INFORMATICA, 2004, Vol. 15, No. 2, 283–290

Ischemic Stroke Segmentation on CT Images Using Joint Features

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Received: August 2003

Abstract. The paper describes a new method to segment ischemic stroke region on computed tomography (CT) images by utilizing joint features from mean, standard deviation, histogram, and gray level co-occurrence matrix methods. Presented unsupervised segmentation technique shows ability to segment ischemic stroke region.

Key words: ischemic stroke of human head brain, computed tomography, image segmentation.

1. Introduction

Automatic segmentation on medical images becomes important field of interest of many researchers in recent decades. Using image processing and computer graphics techniques performs a big part of medical data processing and transforming to human understandable format.

Problem. There is a problem automatically segment objects on human brain computed tomography (CT) slices at present time. Two points at least complicate recognition of brain structures: not high contrast between different textures (all necessary information occupied 100 gray levels from 4096 levels available in DICOM image), and overlapping of classes in the histogram of image intensity.

Task. The task of this paper is to develop simple method that requires no training for automatic segmentation of ischemic stroke region on CT slices of human brain. Ischemic stroke is characterized by the sudden loss of blood circulation to a region of the brain, resulting in a corresponding loss of neurological function. Stroke is the third leading cause of death and the leading cause of disability in the US (Arnold, 2001). Strokes are classified as either hemorrhagic or ischemic. Acute ischemic stroke refers to strokes caused by thrombosis or embolism and accounts for 80% of all strokes.

Although magnetic resonance imaging (MRI) gives more detailed pictures of the brain, CT is a fundamental branch point in the stroke evaluation. Disadvantages of MRI include its high cost, lack of ready availability at most centers, and insensitivity for detecting early hemorrhages. A MRI can be performed afterwards if finer details are required for further medical decision making (Medterms Medical Dictionary).

Motivation. Patient health status depends on stroke region size and location in human brain. It is important to calculate stroke volume for making prognosis of patient disability. Usually radiologists must to segment stroke region in each CT slice for automatic computation of its square and total volume through all slices of head. Human brain segmentation methods can be categorized as manual, semi-automated and automated methods. Manual segmentation procedures of ischemic stroke area in CT images by human expert are tedious, time and labour consumptive, results are often difficult to reproduce, and finally they are subjective. There was no presented technique to automatically segment ischemic stroke on CT slices up to date. For this reason, automatic techniques of computer-aided image analysis are necessary.

Literature survey. While only one technique for object recognition (Li *et al*., 1995) and for automatic segmentation and labeling of stroke lesions (Matesin *et al*., 2001) in brain CT images was presented in up to date literature, a huge of various algorithms have been developed for brain segmentation of MRI images ranging from semi-automated to fully automated methods (Tsai *et al*., 1995; Atkins *et al*., 1998; Leemput *et al*., 1999; Shan *et al*., 2002). Above-mentioned (Matesin *et al*., 2001) method is composed of three steps. The first step is an automatic determination of head symmetry axis. In the second step the seeded region-growing algorithm is used to segment input image into number of regions having uniform brightness. Features of these regions, such as brightness, area, nationhood and relative position to symmetry axis are used to create facts for rule-based expert system. Then such expert system is used in the third step to label regions as background, scull, gray, white matter, cerebrospinal fluid, and stroke. The method is fast (takes less than 30 s per slice), but there is one disadvantage: it is not possible to determine clear boundaries of stroke region with the seeded region-growing algorithm.

Methods of image segmentation usually utilize statistical pattern recognition techniques (Jain *et al*., 2000): such as Markov random fields (Zhang *et al*., 2001), artificial neural networks, and support vector machines (Bao *et al*., 1998; Raudys, 2000; Raudys, 2001; Egmont-Petersen *et al*., 2002), gray level co-occurrence matrix (Haralick *et al*., 1973), correlation (Elsen *et al*., 1995), etc.

