Geometrical methods for level set based abdominal aortic aneurysm thrombus and outer wall 2D image segmentation exploiting the presence of calcifications

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Abstract

Abdominal Aortic Aneurysm (AAA) is a localized dilatation of the aortic wall. Accurate measurements of its geometric characteristics are critical for a reliable estimate of AAA rupture risk. However, current imaging modalities do not provide sufficient contrast between thrombus and surrounding tissue thus making the task of segmentation quite challenging. The main objective of this paper is to address this problem and accurately extract the thrombus and outer wall boundaries from cross sections of a 3D AAA image data set (CTA). New geometrical methods applying tools like the inversion mapping and the convex hull of a closed curve are used to trace these boundaries exploiting the presence of calcifications and to address the problem of leakage of a moving front into sectors of similar intensity. They are applied to the boundary curve obtained by a Level Set Method (LSM). A Fast Marching Method (FMM) is used initially to resolve the problem of speed that LSM’s

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present. The versatility of the methods is tested by creating artificial images which simulate the real cases. Segmentation quality is quantified by comparing the results with a manual segmentation of the slices of ten patient data sets. Sensitivity to the parameter settings and reproducibility are analyzed. This is the first work to our knowledge that utilises the level set framework to extract both the thrombus and external AAA wall boundaries.

*Keywords:* abdominal aortic aneurysm, level set methods, thrombus and outer wall segmentation, stopping criterion, wall thickness
1. Introduction

The aorta is the largest artery in the human body and the main blood vessel leading away from the heart. An Abdominal Aortic Aneurysm (AAA) is a permanent and irreversible localized dilatation of the abdominal section of this vessel. In clinical practice, diagnostic information of the 3D anatomy of an AAA is extracted non-invasively in-vivo, through Computed Tomography Angiography (CTA). AAA can grow progressively larger and may eventually rupture if not diagnosed and treated. Accurate estimation of AAA rupture risk remains an open problem. Numerous risk indicators beyond the peak transverse diameter, which is not always reliable, such as wall stress, wall stiffness, intraluminal thrombus thickness and wall tension have been proposed. To study these indicators and obtain a more reliable patient specific estimate of AAA rupture risk, accurate geometric characterization of the aneurysm is critical.

3D reconstruction of the complex anatomy of an AAA from medical imaging data can be achieved through either a slice-by-slice 2D segmentation of the structures of interest and the subsequent application of a 3D surface reconstruction method [1, 2] on the extracted boundary points, or by utilization of a 3D segmentation approach that extracts the surfaces of interest in one step [3–6]. A manual 2D segmentation is a rather time-consuming procedure with the additional drawback of large intra- and inter-observer variability. An automatic segmentation method, which is accurate and robust, would alleviate these problems. Level Set Methods (LSM’s) [7, 8] have been used in this direction due to their advantages compared to other methods, such as the formulation of the level set without a parametrization, resulting to a free
transform and change of its topology, and the relative ease in extending the method to 3D problems. Unfortunately, AAA segmentation is a rather complicated task for this type of methods, due to the low image contrast between thrombus and surrounding tissue that current imaging modalities provide and due to the strong edges that many neighboring structures present. As LSM’s are based on the modulus of the intensity gradient, the basic problem that arises is the distinction between the thrombus and the outer wall boundaries. Other drawbacks of these methods are the leakage of the advancing front into regions of similar intensity, not stopping at the outer wall boundary, and the fact that they are computationally expensive and thus slow. These problems explain the fact that LSM’s have been used in the past mainly for lumen segmentation.

Level Set Methods have been employed several times in the past for AAA outer wall segmentation. Subasic et al. [3] implemented a 3D LSM. Loncaric et al. [9] used a 2D LSM with a narrow band extension and introduced a stopping criterion curve. Magee et al. [4] combined the 3D deformable model, which is based on a triangulated mesh, for an initial segmentation, with an efficient level set implementation. Zhuge et al. [10] performed segmentation of the outer wall of AAA in five steps: preprocessing, global region analysis, surface initialization, local feature analysis and level set segmentation. Sonka et al. [6] applied a novel 4D optimal border detection algorithm for automatic surface segmentation of the aortic lumen.

Many other methods have been used for segmenting an AAA. De Bruijne et al. [11] presented an interactive method for aneurysm sac segmentation which relies on the fitting of a shape model to points with high correlation
with the reference contour. De Bruijne et al. [12] proposed a method based
on Active Shape Models (ASMs) [13], for automated delineation of the outer
aneurysm boundary in multiple MR sequences. Olabarriaga et al. [14] intro-
duced a new method for deformable model-based segmentation of thrombus
in AAA based on a 3D discrete deformable model (DM). Bodur et al. [15]
computed a centerline and presented an automatic segmentation of the aortic
border of the orthogonal slices using a novel variation of the isoperimetric
algorithm which incorporates circular constraints. Borghi et al. [16] re-
constructed patient-specific aneurysm models, combining information from
two different sets of MR imaging sequences. A manual segmentation and a
semi-automatic approach based on the region growing method were used. De
Putter et al. [5] created an initial 3D active object from the lumen centerline.
This is iteratively deformed via a time-discretized second order Newtonian-
evolution equation. Tam et al. [17] combined simple cropping and percentage
classification to create smooth and accurate boundaries between the metal
tynes that support the stent graft and the aorta and between the aneurysm
and air.

In all the above works, there is no distinction between thrombus and
wall, except from Borghi et al. [16], where the wall was assumed to have
a constant thickness along the entire aneurysm. To our knowledge, there is
only one recent work extracting the wall thickness of the AAA wall using,
however, a completely different approach: Martufi et al. [18] used intensity
histograms for the thrombus segmentation and a neural network for the outer
wall segmentation.

In this paper we utilize the level set framework and geometrical meth-
ods for a semi-automatic 2D segmentation of the thrombus and outer wall boundaries from cross sections of a 3D AAA image data set (CTA). The main objective of this paper is to accurately distinguish the thrombus and the outer wall boundaries whenever there is adequate information provided by the CTA scans for the arterial wall. This is the case when calcifications, which appear in AAA CTA images as very high intensity regions, are present, or there is sufficient intensity gradient or when information can be extracted from neighboring regions through interpolation. We present two geometrical methods which exploit the presence of calcifications. These methods reconstruct the thrombus and wall boundaries from the toothed-shaped, due to the presence of calcifications or weak intensity gradient change, boundary curve obtained by LSM. Our algorithms have been applied to ten patient data sets (450 slices) and the extracted results have been compared with a manual segmentation obtained from a medical expert.

