Reconstruct 3D brain vasculature from multiple 2D images

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***Abstract*—This paper is a project report of 3D brain vasculature reconstruction from multiple 2D images. It introduces the methods and techniques we implemented for reconstruction. Appropriated machine learning model and feature vectors are proposed as well. The overall performance is discussed, and some future improvements are listed.**

***Keywords*—brain vasculature; reconstruction; 2D X-ray images; machine learning; back projection.**

I. INTRODUCTION

In clinical practice, 3D modeling of the brain vasculature plays the role of very important and helpful support to surgeon. It is generally performed using magnetic resonance imaging (MRI). However, during surgery, it's not possible to run MRI as it takes too much time and the patient would have to be placed in the MRI machine. Instead, 2D x-ray images can be acquired at multiple angles. In consequence, there is a need to reconstruct a 3D volumetric representation to help with decision support during surgery. The objective of this project is to reconstruct a 3D representation of the vasculature from a pair of 2D views. We have access to 61 3D reconstructed vascular models from dataset Brava (http://cng.gmu.edu/brava) [1]. The Brain Vasculature (BraVa) database contains digital reconstructions of the human brain arterial arborizations from 61 healthy adult subjects along with extracted morphological measurements.

II. METHODOLOGY OVERVIEW

This work utilized back projection of a set of x-ray images reconstruct the centerlines of brain vessels in 3D space. Due to time constrain, this project works with dummy input images which are projected from ground truth 3D models. Therefore, our input images are six greyscale images representing the projected centerlines of brain vessels as shown in Figure 1.

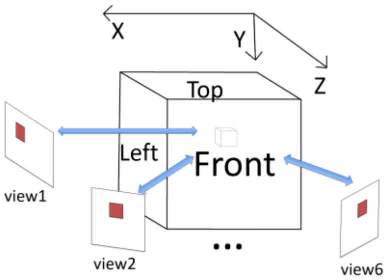


Figure 1. Illustration of input images of various angle, number of 2D images = 6

Therefore, for each voxel in the 3D space where we want to reconstruct our 3D model, homogenous transform can be applied to calculate the corresponding pixels in each of the six images. Then machine learning is applied to predict the value of voxel based on features includes values of corresponding pixels in input images. Finally, postprocessing techniques can be applied to improve model quality.

III. METHODS

A. Homogenous transform

Homogenous transform is used to convert a 3D coordinate to a 2D coordinate based on the angle of projection. The formula is:

$$\begin{bmatrix} \sim \\ y \\ x \\ 1 \end{bmatrix} = \begin{bmatrix} cos\theta & 0 & sin\theta & C_x \\ 0 & 1 & 0 & C_y \\ -sin\theta & 0 & cos\theta & C_z \\ 0 & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} 1 & 0 & 0 & -C_x \\ 0 & 1 & 0 & -C_y \\ 0 & 0 & 1 & -C_z \\ 0 & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} x_{3D} \\ y_{3D} \\ z_{3D} \\ 1 \end{bmatrix}$$

Where x and y are the coordinate of target pixel in 2D image, θ is the angle of viewpoint, C_x, C_y and C_z are the coordinate of center voxel in 3D space, x_{3D}, y_{3D} and z_{3D} are the coordinate of resource voxel.

B. 2D nearest neighbor

The 2D coordinate we obtained in previous stage is float number, hence, for the ease of simplicity, we applied 2D nearest neighbor to decide the value of the pixel. In this way, there might be some distortion to original information. But it's unavoidable due to finite resolution, and it could be learned by the model hopefully.

C. Classification

After previous steps, we are able to generate 2D images of brain vessel from different angles. However, we could not generate images from top view or non-horizontal view, i.e., the image plane must be parallel to the spinal column.

Given the 2D projection from six different views, we have to build a classifier to predict whether a voxel is vessel or not. Obviously, for every specific point, not all the pixel values in the image contain useful information of it. More precisely, we believe the information is included in the projection of the pixel itself and its adjacent pixels. So the input features for a voxel classifier include 3x3 matrix centered at itself in images from every angle. For example, we have six images here, so it would be 3x3 matrix from 6 views, i.e., 54 features in total.

Besides, we could have some more relevant features, such as the Cartesian coordinates or spherical coordinates of the voxel. The general idea is that the brain vessel may have similar structure at some region.

D. Performance metric

Performance of the model is evaluated by the difference between predicted structure with the ground truth structure. To find the proper metric, consider the brain vasculature as a matrix of 3 dimension with corresponding elements “1” or “0”, which indicates there is or is not a vessel. Alternatively, the overall structure can be viewed as a tree-like structure, with multiple branches on it. There are many ways to measure the difference between two brain vessels. The metric should be calculated properly for better understanding and evaluating the model. Since the conventional accuracy doesn’t quite work here due to a large portion of black voxels which can be classified easily, these metrics below are used.

1) Root mean squared error (RMSE)

RMSE is the square root of mean of squared error. It captures the sample standard deviation of the differences between prediction and ground truth. Since it’s scale-dependent, we could only use it for comparison between our own models.

2) Structural similarity (SSIM)

Structural similarity is a measurement of similarity between prediction and ground truth. It focuses more on similarity rather than merely difference. Here, we use the SSIM measurement from skimage library in python.

