ROBUST VESSEL REGISTRATION AND TRACKING OF MICROSCOPE VIDEO IMAGES IN TUMOR RESECTION NEUROSURGERY

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ABSTRACT

This paper proposes a new method designed to track operative microscope video images recorded during tumor resection neurosurgery. Two steps are involved in this method. The first uses feature vectors constructed from color information of video images and shape information of selected vessels to find homologous points in consecutive frames. The second uses smoothing thin-plate splines (TPS) to interpolate the transformation computed with the vessels over the entire image. This approach only requires several pairs of starting and ending points selected on segments of vessels in the first frame of a video sequence. Then, the proposed method tracks the identified vessels automatically, rapidly, and robustly, even when surgical instruments obscure parts of the image frames.

Index Terms— Brain shift, registration, tracking, vessel, image guided neurosurgery

1. INTRODUCTION

Most image-guided surgery systems in current clinical use only address the rigid body alignment of pre-operative images to the patient in the operating room despite the fact that substantial brain shift happens as soon as the dura is opened. The problem is even more acute for cases that involve tumor resection. A possible solution to this problem is to use models that can predict brain shift and deformation based on data acquired intra-operatively such as ultrasound or video images [1][2].

Video images, attached or integrated with the operating microscope, have been proposed to register pre- and intra-operative data as early as 1997 by Nakajima et al. [3]. This approach was extended by Sun et al. who used a pair of cameras [4]. They demonstrate their ability to track the shape of the cortical surface after the opening of the dura on two neurosurgical cases. Skrinjar et al. used a similar approach [5]. More recently, Delorenzo et al. 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 [6][7]. They propose a method by which registration and camera calibration is performed simultaneously. In this work, sulcal grooves were segmented by hand. But, the work described above was carried out on data acquired just after the opening of dura [4] or on procedures such as epileptic surgery for which brain shift is relatively small as compared to tumor resection surgeries [6][7].

Over the last several years, we have begun to develop methods that will permit real-time tacking of brain shift [2][8][9] during tumor resection cases. The approach we have proposed relies on a tracked laser range scanner. This scanner permits both acquiring the physical coordinates of surface points (e.g., cortical surface), and a correlated digital image of these surfaces. Through calibration, the 3D physical coordinates of pixels in the images are known. Tracking the 3D displacement of the surfaces can thus be achieved by registering the 2D images. Although acquiring data with the laser range scanner is minimally intrusive it cannot be done continuously. Indeed, it requires positioning the scanner above the resection and scanning it, which takes about one minute. The procedure we currently follow is to acquire one scan just after the opening of the dura and one or several scans during the procedure as the tumor is removed. We have developed a semi-automatic method that only requires selecting starting and ending points on vessel segments that are visible in the images that need to be registered. But, automating the method further is challenging because the resection of the tumor drastically alters the appearance of the cortical surfaces. Here, we propose to use videos recorded through the operating microscope to track surface deformation. The overall procedure we propose to use is as follows: (a) acquire 3D/2D data with the laser range scanner at time t_0 and t_1 (the time interval between t_0 and t_1 can be large), (b) acquire a video stream through the microscope from t_0 to t_1 and track frames within that stream, and (c) register the first and last frame of the video stream to the 2D images acquired with the scanner at time t_0 and t_1, respectively.

In this paper, we present the method we have developed to track vessels in the video stream as well as preliminary results we have obtained on two clinical cases.

2. DATA ACQUISITION

In this study, we use a Zeiss OPMI®Neuro/NC4 microscope integrated with a video camera to acquire the videos. Seven video sequences were recorded from two patients who underwent surgery at Vanderbilt with their informed consent and IRB approval for a total of 14 sequences. The approximate pixel dimension in the video images is .01 mm^2. At that resolution, cortical capillaries and small vessels can be seen in the images and used for tracking.

3. METHOD

A number of methods can be used to register sequential frames in video streams. In the past, we have used non-rigid intensity-based algorithm to estimate heart motion in video streams [10]. This approach is not adapted to our current problem because surgical instruments appear and disappear from the field of view. To address this problem, we have opted for a feature-based method. This requires finding homologous structures in sequential frames. These structures are then used to compute transformations, which are subsequently utilized to register the entire images. Because the most visible structures in our video images are the blood vessels, we have used them as features.

Our current approach requires the user to identify a certain number of vessel segments in the first frame of the video stream. This is done by selecting starting and ending points on these segments. A minimum cost path finding algorithm is then used to join the starting and ending points and segment the vessels (more details on this approach can be found in [2]).

3.1. Features used for tracking

Once the vessels are identified, their centerline is sampled to produce a number of *active points*. In the current version of our algorithm, we have simply taken one out of every four points along the vessel centerlines to generate these active points. This was found to be a good compromise between speed and accuracy. For each of the active points, a line perpendicular to the centerline passing through the point is computed as shown in Figure 1.

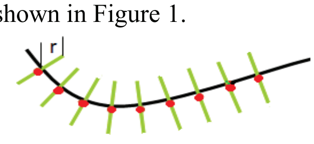

Figure 1. Active points along the curve.

