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A fully automated tool to identify the aorta and compute flow using Phase-contrast MRI: validation and application in a large population based study

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Abstract

Purpose—To assess if fully automated localization of the aorta can be achieved using phase contrast (PC) magnetic resonance (MR) images.

Materials and Methods—PC cardiac gated MR images were obtained as part of a large population-based study. A fully automated process using the Hough transform was developed to localize the ascending aorta (AAo) and descending aorta (DAo). The study was designed to validate this technique by determining: 1) its performance in localizing the AAo and DAo; 2) its accuracy in generating AAo flow volume and DAo flow volume; and 3) its robustness on studies with pathological abnormalities or imaging artifacts.

Results—The algorithm was applied successfully on 1,884 participants. In the randomly selected 50-study validation set, linear regression shows an excellent correlation between the automated (A) and manual (M) methods for AAo flow ($r = 0.99$) and DAo flow ($r = 0.99$). Bland-Altman difference analysis demonstrates strong agreement with minimal bias for: AAo flow (mean difference (A-M) = 0.47 ± 2.53 ml), and DAo flow (mean difference (A-M) = 1.74 ± 2.47 ml).

Conclusion—A robust fully automated tool to localize the aorta and provide flow volume measurements on phase contrast MRI was validated on a large population-based study.

Keywords

automatic; localization; phase contrast; aorta; segmentation

INTRODUCTION

Cine phase contrast MRI (PC-MRI) has been used to non-invasively measure flow in a wide range of vessels (1–7). The resultant flow curves can then be used to determine flow per unit time (flux) and total vessel flow volume hereinafter referred to as flow (8). These flow curves have important implications in determining physiologic parameters such as cardiac output, and clinically important markers such as aortic pulse-wave velocity (PWV), which is independently associated with cardiovascular disease and mortality (9). MRI-based PWV is commonly measured with CINE 2D Phase Contrast (PC) MRI (10, 11). More recently, flow-sensitive 4D MRI have demonstrated reproducible PWV measurements along the entire thoracic aorta (12).

Given the value of MRI based aortic flow measurements, the application of PC-MRI in routine clinical care and large population based studies has been limited. This is due in part to the time required to produce measurements, as current semi-automated segmentation methods require manual identification of the aorta in the form of a region-of-interest (ROI) or seed point.

Accordingly, we developed a fully automated approach that localizes the ascending aorta (AAo) and descending aorta (DAo), and produces their respective flow curves. The aim of our study is to validate this technique by determining: 1) its performance in localizing the AAo and DAo on a large multiethnic, population-based study; 2) its accuracy in generating clinically useful flow parameters such as AAo flow and DAo flow; and 3) its robustness on studies with pathological abnormalities or imaging artifacts.

MATERIALS AND METHODS

Data source

Phase contrast (PC) cardiac gated MRI images were obtained as part of the Dallas Heart Study-2 (DHS-2), a multiethnic, population-based study of cardiovascular health (13). Demographics for this database are provided in Table 1. Informed consent was obtained for each participant as approved by the University Institutional Review Board. We utilized 1,884 image studies from this cohort for this study.

MR Image acquisition

All images were obtained using a 3 Tesla MRI system (Achieva; Philips Healthcare, Best, the Netherlands). A single-slice axial acquisition was planned from an initial coronal survey to capture the AAo and DAo at the level of the pulmonary artery. Images were acquired with $1.25 \times 1.25 \times 8$ mm voxels, TR-4.99 ms, TE-2.94 ms, Echo train length-3, VENC-150 cm/s, and atemporal resolution of 20 ms or better across the entire R-R cycle. Magnitude images and phase images were saved for later analysis.

Approach to the Problem

Image processing—The general technical strategy is outlined in Figure 1. ImageJ (v. 1.46) was used to process magnitude MR images into a preprocessed binary image, which was then converted to edges using the built in Sobel edge detector to highlight sharp changes

in intensity in the original image (Step 2 of Fig. 1) (14). Specifically, to preprocess the image, we sharpened the image with a 3×3 difference filter to replace each pixel by a weighted average of the 3×3 neighborhood. Next, we used an operator to remove outliers (replaces a pixel by the surrounding median of 7 pixels if it is brighter from the mean using a threshold value of 50), and lastly binarized the image using a threshold automatically determined by the histogram of the image. Aside from the operator to remove outliers, we used the default settings in ImageJ for each command (15). These preprocessing steps were determined on a small set of 20 participants and then fixed for all subsequent analysis of the database. The processed image was then analyzed using the circle detecting Hough Transform (HT), which is an algorithm that produces a spatial density map of all circular objects in an image (Step 3 of Fig. 1) (16). The HT was utilized as an open source ImageJ Java plugin (17).

