AUTOMATIC HUMAN BRAIN 3D SEGMENTATION

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Abstract: This paper describes automatic 3D segmentation of human brain CT scans using data mining techniques. Brain scans are processed in 2D and 3D. Whole procedure has several steps – image preprocessing, segmentation, feature extraction from segments, data mining and post processing. Introduced method is implemented in 3D image processing extension for RapidMiner platform and both are provided as open source. Result performance of brain selection on testing data was 95.08%.

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

1. INTRODUCTION

Measurement of brain volume is a challenging task because it is difficult to distinguish brain tissue from other neighbor structures. This paper introduces human brain segmentation and selection from Computer Tomography (CT) scans. The aim of the whole process was accurate tissue selection. Extracted brain represented by voxels can be used to measure and monitor brain volume during time.

Image processing is a complex task consisting of several steps. These steps may vary depending on the purpose of processing. General steps of creating model for pattern recognition will be described in second chapter. Third chapter introduces RapidMiner and IMMI3D extension. Fourth chapter describe CT brain scans processing and concrete example. Chapter five shows results. Chapter six is summary of the whole paper.

2. 3D IMAGE PROCESSING

2.1. FITNESS MASK CREATION

In order to assess the results achieved, so-called fitness mask was created, which stands for segmentation by human expert. Fitness mask is black and white image that defines positive matches (pattern to detect with) with white color and negative samples with black color.

A bit map editor is usually used for creating fitness mask from original image. This step must be done by human and it is time consuming and challenging.

2.2. PREPROCESSING

Image preprocessing consists of applying filters (mean, Gaussian blur, edge detection) and bit operations like histogram equalization, normalization. These operations could be applied on each image separately, or there are versions of these algorithms in 3D.

Scene in 3D is represented by series of 2D images (slices) which are arranged in a row. Each voxel has three coordinates. First two coordinates x and y represent pixel on slice and third one z represents order of slice.

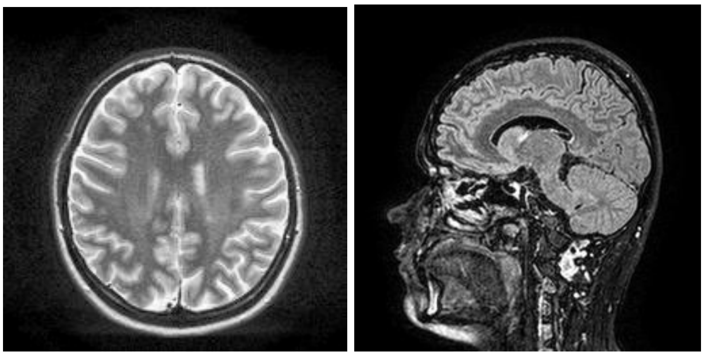

Fig. 1: Transversal and sagittal plane scan.

2.3. SEGMENTATION

The segmentation is a process of splitting an image into parts. These parts can be overlapping and can together cover whole image.

2.4. FEATURE EXTRACTION

Process of feature extraction converts unstructured data into a form that is suitable for learning algorithms. This form is usually table where rows are individual segments and columns are features. Selected features are computed from whole segment.

2.5. MODEL CREATING

Models are created based on extracted features. These learning algorithms for supervised machine learning were tested: Decision trees, Support Vector Machine, Naïve Bayes Classification and Neural Network.

3. 3D IMAGE PROCESSING EXTENSION FOR RAPIDMINER PLATFORM

The RapidMiner [2] is one of the world's leading open source system for data mining. It provides algorithms for preprocessing, feature selection, parameters optimization and over 200 different learning algorithms.

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

3.1. VISUALIZATION

IMMI3D is capable to visualize whole scene and its segments. This visualization is based on ImageJ 3D Viewer library [3]. Each segment can be visualized as volume; orthoslice or surface (see Fig. 2).

Fig. 2: Brain visualization.

4. USE CASE – BRAIN CT SEGMENTATION

There were three slices series of three patients. First series has 263 slices; second series has 175 slices and third series 262 slices. First and second patients were chosen as a training set. Third one served for performance testing purpose. Resolution of each slice is 256 x 256 pixels.

Fig. 3: CT scan and its mask.

For each of 700 slices was manually creates mask. Fig. 3 shows mask of one slice.

