Published in final edited form as:

Med Eng Phys. 2013 September ; 35(9): 1358–1367. doi:10.1016/j.medengphy.2013.03.005.

Robust infrarenal aortic aneurysm lumen centerline detection for rupture status classification

Hong Zhang^a, Vitaly O. Kheyfets^b, and Ender A Finol^{b,*}

^aInstitute for Complex Engineered Systems, Carnegie Mellon University, Pittsburgh, PA, United States

^bDepartment of Biomedical Engineering, The University of Texas at San Antonio, San Antonio, TX, United States

Abstract

The objective of this work is to develop a robust method for human abdominal aortic aneurysm (AAA) centerline detection that can contribute to the accurate computation of features for the prediction of AAA rupture risk. A semiautomatic algorithm is proposed for detecting the lumen centerline in contrast-enhanced abdominal computed tomography images based on online adaboost classifiers, which does not require prior image segmentation. The algorithm was developed and applied to thirty ruptured and thirty unruptured AAA image data sets and the tortuosities of the detected centerline were measured to assess the correlation between AAA tortuosity and the binary ruptured and unruptured labels. The lumen of each data set was segmented manually by a trained radiologist and the resulting centerlines of each data set were defined as the gold standard to evaluate the accuracy of the algorithm and to compare it against two widely used segmentation techniques. The average mean relative accuracy of the offline adaboost classifier is 91.9% with a standard deviation of 1.6%; for the online adaboost classifier it is 93.6% with a standard deviation of 1.9% ($p < 0.05$). The online adaboost classifier outperforms the offline adaboost classifier while their computational costs are similar. Aneurysm tortuosity computed from an accurately derived lumen centerline using online adaboost is statistically higher for ruptured aneurysms compared to unruptured aneurysms, indicating that tortuosity can be used to assess rupture risk in the vascular clinic.

Keywords

Abdominal aortic aneurysm; Computed tomography; Lumen centerline; Adaboost; Online classification; Machine learning

1. Introduction

Abdominal aortic aneurysms (AAAs) are defined as an aortic dilation that is at least 50% larger in diameter than the proximal or normal infrarenal aorta [1]. Unruptured AAAs

© 2013 IPED. Published by Elsevier Ltd. All rights reserved.

*Corresponding author at: The University of Texas at San Antonio, Department of Biomedical Engineering, AET 1.360, One UTSA Circle, San Antonio, TX 78249, United States. Tel.: +1 210 458 8058; fax: +1 210 458 7007. ender.finol@utsa.edu (E.A. Finol).

Appendix A. Supplementary data

Supplementary data associated with this article can be found, in the online version, at <http://dx.doi.org/10.1016/j.medengphy.2013.03.005>.

Conflict of interest statement

No conflict of interest.

usually enlarge at the rate of 0.25 mm or more per year and can ultimately lead to rupture in some instances [1], an event that carries a mortality rate of 50–75% [2]. AAA disease is the 13th leading cause of death in the United States [3] and is clinically managed by elective repair or by placing the patient in a periodic surveillance program. Since the form of treatment is interventional, it is only necessary for patients with an estimated high risk of rupture. The current clinical guidelines are that patients with AAAs having a maximum diameter exceeding 5.0–5.5 cm are recommended repair [4]. However, in addition to maximum diameter, AAA rupture risk is believed to be dependent on other factors, such as asymmetry of the AAA sac [5], peak wall stress (PWS) [6], while the tortuosity of the AAA centerline is also related to PWS [7]. Among them, the estimation of PWS obtained from finite element (FE) models over performs maximum diameter in discriminating between ruptured and unruptured AAAs [8].

Computed tomography angiography (CTA) provides a non-invasive means to diagnose/follow-up patients and to generate computational models from which the aforementioned factors (geometric indices, PWS, etc.) can be estimated. The main disadvantage is that the process of creating such models usually takes several hours for one patient and requires computationally expensive methods to guarantee the accuracy of the FE predictions. In addition, with the existence of regions of similar AAA voxel intensity in adjacent organs, the required segmentation process preceding *individualized* FE modeling requires significant human interaction. To this end, Georgakarakos et al. [7] reported that the tortuosity of the AAA centerline is positively correlated to PWS. Thus, if it were possible to detect the centerlines from CTA images directly without prior segmentation, this would contribute to a faster modeling strategy. Accordingly, a robust method for center-line detection devoid of CTA image segmentation would be helpful in the prediction of AAA rupture risk.