Algorithm strategy—The HT assigns high values to circular objects in an image and outputs these values as a spatial density map. Each value contains a pair of Cartesian coordinates with a corresponding radius. (The HT has previously been combined with other computer science techniques to localize the boundary of the carotid artery in both ultrasound and MRI imaging (18, 19).) The spatial density map was analyzed using spatial anatomic constraints and flow constraints to determine the location and size of the AAo and DAo. These locations were determined for each phase image of the cardiac cycle and then validated with each other to ensure anatomic alignment. Once the AAo and DAo were located, flow was computed for the AAo and DAo (Steps 5 and 6 of Fig. 1) for each phase image in the cardiac cycle using perfect circle contours derived from the HT value as an approximate segmentation of the aorta. (To compute flow for each phase image: the pixel velocity (m/s) is multiplied across the pixel area (m^2) for all pixels within the circles representing the AAo and DAo respectively). The final flow curve was generated by interpolating these flow values using a cubic spline, which when integrated equals the total flow volume.

Assessing validity—Our automated process was run against the entire DHS-2 dataset ($n = 1,884$). We randomly selected a subset of fifty studies for analysis using the manual standard approach; this approach uses QFlow (v. 4.1.6, Medis, Leesburg), which has been validated and utilized in previous studies (20–23). Outlier analysis was performed to ensure the algorithm performed accurately for the highest and lowest flow results, by manually analyzing 1% of AAo flow outliers and 1% of DAo flow outliers. Note: a percentage of flow outliers is defined as an equal set of the maximum and minimal flow values comprising x percent of the database.

Algorithm Methodology

The algorithm uses 1) the spatial density map produced by the HT and 2) velocity encoded phase images, to determine the location of the AAo and DAo. The HT produces a spatial density map over a range of radii, such that the highest Hough values in this density map contain the location and radius of the most circular objects in the original image over a range of radii. Since the AAo and DAo are highly circular structures in an axial plane, they are likely to have large values at their respective locations (see arrows in Step 3 and 4 of Fig. 1).

Spatial parameter selection—To determine the range of radii for the HT, thirty participants were randomly selected and analyzed, demonstrating a maximum AAO radius of 22.5 mm and a minimum DAO radius of 12.5 mm. The radius search range for the HT was accordingly set for the AAO (27.5 to 10.0mm) and the DAO (21.25 to 6.25mm) to provide a comfortable distance margin outside these limits. This range could be adjusted after our outlier analysis if algorithm failures due to a constricted range were noted, however no such failures occurred.

To identify the AAO and DAO, pairs of values from the density map were recursively filtered against three spatial anatomic constraints:

1. The AAO must be anterior to the DAO.
2. The AAO must be right of the DAO.
3. The AAO and DAO must be separated by at least 18 mm.

The third constraint was specifically used to filter values, which are in the same spatial area and thus represent the same structure. The pairs were arranged such that largest values were evaluated first, ensuring the pair representing the most circular structures was ultimately selected. Once the AAO and DAO were located, the next image of the cardiac cycle was processed using the same methodology. This was repeated for all phases of the cardiac cycle.

Given the changes in structure and contrast during the cardiac cycle, differences in detection on different phase images were expected. To ensure that the AAO and DAO locations for all phases were consistent, the algorithm created clusters for the AAO locations and DAO locations after analyzing all phases. A cluster is defined as a Hough value paired with a measure of frequency. A cluster's frequency is updated, when a new value is accepted as the AAO or DAO for a phase and lies within a spatial location *similar* to the AAO cluster or DAO cluster respectively. Otherwise a new cluster is created. (Two Hough values were defined as *similar* if they had a radius length within 2.5 mm of each other and contained a Cartesian distance within 30% of the radius length). If the AAO location or DAO location for a phase did not correspond to the respective cluster with the largest frequency, the algorithm continued to evaluate the density map until a corresponding pair was located. Ultimately, if no pair was found, the phase image was removed before interpolating values to produce the output flow curve. The vast majority of studies (97.3%) had fewer than 10 phase images removed prior to interpolating the flow values with an average of 0.25 phase images excluded per participant. Of the full database, the maximal phases removed were 30 phase images. The 18 studies (1%) with greatest phases removed were analyzed in the outlier analysis to ensure robustness. This global validation technique eliminated the possibility of making errors in analyzing an individual phase.

