segmentation methods, visualisation,
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SEGMENTATION AND VISUALISATION MR IMAGES OF THE HUMAN BRAIN

Segmentation and visualisation of anatomical regions of the brain are fundamental problems in medical image analysis. In this paper, we present a fuzzy-logic segmentation system that is capable of segmenting magnetic resonance (MR) images of a human brain. The presented method consists of two main stages: histogram thresholding and pixel classification using a rule-based fuzzy logic inference. After the segmentation is complete, attributes of different tissue classes may be determined (e.g., volumes), or the classes may be visualised as spatial objects. The implemented system provides many advanced 3D imaging tools.

1. INTRODUCTION

Image segmentation is a process of locating interesting areas or volumes. In general, autonomous segmentation is one of the most difficult tasks in image processing. This step in the process determines the eventual success or failure of the analysis. In this paper we present a method of automatic brain segmentation from MR images and methods for visualisation of segmented structures.

Manual interpretation of MR images taken from a scanner is very time consuming and does not always lead to the same result on the same data set. What is required is a method of segmentation that both minimizes the subjectivity and is fast. This is true for a numerical algorithm even if it is only used to aid the interpretation of the images, and not for making decisions. The presented method combines region-growing and thresholding techniques using rule based fuzzy logic for distance and value measurement, and fuzzy entropy for automatic histogram thresholding for magnetic resonance brain image segmentation. The results from this research show that this method is reliable and efficient for MR brain image segmentation.

Visualisation of anatomical models is also an important task in medical diagnosis or therapy planning. In this paper we present various 3D visualisation techniques that significantly enhance the perception of three-dimensionality during the examination and offer a valuable tool in the comprehension of complex 3D structures.

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2. SEGMENTATION OF BRAIN IMAGES

Segmentation subdivides an image into objects of interests. These objects are often referred to as regions of interest (ROI) or volumes of interest (VOI) and are stored in a mask in which every position corresponds to the same position in the image segmented. With MR images of the human brain it is important to segment such structures as white matter, grey matter, cerebro-spinal fluid, fat and skin.

2.1. BASIC BRAIN IMAGE SEGMENTATION METHODS

There are a few different approaches to segmenting MRI brain images, and the most common approach is based on automatic grey-level thresholding (for example [2]). This technique uses histogram analysis, from which the threshold levels are determined to produce a binary mask. This is not a complete survey of MRI segmentations method and there are several reasons why this technique is insufficient: its main criterion is based on local pixel information so outer structures are often linked to brain tissue and noise, imaging artifacts, and sometimes poor distribution of grey levels increase the difficulties in distinguishing brain tissue from non brain tissue. There are also a few region-oriented methods [3]: region growing, region merging and region splitting that groups homogeneous pixels or subregions into larger regions. In these methods the seeds are planted manually and they usually use binary morphology to break connections to non-brain tissues. The main problems are how to find the seed pixels in an image, and that the different seed pixels may generate inconsistent segmentation results. There are several techniques for detecting discontinuities in a digital image [3], but edge detection is by far the most common approach for such a method of segmentation. The basis underlying most edge detector techniques is the computation of a local derivative operator, such as gradient operator or laplacian. Furthermore, there are those methods that have a more statistical approach, and similar to these are methods that utilize artificial neural networks or some statistical methods that employ one MRI scan or both T1- and T2-weighted MRI-data sets.

2.2. FUZZY SEGMENTATION ALGORITHM

Our segmentation algorithm is a combination of some of the above methods and uses fuzzy logic as a decision criterion. This segmentation method is based on general anatomical knowledge of the brain seen from three different directions: transversal, sagittal and coronal. The full algorithm was described in [1], and in this paper we present only a brief overview of this algorithm plus a few changes that we have added to our earlier algorithm.

Generally, the algorithm consists of four stages (see fig.1). A whole segmentation process is performed for one MR human brain data set, but the MR type may be T1 or T2-weighted, or proton density. The first stage of our method is the preprocessing, where the main purpose is to reduce the background noise. The quality of the noise reduction is very significant for the accuracy of the whole segmentation process. At first, the standard “region-growing” algorithm [3] eliminates the noisy background and the following binary

opening operation [3] eliminates the remaining larger noise clusters in the segmented background mask.