Next, a feature matrix **F** is associated with each point. To create this matrix, the R, G, B, and vesselness values are extracted from the image along the perpendicular lines. The length **r** of the perpendicular lines on either side of the centerline is a free parameter. Each active point is thus associated with the following matrix:

$$F_{a_i} = \begin{bmatrix} R_{-r} & R_{-r+1} & \dots & R_r \\ G_{-r} & G_{-r+1} & \dots & G_r \\ B_{-r} & B_{-r+1} & \dots & B_r \\ 3V_{-r} & 3V_{-r+1} & \dots & 3V_r \end{bmatrix}$$

Vesselness, defined as in [11], is a multi-scale filter based on the Hessian of the image that can be used to enhance tubular structures. Pixels, which pertain to tubular-like structures that are bright on a dark background, have a larger vesselness value than other pixels. Here we have used scales ranging from 1 to 8 pixels to compute vesselness. Because the R, G, and B values are intensity features while vesselness is a shape feature, we multiply the vesselness value by 3 in the feature matrix to avoid weighing one type of feature over the other.

3.2. Finding homologous points in consecutive frames

To match one frame to the other, homologous points need to be localized. This is done as follows. First, one feature matrix is associated with every pixel in the new frame. Second, the active points and the centerlines found in the previous frame are projected onto the new frame. Then the similarity between (a) the feature matrix of every pixel in the new frame along lines perpendicular to the centerlines and passing through the active points and (b) the feature matrix of the corresponding active point in the previous frame is computed as:

$$\boldsymbol{s(i,j)} = \sum_{\boldsymbol{c}=1,\boldsymbol{d}=1}^{\boldsymbol{c}=4,\boldsymbol{d}=2\boldsymbol{r}+1} \left| \boldsymbol{F}_{\boldsymbol{a}_i}(\boldsymbol{c},\boldsymbol{d}) - \boldsymbol{F}_{\boldsymbol{p}_{i,j}}(\boldsymbol{c},\boldsymbol{d}) \right|, \qquad [1]$$

in which i refers to the i_{th} point on the centerline and j is the position on the line perpendicular to the centerline at that point with $-s_r < j < s_r$, i.e., the computation is done in band of width $2*s_r+1$. $\mathbf{F}_{\mathbf{a_i}}$ is the feature matrix in the previous frame of the i_{th} active point and $\mathbf{F}_{\mathbf{p_{i,j}}}$ is the feature matrix in the new frame of the j_{th} point along the perpendicular passing through the i_{th} active point.

The point b_i with the feature matrix most similar to the feature matrix of the active point a_i in the previous frame is selected as the homologous point for this active point.

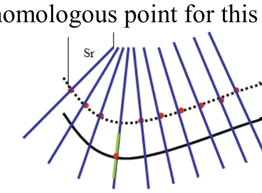

Figure 2. Search for homologous points in the next frame.

This process is illustrated in Figure 2. In this figure, the dotted line represents the projection of the centerline from the previous frame to the current frame. The lines perpendicular to the dotted lines are the search direction for each active point. The continuous line represents the position of the vessel in the new frame.

3.3. Smoothing TPS

Smoothing Thin Plate Spines (TPS) are regularized TPS, which minimize the following functional

$$E(f)=\min_f \sum_{i=1}^{l}\left\|b_i - f(a_i)\right\|^2 + \lambda\iint\left[\frac{\partial^2 f}{\partial x^2}+2\left(\frac{\partial^2 f}{\partial x\partial y}\right)+\frac{\partial^2 f}{\partial y^2}\right]dxdy,$$

Here, smoothing TPS are used to compute the transformation that registers the active points $\{a_1, a_2, \ldots, a_l\}$ in one frame to the corresponding points $\{b_1, b_2, \ldots, b_l\}$ in the next frame. For a fixed λ there exists a unique minimizer f. To solve this variational problem, we have used the QR decomposition proposed by Wahba [12].

The parameter λ is used to control the rigidity of the deformation. When $\lambda \to \infty$, the transformation is constrained the most and is almost affine. Our experiments show that λ = 1 is a good value to capture the deformation between consecutive frames. When frames are missing, the value of λ needs to be reduced to capture larger deformations that occur over longer time intervals. Because we aim at developing an automatic method capable of tracking videos over long time periods, even when frames are missing, we have implemented a scheme to automatically adjust the rigidity of the transformation. To do this, we compute the mean displacement D_c between homologous points in consecutive frames for each curve. If max $(D_c) > D_0$, we assume that a large shift occurred, most probably because frames are missing. To permit larger adjustments in this situation, the tracking range is increased from s_r to $2s_r$ and the value of λ is reduced to 0.5. The transformation computed with the homologous points is then extrapolated over the entire frame. The algorithm we have developed is summarized in table 1.

Table 1. Automatic frame tracking in intra-operative videos.