What's new? None of the image segmentation algorithms are generally applicable to all images in general. For each application the unique approach must be developed. There are no published methods to automatically evaluate and visualize ischemic stroke region on CT slices (Fig. 1) up to date. In this paper we are going to extend started investigation (Usinskas *et al*., 2002b; Usinskas *et al*., 2002a) of automatic methods for ischemic stroke region segmentation in CT images. At first we started classify stroke regions by utilizing

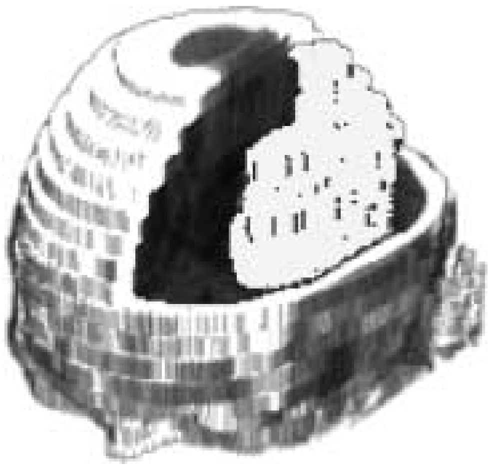


Fig. 1. Visualization of ischemic stroke region (light gray color) in the human head.

training data marked by radiologist. There were difficulties to build features database of known stroke and non-stroke regions. A lot of images with various samples of ischemic stroke were needed. Retraining of classifier of rebuilding database of features complicates future work. There was no guarantee that recognition system would work after including one more new stroke sample. So we decided to compare features from the same image – there will be no point to implement experience of known brain regions. Moreover we will use combination of methods, which were ranked as best by experts-radiologists (Usinskas *et al*., 2002a).

Our method is unique by implementing eighteen unified textural features with unsupervised classifier in such field of medical image analysis.

2. The Method

Eighteen features were combined to describe brain texture in human head CT slices: mean, standard deviation, ten features of histogram and six features of gray level co-occurrence matrix.

So 18-dimensional feature vector was calculated for each sliding window position. Then similar vectors were grouped by comparing their Euclidean distances. Output images were produced as the result of such comparison process: numbers of different groups were assigned as values of pixels of output image.

2.1. *Mean and Standard Deviation*

If we assume image texture belongs to normal distribution, then the mean:

$$\mu = \frac{1}{a^2} \sum_{i=0}^{a-1} \sum_{j=0}^{a-1} x_{ij}, \tag{1}$$

where a – width of sliding window,

x_{ij} – value of pixel in i-th row and j-th column of sliding window,

and standard deviation:

$$\sigma^2 = \frac{1}{a^2-1}\sum_{i=0}^{a-1}\sum_{j=0}^{a-1}\big(x_{ij}-\mu\big), \tag{2}$$

will fully describe 2-dimensional signal (Usinskas and Mikelaitis, 2002).

2.2. *Histogram*

The histogram is a function $H(i)$ of the number of occurrence of each gray level in the image:

$$H\big(i\big) = j, \tag{3}$$

where i – the number of gray level,

j – the number of i-th gray level occurrence.

Each of ten features were the possibility of occurrence of 5 contiguous gray levels:

$$F_n = \frac{1}{a^2}\sum_{i=5(n-1)}^{5(n-1)+4} H\big(i\big), \tag{4}$$

where n – the number of histogram feature.

2.3. *Gray Level Co-occurrence Matrix*

Gray Level Co-occurrence Matrix represents an estimate of the probability that one pixel has intensity $L1$ in row i_1, column j_1 and another – $L2$ in row i_2, column j_2, where $L1$, $L2 \in [0..N_g-1]$, and N_g is the number of available gray levels in the image:

$$\Psi(d,\Theta) = \mathrm{card}\big\{f(i_1,j_1)=L1,\ f(i_2,j_2)=L2\big\}, \tag{5}$$

where $d=\sqrt{(i_2-i_1)^2+(y_2-y_1)^2}$ – the distance between two pixels,

$\Theta = \mathrm{arctg}(\frac{j_2-j_1}{i_2-i_1})$ – the angle between two pixels.

