Precise Segmentation of Vessels from MRA Brain Images Based on Neural Algorithm

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Abstract—*Accurate 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 voxel intensities. To identify the models, 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. Then Support Vector Machine Algorithm is used for classifying 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. There has been a considerable amount of work done on the enhancement and extraction of curvilinear structures from three-dimensional (3-D) medical images, most of which has 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 noise reducing smoothing filter. 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:

- Its formulation is simple: each pixel is replaced by a weighted average of its neighbors. This aspect is important because it makes it easy to acquire intuition about its behavior, to adapt it to application-specific requirements, and to implement it.
- It depends only on two parameters that indicate the size and contrast of the features to preserve.
- It can be used in a non-iterative manner. This makes the parameters easy to set since their effect is not cumulative over several iterations

$$\mathbf{I}^{\mathbf{filtered}}(\mathbf{x})=$$

$$\sum_{x_j \in \Omega} \boldsymbol{I}(\boldsymbol{x}_i) \boldsymbol{f}_r(|\boldsymbol{I}(\boldsymbol{x}_i)-\boldsymbol{I}(\boldsymbol{x})|) \boldsymbol{g}_x(|\boldsymbol{x}_i-\boldsymbol{x}|)$$

Where:

$\mathbf{I}^{\mathbf{filtered}}$ is the filtered image;

I is the original input image to be filtered;

x are the coordinates of the current pixel to be filtered;

Ω is the window centered in ;

$\mathbf{f}_\mathbf{r}$ is the range kernel for smoothing differences in intensities. This function can be a Gaussian function;

$\mathbf{g}_\mathbf{s}$ is the spatial kernel for smoothing differences in coordinates. This function can be a Gaussian function

III. SEGMENTATION WITH THE LCDG MODEL

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

The discrete Gaussian (DG) is defined as the probability distribution $\Psi\theta = (\psi(q|\theta){:}\ q \in Q)$ on Q of gray levels such that each probability $\psi(q|\theta)$ relates to the cumulative Gaussian probability function $\Phi\theta\,(q)$ as follows (here, θ is a shorthand notation $\theta = (\mu, \sigma^2)$ for the mean, μ, and variance, σ^2):

$$\Psi(q|\theta) =$$

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

The LCDG with Cp positive and Cn negative components such that $Cp \geq K$

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

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 **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:

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

The entire segmentation algorithm is as follows:

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

a) Collect the marginal empirical probability distribution $\mathbf{F}s = (fs\,(q)\colon q \in \mathbf{Q})$ of gray levels.

b) Find an initial LCDG-model that closely approximates $\mathbf{F}s$ 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) Refine the LCDG-model with the fixed Cp and Cn 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) Extract the blood vessels' voxels in this MRA slice 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

Feature extraction is a special form of dimensionality reduction. When the input data to an algorithm is too large to be processed and it is suspected to be notoriously redundant e.g. the same measurement in feet and meters then the input data will be transformed into a reduced representation set of features also named features vector. Transforming the input data into the set of features is called *feature extraction***.** If the features extracted are carefully chosen it is expected that the features set will extract the relevant information from the input data in order to perform the desired task using this reduced representation instead of the full size input.

A. 3D Local geometry features

Three-dimensional geometric data play fundamental roles in many computer vision applications. Geometric features are features of objects constructed by a set of geometric elements like points, lines, curves or surfaces. These features can be corner features, edge features, Blobs, Ridges, salient points image texture and so on, 3D Local geometry features are used for the detection of vascular patterns.

Gaussian derivative

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

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

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 the literature, it can be found several fields in which SVM are applied: cancer, tumor, or nodule detection, vascular analysis, dementia detection, etc. Regarding image modalities, 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, also support vector networks are supervised learning models with associated learning algorithms that analyze data and recognize patterns, used for classification and regression analysis. The basic SVM takes a set of input data and predicts, for each given input, which of two possible classes forms the output, making it a non-probabilistic binary linear classifier. Given a set of training examples, each marked as belonging to one of two categories, an SVM training algorithm builds a model that assigns new examples into one category or the other. An SVM model is a representation of the examples as points in space, mapped so that the examples of the separate categories are divided by a clear gap that is as wide as possible. New examples are then mapped into that same space and predicted to belong to a category based on which side of the gap they fall on. 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 is essential to achieve more precise and repeatable radiological diagnostic systems. Accuracy can be 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.

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