Automatic segmentation of cortical vessels in pre- and post- tumor resection laser range scan images

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ABSTRACT

Measurement of intra-operative cortical brain movement is necessary to drive mechanical models developed to predict sub-cortical shift. At our institution, this is done with a tracked laser range scanner. This device acquires both 3D range data and 2D photographic images. 3D cortical brain movement can be estimated if 2D photographic images acquired over time can be registered. Previously, we have developed a method, which permits this registration using vessels visible in the images. But, vessel segmentation required the localization of starting and ending points for each vessel segment. Here, we propose a method, which automates the segmentation process further. This method involves several steps: (1) correction of lighting artifacts, (2) vessel enhancement, and (3) vessels' centerline extraction. Result obtained on 5 images obtained in the operating room suggests that our method is robust and is able to segment vessels reliably.

Keywords: Image guided neurosurgery, vessel segmentation, denoising, brain shift, skeletonization.

1. INTRODUCTION

Estimating cortical surface shift accurately during surgery is of great importance in image guided neurosurgery. Although interventional MR method can be used, they are expensive and therefore not widely available. Tracked ultrasound-based methods are an alternative but they suffer from relatively poor spatial resolution. Vessel and sulci based registration methods have been proposed to estimate brain shift after opening of the dura from video images as early as 1997 by Nakajima et al. [7]. In their work, vessels segmented in pre-operative MR images (using a threshold) were registered to surface vessels from the intra-operative video images. However, the vessels were manually segmented from the video images. This approach was extended by Sun et al. [8] who used a pair of cameras. They demonstrate their ability to track the shape of the cortical surface after the opening of the dura on two neurosurgical cases. A similar approach is followed by Skrinjar et al. [9] More recently, Delorenzo et al. [10][11] have used a pair of stereo images and they register pre-operative images with intra-operative video images using a combination of sulcal and intensity features. They propose a method by which registration and camera calibration are performed simultaneously and they show that this approach permits to correct calibration errors. In their work, sulcal grooves were segmented by hand and the system was applied to patients undergoing stage 1 epilepsy surgery. This is a procedure, which requires the opening of the dura for the placement of an array of intracranial electrode on the surface of the brain but it does not require resection.

As discussed above, a number of methods have been proposed to measure brain shift during surgery but, to the best of our knowledge, these have not been evaluated on data sets acquired after tumor resection. Previous clinical evaluation has been largely limited to measuring cortical or tumor shift following craniotomy or opening of the dura. Although difficult, this is considerably less challenging than attempting to measure shift during the case after resection because the resection alters the appearance of the images substantially. Indeed, the resection creates a hole in the images and induces brain sagging. As a result, parts of the cortex visible through the craniotomy before the resection become invisible after the resection, and vice versa. Furthermore, bleeding that occurs during the procedure alters the image contrast. To address these issues we have recently proposed a method based on manually extracted vessels [3].

At our institution, we use a tracked laser range scanner, which acquires simultaneously 2D images and 3D point clouds.

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Through calibration, these data sets are registered. The 3D coordinates of any points in the 2D image are thus available. Intra-operative brain displacement measurement can thus be achieved by registering 2D images acquired over time during the procedure. We are particularly interested in measuring brain displacement after tumor resection.

In [3], we have shown that using cortical vessels visible in the pre- and post- tumor resection images was a possible solution to register the images based on manually extracted vessels. We expanded this work by proposing a semiautomatic vessel extraction method in [6]. This method requires labeling of homologous starting and ending points for each vessel segment for both pre- and post- resection images. A minimal-cost path algorithm is then used to connect these points automatically. In this paper, we present our efforts to further automate the task and we focus on the automatic segmentation of the vessels. Challenges that need to be overcome include lighting conditions that create reflections and the appearance of blood, which reduces the contrast between the vessels and brain tissue. The method we propose consist in three steps: (1) correction of lighting artifacts, (2) vessel enhancement, and (3) vessel segmentation. These are detailed in our method section. The result section presents segmentation results we have obtained on a number of pre- and post-operative images.

