DEVELOPMENT OF A BRAIN BLOOD VESSEL SEGMENTATION METHOD IN CT-ANGIOGRAPHY

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Abstract: Accurate detection and segmentation of Intracranial Aneurysms in Computed Tomography Angiography is of major importance for radiologists. In this study, a pixel-based classification algorithm was designed for localization of aneurysms in CTA images. A series of thirty-eight DICOM CTA brain images, was collected from the Department of Radiology of the University Hospital of Patras, Greece. Pixel classification was performed as a two-level hierarchical decision tree. In the first level, the bone-class was discriminated from the vessel-parenchyma class. In the second level, the vessel-class was discriminated from the parenchyma-class. Segmented images were evaluated by an expert radiologist regarding missed, false, or correctly segmented brain blood vessels. The method proved accurate enough for brain blood vessel detection to be used in 3-D blood vessel reconstruction.

Introduction

Intracranial aneurysm (IA) is a protruding bubble or sac on a brain artery that balloons out over time. Aneurysms have a tendency to rupture causing hemorrhage into and around vital brain structures. Autopsy studies indicate a prevalence in the general population of approximately 5%[1-3].

Detection of IA has been traditionally performed using the standard Digital Subtraction Angiography (DSA)[4, 5]. Computed Tomography Angiography (CTA) is a new non-invasive imaging modality that has recently started to be recognized as rapid and accurate alternative to the standard DSA technique for brain aneurysms visualization[6-9]. Although numerous studies have been devoted to the demanding task of vessel segmentation[10-12], few specialize in CTA images[11, 12] and even fewer to the detection of intracranial aneurysms[12]. However, brain aneurysm detection is of crucial importance, since it enables the quantification of a variety of crucial parameters (i.e. the neck of the aneurysm, its orientation and its relation to the parent vessel) that significantly affect treatment planning and surgical intervention[13, 14]. Thus, accurate detection and segmentation of IA in CT angiograms is of major importance for radiologists. The purpose of this study was to develop a computer-based method for blood vessel segmentation in CT-angiography, for facilitating localization of aneurysms in subsequent 3-D reconstruction of brain blood vessels.

Materials and Methods

A series of thirty-eight DICOM CTA brain images (Siemens Somaton Plus 4), obtained from the same patient, was collected by an expert physician (T.P.) from the Department of Radiology of the University Hospital of Patras, Greece.

To enhance the contrast between vessels and bones, all images were initially processed using a simple-window transformation (width=1000, center=1300). Following, images were transformed to BMP format (512x512x8bit) for further processing.

The segmentation algorithm was designed as a decision tree classification scheme (see figure 1): At the first level regions of bones were discriminated from regions of “vessels&parenchyma” content. At the second level, blood vessels were differentiated from parenchyma.

At each level of the decision tree, a pixel-based classification algorithm was designed to discriminate image pixels as belonging to one of three classes: blood vessel, brain parenchyma, and bone. Firstly, we manually sampled a number of image-samples (5x5 pixel ROIs) from each class (50 samples from bone, vessel and parenchyma class respectively). From each one of the samples, 38 features were extracted by means of first and second order statistics. Four features from the image-sample histogram[15], 24 from the co-occurrence matrix[16] and 10 from the run-length matrix[17].