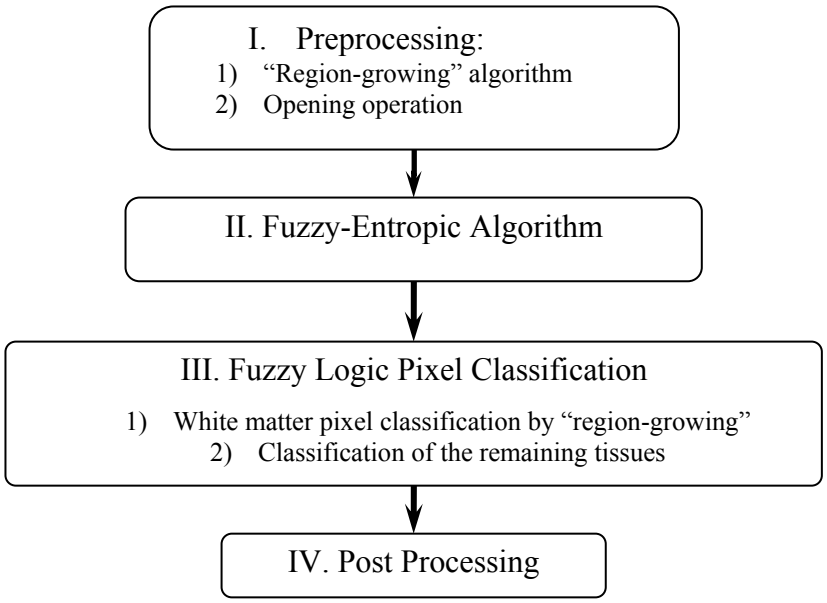


Fig. 1. The algorithm flow chart

The second stage is based on the "fuzzy entropic algorithm" [2]. The purpose of the stage is to threshold the image histogram to find the local minima that designate the pixel values for tissues in the MR scan. In comparison with a two-tone image, a grey-level image appears fuzzy. We need to define a measure of the fuzziness to enable us to choose segmentation levels (boundary threshold values describing a specified region) that will minimize the fuzziness. The information theoretic entropy [8], which measures the mean value of the statistical uncertainty, is defined as follows:

$$H = -\sum_{i=1}^{n} p_i \log_2 p_i \qquad H[0,1] \tag{1}$$

H is the average information supplied by a set of i symbols whose probabilities are given by: $p_1, p_2, p_3, \ldots p_i, \ldots, p_n$.

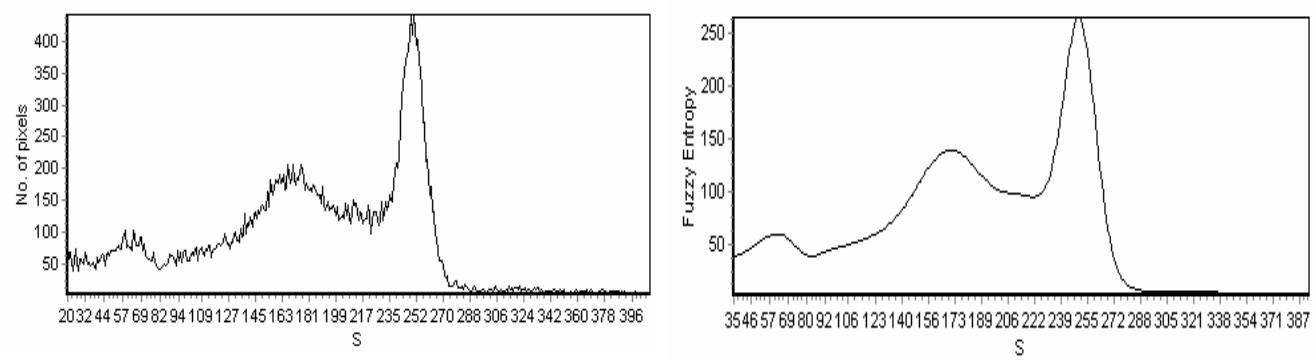
The fuzzy membership is regarded as a membership graduation of a set with statistical uncertainty. This is the exact situation where the image histogram does not display a smooth set of valleys between peaks. In our approach the standard S-function [9] has been selected for the purpose of the membership graduation. It is possible to apply Shannon's function to this membership function for a particular bandwidth, and now we can give the fuzzy entropy measure as:

$$H_{fuzzy}(A) = \frac{1}{n \ln 2} \sum_{i=1}^{n} Sn(\mu_A(x_i)) \tag{2}$$

where *A* is the fuzzy set of the concern containing *n* members. To apply this equation to the image histogram *H* with *n* grey-levels within the fuzzy region g_i and width h_i pixels in the *i*-th histogram bin, we use:

$$H_{fuzzy}(H) = \frac{1}{n \ln 2} \sum_{i=1}^{n} Sn(\mu_H(g_i))h_i \qquad (3)$$

The sample histogram and the fuzzy entropy histogram are shown in Figure 2. To detect the fuzzy entropy valleys (histogram local minima) we need to find only where *e(k-1) < e(k) < e(k+1)* for successive discretely sampled values of fuzzy entropy *e(k)* corresponding to each starting position of the bandwidth window.



a) b)

Fig. 2. The fuzzy entropy histogram of one MR slice for: the original histogram (a), the fuzzy histogram with bandwidth *b=15* (b).

The third stage of the presented algorithm is the pixel classification process. We use a fuzzy inference mechanism with applied IF-THEN rules.

IF- THEN rules for MRI T1 images:

IF *pixel* IS *bright* AND *Pixel* IS NOT *far* THEN *pixel* IS *white matter*
IF *pixel* IS *gray* AND *Pixel* IS NOT *far* THEN *pixel* IS *gray matter*
IF *pixel* IS *very bright* AND *Pixel* IS NOT *close* THEN *pixel* IS *CSF*, *muscle*, *fat*
IF *pixel* IS *dark* AND *Pixel* IS NOT *close* THEN *pixel* IS *bone*

MRI T2 images:

IF *pixel* IS *dark* AND *Pixel* IS NOT *far* THEN *pixel* IS *white matter*
IF *pixel* IS *gray* AND *Pixel* IS NOT *far* THEN *pixel* IS *gray matter*
IF *pixel* IS *very bright* AND *Pixel* IS NOT *close* THEN *pixel* IS *CSF*
IF *pixel* IS *dark* AND *Pixel* IS NOT *close* THEN *pixel* IS *bone, muscle*

and proton density:

IF *pixel* IS *gray* AND *Pixel* IS NOT *far* THEN *pixel* IS *white matter*
IF *pixel* IS *bright* AND *Pixel* IS NOT *far* THEN *pixel* IS *gray matter*
IF *pixel* IS *very bright* AND *Pixel* IS NOT *close* THEN *pixel* IS *CSF*
IF *pixel* IS *dark* AND *Pixel* IS NOT *close* THEN *pixel* IS *bone, muscle*

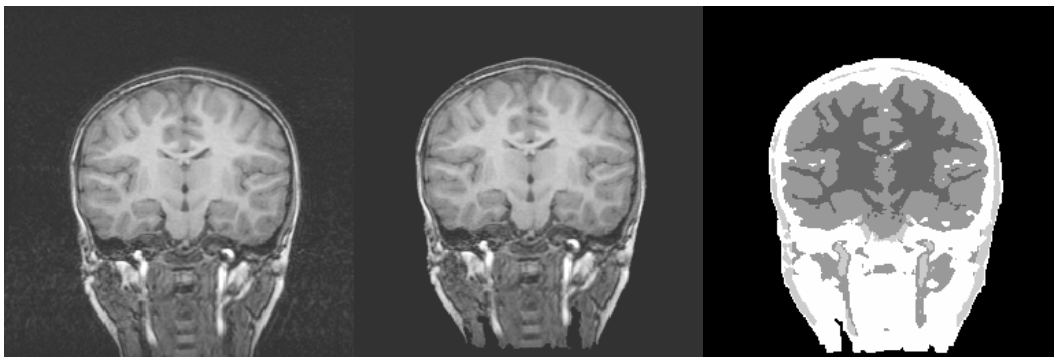
In the next stage we have to find the geometrical centre of the processed data set and for each pixel we have to create its own trapezoid membership function [5] for a close, an average and a far distance from the centre. We have also decided to choose the *G* function [5] as the membership function for the pixel intensity. This membership function is

generated automatically on the basis of data obtained from the fuzzy-entropic stage. The inference process is the Takagi-Sugeno type [5], where the AND operator is defined as a minimum operator [5]. The de-fuzzyfication process is executed by the maximum height method [5].

