Towards Automated Quantification of Vessel Wall Composition Using MRI

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Background: MRI can be used to generate fat fraction (FF) and R2* data, which have been previously shown to characterize the plaque compositional features lipid-rich necrotic core (LRNC) and intraplaque hemorrhage (IPH) in the carotid arteries (CAs). Previously, these data were extracted from CA plaques using time-consuming manual analyses.

Purpose: To design and demonstrate a method for segmenting the CA and extracting data describing the composition of the vessel wall.

Study Type: Prospective.

Subjects: 31 subjects from the Swedish CArdioPulmonary bioImage Study (SCAPIS).

Field Strength/Sequences: T1-weighted (T1W) quadruple inversion recovery, contrast-enhanced MR angiography (CE-MRA), and 4-point Dixon data were acquired at 3T.

Assessment: The vessel lumen of the CA was automatically segmented using support vector machines (SVM) with CE-MRA data, and the vessel wall region was subsequently delineated. Automatically generated segmentations were quantitatively measured and three observers visually compared the segmentations to manual segmentations performed on T1w images. Dixon data were used to generate FF and R2* maps. Both manually and automatically generated segmentations of the CA and vessel wall were used to extract compositional data.

Statistical Tests: Two-tailed t-tests were used to examine differences between results generated using manual and automated analyses, and among different configurations of the automated method. Interobserver agreement was assessed with Fleiss’ kappa.

Results: Automated segmentation of the CA using SVM had a Dice score of 0.89 ± 0.02 and true-positive ratio 0.93 ± 0.03 when compared against ground truth, and median qualitative score of 4/5 when assessed visually by multiple observers. Vessel wall regions of 0.5 and 1 mm yielded compositional information similar to that gained from manual analyses. Using the 0.5 mm vessel wall region, the mean difference was 0.1 ± 2.5% considering FF and 1.1 ± 5.7[1/s] for R2*.

Level of Evidence: 1.

Technical Efficacy Stage: 1.

ATHEROSCLEROSIS causes more deaths worldwide than any other disease, primarily from myocardial infarction (MI) or strokes.1 Atherosclerosis is a chronic disease of the arteries but remains asymptomatic for long periods of time. During this time, the presence and buildup of lipids in the vessel wall triggers inflammatory and other responses that continually alter the composition of the vessel wall.2,3 Eventually, this can lead to focal atherosclerotic plaques that can produce hemodynamically significant arterial narrowing.

Non-invasive imaging of atherosclerotic carotid arteries is most often used for measuring stenosis severity or vessel wall thickness. Stenosis severity alone is most frequently used to make treatment decisions or assess the risk posed by atherosclerotic plaques, despite evidence that it is not sufficient.4 Recently, it has become possible to further characterize the...
tissue of the vessel wall or atherosclerotic plaques and there is increasing evidence that plaque composition is a predictor of cardiovascular events. Specifically, plaque compositional features such as lipid-rich necrotic core (LRNC) and intraplaque hemorrhage (IPH) are recognized as hallmarks of rupture-prone plaques and predictors of cardiovascular events. Therefore, the ability to directly and non-invasively assess compositional features such as the extent of lipid accumulation and hemorrhage in the arterial wall may help to improve the detection of atherosclerosis in its early stages and may identify rupture-prone plaques that can cause stroke.

Magnetic resonance imaging (MRI), with its excellent soft-tissue contrast, offers the ability to examine the composition of the vascular wall. One approach is to use multi-contrast MRI, which leverages a combination of T1-weighted (T1w), T2-weighted (T2w), proton-density-weighted (PDW), gradient echo, and time-of-flight (TOF) sequences to identify plaque components in the carotid arteries by comparing their relative intensities to the signal intensity of surrounding reference tissue. Unfortunately, this approach is limited by its reliance on a large number of sequences, operator-dependent selection of comparison tissue, and imaging artifacts that create intensity inhomogeneity within a single tissue.

By enabling direct measurements of relevant tissue properties, quantitative MRI techniques have the potential to overcome several limitations in the conventional multi-contrast approach. For example, a four-point Dixon gradient-echo sequence was recently demonstrated for the quantitative measurement of the fat-fraction (FF) and R2* inside atherosclerotic plaques in the carotid arteries, and it was shown that these measurements accurately represent the extent of LRNC and IPH inside the plaques. This single-sequence 3D technique achieves high spatial resolution with a relatively short scan time, making it more suitable for clinical use or large-cohort studies. However, to deploy such a technique requires data processing and analysis methods, preferably with a minimal amount of user interaction.