Using these three spatial anatomic constraints and the validation technique, our automated process performed well; occasionally, however, competing structures such as the pulmonary artery, pulmonary veins, and the superior vena cava were detected instead of the AAO or DAO. These errors occurred at least 2% of the time, based on an estimate from our initial outlier analysis, which was performed after running our automated process on the entire

database. To determine this failure rate, we manually assessed the algorithm's localization of the AAO and DAO on the 3% outliers. These failures were often due to imaging artifacts and enlarged competing structures (Fig. 2a). To eliminate this source of error, additional constraints were designed.

Given that the AAO and DAO have higher flow velocities and total volume flow relative to competing structures we used flow as an additional metric for filtering. The final flow for the AAO and DAO is computed by traversing all of the pixels within the Hough circle (values) that comprise the respective structure for each phase of the cardiac cycle. The *estimated* flow assumes the Hough circles are the same across all across all phases of the cardiac cycle. This assumption is necessary at this stage of the algorithm, as the definitive locations of the AAO and DAO at each phase are not known.

Flow parameter selection—The minimum boundary for the AAO flow constraint and DAO flow constraint was established by assessing the minimum estimated flow calculated for a random set of 50 participants. The flow constraints were set well below this minimum and were specified as:

4. The AAO must contain an estimated flow greater than 25 ml.
5. The DAO must contain an estimated flow greater than 12 ml.

To avoid several computationally expensive flow computations, spatial anatomic constraints were assessed first, which eliminated the need for flow calculations for many candidate Hough values. Furthermore, once flow was approximated for a Hough value it was indexed in a data structure to avoid computing estimated flow for *similar* Hough values.

In comparing the importance of the flow constraint relative to the spatial anatomic constraints, the flow constraint allowed the algorithm to succeed on all cases that previously caused failures. The flow constraint specifically allows the algorithm to function across structural deviations, MR artifacts, and pathological abnormalities. However, the spatial anatomic constraints are heavily employed to filter out values before evaluating the flow constraint, which significantly increases the algorithm's efficiency, as pairs that fail the spatial anatomic constraints require no flow computation. The spatial anatomic constraints are computationally cheap to apply, and when supplemented with the flow constraint, produce a robust, efficient algorithm that functions on a wide variety of participants.

Validation compared to Manual Measurement

Fifty studies were randomly selected from the database of 1,884 studies for analysis using the manual approach. No participants were excluded pre or post selection. This 50-study validation set was then manually analyzed with the standard manual approach using QFlow, to identify and contour the AAO and DAO and generate the respective flow curves. We then used the same function used by our automated process to load the saved flow curve and compute AAO flow, and DAO flow for all fifty participants. This validation set is powered to demonstrate a difference of 7.2 ml for the AAO and 6.1 ml for the DAO with a (power = 0.8 and significance = 0.05). To quantify the precision of localization the contours produced by the manual approach, defined by a set of vertices, were analyzed to compute a centroid for

each contour (24). The centroids for the manual contours were then compared to the center of the automated circle contour produced by the automated approach.

Outlier Analysis

The 1% flow outliers for AAo flow and the 1% flow outliers for DAo flow were selected for analysis (in addition to the validation set) using the manual approach, with review by an expert in cardiac MRI (RMP). 1% flow outliers of our database with 1,884 participants were defined specifically as the nine largest flow values and nine smallest values for both the AAo and DAo respectively. The manual results on these thirty-six studies were compared to the automated results to assess for potential algorithm failures. Outliers contained pathological abnormalities such as: aortic dilation, superior vena cava dilation (Fig. 2), and a single case with a repaired aortic dissection. They also contained MRI SENSE artifact (25) and studies with low resolution due to participant motion or cardiac gating. A second manual analysis of the 1% of studies with the greatest number of phases removed for the AAo and DAo was also conducted to ensure robustness of the flow computation on these studies.