This stage is divided into two phases. The first one is the classification of the brain white matter and grey matter. Only the first pixel classified as white matter by the inference mechanism is found iteratively from the geometrical centre. This pixel is a seed for the 3D region-growing algorithm with the fuzzy inference as a homogeneity criterion. We also use binary morphology to break connections to non-brain tissues. After the brain matter tissues are classified, the second phase classifies all remaining pixels, excluding background. In this phase, image pixels are examined sequentially with the fuzzy inference as the decision criterion. In the pixel classification process we have to apply a low pass filter with the 3x3x3 mask to prevent classifying a false single pixel.

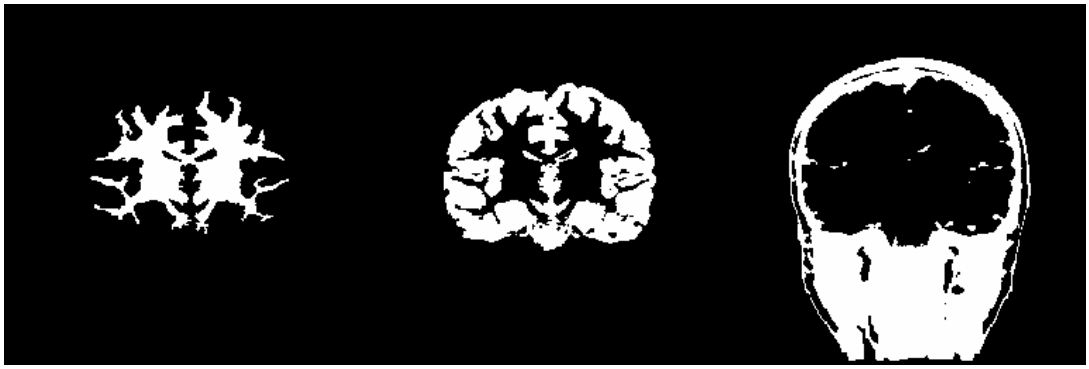
The last stage of the presented algorithm is the postprocessing step. Each as yet unclassified pixel is now assigned to the class with the largest quantity of neighbours, which is achieved by applying the 3x3x3 filtering mask.

We have tested the method presented in this paper to segment MRI data sets of a human head, and the required computational time of the segmentation process for test data set (256x256x128) was less then two minutes.



a) b) c)

Fig. 3. Segmentation results of a MR human head: the original image (a), the image after background noise removal (b), the result of segmentation process (c).



a) b) c)

Fig. 4. Segmented tissues for example scan: the white matter (WM) (a), the grey matter (GM) (b), skin, fat, CSF (c)

The results of our fuzzy rule-based segmentation algorithm are presented in figs. 3 and 4. The separated segmented anatomical structures are illustrated in fig. 4. The selected images show good separation between air and bone, fat, soft tissues (such as skin and muscle), cerebro-spinal fluid (CSF), grey matter (GM) and white matter (WM). The acquired segmented images were compared to a normally created masks manually prepared by a highly experienced operator, using two similarity measures: the difference between number of pixels in our class and the manual class (4) and pixels covering measures in both the data sets (5). The normally segmented mask contains only the white matter and grey matter tissues, and for this reason we were only able to compare two structures.

$$r_{NP} = \left| \frac{N_{pat} - N}{N_{pat}} \right| \tag{4}$$

where

r_{NP} – difference between number of pixels in our class and the 'manual' class

N - number of pixels of comparing class in our image

N_{pat} - number of pixels of comparing class in the 'manual' image

$$r_{cover} = \left| \frac{N_{cover}}{N_{pat}} \right| \tag{5}$$

where

r_{cover} – pixels covering measure

N_{cover} - number of covering pixels of comparing class in our image

N_{pat} - number of pixels of comparing class in the 'manual' image

Table 1. Results of the comparison between our segmented image and the manually segmented image

Criterion	Results	
	White matter	Grey matter
r_{NP}	0.12	0.13
r_{cover}	0.85	0.91

Preparation and segmentation of images constitute only the first stage of the whole MR brain image processing. The next stage is to create virtual anatomical models from the data obtained in the segmentation process. Such a representation of anatomical structures can be visualised using many advanced three-dimensional imaging techniques.

3. VISUALISATION OF BRAIN IMAGES

Three-dimensional (3D) visualisation aims at presenting objects in a photorealistic way that gives the viewer the possibility to explore the 3D structure. Various 3D imaging techniques may be applied for effective visualisation of the spatial relationships and to reveal some information that is not visible optimally in 2D. Depending on the representation used, methods can be classified in two major categories: volume visualisation and surface visualisation methods.