The common method of detecting vessel lumen centerlines is based on prior image segmentation and subsequent path extraction, which can be a time-consuming and laborious task if performed manually or on multiple vessel segments. Previous studies have reported on techniques for lumen segmentation. Borghi et al. [9] made use of a 3D region growing algorithm, which is a method subject to leakages and requires an optimal threshold to be evaluated individually for each data set. These disadvantages place a limitation on the robustness and universality of region growing. To overcome the problem, Yi and Ra [10] proposed an adaptive region growing to overcome the difficulty of selecting an adequate threshold. However, the segmentation still failed on cases with blood leakage. Frangi et al. [11] used a multiscale vessel enhancement filtering based on the eigenvalue of a Hessian matrix to segment vessels, resulting in a successful method for high-quality images. Nevertheless, the Hessian matrix is derived from the second-order deviation of the image intensity and it is sensitive to noise. In addition, the computation is expensive due to the eigenvalue calculation. Alternatively, deformable models of active contours (snakes) are model-based techniques that use parametric curves, which deform under the influences of internal and external forces, resulting in a smooth fit of the lumen boundary [12]. The main drawback of snakes is that the external forces are generated from the gradients of image intensity, which is sensitive to noises. Level sets [13] have also been applied successfully for lumen segmentation. They are based on the representation of propagating curves converging to the lumen boundary as the zero level set of a higher dimensional function given in an Eulerian coordinate system. This method can handle complex topologies and does not need the adjustment of parameters for the segmentation strategy. Nevertheless, the required computational time is an important limitation.

Various direct centerline detection methods have been implemented previously via the definition of one or two points on the centerline as user-defined a priori knowledge. Bodur et al. [14] proposed the use of a histogram of lumen intensities and a Gaussian estimator to

find an optimized path connecting two pre-defined points on the centerline. This method requires two assumptions that are not always valid: (i) that the intensities along the centerline follow a Gaussian distribution and (ii) that they follow the same (Gaussian) distribution. Conversely, Hoyos et al. [15] applied moments of inertia to predict the projection of the centerline iteratively. The results are superior on cases with adequate contrast mixing and small data sizes, but the method has a similar disadvantage to the Hessian matrix based solution. Agam et al. [16] used a gradient vector distribution to extract centerlines, which showed advantages for lung nodule detection. While the outcome of this method on large vessels such as the aorta is uncertain, the computation speed is modest due to the eigenvalue calculation.

In this work, we report on the development and application of a robust and fast semi-automatic AAA lumen centerline detection method based on online classification with steerable features. The algorithm has the advantages of being able to achieve real-time processing and compute individual centerlines without requiring patient specific parameters or segmentation of the images a priori. Following we describe the method, validate it against digital AAA phantoms, compare it against manual centerline detection, and apply it to sixty CTA data sets.

2. Methods

2.1. Offline and online adaboost classifiers

For each voxel on the CTA image, the steerable feature [17] can capture both local and global features, and increase the accuracy of the centerline detection samples a few points from the image following a special pattern. Since AAAs are either fusiform or saccular and the luminal cross-sections perpendicular to the axial direction are approximately circular, the sampling points are placed evenly on a circle centered at the voxel. The local features (here we use haar-like features as reported in [18]) for each sampling point are grouped as steerable features of the voxel. The user crops the AAA on the first image and a classifier is trained based on the sampled training data based on the cropped rectangle. For the remaining images, the classifier tests the voxel on the image with the output of 'AAA' or 'non-AAA' label, and the detected centroids are placed at the center of voxels labeled as 'AAA'. These centroids are connected to form the detected centerline.

Centerline detection on medical images based on offline boosting has been reported elsewhere [19] with some successful results. The boosting is a linear combination of weak classifiers called *stumps*, which can be any classifier performing slightly better than random guessing such as a one-layer decision tree [19]. During the training step, all training data are assigned weights equally, and at each iteration a weak classifier, $f_m(\cdot)$, is applied on the training data. The weights on false prediction data are increased and passed to the next iteration, and the weight of a current weak classifier, c_m , is calculated according to a level of accuracy. The iterative process stops at a preset number M and the weak classifiers and corresponding weights are recorded. During the testing step, the weighted linear sum of weak classifiers is used as output. In this way, offline boosting combines a group of weak classifiers into a strong one by means of weighted voting. Given a training set $= \{ \langle x_1, y_1 \rangle, \dots, \langle x_N, y_N \rangle \mid x_i \in \mathbb{R}^m, y_i \in \{-1, +1\} \}$, a strong classifier is combined from M weak classifiers as follows:

