Precise Segmentation of Vessels from MRA Brain Images

D.Jenefa Magdalene[1]
PG Scholar
Department Of Computer Science & Engineering
Dr.sivanthi Aditanar College of Engineering
Tiruchendur, Tamil Nadu.

G.R.Jainish[2]
Assistant Professor
Department Of Computer Science & Engineering
Dr.sivanthi Aditanar College of Engineering,
Tiruchendur, Tamil Nadu.

***Abstract*--Accurate automatic extraction of cerebrovascular system from magnetic resonance angiography (MRA) images is one of the most important problems in practical computer assisted medical diagnostics due to the small size objects of interest and complex surrounding anatonomical structures. There has been a considerable amount of work done on the enhancement and extraction of curvilinear structures from medical images, from a specific imaging modality. The proposed technique is of segmenting the vessels from MRA brain images. The technique thus use the bilateral filter for smoothing the image, and then blood vessels can be separated from background using a voxel wise classification based on precisely identified probability models of intensities of voxel. For that, an empirical marginal probability distribution of intensities is approximated with a linear combination of discrete Gaussians (LCDG). And then Gaussian derivative, local maxima and gradient vector flow are extracted as features from the input image. And then Support Vector Machine is used to classify the vessels and non vessels. The result indicates a very good ability of the proposed method for segmenting the vessels from MRA brain images.**

Key-words: Cerebrovascular system, magnetic resonance angiography (MRA), linear combinaiton of discrete Gaussians (LCDG), segmentation

I.INTRODUCTION

The dramatic increase of the number and sheer size of three dimensional (3D) angiographic data sets (magnetic resonance angiography – MRA and computed tomography angiography – CTA) has lead to an almost overwhelming amount of 3D information to be evaluated by clinicians. Since manual procedures to process these data are often tedious, time consuming and subject to inter- and intraobserver variability, there is a strong demand for segmentation methods that are (semi-) automatic. The methods for the specific task of vessel segmentation have received considerable interest in the last decade. They have been applied for improving visualization, therapy planning, detection of abnormalities, in quantification (e.g., of diameters or stenosis grade) and as preprocessing step for 3D vessel modeling, and in the design of computer aided diagnosis systems. The human body contains various types of curvilinear structures—blood vessels, bronchial trees, bile ducts etc.—the visualization of which is crucial for planning and navigation during interventional therapy and biopsy as well as for diagnostic purposes. Most of the enhancement and extraction of curvilinear structures from three-dimensional (3-D) medical images, focused on the extraction of a specific anatomical structure from a specific imaging modality—for example, cerebral blood vessels from magnetic resonance angiography (MRA) images.

There are so many popular techniques for extracting blood vessels from MRA data. They are scale-space filtering, centerline-based methods, deformable models, statistical models, and hybrid methods.Multiscale filtering enhances curvilinear structures in 3-D medical images by convolving an image with Gaussian filters at multiple scales. The multiscale filter output forms a new enhanced image such that the curvilinear structures become brighter whereas other components become darker [1]. Centerline minimal path-based techniques [4] formulate the two-point centerline extraction as the minimum cost integrated along the centerline path. Deformable model approaches to 3-D vascular segmentation attempt to approximate the boundary surface of the blood vessels [6]. An initial boundary, called a snake, evolves in order to optimize a surface energy that depends on image gradients and surface smoothness. Statistical extraction of a vascular tree is completely automatic, but its accuracy depends on the underlying probability models. The MRA images are multimodal in that the signals (intensities, or gray levels) in each region of interest (e.g., blood vessels, brain tissues, etc.) are associated with a particular dominant mode of the total marginal probability distribution of signals.In this paper we present a new approach for extraction of cerebrovascular system that is suitable for MRA image.

II. NOISE REDUCTION

Images are often corrupted by random variations in intensity, illumination, or have poor contrast called Noise and can't be used directly. In order to avoid certain phenomena such as atmospheric and terrain effects, but also image transformation by the vendor, several corrections need to be applied to your image data before you can proceed to serious analysis.Noise reduction is the process of removing noise from a signal.In the field of image processing several filtering methods have been proposed for noise reduction.