Processing multi-contrast or Dixon data requires isolating the vessel(s) of interest in order to extract the underlying compositional information. This has previously predominantly entailed manual segmentations of the carotid arteries and plaques using T1w black-blood images, subsequently reformatted or registered to T2w, PDW, TOF, or Dixon acquisitions (among others) to facilitate analysis of the compositional features of interest. Manually segmenting the carotid arteries and plaques is a tedious and time-consuming process, hampering the possibility to assess individual patients clinically and rendering large cohort studies impractical. Moreover, manual segmentation introduces intra- and interobserver variability as delineating the boundaries of the vessel walls and identifying plaque components is non-trivial. Clearly, automated methods for segmentation and the extraction of compositional information would be valuable and help alleviate these problems.

Therefore, in this work we aimed to design and demonstrate a method for segmenting the carotid arteries and extracting data describing the composition of the vessel wall, by examining FF and R2*, with minimal user input.

Materials and Methods

Study Participants

Data from 10 study participants was used for quantitative examination of the automated segmentation workflow, and data from an additional 15 study participants was used in qualitative analysis for that method. Data from an additional 10 study participants was used to demonstrate the extraction of compositional information from the vessel wall. Table S1 in the Supplemental Material lists which study participants were used for each test. Study participants were between 50 and 64 years old and had nonsymptomatic atherosclerotic plaques of at least 2.7 mm as measured by ultrasound. Data from both carotid arteries was used, although study participants most frequently presented with unilateral plaque. Study participants were recruited as part of the Swedish Cardiopulmonary bioImage Study (SCAPIS).

This study received ethical approval and all participants gave written, informed consent.

Magnetic Resonance Imaging

Data was acquired on a 3T Philips Ingenia system (Philips Healthcare, Best, the Netherlands) using an 8-channel dedicated carotid coil (Shanghai Chenguang Medical Technologies, Shanghai, China).

T1-WEIGHTED. T1W quadruple inversion recovery images were acquired and used to manually delineate the vessel wall, including any plaques. Scan parameters included: echo time 10 msec, repetition time 800 msec, flip angle 90°, matrix size 320 × 320, pixel size 0.5 × 0.5 mm, 18 slices, slice thickness 2 mm. The axial image stack was vertically centered on the flow divider in the carotid bulb. Acquisition time was 6 minutes.

DIXON. A four-point Dixon sequence was used to generate high-resolution maps of the FF, and the R2* relaxation rate as a measure of iron (ie, heme), corresponding to IPH, as described previously. Briefly, this is achieved by modeling the MR signal of a voxel as $S_0 = \frac{W}{1 + e^{-\frac{-TR}{T_1}}} \left[1 + e^{-\frac{-TR}{T_2}}\right]$ for $TR = \text{echo time}, W = \text{water fraction within the voxel}, F = \text{fat fraction within the voxel}$, and 2.4 msec is the phase cycling period of the oscillating fat signal at 3T. It was assumed that all voxels exhibited a single, effective R2* relaxation rate. Proton density and T1 relaxation differences between water and fat were not considered. Scan parameters included: a coronal slab with 3D field of view (FOV) = 220 × 220 × 60 mm3, centered on the flow divider in the carotid bulb with isotropic acquisition resolution 0.75 mm, matrix size 320 × 320 × 80, echo time 4 × 3.6 msec, repetition time 18 msec, turbo field echo (TFE) factor 12, and flip angle 10°. The acquisition used a Cartesian 3D readout where $k$-space was filled from the center outward (low-high, radial), and the corners of $k$-space were not included. Two regional saturation slabs of 80 mm were added inferior and superior to the
acquisition volume, with a gap of 40 mm, to suppress inflowing blood signal. Fat, water, and R2* maps were generated at a voxel size of $0.60 \times 0.60 \times 0.70 \text{ mm}^3$ using in-house modeling and post-processing tools. The acquisition time was 8 minutes and post-processing required 2 minutes.

**CONTRAST-ENHANCED MR ANGIOGRAPHY.** Contrast-enhanced MR angiography (CE-MRA) data was acquired postinjection of a gadolinium-based contrast agent (Gadovist, Bayer Schering Pharma, Berlin, Germany) to generate bright-blood images for automated segmentations of the vessel lumen and wall area. Scan parameters included: a coronal slab with 3D FOV $= 200 \times 200 \times 50 \text{ mm}^3$ and matrix size $512 \times 512 \times 100$ set to cover the carotid arteries from the clavicle to the Circle of Willis, flip angle $27^\circ$, echo time $1.8 \text{ msec}$, repetition time $4.9 \text{ msec}$, parallel imaging (SENSE) factor 2, and reconstructed spatial resolution of $0.48 \times 0.48 \times 0.50 \text{ mm}^3$. The acquisition time was 2 minutes.