2. Overview of the Methods

The basic steps of the segmentation framework proposed in this work, which combines the level set framework with geometrical methods, are shown in Fig. 1. Initially, a suitable cropping is performed to the selected slice of the AAA CTA scan to extract the region of interest in order to reduce segmentation time. The FMM is first applied with a proper modification. The user is interactively asked to enter up to four pairs of starting and ending points in order to obtain an optimized initialization used for the thrombus and the outer wall segmentations. For the thrombus boundary segmentation, the LSM is applied to the thrombus initialization to obtain a boundary curve
to which the thrombus boundary reconstruction method is then applied.

In the outer wall boundary reconstruction, the leakage issues of the advancing front are resolved by using the LSM to the thrombus initialization accompanied by one or more, if required, of the three stopping criteria introduced in this work. These are the Sector Criterion (SC), the Length Difference Rate Criterion (LDRC) and the Internal-External Contact Criterion (IECC). The leakage region of a slice can be also detected if it is desired by the user, using the Detection of Leakage Region (DLR) method. The outer wall boundary reconstruction method is then applied to the stopped boundary curve. As part of the method, the user is interactively asked to apply an appropriate thresholding to the image in order to locate the existing calcifications. In case the resulting thrombus and outer wall boundaries coincide in some regions, due to lack of calcifications and low intensity gradient, the Thrombus and Wall Boundaries Distance (TWBD) method is performed to the thrombus boundary to set a proper distance by an interpolation technique.

3. Level set framework

3.1. First phase of the model-Fast Marching Method (FMM)

The application of the level set framework consists of two phases. In the first phase we use the FMM. In this method, the position of the expanding front is characterized by computing the arrival time $T(x, y)$ of the front as it crosses each point $(x, y)$ [7]. If $\Gamma$ is the initial location of the interface then $T = 0$ on $\Gamma$. At time $t$ the moving front is given by

$$\Gamma(t) = \{(x, y) \in \mathbb{R}^2 | T(x, y) = t\}.$$  

(1)
Figure 1: Diagram of the segmentation methods.
The front is moving with a speed function in the normal direction \( g_t > 0 \), so the equation for the arrival function \( T(x, y) \) is

\[
g_t |\nabla T| = 1 .
\] (2)

Here, the proposed edge-indicator function, which restrain the evolving front from leaking out of the desired region is

\[
g_I(x, y) = \frac{1}{1 + \lambda |\nabla G_s * I(x, y)|^2} .
\] (3)

\( I \) is the image intensity and for \( \alpha \in \mathbb{R}^2 \), \( G_s(\alpha) \) is the Gaussian with width \( s \),

\[
G_s(\alpha) = \frac{1}{4\pi s} e^{-\frac{\|\alpha\|^2}{4s}} ,
\] (4)

which is used to reduce possible noise effects in the image. \( \lambda \) is a positive parameter. \( g_I \) is close to unity away from the boundaries and drops to zero near sharp changes in the image gradient. These changes presumably correspond to the edges of the desired shape. Efficient numerical schemes (upwind differencing) can be used to solve equation (2) (see [7]).

3.2. Second phase of the model-Level Set Method (LSM)

3.2.1. The Level Set Method equation

In the second phase we embed the initial position of the front as the zero level set of a higher-dimensional function \( \phi \) and we link the evolution of this function to the propagation of the front itself through a time-dependent initial value problem. At any time, the front is given by the zero level set of the time-dependent level set function \( \phi \). So, at time \( t \geq 0 \), the front is

\[
\Gamma(t) = \{(x, y) \in \mathbb{R}^2 | \phi(x, y, t) = 0 \} ,
\] (5)
where $\phi(x, y, 0)$ is the result of the FMM. The level set equation used in this phase is

$$
\phi_t = g_I(x, y)(\kappa - c)|\nabla \phi| + \nabla \phi \cdot \nabla P .
$$

(6)

$g_I$ is the same as before, $\kappa$ is twice the mean curvature, $c > 0$ a parameter used for faster convergence [7] and

$$
P(x, y) = -|\nabla G_s * I(x, y)| .
$$

(7)

This level set equation consists of three terms: $g_I\kappa|\nabla \phi|$ which acts as a smoothing term for the front away from the boundary under detection, $g_I(-c)|\nabla \phi|$ which is a driving expansion force and $\nabla \phi \cdot \nabla P$ which has a stabilizing effect, as $P$ constantly attracts the front to the edges in the image [7, 8, 19]. Sapiro [19] and Antiga [20] derive analytically an equation similar to (6). The only differences between this and the object-detection model adopted by Sapiro [19] are parameter $\lambda$ in (3) and the use of opposite signs for $c$. The forward Euler time discretization combined with high-order upwind differencing for the hyperbolic $\nabla \phi \cdot \nabla P$ term, Godunov’s scheme for the hyperbolic $g_I(-c)|\nabla \phi|$ term and central differencing for the parabolic $g_I\kappa|\nabla \phi|$ term are used to solve equation (6) (see [8]). Two other variational formulations of the LSM can be found in C. Li et al. [21] and Gelas et al. [22].

### 3.2.2. Detection of Leakage Region method (DLR method)

The main problem of the LSM in segmenting the outer aortic boundary is the leakage of the moving front (which is the thrombus initialization) into surrounding tissue in regions with similar image intensity to that of the aortic wall (see the yellow curve in Fig. 2(d)). Before addressing this issue, we
describe a method which can optionally be used to detect the regions where
the leakage takes place (see Fig. 2(a)). The method is called Detection of
Leakage Region (DLR) method. We first split the interior of the thrombus
initialization curve into sectors, using radials starting from its center of mass,
which are equally spaced by a user-defined sector angle $\phi$. The initialization is
evolving with the level set equation and a reinitialization as a signed distance
function takes place every ten iterations. A calculation of the area of each
sector is also made every ten iterations. We then calculate the relative change
of its area by comparing it with the sector area at the end of the previous
ten iterations. The evolution is interrupted when a local minimum of the
relative area change has appeared for all the sectors. When the curve stops,
we select the sectors for which the relative area change is of order $r$ for all
iterations, to be the ones that give the leakage region in the image. For the
choice of the value of $r$, see Sec. 5.1.

The use of the area change as a leakage detection has been previously used
[23]. However, herein we adopt a local approach, which allows the detection
of even small, localized leakages and also the precise identification of the
regions where the leakage occurs.

3.2.3. Three stopping criteria

The DLR method as described in Sec. 3.2.2 provides a stopping criterion
which we will call Sector Criterion (SC) (see Fig. 2(b)). The second stopping
criterion, called Length Difference Rate Criterion (LDRC), stops the curve
when the first minimum of the absolute value of the length difference rate of
the curve appears. Here, as length difference rate we consider the difference
of the total length of the curve every ten iterations. A sudden increase of
this rate is due to the leakage, so the curve has to stop (see Figs. 2(c,d)).