3.1. VOLUME VISUALISATION

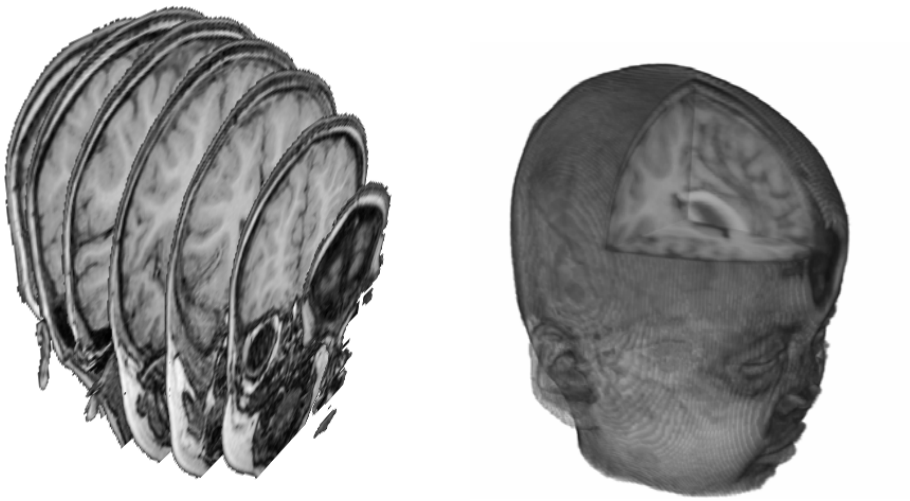


Fig. 5. Volume visualisation methods of a human head (MRI): volume slicing (left), volume rendering (right)

Volume visualisation methods visualise an object as a whole by assigning to each voxel certain transparency and opacity values (through some specified transfer functions). Such techniques do not require preprocessing of the input 3D data and can be used for successive exploration of object details. One of the simplest direct visualisation methods is volume slicing (see Figure 5 left) – the method displays in 3D space only a few planar cuts of a whole volume. The method is very fast but delivers only limited spatial information of a datasets structure. The most realistic and highly detailed direct visualisation method is the volume rendering (see Figure 5 right), it is one of the most powerful and popular methods in the medical 3D imaging field. Volume rendering, with its ability to easily emphasize different structures through modifications of opacity and colour transfer functions, is the only tool we need when 3D volume exploration is required. Despite its undeniable advantages this method has one main drawback – it requires that all voxels within the scene, along with their optical properties, be stored and manipulated. This makes the whole process time and memory consuming procedure, but the volume rendering process can be accelerated by the use of specialized and dedicated graphics hardware [4].

3.2. SURFACE VISUALISATION

Surface visualisation (see fig. 6) aims at representing objects by means of their bounding surfaces, which requires that the boundary of the every single 3D object should be somehow specified. To achieve this goal, several preprocessing steps should be performed; filtering operations and segmentation procedures are indispensable to obtain clearly defined boundaries of the 3D structure. When a boundary is clearly defined we need to reconstruct the objects surface, and one of the most popular and most often used techniques is the marching cubes algorithm [5] that can be described as a table-based surface-fitting algorithm. This method results in a triangle mesh representing the 3D surface of the object, and this mesh can be further processed (smoothed, decimated, textured etc) to obtain higher quality and better-looking objects. There are many advantages of representing 3D objects as triangle meshes, such objects are clearly geometrically defined and for this reason we can easily manipulate them (transform, deform, cut, etc.). The spatial surface reconstruction of the 3D object makes it possible to consider relationships between distant parts of its structure, to improve measurements, to define geometrical shapes and to simulate operative treatments. Surface visualisation enables a fully interactive exploration of the data – the visualised information is limited and accelerated through graphics hardware [8].