1. Start with weights $w_i = 1/N, i = 1, \dots, N$
2. Repeat for $m = 1, 2, \dots, M$:
 - a. Fit the classifier $f_m(\cdot) \in \{-1, 1\}$ using weights w_i on $\cdot$;

- b. Compute $err_m = \sum_{i=1}^N w_i \cdot 1_{(y_i \neq f_m(x_i))}$, $c_m = 0.5 * \log((1 - err_m)/err_m)$;
- c. Set $w_i = w_i \exp [c_m \cdot 1_{(y_i \neq f_m(x_i))}]$, $i = 1, 2, \dots, N$, and renormalize so that $\sum_i w_i = 1$
3. Output the classifier $sign \left[\sum_{m=1}^M c_m f_m() \right]$.

Here w_i are the weights on the training data, err_m is the weighted error of the classifier, $1_{(s)}$ is 1 when statement s is true and 0 when s is false, while c_m is the voting weight for each weak classifier. In 'Nomenclature' section, we include a complete definition of the variables used in this algorithm. Fig. 1 shows the tracking results of the offline classification demonstrating that it begins to lose track of the object after several tracking steps.

Different from the offline version, an online classifier [20] induces the concept of a selector, which is a classifier pointer. Given a set of $M = 12,900$ weak classifiers, $P = 20$ selectors point to P classifiers and the strong classifier is obtained from the combination of the P classifiers. Given a new training sample, the selectors are updated accordingly. The updating process is to rank the classifiers according to the errors and switch the selectors to the first P classifiers. Given new training data $\langle x, y \rangle$, the online version of the adaboost classifier is obtained as follows:

1. Start with weight $w = 1$
2. Repeat for $p = 1, 2, \dots, P$:
 - a. Repeat for $m = 1, 2, \dots, M$:
 - i. Update the classifier $f_m()$ $\{-1, 1\}$ using weight w and $\langle x, y \rangle$
 - ii. Compute err_m
 - b. Make p th selector $s_p()$ point to weak classifier $f()$ with the lowest error err
 - c. $c_p = \log(1 - err/err)$
 - d. If $f() == y$, $w = w \cdot (1/2(1 - err))$ else $w = w \cdot (1/2err)$
3. Output the classifier $sign \left[\sum_{p=1}^P c_p s_p() \right]$.

Here w is the importance weight of the current data to the new data and c_p is the voting weight for each selector. In 'Nomenclature' section, we include a complete definition of the variables used in this algorithm. Fig. 2 shows that the online version can track the object robustly in the same data set used to test the offline version. The online classification is robust to noise and changes in the object, as well as the background's intensity configuration. In Appendix, we provide an alternative method for detecting centerlines in bifurcating or branching vessels, by combining online adaboost with particle filters.

2.2. Tracking process

Given a non-segmented AAA CTA data set and a rectangular box in the first image enclosing the lumen, the classifier is updated during the tracking process by using the testing outcome of the previous image as the new training data. The process starts from the first image and stops at the last image in the axial direction resulting in a sequence of rectangles enclosing the lumen, the centroids of which form the desired AAA centerline. The reference standard of the centerline is obtained from the manual lumen segmentation of the data set by a trained radiologist. The mean relative accuracy of the algorithm is given by $1 - \text{mean}(E)/$

$mean(D)$, where E is the Euclidean distance between the centroids of the tracked center-line and the centroids obtained by the manual segmentation, while D is the *hydraulic diameter* of the aneurysm at each cross-section obtained from the manual segmentation.

2.3. Validation and comparative analysis

We generated a digital AAA phantom of known dimensions and predefined centerline as the basis to validate the proposed method. The cross sections of the model in the axial direction were represented by binary masks containing the wall, thrombus and lumen regions, defined by the outer wall, inner wall and lumen boundaries, similar to a patient-specific AAA. By adding various degrees of Gaussian noise, we measured the robustness of our method as it relates to its ability for tracking the lumen centerline under increasing levels of image distortion.