Preprocessing consists of process image in 2D and 3D. First step is equalizing histogram in 2D. This step improves readability of scan and increase image dynamics. Second step is conversion slice series to 3D object. 3D filters are applied in next step. These filters are minimum, maximum and mean in a row. Minimum filter is nonlinear filter. Voxel in center of this filter is replaced by voxel with minimum value in its neighborhood. This neighborhood is cube with edge size $2 \cdot r+1$. Where r means radius. Minimum filter has *radius* value 2. This size was chosen empirically. Maximum filter radius is same as the minimum with one difference. The difference is that central voxel is set to maximum of neighborhood. *Radius* was also set to value 2. Another step of preprocessing consists of the Mean filter, which is a linear filter. Central voxel is set to mean value of neighborhood. *Radius* was set to value 1. First two filters remove local extremes. Mean filter is for smoother result textures.

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

For each segment was calculated label. Label is a set of white voxels from the whole mask. Later label is converted from numerical value to binominal with threshold of 0.97. It means that segments with 97% overlap with mask are marked as positive and all others as negative. Label is used for training and testing to create model and evaluates its performance.

$$L = \frac{v_w}{s_v} \quad (1)$$

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

From each segment were extracted these features:

Edge voxels

Segments, which touch edges of 3D image, are marked with value of one, others with zero value. This feature is suitable for marking background.

Relative size

Relative size stands for size of a segment compared to the whole image.

$$s_r = \frac{s_v}{i_v} \quad (2)$$

Where s_r is relative size s_v is segment volume and i_v is whole image volume.

This feature is suitable when small segments need to be removed.

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

After feature extraction process a model was built. As a learning algorithm the decision tree algorithm was chosen because of best accuracy from previously mentioned algorithms. Model performance on training data was evaluated by 10 folds cross validation. The overall accuracy was 98.39% +/- 1.61%. Recall and precision of each class is in Tab. 1.

Tab. 1: 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%	

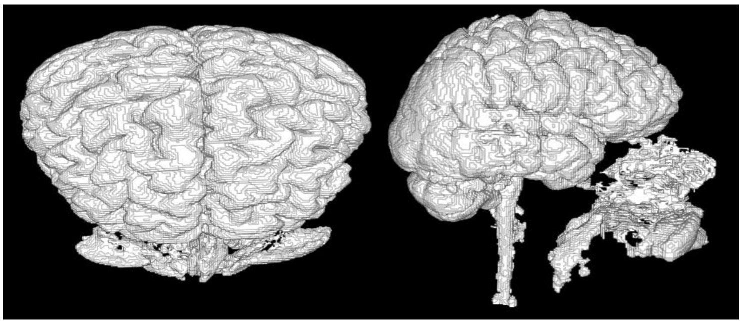

Fig. 4: Extracted brain.

5. DISCUSSION

Accuracy of resulting model on the testing data was 95.08%. As shows Table II, there were only 9 segments misclassified as true. Fig. 4 shows extracted segments merged together.

Tab. 2: 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%	

In order to achieve better results and to remove misclassified artifacts in the image post-processing were 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. 3D median filter with radius 3 pixels and 3D mean filter with radius 2 pixels is applied in the second step. Median filter removes small outcrops and mean filter smooth result image. Fig. 5 shows the final image.

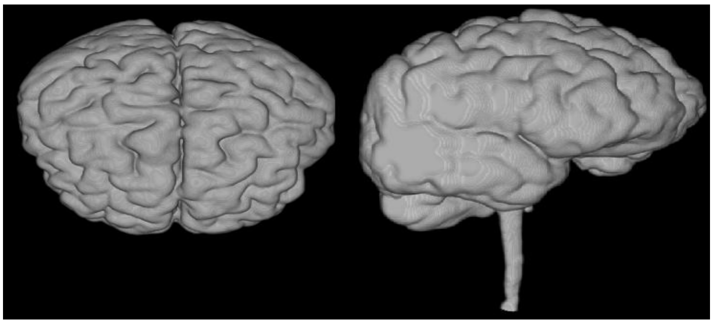

Fig. 5: Post processed brain.

6. CONCLUSION

This paper introduced automatic method for 3D brain segmentation. Steps of image processing were described. Created model for selecting brain segments worked with 95.08% accuracy on testing data set. This performance can be increased by additional post processing.

7. REFERENCES

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