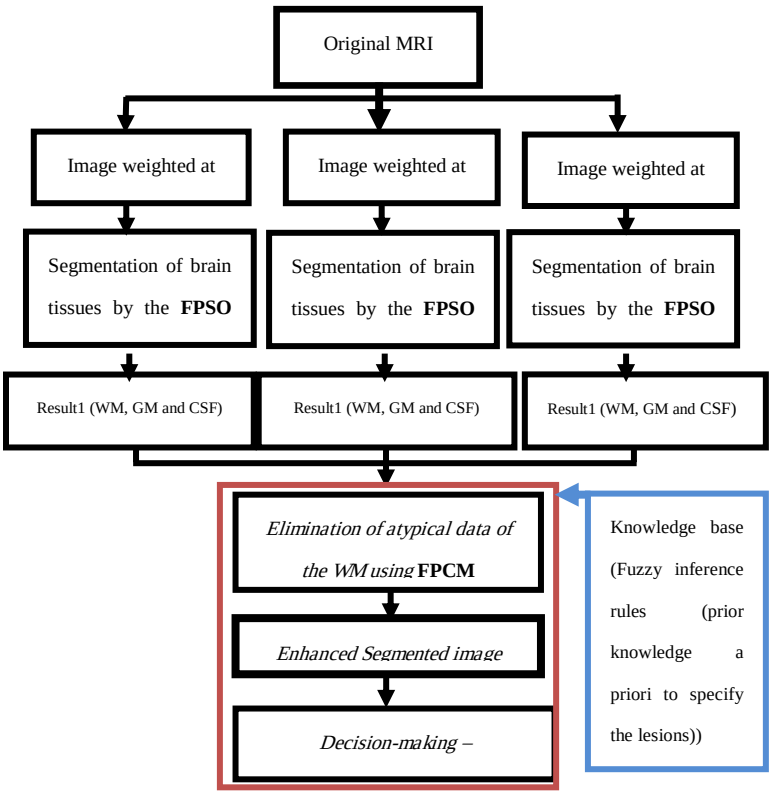

Fig. 1 Block diagram of the proposed approach for automatic segmentation of MS lesions.

Particle swarm optimization (PSO)

Particle swarm optimization (PSO) is a population-based stochastic optimization technique inspired by bird flocking and fish schooling originally designed and introduced by Kennedy and Eberhart[48] in 1995 and is based on iterations/generations. The algorithmic flow in PSO starts with a population of particles whose positions represent the potential solutions for the studied problem, and velocities are randomly initialized in

the search space. In each iteration, the search for optimal position is performed by updating the particle velocities and positions. Also in each iteration, the fitness value of each particle's position is determined using a fitness function. The velocity of each particle is updated using two best positions, personal best position and global best position. The personal best position, *pbest*, is the best position the particle has visited and *gbest* is the best position the swarm has visited since the first time step. A particle's velocity and position are updated as follows.

$$V(t+1) = w.V(t) + c_1.rand_1.(Pbest(t) - X(t)) + c_2.rand_2.(Gbest(t) - X(t)) \quad (1)$$

$$X(t+1) = X(t) + V(t+1) \quad (2)$$

Where:

X and V are position and velocity of particle respectively. w is inertia weight, c_1 and c_2 are positive constants, called acceleration coefficients which control the influence of *pbest* and *gbest* on the search process, P is the number of particles in the swarm, r_1 and r_2 are random values in range [0, 1].

PSO can be implemented and applied easily to solve various function optimization problems, or the problems that can be transformed to function optimization problems[50]. However, the PSO algorithm suffers a serious problem that all particles are prone to be trapped into the local minimum in the later phase of convergence. The optimal value found is often a local minimum instead of a global minimum[51]. Pang et al.[52] proposed a version of particle swarm optimization for TSP called fuzzy particle swarm optimization (FPSO).

Fuzzy particle swarm optimization for fuzzy clustering

Peng et al.[49] proposed a modified particle swarm optimization for TSP called fuzzy particle swarm optimization (FPSO). In their proposed method the position and velocity of particles redefined to represent the fuzzy relation between variables. In this sub-section we describe this method for fuzzy clustering problem.

