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Research paper

Using the fuzzy methods to examine changes in brain lesions and atrophy from MRI images for rapid diagnosis of MS

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Abstract

Multiple sclerosis (MS) is a disease that affects the central nervous system, during which the myelin present on the nerve fibers that have a protective role is destroyed, and therefore the conduction of electric current is disturbed and the symptoms of MS disease appear. In this disease, the white blood cells that play a defensive role in the body attack the myelin, which is a protection for nerve fibers, as a foreign agent, and each time these blood cells attack the nerve fibers of one of the organs of the patient's body. Which is unclear, that organ will have problems. The best way to diagnose MS is to examine brain MRI images. Therefore, the existence of a fast and accurate method to evaluate changes in brain atrophy or the creation and increase of lesions (plaques) caused by this disease is a key component in diagnosing and evaluating the progress of the disease and the effectiveness of its treatment courses. Manual detection of changes in lesions (plaques) and brain atrophy caused by this disease usually requires a trained specialist and is very slow and difficult, and the results are somewhat subjective. Therefore, the existence of an automatic system for extracting and checking these changes is essential. Although many automatic methods have been proposed, the segmentation results are not accurate enough. As a result, there is a great need to develop a strong, fast, and accurate method to diagnose MS and brain lesions caused by it. In this article, by combining two fuzzy methods and the controlled watershed algorithm, we propose a fast method with high accuracy to diagnose MS from brain MR images.

1. Introduction

Paying attention to MS or multiple sclerosis is very important and necessary because we still do not know its treatment. However, scientists are working on it and hopefully in the near future we will be able to successfully assess its behavior and eventually treat it. We now know that the protective covering of axons is made of myelin, a white fatty substance, which is lost in patients suffering from MS. As a result, they experience severe sensory or motor impairment. There are different types of MS and different stages of the disease. Some patients report that their condition keeps going back and forth. This is because relapsing-remitting MS is a condition where the myelin sheath is destroyed but can be repaired, but unfortunately, it is destroyed again after a while. On the other hand, progressive MS leads to neuronal death caused by axonal damage, which is an irreversible state. A review of past works shows that the most important factor in the process of treating the disease is the rapid diagnosis of the disease. Rondinella, A. (2023) and colleagues in their article have used a U-Net structure reinforced with a convolutional short-term memory layer to more accurately segment and measure multiple sclerosis lesions detected in magnetic resonance images. To cope with inter- and intra-observer variability and reduce the burden and complexity of lesions identification for clinicians, a large number of techniques have been proposed in the literature for the automatic segmentation of MS lesions (see Garcia-Lorenzo et al., 2013; Valverde et al., 2017; Danelakis et al., 2018 for reviews). Several challenges have been proposed to evaluate the performances of these methods (e.g., Carass et al., 2017; Commowick et al., 2021 to cite the most recent ones). Moreover, recently Bonacchi et al. (2022) proposed an overview of Artificial Intelligence applications for MS clinical practice. Initial studies mainly enrolled patients with longstanding severe progressive multiple sclerosis, when inflammatory features are less prominent and neurodegeneration is the main underlying mechanism (Trapp and Nave, 2008). Benefit generally was modest, although some patients exhibited sustained slowing or stabilization of disability, but improvement in neurologic function was rarely seen (Burt et al., 2015; Mancardi et al., 2015). Also, patients with more severe neurologic disability had increased risk of adverse events (Mancardi and Saccardi, 2008). More recent studies (Table 1) focused on relapsing-remitting multiple sclerosis and demonstrated that patients with active inflammatory features appear to derive the most benefit from this approach (Burt et al., 2012; Saccardi et al., 2012; Muraro et al., 2017).

In this article, we present a new method of rapid diagnosis of MS disease by examining changes in brain lesions and atrophy from MRI images using fuzzy methods.

2. Materials and Methods

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3. Page Layout

Since image noise and heterogeneity have major effects on non-brain tissue such as skull and fat, non-brain tissue is removed from the patient's MR image in order to reduce calculation time and increase efficiency. In MR brain image slices, by using two important factors to recognize the skull, i.e. thresholding on the intensity of light and also considering the approximate width of the skull, we reach very good results for removing the skull. In order to remove the skull, we first extract the image from each slice by considering a suitable threshold limit for only the skull, and then by comparing it with the original image, we separate the skull from the image in all slices of the MR image. Because MR images encounter different types of noise such as Gaussian, Poisson, Rayleigh and impact noise (pepper-salt). Therefore, the use of noise reduction and removal methods to improve the quality of these images will be vital for better diagnosis of diseases. Therefore, in the next step, using morphological operators, the noise is reduced as much as possible and the image quality is improved. First, by using the opening operation, a part of the broken narrow paths or small protrusions caused by fluctuations or non-linear effects are removed from the image. Then, in order to further reduce and eliminate noise, we use the combined opening-closing operation. By doing this, the effects of the remaining noise on the edges and also on the edges of the narrow edges of the image will be removed from the image, and an image will be obtained in which the edge noise has almost disappeared and the edges will be easily distinguishable. Figure 1 shows the result of removing the skull with this method from the middle slice of the T1-w weighted MR image.