We found the six Haralick features (Haralick *et al.*, 1973) best describing stroke and brain texture: contrast, sum of squares (variance), sum average, sum variance, sum entropy, and difference variance.

2.4. *Classification*

There was idea to classify textural features according similarity of features from the same image. Since images differ even from the same head scan, it was difficult to implement approach by utilizing base of known features. At beginning it was assumed the class number is equal to the number of pixels in image. Later such classes were grouped by Euclidean distance criteria comparing all features inside image:

$$Class(i) = Class(j), \quad \frac{d}{d0} < k, \tag{6}$$

where $Class$ – number of class in the image,

i, j – indexes of class – define a location of classified pixel,

$d = \sqrt{\sum_{n=1}^{18} \left(F_n^i - F_n^j\right)^2}$ – Euclidean distance between features vectors F^i and F^j (n – number of feature in vector),

$d0 = \sqrt{\sum_{n=1}^{18} \left(F^i\right)^2}$ – module of feature vector,

k – classification criteria.

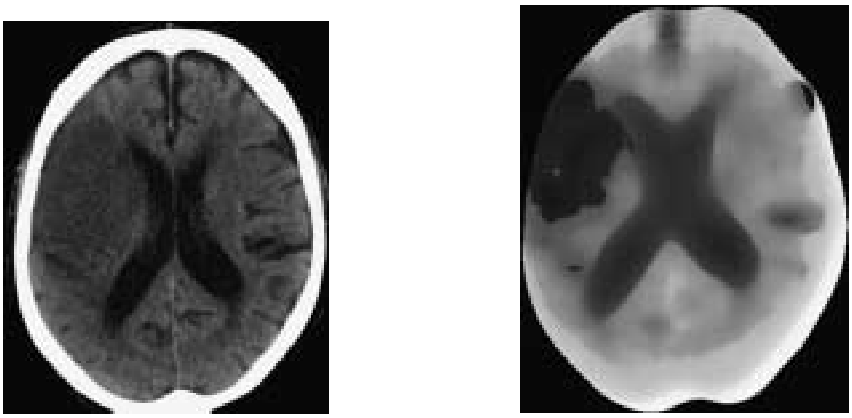
The final classes were get after elimination of empty classes and reindexing all non-empty classes in series.

Thus assigned classes to output image will show brain regions with similar features.

3. Results

Features we used show better ischemic stroke recognition for great regions. So we chose sliding window 31×31. To reduce initial number of classes, step of sliding window was determined as 2.

Fig. 2 shows input (a) and output images (b). There were $29'615$ positions of sliding window. After elimination of empty classes ($k = 0.3$), 819 classes survived.



a b

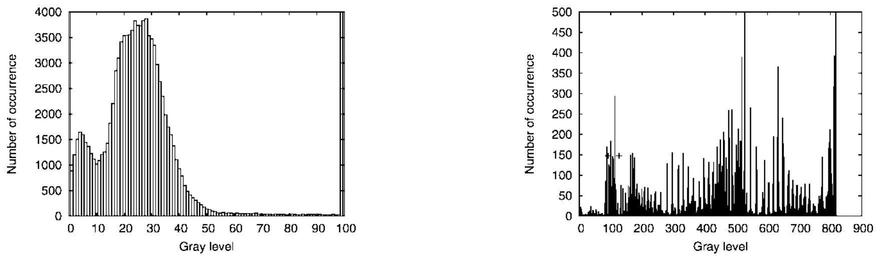
Fig. 2. Input image (a) with 99 gray levels and output image (b) with $29'651$ gray levels.