In FPSO algorithm X , the position of particle, shows the fuzzy relation from a set of data objects, $O = \{o_1, o_2, ..., o_n\}$, to set of cluster centers, $Z = \{z_1, z_2, ..., z_n\}$. X Can be expressed as follows:

$$X = \begin{bmatrix} \mu_{11} & \cdots & \mu_{1c} \\ \vdots & \ddots & \vdots \\ \mu_{n1} & \cdots & \mu_{nc} \end{bmatrix} \quad (3)$$

In which μ_{ij} is the membership function of the i^{th} object with the j^{th} cluster with constraints stated in (1) and (2). Therefore, we can see that the position matrix of each particle is the same as fuzzy matrix μ in FCM algorithm. In addition, the velocity of each particle is stated using a matrix with the size n rows and c columns the elements of which are in range [-1, 1]. We get the equations (4) and (5) for updating the positions and velocities of the particles based on matrix operations[53].

$$V(t+1) = w \otimes V(t) \oplus (c_1 r_1) \otimes pbest(t) \ominus X(t)) \oplus (c_2 r_2) \otimes (gbest(t) \ominus X(t)) \quad (4)$$

$$X(t+1) = X(t) \oplus X(t+1) \quad (5)$$

After updating the position matrix, it may violate the constraints given in (1) and (2). So it is necessary to normalize the position matrix. First we set all the negative elements in matrix to zero. If all elements in a row of the matrix are zero, they need to be re-evaluated using series of random numbers within the interval [0, 1] and then the matrix undergoes the following transformation without violating the constraints:

$$X_{normal} = \begin{bmatrix} \mu_{11} \Big/ \sum_{j=1}^{c} \mu_{1j} & \cdots & \mu_{1c} \Big/ \sum_{j=1}^{c} \mu_{1j} \\ \vdots & \ddots & \vdots \\ \mu_{n1} \Big/ \sum_{j=1}^{c} \mu_{nj} & \cdots & \mu_{nc} \Big/ \sum_{j=1}^{c} \mu_{nj} \end{bmatrix} \quad (6)$$

In FPSO algorithm the same as other evolutionary algorithms, a function is needed to evaluate the generalized solutions called fitness function. In this paper Eq. (7) is used for evaluating the solutions:

$$f(X) = \frac{K}{J_m} \quad (7)$$

There in K is a constant and J_m is the objective function of FCM algorithm. The smaller is J_m, the better is the clustering effect and the higher is the individual fitness $f(X)$. The FPSO algorithm for fuzzy clustering problem can be stated as follows:

Algorithm 1

Input original image.

1. Initialize the parameters including population size P, c_1, c_2, w, and the maximum iterative count.
2. Create a swarm with P particles (X, *pbest*, *gbest* and V are $n*c$ matrices).
3. Initialize X, V, *pbest* for each particle and *gbest* for the swarm.
4. Calculate the cluster centers for each particle using Eq. (11).
5. Calculate the fitness value of each particle using Eq. (7).
6. Calculate *pbest* for each particle.
7. Calculate *gbest* for the swarm.
8. Update the velocity matrix for each particle using Eq. (4).
9. Update the position matrix for each particle using Eq. (5).
10. If terminating condition is not met, go to step 4.

Output segmented image

The termination condition in the proposed method is the maximum number of iterations or no improvement in gbest after a number of iterations.

Segmentation of the white matter using Fuzzy Possibilistic C-Means algorithm

The next stage in our methodology consists in removing the clearly hyper-intense voxels in the previously identified WM voxels in order to highlight the different MS lesions. This is because the lesions of the MS are not well contrasted due to the partial volume in the surrounding tissues, which renders their segmentation rather a difficult task. Motivated by the lack of a fully comprehensive labeled database as reported in[55] a non-supervised like strategy based on Fuzzy Possibilistic C-Means algorithm has been advocated. The FPCM algorithm solves the noise sensitivity defect of Fuzzy C-Means algorithm and overcomes the problem of coincident clusters of Possibilistic C-means algorithm[54]. This is backed by its reported success in image analysis and medical diagnosis including magnetic imaging regardless of the modality and the type of acquisition (mono or multimodal)[56-58] its reduced complexity, easy implementation (especially for large and high dimension dataset).