Statistical Analysis

All statistical analysis was performed using the R Language and Environment for Statistical Computing (26). To assess the normality of the distribution of our results on the DHS-2 database we used quantile-quantile plot (QQ-plot) analysis (27). The unpaired Student's t-test was used to test for the differences in means between the 50-study validation set and the DHS-2 database. Bland-Altman difference analysis was used to compare our fully automated process to the manual standard.

RESULTS

The mean $\pm$ SD on this dataset, were 78.1 ± 17.8 ml for AAo flow ($p = \text{NS}$), and 59.6 ± 15.3 ml for DAo flow ($p = \text{NS}$). Both distributions showed alignment to a normal distribution with a slight positive skew using quantile-quantile plot (QQ-plot) analysis (Fig. 3) (27).

In the 50-study validation set, linear regression (green line Fig. 4) shows an excellent correlation between the automated (A) and manual (M) methods for AAo flow ($r = 0.99$, $A = 1.01 \times M - 0.16$ mL) and DAo flow ($r = 0.99$, $A = 1.02 \times M + 0.49$ mL). Bland-Altman difference analysis demonstrates strong agreement with minimal bias for: AAo flow (mean difference (A-M) = 0.47 ± 2.53 ml), and DAo flow (mean difference (A-M) = 1.74 ± 2.47 ml). This small difference is most likely attributed to differences in the contour shape used to estimate flow. Values on the Bland-Altman plot that occurred outside of the limits of agreement were manually inspected and tended to have ovoid aortas, which made the perfect circle approximation less accurate. In all fifty cases, the algorithm was manually verified to correctly localize the AAo and DAo. The average of the absolute distance between the centers of the automated perfect circle contour estimates and the centroids of manual contours was 1.7 ± 1.0 mm for the AAo and 0.6 ± 0.7 mm. In the 1% flow outlier analysis on thirty-six studies, the AAo and DAo flow results fit the trend for both the regression line on our validation set, and the line of equivalence. In the outlier analysis of 18 studies with

the move phases removed, the AAo average absolute flow difference was 4.9 ml with a maximum difference of 7.0 ml and the DAo the average absolute flow difference was 4.3 ml with a maximum difference of 8.2 ml. In all outlier cases, the algorithm was manually verified to correctly localize the AAo and DAo.

Time saved

Our tool takes approximately 20 seconds to compute transit time, AAo flow, and DAo flow for a single participant using standard PC-type computer hardware without any manual intervention. In contrast, processing a study manually requires at least 1 minute and 30 seconds, which requires loading a study, segmenting the AAo and DAo, and exporting the intermediate data.

DISCUSSION

This study demonstrates an automated process which has the ability to: 1) localize the AAo and DAo on a cohort of 1,884 participants in the DHS-2, a large multiethnic, population-based study; 2) perform with a high level of accuracy as evidenced by equivalence analysis using a 50-study validation set with Bland-Altman difference analysis; and 3) perform on studies with pathological abnormalities or image artifact as evidenced in our outlier analysis.

Several approaches have been reported that automatically segment the aorta; however, to our knowledge all of them require a user to define a region-of-interest or place a seed point for defining the aorta as an input to the automated process (23, 28–32). Herment et al. (31) presented an automated segmentation of the aorta that requires the user to create a square ROI around the aorta and Martin et al. (28) presented an automated algorithm which measures the tortuosity of the aorta which requires manual selection of the centroid of the vessel lumen in the first image of the set.

The results of this study demonstrate that our fully automated process localizes and measures flow in the AAo and DAo. This process however does not replace previous approaches that semi-automatically segment the aorta (33, 34). An accurate segmentation of the aorta is particularly important for evaluation of aortic strain, plaque measurement, among other measurements. Instead, our method enhances these approaches that analyze the aorta by providing a very accurate location for the ROI or seed point as an input to their process. Our results and analysis also demonstrate that our tool can directly compute flow-based measurements such as total flow for the AAo and DAo with a small average volume difference.

In our outlier analysis, we demonstrated that the algorithm accurately localizes the AAo and DAo on cases with structural abnormalities and imaging artifacts; however it was tested on a cohort of healthy participants. To further determine its robustness it should be assessed on cohorts with disease. We also demonstrated our algorithm performs well on the small number of cases that have phase images removed prior to interpolation, however flow measurement differences between manual and automated were on average greater than the average of our 50 participant validation set. Improving measurements on these cases should be explored in the future, potentially by using more precise semi-automated contouring

methods. Because our database was acquired using a single MRI scanner, our automated process could be further tested on multiple machines to further demonstrate its generalizability.