In the third stopping criterion, called Internal-External Contact Criterion (IECC), we consider an inner and an outer (to the aortic wall) initialization which move towards each other simultaneously; this is achieved by applying the level set equation (6), with parameter c positive in the case of the inner initialization and negative in the case of the outer initialization (with the same absolute value). The evolution is interrupted as soon as the two evolving curves come into contact. As an inner initialization we take the result of the FMM. As an outer initialization we consider the smallest circle containing the inner initialization, extended by a proper number of pixels p. For the value of p see Sec. 5.1. The final result is the inner curve at the time of contact of the two curves (see Figs. 2(e,f)).

A comparison of these three stopping criteria, in terms of the speed of their response to a leakage, is presented in Sec. 5.6. The resulting curve is then used for the reconstruction of the outer wall boundary (Sec. 4.2).

4. Geometrical methods for the reconstruction of thrombus and outer wall boundaries

4.1. Thrombus boundary reconstruction in the presence of calcifications

The presence of calcified deposits which are located within the AAA wall and the reduced contrast between thrombus and outer wall result in a “toothed” thrombus boundary, as the evolving curve enters the regions between the calcifications (see Fig. 3, that describes the method). To eliminate these regions, we consider the inversion mapping with respect to the curve Γ obtained by the LSM. The inversion mapping is the usual transformation
Figure 2: Results of the DLR method and the three stopping criteria for the same cross section: (a) The leakage regions detected by the DLR method are shown in black ($r = 10^{-2}$). The angle of the sectors is $\frac{\pi}{24}$. (b) The result of SC which stops the curve after 80 iterations. (c) The initial curve used for LDRC obtained by the FMM. (d) The black curve is the result of LDRC (40 iterations) and the yellow curve the result after 100 iterations, showing the leakage if LDRC had not been used. (e) The outer and the inner initialization used for IECC. (f) The final outer and inner curves, where the latter is the IECC result (60 iterations).
\( T(z) = 1/(z - z_0) \) in the complex plane, where \( z_0 = (x_0, y_0) \) is the center of mass of the domain bounded by \( \Gamma \). We consider the domain bounded by \( T(\Gamma) \) in the image plane under \( T \), and we find the points of its convex hull. To obtain the thrombus boundary we take the image under \( T^{-1} \) of the boundary of the constructed convex hull and we apply the LSM for a few iterations.

By using the inversion mapping, the possible existence of leakage does not affect the reconstruction of thrombus. So, the final result is not sensitive to the initialization of the method. Note that the stopping criteria are not used (they are used, however, for the reconstruction of the outer wall boundary, as we will explain in the following section).

4.2. Reconstruction of the outer wall boundary in the presence of calcifications

The circumferential distribution of calcifications in the AAA wall can be exploited to segment both the outer wall and thrombus boundaries. The first step in the procedure for the reconstruction of the outer wall boundary is a thresholding of the image to extract the calcification regions (Fig. 4(a)). The total area of the pixels above the threshold is computed and displayed and the user selects an upper and lower bound for the threshold. Then an iterative process seeks within this range the threshold value that minimizes the derivative of calcification area with respect to threshold value. If the result is satisfactory (i.e. the SNR of the final thresholded image is high, where calcifications are the signal and all the other parts constitute noise, and also judging from the grayscale image) it is accepted by the user. Otherwise a new threshold range is specified and the process is repeated until a satisfactory result is obtained.
Figure 3: The steps for the reconstruction of the thrombus boundary of the cross section of Fig. 2: (a) The yellow curve is the thrombus initialization obtained by the FMM and the black curve the result of the LSM (200 iterations). (b) The image of the black curve under the inversion mapping with respect to its centroid (in orange) and the boundary of its convex hull (in black) are depicted. (c) The preimages of the points of the convex hull under the inversion mapping form a domain, whose boundary is the yellow curve. (d) The yellow curve is the final result, after applying the level set equation for 20 iterations.
Following the application of a stopping criterion to the evolution of the thrombus initialization with the LSM, we consider the extracted curve and the smallest circle containing this curve. At least one point of each calcification will be interior to this circle (see Fig. 4(b)). We then apply the region growing method with each calcification pixel interior to the circle acting as a seed and we use the threshold extracted in the previous step as a rule of similarity to locate all the calcification pixels in the image. We then compute the convex hull of the union of all mid-edge points of the calcification pixels and the points of the curve which was the result of the LSM on the thrombus initialization curve. The boundary of the convex hull (the dashed black curve in Fig. 4(e)) will certainly contain all the calcifications. The procedure is concluded by applying the level set equation to this boundary, but taking an inward motion this time, aiming at a smoother result which is more biologically plausible (yellow curve in Fig. 4(e)). Fig. 4(f) depicts both the thrombus and outer wall boundaries extracted by the methods presented in this and the previous section which exploit the presence of calcified deposits.

4.3. Case of few (or no) calcifications-Thrombus and Wall Boundaries Distance (TWBD) method

In the case where there exist only few or no calcifications inside the AAA wall, regions might appear in the image, where the reconstructed thrombus and outer wall boundaries obtained using the methods of Sec. 4.1 and 4.2 almost coincide. In some regions, though, even when calcified deposits are absent, the two reconstructed boundaries may not coincide due to the use of the LSM, if sufficient intensity contrast between thrombus and outer wall exists. In general, regions where the two boundaries almost coincide are rare.
Figure 4: (a)-(d) The steps for the reconstruction of the outer wall boundary in the cross section of Fig. 2: (a) Appropriate thresholding to locate the calcifications. (b) The LSM extracted curve in black (using LDRC, 40 iterations) and the smallest circle containing this curve are depicted. (c) Detection of the calcification pixels (shown in black) using this circle. (d) The dashed curve is the boundary of the convex hull of the union of the mid-edge points of these pixels and of the black curve depicted in (b). The yellow curve is the final result, after applying the level set equation to this boundary for 20 iterations. (e) depicts the result of the methods (thrombus and outer wall boundaries in black and yellow, respectively) for the same cross section.
in a cross section with significant presence of calcifications. Moreover, such
regions cover approximately 40% of the outer wall contour in the case of the
cross sections with almost no calcifications taken from the patient data sets
studied in Sec. 5. Assuming that wall thickness distribution should present
a smooth continuity, interpolation can be applied to extract wall thickness
in regions where thrombus and outer wall boundaries are too close to each
other.