Formulating of FPCM algorithm clustering

Clustering is a process of finding groups in unlabelled dataset based on a similarity measure between the data patterns (elements)[54]. A cluster contains similar patterns placed together. One of the most widely used clustering methods is the FPCM algorithm. The FPCM algorithm solves the noise sensitivity defect of Fuzzy C-Means algorithm and overcomes the problem of coincident clusters of Possibilistic C-Means algorithm. the FPCM algorithm allows to partition the pixels of X into C classes (here C=3) pertaining to WM, GM and CSF by calculating the centres b_j $(j=1, C)$ of j-th class and the membership matrix (U), Given a set of N total number of pixels of the image $X = \{ x_1, x_2, ..., x_N \}$ the Fuzzy Possibilistic C-Means (FPCM) clustering algorithm minimizes the objective function given bellow[32- 33]:

$$J(B,U,T,X) = \sum_{i=1}^{C}\sum_{j=1}^{N}\left(u_{ij}^{m} + t_{ij}^{\lambda}\right) d^2\left(x_j, b_i\right) \quad (8)$$

Where x_j is the j-th P-dimensional data vector, b_i is the centre of cluster i, m >1 is the weighting exponent, $\lambda \in$ [3,5] is the typicality exponent, $d^2\left(x_j, b_i\right)$ is the Euclidean distance between data x_j and cluster centre b_i, $[U]_{CxN}$ is the fuzzy matrix and $[T]_{CxN}$ is the typicality matrix.

The minimization of objective function $J(B,U,T,X)$ can be guided by an iterative process in which updating of membership degrees u_{ij}, typicality degrees t_{ij} and the cluster centers are done for each iteration by :

$$u_{ij} = \left[\sum_{k=1}^{C}\left(\frac{d\left(x_j, b_i\right)}{d\left(x_j, b_k\right)}\right)^{\frac{2}{(m-1)}}\right]^{-1} \quad (9)$$

$$t_{ij} = \left[\sum_{k=1}^{C} \left(\frac{d(x_j, b_i)}{d(x_j, b_k)} \right)^{\frac{2}{(\lambda-1)}} \right]^{-1} \quad (10)$$

$$b_i = \frac{\sum_{k=1}^{N} (u_{ik}^m + t_{ik}^\lambda) x_k}{\sum_{k=1}^{N} (u_{ik}^m + t_{ik}^\lambda)} \quad (11)$$

Where :

$$\forall\, i \in \{1 .. C\},\ \forall\, j \in \{1 .. N\} \begin{cases} u_{ij} \in [0,1] \\ 0 \prec \sum_{i=1}^{N} u_{ij} \prec N \end{cases} \quad (12)$$

$$\forall\, j \in \{1 .. N\} \sum_{i=1}^{C} u_{ij} = 1 \quad (13)$$

$$\forall\, i \in \{1 .. C\} \sum_{i=1}^{N} t_{ij} = 1 \quad (14)$$

FPCM algorithm consists then of iteratively applying equations (9), (10) and (11) until stability of the solutions. The above equations show that membership u_{ik} is affected by all *c* cluster centres, while possibility t_{ik} is affected only by the *i*-th cluster centre c_i. The possibilistic term distributes the t_{ik} with respect to all *n* data points, but not with respect to all *c* clusters. Thus, membership can be called relative typicality, it measures the degree to which a point belongs to one cluster relative to other clusters and is used to crisply label a data point. And possibility can be viewed as absolute typicality, it measures the degree to which a point belongs to one cluster relative to all other data points, it can reduce the effect of outliers. Combining both membership and possibility can lead to a better clustering result[59].

Overall, the FPCM algorithm consists of the following steps[15]**:**

Algorithm 2

Input WM image.

S1: Given a preselected number of clusters *c* and a chosen value for *m*, initialize the fuzzy partition matrix and typically the partition matrix with constraint in (13) and (14), respectively.

S2: Calculate the center of the fuzzy cluster, b_i for *i* = 1,2, … , *c* using Eq. (11).

