IOSR Journal of Electronics and Communication Engineering (IOSR-JECE)
e-ISSN: 2278-2834,p- ISSN: 2278-8735.Volume 9, Issue 2, Ver. V (Mar - Apr. 2014), PP 01-04
www.iosrjournals.org

Blockage detection in Angiography images

Mr. Pavan D. Patil*[1], Prof. Girish A. Kulkarni*[2]
**1Department of Electronics and Communication Engineering, Shri sant Gadge baba college of engineering & Technology, Bhusawal, India,*
**2Department of Electronics and Communication Engineering, Shri sant Gadge baba college of engineering & Technology, Bhusawal, India,*

Abstract: *Accurate visualization and quantification of the images is an important prerequisite for a number of applications. In clinical procedure grading of stenoses is important in the diagnosis of the severity of vascular disease since it determines the treatment therapy. Interventional procedures such as the placement of prosthesis in order to prevent aneurysm rupture or a bypass operation require an accurate insight into the three dimensional vessel architectures. Both two-dimensional projection techniques, such as DSA, and three-dimensional modalities as X-ray rotational angiography, CTA and MRA are employed in clinical practice. Although CTA and MRA provide volumetric data, the common way of interpreting these images is by using a maximum intensity projection.*

The main drawbacks of maximum intensity projections are the overlap of non vascular structures and the fact that small vessels with low contrast are hardly visible. When the angiography images are of such high intensity projection then it is very difficult for the doctors to observe blockage in vessels. Due to such high intensity images the blockage in small vessels can't be identified by doctors. So this variation in the intensity of an angiography images is analyzed by using Hessian matrix. The Eigen values of hessian matrix are used for analysis of images which are having high intensity variation.

Keyword: *Hessian Matrix, Eigen values*

I. Introduction

Images play an increasingly important role in many fields of science and its countless applications. Most of fields are depend heavily upon images for their further progress. As a consequence of the ever increasing resolving power and efficiency of image acquisition hardware and the rapidly decreasing cost of mass storage and communication media, images data sets grow exponentially in size and carry more and more information. Extracting this information by visual inspection and manual measurement is labor intensive, and the results are potentially inaccurate and poorly reproducible. Hence there is a growing need for computerized image processing and analysis, not only to cope with the rising rate at which images are acquired, but also to reach a higher level of sensitivity, accuracy, and objectivity than can be attained by human observers.

Accurate visualization of images is very important in the field of medical science. Depending upon the accurate visualization of images, doctors decide the treatment of therapy. The angiography images are of high intensity hence it is very difficult of the doctors to detect the blockages in the vessels.

The largest Eigen value of the Hessian matrix provides the most curvature and consequently a greater likelihood with the vasculature[1]. The largest Eigen values of a two-dimensional image are represented by λ_1 and λ_2 where $|\lambda_1| \geq |\lambda_2|$, and its Eigenvectors are represented by v1 and v2, respectively.

"Affine adaption of local image feature using hessian matrix" concerned with a class of feature detector that computes a saliency map of the image and locates the extreme of the saliency map. The saliency map shows the regions of the image that have high information content or high curvature and is a function of image partial derivatives [2]. The saliency map based feature detectors are inherently sensitive to changes in scale and projective deformations and do not produce features that are covariant under these changes directly..

In general, the method based on the Hessian Eigen values analysis is capable of detecting not only tubular structures, but also blob-like and sheet-like structures within the image [3]. This only requires finding proper formulas for "blobness" and "sheetness" as functions of λ_i.

In particular that a negative second Eigen value is directly linked to edge sharpening behavior. Based on this observation, it classifies the diffusivity functions into two categories, one incapable of edge-sharpening and the other capable of selective edge-sharpening [4]. It then proposes a third class whose second Eigen value of Hessian matrix starts from a small value and monotonously decreases with gradient magnitude so that the stronger the edge is, the more it is sharpened.

The purpose of this paper is by using hessian matrix determinant; its Eigen value the angiography images are of high intensity can be analyzed for detecting the blockage in vessels.

II. Technical concept

2.1 Second order partial Derivative

The the partial derivatives of a differentiable function $\phi(X) = \phi(x_1, x_2, ..., x_n)$ are again functions of n variables in their own right, denoted by

$$\frac{\partial \phi}{\partial x_k}(x_1, x_2, \ldots, x_n), \quad k = 1, 2, \ldots, n.$$

If these functions, in turn, remain differentiable, each one engenders a further set of n functions, the second order partial derivatives of ϕ $(x_1, x_2, ..., x_n)$

$$\frac{\partial \phi}{\partial x_k}(x_1, x_2, ..., x_n) \longrightarrow \frac{\partial^2 \phi}{\partial x_j \partial x_k}(x_1, x_2, ..., x_n), \quad j = 1, 2, ..., n.$$

The function ϕ $(x_1, x_2, ..., x_n)$ is said to be twice continuously differentiable in a region D if each of these second order partial derivative functions is, in fact, a continuous function in D. The partial derivatives $\delta\phi/\delta x_j \delta x_k$ for which $j \neq k$ are called mixed partial derivative.