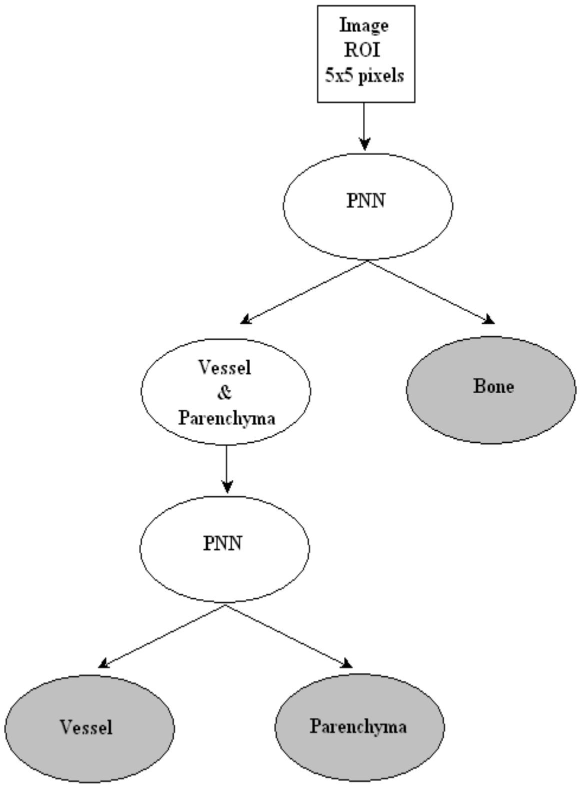

Figure 1: Decision tree classification scheme for brain vessel extraction

A classifier (Probabilistic Neural Network-PNN) was trained to discriminate different classes at each level of the decision tree, as shown in Figure 1. For feature reduction purposes, the statistical t-test was used at each level of the decision tree. Only those features that exhibited significant difference ($p<0,001$) were selected for further processing. The selected features were then combined exhaustively (up to 5 feature combinations) for further feature reduction. The classifier's performance was evaluated separately for each feature combination using the leave-one-out method at both levels of the decision tree.

After training, the PNN classified each image pixel as belonging to one of the three classes, resulting to a segmented image (figure 2e).

Results and Discussion

At the first level of the decision tree, the PNN classifier resulted in 90.7% accuracy with best feature combination the *standard deviation* (histogram based feature), the *difference variance* (co-occurrence based feature) and the *gray level non-uniformity* (run length feature).

The *mean value* and *gray level non-uniformity* optimized classification accuracy of the PNN classifier at the second level of the decision tree, resulting in 93% accuracy.

Table 1: PNN classification results for both levels of the decision tree for the training stage

1st level		
Bone	**vessel-parenchyma**	**overall accuracy**
44	*8*	*88%*
6	*92*	*92%*
50	*100*	***90.7%***
2nd level		
Vessel	**parenchyma**	**overall accuracy**
47	*4*	*94%*
3	*46*	*92%*
50	*50*	***93%***

Gray level non-uniformity provided optimal operation of the PNN classifier at both levels of the hierarchical tree. This feature is related to the length and direction of neighboring pixels having same gray-level value and refers to a coarse or fine texture.

Figure 2a illustrates a CT angiography image of a patient with aneurysm (see arrow in figure 2b). Because in CTA images bones and contrast-enhanced vessels usually have high gray values, images were processed with a windowing technique (figure 2b). The result of the classification process for the first level of the decision tree using the PNN classifier is demonstrated in figure 2c, where pixels that were classified as belonging to the bone class are marked with white color, whereas pixels recognized as belonging to the vessel-parenchyma class were marked with black color. The result of the pixel classification process for the second level of the decision tree is illustrated in figure 2d, where vessels have been extracted from parenchyma. Figure 2e shows the final segmented image, where the boundaries of the vessels are clearly delineated. Figure 2e was produced by superimposing Figure 2d onto Figure 2b.

Segmented images were evaluated by an expert radiologist (N.D.) regarding missed, false, or correctly segmented brain blood vessels. Segmentation results revealed average accuracies of 85% of correctly identified, 6% of falsely indicated, and 9% of missed blood vessels. Results indicated that the proposed algorithm might assist radiologists in localization of aneurysms in subsequent 3-D reconstruction (see figure 3) of brain blood vessels in CTA images.