The usual thinning algorithm [21] for centerline detection requires prior image segmentation and can only be applied on binary masks while our algorithm is applied on the medical image directly. Nevertheless, we performed a qualitative comparison of our proposed method with the 3D Frangi filter [11], which is a state-of-the-art algorithm for blood vessel detection [22] (see Vascular Modeling Toolkit: <http://www.vmtk.org> and 3D Slicer: <http://www.slicer.org/>), for the centerline derivation and centroid calculation with the online adaboost classifier.

2.4. Subjects and clinical image data

Abdominal CTA images were obtained following an approved human subjects research protocol by the Institutional Review Boards at Allegheny General Hospital – AGH (Pittsburgh, PA) and Carnegie Mellon University (Pittsburgh, PA). The clinical images were acquired retrospectively from 2008 to 2010 and consisted of the last CTA exam available prior to either elective or emergent repair. For the emergent repairs, the additional inclusion criterion was the availability of an exam within 1 month prior to the repair. For the elective repairs, the additional inclusion criterion was the availability of an exam within 6 months prior to the repair. The exclusion criteria consisted of unavailability of images within the aforementioned time periods. No data was collected concerning exposure to radiation during CTA. Images post-repair were not collected for this analysis. Follow-up CT images for those patients who were once placed under surveillance at AGH were acquired, but did not form part of this study. Not all electively repaired subjects had a history of surveillance as some patients were referred to AGH from regional clinical centers and any existing CT exams performed at these alternate locations were not always acquired by the AGH primary physician. All data sets that met the inclusion/exclusion criteria were eligible for this study. No patient identifiable information was collected during the acquisition of the clinical images. All data were located by a research coordinator in a database maintained by the Radiology Department at AGH and saved on digital media (CDs) for use in the present work. The contrast-enhanced CT images of thirty ruptured and thirty unruptured AAA subjects ($n = 60$ total subjects) were acquired using a Siemens Sensation 4 scanner with the following imaging parameters: scan matrix size = 512×512 and slice thickness = 1.25–2.5 mm. Thirty CT datasets were chosen randomly from the group of unruptured AAAs and the other thirty from the group of ruptured AAAs. There were no age matching, gender matching or diameter matching approaches followed. In this investigation, a “ruptured” AAA is defined by the availability of a CTA exam within 1 month prior to the emergent repair. There were no other sources of potential bias or imprecision.

2.5. Tortuosity and assessment of rupture risk

The tortuosity of a centerline is defined as $L/d - 1$. Here L is the length of the centerline and d is the Euclidean distance between the first and last points on the centerline [23–25]. The

tortuosities of the thirty unruptured (U1, U2, ..., U30) and thirty ruptured data sets (R1, R2, ..., R30) are computed while excluding the iliac bifurcation, since the tortuosity of the common iliac arteries is not a feature that determines AAA rupture risk.

3. Results

3.1. Validation and comparative analysis

Fig. 3 shows two exemplary detected centerlines overlapped with the reference standard obtained from manual segmentation of the same image data sets, revealing the qualitative accuracy of the proposed method and resulting in an average mean relative distance of 97.2% for Fig. 3A and 90.9% for Fig. 3B. Fourier smoothing yielded a minor increase in accuracy of the method, such that the average mean relative distance increased to 97.3% for the model shown in Fig. 3A. After detecting a centerline, its tortuosity can be used as a geometric feature for AAA rupture risk assessment.

Fig. 4 shows the centerline tracking outcome for the digital AAA phantom as a function of Gaussian noises ranging from 0 to 100%. The relationship between the mean relative accuracy (mean relative distance of the centroid location at each cross-section of the AAA phantom) and Gaussian noise for each of the phantoms is illustrated in Fig. 5. Even with more than 50% noise our method can still yield up to an average 85% accuracy.

Due to the sensitivity of the gradient intensity to noise and wall calcification when applying the thinning algorithm, we observed false connections to adjacent organs even though it can locate the AAA in the first several images of the data set. We applied threshold segmentation on the filter results and then used the thinning algorithm on the binary segmentation to obtain the centerline. In addition, a centerline was calculated using Mimics® (Materialize, Leuven, Belgium), which requires prior segmentation of the AAA lumen. Fig. 6A–F show the outcome of applying the 3D Frangi filter, threshold segmentation and the thinning algorithm on six random cross-sections of an exemplary data set (U6), while Fig. 6G illustrates the centerline resulting from this algorithm compared to the thinning algorithm based on the Frangi filter, the Mimics® centerline, and the gold standard centerline for the same exemplary model (U6). Ten data sets (five ruptured and five unruptured) were tested with the thinning algorithm and the accuracy and computational time were compared to the online adaboost method. The mean relative accuracy of both methods is shown in Fig. 6H for each of the data sets. The average CPU time for processing each image with the thinning algorithm is 3.509s on a workstation with an Intel Core 2 Duo E7500 2.93 GHz processor, 3 GB RAM, Windows XP and Matlab 7.1, compared to 1.973s with online adaboost. The speed can meet a real-time application requirement when using the adaboost algorithms.