2. DATA ACQUISITION

In this study, a high resolution commercial LRS (RealScan3D USB, 3D Digital Inc., Bethel, CT, USA) system is used. This device is capable of generating 500,000 points with a resolution of 0.15mm-0.2mm at the approximate range used during neurosurgery. The resolution varies slightly according to the distance between the camera and the patient. The 3D position of each point on the scan is calculated via triangulation. At the same time, a digital camera (Canon Optix 400) acquires a texture image with a resolution up to 2592 by 1944 pixels. The texture image and the 3D point cloud are registered. A complete data set thus includes a set of image pixels with coordinates (u, v) and a series of points with coordinates (x, y, z). The (u, v) coordinates of any (x, y, z) point can be computed and vice-versa. In this study, the obtained texture images will be used to segment cortical surface vessels.

The following protocol, which was approved by the Vanderbilt Institutional Review Board, was used to acquire data from consented patients. After opening of the dura, the LRS system, which is mounted on the adjustable arm or a monopod, is placed within 20-30cm of the patient. A pre-resection scan is taken, which takes on the order of 1 minute. This includes moving into the field, and collecting the data. The system is removed from the field and the procedure proceeds normally. After tumor extraction, a post-resection scan is acquired by moving the scanner back into place above the craniotomy. Because the scanner is tracked, the pre- and post-resection positions do not need to be exactly the same. More details about the data acquisition procedure can be found in [12]. Figure 1 shows a patient in the OR with the tracked laser range scanner positioned on the top of the craniotomy.



Figure. 1 shows a laser range scanner acquiring data in the operating room. The height and angle of the scanner are both adjustable. A built in digital camera inside the scanner acquires high resolution digital images immediately after the range data has been acquired.

3. METHODOLOGY

As discussed in the previous section, images acquired intra-operatively are affected by two major sources of artifacts: lighting and bleeding. Lighting artifacts area caused by the reflection of the intra-operative lights on the surface of the brain. Bleeding, which occurs during the procedure, affects the contrast in the images and makes vessels more difficult to segment. In this work, we propose a three-step approach to segmenting surface vessels. These steps are (1) correction of the lighting artifacts, (2) enhancement of the images, and (3) segmentation.

3.1 Correction of lighting artifacts

Elimination of lighting artifacts involves first localizing regions in the image, which are affected. This is done via clustering of the points in the RGB space. The images are classified into several classes using an unsupervised K-means clustering algorithm, which aims at minimizing

$$V = \sum_{i=1}^{k} \sum_{x_j \in S_i} (x_j - \mu_i)^2.$$
(1)

The 3D feature vector x_j is constructed using values in the R, G and B channels. S_i is the label of class *i*, and *k* is the number of classes. μ_i is the centroid of each class. Since there are only background, tissue, vessels, and artifacts in our image, four points are randomly chosen as centroids for each class and iteratively updated until converge. Every point in the image is assigned to the class, which has a center closest to its own. This unsupervised clustering method is not good enough for segmenting the vessels or the tissue but the class with the brightest centroid captures the artifact pixels. This is shown in figure 2. Panel (a) shows one original intra-operative image; the very bright regions are regions affected by the lighting artifact. Panel (b) shows the clustering results. The brightest pixels correspond to regions that have been identified as being affected by reflection and that need to be corrected. The other three classes are not used in subsequent steps.

The artifact regions are then expanded by dilating them by three pixels to incorporate edge pixels, which may not have been classified as artifact. Panel (c) in figure 2 is the artifact regions after dilation. Finally, the R, G, B values of the pixels in these regions are replaced by new R, G, B values obtained by extrapolating the R, G, and B values using surrounding pixels. Panel (d) shows the results after correction. Most of the lighting artifacts are automatically identified and removed in this image. The quality of the image is greatly improved for later processing.



Figure. 2. shows the results after clustering and the results after correction of artifacts. Panel (a) shows one intra-operative image, which is degraded by lighting artifacts. Some of the pixels affected by these artifacts are inside the vessels, and some of them are outside the vessels; Panel (b) is the labeled map obtained with k-means clustering, and the very bright regions are dilated by 3 pixels and showed in (c); (d) is the image after artifacts correction.