**Segmentation**

**MANUAL SEGMENTATION.** Manual segmentation of the carotid artery was performed by an observer with 4 years of experience in vascular MRI (E.G.) for 10 study participants using ITK-SNAP$^{22}$ software and the T₁w images. Segmentations were unilateral. The inner and outer boundaries of the vessel wall were delineated, and therefore any plaques present were included in this segmentation. The complete segmentation was divided into the common (CCA), internal (ICA), and external (ECA) carotid arteries for each study participant by the observer, using the bifurcation as a reference point. An example segmentation is shown in Fig. 1.

**AUTOMATED SEGMENTATION.** Automated segmentation of the lumen of the carotid arteries was performed on the CE-MRA data using support vector machines (SVM). SVM is a machine-learning model that represents data points using n-dimensional feature vectors and is subsequently trained to classify these data points by finding an optimal hyperplane that separates the data.$^{23}$ Software for automated segmentation was developed in MATLAB R2018b (MathWorks, Natick, MA).

A linear, hard-margin SVM segmentation method was implemented to determine whether or not voxels were within the lumen of the carotid artery based on the following features: voxel intensity, mean voxel intensity in $3 \times 3 \times 3$ neighborhood, standard deviation in the same neighborhood, magnitude of the intensity gradient, magnitude of the Sobel kernel for three directions, magnitude of the Frangi$^{24}$ filter for that voxel, and the distance between that voxel and the local maximum of the Frangi filter. Features were chosen to exploit the bright-blood contrast pattern found in the CE-MRA datasets.

All features were normalized and centered around zero to remove bias. The SVM classifier used a radial basis function kernel. CE-MRA data for 10 randomly chosen study participants was manually segmented, using ITK-SNAP by an observer with 4 years’ experience in vascular MRI (M.Z.) and served as ground-truth. Five of
these ground-truth segmentations were used to train the SVM classifier, and the remaining five were used for validation.

Segmentations were smoothed using a Gaussian kernel, and any noncontiguous regions were removed. Subsequently, segmentations were examined manually, and adjustments to the masks were made manually if necessary. Next, centerlines were calculated and used to standardize the length of the CCA, ICA, and ECA. The length of each branch was standardized to 2.5 cm from the bifurcation point in the bulb, defined using the vessel skeleton.

The vessel wall region was automatically delineated by expanding the lumen masks a predefined distance using binary morphological operations (dilation). Subtracting the vessel lumen mask from this expanded volume generates a mask that represents the tissue immediately surrounding the lumen, i.e., the vessel wall and any atherosclerotic plaques within that volume. Four expansion distances were compared: 0.5, 1, 2, and 3 mm. These expansion distances were set considering the inclusion criteria for this cohort, which indicated plaques of at least 2.7 mm. A typical segmentation of the vessel and vessel wall region generated using this technique, with 2 mm vessel wall region, is shown in Fig. 1.

**Compositional Analysis**

Sampling of FF and R2*, representing compositional information from the vessel wall, using the manual analysis method, was done by first registering the manually generated segmentations to the Dixon data. Registrations were performed using MATLAB’s `imregister` function with a One-Plus-One Evolutionary optimizer and the Mattes Mutual Information similarity metric. The geometric transformation was nonreflective, and was allowed to consist of translation, rotation, and scaling. Next, the average R2* and FF value at each voxel was calculated as an average of its immediate neighbors that were within the mask.

Sampling FF and R2* from the vessel wall using the automated analysis method was done by first registering the Dixon data to the CE-MRA data upon which the segmentations were generated. Registrations were performed using MATLAB’s `imregister` function with the same optimizer function, similarity metric, and transformation parameters as above. Next, for each voxel in contact with the vessel lumen the FF and R2* values were sampled from the vessel wall region by using a spherical convolution kernel with the same radius as the expansion distance. Therefore, at each voxel along the surface of the lumen an average FF and R2* value was generated from the surrounding tissue in the delineated vessel wall region.