We consider many rays starting from the centroid of the thrombus, so
that two successive rays form the same angle $\phi$, and find the distance (wall
thickness) between the two intersection points of each ray with the thrombus
and outer wall curves. We find the thrombus points which are connected
with distances of order $d/10$ mm. For the value of the parameter $d$, see
Sec. 5.1. For each point, we find the nearest $n$ thrombus points in the
counterclockwise direction whose distances (wall thicknesses) are of order $d$
mm and calculate the mean of these distances. Then, we find which of these
$n$ points has distance closer to this mean. We denote this distance as $d_l$ and
the distance found following the same procedure in the clockwise direction
as $d_r$. Then a linear interpolation between $d_l$ and $d_r$ is made to obtain a new
wall thickness (and a new thrombus point) for each point in the region with
distances of order $d/10$ mm. Finally, we apply the level set equation to the so
reconstructed thrombus boundary for a small number of iterations (e.g. 10)
taking an outward motion, to obtain a smoother and physiologically more
realistic result.

Numerical tests have shown that for $n \in \{4, 5, \ldots, 10\}$ the results are very
similar, because of the very small angle $\phi$. Figure 5 shows the result of the
method for two cross sections, one with few calcifications, approximately 30% of the boundary parameter (Fig. 5(a)) and one with almost no calcifications, approximately 8% of the boundary parameter (Fig. 5(d)).

5. Experiments

5.1. Implementation of the FMM and LSM

We applied the FMM using the MATLAB-based Fast Marching Toolbox [24] created by Gabriel Peyré to obtain a thrombus initialization for the LSM. We took $\lambda = 50$ for $g_I$ and we used a $5 \times 5$ Gaussian filter with $s = 1$. In this Toolbox, the user typically gives a pair of points, a start and an end point (a point, here and in the rest of the paper, is the center of a pixel). The front is initialized with the start point inside the desired region and expands until the solution has almost reached the desired edge. It stops expanding when it meets the end point for the first time. These points are specified either by their coordinates or interactively by cursor positioning on the image.

It should be noted that a good initialization is important for a satisfactory final result. So, the initial curve: a) must be close to the contour we want to detect, b) must not have leaked out of it, and c) should not have been captured by the lumen in some region. In order to obtain an initialization with the above principles, some general rules are provided for the selection of the start and end points: the start point is chosen either near a conceivable center of mass of the thrombus or next to a region of high contrast, but end point should be chosen at a low contrast region, in order to avoid the leakage.

Unfortunately some images are rather difficult to segment and extract a proper thrombus initialization (due to many leakage problems or strong
Figure 5: Application of the TWBD method for two cross sections with few (a) and no (d) calcifications ($d = 1$ mm, $n = 4$ and $\phi = \frac{\pi}{200}$). Thrombus and outer wall boundaries coincide in some regions in (a), due to the lack of calcifications. The result of the TWBD method is shown in (b) and the final result, after applying the LSM, in (c). A proper distance between the two boundaries has been settled. A cross section with very few calcifications is depicted in (d). (e) presents the intensity profile along the dashed line of (d). This shows that there is intensity difference inside the wall (regions A-B and E-F) compared to thrombus (regions B-C and D-E). The two boundaries may coincide in some regions but the existence of regions with distance between the boundaries due to this difference is exploited via the TWBD method. The final thrombus boundary (dashed line), after applying the TWBD method and the LSM, and the outer wall boundary (continuous line) are shown in (f).
responses from neighboring objects, such as the spine, lumen and calcifications). To solve this problem we modified the aforementioned Toolbox to allow the user to select up to four pairs of points (this is the minimum number of pairs required to produce a good initial curve for the most difficult to segment cases and it was determined after extensive experimental work). In this case the initialization is the union of the results extracted for each pair. For the 2D version of the Toolbox the code is in C++ which makes the application of the method very fast.

For the implementation of the LSM we used the Level Set Toolbox [25] created by Baris Sumengen. In this Toolbox there are two basic routines, the first one for the reinitialization of the level set function $\phi$ as a signed distance function (usually every five or ten iterations) so that $\phi$ remains smooth as it evolves and the second one for the evolution of the curve where all three types of motion are applied (motion in the normal direction, motion involving mean curvature and motion in an externally generated velocity field). We took $\lambda = 0.1$, $c = 5000$ and a $5 \times 5$ Gaussian filter with $s = 1$. Moreover, we took $r = 10^{-2}$ as the order of the relative area change in the DLR method, $p = 1.5$ pixels in the IECC and $d = 1mm$ as the order used in the TWBD method. For an explanation of the values of all the parameters used and for a sensitivity analysis, see Sec. 6.

To perform the thrombus boundary segmentation, the LSM is applied to the thrombus initialization for 200 iterations before the boundary is reconstructed with the method described in Sec. 4.1. The above number of iterations has been obtained after experimentation with various values and it is parameter-independent. In contrast to that, the number of iterations
of the LSM (applied again to the thrombus initialization) for the outer wall segmentation is determined by a stopping criterion.

5.2. Results for artificial images

We created some artificial images (Fig. 6) to test the versatility of our methods and the two major problems that CTA images of an AAA present: difficulty in distinguishing the thrombus and the outer wall and leakage outside the outer wall. Figure 6(a) shows five areas of different intensity, with constant intensity in each of them. The contrast ratio is 1138:1 and, assuming that the intensity value for black (background) is 0, “lumen”, “thrombus”, “outer wall” and the four “calcifications” have constant intensity values of 209, 116, 162 and 1137, respectively. There is also a region in which “thrombus” and “outer wall” have similar intensity (right side). Noise was not added to the image since noise was quite low in the data sets of our experiments and the Gaussian filter used properly diminishes its effects.

Figure 6(d) shows a different test image, where we have taken the (extreme) case of exactly the same intensity for “thrombus” and “outer wall”. There are also two outer leakage regions and eight “calcifications”. Contrast ratio and intensity values are the same as in Fig. 6(a). The intensity value inside “thrombus”, “outer wall” and leakage regions is 116. No noise was added to this image, as well. In Fig. 6(f) the maximum error in the two leakage regions is about six pixels, while the borders of these regions are placed 15 pixels outside the “outer wall”. In these artificial images the pixel size is approximately equal to 0.265mm, so this maximum error is about 1.59mm. This shows the effectiveness of LDRC. In addition, due to the presence of the eight “calcifications” a satisfactory result is extracted, although there is
no intensity difference between the two areas.

5.3. Manual and semi-automatic segmentation

A quantitative validation of our algorithm was performed using ten CTA scans acquired from ten different patients at the University Hospital of Heraklion. All the slices consist of $512 \times 512$ pixels and the pixel size varies in these data sets from 0.639mm to 0.898mm. The number of slices that contained aneurysmal tissue in each data set varies from 29 to 56.