3.2 Vessel enhancement

Vessels in the image are enhanced using a line searching algorithm akin to the line detection filter proposed in [2]. Here, we do not use the filter to segment the vessels but to reduce intensity variations within the vessels and to eliminate very small vessels for which finding a homologous vessel in another image may be difficult.

To filter the image, a circular window of radius w is first placed on a foreground pixel. Straight lines oriented in increment of α degrees are then defined (see figure 3. (a)). The average intensity along these lines is computed and the line with the smallest average values is identified. For each pixel in the foreground of the image, the direction of the vessels is the direction of the line with the lowest mean value (vessels are dark in our images), and the intensity value of the pixel on which the window is centered is substituted by this minimal mean intensity value.

Values of w = 7 and $\alpha = 15^{\circ}$ were chosen experimentally.



Figure. 3. (a) Illustrates the neighborhood and searching directions used for vessel enhancement. The center of the circle is the pixel of interest. Panel (b) shows an intra-operative image before vessel enhancement. Panel (c) shows the result after vessel enhancement.

3.3 Vessel segmentation

3.3.1 Multiscale vesselness

Vessels in the enhanced images are segmented in two steps (More details can be found in [6]). First, the images are filtered with the vesselness filter propose by Frangi et al [1]. In their work, they propose a multi-scale filter based on the Hessian of the image, which can be used to enhance tubular structures. The approach they propose is to (1) convolve the image with Gaussian filters with various standard deviations, (2) compute the Hessian of the smoothed images, defined as

$$\nabla^2 I(x) = \begin{bmatrix} I_{xx}(x) & I_{xy}(x) \\ I_{yx}(x) & I_{yy}(x) \end{bmatrix},$$
(2)

in which I_{ij} is the second spatial derivative of the image in the *i* and then *j* directions, and (3) compute the eigenvalues of the Hessian. An analysis of the values of these eigenvalues permits to determine the type of structure a particular pixel belongs to. Pixels, which pertain to tubular-like structures that are bright on a dark background, will satisfy the following conditions:

$$\begin{cases} 0 \approx |\lambda_1| << |\lambda_2| \\ \lambda_2 < 0 \end{cases}$$
(3)

Based on this observation, the vesselness filter. Frangi et al. proposed, is as follows:

$$V(i,j) = \begin{cases} 0 & \text{when } \lambda_2(i,j) > 0 \\ \exp(-\frac{\lambda_1(i,j)^2}{2\lambda_2(i,j)^2\beta^2})(1 - \exp(-\frac{\lambda_1(i,j)^2 + (\lambda_2(i,j))^2}{2c^2})) \end{cases}$$
(4)

The first term in this equation is large when λ_1 is small and λ_2 is large. The second term, which is called the "second order structureness", is large for non-background pixels. To detect vessels of various dimensions, the filter is applied to images that have been convolved with Gaussian filters whose standard deviation is changed from small to large. The vesselness filter responds to small vessels in an image blurred with a Gaussian filter with a small standard deviation. It

responds to large vessels in an image blurred with a Gaussian filter with a large standard deviation. The coefficient β and c are chosen experimentally. Here, β was chosen *as* 0.5, and c was chosen as 0.05 times the maximum intensity value in the image. In this application, we use six scales with variances ranging from one to six pixels. The response of the filter at the scale with the maximum response is used as the filter's output

$$V(x, y) = \sum_{k=1}^{\infty} w_k V_k(x, y),$$
(5)

in which the value of the weight w_k is -1 for the standard deviation that produces the largest response and zero for all the others. This produces a gray scale image V(x,y) in which tubular structures are enhanced. The darker the pixel is, the more likely it belongs to a vessel structure.



Figure. 4. (a) shows one intra-operative image after vessel enhancement; (b) shows the vesselness map.

3.3.2 Centerline extraction

Next, we detect edges in the vesselness image using a Canny edge detector to create a binary edge map E(x,y) as shown in fgure 5. (a). A distance map is then created from this image using a fast marching method [5]. In the distance map shown in figure 5. (b), pixels on the vessels' edges are local minima and pixels on the vessels' centerlines are local maxima; the gradient of the distance map is thus small for these pixels, as shown in figure 5. (c). In this image, black corresponds to small values of the gradient magnitude.