S3: Use Eq. (9) to update the fuzzy membership u_{ij} .

S4: Use Eq. (10) to update the typically membership t_{ij} .

S5: If the improvement in $J(B, U, T, X)$ is less than a certain threshold (ϵ), then stop; otherwise, go to S1

Output The images of extracted MS

Decision-making

The last step determines whether a given WM voxel is an MS lesion or not. For this purpose, a Mamdani-type fuzzy inference system has been adopted. In the latter, (global) information about the image contrast and signal's type are used as global variables. The outcome corresponds to the extent to which the MS attribute is persistent in the underlying WM voxel. Especially, the weighted images in T2 and PD underline the myelin component in the lesions characterized by the edemas with hyper-intense appearance in comparison to the WM. Furthermore, T1-w underlines the irreversible destruction of the tissues with the appearance in the white matter of persistent "*black holes*" (Hypo-signal)[50].

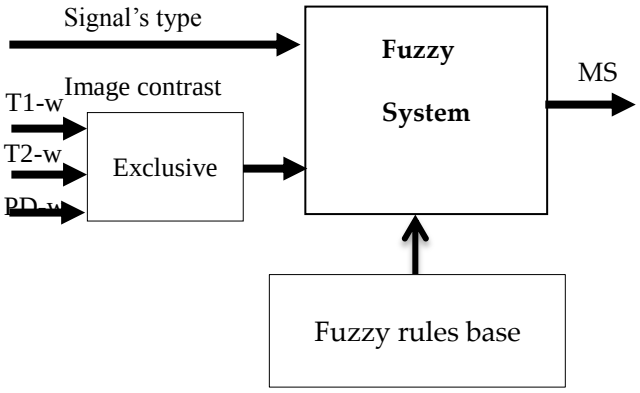

Fig. 2 Diagram of fuzzy system of the MS disease.

Table 2. Rules' base in the form of a matrix.

	T1-w	T2-w	DP-w
Hyper signal	Low/Normal	High	High
Hoper signal	Low	High	High
Hyper signal after injection of gadolinium	Normal	High	High

An instance of fuzzy rules is described below:

1. **If** [(the image contrast is T1-w active) AND (the signal is hyperintense)] **then** (MS is low).
2. **If** [(the image contrast is T1-w active) AND (the signal is hyperintense)] **then** (MS is normal).
3. **If** [(the image contrast is T2-w active) AND (the signal is hyperintense)] **then** (MS is high).
4. **If** [(the image contrast is PD -w active) AND (the signal is hyperintense)] **then** (MS is high).
5. **If** [(the image contrast is T1-w active) AND (the signal is hypointense)] **then** (MS is low).
6. **If** [(the image contrast is T2-w active) AND (the signal is hypointense)] **then** (MS is high).
7. **If** [(the image contrast is PD-w active) AND (the signal is hypointense)] **then** (MS is high).
8. **If** [(the image contrast is T1-w active) AND (the signal is hyperintense after injection of gadolinium)] **then** (MS is normal).
9. **If** [(the image contrast is T2-w active) AND (the signal is hyperintense after injection of gadolinium)] **then** (MS is high).
10. **If** [(the image contrast is PD-w active) AND (the signal is hyperintense after injection of gadolinium)] **Then** (MS is high).

The quantification of image contrast, signal type and the MS disease is described in the as follows :

For the fuzzification of the signal's type, we choose two fuzzy intervals and belonging functions of Gaussian types. Figure 3 shows the fuzzy repartition of the input variable of signal's type.

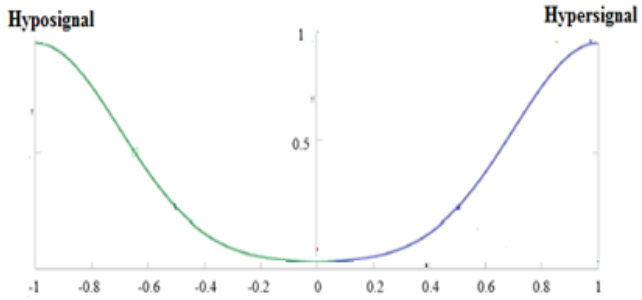

Fig. 3 Fuzzy repartition of input variable of signal's type[11].

