BIOMEDICAL USAGE OF 3D WATERSHED IN DODECAHEDRAL TOPOLOGY

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Abstract

This paper deals with image segmentation and its use in recognizing Alzheimer's disease. Segmentation is performed by using the morphological method called watershed, in the image in the dodecahedral topology. The following describes the technique for converting the image into dodecahedral topology and the method for image filtering and edge detection. Finally, these methods are tested on the human brains, which are obtained by Single-Photon Emission Computed Tomography (SPECT).

1 Introduction

Alzheimer's disease, which is characterised by loss of neurons and their's synapses, is the most common form of dementia. This disease is still incurable by modern medicine, but it can be slowed down. Therefore time of recognition of diseased patient has highest priority.

SPECT is a technique using gamma rays to provide 3D imaging. Before the technique begins, an injection of radionuclide is introduced into the bloodstream of the patient. The result of this technique is the set of 2D slices of radionuclide distribution in the brain from which the final image is built.

This work is based on hypothesis that the brain scans of patients with Alzheimer's disease differ from the brain scans of healthy people. These changes are observed using watershed, which is the method for image segmentation based on morphological understanding the image and modeling of gradual flooding of virtual terrain. Moreover, watershed is implemented in dodecahedral topology to eliminate its sensitivity to the number of neighboring voxels. We calculate four main characteristics for each image: number of regions ($|r|$), volume of regions ($\sum r$), cardinalty of wateshed shapes ($\sum w$) and average volume of region ($\bar{r}$). The results of the measurement are summarized in the paper.

2 Dodecahedral topology of 3D image

Each 3D image is represented by a finite set of points in the computer. These points are generated by using three rectangular vectors of the same length in the cubic topology. Consequently, every voxel has 26 neighbors. Given that the neighbors vary in distance from the central voxel, this distribution of the voxels can cause a problem for the methods that work within the neighborhoods of the central voxel.

The points in the dodecahedral topology are generated by vectors of same length with mutual angles equal to $\frac{\pi}{3}$. A sample of three vectors (1) is used in foloving calculations. Based on this equation, the image can still be represented by the 3D matrix in the computer. Unlike the cubic topology, the image in dodecahedral topology consists of voxels in the shape of a rhombic dodecahedron. Every dodecahedral voxel has 12 neighbors, but distances from the central voxel to each neighboring voxel are equal.

$$\vec{a} = \begin{pmatrix} \cos\frac{1}{12}\pi \\ \sin\frac{1}{12}\pi \\ 0 \end{pmatrix}, \vec{b} = \begin{pmatrix} \cos\frac{5}{12}\pi \\ \sin\frac{5}{12}\pi \\ 0 \end{pmatrix}, \vec{c} = \begin{pmatrix} \frac{1}{\sqrt{3}}\cos\frac{\pi}{4} \\ \frac{1}{\sqrt{3}}\sin\frac{\pi}{4} \\ \frac{\sqrt{6}}{3} \end{pmatrix} \quad (1)$$

The conversion of 3D image (rectangular) input into the dodecahedral topology is performed via linear interpolation. Positions for neighboring voxels are show in Fig. 1.

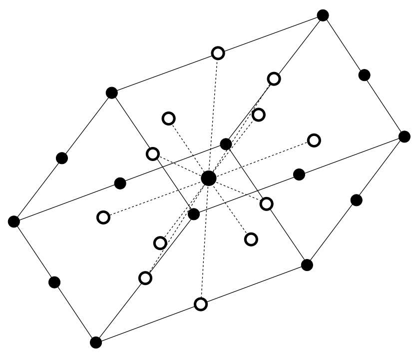

Figure 1: Neighbors in dodecahedral topology

Final representation for the computer in the form of a 3D matrix is shown in Fig. 2.

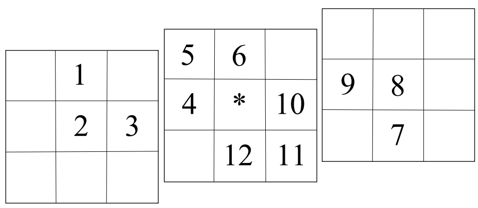

Figure 2: Neighbors representation in matrix

3 Edge detection

We used linear filters to reduce the noise level and detect the edges. In this paper we discuss the best filter we tested: the DoG (Difference of Gaussian) filter. This method is based on the subtraction of two blurred images, where the images are blurred with a Gaussian kernel with a different parameters σ_1, σ_2 using the convolution.

$$F_1(x,y,z) = g_{\sigma_1}(x,y,z) * f(x,y,z) \quad (2)$$

$$F_2(x,y,z) = g_{\sigma_2}(x,y,z) * f(x,y,z) \quad (3)$$

We can calculate the convolution of the kernel, but we can only use the convolution once because the it is distributive. This operation provides the same results two times faster.

$$F_1(x,y,z) - F_2(x,y,z) = (g_{\sigma_1}(x,y,z) - g_{\sigma_2}(x,y,z)) * f(x,y,z) \quad (4)$$

4 Dodecahedral watershed

Watershed is a morphological method based on the modeling of a gradual flooding of virtual terrain. It starts in each local minimum to flood and build barriers (watershed shapes) in voxels where different domains join. This method gives us an image that is divided into regions.