In conclusion, this algorithm can now be applied on large databases to assess flow, or in combination with approaches to segment the aorta (30, 31) to study aortic strain (35) or other characteristics such as tortuosity (28). We also can apply this algorithm to investigate the accuracy of determining a transit time from derived flow-curves, which is a component in the measurement of aortic pulse-wave velocity (36). Measuring aortic pulse-wave velocity in large population studies is of increasing importance, as it is a non-invasive measure of aortic stiffness, independently associated with cardiovascular organ damage and death (37–42). We also may expand our algorithm to localize and measure features in other vessels that have clinical applications such as the pulmonary artery, which has recently been shown to have importance in chronic obstructive pulmonary disease (COPD) (43).

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References

1. Mohiaddin RH, Firmin DN, Longmore DB. Age-related changes of human aortic flow wave velocity measured noninvasively by magnetic resonance imaging. *J Appl Physiol.* 1993; 74(1):492–7. [PubMed: 8444734]
2. Grotenhuis HB, Westenberg JJ, Steendijk P, et al. Validation and reproducibility of aortic pulse wave velocity as assessed with velocity-encoded MRI. *J Magn Reson Imaging.* 2009; 30(3):521–6. [PubMed: 19711407]
3. Shan Y, Lin J, Xu P, Zhou J, Zeng M. Comprehensive assessment of aortic compliance and brachial endothelial function using 3.0-T high-resolution MRI: a feasibility study. *J Comput Assist Tomogr.* 2012; 36(4):437–42. [PubMed: 22805674]
4. Versluis B, Dremmen MH, Nelemans PJ, et al. MRI of arterial flow reserve in patients with intermittent claudication: feasibility and initial experience. *PLoS One.* 2012; 7(3):e31514. [PubMed: 22412836]
5. Ibrahim el SH, Johnson KR, Miller AB, Shaffer JM, White RD. Measuring aortic pulse wave velocity using high-field cardiovascular magnetic resonance: comparison of techniques. *J Cardiovasc Magn Reson.* 2010; 12(1):26. [PubMed: 20459799]
6. Joseph AA, Merboldt KD, Voit D, et al. Real-time phase-contrast MRI of cardiovascular blood flow using undersampled radial fast low-angle shot and nonlinear inverse reconstruction. *NMR Biomed.* 2012; 25(7):917–24. [PubMed: 22180216]
7. Prowle JR, Molan MP, Hornsey E, Bellomo R. Measurement of renal blood flow by phase-contrast magnetic resonance imaging during septic acute kidney injury: a pilot investigation. *Crit Care Med.* 2012; 40(6):1768–76. [PubMed: 22487999]
8. Wedeen VJ, Rosen BR, Buxton R, Brady TJ. Projective MRI angiography and quantitative flow-volume densitometry. *Magn Reson Med.* 1986; 3(2):226–41. [PubMed: 3713488]