2.2 Hessian Matrix

Suppose ϕ (x, y) is twice continuously differentiable and $X_0 = (x_0, y_0)$ is a stationary point for the function. In the minima and maxima and the gradient method we began to explore the use of the second order partial derivatives at the stationary point X_0 as a tool for determining whether X_0 is a maximum, a minimum, or neither. It is easy to see, in this two dimensional context, that evaluation of $\delta^2\phi/\delta x^2$ and $\delta^2\phi/\delta y^2$ will not always be significant this way.

Example The function $\phi(x, y) = x^2 + 4xy + y^2$ is easily seen to have a critical point at the origin, x = y = 0, and the second order partial derivatives $\delta^2\phi/\delta x^2$ and $\delta^2\phi/\delta y^2$ there are both equal to 2. But (0, 0) is not a minimum because on the diagonal line x = t, y = −t we have ϕ $(t,-t) = 2t^2 - 4t^2 = -2t^2$, so that ϕ decreases as the point (x, y) moves away from the origin along this line. We need a more systematic analysis to assist us in classifying stationary points.

Such an analysis can be developed in a general context in R^n if we assume the function ϕ (X) is twice continuously differentiable; the first and second order partial derivatives are all defined and continuous throughout the region D of interest. When this is the case we can define the Hessian matrix**.** The Hessian matrix or Hessian is a square matrix of second-order partial derivatives of a function. It describes the local curvature of a function of many variables. Hessian matrix is given by

$$H_\phi(X) = \begin{pmatrix} \frac{\partial^2 \phi}{\partial x_1^2}(X) & \frac{\partial^2 \phi}{\partial x_2 \partial x_1}(X) & \cdots & \frac{\partial^2 \phi}{\partial x_n \partial x_1}(X) \\ \frac{\partial^2 \phi}{\partial x_1 \partial x_2}(X) & \frac{\partial^2 \phi}{\partial x_2^2}(X) & \cdots & \frac{\partial^2 \phi}{\partial x_n \partial x_2}(X) \\ \vdots & \vdots & & \vdots \\ \frac{\partial^2 \phi}{\partial x_1 \partial x_n}(X) & \frac{\partial^2 \phi}{\partial x_2 \partial x_n}(X) & \cdots & \frac{\partial^2 \phi}{\partial x_n^2}(X) \end{pmatrix}.$$

This matrix is always symmetric, i.e., $H_\phi(X)^* = H_\phi(X)$,
Critical point

If the vector of the partial derivatives of a function ϕ is zero at some point x, then ϕ has a critical point (or stationary point) at x. The determinant of the Hessian at x is then called the discriminant. If this determinant is zero then x is called a degenerate critical point of ϕ .Otherwise it is non-degenerate.

The Eigen values of the Hessian are the principal curvatures and their product is the Gaussian curvature, which is the determinant of the Hessian. Thus, for the Hessian matrix, the Eigen vectors form an orthogonal basis showing the direction of curve, which is the gradient of the image.

1. If both the Eigen values are positive, then it is a local minima,
2. If both the Eigen values are negative, then it is a local maxima,
3. If the Eigen values have mixed sign, then it is a saddle point.

So, if the product of the Eigen values are positive, then they are either both positive and both negative, which means that they are at the local extremes.

III. Proposed System Model

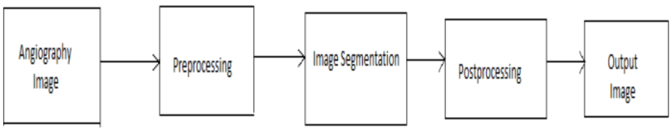

Fig 3.1Block diagram for blockage detection in angiography images

3.1 Angiography image

Angiography is a medical imaging technique used to visualize the inside, or lumen, of blood vessels and organs of the body, with particular interest in the arteries, veins and the heart chambers. This is traditionally done by injecting a radio-opaque contrast agent into the blood vessel and imaging using X-ray based techniques such as fluoroscopy.

3.2 Preprocessing

Preprocessing of microcirculatory images is essential considering the low local contrast of microcirculation images. Preprocessing usually comprise a series of operations to improve the quality of images in order to maximize the difference between image background and objects of interests. In microcirculation images, the intensity of capillaries and small blood vessels are exceptionally close to that of background and tissues. In order to process the images, the first main step is preprocessing.