Step 1. Select features in the first frame $k = 1$.
Step 2. Downsample the selected curves into active points a_i
For each active point, compute $\mathbf{F}_{\mathbf{a_i}}$.
Set parameter values $s_r = 75$, $\lambda = 1$.
Step 3. In frame $k + 1$, search homologous point b_i for each active point a_i.
Step 4. If the maximal average shift is larger than D_0=50, set $\lambda = 0.5$, and $s_r = 150$. Repeat steps 3 and then go to step 5.
Else go to step 5.
Step 5. Calculate transformation T_k that registers points a_i's to b_j's.
Step 6. Use T_k to deform the entire frame. $k = k+1$.
If k is not the last frame n, go to step 2.

4. EXPERIMENTS

Figure 3 shows several frames in one of the video sequences we have used to test our system. In this sequence, a relatively fast, medium amplitude motion could be observed between frames. This is illustrated in Figure 4, which plots the x and y coordinates of one visible landmark from frame to frame. Vessel segments identified on the first frame are shown in green and are tracked over 220 frames. The yellow points designate the intersection of small vessels not used in the registration process. As can be observed from the images, the yellow target points are tracked accurately and demonstrate the accuracy of our method over the entire frame.

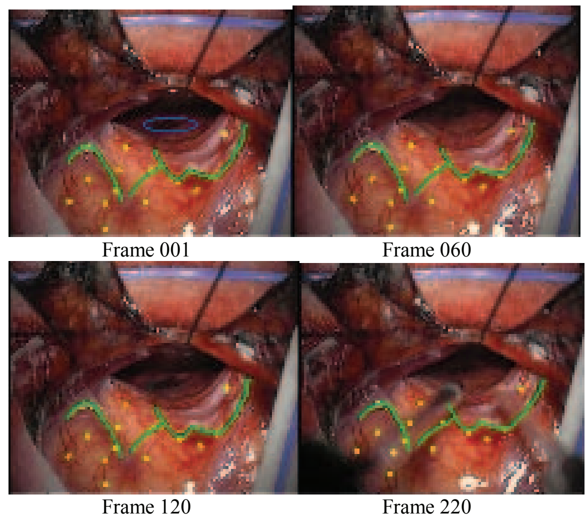

Figure 3. Tracking in sample frames from the video of patient1.

Figure 4. x and y position of one visible landmark from frame to frame shows the magnitude and frequency of movement observed in the video sequence.

Figure 5 shows a more challenging example. Here, a surgical instrument appears in the field of view. As can be seen in the sequence, the method we have developed is not affected by this instrument. Even though the vessels cannot be tracked accurately when the instrument is visible, the algorithm is capable of re-acquiring it as soon as the instrument disappears. Again, the yellow dots show that the registration is accurate over the entire frame.

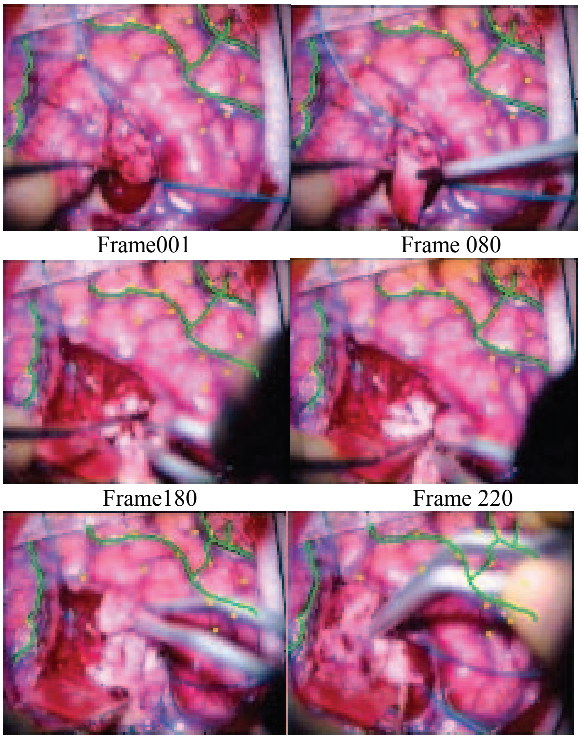

Figure 5. Tracking results in sample frames from the video of patient2.

5. DISCUSSION

In this paper, we propose a method to track brain motion in video streams. Coupled with a laser range scanner, this will permit estimating intra-operative brain shift. Preliminary results indicate that this method is capable of tracking vessels even when surgical instruments obscure parts of the images. It is relatively simple, which makes it fast and applicable in real time (a MATLAB implementation takes about 1sec./frame but the algorithm does not need to be applied to every frame). We have tested the method on 14 video sequences ranging from 300 to 1000 frames and our method was able to track the frames in 12 of these sequences. In one of the sequences for which the algorithm did not work, cotton pads obscured a large portion of the image for a long period of time. In the second sequence, visible vessels were very small and the algorithm lost some of them. We are currently acquiring a series of long video sequences and are in the process of validating our algorithm on these.

6. ACKNOWLEDGEMENT

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