9. Vlachopoulos C, Aznaouridis K, O'Rourke MF, Safar ME, Baou K, Stefanadis C. Prediction of cardiovascular events and all-cause mortality with central haemodynamics: a systematic review and meta-analysis. *European heart journal*. 2010; 31(15):1865–1871. [PubMed: 20197424]
10. Laffon E, Marthan R, Montaudon M, Latrabe V, Laurent F, Ducassou D. Feasibility of aortic pulse pressure and pressure wave velocity MRI measurement in young adults. *Journal of Magnetic Resonance Imaging*. 2005; 21(1):53–58. [PubMed: 15611948]
11. Peng HH, Chung HW, Yu HY, Tseng WYI. Estimation of pulse wave velocity in main pulmonary artery with phase contrast MRI: preliminary investigation. *Journal of Magnetic Resonance Imaging*. 2006; 24(6):1303–1310. [PubMed: 17096389]
12. Markl M, Wallis W, Strecker C, Gladstone BP, Vach W, Harloff A. Analysis of pulse wave velocity in the thoracic aorta by flow - sensitive four - dimensional MRI: Reproducibility and correlation with characteristics in patients with aortic atherosclerosis. *Journal of Magnetic Resonance Imaging*. 2012; 35(5):1162–1168. [PubMed: 22271330]
13. Victor RG, Haley RW, Willett DL, et al. The Dallas Heart Study: a population-based probability sample for the multidisciplinary study of ethnic differences in cardiovascular health. *Am J Cardiol*. 2004; 93(12):1473–80. [PubMed: 15194016]
14. Rasband, W. ImageJ. U. S. National Institutes of Health; Bethesda, Maryland, USA: 1997–2012.
15. Tiago, F.; Wayne, R. ImageJ User Guide — IJ1.46. 2010–2012. Available from: <http://imagej.nih.gov/ij/docs/guide/>
16. Ballard DH. Generalizing the Hough transform to detect arbitrary shapes. *Pattern Recognition*. 1981; 13(2):111–122.
17. Hemerson Pistori ERC. HoughCircles. 2004.
18. Cheng DC, Billich C, Liu SH, et al. Automatic detection of the carotid artery boundary on cross-sectional MR image sequences using a circle model guided dynamic programming. *Biomed Eng Online*. 2011; 10:26. [PubMed: 21477378]
19. Stoitsis J, Golemati S, Kendros S, Nikita KS. Automated detection of the carotid artery wall in B-mode ultrasound images using active contours initialized by the Hough Transform. *Conf Proc IEEE Eng Med Biol Soc*. 2008; 2008:3146–9. [PubMed: 19163374]
20. Grotenhuis HB, de Roos A, Ottenkamp J, Schoof PH, Vliegen HW, Kroft LJ. MR imaging of right ventricular function after the Ross procedure for aortic valve replacement: initial experience. *Radiology*. 2008; 246(2):394–400. [PubMed: 18056856]
21. Grotenhuis HB, Ottenkamp J, de Bruijn L, et al. Aortic elasticity and size are associated with aortic regurgitation and left ventricular dysfunction in tetralogy of Fallot after pulmonary valve replacement. *Heart*. 2009; 95(23):1931–6. [PubMed: 19710028]
22. Paelinck BP, Lamb HJ, Bax JJ, van der Wall EE, de Roos A. MR flow mapping of dobutamine-induced changes in diastolic heart function. *J Magn Reson Imaging*. 2004; 19(2):176–81. [PubMed: 14745750]
23. van der Geest RJ, Niezen RA, van der Wall EE, de Roos A, Reiber JH. Automated measurement of volume flow in the ascending aorta using MR velocity maps: evaluation of inter- and intraobserver variability in healthy volunteers. *J Comput Assist Tomogr*. 1998; 22(6):904–11. [PubMed: 9843231]
24. Bourke P. Calculating the area and centroid of a polygon. Swinburne Univ. of Technology. 1988
25. Deshmane A, Gulani V, Griswold MA, Seiberlich N. Parallel MR imaging. *J Magn Reson Imaging*. 2012; 36(1):55–72. [PubMed: 22696125]
26. R-Core-Team. R: A language and environment for statistical computing. R Foundation for Statistical Computing; Vienna, Austria: 2012.
27. Henderson AR. Testing experimental data for univariate normality. *Clin Chim Acta*. 2006; 366(1–2):112–29. [PubMed: 16388793]
28. Martin Rodriguez Z, Kenny P, Gaynor L. Improved characterisation of aortic tortuosity. *Med Eng Phys*. 2011; 33(6):712–9. [PubMed: 21317017]
29. Odille F, Steeden JA, Muthurangu V, Atkinson D. Automatic segmentation propagation of the aorta in real-time phase contrast MRI using nonrigid registration. *J Magn Reson Imaging*. 2011; 33(1):232–8. [PubMed: 21182145]