5.2.1 Denoiseing

The first step is to reduce the effects of background noise, wavelet transformation is incorporated in this step. Wavelets have an important application in signal denoiseing Wavelet transformation decomposes the image into its different frequency contents. After wavelet decomposition, the high frequency sub bands contain most of the noise information and little signal information. The image is transformed to wavelet domain and decomposed with mother wavelet of different wavelet transforms the threshold is set to higher values for high frequency sub bands and lower values for low frequency sub bands. Following that, high frequencies present within the image are filtered. Then the image is reconstructed in the original domain. The noise in the resulting image is much lesser than the input image

3.2.2 Histogram equalization

The histogram of an image is a plot of the number of occurrences of gray level in the image against the gray level values. The histogram provides a convenient summary of the intensities in an image, but it is unable to convey any information regarding spatial relationship between pixels. It provides more insight about image contrast and brightness

Equalization is a process that attempts to spread out the gray level in an image so that they are evenly distrusted across their range. It reassigns the brightness value of pixel based on the image histogram. It is a technique where the histogram of the resultant image is as flat as possible. Histogram equalization provides more visually pleasing results across a wider range of images

3.3 Image segmentation:

Image segmentation is performed to partition image into its comprising components. The objective of image segmentation is to separate background from blood vessels and capillaries using grayscale values. Such separations make the analysis of the image an easier task. The outcome of segmentation is a binary image whose background is shown with white pixels and objects of interest with black pixels

In the last decade many methods were developed to facilitate the segmentation task, over even take over the task completely. In our project we are using Eigen values of hessian matrix for segmentation purpose

3.4 Post processing

In the post processing we are using the thresholding technique to detect blockage from the segmented angiography image. In image processing, the gray levels of pixels belonging to the object are substantially different from the gray levels of the pixels belonging to the background. Thresholding is a simple but effective tool to separate objects from the background. The thresholding methods can be categorized in six groups according to the information they are exploiting. These categories are:

1. Histogram shape-based methods, where, for example, the peaks, valleys and curvatures of the smoothed histogram are analyzed.
2. clustering-based methods, where the gray-level samples are clustered in two parts as background and foreground object or alternately are modeled as a mixture of two Gaussians.
3. Entropy-based methods result in algorithms that use the entropy of the foreground and background regions, the cross-entropy between the original and binaries image, etc.
4. Object attribute-based methods search a measure of similarity between the gray-level and the binarized images, such as fuzzy shape similarity, edge coincidence, etc.
5. The spatial methods use higher-order probability distribution and/or correlation between pixels.
6. Local methods adapt the threshold value on each pixel to the local image characteristics.

IV. Conclusion

Images are taken for the different analysis purpose. The accurate visualization of images is very important. But the analysis of images becomes difficult due to variation of intensity projection which causes overlapping of different structure in images. So analysis of such images can be done using Hessian matrix.

The Eigen values of Hessian matrix are calculated. Depending upon these Eigen values points of local maxima, local minima and stationary points in images are decided during processing it which gives better visualization of high intensity images. Due to this better visualization of angiography images it's very easy to find out blockage in the vessels.

References

[1]. A. F. Frangi, W. J. Niessen, K. L. Vincken, and M. A. Viergever, "Multiscale vessel enhancement filtering," International Conference on Medical Image Computing and Computer Assisted Intervention, 1998 Vol No.25, PP130-137.

[2]. Ruan Lakemond, Clinton Fookes, Sridha Sridharan, "Affine Adaptation of Local Image Features Using the Hessian Matrix" Advanced Video and Signal Based Surveillance,2009, Vol No.56, PP 104-115

[3]. Yang Yu,Hong Zhao, "Enhancement Filter for Computer-Aided Detection of Pulmonary Nodules on Thoracic CT images", Proceedings of the Sixth International Conference on Intelligent Systems Design and Applications (ISDA'06) IEEE,2006, Vol No.89, PP108-16

[4]. Wenhua Ma,"Monotonicall descreasing Eigen value for edge sharpening diffusion", IEEE, 2011, Vol No.56, PP 205-212

[5]. Albert C. S. Chung,"Image Segmentation Methods for Detecting Blood Vessels in Angiography", ICARCV IEEE, 2006, Vol No 65. PP 315-326

[6]. Hang-Ki Ryu, Jae-Kook Lee, Eoun-Taeg Hwang, Liu Jing, Hong-Hee Lee and Won-Ho Choi," A New Corner Detection Method of Gray Level Image Using Hessian Matrix" IEEE 2007, Vol No 18. PP 410-421

[7]. Liqian Guo2 and Junbi Liao, "A Semi-Automated Methodology for Rock Mass Discontinuity Trace Map Construction" Image Analysis and Signal Processing (IASP) IEEE, 2012, Vol No.16 , PP 220-231

[8]. Rafael C. Gonzalez Richard E. Woods, "Digital image processing",2nd edition, prentice hall,2002 PP 15-42