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Simultaneous Segmentation of MR and X-ray Angiograms for Visualization of Cerebral Vascular Anatomy

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Introduction

The two most common modalities for viewing vascular structure in humans are X-ray angiography (DSA) and the recently developed technique of magnetic resonance angiography (MRA) [3]. Unfortunately, with present technology, neither modality is able to provide high resolution 3D vascular detail.

While conventional X-ray images provide high resolution information their use is limited since they contain only 2D information. Further, reconstructing a 3D image from a limited number of 2D X-ray images is a severely under constrained problem and is very sensitive to ambiguities in vessel identification, geometric errors and motion artifacts. Although MR angiography provides 3D information, the spacial resolution currently does match the resolution of X-ray angiography and as such it can not always be used alone in making a diagnosis. The problem is further complicated by discontinuous vascular image detail in both modalities due to missing information caused by obscuring anatomy and/or signal drop out.

Currently researchers are beginning to explore the means for creating high resolution 3D vascular images from multiple modalities[1]. This paper presents a new technique to simultaneously segment registered MR and X-ray angiograms there by creating a high resolution 3D vascular image.

Methods

In performing the segmentation on a single 3D MR image a region growing technique using an adaptive threshold based on local gray scale statistics was used. The threshold value was based upon those voxels previously labeled as vessel. The comparison value incorporated not only the voxel being inspected but also several of its local neighbors. A similar technique is described in [2]. The complete implementation is described below using the assumption that the vessels of interest are brighter than the surrounding background.

The segmentation was implemented by dividing the N x N x N neighborhood of an unlabeled voxel into two sets: S_1 contained those voxels already labeled as vessel; S_2 contained the N/2 brightest voxels which were connected to the seed voxel but not labeled as vessel (Figure 1). A threshold value of the mean minus M standard deviations was calculated from the gray scale voxel values in S_1. Where M was a user defined number of standard deviations ranging from 1.0 to 4.0. Only the mean gray scale value was calculated for S_2. A voxel was labeled as vessel if the mean value in S_2 was greater than the threshold value in S_1; otherwise it was labeled as background (EQ 1).

$$Accept = \begin{pmatrix} Vessel \rightarrow \bar{S}_2 \geq \bar{S}_1 - M \times \sigma_1 \\ Background \rightarrow Otherwise \end{pmatrix} \quad (EQ\ 1)$$

Each voxel was subjected to the thresholding beginning with a seed voxel selected by the user. The thresholding was repeated by placing the seed voxel's 26 nearest neighbors into a priority queue. The voxel with the highest gray scale value was retrieved from the queue and acted as the seed voxel for the next iteration. Similarly, if that voxel was labeled as vessel its 26 nearest neighbors not already in the queue or labeled as vessel were added to the queue.
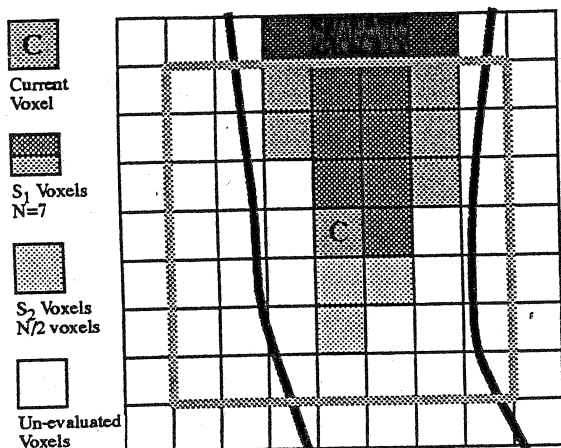
Figure 1 Search neighbor (N=7) for one voxel.

The thresholding was repeated until no new voxels were added into the queue.

A similar region growing technique was implemented for segmenting a 2D X-ray images. The only difference was that a 2D region consisting of the eight nearest neighbors was used.

To combine the two modalities all of the images had to be registered and placed into a world coordinate system. Further, the world coordinate system was required to have a resolution greater than all of the images. This requirement insured that no MR voxels or X-ray pixels were skipped during the region growing due to having different scaling factors within each image.

The registration and establishment of the world coordinate system was done by placing eight or more fiducial markers on the patient's head or on a vascular phantom. The markers were visible on all images and allowed for the registration of the MR and X-ray angiograms [4]. For these experiments one MR and four X-ray cerebral angiograms were used.

By establishing a world coordinate system which related each modality, simultaneous segmentation was possible. The segmentation was accomplished by conducting the region growing in the world coordinate system and projecting only the seed voxel into each of the 2D or 3D images. This allowed the region growing technique to capture the local gray scale characteristics in all of the images using the local image resolution. The same thresholding criteria was used in the simultaneous segmentation as with an individual image.

In order to prevent the segmentation from growing into ambiguous vessel segments that could arise from the backprojection of X-ray data it was necessary to have all X-ray pixels labeled as vessel before a voxel in world coordinates would be labeled as vessel. However, failing that criteria, it was still possible to have the voxel labeled as vessel depending on the outcome of the MR thresholding.