30. Kozerke S, Botnar R, Oyre S, Scheidegger MB, Pedersen EM, Boesiger P. Automatic vessel segmentation using active contours in cine phase contrast flow measurements. *J Magn Reson Imaging*. 1999; 10(1):41–51. [PubMed: 10398976]
31. Herment A, Kachenoura N, Lefort M, et al. Automated segmentation of the aorta from phase contrast MR images: validation against expert tracing in healthy volunteers and in patients with a dilated aorta. *J Magn Reson Imaging*. 2010; 31(4):881–8. [PubMed: 20373432]
32. Chwialkowski MP, Ibrahim YM, Li HF, Peshock RM. A method for fully automated quantitative analysis of arterial flow using flow-sensitized MR images. *Comput Med Imaging Graph*. 1996; 20(5):365–78. [PubMed: 9007364]
33. Herment A, Kachenoura N, Lefort M, et al. Automated segmentation of the aorta from phase contrast MR images: validation against expert tracing in healthy volunteers and in patients with a dilated aorta. *Journal of Magnetic Resonance Imaging*. 2010; 31(4):881–888. [PubMed: 20373432]
34. Adame I, Van der Geest R, Wasserman B, Mohamed M, Reiber J, Lelieveldt B. Automatic segmentation and plaque characterization in atherosclerotic carotid artery MR images. *Magnetic Resonance Materials in Physics, Biology and Medicine*. 2004; 16(5):227–234.
35. Herment A, Lefort M, Kachenoura N, et al. Automated estimation of aortic strain from steady-state free-precession and phase contrast MR images. *Magn Reson Med*. 2011; 65(4):986–93. [PubMed: 21413062]
36. Dogui A, Redheuil A, Lefort M, et al. Measurement of aortic arch pulse wave velocity in cardiovascular MR: comparison of transit time estimators and description of a new approach. *J Magn Reson Imaging*. 2011; 33(6):1321–9. [PubMed: 21591000]
37. Nichols WW. Clinical measurement of arterial stiffness obtained from noninvasive pressure waveforms. *Am J Hypertens*. 2005; 18(1 Pt 2):3S–10S. [PubMed: 15683725]
38. Vlachopoulos C, Aznaouridis K, Stefanadis C. Prediction of cardiovascular events and all-cause mortality with arterial stiffness: a systematic review and meta-analysis. *J Am Coll Cardiol*. 2010; 55(13):1318–27. [PubMed: 20338492]
39. Alecu C, Labat C, Kearney-Schwartz A, et al. Reference values of aortic pulse wave velocity in the elderly. *J Hypertens*. 2008; 26(11):2207–12. [PubMed: 18854762]
40. Willum-Hansen T, Staessen JA, Torp-Pedersen C, et al. Prognostic value of aortic pulse wave velocity as index of arterial stiffness in the general population. *Circulation*. 2006; 113(5):664–70. [PubMed: 16461839]
41. Brandts A, van Elderen SG, Westenberg JJ, et al. Association of aortic arch pulse wave velocity with left ventricular mass and lacunar brain infarcts in hypertensive patients: assessment with MR imaging. *Radiology*. 2009; 253(3):681–8. [PubMed: 19864506]
42. Boutouyrie P, Tropeano AI, Asmar R, et al. Aortic stiffness is an independent predictor of primary coronary events in hypertensive patients: a longitudinal study. *Hypertension*. 2002; 39(1):10–5. [PubMed: 11799071]
43. Stanbrook MB. The pulmonary artery in COPD--does size matter? *N Engl J Med*. 2012; 367(10):946–8. [PubMed: 22938714]

Figure 1.
Automated approach overview.

Figure 2.

Flow constraints solve algorithm failure on a participant with an enlarged superior vena cava. **a:** Failed detection of AAo without flow constraint. **b:** Accurate detection of DAo without flow constraint. **c–d:** Successful detection of AAo and DAo after adding flow constraints.

Automated Results on DHS2

(n = 1884)

Figure 3.
Summary of automated results.

Figure 4.

Equivalence analysis with Bland-Altman difference plots using 50-study validation set with outliers included. **A:** Equivalence plot for AAo flow. **B:** Bland-Altman plot for AAo flow. **C:** Equivalence plot for DAo flow. **D:** Bland-Altman plot for DAo flow.

Table 1

Cohort characteristics of 1,884 participants imaged in DHS-2.

Dallas Heart Study-2 Imaging	
Age	50.2 ± 10.5 years
Gender	Female: 1,098 (58.2%) Male: 786 (41.7%)
Weight	83.5 ± 17.0 kg
Height	1.682 ± 0.095 m
BMI	29.5 ± 5.6
Systolic BP	131.0 ± 18.7 mm Hg
Diastolic BP	80.4 ± 9.0 mm Hg
HR	66.4 ± 10.3 beats per minute