Carotid Artery Localization and Lesion Classification on 3D-MERGE MRI using Neural Network and Object Tracking methods

Li Chen[1], Huilin Zhao[1,2], Niranjan Balu[1], Xihai Zhao[3], Rui Li[3], Jianrong Xu[2], Thomas S Hatsukami[1], Jenq-Neng Hwang[1], and Chun Yuan[1]

[1]University of Washington, Seattle, WA, United States, [2]Radiology, Renji Hospital, School of Medicine, Shanghai Jiao Tong University, Shanghai, China, [3]Department of Biomedical Engineering, Tsinghua University School of Medicine, Beijing, China

Synopsis

Carotid vessel wall imaging (VWI) with MRI provides additional prognostic value for cerebro/cardiovascular ischemic events, beyond current clinical diagnostic imaging methods. While fast 3D carotid MRI is possible, manual review of the large 3D dataset is time consuming. Automatic identification of artery locations and lesion categories are therefore required for VWI screening protocols. With neural network and object tracking methods, we developed a fully automated analysis tool to find common/internal/external carotid arteries and flag possible high-risk lesion locations. The tool achieved 0.782 Intersection over Union (IoU) for artery localization, and 0.895 sensitivity for high-risk lesion classification.

INTRODUCTION

Atherosclerosis is a major cause of cardio- and cerebrovascular disease mortality and morbidity globally [1–3]. Atherosclerotic lesion progression leads to arterial stenosis and/or occlusion, which may cause downstream ischemic events due to atheroembolization or hypoperfusion [4]. Several fast 3D carotid black blood MRI sequences are now available [5,6]. 3D Motion Sensitized Driven Equilibrium prepared Rapid Gradient Echo (3D-MERGE) [5] black blood MRI can image the carotid vessel wall with high isotropic resolution in a short 2-minute scan thus ensuring patient compliance and diagnostic image quality (becoming available in clinical MRI scanners). However, screening for high-risk lesion is limited by manual image review time. Therefore, fully automated analysis tools on 3D-MERGE are needed.

An automated method to flag locations of atherosclerotic lesions and classify lesion types can help reduce radiologist workload [7–9] and improve screening for atherosclerotic lesions. Identification using deep learning and object tracking may provide a time-efficient solution.

Therefore, the goal of this study is to develop a fully automated analysis tool to identify the locations of the carotid vessel wall from 3D-MERGE images and then flag slices with characteristics of high-risk atherosclerotic lesions.

METHODS

The workflow for this model is shown in Figure 1.

Study sample

3D-MERGE MRI of 269 subjects were collected as part of the Carotid Atherosclerosis Risk Assessment (CARE-II) study [10] with IRB approval and informed consent.

MR imaging

Scans was performed on a 3T Philips (Best, The Netherlands) MR scanner with: TR/TE=10.35/4.87, acquired resolution =0.7mm isotropic (interpolated to 0.35mm isotropic) using bilateral carotid phased array coils.

Image pre-processing

3D-MERGE images were resampled in the axial direction with isotropic resolution of 0.4mm. Each image slice was filtered using a vessel wall enhanced model [11] emphasizing on vessel wall edges, as wall thickness is a key characteristic in determining lesion types.

Human labeling

An experienced radiologist labeled the dataset using unfiltered axial slices. For each slice, bounding boxes of each carotid artery (minimum encompassing rectangle around each vessel wall region) were drawn and classified into three categories (normal artery, early lesion and advanced lesion), based on modified AHA classification for MRI [12] defined in Table 1. An online learning method [13] was used to minimize tedious human labeling by iteratively correcting prediction results. Slices with poor image quality or where part of artery was out of the field of view were excluded (87 subjects). Ultimately, 151, 17, 14 subjects were used as training, validation and testing sets. An average of 95.9±41.1 slices were labeled per subject.

Artery localization

The Yolo V2 neural network [14] model was trained to identify bounding boxes in each slice. Predicted bounding boxes along the slices were reconstructed into tracklets (trajectory fragments) and refined using a tracking by detection method [15,16], which utilizes the neighboring information of bounding boxes to maintain the robustness and continuity of predicted artery wall location.

Lesion classification

The vessel walls in consecutive five slices were cropped using the location of refined bounding boxes and the box in the center slice was classified using a convolutional neural network (8 layers of convolutional layers followed by 3 layers of fully connected layers and softmax layer).