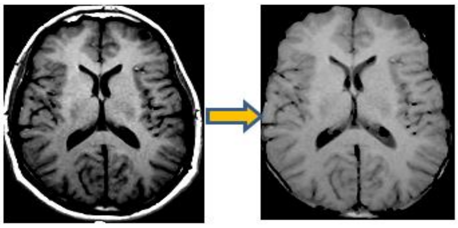

Figure 1: Removing the skull from a slice of an MRI brain image

After removing the skull using two factors of approximate width and thresholding, the area of each slice is measured and recorded so that they can be compared with each other over time and in periodic MRIs of the patient. Also, we consider the effect coefficient of each slice on the brain volume based on the area of each slice. We calculate the coefficient of 1 for the slice that has the largest area, and the effect coefficient of the rest of the slices is calculated by dividing the area of that slice by the area of the largest slice. Since the lesions (plaques) in MS occur only in the white area of the brain, in order to increase the accuracy of the system, first, the white, gray and cerebrospinal fluid areas of the brain are extracted using the fuzzy c-mean algorithm. Now, if the detected lesion is in the white area of the brain, then the segmentation is correct and the lesion is accepted and goes to the next stage, otherwise the lesion is removed. Another factor is measuring and comparing the area of each of the white, cerebrospinal, and gray areas of the brain, which should be evaluated over time on periodic MRIs of patients.

C means clustering algorithm:

In this algorithm, the number of C clusters is specified in advance. The objective function defined for this algorithm is as follows:

$$J = \sum_{i=1}^{c}\sum_{k=1}^{n} u_{ik}^{m} d_{ik}^{2} = \sum_{i=1}^{c}\sum_{k=1}^{n} u_{ik}^{m} \left\| x_k - v_i \right\|^2$$

Equation 1

In equation 1, m is a real number greater than 1, which is chosen as 2 for m in most cases. is the kth sample and is the representative or center of the ith cluster. It shows the membership of the i-th sample in the k-th cluster. The symbol ||*|| The degree of similarity (distance) of the sample with (from) the center of the cluster, which can be used any function that expresses the similarity of the sample and the center of the cluster. A U matrix can be defined from and its components can take any value between 0 and 1. If all the components of the matrix U are 0 or 1, the algorithm will be similar to k average, although the components of the matrix U can take any value between 0 and 1 but the sum of the components of each of the columns must be equal to 1 and we have:

$$\sum_{i=1}^{c} u_{ik} = 1, \forall k = 1,\ldots,n$$

Equation 2

This condition states that the membership of each sample to c clusters must be equal to 1. Using this condition and minimizing the objective function, we will have:

$$v_i = \frac{\sum_{k=1}^{n} u_{ik}^{m} x_k}{\sum_{k=1}^{n} u_{ik}^{m}}$$

Equation 3

$$u_{ik} = \frac{1}{\sum_{j=1}^{c} (\frac{d_{ik}}{d_{jk}})^{2/m-1)}}$$

Equation 4

In this algorithm, the initial values for c, m and U^0 are done, the initial clusters are guessed and the centers of the clusters are calculated. Then the membership matrix is obtained from the calculated clusters. Now, if equation 5 is true, the algorithm ends, and otherwise, the algorithm returns to the previous step.

$$\left\| U1+1-U1 \right\| \leq \varepsilon$$

Equation 5

The use of the fuzzy algorithm makes the curve of the membership function smoother than the classical k-means algorithm, and the border between the clusters is not defined accurately and definitively. In order to segment the brain in the proposed algorithm, the number of clusters is considered equal to 3, which includes white area, cerebrospinal fluid and gray area of the brain. After clustering, the gray area and CSF are removed so that only the white area of the brain remains and the search space is limited to this area. Figure 2 shows the results of this clustering. In the testing phase of the system, after the lesions are detected, only the lesions located in the white area of the brain are accepted, and otherwise they are removed.

