Improvements on the gray level co-occurrence matrix technique to compute ischemic stroke volume

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Abstract. The purpose of this work was to apply and test Haralick's gray level co-occurrence matrix (GLCM) technique for automatic calculation and segmentation of the ischemic stroke volume from CT images. For this task, the 3-nearest neighbors classifier was trained to perform stroke and non-stroke area classification. The segmentation and classification results were compared versus a manual segmentation. Approximately half of the automatically computed and segmented stroke volumes from CT images differed less than 15 % from the corresponding manually segmented stroke volumes.

1 Introduction

Today, computer tomography (CT) is the modality of first choice for the examination of patients with acute stroke. Within the first hours after onset of the stroke appearance, the detection of ischemic regions in the brain using CT images is at the same time a very critical and a very difficult task. Later ischemic edema can be recognized as a hypodense area that is clearly visible. For scientific and medical studies dealing with ischemic stroke it is necessary and useful to calculate the volume of the stroke, since the patient status depends on the size and localization of the ischemic stroke. The manual calculation of the location and the volume of the stroke is very tedious and time consuming. In order to speed up possible early detection and diagnosis, Haralick's gray level co-occurrence matrix (GLCM) technique was applied and tested for automatic calculating and segmentation of the volume of an ischemic stroke from CT images.

2 Research

There exist several methods to describe image texture. They are based on application of artificial neural networks, or 2D Fourier transformation, or histogram, or gray level co-occurrence matrix (GLCM), etc. All these methods have their advantages and disadvantages. The Fourier transform of an image reveals the periodicity and directionality of the texture [1]. Artificial neural networks are complicated to train [2]. One of the most popular and powerful ways to describe texture is using of GLCM [3]. It represents an estimate of the probability that a pixel has a gray level intensity g_i and a neighboring pixel has an intensity g_j, where g_i, $g_j \in [0; Ng–1]$, and Ng is the number of available gray levels in the image. Using Haralick features, 14 parameters can be extracted from the above-mentioned probability distribution [4]. It is presumed that these parameters can characterize image texture.

2.1 Material

For a comparison of the automatic and the manual approach, the ischemic stroke volumes of 50 patients were both hand and automatically segmented from CT scans. All CT-scans were made on a SOMATOM Volume Zoom (SIEMENS) at the Department of Neuroradiology at the University Hospital of the University of Erlangen. All recordings were made in a time span of ten months. The data subset containing the stroke volume consisted of approximately twenty slices per CT-scan. All images were archived using DICOM standard, where each image header contained information about slice thickness and pixel spacing for computing stroke volume

2.2 Parameter Extraction

The goal of this research was compute the volume of ischemic stroke automatically in each head from CT-slices. Fig. 1 shows nine slices with automatically detected stroke area (light gray).

The first step, before applying the GLCM technique to calculate the stroke volume from the 50 CT scans, is to decrease the number of available gray level values and therefore the bins in the co-occurrence-matrix as well as the amount of data to be processed. Experiments showed that 100 gray levels were enough to describe textural information of the human brain instead of 4096 gray levels (12-bit) supported in DICOM standard (Fig.2a). We accepted gray levels in the range from 1024 to 1123 only. Thus gray levels below 1024 were set equal to zero and values of above 1123 were set to 99 (Fig. 2 b). All values between 1024 and 1123 were transformed to levels between 0 and 99:

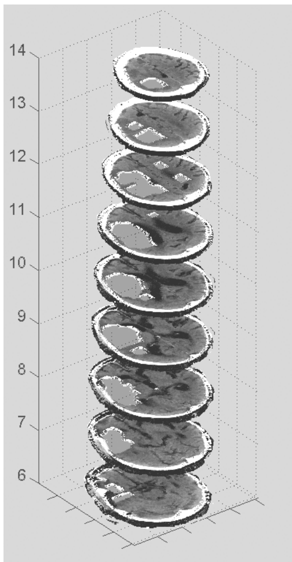


Fig. 1. Automatically detected stroke area (middle gray)

$$g_{100} = \begin{cases} 0, & g_{4096} < 1024 \\ g_{4096} - 1024, & 1024 < g_{4096} < 1123 \\ 99, & g_{4096} > 1123 \end{cases} \qquad (1)$$

Using this mapping function we decreased the size of GLC-Matrix from 4096^2 to 100^2 entries.