3) Sørensen–Dice coefficient

Sørensen–Dice coefficient is a metric that evaluate the prediction. It is also known as F1-score. It has the formula of

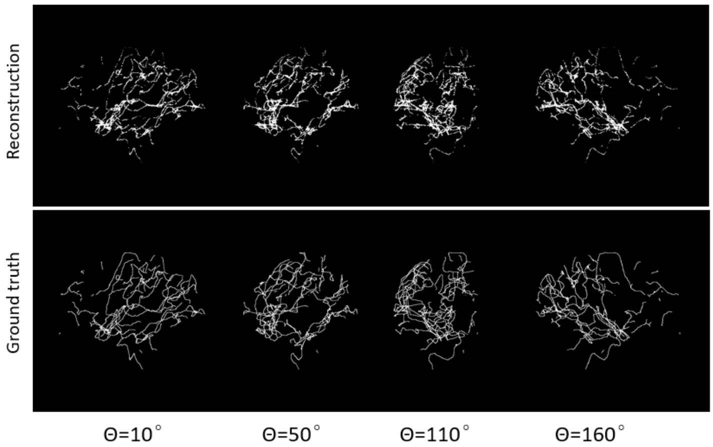
$$\mathrm{DSC} = \frac{2TP}{2TP + FP + FN}$$

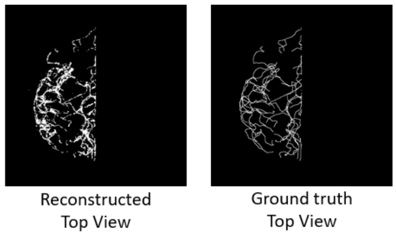
IV. RESULTS

All the results listed below are based on model trained on brain 2-19 and tested on brain 1.

Configuration				
Trial	1	2	3	4
Number of images	6	6	6	4
Coordinate system	None	Spherical	Cartesian	None
Result				
SSIM	0.9359	0.9355	0.9242	0.8925
Dice	0.5018	0.4567	0.3969	0.3338
RMSE	25789	18867	21230	45020

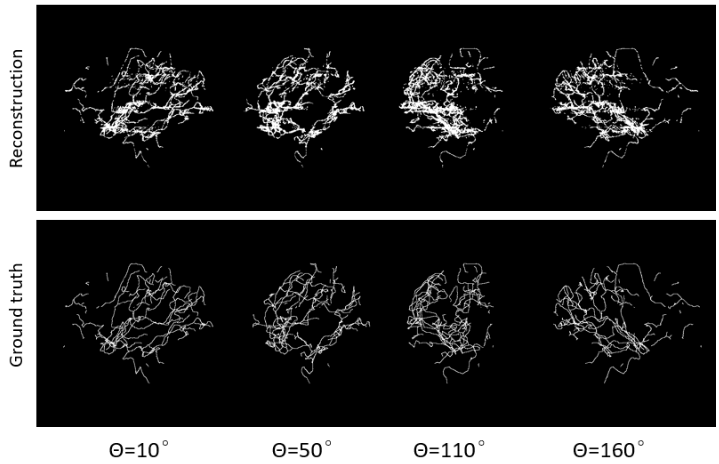
Table 1. Results of different configuration

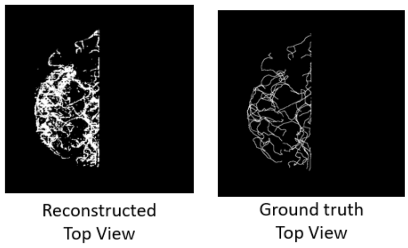




Matric	Value
SSIM	0.9359
Dice	0.5018
RMSE	25789.1201

Figure 2. Comparison between reconstructed 3D model and the ground truth 3D model from 6 views without coordinate (trial 1)





Matric	Value
SSIM	0.8925
Dice	0.3338
RMSE	45019.6149

Figure 3. Comparison between reconstructed 3D model and the ground truth 3D model from 4 views without coordinate (trial 4)

V. DISCUSSION

During the project, we explore several settings and different parameters to find the optimal configuration for our model. In general, models, features and techniques are compared.

To be precise, the RSME metric is not generalizable in this case. It is scale-dependent, so it doesn't provide useful information, but just as a measurement of performance for us to improve. It is the same case as Dice. Dice measures the voxels whose either ground truth or prediction is 1, but it ignores the black voxels adjacent to the vessel predicted correctly. They are very important and should be counted into performance as well. SSIM is an appropriate metric to evaluate the model.

First, we compared different models using basic configuration, such as SVM, Naïve Bayes classifier, random forest and logistic regression model. Logistic regression model gives us the best result, which can reach 98% for validation accuracy.

Features of coordinate systems are tested as well. We thought coordinates may provide some information of how vessel distributes. However, adding Cartesian or Spherical coordinates doesn't improve the model at all, but degrade the performance instead.

We also tried to reduce the number of image views from 6 to 4. It is still able to reconstruct the structure, but with more noise and lower accuracy. It is a trade-off that can reduce the requirement in input but would have a degradation in performance.

In all, the best configuration of our model is using 6 image views without coordinates into a logistic regression model. It could achieve high SSIM as 0.9359 and the reconstructed model is very similar to the ground truth.

VI. FUTURE WORK

For future work, there are still some postprocessing techniques to improve the performance. Some filter can be used to remove some noise or redundant voxels. For example, Frangi filter can be introduced to the system. It can enhance the vessel structure using eigenvectors and Hessian t matrix to compute the likeliness of vessel. As introduced before, RMSE and Dice are not perfect metrics for this project. More proper metric evaluation should be discovered.

VII. CONCLUSION

In conclusion, reconstruction 3D vasculature from X-ray images is feasible via state-of-art techniques in image processing. Our reconstruction model can rebuild the brain vessel by multiple 2D X-ray images from different angles in real time. The performance is promising and still can be improved by some methods in future work. This technique can save a lot of time and resources when providing necessary help to analyze brain vasculature.

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APPENDIX