Automatic 3D Segmentation of Human Brain Images Using Data-mining Techniques

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Abstract — **This paper proposes a method for automatic 3D segmentation of human brain CT scans using data mining techniques. The brain scans are processed in 2D and 3D. The proposed method has several steps – image pre-processing, segmentation, feature extraction from segments, data mining, and post-processing. The method introduced is implemented in 3D image processing extension for the RapidMiner platform, and both are provided as open source. With testing data the resultant performance selection of tissue slices from the brain image was 98.08% when compared to human expert results.**

Keywords — **Image processing, 3D segmentation, visualization, CT, brain scan, RapidMiner, open source, data mining.**

I. Introduction

THE selection of brain tissue is a challenging task because it is difficult to distinguish neural tissue from other neighbouring structures. Segmentation is often very important for the evaluation of medical treatment and its success for some diseases, e.g. for expressing the ratio between brain volume and the affected part of the brain. For an expert measuring brain volume is a relatively trivial but time consumption task.

This paper introduces automatic human brain segmentation and selection from Computer Tomography (CT) scans. This method is based on data-mining principles. 438 CT slices were used for training and the trained model was tested on 262 slices. Extracted brain image represented by voxels can be used to measure and monitor the brain volume in time or for other medical purposes. The visualized 3D model can also help a surgeon to perform an operation more accurately.

The proposed method consists of a pre-processing part and a data-mining part. The rest of the paper is structured as follows. The next section describes general image processing steps. The third chapter describes the proposed method. Chapter four shows the results. The fifth chapter introduces the RapidMiner platform and IMMI3D extension. These tools were released as open-source software and therefore the results described are easy to be repeated. Chapter six is a summary of the whole paper.

II. 3D Image Processing

A. Training data preparation

For training and testing, 700 CT slices were used - 438 slices for training and 262 slices for testing. Each slice of the set was labelled by a human expert. Brain areas were marked in white colour and the rest in black colour. Since this label is used for data-mining, it is called the fitness mask in this paper.

A bit map editor is usually used for creating the fitness mask from the original image. This step must be done by a human and is time-consuming and challenging. The objective of this work is to automate this step and, using the training data**,** to train automatic segmentation.

B. Pre-processing

In order to increase the segmentation accuracy, the images are pre-processed first. The pre-processing consists of applying several filters (mean, Gaussian blur, edge detection) and bit operations like histogram equalization and normalization. These operations could be applied to each image separately, or there are versions of these algorithms in 3D.

A scene in 3D is represented by a series of 2D images (slices) arranged in a row. Each voxel has three coordinates. The first two coordinates, x and y, represent one pixel on a slice and the third one, z, represents the order of slice.

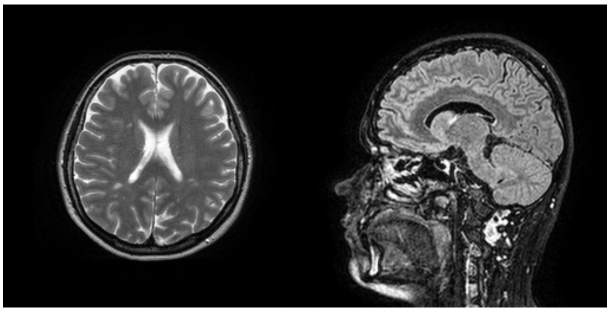

Fig. 1 Transversal and sagittal plane scan

C. Segmentation

After the pre-processing, the 3D image is ready for segmentation. The goal of this process is to split the image into uninterrupted parts. These parts can be overlapping and together can cover the whole image. Features are calculated for each of these segments.

D. Feature extraction

The process of feature extraction converts unstructured data into a form that is suitable for learning algorithms. This form is usually a table where rows are individual segments and

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columns are features. Selected features are computed from the whole segment.

E. *Creating the model*

Creating the model is based on extracted features. The following learning algorithms for supervised machine learning were tested: Decision trees, Support Vector Machine, Naïve Bayes Classification, and Neural Network. The created model is used on independent testing data to evaluate its performance.

