Stroke detection through a nonparametric estimation-based level set approach based on the Parzen windows

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***Abstract*—This paper aims to aid stroke medical diagnosis through medical images of the brain. We propose a new approach to segment stroke brain Computerized Tomography (CT) images. The proposed approach uses level set method based on the nonparametric estimation approach via parzen-window. Besides this, by optimizing the criterion function, an optimal global threshold is obtained. The results demonstrated the success of the proposed method, when it was compared with the level set algorithm based on the coherent propagation method, using a ground truth built by a specialist. The results obtained show that the proposed method is better than the method based on coherent propagation. This method is a promising approach to be used in clinical routine diagnosis, since it requires less than 2 seconds for the analysis using a personal computer.**

***Keywords*-Medical imaging; stroke; level set; parzen-window.**

I. Introduction

A stroke is caused by the interruption of the blood supply to the brain, usually because a blood vessel burst or a clot. The interruption of oxygen and nutrient supply causes damage to the brain tissue [1]. According to the World Health Organization (WHO), it is estimated that 17.5 million people died from cardiovascular disease, particularly heart attacks and strokes, every year [1]. The two procedures regularly used for stroke lesion mapping are Computed Tomography (CT) and Magnetic Resonance Imaging (MRI) [2]. CT remains the procedure of choice for many clinical studies, with advantages typically including cost, speed, and reduced exclusion criteria relative to MRI [3]. Usually, the standard method for lesion identification is the manual delineation of abnormal brain tissue by trained professionals [4]. However, manual method produces variability across operators because there is often no clear division between the lesion and non-lesioned tissues, particularly at the borders of the brain and around the ventricles.

In recent years, many efforts have been made by several researchers in order to contribute with aid diagnosis using brain medical images, such as: the segmentation of brain lesions in diffusion-weighted MRI [5], automatic stroke detection and classification from brain CT images [6, 7], brain tumor segmentation [8, 9].

In this work we propose a new level set approach to stroke segmentation using a nonparametric estimation approach based on the parzen-window [10, 11].

The remainder of this paper is organized as follows: Section 2 briefly describes the level set algorithm and parzen-window. Our proposal is presented in Section 3. In Section 4, the experimental results are presented and discussed. Finally, some conclusions and future work are presented in Section 5.

II. Background

In this section we present the Parzen method used to estimate the level set evolution function proposed in this paper. In addition, a method described in the literature which is used to compare the results obtained in stroke segmentation is also presented.

A. Level set algorithm based on the coherent propagation method (LSCPM)

Wang et al. [12] proposed a periodic monotonic speed function to accelerate the level set algorithm, which allows to expand the segmentation contour and to shrink it in the next period, i.e., coherent propagation. Using coherent propagation, these faster points will, instead, stay in their positions waiting for their neighbors. The segmentation stops naturally when all points on the contour are stationary. Wang et al. [12] applied this method on the segmentation of splenic artery, aorta, and liver.

B. Parzen Windows

Parzen Windows [13] is a well-known method for non-parametric estimation, which does not assume a probability distribution of the data. The method computes the probability of a point z with respect to the class $Z = \{z_i\}_{i=1}^{k}$ as

$$p(\boldsymbol{z}) = \frac{1}{k}\sum_{i=1}^{k}\varphi\left(\frac{\boldsymbol{z}-\boldsymbol{z_i}}{h}\right), \quad (1)$$

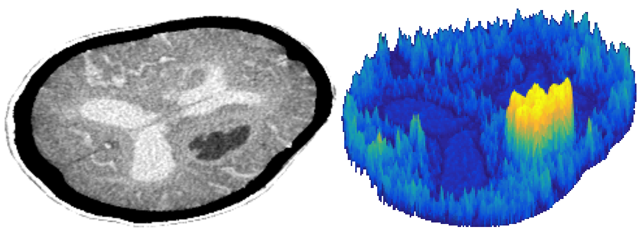
where φ is a kernel function used to limit the neighborhood, h is the window size and k is the cardinality of $\in Z$. The Gaussian kernel, which is one of the most used kernels in the literature, can be defined as

$$\varphi(\boldsymbol{z},\boldsymbol{z_i}) = \frac{1}{\sqrt{(2\pi)^d|\sum|}}exp\left(-\frac{(\boldsymbol{z}-\boldsymbol{z_i})^T\Lambda^{-1}(\boldsymbol{z}-\boldsymbol{z_i})}{2}\right), \quad (2)$$