A bilateral filter is used for reducing noise and to smoothing the image. In which The intensity value at each pixel in an image is replaced by a weighted average of intensity values from nearby pixels. The bilateral filter has several qualities that explain its success:

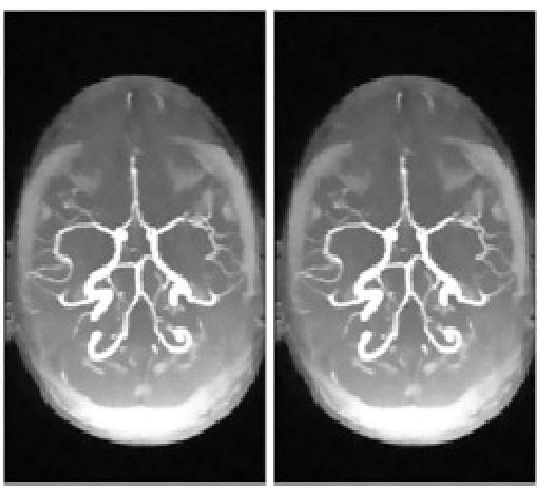

Fig 1. (a) Input Image (b) Preprocessed Image

- Its formulation is simple: each pixel is replaced by a weighted average of its neighbors. This makes it easy to acquire intuition about its behavior
- It depends on the parameters that indicate the size and contrast of the features to preserve.
- In a non-iterative manner It can be used.

$$I^{\text{filtered}}(x) = \sum_{x_i \in \Omega} I(x_i) f_r(\|I(x_i) - I(x)\|) g_s(\|x_i - x\|)$$

where:

I^{filtered} = the filtered image;
I = the original input image to be filtered;
X =coordinates of the current pixel to be filtered;
Ω = the window centered in ;
f_r = range kernel for smoothing differences in intensities.
g_s = spatial kernel for smoothing differences in coordinates.

III. SEGMENTATION WITH THE LCDG MODEL

The proposed method use the expected log-likelihood as a model identification criterion. Let X = (Xs : s = 1, . . . , S) denote a 3-D MRA image containing S co-registered 2-D slices Xs = (Xs (i, j):(i, j) R;Xs (i, j) Q). Here, R and Q = (0, 1, . . .,Q − 1} are a rectangular arithmetic lattice supporting the 3-D image and a finite set of Q-ary intensities (gray levels), respectively. Let Fs = (fs (q): q Q; Σq Q fs (q) = 1, where q denotes the gray level, be an empirical marginal probability distribution of gray levels for the MRA slice Xs.

The discrete Gaussian (DG) is defined as the probability distribution Ψθ = (ψ(q|θ): q Q) on Q of gray levels such that each probability ψ(q|θ) relates to the cumulative Gaussian probability function Φθ (q) as follows (here, θ = (μ, σ2) for the mean, μ, and variance σ2)

$$\Psi(q|\theta) = \begin{cases} \Phi_\theta(0.5) & \text{for } q = 0 \\ \Phi_\theta(q+0.5) - \Phi_\theta(q-0.5) & \text{for } q = 1, \ldots, Q-2 \\ 1 - \Phi_\theta(Q-1.5) & \text{for } q = Q-1 \end{cases}$$

The Cp positive and Cn negative components of LCDG such that Cp ≥ K

$$p_{w,\Theta}(q) = \sum_{r=1}^{C_p} \omega_{p,r}\psi(q|\theta_{p,r}) - \sum_{l=1}^{C_n} \omega_{n,l}\psi(q|\theta_{n,l})$$

has obvious restrictions on its weights$\mathbf{w} = [wp,., wn,.]$, namely, all the weights are nonnegative and

$$\sum_{r=1}^{C_p} \omega_{p,r} - \sum_{l=1}^{C_n} \omega_{n,l} = 1$$

Our goal is to find a *K*-modal probability model that closely approximates the unknown marginal gray level distribution. Given $\mathbf{F}s$, its Bayesian estimate $\mathbf{F}$ is as follows : $f(q) = (|\mathbf{R}|fs\ (q) + 1)/(|\mathbf{R}| + Q)$, and the desired model has to maximize the expected log-likelihood of the statistically independent empirical data by the model parameters:

$$L(w,\theta) = \sum_{q \in Q} f(q) \log p_w, \theta(q)$$

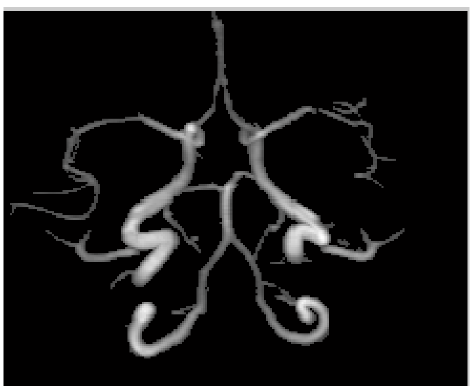

Fig 2.Segmented output with LCDG model

The entire segmentation algorithm is as follows:

1) For each successive MRA slice $\mathbf{X}s$, $s = 1, \ldots, S$,

a) Initially the marginal empirical probability distribution $\mathbf{F}s = (fs\ (q): q \in \mathbf{Q})$ of gray levels is collected.

b) An initial LCDG-model that closely approximates $\mathbf{F}s$ is calculated by using the initializing algorithm to estimate the numbers $Cp - K$, Cn, *and* parameters $\mathbf{w}$, $\mathbf{\Theta}$ (weights, means, and variances) of the positive and negative DGs.

c) Then the LCDG-model with the fixed *Cp* and *Cn is* refined by adjusting all other parameters with the modified EM algorithm

d) Split the final LCDG-model into *K* submodels, one per each dominant mode, by minimizing the expected errors of misclassification and select the LCDG-submodel with the largest mean value (i.e.,the submodel corresponding to the brightest pixels) as the model of the desired blood vessels.

e) Blood vessels' voxels in this MRA slice is extracted using the intensity threshold *t* separating their LCDG-submodel from the background ones.

2) Eliminate artifacts from the whole set of the extracted voxels using a connectivity filter that selects the largest connected tree structure built by a 3-D volume growing algorithm.

The main goal of the whole procedure is to find the threshold for each MRA slice that extracts the brighter blood vessels from their darker background in such a way that the vessels' boundaries are accurately separated from the surrounding structures that may have similar brightness along these boundaries.

IV.FEATURE EXTRACTION

A special form of dimensionality reduction is called Feature extraction. When the inputs data is too large to process by an algorithm and suspected to be notoriously redundant, then the features are reduced i.e. the reduced representation of set of features also named features vector. Transformation of input data into the set of features is called *feature extraction***.** The desired task is performed only when the features extracted are chosen carefully.

A. 3D Local geometry features

Three-dimensional geometric data play fundamental roles in many computer vision applications. Geometric elements like points, lines, curves or surfaces, the Geometric features of objects are constructed. Features such as corner, edges, Blobs, Ridges, image texture and 3D Local geometry features are used for the detection of vascular patterns.

Gaussian derivative

Gaussian derivative have been intensively considered for thin structures analysis. By applying the exponential function to a general quadratic function Gaussian functions arise. The Gaussian functions are thus those functions whose logarithm is a quadratic function.

$$= \frac{1}{\sigma\sqrt{2\pi}} EXP\left[-\frac{x^2}{2\sigma^2}\right]$$

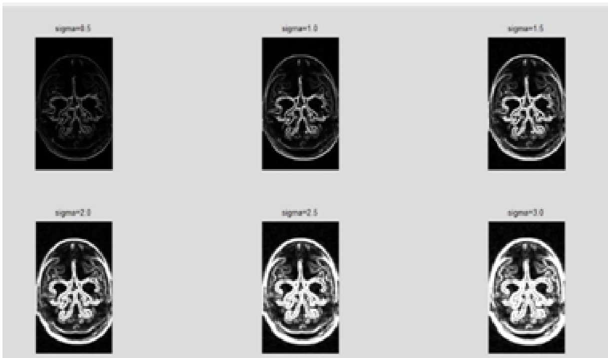

Fig.3 Gaussian Derivative of MRA brain image

When derivatives to x (spatial derivatives) of the Gaussian function is taken repetitively, a pattern emerging of a polynomial of increasing order can be seen, multiplied with the original normalized Gaussian function again. Gaussian functions are used to define some types of artificial neural networks.

B. Isotropic features

Isotropic features focus on estimating the location and/or scale of target vessels. They do not exploit assumptions on the directionality of the vessels.

Local Maxima

Locating the maxima and minima of a function is an important task which arises often in applications of mathematics to problems in engineering and science. A function f has a local maximum or relative maximum at c if $f(c) \geq f(x)$ when x is near c. This means that $f(c) \geq f(x)$ for all x in some open interval containing c.

Let f be a function defined on an interval [a,b] or (a,b), and let p be a point in (a,b), i.e., not an endpoint, if the interval is closed.