For the output variable, we choose three fuzzy intervals and Gaussian membership functions, which define predicates: *low, normal and high* of the MS disease in comparison to the white matter. Figure 4 shows the fuzzy repartition of the output variable of the decision of the MS disease.

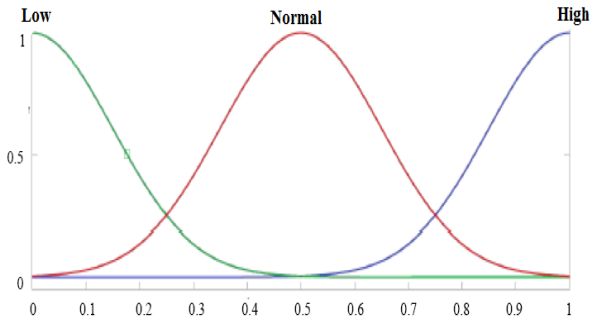

Fig. 4 Fuzzy repartition of the output variable giving the decision of the MS disease[11].

The selected inference method is Mamdani's method. Consequently, the operator is realized by the calculation of the minimum, whiles the operator OR is realized by the calculation of the maximum. The defuzzification step is done using the method of calculating the centre of attraction.

RESULTS AND DISCUSSION

Dataset

The dataset was provided as part of a collaboration agreement between LSI laboratory (Laboratory Intelligent Systems: image and signal team) Ferhat Abbas University of Sétif and LAMIH UMR CNRS 8201 (Laboratory of Industrial and Human Automation control, Mechanical engineering and Computer Science) University of Valenciennes. The various T1-w, T2-w and PD images corresponding to relatively older patients. These images are in the form of DICOM (Digital Imaging and

Communications in Medecine) and were already pre-processed and spatially normalized.

Computational requirement

The proposed algorithm was implemented in Net-Beans IDE 8.2 and run on a laptop with 2.40 GHz Intel(R) Core (TM) i5-4210U CPU and 4 GB RAM. The operating system was 64-bit Windows 8.1. To compare the performance of these images, we compute different coefficients reflecting how well two segmented volumes match. Four measures are used as follows[43]:

$$Overlap\,(ovrl) = \frac{TP}{TP + FN + FP} \quad (15)$$

$$Similarity\,(Si) = \frac{2TP}{2TP + FN + FP} \quad (16)$$

$$Sensitivity\,(Sen) = \frac{TP}{TP + FN} \quad (17)$$

$$Specificity\,(\mathrm{Spc}) = \frac{TN}{TN + FP} \quad (18)$$

Where, TP (True Positive) means an MS patient is correctly identified as MS, FP (False Positive) means healthy people were incorrectly identified as MS, TN (True Negative) means healthy people were correctly identified as healthy, and FN (False Negative) means MS patients incorrectly identified as healthy.

Analysis of the results

The brain segmentation was successfully applied on some real images and results are shown in Figure 5.

Automatic tissues and white matter lesion segmentation by FPSO and FPCM algorithms

The following figure 5 illustrates axial slices of the segmentation results by the FPSO algorithm for the T2-w, PD-w and T1-w MR images in order to obtain a characterization of the different healthy tissues WM, GM and CSF. After the segmentation by FPSO algorithm we extracted the WM. Then, the use of FPCM allowed us to eliminate the atypical data of the WM for each image (T2-w, PD-w, T1-w) as exhibited in figure 5.