**Validation**

Segmentations of the vessel lumen generated using the automated method were evaluated quantitatively against the manual segmentations using the Dice similarity coefficient (DSC), Matthews

| Dataset | DSC  | MCC  | TPR  | FPR  | Dataset | O1  | O2  | O3  |
|---------|------|------|------|------|---------|-----|-----|-----|
| QN01    | Training |      |      |      | QL01    | 3   | 2   | 2   |
| QN02    | Training |      |      |      | QL02    | 2   | 1   | 1   |
| QN03    | Training |      |      |      | QL03    | 2   | 3   | 3   |
| QN04    | Training |      |      |      | QL04    | 3   | 2   | 3   |
| QN05    | Training |      |      |      | QL05    | 2   | 2   | 2   |
| QN06    | 0.898 | 0.898 | 0.868 | 0.99991 | QL06    | 0   | 0   | 0   |
| QN07    | 0.890 | 0.890 | 0.921 | 0.99984 | QL07    | 3   | 3   | 3   |
| QN08    | 0.899 | 0.899 | 0.907 | 0.99979 | QL08    | 2   | 2   | 3   |
| QN09    | 0.917 | 0.917 | 0.902 | 0.99989 | QL09    | 3   | 3   | 3   |
| QN10    | 0.891 | 0.892 | 0.956 | 0.99967 | QL10    | 3   | 3   | 3   |
| Mean (sd) | 0.899 (.010) | 0.899 (0.009) | 0.911 (0.029) | 0.9998 (0.001) | QL11    | 0   | 0   | 2   |
|         | QL12   | 3    | 2    | 2    | QL13    | 3   | 3   | 3   |
|         | QL14   | 3    | 3    | 3    | QL15    | 3   | 3   | 2   |
|         | Median | 3    | 2    | 3    |         |     |     |     |

Ground-truth segmentations consider the lumen for both left and right carotid arteries. O1–Observer 1, O2–Observer 2, O3–Observer 3.
Correlation Coefficient (MCC), true-positive ratio (TPR), and the false-positive ratio (FPR). Automatically generated segmentations for 15 additional study participants were also qualitatively examined, and the quality of these segmentations was scored using a 6-point scale by three observers with at least 4 years of experience in vascular MRI (M.Z.: 4 years, E.G.: 4 years, P.D.: 15 years). The quality was assessed visually by overlaying the segmentations for both bifurcations onto the CE-MRA source data. The quality scale was as follows: 0 = segmentation failure of one or more branches, while 1 = acceptable, 2 = good, 3 = very good or perfect. The level of agreement between the observers was examined using Fleiss’ kappa.27,28 A P-value of less than 0.05 was considered significant.

Automatically generated segmentations of the vessel lumen and wall were compared to the manually generated segmentations by calculating their total overlap, DSC, TPR, true-negative ratio (TNR), accuracy, and the relative volume between manual and automated masks. To do so, the manual segmentations and source data were registered to the corresponding CE-MRA data for each dataset. Overlap was calculated per vessel as the number of voxels contained in both segmentations divided by the total number of voxels contained in the manual segmentation. A larger value indicates that a larger proportion of the manual segmentation is included in the automated segmentation.

The volume-average FF and R2* values were used to compare the manual and automated methods for 10 bifurcations, and the mean difference was reported. The volume-average FF and R2* results generated using each vessel wall region size were compared to manually generated results per branch using a paired, two-tailed t-test to determine whether or not there was a statistically significant difference between them. This procedure was repeated among the different configurations of the automated analysis method to determine whether or not there were differences between the automated analyses. A P-value of less than 0.05 was considered significant.

Results

SVM training, using five datasets (i.e. 10 vessels), was completed in 13 hours using a workstation with a 2.2 GHz 6 core CPU with 64 GB RAM. Segmenting each new dataset took <2 minutes on the same machine. Manual segmentations required -10–15 per bifurcation.

The DSC and TPR scores for the automated segmentations of the vessel lumen are shown in Table 1. The mean ± SD DSC, MCC, TPR, and FPR were 0.899 ± 0.010, 0.899 ± 0.009, 0.911 ± 0.029, and 0.999 ± 0.001, respectively. In qualitative assessments, the median score was 3, and interobserver agreement was moderate (k = 0.41, P = 1 × 10−4). Figure 2 shows an example segmentation overlaid with ground truth.

The similarity between the automated segmentations with varying vessel wall region sizes and the manual segmentations of the lumen and wall is presented in Table S2 in the Supplemental Material. As the vessel wall region increases in size, overlap tends to increase and is therefore maximized using the 3-mm configuration. However, DSC and TPR are maximized at the 1 mm vessel wall region size configuration, 0.66 ± 0.05 and 0.50 ± 0.05, respectively.