Figure 5. Panel (a) shows the edge map of the image shown in figure 4 (b); Panel (b) shows the distance map of (a); (c) is the magnitude of the gradient of (b);

Centerline pixels are localized by first taking the gradient of the distance map and keeping the voxels in the gradient image below a threshold (here we have an experimentally determined value of 0.7) to create a binary image S(x,y). The edge image E(x,y) is then subtracted from this image and shown in figure 6. (a). This result in an image which contains all the pixels that are localized midway between two edges. Some of these pixels are inside the vessels, others outside. To eliminate outside pixels, those pixels with a vesselness value lower than 0.1 are eliminated. This creates the result shown in figure 6. (b). Finally, we apply an eight connected component labeling algorithm. Regions, which are smaller than 5 pixels are eliminated.



Figure. 6. Panel (a) shows S(x,y), which is obtained from thresholding figure 5. (c), after the the edge map E(x,y) has been subtracted. Panel (b) is after elimination of the pixels with very low vesselness value, some of which are pointed by green arrows in (a). (c) is the final results after eliminating small connected regions, some of which are pointed by green arrows in (b).

4. RESULTS

The proposed automatic vessel segmentation method has been tested on clinical digital images obtained intra-operatively. Figure 7 shows representative results. Panel (a) shows the original vesselness image obtained from the image shown in figure 2 without any pre-processing. Panels (b) shows the same when the lighting artifact is removed. Panel (c) shows the results when the lighting artifact is removed and the vessels are enhanced. As seen in this figure, removal of the lighting artifact helps in preserving the integrity of the vessels. Without correction, some of the large vessels are split in two because they reflect the light. The vesselness map obtained after vessel enhancement is clearly less noisy than the map obtained without enhancement. Panels (d) and (e) show the vesselness map for another intra-operative image without and with lighting artifact removal, respectively.



Figure. 7. Panels (a) and (d) show results when the vesselness filter is applied to the original images; Panels (b) and (e) show the vesselness images obtained by applying the vesselness filter on the image after lighting artifact correction. Panel (c) shows the vesselness image after both lighting artifact removal and vessel enhancement

Figure 8 illustrates the results obtained without (panel a) and with (panel b) lighting artifact removal and vessel enhancement overlaid on the original image. As can be seen, the artifact and vessel enhancement method we propose improve the segmentation of the large vessels and reduces the number of spurious vessels. As can also be seen, this comes at the expense of the number of small vessels that can be segmented. This is, however, not a significant issue for our application because it is difficult to establish a correspondence between small vessels in the pre- and post-resection images. Registration between these images will thus be based on the largest vessels.



Figure. 8. The left panel shows vessels extracted without lighting artifact removal and vessel enhancement. The right panel shows vessels extracted using the method proposed in this paper.

Figure 9 shows the final results on four images obtained intra-operatively. The left panels show pre-resection images, and the right panels show post-resection images. Note the holes left by the resection of the tumor.



Figure. 9 shows the extracted vessels overlaid on the original images. The left two images were acquired before tumor resection; the right two images were obtained after tumor resection.

5. CONCLUSION

Updating pre-operative tomographic information is critical for image guided surgery. Systems designed to solve this problem typically rely on mechanical models driven by intra-operative measurements. Clinical acceptance of these systems will require solutions, which are fast, robust, and minimally intrusive. Acquiring images with our tracked laser range scanner is fast (on the order of one minute) and minimally intrusive because the scanner can be moved in and out of the operating field. The work presented herein indicates that automatic segmentation of cortical vessels is achievable. The next step will involve testing the hypothesis that automatically detected vessels can also be used for automatic registration of image acquired over time without labeling of homologous points, which would permit automatic intraoperative brain displacement measurement.

6. ACKNOWLEDEGMENTS

This project is funded by National Institute for Neurological Disorders and Stroke Grant # R01 NS049251-01. We acknowledge the Vanderbilt University Medical Center, Department of Neurosurgery, and the operating room staff for their support of the data collection.

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