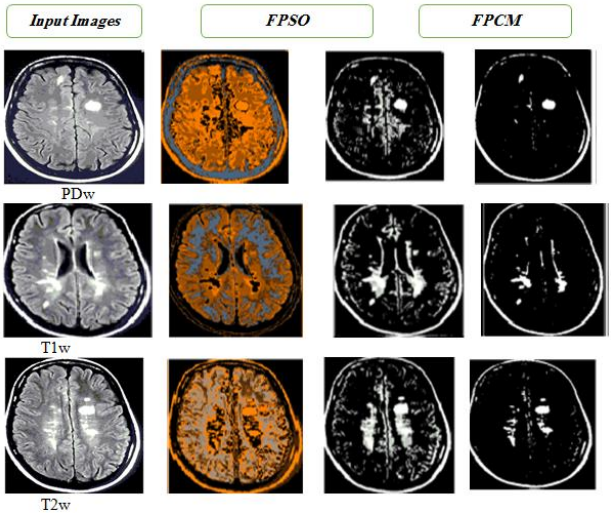

Fig. 5 Scheme of the full MS lesion segmentation process. The left column shows the the used strategy for of tissues (WM, GM, and CSF) segmentation steps, while the right column depicts the used strategy for MS lesion segmentation.

Comparative results are presented in Table 3 below:

Table 3: Comparison of the results obtained by FPSO and FPCM algorithms

		GSF	WM	GM	MS lesions
	Si	0.81	0.91	0.85	0.93
T1-w	***Ovrl***	0.63	0.88	0.84	0.94
	Sen	0.70	0.95	0.91	0.91
	Spc	0.75	0.96	0.90	0.93
	Si	0.92	0.94	0.92	0.99
T2-w	***Ovrl***	0.89	0.93	0.90	0.95
	Sen	0.90	0.93	0.92	0.94
	Spc	0.92	0.96	0.93	0.96
	Si	0.77	0.81	0.81	0.96
PD-w	***Ovrl***	0.58	0.77	0.70	0.95
	Sen	0.66	0.83	0.72	0.85
	Spc	0.88	0.86	0.85	0.93

The results obtained by FPSO and FPCM algorithms are very satisfactory and confirm the validity of the algorithms, its ease of implementation gives us a substantial advantage. We have made an improvement in optimizing the white matter and atypical localization data for all tissues using T1-w, T2-w and PD-w.

Decision-making

The implementation of the Mamdani fuzzy inference system makes use of min operator for AND connective and max for OR connectives. The result of the implementation is shown in Table 4.

Table 4: Results of MS lesions of the defuzzification values for the different sequences

	T1-w(%)	T2-w(%)	PD-w(%)
MS	49.64	59.51	51.71

Involving people with MS proactively in decision-making and in managing their disease is also key to the successful management of MS. The decision-making depends always on the expertise, it is evident from the Table 4 that the patient suffers from the multiple sclerosis and the MS lesions are detected in all the sequences by a normal or a high characterization.

Table 5. Comparison of the results gotten by different algorithms.

	GM (%)	CSF (%)	WM (%)	MS (%)
FPSO	83.7	69	87	77
FPCM	70.2	55.9	81.5	76
FPSOFCM	85.2	64.1	88.4	90.6
Proposed approach	89.9	69	95	97.9

Experimental Results

In this section, we compare the proposed algorithm with the FPSO, FPCM, FPSOFCM algorithms and the segmentation realized by the expert on a set of MRI brain images. In order to study the robustness of the proposed algorithm for MRI brain segmentation, test images (256x256 pixels) are from three MRI modalities (T1-w, T2-w and PD-w), corrupted by different levels of white Gaussian noise (0%, 3%, 4%) and intensity non-uniformity (RF)(0%, 20%, 40%). Segmentation results are shown in Figure 6.