A vascular surgeon made a selection of the slices of interest, between the proximal and distal ends of the aneurysm and selected points for the outer wall boundary for each slice. The number of the points was large enough so that details of the shape of the boundaries could be captured. The contours were then obtained by linear interpolation of the selected points. For the thrombus, the aforementioned difficulty of similar intensity with the surrounding tissue is presented in many CTA slices and makes the task of selecting points which will provide a closed curve as its boundary rather difficult or even impossible if a guess is not allowed. To avoid this (such a guess) and use the manual segmentation result as our “gold standard” to validate our methods, the expert was requested to provide for each slice only the points of the thrombus boundary that he was certain of their position.

The manual segmentation was performed by a point selection tool of the medical image processing software ImageJ [26]. We then applied our segmentation method to all these slices of the ten data sets, tracing the thrombus and outer wall boundaries for each slice. A suitable cropping of each slice was made beforehand, selecting the region of interest, to decrease segmentation time as much as possible. We used parameter values mentioned
Figure 6: Artificial images ((a) and (d)) used to test the flexibility of the methods. (a) is characterized by a region with similar intensity between “thrombus” and “outer wall”. (b) shows the thrombus initialization from the FMM and (c) depicts the result of our methods for the two boundaries. In artificial image (d), the same intensity between “thrombus” and “outer wall” has been set and there are two outer leakage regions. The DLR method result is shown in (e), where the leakage regions are in yellow (angle $\frac{\pi}{4}$). (f) shows the final result (LDRC is used, 30 iterations).
in Sec. 5.1 and LDRC as the stopping criterion of choice.

5.4. Validation for the outer wall boundary

The quantities used to evaluate segmentation error for the outer wall boundary for a slice were: Absolute and Relative Area Error (AAE and RAE), Mean Distance (MEDIS), Hausdorff Distance (HADIS) and Area Overlap (AO). We also extracted the Absolute and Relative Volume Errors (AVE and RVE) for each patient. AAE and RAE are given by

\[
AAE = |A(M) - A(A)| \quad \text{and} \quad RAE = \frac{AAE}{A(M)},
\]

where \(A(M)\) and \(A(A)\) are the areas of the manual and automatic contours, respectively, measured in \(cm^2\).

Mean and Hausdorff distances are used to quantify the similarity of the two curves. They are defined for the point clusters A and B as

\[
MEDIS(A, B) = \max\{m(A, B), m(B, A)\}, \quad (9)
\]

\[
HADIS(A, B) = \max\{h(A, B), h(B, A)\}, \quad (10)
\]

where

\[
m(A, B) = \text{mean}_{a \in A}\{\min_{b \in B}\{d(a, b)\}\}, \quad (11)
\]

\[
h(A, B) = \max_{a \in A}\{\min_{b \in B}\{d(a, b)\}\}, \quad (12)
\]

where \(d(a, b)\) is a L2 norm for the points \(a\) and \(b\). The main issue regarding these distances is that they only take into account the sets of points on both curves and do not reflect the course of the curve. We overcome this problem by finding 400 points on each of the two contours. These points are taken as the intersections of the curve with rays which start at the centroid of the
contour and each two successive ones form an angle equal to \( \frac{\pi}{200} \). In this way, we consider a large amount of points which are uniformly distributed along these convex or, in the worst case, star-shaped curves. We then calculate their MEDIS and HADIS (in mm), making these quantities together a very reliable measure of the resemblance of the two contours. Mean Distance denotes how close they really are and Hausdorff Distance identifies any outliers, which may be hidden in the averaging process of the Mean Distance, by providing the worst possible disagreement between the curves.

Area Overlap is defined as

\[
AO = 2 \frac{A(A \cap M)}{A(A) + A(M)},
\]

(13)

where \( A(A \cap M) \) is the area of the intersection of the manual and automatic contours. For the per patient results, Absolute and Relative Volume Errors are defined as follows:

\[
AVE = |V(M) - V(A)| \quad \text{and} \quad RVE = \frac{AVE}{V(M)},
\]

(14)

where \( V(M) \) and \( V(A) \) are the volumes of the manual and the semi-automatic segmentation, respectively. Volume for a data set is calculated as the product of the sum of the areas of the curves for all the slices of the set and the slice thickness [27]. Let us note that we do not present these volume errors as an error indication of the actual 3D volume. Given the fact that the in-slice distance is the same for all slices, the volume errors could be considered as a weighted error of all slices for each patient.

Table 1 summarizes the average results for the outer wall over the ten patient data sets. The mean of a quantity in these tables is the mean of the ten \( M_i \)'s, \( i = 1, \ldots, 10 \), where \( M_i \) is the mean of this quantity over the
slices of the $i_{th}$ data set. Minimum and maximum values are also referring to these ten $M_i$’s. Figure 7 presents analytically the results for each of the data sets for three of the above quantities used for evaluating the outer wall boundary segmentation error, namely the Mean Distance, the Hausdorff Distance and the Area Overlap. In Fig. 8 there are two slices with the manual and automatic outer wall contours superimposed (a) and (b).

Table 1: Summarized results for the outer wall: Mean, standard deviation, minimum and maximum values over ten patient data sets are provided for the quantities used to evaluate the segmentation error.

<table>
<thead>
<tr>
<th></th>
<th>mean±s.d.</th>
<th>[min,max]</th>
</tr>
</thead>
<tbody>
<tr>
<td>No. of slices</td>
<td>45 ± 7</td>
<td>[29, 56]</td>
</tr>
<tr>
<td>Absolute Area Error (AAE, cm$^2$)</td>
<td>1.147 ± 0.355</td>
<td>[0.654, 1.729]</td>
</tr>
<tr>
<td>Relative Area Error (RAE, %)</td>
<td>6.0 ± 3.3</td>
<td>[2.5, 13.1]</td>
</tr>
<tr>
<td>Absolute Volume Error (AVE, cm$^3$)</td>
<td>4.563 ± 2.083</td>
<td>[0.237, 7.079]</td>
</tr>
<tr>
<td>Relative Volume Error (RVE, %)</td>
<td>4.0 ± 3.7</td>
<td>[0.3, 12.4]</td>
</tr>
<tr>
<td>Mean Distance (MEDIS, mm)</td>
<td>1.320 ± 0.318</td>
<td>[0.978, 1.910]</td>
</tr>
<tr>
<td>Hausdorff Distance (HADIS, mm)</td>
<td>4.160 ± 1.096</td>
<td>[2.656, 5.999]</td>
</tr>
<tr>
<td>Area Overlap (AO, %)</td>
<td>94.6 ± 1.8</td>
<td>[91.8, 97.0]</td>
</tr>
</tbody>
</table>