FF and R2* derived from the Dixon data using both the automated and manual analysis methods is shown in Fig. 3, which depicts the FF and R2* for the CCA, ICA, and ECA of each study participant. Figure 4 depicts example FF and R2* surfaces. A complete listing of results for the FF and R2* analyses is presented in Tables S3 and S4 in the Supplemental Material, respectively.

The differences between the manual and automated analysis methods are quantified in Table 2, which lists the average difference (manual – automated) between the two methods for each vessel wall region size. The automated method on average yielded lower FF and R2* values when
compared to the manual method. The 0.5 mm vessel wall region configuration had the smallest mean difference to manual analyses considering both FF and R2*. For FF analyses, only the 3-mm configuration had a statistically significant difference when compared to manual. With respect to R2*, the 2-mm and 3-mm vessel wall region configurations were significantly different than manual analyses. Bland–Altman analyses for the 1-mm configuration is shown in Fig. 5.

Comparing automated analyses, significant differences were found between the 0.5 and 3 mm configurations for FF, while for R2* significant differences were found between the following configurations: 0.5 and 2 mm, 0.5 and 3 mm, 1 and 2 mm, and 1 and 3 mm. For all other configuration pairs, no significant differences were found, as shown in Table 2.

**Discussion**

In this study we demonstrated an automated method for the analysis of carotid artery wall composition, represented by FF and R2*, and validated this method against manual analysis. The automated method uses the bright-blood CE-MRA data to first segment the lumen, and subsequently delineates a fixed region surrounding the lumen presumed to be the vessel wall as well as any plaque(s). This enables automated quantification of the vessel wall’s composition, using FF and R2* derived from 4-point Dixon data, in the carotid arteries in a systematic manner.

There was good agreement between FF and R2* data extracted using the automated segmentations and the manual segmentations when considering the volumetric mean in this cohort of study participants with asymptomatic carotid
Atherosclerosis. While there was a small mean difference, this is to be expected, as the vessel wall region is defined differently between the two approaches and the FF and R2* data are extracted in a different manner. Specifically, the spherical convolution kernel used in the automated method has a small smoothing effect. Moreover, differences between vessel branches can exist as a result of the subjectivity of the manual segmentation process. Our data shows that the automated analysis method with vessel wall regions of 0.5 and 1 mm were found to return results that are similar to manual

![R2* and FF surfaces](image)

**FIGURE 4:** Example R2* and FF surfaces. R2* and FF surfaces generated for one study participant (DX09, left) using both the automated analysis method with a 1.0 mm vessel wall region configuration (a,c) and the manual analysis method (b,d). As segmentations were generated independently, and have different anatomical coverage, their appearance can differ.

| Test pair          | FF Difference [%] | P      | R2* Difference [1/s] | P    |
|--------------------|-------------------|--------|----------------------|------|
| Manual vs. 0.5 mm  | 0.04 ± 2.69       | 0.978  | −0.96 ± 6.48         | 0.559|
| Manual vs. 1 mm    | −0.96 ± 2.81      | 0.538  | −2.80 ± 6.62         | 0.096|
| Manual vs. 2 mm    | −2.71 ± 2.74      | 0.079  | −5.98 ± 6.89         | 9.05e-4|
| Manual vs. 3 mm    | −3.60 ± 2.71      | **0.018** | −8.18 ± 6.81         | 1.29e-5|
| 0.5 vs. 1 mm       | −1.01 ± 0.97      | 0.552  | −1.84 ± 1.36         | 0.223|
| 0.5 vs. 2 mm       | −2.75 ± 2.12      | 0.075  | −5.01 ± 3.16         | 0.002|
| 0.5 vs. 3 mm       | −3.64 ± 2.72      | **0.016** | −7.22 ± 4.34         | 2.16e-5|
| 1 vs. 2 mm         | −1.74 ± 1.54      | 0.270  | −3.17 ± 2.16         | 0.048|
| 1 vs. 3 mm         | −2.64 ± 2.36      | 0.090  | −5.38 ± 3.62         | 0.001|
| 2 vs. 3 mm         | −0.89 ± 1.11      | 0.548  | −2.20 ± 1.81         | 0.184|

**TABLE 2.** Cohort Mean Differences Between Manual and Automated Analyses, Considering the CCA, ICA, and ECA

Values are presented as mean ± SD.