3.2. Application of the proposed method to the AAA subject population

Based on the tracking of the 60 data sets, Fig. 7 illustrates the mean relative accuracy of the offline and online adaboost classifiers for thirty unruptured (A) and thirty ruptured (B) AAAs. For the unruptured data sets (U1, ..., U30), the average of the mean relative accuracy is $91.2 \pm 1.1\%$ and $92.4 \pm 1.4\%$ for the offline and online classifiers, respectively ($p < 0.001$). Likewise, for the ruptured data sets (R1, ..., R30), the average of the mean relative accuracy is $92.7 \pm 1.6\%$ and $94.8 \pm 1.5\%$ for the offline and online classifiers, respectively ($p < 0.001$). The online adaboost classifier increases the accuracy and reduces the variance of the tracking process, resulting in a robust centerline detection algorithm. By combining the sixty data sets we obtained averages of the mean relative accuracy equivalent to $91.9 \pm 1.6\%$ (offline) and $93.6 \pm 1.9\%$ (online). This is proven by two-sample t tests and the null hypothesis stated as “the mean relative accuracy of the online adaboost classifier minus the

mean relative accuracy of the offline adaboost classifier is 0" against the alternative hypothesis "greater than 0". The null hypothesis is thus rejected for a significance level of $\alpha = 0.05$ with $p = 0.001$.

The centerline tortuosities sorted by the maximum diameters of the 60 data sets are displayed in Fig. 8. The mean tortuosity of the ruptured data sets is 0.4689 with a standard deviation of 0.207. The mean tortuosity of unruptured data sets is 0.2518 with a standard deviation of 0.0796. This is proven by two-sample t tests and the null hypothesis stated as "the mean tortuosities of the ruptured data sets minus the mean tortuosities of the unruptured data sets is 0" against the alternative hypothesis "greater than 0". The null hypothesis is thus rejected for a significance level of $\alpha = 0.05$ with $p = 0.001$. We randomly divided the data sets evenly into six balanced groups and ran a six-fold cross validation with the Naïve Bayes classifier. The receiver operator characteristic (ROC) analysis curves for each round are shown in Fig. 9 and the average area under the curve was 0.8713 ± 0.0027 . The area falls in the range of 0.8–0.9, which translates to the test accuracy being *very good*. To demonstrate the improvement after taking tortuosity into consideration, we build up the Naive Bayes classifier using maximum diameter as the only feature. The accuracy was $91.67\% \pm 2.04\%$, which increased to $93.33\% \pm 1.63\%$ after adding tortuosity as the other feature. This indicates that tortuosity is an important geometric variable to predict rupture status in addition to maximum diameter.

4. Discussion

In this investigation, we report on a semi-automatic method to detect the lumen centerline of an AAA devoid of prior image segmentation. The method was validated against digital AAA phantoms with varying degrees of image distortion and its performance compared against a standard thinning algorithm with a 3D Frangi filter, which requires image segmentation to be performed a priori. Based on detecting centerlines in ruptured and unruptured AAA data sets, the tortuosity of the aneurysmal aorta can be computed and the relationship between tortuosity and AAA rupture status estimated by two-sample t tests. Our method was tested on 60 cases (30 ruptured and 30 unruptured AAA CTA image data sets) and statistical analyses were performed to (i) determine the improvement in accuracy of online vs. offline classification methods and (ii) quantify the tortuosity of the AAAs to estimate the ability of this geometric feature to discriminate between ruptured and unruptured AAAs. We found that the centerline detection algorithm is robust for both types of data sets and that tortuosity can potentially be used to estimate rupture risk in AAA patients deemed eligible for elective repair based on their aneurysm size. In addition, we established a solution for detecting centerlines in bifurcating blood vessels without needing prior image segmentation by combining the online adaboost classifier seamlessly with particle filters, and demonstrated that these methods are not robust when applied individually.