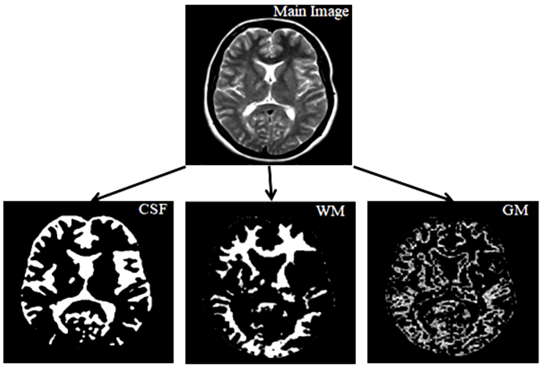

Figure 2 : The results of clustering by the c-means fuzzy algorithm by selecting three clusters

In the next step, in order to optimally separate the brain regions, the average brightness intensity of each image slice is taken and the corresponding coefficients are obtained according to the average so that an optimal threshold is applied to the corresponding slice for each MR image. By comparing the results of the implementation of the proposed system of images used in two cases, once with noise removal by Gaussian filter and once without noise removal, it was determined that due to the removal of noise, some of the information related to the texture was also removed or They change, so noise removal methods should not be used as much as possible.

Diagnosis of lesioned hemispheres

In the diagnosis of hemispheres with MS lesions, the main idea is the asymmetry of the histogram between the healthy and lesioned hemispheres. Therefore, the hemispheres of the brain must be extracted first. Dividing the brain into two hemispheres is done by finding the diameter of the oval containing the brain. The advantage of this method is its resistance to head rotation and patient movement during imaging. For this purpose, after the complete extraction of the brain, the obtained image becomes binary. The resulting mask has an area that can be separated from the right and left hemispheres by determining the ellipse containing the area and considering its large diameter as the midline of the brain. (Nabizadeh and Kubat, 2015) Figure 3 shows the separation of the right and left hemispheres of all slices of an MR image.

4. Diagnosis of lesioned hemispheres

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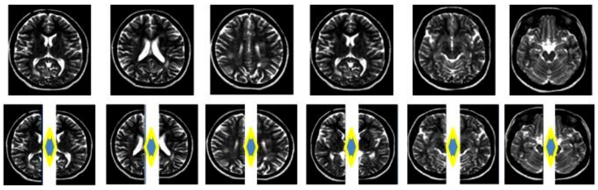

Figure 3: Separation of the right and left hemispheres of all slices of an MR image

After separating the right and left hemispheres of the brain, in the next step, we want to determine the hemisphere containing MS based on histogram information. In the algorithm used in this article, both training and test data, the number of slices for all samples in the neural network are selected equally. In this case, the corresponding slices from different samples represent the same part of the brain and therefore have the same structure. Due to this, it will be possible to create a standard histogram for healthy hemispheres for all slices using the training data. The standard histogram of all slices is extracted using the average histogram of the healthy hemispheres and fitting the Gaussian function in the training phase. In the system test phase, the obtained standard histogram is compared with the histogram of the test data and the hemisphere with the lesion is determined. To check the histograms, the sum of squared errors was used. Figure 5 shows the standard histogram extracted from the middle slice of the MR image and the histograms for the left and right hemispheres of this slice of the brain, which is slice number 255 of the database images of a 40-year-old healthy woman.

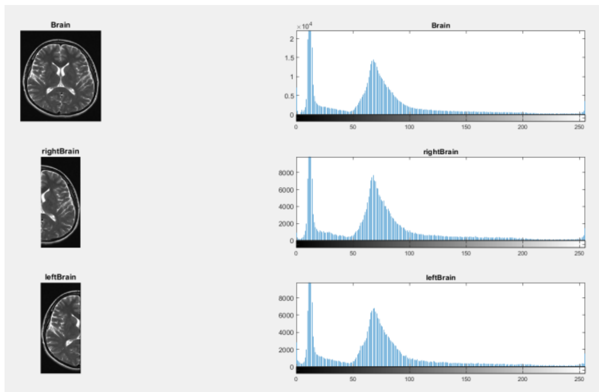

Figure 4 : The standard histogram extracted from the middle slice of the MR image and the histograms related to the left and right hemispheres of this slice from the brain of a 40-year-old healthy woman

In Figure 5, as can be seen, the standard histogram and the histogram of the left and right hemispheres of the middle slice for a 45-year-old female patient with MS have one peak, but the histogram of the hemisphere with a lesion has another peak, which is actually related to the brightness of the lesion.

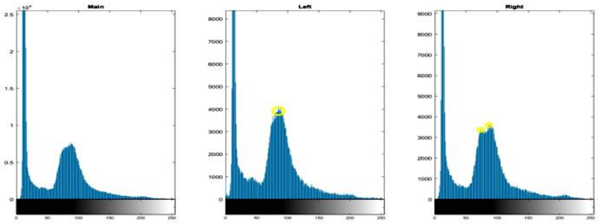

Figure 5: Standard histogram,histogram related to the left and right hemispheres of a 47-year-old female patient with MS.

In this method, by using the neural network by comparing between the hemispheres and comparing it with the histogram samples of healthy people, in addition to distinguishing sick from healthy people, it is possible to identify the hemisphere that is more involved in MS disease from the peaks created on the histogram. can be identified. Therefore, the search space of our segmentation step is reduced in this method. Since the number of slices in the samples may not be equal according to the imaging diameter, in this case it is possible to identify the disease separately for that person by comparing the histogram of the two hemispheres of the same person. In this case, if the two histograms are different from each other, it means that the person has MS. But it is not possible to accurately determine the hemisphere containing the lesion, so both hemispheres should be examined after segmentation.