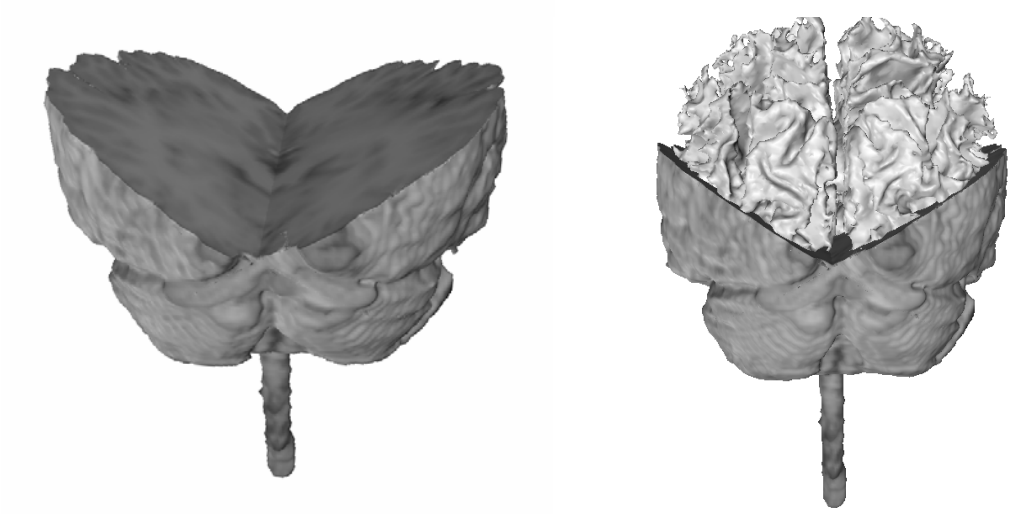


Fig. 6. Surface visualisation method – textured triangle meshes of a human brain

Combining all the described visualisation methods (see fig. 7) significantly enhances the perception of three-dimensionality during the examination and offers a valuable tool in comprehension of complex 3D structures.

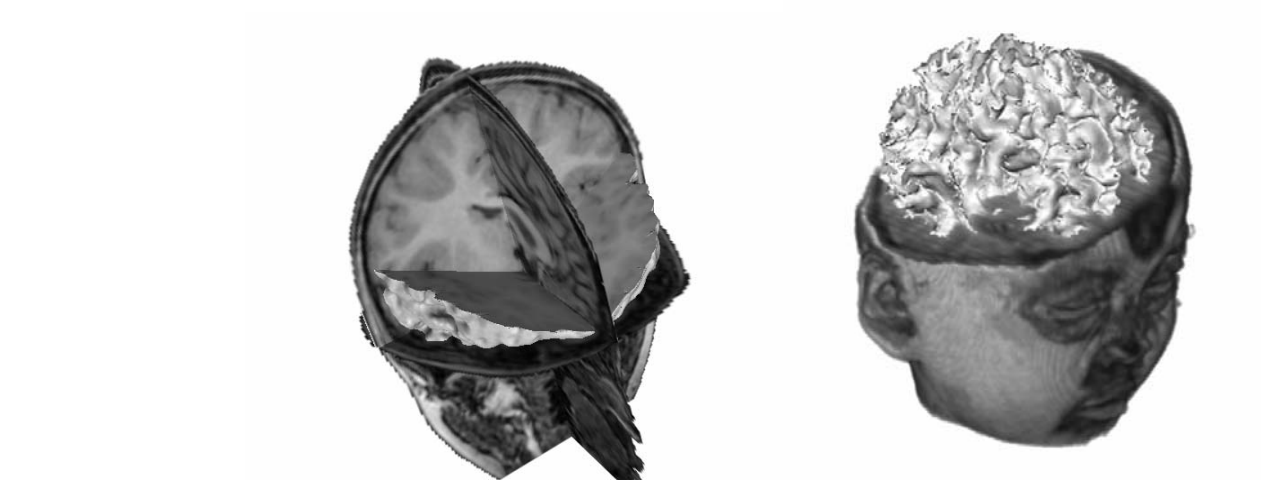


Fig. 7. Combining volume and surface visualisation methods: 3D slices + surface rendering (left), surface rendering + volume rendering (right)

4. CONCLUSIONS

We have examined the idea of using a fuzzy rule-based inference system and a fuzzy entropy system as the basics for an MR image segmentation algorithm for the human head. We used the fuzzy logic inference as a decision criterion for assigning pixels of an MR image to specified classes. Evaluation results show that this algorithm is fast and, although it is not completely automatic, the procedure is less time consuming than manual methods and produces masks that are more realistic for 3D visualisation. This visualisation may be a tool to interpret what is present in a set of anatomical images and can be done either as a 3D volume rendering, or as surface rendering. We can also combine these visualisation methods to enhance the perception of complex 3D structures.

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