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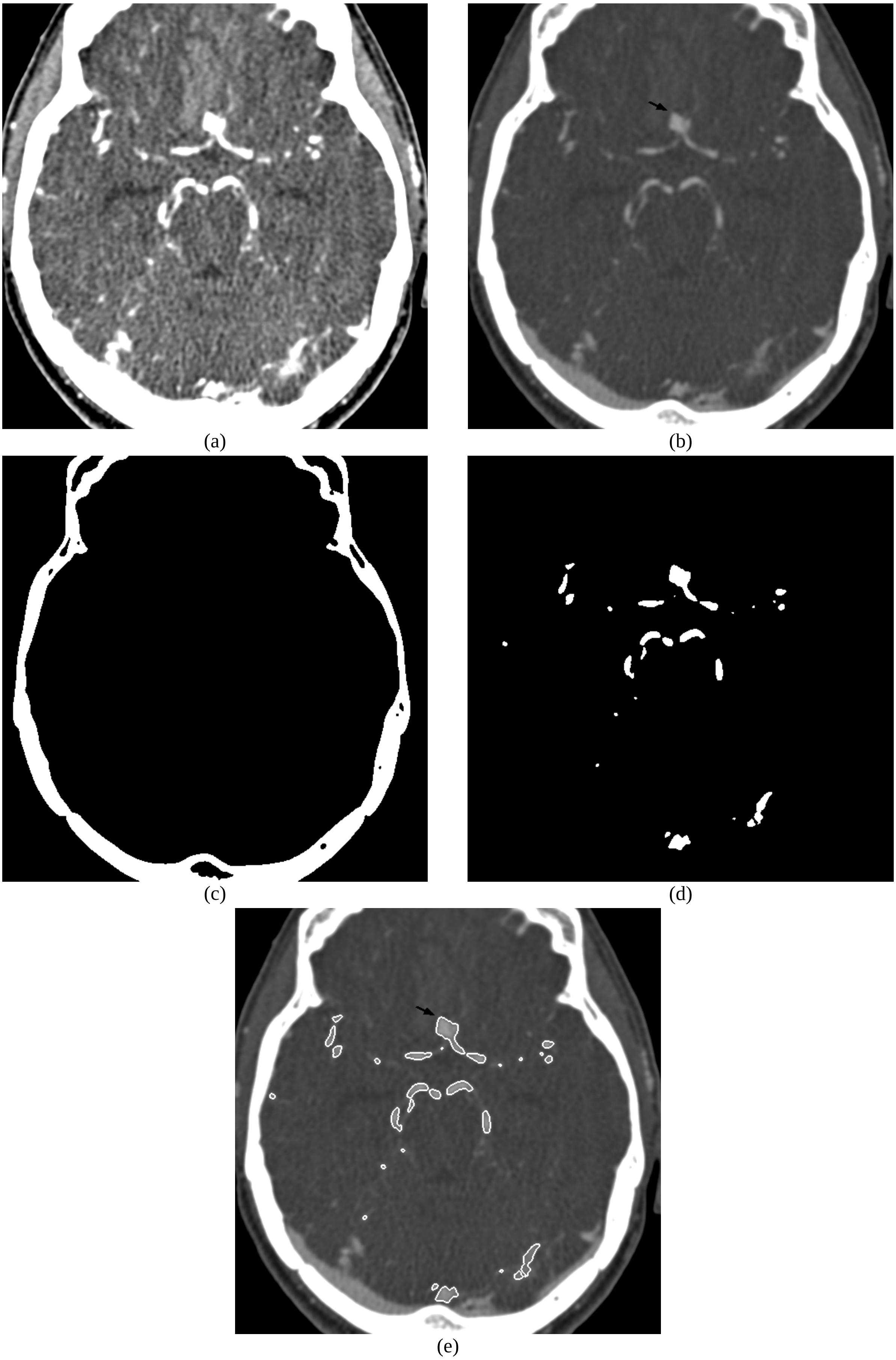

Figure 2: (a) Initial CTA image, (b) simple window processed image (black arrow shows the aneurysm), (c) 1st level segmentation of the decision tree, (d) 2nd level segmentation of the decision tree, (e) boundaries of segmented vessels.

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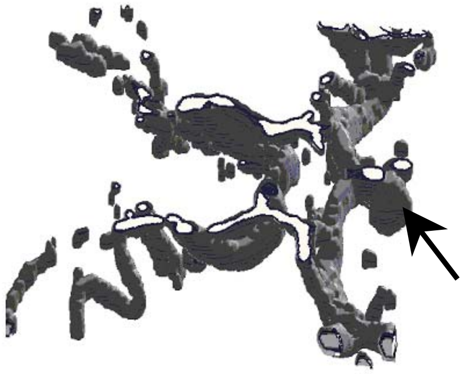

Figure 3: 3-D blood vessel reconstruction from segmented 2-D CTA consecutive slices (black arrow shows the aneurysm)

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