5.5. Validation for the thrombus boundary-Comparing wall thickness

The fact that the manual segmentation for the thrombus after the linear interpolation of the selected points includes only segments and not a closed curve for some slices is due to our desire of comparing only the points that the expert is certain of their position (see Sec. 5.3). We introduce a method for approximating the mean wall thickness of an AAA in a slice-by-slice fashion,
Figure 7: Evaluation of the segmentation error for the outer wall boundary: Mean Distance (MEDIS) in (a), Hausdorff Distance (HADIS) in (b) and Area Overlap (AO) in (c) for each of the ten data sets. Mean and Maximum values are depicted by the dots and the bars, respectively. Standard deviation is indicated by the error bars.

which is used as a thrombus boundary validation. Following proper alignment of the thrombus and outer wall curves, we draw rays from the centroid of the wall, so that every two successive rays form the same angle \( \phi \). Six successive rays define a sector, so there are \( \frac{2\pi}{5\phi} \) sectors (the angle of each sector is \( 5\phi \) and \( \phi \) should be chosen so that \( \frac{2\pi}{5\phi} \in \mathbb{N} \)). For a ray which intersects both the thrombus and outer wall curves, we define Ray Wall Thickness (RWT) to be the distance between these two intersection points. For a sector we define Sector Wall Thickness (SWT) to be the mean of the existent RWT over the rays of the sector. The mean SWT over all the sectors of all the slices of an AAA scan provides an evaluation of the mean wall thickness of the AAA.

One of the advantages of this method for estimating the wall thickness is that since we can increase the number of the sectors by reducing angle \( \phi \), we can have a detailed analysis of the wall thickness along the thrombus boundary. In addition, the result is independent of the number of points of the thrombus and outer wall curves. In Fig. 8(c) there is a slice which shows the manual and automatic thrombus and outer wall boundaries.

SWT is not calculated for all the sectors in the manual segmentation. For
Figure 8: Examples of semi-automatic (continuous line) and manual (dashed line) segmentations for some slices, for the outer wall ((a) and (b)) and for the wall thickness ((c)). In (c) the method for evaluating mean wall thickness is depicted, with manual and automatic thrombus in black and manual and automatic wall in yellow. The angle $\phi$ of the rays is $\frac{\pi}{60}$. The first sector is shown in magenta.

For each patient that SWT is calculated, we define the Absolute Error of the Sector Wall Thickness (AESWT) as

$$AESWT = |MANSWT - AUTSWT|,$$  \hspace{1cm} (15)

where MANSWT is the SWT of this sector for the manual segmentation and AUTSWT is the SWT of the corresponding sector for the semi-automatic segmentation. Corresponding sectors are the ones which possess the same order when they are sorted by moving clockwise starting from the first sector shown in Fig. 8(c) in magenta. The mean AUTSWT and mean MANSWT for each patient (which is the mean over all sectors) give a good approximation of the mean wall thickness of the AAAs that the two methods produce. For each patient we calculated the Absolute and Relative Errors of the Mean Sector Wall Thickness (AEMSWT, REMSWT), defined as

$$AEMSWT = |meanAUTSWT - meanMANSWT|$$  \hspace{1cm} (16)
and

\[ REMSWT = \frac{AEMSWT}{\text{meanMANSWT}}. \]  \hspace{1cm} (17)

Table 2 includes the average results of all these quantities for the ten data sets we used. The mean of a quantity in these tables is the mean of the ten \( M_i \)'s, \( i = 1, \ldots, 10 \), where \( M_i \) is the mean of this quantity over the slices of the \( i \)th data set. Minimum and maximum values are also referring to these ten \( M_i \)'s. The mean wall thickness for the ten patients is 2.575 ± 0.393mm and 2.993 ± 0.545mm for the semi-automatic and the manual segmentation, respectively. These results are close to the results of Di Martino et al. [28] where twenty six rectangular, circumferentially oriented AAA wall specimens were obtained fresh from the operating room from 16 patients undergoing elective repair of their AAA and the wall thickness measured was 2.5 ± 0.1mm, while 13 specimens were resected from nine patients during repair of their ruptured AAA and the measurement for wall thickness was 3.6 ± 0.3mm. This shows the effectiveness of this method. The difference between the manual thickness and the result of Di Martino et al. [28] can be explained: Our results are obtained from cross sections only, contrary to the referenced work where specimens were measured (that is why we presented this method basically for thrombus boundary validation and then for evaluating the mean wall thickness, not as a new method for a very accurate wall thickness measurement). In addition, the large manual wall thickness of the 3rd, 6th and 7th data sets (see Fig. 9(c)) which contribute to the large average manual mean wall thickness over the ten data sets, are due to the existence of quite a lot of large calcifications situated all around the circumference of the AAA wall.
Table 2: Summarized results for the wall thickness, which is used as evaluation of the thrombus boundary segmentation error: Mean, standard deviation, minimum and maximum values over ten patient data sets are provided for all the quantities. Angle $\phi = \frac{\pi}{60}$.

<table>
<thead>
<tr>
<th></th>
<th>mean±s.d.</th>
<th>[min,max]</th>
</tr>
</thead>
<tbody>
<tr>
<td>No. of slices</td>
<td>45 ± 7</td>
<td>[29, 56]</td>
</tr>
<tr>
<td>Absolute Error of the Sector Wall Thickness (AESWT, mm)</td>
<td>1.127 ± 0.292</td>
<td>[0.742, 1.683]</td>
</tr>
<tr>
<td>Automatic (segmentation) Sector Wall Thickness (AUTSWT, mm)</td>
<td>2.575 ± 0.393</td>
<td>[1.992, 3.129]</td>
</tr>
<tr>
<td>Manual (segmentation) Sector Wall Thickness (MANSWT, mm)</td>
<td>2.993 ± 0.545</td>
<td>[2.192, 3.814]</td>
</tr>
<tr>
<td>Absolute Error of the Mean Sector Wall Thickness (AEMSWT, mm)</td>
<td>0.510 ± 0.411</td>
<td>[0.017, 1.115]</td>
</tr>
<tr>
<td>Relative Error of the Mean Sector Wall Thickness (REMSWT, %)</td>
<td>15.84 ± 11.38</td>
<td>[0.66, 29.23]</td>
</tr>
</tbody>
</table>

The mean AEMSWT and REMSWT for the ten data sets are 0.510mm and 15.84%, respectively. In absolute terms this relative error may be considered large. Martufi et al. [18] reports an average relative difference in AAA wall thickness of 7.8% after validating a wall thickness estimation algorithm by comparing with discrete point measurements taken from a cadaver tissue model. However, as no other similar result (i.e. using a manual segmentation) is available in the literature, we cannot deduce that our result is indeed large. In addition, the absolute error can be considered acceptable as it corresponds approximately to 0.68 pixels, taking into consideration the mean pixel width for the ten data sets. This shows that the thrombus boundary segmentation, using our methods, is fairly accurate. Tests showed that these results are not sensitive to the choice of angle $\phi$ and for every angle smaller than $\frac{\pi}{60}$ the differences of the errors of Table 2 are very small. Figure 9 presents analytically the results for each of the data sets for AESWT, AUTSWT and MANSWT. Some difficult to handle case-slices, which provide
some of the worst results as shown in this figure, are presented in Sec. 7.1 and highlight the limitations of our methods.