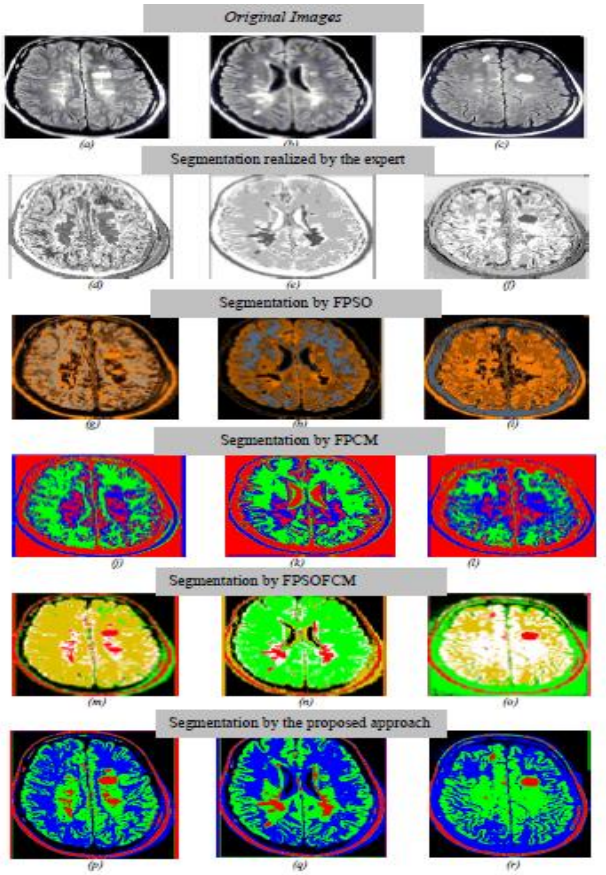

Fig. 6 Comparison of segmentation results on T1-w, T2-w and PD-w images.

The interpretation of our results is done by an expert (hospital center of Ain Naadja Algiers) on simulated and real images. By analyzing the images of figure 10, the expert has established the following statement:

_ **Image (d):** The interpretation of the classes is totally improved in relation to (FPSO, FPCM), we notice the distinction between the three classes of the brain and the class of the pathology SEP.

_ **Image (g):** FPSO is unsuitable in this segmentation in relation to the image (FPSOFCM).

_ **Image (j)** : The FPCM does not bring much compared to the FPSO.

_ **Image (m):** The class CSF does not conform to the class of the original image. The lack of information about the small grooves (image (a)) and the poor discrimination CSF/GM make that the segmented CSF class does not well represent the fluid distribution. The distributions of the WM and GM get closer to those given by the original image. The detection of the pathology is indicated according to the expert but the details are not well expressed.

_ **Image (p):** the proposed approach brings a great performance to the segmentation for the three classes and especially for the fourth one which is the pathology that specifies well the size and the details about this later.

Next, we compare in Table 5 the segmentation of T2-w MRI between segmentation made by the expert, FPSO, FPCM, FPSOFCM for a given time of acquisition and the segmentation by the proposed approach.

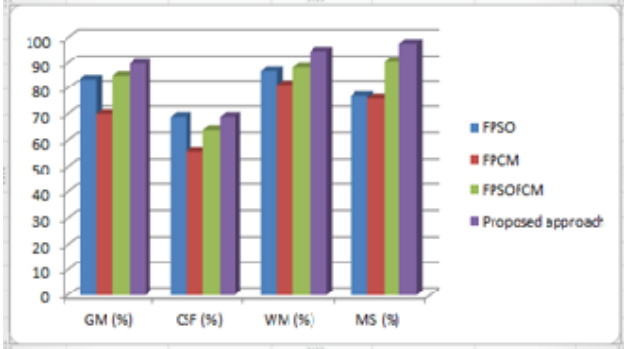

Fig. 7 Performance measures of the results gotten by different algorithms

Table 5 summarizes the results of the lesion detection algorithms reviewed in terms of reproducibility and agreement with the experts. The results highlighted in this Table and Fig.7 underline the advantages of the proposed approach in comparison to the segmentation by FPSO, FPCM and FPSOFCM for all tissues CSF, WM, GM and MS lesions. From these outcomes, it is evident that our extension of a previous work provides a very good performance method for the segmentation of abnormal anatomy in MRI data, such as MS lesions.

CONCLUSION

The goal of the research presented in this article was to propose an automatic approach of segmentation of the MS lesions images based on FPSOFPCM algorithm. Comparison results to other similar approaches shows that the proposed method outperforms is better than the other previous ones in extracting MS lesions. The prospects of improvement and development of this work are multiple: we can consider improving the post-treatments done after the detection of outliers in order to keep only the SEP lesions. At present, only the outliers for which the segmentation of the WM given by the FPCM algorithm will be kept. The main limitation of this method is that it depends on the employed method of registration. Another solution may consist of using the obtained segmentation of tissues. Thus, we can keep the outliers situated in the mask of the obtained segmentation of the WM.

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