- f has a local minimum at p if $f(p) \leq f(x)$ for all x in a small interval around p.
- f has a local maximum at p if $f(p) \geq f(x)$ for all x in a small interval around p.

Gradient vector flow

The gradient is a vector which has magnitude and direction. Magnitude indicates edge strength. Direction indicates edge direction. The gradient vector flow (GVF) refers to the definition of a bidirectional external force that can capture the object boundaries from either sides and can deal with concave regions. Such a field is recovered through the diffusion of the edge-driven information and has an interpretation similar to the optical flow. This field can be interpreted as the direction to be followed to reach the object boundaries.

V.SUPPORT VECTOR MACHINE

Support vector machine (SVM) is a widely used technique for pattern recognition and classification in a variety of applications for its ability for detecting patterns in experimental databases. SVM has become an essential machine-learning method for the detection and classification of particular patterns in medical images. In general, SVM are applied to several fields such as: cancer, tumor, or nodule detection, vascular analysis, dementia detection, etc. Also SVM has been applied to a variety of image types: magnetic resonance images (MRI), magnetic resonance angiography (MRA), SPECT or PET, ultrasound images etc.

In machine learning, support vector machines SVMs, are supervised learning models.SVM associated with the learning algorithms analyze data and recognize patterns, which used for classification and regression analysis. Basically SVM takes a set of input data and makes prediction for each given input and forms possible classes of output. For a given set of training examples, they are marked as belonging to one of two categories; an SVM training algorithm assigns new examples into one category or the other.. SVM techniques consist of two separate steps: first of all a given set of binary labeled training data is used for training; then new unlabeled data can be classified according to the learned behavior. SVM separates a given set of binary labeled training data by means of a hyperplane that is maximally distant from the two possible classes.

VI. CONCLUSION

Segmentation algorithms form the essence of medical image applications such as radiological diagnostic systems, creating anatomical atlases, visualization, computer-aided surgery and multimodal image registration. Even though many promising techniques and algorithms have been developed, it is still an open area for more research. Accuracy of the segmentation process is crucial due to the nature of the work and the need for the more precise diagnostic systems. Accuracy is improved by incorporating a priori information on letting high level knowledge and vessel anatomy guide the segmentation algorithm. This paper presents an approach for vessel segmentation in the field of medical Image processing using Medical Image Resonance (MRA) images. The result indicates a very good ability of the proposed method for segmenting the vessels from MRA brain images.

ISSN: 2278 – 1323

REFERENCES:

[1] Y. Sato, S. Nakajimaa, N. Shiragaa, H. Atsumia, S. Yoshidab, T. Kollerc, G. Gerigc, and R. Kikinisa, "Three-dimensional multi-scale line filter for segmentation and visualization of curvilinear structures in medical images," *Med. Image Anal.*, vol. 2, no. 2, pp. 143–168, 1998.

[2] C. Lacoste, G. Finet, and I. E. Magnin, "Coronary tree extraction from X-ray angiograms uses marked point processes," in *Proc. IEEE Int. Symp. Biomed. Imag.*, 2006, pp. 157–160

[3] Fethallah Ben mansour · Laurent D. Cohen "Tubular Structure Segmentation Based on Minimal Path Method and Anisotropic Enhance Enhancement" Int J Comput Vis March 2010

[4] H. Li and A. Yezzi, "Vessels as 4-D curves: Global minimal 4-D paths to extract 3-D tabular surfaces and centerlines," *IEEE Trans. Med. Imag.*, vol. 26, no. 9, pp. 1213–1223, Sep. 2007

[5] L. M. Lorigo, O. D. Faugeras, W. E. Grimson, R. Keriven, R. Kikinis, A. Nabavi, and C. F.Westin, "Curves: Curve evolution for vessel segmentation," *Med. Image Anal.*, vol. 5, no. 3, pp. 195–206, 2001

[6] R. Manniesing, B. K. Velthuis, M. S. van Leeuwen, I. C. van der Schaaf, P. J. van Laar, andW. J. Niessen, "Level set based cerebral vasculature segmentation and diameter quantification in CT angiography," *Med. Image. Anal.*, vol. 10, no. 2, pp. 200–214, 2006

[7] A. C. S. Chung and J. A. Noble,"Statistical 3D vessel segmentation using a Rician distribution," in *Proc. Int. Conf.Med. Image Comput. Comput.—Assist. Intervent.*, 1999

ISSN: 2278 – 1323