III. BRAIN CT SEGMENTATION METHOD

There were three series of slices from three patients. The first series has 263 slices; the second has 175 slices and the third has 262 slices. The first and the second patients were chosen as a training set. The third one served the performance testing purpose. The resolution of each slice is 256 x 256 pixels.

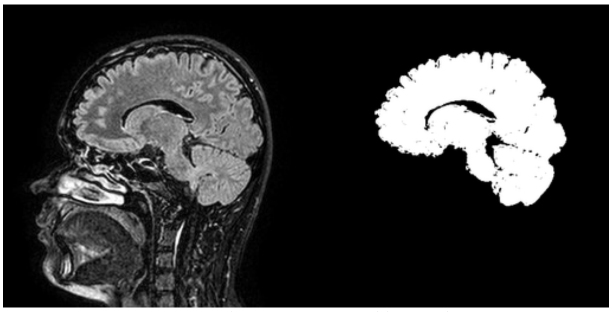

Fig. 2 CT scan and its mask

For each of the 700 slices a mask was manually created. Fig. 2 shows the mask of one slice.

Pre-processing consists of processing an image in 2D and 3D. The first step is the equalizing histogram in 2D. This step improves the readability of scan and increases image dynamics. The second step is the conversion of the slice series to a 3D object. 3D filters are applied in the next step. These filters are the minimum, maximum and mean filter in a row. The minimum filter is a nonlinear filter. The voxel in the centre of this filter is replaced by the voxel with minimum value in its neighbourhood. This neighbourhood is a cube with an edge size of $2{\cdot}r{+}1$, where r is the radius. The value of the minimum filter radius is 2. This size was chosen empirically. The maximum filter radius is the same as the minimum, with one difference. The difference is that the central voxel is set to the maximum of the neighbourhood. The radius was also set to value 2. Another step of pre-processing consists of the Mean filter, which is a linear filter. The central voxel is set to the mean value of the neighbourhood. The radius was set to value 1. The first two filters remove local extremes. The mean filter is for smoothing the resultant textures.

The segmentation algorithm works on a principle similar to that of the commonly known wand tool from bitmap editors. The whole process of segmentation works as follows: 3D points are generated in the area of brain. Each point is starting voxel for segmentation. By subtracting the tolerance value from the voxel, the minimum voxel value is obtained while by adding the tolerance value the maximum voxel value is obtained. Voxels in 6 neighbourhoods (top, down, front, rear, left right) with values greater than the minimum and smaller than the maximum are added to the segment and the neighbourhoods of these pixels are examined, etc.

For each of the three patients 250 starting points were generated. Some points represented the same segment and so they were filtered out. 3D images with 186 and 123 segments were used for final training while one 3D image with 185 segments was used for testing.

For each segment the label was calculated. The label is a set of white voxels from the whole mask. Subsequently the label is converted from the numerical value to the binomial value with a threshold of 0.97. This means that segments with a 97% overlap with mask are marked as positive and all the others as negative. The label is used for training when creating a model) and testing (when evaluating its performance).

$$L = \frac{v_w}{s_v} \tag{1}$$

Where L is the label, v_w is the number of white voxels from the mask in the segment, and s_v is the segment volume.

From each segment these features were extracted:

A. *Edge voxels*

If one or more voxels in the segment have zero or maximum coordinate value then the value of this feature is set to one, else the value is set to zero. This feature is suitable for marking the background.

B. *Relative size*

The relative size is the size of a segment compared to the whole image.

$$s_r = \frac{s_v}{i_v} \tag{2}$$

Where s_r is the relative size, s_v is the segment volume, and i_v is the whole image volume. This feature is suitable when small segments need to be removed.

Other standard statistics operations like segment volume, mean, geometric mean, standard deviation, sum, sum of squares, minimum, maximum, variance, skewness, and kurtosis were also used [4].

After the feature extraction process the model was built. The decision tree algorithm was chosen as the learning algorithm because of its best accuracy from among the previously mentioned algorithms. The model performance on training data was evaluated by 10-fold cross validation. The overall accuracy was 98.39% +/- 1.61%. Recall and precision of each class are given in Table I.