RESULTS

Location sensitivity is 0.985, precision is 0.998, mean Intersection over Union (IoU) is 0.782.

The percentages of artery categories labeled by the radiologist are 27.4% for normal artery, 27.5% for early lesion, and 45.1% for advanced lesion. The classification accuracy of three categories is 0.746, and the weighted kappa for agreement between the radiologist and the tool is 0.77 (0.76-0.78). For advanced lesions, the accuracy is 0.895, the sensitivity is 0.892, and the precision is 0.877. An example showing prediction on one slice is shown in Figure 2. Confusion matrix is shown in Table 2.

Slices with lesions can be flagged onto artery centerlines acquired from centers of bounding boxes in 3D space. 3D Visualization of carotid artery centerline and lesions is shown in Figure 3.

DISCUSSION

The localization and classification models were shown to accurately identify artery locations and detect lesion types with high performance. Although the training process took days, the prediction was completed within a minute. 3D visualization that flags the area of high-risk lesions will substantially reduce review burden for radiologists in clinical practice.

The most common mistakes for the classification model occur mostly near the common carotid bifurcation where complex geometry of the carotid bifurcation and bulb is a challenge.

CONCLUSION

The proposed fully automated carotid 3D-MERGE MRI image analysis tool is capable of artery localization and lesion classification with a high level of accuracy and agreement compared to findings from expert reviewers. This tool can potentially provide a rapid technique for rapid high-risk lesion screening in large populations.

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Figures

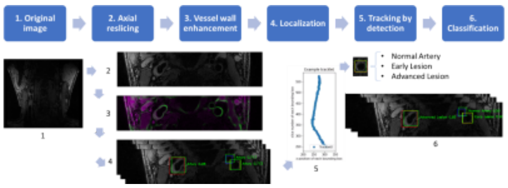


Figure 1 Workflow for fully automated artery localization and lesion classification model in this study

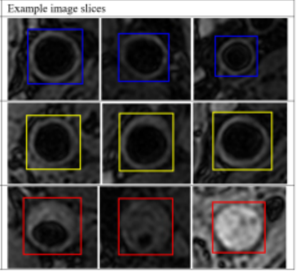
Category	Definition	Example image slices
Normal artery	AHA type I-II lesion, normal or near-normal wall thickness	
Early lesion	AHA type I-II lesion, mild wall thickening <1.5mm with no calcification	
Advanced lesion	AHA type IV-VIII lesions, plaque lesion with wall thickening ≥1.5mm or occlusion	

Table 1 Carotid vessel wall categories with definition and example image slices

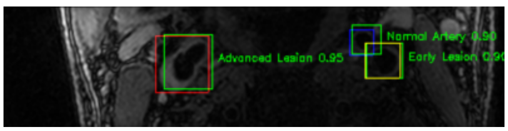
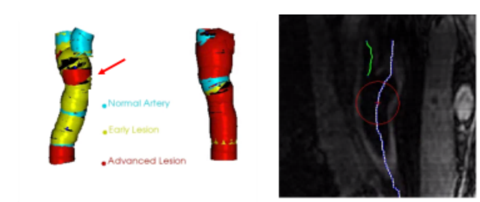


Figure 2 One slice of carotid artery from testing set with green bounding boxes showing prediction locations and artery type (text right to the bounding boxes), classification confidence follows the artery type. Reference locations by the radiologist shown in blue, yellow and red bounding boxes representing normal arteries, early lesions and advanced lesions, respectively.

Bounding box based		Prediction from the tool: Normal artery	Early Lesion	Advanced Lesion
Reference from the radiologist's classification	Normal artery	835	179	46
	Early Lesion	398	495	171
	Advanced Lesion	42	146	1553

Table 2 Heat-map of confusion matrix for prediction results of all slices in test sets. Rows are Reference and columns are predictions. Color for cells indicates level of counts (incremental from red to green)



(a) 3D rendering of probable lesion locations

(b) Coronal slice at pointed location (red arrow)

(c) Axial slice at pointed location (red arrow)

(d) Sagittal slice at pointed location (red arrow)

Figure 3 (a) 3D visualization of carotid arteries (blue for normal artery) with predicted probable lesion locations marked by red or yellow colors for a subject in test set. Three slice views of a certain lesion location pointed by the red arrow are displayed in (b, c, d). Red circles show estimated radius of vessel wall. Green and blue (current selected) lines show centerline of arteries.