Bolded text denotes significant difference (ie, $P < 0.05$).
analyses when considering both FF and R2*. Indeed, for an average 25% increase in mask volume when moving from 0.5 mm to 1 mm vessel wall region sizes, the FF and R2* data extracted was still indistinguishable from that extracted via manually generated segmentations. This suggests some flexibility with respect to the choice of the vessel wall region size for different cohorts and that this method shows promise for extracting compositional information.

Utilizing CE-MRA data for segmentation facilitated the generation of high-quality masks of the lumen geometry, using a relatively fast acquisition that also provides broad anatomical coverage. As demonstrated, the segmentations generated using the proposed method have high DSC and TPR scores even while using a relatively small number of datasets for training. This is a result of the strong difference in signal between the blood and other tissues. The relatively short acquisition time for this image has self-evident benefits, while the broad acquisition coverage allows the image to more easily act as a target during image registration procedures. Future development of the segmentation process to increase the number of features used for classification, or including more datasets while training the classifier, may yield increased performance. Alternatively, methods such as convolutional neural networks may boost performance and enable automatic identification of each arterial branch.

We calculated several parameters describing the similarity between the segmentations automatically generated using CE-MRA data and those generated manually using T1w data to quantify their quality. While the DSC and overlap scores are moderate, these scores account for differently defined segmentations as well as registration errors and cannot be considered to solely describe the quality of the segmentations. Registering the CE-MRA-generated masks and the T1w stack was necessary to evaluate the automatically generated segmentations against ground-truth. This registration pair has substantially different resolutions, anatomical coverage, and contrast patterns. In view

![Bland–Altman analysis for R2* and FF](image)

FIGURE 5: Bland–Altman analysis for R2* and FF, considering each branch of the carotid arteries.
of these factors, the high DSC and TPR scores for the automated segmentations, and the fact that this registration does not occur in the normal workflow, we considered the overlap scores acceptable for further development of the automated method.

The automated method standardizes segmentations such that the CCA, ICA, and ECA branches have equal lengths, using the bifurcation, defined using centerlines, as the reference point. This is a simple and repeatable way to ensure that the same anatomical regions are considered in subsequent follow-up scans. Alternate choices include using the diameter of each branch to denote the region several diameters upstream and downstream, or maximally inscribed spheres. However, these choices could induce variance, as the diameter of the vessel may change between follow-up scans and selecting the point at which to measure the branch diameter is non-trivial with complex bulb or branch geometries.

The automated analysis method takes into consideration the tissue located within a predefined distance from the lumen-wall interface and does not seek to segment plaques specifically from the vessel wall, nor define an exact outer boundary to the vessel wall. In this way, the proposed method is not dependent on images with excellent contrast in the vessel wall area for segmentation and will always isolate the area of interest. While this approach decreases the specificity of the FF and R2* analysis, it also yields increased sensitivity, since this method enables the extraction of FF and R2* from the whole vessel wall region, and not solely the plaque region. This may be particularly useful in the early stages of atherosclerosis, where changes in the vessel wall composition may be occurring but no definite plaque has formed. The proposed method could also be used for longitudinal studies of atherosclerotic development alongside the use of lipid-lowering agents or as the patient undergoes a new exercise regimen. Ideally, the result of such studies would be quantifiable changes in vessel wall composition linked to a given intervention. Examining vessel wall composition in larger cohorts may also enable cardiovascular risk stratification based on R2* or FF measurements.

**Limitations**

This study focused on developing an automated method for segmentation and analysis of vessel wall composition. Therefore, the intriguing task of automatically identifying individual plaques was not a primary goal of this study, but is a possible next step in the development process. This study is also limited in that we lack an ex vivo reference to confirm the compositional features of the vessel wall, although prior work using 3D histology confirmed the validity of the Dixon sequence used here. Finally, another limitation is the small number of participants included in this pilot study.

**Conclusion**

We have demonstrated and validated an automatic method for extracting FF and R2*, which represent compositional information, from the carotid arteries. This automated analysis method uses minimal input and generates results similar to manual analyses. Automatic quantification of vessel wall composition in vivo non-invasively may be a useful tool for systematic analyses of large study cohorts longitudinally, which enables investigations of the initiation and growth patterns of atherosclerotic plaques or cardiovascular risk stratification.

**Disclosures**

Marcel Warntjes is a consultant to SyntheticMR AB, Linköping, Sweden, and he holds shares in this company. The fat fraction and R2* quantification software used in this study is an adapted version of the commercially available product SyMRI. SyntheticMR has not funded or supported this study.

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