To reduce the computing time further each of the 14 Haralick features were calculated to understand which of these parameters is able to separate the stroke area in

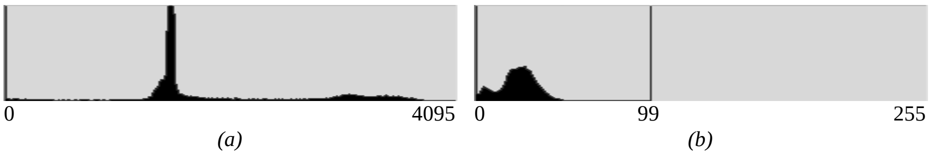


Fig. 2. Histogram of 12-bit DICOM image (a) and of preprocessed image converted to 8-bit (b)

each CT-slice from the remaining brain texture, bone and air. Combining one feature with another, we discovered that six Haralick features (f_2:Contrast; f_4:variance; f_6:Sum average; f_7:Sum variance; f_8: Sum entropy; and f_{10}:Difference variance) are sufficient to separate stroke and brain texture in the best way.

2.3 Classification

To classify the micro texture of the brain, a sliding window approach was utilized. Experiments with different sliding window sizes showed an optimum classification result with a window size of 31² pixel. Therefore each CT-slice with a spatial resolution of 512² pixels was subdivided into (232324 sliding-window positions per slice where the GLCM and the corresponding 6 Haralick features were calculated.

As classifier a 3-nearest neighbor rule [5] was applied, which classified a vector x to the class C_n, where x_n is the nearest neighbor to x and x_n belongs to class C_n. A classification mistake is made if C_n is not the same category. If the number of pre-classified points is large it makes sense to use n nearest neighbors, instead of one single neighbor. Thus we chose the nearest 3 neighbors. The classifier must be trained with known data (training pattern). For this purpose we randomly selected a CT slice and defined two classes on it: C_1 describing the part of non-stroke brain, and C_2 describing the part of the brain with the stroke (Fig. 3a). Thus 35000 samples for class C_1 and 6000 samples for class C_2 were calculated.

2.4 Feature optimization

For each sliding window, feature extraction for the training pattern set was performed, yielding 35000 and 6000 feature vectors for classes C_1 and C_2, respectively. To increase the classification speed, the training pattern set was optimized to eliminate similar features. The criterion of elimination was the absolute difference between quadratic lengths of feature vectors: $d = \left| \sum_{i=1}^{N} F_1(i)^2 - \sum_{i=1}^{N} F_2(i)^2 \right|$, where N denotes the total number of features in each vector, and $F_1(i)$, $F_2(i)$ the feature vectors to be compared. If the distance d between two feature vectors was equal or less than 0.0001, we presumed that these feature vectors were very similar or the same. As result of the optimization step we reached a reduced training data set with 12000 and 3000 vectors for classes C_1 and C_2 respectively.

After the learning process, we were able to classify unknown patterns using sliding window. For each sliding window, the feature vector was calculated and compared with each vector of classes C_1 and C_2 using the 3-nearest-neighbor and the Euclidean distance between feature vectors.

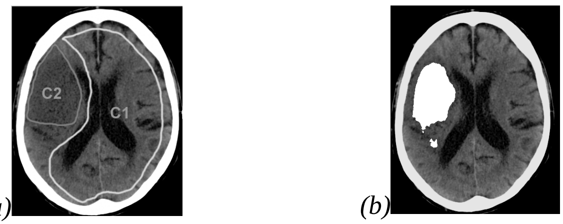
2.5 Segmentation post processing

Morphology dilation operation was performed as the last operation of computing stroke volume. As can be seen in Fig. 3b, the detected stroke area was less than observed in the original image, so we added half of sliding window to each pixel from class C_2. Finally the stroke volume V can be calculated using $V = Vol_{Voxel} \times \Sigma S_i$, where S_i denotes the number of pixels in the stroke region of i-th slice.

3 Results and Conclusions

We computed and classified 1204 CT slices (302 MB) in 56 hours with PIII 450 MHz computer. The classification of one slice took about 2-3 minutes, and the computation of stroke volume of one patient took approximately one hour. About half of automatically computed from CT images stroke volumes differed less than 15 % from manually calculated corresponding stroke volumes. Some of computed volumes differed from defined and calculated manually up to 100 % and even more.
Since the automatic computation and segmentation of ischemic stroke volume showed viability of utilization of GLCM technique, the next steps in searching of more precise and more reliable results of computing using textural features will be:

- Testing different features to classify unknown brain areas,
- Improve the classifier training set,
- Propagation of stroke location from slice to slice.



(a) *(b)*

Fig. 3. CT slice with two classes ($C1$ – non-stroke, $C2$ – stroke) (*a*), and the same area after segmentation (*b*)

Literature

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