Based on our pilot study of sixty AAA CTA data sets, the online adaboost classifier outperforms offline classifiers both in accuracy and computation speed. By measuring tortuosity from the detected centerlines, we found that this geometric parameter is a statistically significant discriminator of ruptured and unruptured AAAs. However, it should be used cautiously and not as the only indicator for rupture risk assessment. Other geometric indices such as wall thickness [14,21], surface curvatures [13,14], volume and surface area [14], thrombus volume [15], etc., should be accounted for to increase the accuracy of this estimation. Fillinger et al. [29] also report on the influence of geometric variables in the classification of ruptured and unruptured AAAs. Their study indicates that the most significant variables for rupture status are aortic tortuosity, diameter asymmetry, and current smoking. However, they also found that when matched for age, gender, and diameter,

ruptured AAAs tend to be less tortuous but have greater cross-sectional diameter asymmetry. Our work is in agreement with Fillinger et al. in that lumen tortuosity is a discriminator of ruptured and unruptured AAAs, but differs from it in that ruptured AAAs were found to be more tortuous. One possible explanation for this discrepancy is the method used in [29] to measure tortuosity, which was a 2D assessment of the relative location of the lumen center between two predefined axial images. Such protocol does not take into account the 3D geometry reconstruction needed to define the lumen centerline and subsequent calculation of tortuosity based on the extent of the centerline in the 3D geometry.

The limitation of the proposed method is that it cannot navigate in a 3D image directly and has to track the centerline in the axial direction from the first to the last available image. Moreover, the accuracy of the algorithm is diminished in cases with extreme tortuosity, nevertheless it is still greater than 90%. In addition, the use of centerline tortuosity as a discriminator of at-risk AAAs could benefit from the application of the online adaboost classifier to a population of small AAA patients, i.e. those that are placed in a surveillance program and followed every 6 months with a CTA exam. However, data from such a population is scarce in many hospitals, which typically perform surveillance imaging with abdominal ultrasound until the patient is deemed eligible for elective repair. Finally, it is uncertain if the online adaboost classifier and its combination with particle filters would perform adequately with unenhanced (non-contrast) medical images or imaging modalities where a sustained breath hold was not enforced during image acquisition.

5. Conclusion

The proposed method for lumen centerline detection using online adaboost is computationally fast, yields high accuracy compared to a reference standard, and can be used for bifurcating vessels when combined with particle filters. In addition, it does not require segmentation of the medical images as a pre-requisite for centerline identification and needs only one user generated seeding point on the lumen of the first medical image of the data set. Upon testing the method on 60 abdominal aortic aneurysm CTA data sets (30 ruptured and 30 unruptured AAAs), the computed lumen centerline tortuosity was found to be a statistically significant discriminator of rupture status, indicating that vessel tortuosity should be further evaluated for rupture risk assessment to guide the clinical management of AAA disease.

Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

Acknowledgments

The authors would like to thank Dr. Satish Muluk and the Department of Radiology at Allegheny General Hospital for supplying the CTA images used in our study. We also acknowledge research funding provided under the 2009 American Recovery and Reinvestment Act (ARRA) and support by Award R21EB008804 from the National Institute of Biomedical Imaging and Bioengineering. The content is solely the responsibility of the authors and does not necessarily represent the official views of the National Institute of Biomedical Imaging and Bioengineering or the National Institutes of Health.

Nomenclature

w_i weights, which represent the importance of the training data. The error of the classifier is calculated from the weighted sum of the error of the weak classifiers based on the weights

$f_m()$	weak classifier at step m and fit from the training data and corresponding weights
err_m	prediction error of the m th weak classifier and based on the prediction error of the weak classifier on the training data
c_m	weight of the weak m th classifier
$1()$	1 when the condition is true and 0 when the condition is false
	importance weight on the current data to the new data
P	number of weak classifiers
err_m	error of the m th weak classifier
c_p	weight of the weak p th selector
n	number of tracking steps
P	number of particles
$s_k^{(i)}$	state variable of i th particle at k th step
$()$	importance function
$w_k^{(i)}$	weight of i th particle at k th step
M_{eff}	variance of the weights