At the end, in the evaluation stage of the neural network, we first obtain the distance between the standard histogram and the histogram of the investigated hemisphere by the sum of squared error method, and by considering a suitable threshold limit, we determine the presence or absence of a lesion in the hemisphere. The size of the lesion determined by this method is dependent on the determined threshold value, if this value is high, small lesions will be easily recognized, but some false positive error will increase, because some healthy slices have a diagnosis lesion. will be given On the other hand, a smaller threshold value reduces the amount of false positive error, but it will no longer be possible to detect small plaques related to MS. Therefore, in order to fully extract the images with lesions, the threshold value is considered to be relatively small so that the hemispheres in which there is a high probability of having MS can go to the next stage and be examined more closely, on the other hand, the images that are rejected in this stage are very unlikely to have MS. In other words, the false negative rate of the system will decrease. In order to extract the feature, we first sweep each hemisphere by a sliding window. We have considered the distance between the central pixel location of the window and the next location to be 5 pixels to increase the processing speed. As a result, the window will overlap at the current and next location. In the training phase, the hemispheres containing the lesion and healthy are cut and windows are obtained from them. In each window, the features are extracted and the target class is trained based on whether each training window has a lesion or not. In the test phase, a window of the same size as the window of the training phase is considered and moved throughout the brain and background area. The features are extracted and classified in this window and in any place where it is placed. Based on the classification results, the center of the window based on belonging to the lesion site or healthy brain tissue is marked. In order to determine the appropriate size of the window, two windows with sizes of 8 x 8 and 16 x 16 are considered.

After the automatic diagnosis of patients' images with the help of neural network, to determine the progress of the disease, it is necessary to extract MS plaques from the image slices and provide them to the doctor. Considering that MS plaques are part of the brain tissue, their accurate segmentation and separation will be of great help in the treatment of the disease by the doctor. In this article, in order to increase the accuracy in the separation of MS plaques, the water conversion method of marker-controlled diffusers and the integration of similar areas have been used. At first, the change is applied by applying a 6x6 Gaussian Laplacian edge filter to calculate the approximation accuracy of the gradient amplitudes. In the segmentation stage, the marker-controlled water spreader (MCWS) method is applied to the gradient domain of the obtained image. Finally, the over-segmented areas are selected and merged using histogram similarity. To obtain a better filtered image, we have used the functions of illumination and dilation, and to improve the results, opening and closing are used. In the proposed algorithm, since the image is of gray scale type, the domain gradient is used as a segmentation function. The results of the segmentation function result in an image that has the foreground and background markers that we target for segmentation. In the segmented output of the final diffuser, the original image of cerebral MS plaques is extracted from the original MRI image. In the figure below, images of plaque extraction from slices for a 47-year-old female patient can be seen. In this figure, inside the yellow dots, you can see the plaques that were correctly extracted from the image by this method, and the black dots inside the red circles are the points that were wrongly detected as plaques.

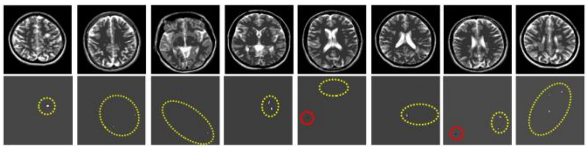

Figure 6: How to extract plaques from the middle eight slices of the MR image of a 47-year-old female patient with MS

This processing was done on 55 people including 28 female patients and 27 male patients. The images were used from the archives of Pars Imaging Center and Hajar Shahrekord Hospital. In total, 98.7% accuracy was recorded for the separation of MS plaques with this method. In similar methods used in other articles, the accuracy of separation of MS plaques was 94.8%, which shows that the method used in this article has a much higher accuracy.[3,5,10,14]

5. Conclusion

MS disease occurs at a young age, usually between 20 and 40 years old and because its complications affect patients from a young age to the end of life, therefore, its rapid diagnosis is necessary to start treatment in the early stages of affected patients. It prevents further progress and prevents severe complications in the patient's body. The proposed method in this article, considering that it is able to automatically diagnose the disease with high speed and accuracy, can be of great help to patients. The combination of fuzzy methods with the controlled watershed algorithm has enabled us to quickly diagnose the disease by comparing the histogram of the two hemispheres of the brain and to extract the plaques caused by the disease using the controlled watershed method. In the next step, after starting the treatment and repeating the MR imaging, we can use this method to evaluate the changing status of the plaques over time. The use of this method can be important in the process of examining the patient's condition in a long period of time and the effectiveness of the treatment process by the doctor.

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