To insure that the region growing process would continue independently of which modality was used to label the voxel as vessel it was necessary to modify the gray scale values of those voxels or pixels labeled as background in one modality but labeled as vessel in the other. For instance, if a voxel in the MRA image was label as background by its thresholding criteria but labeled as vessel by the X-ray images then the MRA voxel would assume the same gray scale value as its parent voxel. Since the parent voxel had to have been previously labeled as vessel it was presumed that if the current voxel had the same value, that it, too, would have been labeled as vessel. This modification caused vessels to grow into areas that if segmented using a single modality would have been labeled as background and the region growing process would have stopped, (Figure 2 and Figure 3). The growing insured that when un-examined voxels were evaluated they would have a neighborhood containing at least one voxel labeled as vessel that could be used in the thresholding process.
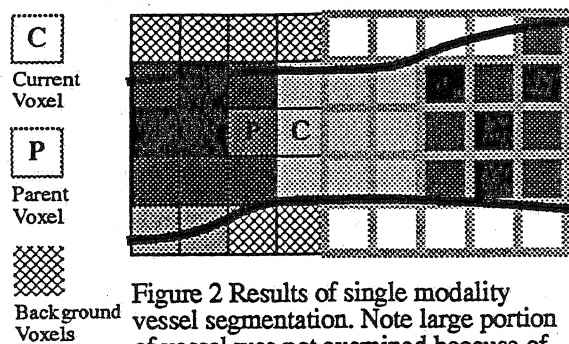
C

Current
Voxel

P

Parent
Voxel

Background
Voxels

Figure 2 Results of single modality vessel segmentation. Note large portion of vessel was not examined because of lack of connecting voxels.

Voxels
consider
background
in one
modality
but vessel in
the other
modality.

Examined
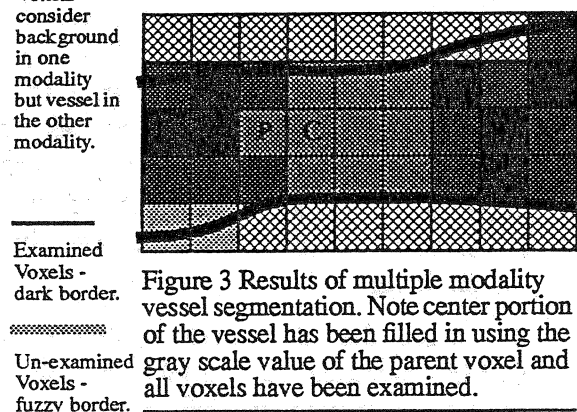Voxels -
dark border.

Un-examined
Voxels -
fuzzy border.

Figure 3 Results of multiple modality vessel segmentation. Note center portion of the vessel has been filled in using the gray scale value of the parent voxel and all voxels have been examined.

Discussion and Results

The use of multi-modality images in the segmentation process utilized the complimentary information contained in both modalities. MR images contain low resolution 3D information while the X-ray images contain high resolution 2D information. By choosing a resolution factor smaller than all of the images we were able to examine all of the necessary voxels/pixels in each image. Although this did result in examining some voxels/pixels multiple times it guaranteed that no voxel was skipped.

This technique has been successfully used on simulated and patient data. In these experiments the technique was able to effectively use the connectivity information found in one modality, typically X-ray images, to overcome the missing or ambiguous information in the other modality, typically

MR images. The low resolution 3D information contained in the MR images was used to remove some backprojection ambiguities from the high resolution 2D X-ray images while the same X-ray information was used to contribute vessel information not found in the MR images.

Due to the restriction that all of the pixels in each of the X-ray projections had to be above their local threshold it was still possible to have missing vessel segments in the final image (false-negatives). This occurred when a pixel/voxel was below the threshold in one of the X-ray images and in the MR image. This was typically caused by vessel obstruction or signal loss. Conversely, it was generally observed that the vessels segmented were larger than their actual size (false-positives). This artifact is analogous to the star artifact prevalent in backprojecting a limited number of views [5].

The only global parameters used in determining how to label a voxel were the number of standard deviations (M) from the local gray scale mean value and the size of the search neighborhood (N). By adjusting this value it was possible to fine tune the segmenting process. Typically 2 or 3 standard deviations and a neighborhood size of 5 or 7 were needed to obtain satisfactory result. Naturally, increasing the number of standard deviations increased the number of voxels/ pixels labeled as vessel. Whereas the neighborhood size (N), had several interesting effects. The larger the neighborhood the smaller the standard deviation. This was directly related to having a greater number of samples to chose from which typically had more uniform values. While at the same time, the mean value of the current voxel would typically decrease since the region growing was almost always moving from a bright region towards a dark region. The converse was true as well. The decrease in mean value was easily explained since the mean value was

based on the N brightest voxels. Typically selecting a larger neighbor caused the region growing process to be more conservative thus reducing the number of voxels/pixels labeled as vessel. Although decreasing the neighborhood size does increase the number voxels/pixels labeled as vessel, it can cause gaps between vessel segments not to be crossed. This was due to the inability of the region growing technique to grow from darker to brighter regions because of smaller mean gray scale values.

Conclusions

We have demonstrated that by combining image data from two modalities during the segmentation process we are able to produce high resolution 3D segmented vascular images which cannot be obtained with either modality alone. Further, we have found that the two modalities are able to complement each other during the region growing process thus allowing for a more complete segmentation than either modality could produce alone.

Although a limited number of vessels were missing and in some cases the vessels were larger than their actual size these disadvantages were outweighed by the overall gain in spatial resolution and in the addition of missing vessels. Further, it is possible to expand this technique to incorporate additional images from the same or other modalities to enhance confidence in the segmentation.

A drawback to this technique is that the segmentation is based on a binary classification from a single modality (if one modality fails the other is used). A future addition is to explore the use a probabilistic classification scheme. This would allow for different weightings to be applied to each image. The classification scheme would incorporate information from all of the images into the decision making process rather than using a binary classification for each.

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