References

1. Anderson LA. Abdominal aortic aneurysm. J Cardiovasc Nurs. 2001 Jul; 15(4):1–14. [PubMed: 11419662]
2. Bettermann, K.; Toole, JF. Diagnostic evaluation and medical management of patients with ischemic cerebrovascular disease. In: Rutherford, R., editor. Vascular surgery. Philadelphia: Elsevier; 2005. p. 1904-1905.
3. Belkin M, Donaldson MC, Whittemore AD. Abdominal aortic aneurysms. Curr Opin Cardiol. 1994 Sep; 9(5):581–590. [PubMed: 7987038]
4. Vorp DA, Raghavan ML, Webster MW. Mechanical wall stress in abdominal aortic aneurysm: influence of diameter and asymmetry. J Vasc Surg. 1998 Apr; 27(4):632–639. [PubMed: 9576075]
5. Doyle BJ, Callanan A, Burke PE, Grace PA, Walsh MT, Vorp DA, et al. Vessel asymmetry as an additional diagnostic tool in the assessment of abdominal aortic aneurysms. J Vasc Surg. 2008 Feb; 49(2):443–454. [PubMed: 19028061]
6. Heng MS, Fagan MJ, Collier JW, Desai G, McCollum PT, Chetter IC. Peak wall stress measurement in elective and acute abdominal aortic aneurysms. J Vasc Surg. 2008 Jan; 47(1):17–22. [PubMed: 18060730]
7. Georgakarakos E, Ioannou CV, Kamarianakis Y, Papaharilaou Y, Kostas T, Manousaki E, et al. The role of geometric parameters in the prediction in the prediction of abdominal aortic aneurysm wall stress. Eur J Vasc Endovasc Surg. 2010 Jan; 39(1):42–48. [PubMed: 19906549]
8. Fillinger MF, Marra SP, Raghavan ML, Kennedy FE. Prediction of rupture risk in abdominal aortic aneurysm during observation: wall stress versus diameter. J Vasc Surg. 2003 Apr; 37(4):724–732. [PubMed: 12663969]
9. Borghi A, Wood NB, Mohiaddin RH, Xu XY. 3D geometric reconstruction of thoracic aortic aneurysms. Bio Med Eng Online. 2006 Nov.5:59.
10. Yi J, Ra JB. A locally adaptive region growing algorithm for vascular segmentation. Int J Imaging Syst Technol. 2003 Dec; 13(4):208–214.
11. Frangi AF, Niessen WJ, Vincken KL, Viergever MA. Multiscale vessel enhancement filtering. Med Image Comput Comput-Assist Intervention (MICCAI). 1998 Sep.1496:130–137.

12. Kass M, Witkin AP, Terzopoulos D. Snakes: active contour models. *Int J Comput Vision*. 1988 Apr; 1(4):321–331.
13. Osher S, Sethian JA. Fronts propagating with curvature-dependent speed: Algorithms based on Hamilton-Jacobi formulations. *J Comput Phys*. 1988 Nov; 79:12–49.
14. Bodur O, Grady L, Stillman A, Setser R, Funka-Lea G, O'Donnell T. Semi-automatic aortic aneurysm analysis. *Proc SPIE*. 2007 Mar.; 6511.
15. Hoyos MH, Ortowski P, Piatkowska-Janko E, Bogorodzki P, Orkisz M. Vascular centerline extraction in 3d mr angiograms for phase contrast MRI blood flow measurement. *Int J Comput Assist Radiol Surg*. 2006 May; 1(1):51–61.
16. Agam G, Armato SG III, Wu C. Vessel tree reconstruction in thoracic CT scans with application to nodule detection. *IEEE Trans Med Imaging*. 2005 Apr; 24(4):486–499. [PubMed: 15822807]
17. Zheng Y, Barbu A, Georgescu B, Scheuering M, Comaniciu D. Four-chamber heart modeling and automatic segmentation for 3D cardiac CT volumes using marginal space learning and steerable features. *IEEE Trans Med Imaging*. 2008 Nov; 27(11):1668–1681. [PubMed: 18955181]
18. Viola PA, Jones MJ. Rapid object detection using a boosted cascade of simple features. *IEEE Conference on Computer Vision and Pattern Recognition*. 2001 Apr.; 511–518.
19. Wang C, Li Y, Ito W, Shimura K, Abe K. A machine learning approach to extract spinal column centerline from three-dimensional CT data. *Proc SPIE*. 2009 Feb.; 7259.
20. Grabner H, Bischof H. On-line boosting and vision. *IEEE Conference on Computer Vision and Pattern Recognition*. 2006 Jul.; 260–267.
21. Shin H, Chavan A, Witthus F, Selle D, Stamm G, Peitgen H-O, et al. Precise determination of aortic length in patients with aortic stent grafts: in vivo evaluation of a thinning algorithm applied to CT angiography data. *Eur Radiol*. 2001 Apr; 11(5):733–738. [PubMed: 11372602]
22. TG, Pock. Robust segmentation of tubular structures in 3D volume data. Master thesis. Institut für Maschinelles Sehen und Darstellen Technische Universität; 2004.
23. Martufi G, Di Martino ES, Amon CH, Muluk SC, Finol EA. Three-dimensional geometrical characterization of abdominal aortic aneurysms: Image-based wall thickness distribution. *J Biomech Eng*. 2009 Jun; 131(6):061015. [PubMed: 19449969]
24. Shum J, Xu A, Chatnuntawech I, Finol EA. A framework for the automatic generation of surface topologies for abdominal aortic aneurysm models. *Ann Biomed Eng*. 2011 Jan; 39(1):249–259. [PubMed: 20853025]
25. Shum J, Martufi G, Di Martino ES, Washington CB, Grisafi J, Muluk SC, et al. Quantitative assessment of abdominal aortic aneurysm geometry. *Ann Biomed Eng*. 2011 Jan; 39(1):277–286. [PubMed: 20890661]
29. Fillinger MF, Racusin J, Baker RK, Cronenwett JL, Teutelin A, Schermerhorn ML, et al. Anatomic characteristics of ruptured abdominal aortic aneurysm on conventional CT scans: implications for rupture risk. *J Vase Surg*. 2004 Jun; 39(6):1243–1252.