TABLE I
PERFORMANCE ON TRAINING DATA

	true false	true true	class precision
pred. false	229	3	98.71%
pred. true	2	75	97.40%
class recall	99.13%	96.15%	

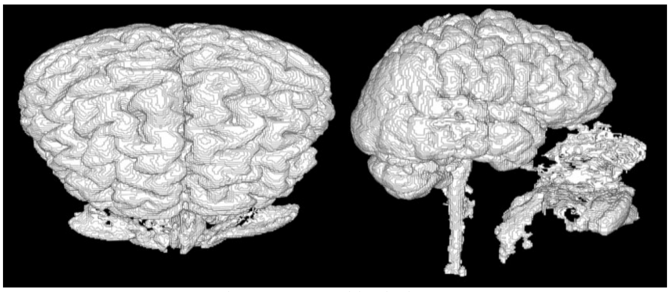

Fig. 3 Extracted brain image

IV. DISCUSSION

The accuracy of the resulting model on the testing data was 95.08%. As Table II shows, there were only 9 segments misclassified as true. Fig. 3 shows extracted segments merged together.

In order to achieve better results and remove misclassified artefacts in the image post-processing was performed. The post-processing consists of two steps. First, the image is segmented in 2D to select the biggest white consistent segment in the slice. This step removes outliers, i.e. the misclassified segments. A 3D median filter with a radius of 3 pixels and the 3D mean filter with a radius of 2 pixels are applied in the second step. The median filter removes small outcrops and the mean filter smoothes the resultant image. Fig. 4 shows the final image.

TABLE II
PERFORMANCE ON TESTING DATA

	true false	true true	class precision
pred. false	111	0	100.00%
pred. true	9	63	87.50%
class recall	92.50%	100.00%	

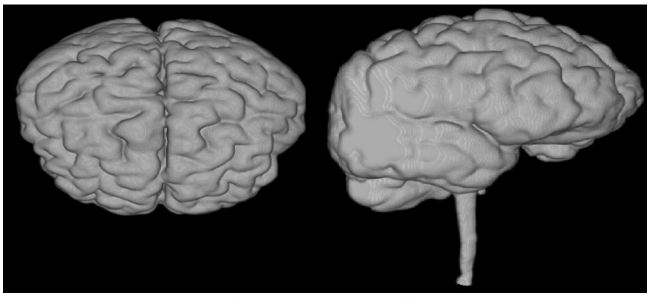

Fig. 4 Post-processed brain

V. 3D IMAGE PROCESSING EXTENSION FOR RAPIDMINER PLATFORM

In order to make this method available, the algorithms were implemented as a plugin for the RapidMiner platform. RapidMiner[1] [2] is one of the world's leading open-source systems for data mining and provides data-mining algorithms for pre-processing, feature selection, parameters optimization, and over 200 different learning algorithms.

3D Image processing extension for RapidMiner (IMMI3D) is a tool for working with 3D images. These images are represented as 2D slices. 3D space is represented by 3 axes – x, y and z. Axes x and y are the same as in the 2D scene. Axis z is represented by previously mentioned slices. Filtering is based on the 3D Fast Filters library [1].

A. Visualization

IMMI3D is capable of visualizing the whole scene and its segments. This visualization is based on the ImageJ 3D Viewer library [3]. Each segment can be visualized as volume, orthoslice or surface (see Fig. 4).

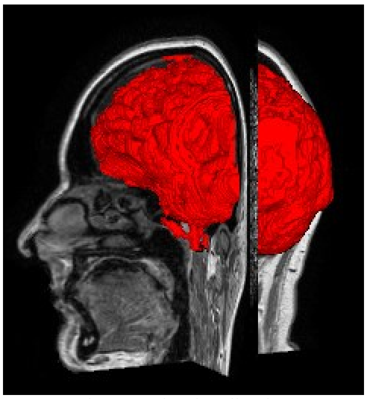

Fig. 5 Brain visualization

VI. CONCLUSION

This paper introduced an automatic method for 3D brain segmentation. The steps of image processing were described. The model created for selecting brain segments worked with a 95.08% accuracy on the testing data set. This performance can be increased by additional post-processing.

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