5.6. Comparison of the three stopping criteria

The most preferable stopping criterion is the one that allows the fewest iterations for the LSM in outer wall segmentation. To compare the three criteria, we applied them on three out of the ten data sets. We used 131 slices for this comparison (see Fig. 10). LDRC gave the best results in 68% of these slices, IECC in 37% and SC in 5%. The performance of the SC is due to the fact that there might be the case of even a single sector for which the relative area change is continuously reducing (so the curve delays to stop). On the other hand in IECC, since the motion of the two curves is produced by applying the level set equation, there might be a delay of their contact. The types of leakage regions in a slice (large or small, many or few) do not prohibit the use of any of the three criteria. However, IECC allows more iterations than the other two when there is a narrow leakage region, as the inner curve delays to enter the leakage region and intersect the outer curve.
Figure 10: Comparison of the performance of the three stopping criteria (SC, LDRC and IECC) for three data sets. The most preferable stopping criterion (the one which detects the leakage earlier than the others) is: LDRC in 73% of the slices in (a), LDRC in 84% in (b) and IECC in 52% in (c).

LDRC generally detects leakage earlier than the other two but not always: IECC can be more preferable (see Fig. 10(c)) if leakage regions are large and wide. On the other hand, if there are a lot of small leakage regions, SC will have a faster response. Ideally, one would apply all three criteria and select the one which allows the fewest iterations, but this is time consuming. In our experiments we used the LDRC.

6. Sensitivity analysis-Reproducibility-Segmentation time

The parameters used are quite a few and we performed experiments to test the sensitivity of the results to the parameter settings. As far as the gaussian filter is concerned, a small change to the size of the filter or to the width $s$ does not affect the accuracy of the method. Parameter $c$ (chosen equal to 5000) makes the curve to move faster and increases the rate of convergence. Other values of the same order of magnitude for $c$ provide very similar results at almost the same segmentation time. The quality of the
results is slightly more sensitive to the parameter $\lambda$, which is the weight of the squared modulus of the convolution of the intensity with the gaussian. From our experiments we concluded that, for the LSM, $\lambda$ should be of order of magnitude $10^{-2}$ when $\sigma = |\max I - \min I|$ is of order $10^3$ (where $I(x, y)$ is the intensity of the point $(x, y)$ in the 2D image). For every decrease of order of magnitude for $\sigma$ (something which usually happens after cropping the image) there should be a similar increase in the order of magnitude for $\lambda$. Image cropping for almost all the cases of the experiments resulted in a $\sigma$ of order $10^2$, therefore we set $\lambda = 0.1$. With this choice, $g_I$ is approximately equal to 1 away from the image boundary (so the front moves fast in these regions) and approximately equal to 0 near the target boundary. If $\lambda$ is larger, the front motion away from the target boundary will be rather slow and if it is smaller the front will not stop at the boundary being tracked, as leakages will occur. This choice of the order for $\lambda$ is not necessary in the FMM due to the speed of this method, so, setting a large value to $\lambda$ ($\lambda = 50$) is sufficient. In conclusion, a slight change in the value of a parameter does not influence the results of the method, thus verifying its robustness.

The value for the order of magnitude of the relative area change in the DLR method ($r = 10^{-2}$ or greater) does not depend on any factors due to the local nature of this method and has been obtained after experimentation. Sectors characterized by a lower order than that refer to the parts of the curve which tend to stop, so they are not taken into account. The extension of the smallest circle containing the inner initialization by $p = 1.5$ pixels in the IECC is the same for every case and with this choice (which is the result of experiments) we make sure that the inner and outer curves do not, initially,
intersect and that they are in proximity to each other. This will allow the inner curve to evolve so that a more accurate (due to the LSM) result is obtained. Finally, in the TWBD method, the order $d = 1\, mm$ is the obvious choice, given the popular mean wall thickness of approximately $2\, mm$, so that a proper distance is set in regions where thrombus and outer wall boundaries are too close to each other.

We will now refer to the sensitivity of the result to the user intervention which amounts to the choice of the start and end points of the FMM. A small perturbation of the start or end point placed for the thrombus initialization may lead to an unsatisfactory result. This is due to the non-uniform intensity distribution that exists near the thrombus boundary or within the thrombus region and the fact that the user must select points of similar intensity for each pair, with a similar intensity path existing between them. These issues have been addressed with the modifications of the FMM presented in Sec. 3.1, in order to establish the reproducibility of the results in a more efficient way.

Time is another important factor in an AAA segmentation, as in a clinical setting it becomes a time-critical application. Execution time of the methods for the initialization and segmentation of thrombus and outer wall boundaries was extracted in five data sets (patients 6 to 10), following appropriate cropping of the initial image. The mean initialization, thrombus, outer wall and total processing times per slice for the five data sets were 1.30, 1.56, 2.69 and 5.96 minutes, respectively. The total processing time for a slice is the sum of the initialization, thrombus and outer wall times increased by 25 seconds, which is the typical execution time of the TWBD method that was
used in almost all cases. These time results include delays caused by the user, such as the time required to make a correct decision regarding the start and end points in the FMM. In addition, the direct user involvement is about 24% of the total processing time. LDRC has been used for these results, as well. These execution times can be considered satisfactory, provided that the codes are in MATLAB (we used a Pentium 4 with CPU 3 GHz and 1 GB of RAM). The wall-clock time for each run of the code implementing the DLR method is about five minutes. Some apparently long execution times are due to the reinitialization routine which is used every ten iterations, in which the level set function becomes a signed-distance function by solving a computationally expensive level set reinitialization equation [8]. Suggestions for reducing segmentation time are made in Sec. 7.1.