Since it was necessary to get two classes only: stroke and non-stroke, the thresholding procedure was performed. Fig. 3 shows histograms of input and output images. The output image contains much more gray levels than input image: $99 \ll 29'651$. However after thresholding procedure stroke region looks better (Fig. 4). Size of segmented ischemic stroke region was $7'288$ pixels (Meilunas *et al*., 2003).

Threshold boundaries (Fig. 4) for input image were 13 (the lower) and 25 (the upper), for output image – 80 (the lower), and 115 (the upper).

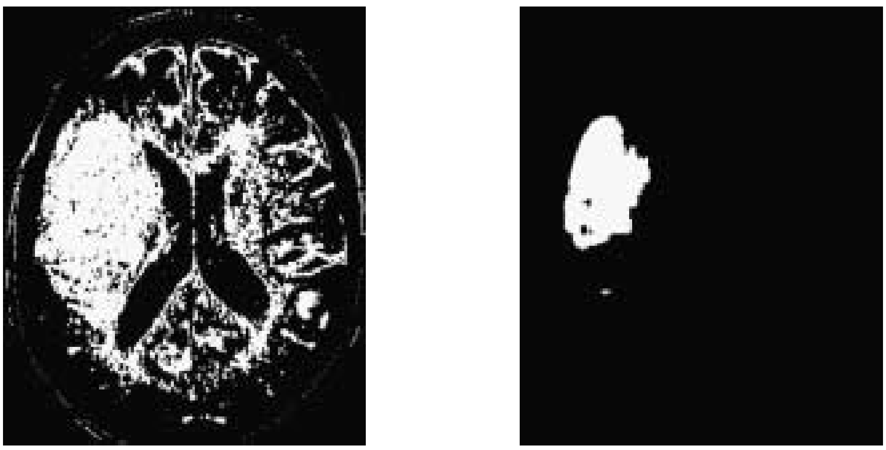
Processing of other CT images showed the similar results. Stroke regions were more clearly visible in the output images.

Processing of one slice took about 3 minutes with 1.7 GHz personal computer. Thus computation of images of the whole human head could last about one hour.



a b

Fig. 3. Histograms of input (a) and output (b) images.



a b

Fig. 4. Segmented input image (a) and output image (b) by thresholding procedure.

4. Discussion

The novel and simple technique without training set or features database for segmentation of ischemic stroke regions on the CT slices was suggested in this paper. 18 joint textural features showed ability to recognize ischemic stroke in the most CT slices. Classification by grouping classes can be alternative way to segment such type of medical images. Volume of stroke region can be computed by multiplying summed labeled stroke pixels with pixel spacing. For full automation it is necessary to find the lower and the upper boundaries of thresholding for each image.

Radiologist evaluated the segmented CT images. There were less fault segmentation by comparing with unsupervised learning methods published in (Usinskas *et al*., 2002a). In addition there is no necessary to use training set or build database of futures for supervised classification. Complicated and unexpected earlier training of classifier is modified by higher-grade unsupervised segmentation technique.

The method was improved with respect to segmentation quality and classification simplicity.

5. Acknowledgements

This investigation was supported by the European Community – Access to Research Infrastructure action of the Improving Human Potential Programme (contract No. HPRI-CT-1999-00026), pan-European network for market-oriented, industrial R&D EUREKA Programme (EUREKA project E!2981 CTBSTROKE), and Lithuanian State Science and Studies Foundation (contract No. V-13).

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Ischeminio insulto segmentavimas kompiuterinėse tomogramose naudojant bendras charakteristikas

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Straipsnyje aprašoma ischeminio insulto segmentavimo technologija žmogaus galvos smegenų kompiuterinėse tomogramose. Segmentavimui naudojamos bendros charakteristikos, pasirinktos iš vidurkio, standartinės deviacijos, histogramos ir skaisčio matricos metodų. Atlikti tyrimai parodė, kad nagrinėjamas metodas tinkamas ischeminio insulto sričių atpažinimui.