Fig. 1.

Offline adaboost classifier tracking results and zoom-in rectangle (the detected centerline is at the center of the rectangle in the left column) for six representative images of U6 (A is immediately distal to the renal arteries; F is immediately proximal to the iliac bifurcation). The yellow and blue circles are the detected centroids by the Frangi filter based method and the offline adaboost classifier, respectively, while the red circles are the gold standard in the right column (they are not shown if they are out of field of view). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of the article.)

Fig. 2. Online adaboost tracking classifier results and zoom-in rectangle (the detected centerline is at the center of the rectangle in the left column) for six representative images of R2 (A is immediately distal to the renal arteries; F is immediately proximal to the iliac bifurcation). The blue circles are the detected centroids and the red squares are the golden standards in the right column. The yellow and blue circles are the detected centroids by the Frangi filter based method and the offline adaboost classifier, respectively, while the red circles are the gold standard in the right column. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of the article.)

Fig. 3.

(A) The detected centerline with online adaboost (in green) and the reference standard (in red) obtained from manual segmentation of R2 resulting in an average mean relative accuracy of 97.2%. The results shown are further smoothed and the accuracy is increased to a nominal 97.3%. (B) R7 is a case with extreme tortuosity (1.0316) is shown with an accuracy of 90.9%; it is inferred that extreme tortuosity can decrease the accuracy of the algorithm. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of the article.)

Fig. 4.

Tracking results and zoom-in rectangle (the detected centerline is at the center of the rectangle in columns 1 and 3) for the AAA phantom validation model: A–K are tracking with 0, 10%, 20%, 30%, 40%, 50%, 60%, 70%, 80%, 90%, and 100% Gaussian noise on the original image, respectively.

Fig. 5. Relationship of mean relative accuracy (non-dimensional) and Gaussian noise (non-dimensional) for the AAA phantom model.

Fig. 6. (A–F) Original images (left column), Frangi filter (middle column) and thresholding (right column) for six representative images of U6; (G) centerlines obtained with the online adaboost, the thinning algorithm based on Frangi filter, Mimics[®] processing, and the gold standard visualized inside the lumen boundary of U6; (H) mean relative accuracy of the online adaboost and the thinning algorithm demonstrated on ten data sets (five unruptured and five ruptured).

Fig. 7. Mean relative accuracy (non-dimensional) of the offline adaboost and online adaboost classifiers applied to the unruptured AAA data sets (A) and ruptured AAA data sets (B).

Fig. 8.

Tortuosity (non-dimensional) and maximum diameter (mm) of thirty ruptured and thirty unruptured AAA data sets. The mean tortuosity of the ruptured data sets was 0.4689 and for the unruptured data sets 0.2518.

Fig. 9. ROC analysis for rupture risk classification based on lumen centerline tortuosity. The average area under the curve (AUC) is 0.8713 ± 0.0027 .