where Λ stands for the covariance matrix, d is the number of features in $\boldsymbol{z}$ and the $|\Lambda|$ is the determinant of Λ. If $d = 2$, the Λ diagonal matrix is $\Lambda = \sigma^2 I_d = \begin{bmatrix} \sigma^2 & 0 \\ 0 & \sigma^2 \end{bmatrix}$. For $\sigma = h$, the final $p(\boldsymbol{z})$ becomes:

$$p(\boldsymbol{z}) = \frac{1}{k} \sum_{i=1}^{k} \frac{1}{(2\,\pi)^{d/2}\, h^d}\, exp\left(-\frac{1}{2\,h^2} ||\boldsymbol{z} - \boldsymbol{z_i}||^2\right), \qquad (3)$$

where $||.||^2$ stands for the Euclidean distance. More details can be found in [13]. Fig. 1 shows an example of an estimate the spatial probability distribution using parzen-window PDF. In this case, by adopting the covariance matrix as the identity n-dimensional one, $\Lambda = \sigma^2 I_d$, we assume that the individual features are mutually uncorrelated and have same variance.



(a) (b)

Fig. 1. Example of a parzen-window PDF estimate: a) segmented brain; b) estimate the spatial probability distribution.

III. Methodology

The method for stroke segmentation presented in this paper uses a nonparametric likelihood model based on parzen-window [14, 15] as the PDF in the level set method proposed by Sethian. Such method is represented by a closed curve $\vec{\phi} : \mathbb{R}^2 \times \mathbb{R}^+ \rightarrow \mathbb{R}$ that evolves with a velocity field $\pm F\vec{\eta}$. The aforesaid closed curve is based on Hamilton-Jacobi equation [16] and its front movement is a consequence of the surface motion $\psi(\mathbf{x})$, in which one is embedded in accordance with:

$$\vec{\phi}(s,t) = \{\mathbf{x}|\psi(\mathbf{x},t) = 0\},\ \mathbf{x} \in \mathbb{R}^n, \qquad (4)$$

where $s \in \mathbb{R}^2$ is the coordinate of the parametric curve $\vec{\phi}$ and $t \in \mathbb{R}^+$ is the evolution time. This process is expressed as [16]

$$\psi^{k+1} = \psi^k + \triangle t \cdot (F_{prop} + \varepsilon\mathcal{K}) \cdot |\nabla\psi^k|, \qquad (5)$$

where ψ^k is the level set function, $\triangle t$ is the time step, and $F_{prop} + \varepsilon\mathcal{K}$ is the evolution function. The operator $|\nabla\psi^k|$ stands for the gradient magnitude. The evolution function comprises a propagation (or velocity) term F_{prop} and a regularization term $\varepsilon\mathcal{K}$ based on the curvature of ψ^k, where $\varepsilon \in \mathbb{R}$ and the curvature $\mathcal{K}$ is computed as in [16].

In the proposed method, the aforementioned propagation term F_{prop} uses parzen-window as PDF. We defined the set of pixels belonging to inner region as $\boldsymbol{Z_1} = \{z_1\}_{i=1}^{n}$ and outer one as $\boldsymbol{Z_2} = \{z_2\}_{i=1}^{m}$, and the PDF of a pixel $\boldsymbol{z}$ with respect to distribution of each region is $p_1(z)$ and $p_2(z)$, respectively. Finally, the propagation term, that should minimize a cost function, is defined by:

$$F_{prop} = p(z, \mu_1, \sigma_1^2)\,\vec{\eta} - p(z, \mu_2, \sigma_2^2)\,\vec{\eta}, \qquad (6)$$

where z is the pixel value, (μ_1, σ_1^2) and (μ_2, σ_2^2) are, respectively, the mean and variance calculated in the inner and outer regions of the level set front $\vec{\phi}$.

We performed tests with parametric and nonparametric models, and the segmentation results with our model were more accurate than the other ones. The evolution of the proposed method is illustrated in Fig. 2, where the Fig. 2a shows the initial contour (zero level set), the intermediary steps of the segmentation process are depicted in Fig. 2b-2d, and the final result is presented in Fig. 2e.

IV. Experimental Results

In this section we present experimental results and their discussions, as well as the image database used to compare level set methods.

A. Images Acquisition

A high resolution CT system was used to acquire the 100 brain CT scans used in this work. These images have 512×512 with 16 *bits* per pixel. All exams were obtained in partnership with the Heart Hospital (CE-Brazil).

The CT scanner used to acquire the images was the GE Medical System HiSpeed (GEMSH). The tomographic planes were defined on the basis of the axial plane, under the following conditions: slice thickness of 0.7 mm, field of view of 230 mm, tube voltage of 120 Kv, electric current in the tube of 80 mA, window size of 512×512 pixels and voxel size of $0.585 \times 0.585 \times 1.5$ mm in 16 *bits*.