The algorithm goes from the lowest level of grey to the highest level of grey. In each step, the Algorithm finds all coherent areas of a given level of grey and marks them depending on the following three conditions:

1. If it is touching just one area, then it will join to this area.
2. If it is touching more than one area, or it is touching only a barrier, then it will join to the barrier.
3. If it is touching neither area nor barrier, then it becomes a new area.

5 Matlab realization

There have been several functions written for loading, converting from cubic to dodecahedral topology, filtering, and rendering.

As mentioned before, we made the conversion from cubic to dodecahedral topology using linear interpolation. In this case, we used the Matlab function `interp3`. To use `interp3` correctly, we cannot rotate the cubic image; therefore, we rotated the future dodecahedral image in the opposite direction and placed the cubic image in the correct position in the space.

Filtering was performed via linear filters. To speed up the algorithm, we used the Fourier transform for convolution and the Matlab functions: `fftn`, `ifftn`, `fftshift`.

Final results are tested using two-sample Students t-test. For this test we used Matlab function `ttest2`.

Since the cut in the image is composed of regular hexagons in dodecahedral topology, we could not use the standard Matlab function for renderig. Instead, we put together regular hexagons using function `fill` to make the final image.

6 Results

The main statistical properties for the DoG filter are similar to an arithmetic mean ($\bar{x}$), standard deviation (s), and coefficient of variation (γ) are collected in the Tab. 1 for groups of diseased and healthy patients. Our results provide a comparision between two sets of samples: ADT (set of testing samples of diseased brain scans), and CNT (set of testing samples of healthy brain scans).

Table 1: Properties for filter DoG ($\sigma_1 = 1.6$, $\sigma_2 = 3.6$)

set	stat.	$\|r\|$	$\sum r$	$\sum w$	$\bar{r}$
ADT	$\bar{x}$	3792	314280	224792	83.27
	s	265	10265	7984	6.78
	γ	0.0698	0.0327	0.0355	0.0814
CNT	$\bar{x}$	3439	335533	211654	98.03
	s	241	14934	6839	8.66
	γ	0.0700	0.0445	0.0323	0.0884

Before the interpolation from cubic to dodecaedric topology, the cubic image can be rotated. Sensitivity to the rotation is documented in the Tab. 2 for typical 3D scan. As shown, the rotation has only an insignificant effect on the final results.

Table 2: Rotation test for filter DoG ($\sigma_1 = 1.6$, $\sigma_2 = 3.6$)

stat.	$\|r\|$	$\sum r$	$\sum w$	$\bar{r}$
$\bar{x}$	4191	304756	238213	72.74
s	70	3261	1585	1.91
γ	0.0167	0.0107	0.0067	0.0262

The next property that we tested was shift resistance. The results for this testing are collected in the Tab. 3 for the typical 3D scan. In this case, the results are slightly better than for the rotation test, which means that the shift has only an insignificant effect as well.

Table 3: Shift test for filter DoG ($\sigma_1 = 1.6, \sigma_2 = 3.6$)

stat.	$\|r\|$	$\sum r$	$\sum w$	$\bar{r}$
$\bar{x}$	4184	304498	237714	72.78
s	59	2176	963	1.12
γ	0.0140	0.0071	0.0041	0.0154

The DoG filter was tested on the set of test samples (ADT and CNT). The results of this testing using two-sample Students t-test are shown in the Tab. 4 on the "training" line. In addition, the DoG filter was verified on the set of verification samples (ADV and CNV). The results for the verification samples are provided on the "verification" line. While the results for the verification samples are worse than the results for the test samples, they are still significant, with a probability of Type 1 error of about 1% for all characteristics.

Table 4: Results for filter DoG ($\sigma_1 = 1.6$, $\sigma_2 = 3.6$)

	p-value			
set	$\|r\|$	$\sum r$	$\sum w$	$\bar{r}$
training	0.0060	0.0016	0.0009	0.0005
verification	0.0121	0.0110	0.0096	0.0065

The difference between typical AD and CN patients is ilustrated in the Fig. 3. As seen, the watershed image of an patient with Alzheimer's disease is divided into more regions.

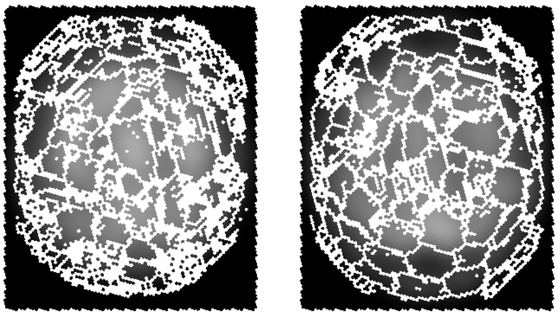

Figure 3: Images after segmentation: AD (left), CN (right)

7 Conclusion

Dodecahedral topology of 3D image is a useful structure for the digital diagnosis of Alzheimer's disease. Optimal parameter for DoG filter and watershed procedure were obtained. The watershed shape volume ($\sum w$) is the most robust measure related to rotation an shifting of the original image (patient) and second best in p-value for the classification of Alzheimer's diseased patient.

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