7. Discussion

7.1. Limitations

The method proposed to segment the AAA outer wall and thrombus boundaries rely on the LSM which is an intensity gradient based technique. As a result the method relies on the presence of an intensity gradient in the vicinity of the boundary that is strong enough to attract the LSM front. Such intensity gradient can be either due to the contrast produced by the imaging method at the interface between tissue of different composition such as the arterial wall and the intraluminal thrombus and/or the existence of calcified deposits in the arterial wall. Our methods exploit the latter source of contrast by introducing various geometrical tools to overcome the insufficient presence of the former source of image contrast. Therefore for the method to
be effective some source of image contrast should be present. This is depicted in Fig. 11(a), where one of the largest maximum HADIS of the ten data sets for the outer wall, equal to 8.192mm, appears (see Fig. 7(b), patient number 5).

As the basic information utilized are calcifications, a reference should be made regarding the frequency of their presence inside the AAA wall. In Siegel et al. [29] thin discontinuous calcifications were found in 27/52 cases in ruptured group and 23/56 in unruptured group. Unfortunately Siegel et al. [29] did not quantify their distribution. Lindholt et al. [30] recorded the circumferential distribution of calcification at the maximal diameter cross section and reported 62/122 AAA patients having more than 50 % of that circumference covered by them. Li et al. [31] studied the effects of calcifications on the computed AAA wall stress distribution and reported for a group of 20 patients a mean value of 4.6 % calcification per total AAA volume ratio. Moreover, a careful study of the geometric characteristics of the AAA wall when calcifications are present is important as their presence may cause a significant alteration of the stress distribution, thus affecting rupture risk assessment [32, 31].

A further limitation is related to the presence of sources of high image contrast, such as the spine, very close to the outer wall, which attract the propagating LSM front away from the tracked boundary. In order to avoid considering the spine as a calcification from our method, due to thresholding, which would result in a large error in the wall boundary detection, we select a large threshold in the method we use for the reconstruction of the outer wall boundary. Inevitably with this choice, some calcifications are not detected
and are thus excluded from the outer wall boundary created (see Fig. 11(b), where the maximum AAE among the slices of the third data set, equal to 2.821cm², appears).

As the method is based on the assumption that calcified deposits are located within the arterial wall in cases where this is not true and they are located within the thrombus then incorrect thrombus boundary tracking results. This is the main cause of the appearance of large values of AESWT in certain slices of the data sets. In Fig. 11(c) there is a slice where this internal calcifications issue is demonstrated and a large AESWT, equal to 7.03mm, appears (see Fig. 9(a), the maximum value of patient number 3). A final issue which is a limitation in terms of the clinical application of the method is the relatively long time required to complete the segmentation which was in this implementation approximately 6 minutes per slice. However, this issue can be resolved by taking measures such as using a narrow band LSM, avoiding the reinitialization step of the method by adding an extra term to (6) associated to an internal energy which penalizes the deviation from a signed distance function and by coding the methods in C++.

7.2. Comparison with other methods

We next compare quantitatively our results with that of related works. Subasic et al. [3] used a 3D level sets method, requiring minimal user intervention. They report an average relative error on a slice 12.35%. 11 real patient data sets were used for the validation (the mean RAE of our segmentation method for the outer wall is 6%, see Table 1). The method is not performing accurately where the AAA has significant concavities. Magee et al. [4] reported a total segmentation time of less than two hours. A com-
Figure 11: Examples of cross sections which are difficult to segment and show the limitations of the methods. Continuous lines depict the semi-automatic segmentation and dashed lines the manual one. The outer wall boundary is in yellow and the thrombus boundary (in (c)) is in black.

Comparison between the automatic method and an interactive segmentation was made by evaluating the minimum distance slice by slice, and the mean was 0.57mm (four volumes were used). In Zhuge et al. [10] user intervention is not required beyond identifying the most proximal and distal slices concerning the aneurysm. The method assumes that the aneurysm is roughly circular in transaxial cross section. The mean segmentation time per patient is $7.4 \pm 3.8$min(s.d.), implying a very fast method. The results of a comparison with a manual tracing for the outer wall were 3.5% for the mean RVE and $0.8cm^2$ for the mean AAE (20 patient data sets were used). Our corresponding results are 4.0% and $1.147cm^2$, respectively (see Table 1).

In De Bruijne et al. [11] the time required for expert segmentation may be reduced by a factor of six, but manual intervention is required in one of six slices and the user must redraw the entire contours. Image data from 23 patients were used and the comparison with a manual segmentation provided an average RVE of 1.5% and an average volume overlap of 95.8% (the mean
AO for the data sets we used is 94.6%, see Table 1). In De Bruijne et al. [12] obtained volume errors with respect to a manual segmentation are comparable to manual inter-observer errors in roughly 90% of the cases (the mean unsigned volume error is 4.0% and the average volume overlap is 94%, values very close to the corresponding ones in Table 1). In Olabarriaga et al. [14] the average per case deformation time for 17 scans was 41 ± 69.3 secs. However, in ten (out of 17) cases, small and localized bumps into the bowels and vena cava were observed and would possibly require manual correction. In addition, the segmentation method’s performance depends on the quality of training. A comparison of the results of the method with a manual segmentation for 17 patient scans provided a mean segmentation overlap of 95.0%, a mean volume error of 4.5%, a mean segmentation error of 1.3 mm and a mean maximum distance of 5.5 mm. The corresponding results as shown in Table 1 are 94.6%, 4.0%, 1.32 mm and 4.16 mm, respectively. Therefore our results are comparable with the results of most of these works which, however, offer no distinction between thrombus and outer wall or assume uniform wall thickness.

8. Conclusions

Geometrical methods and tools for the LSM based segmentation of AAA thrombus and outer wall boundaries in CTA images exploiting the presence of calcifications in the arterial wall are presented. Stopping criteria were introduced to address the problem of leakage that intensity gradient based methods are susceptible to. Validation of the methods by comparison with manual segmentations from an expert showed a 4.0% relative volume error, a
1.32mm mean distance and a 94.6% area overlap for the outer wall boundary, averaged over ten patient data sets. Similarly the comparison for the mean wall thickness produced a mean absolute error of 0.51mm and a relative error of 15.84%. The robustness of the method was also assessed through sensitivity and reproducibility analyses. These results indicate that geometrically accurate 3D reconstructions of AAA anatomy and reliable measurements of the wall thickness distribution can be produced through LSM based segmentation of image data obtained from currently available imaging technology. Such information is important in estimating wall stress distribution which is required in obtaining a reliable patient specific measure of AAA rupture risk. Future work will include improvements in the model to reduce user intervention and accelerate the segmentation process and the extension of our model to three dimensions to avoid the 2D segmentation phase.

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