B. Results and Discussion

In the experimental assessment, the proposed Parzen level set method was compared to the level set algorithm based on the coherent propagation method (LSCPM). In present study, we have used a manual initialization performed by a specialist within the cerebral vascular accident region.

In order to improve the evaluation and discussions, we employed four statistical measures, which are: sensitivity (SEN), specificity (SPC), accuracy (ACC) and the Matthews Correlation Coefficient (MCC). These measurements are functions of true positive (TP), false positive (FP), true negative (TN), and false negative (FN) metrics, as follows:

$$SEN = \frac{TP}{TP + FN}, \qquad (7)$$

$$SPC = \frac{TN}{FP + FN}, \qquad (8)$$

$$ACC = \frac{TP + TN}{TP + TN + FP + FN}, \qquad (9)$$

$$MCC = \frac{TP \times TN - FP \times FN}{\sqrt{(TP + FP)(TP + FN)(TN + FP)(TN + FN)}}, \qquad (10)$$

where TP is defined as the number of stroke pixels correctly detected in the brain images; FP is the number of non-stroke pixels detected as stroke; TN is the number of non-stroke pixels correctly detected and FN is the number of stroke pixels detected as non-stroke points.

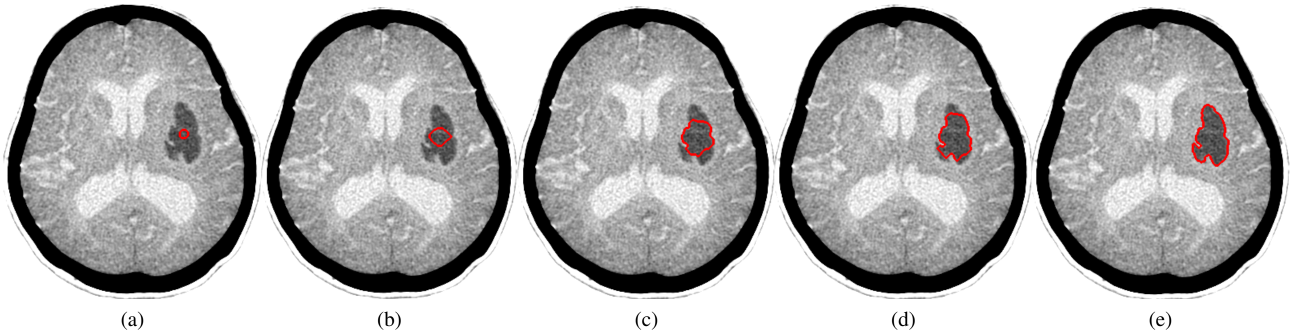


Fig. 2. Example of a segmentation obtained by the proposed method: a) initialization; b) - d) evolution of the method; and e) final segmentation result.

Fig. 3 shows three segmentation results of stroke in CT images of the brain. Fig. 3a presents the ground truth results. Fig. 3b-3c show, respectively, the results obtained by the Parzen level set (in red) and LSCPM (in yellow). The reference images used as ground truth were built manually by a specialist.

Table I presents quantitative results of aforementioned assessment metrics: SEN, SPC, ACC and MCC. The score μ and σ are, respectively, the mean and standard deviation of data base results.

The proposed method achieved higher scores in 3 of 4 metrics. As the stroke detection problem is an unbalanced one, i.e., there are more pixels to classify as non-stroke than stroke ones, it is important to measure the percentage of prediction regardless of class sizes. The MCC metric computes the correlation of prediction, regardless the class sizes, thus, this metric becomes relevant in this study. In that case, the proposed method achieved the best MCC.

TABLE I
RESULTS OF PERFORMANCE EVALUATION METRICS.

Method		SEN	SPC	ACC	MCC
Parzen level set	μ	0.9987	**0.9690**	**0.9984**	**0.9292**
	σ	0.0009	**0.0392**	**0.0008**	**0.0236**
LSCPM	μ	**0.9996**	0.8299	0.9972	0.8931
	σ	**0.0005**	0.1116	0.0023	0.0573

Regarding the runtime (in seconds), the propose method was most efficient with mean computation time of 1.51 ± 0.70 seconds. Level set algorithm based on the coherent propagation has mean computation time of 1.96 ± 0.29 seconds.

V. CONCLUSION

In this work we propose a new level set approach to stroke segmentation using a nonparametric estimation approach based on the parzen-window. The proposed level set approach was compared against the Level set approach based on the coherent propagation using a ground truth built by a specialist. The proposed method was comparatively more stable than the other one, obtaining in average accuracy a value higher than 99%. The results obtained show that the proposed method is a promising approach to be used in clinical routine diagnosis, since it requires less than 2 seconds for the analysis using a common personal computer. For future works, we intend to apply other level set methods and apply computational intelligence and pattern recognition techniques to identify the segmented stroke.

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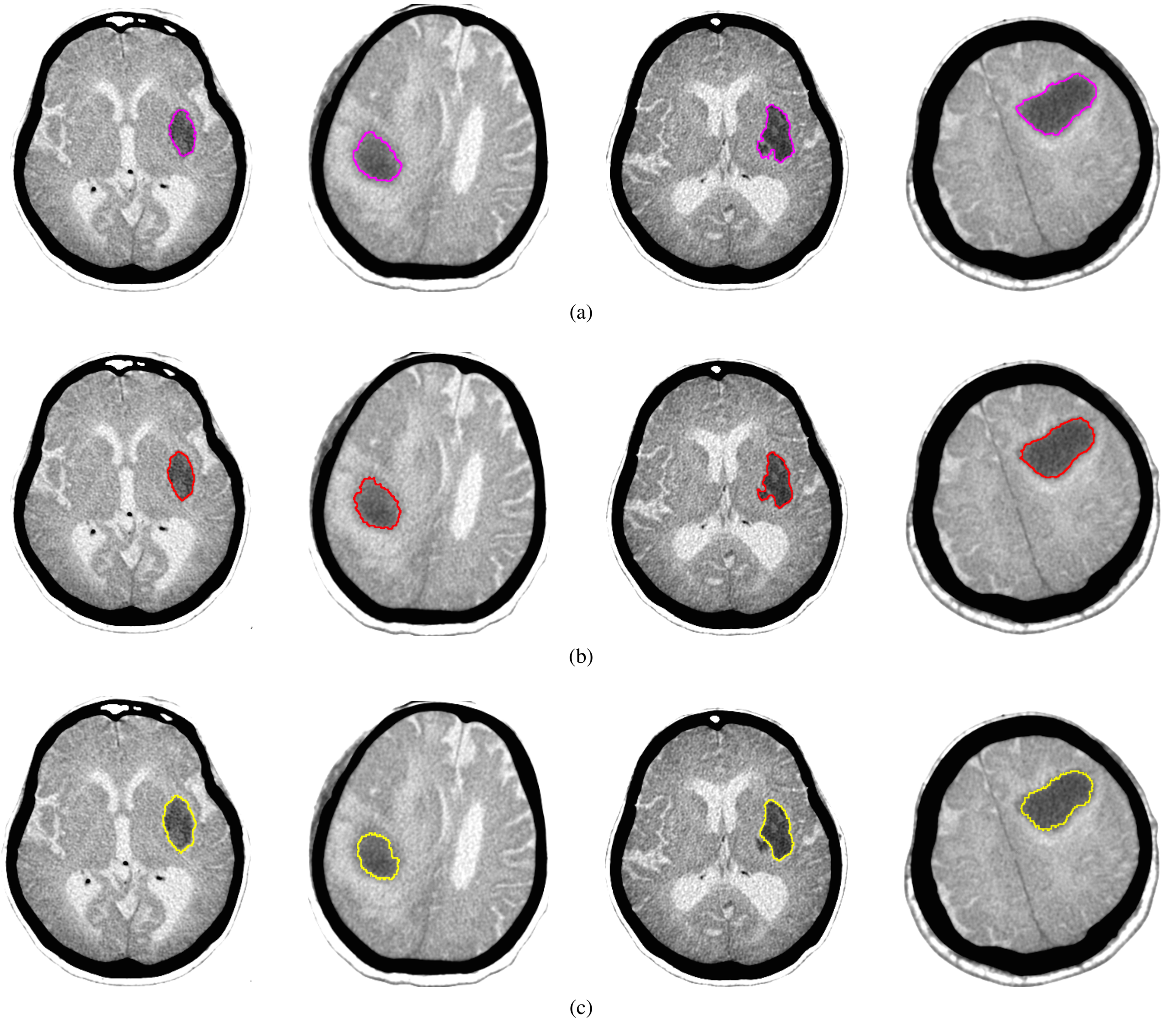

Fig. 3. Stroke segmentations obtained by the methods under comparison in CT images: a) ground truth in pink; b) proposed method in red; c) LSCPM in yellow.

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