Automatic Vessel Tracking and Segmentation Using Epicardial Ultrasound in Bypass Surgery

Alex S Jørgensen[1], Samuel E Schmidt[1], Niels-Henrik Staalsen[2], Lasse R Østergaard[1]

[1]Department of Health Science and Technology, Aalborg University, Denmark
[2]Department of Cardiothoracic Surgery, Center for Cardiovascular research, Aalborg Hospital and Institute of Clinical Research, Skejby Sygehus, Aarhus University Hospital, Denmark

Abstract

Epicardial ultrasound has been suggested as an alternative approach for assessing the quality of coronary artery bypass graft anastomoses. Using automatic tracking and segmentation of the anastomotic vessel lumen in transverse epicardial ultrasound images it is possible to quantitatively assess the stenosis degree of surgical errors. We propose an automatic vessel tracking and segmentation framework that can detect, track, and segment vessels through ultrasound sequences with the purpose of enabling stenosis quantification. An average accuracy of 92.86% in detecting vessels was obtained 78.51% of the vessel segmentations were assessed as correct.

1. Introduction

Coronary heart disease can be treated using coronary artery bypass graft surgery. Even though it is viewed as a safe procedure Mack et al. [1] has shown that up to 9% of anastomoses are more than 50% stenosed. That can lead to unfavorable outcomes for the patient [2]. It is presumed a significant portion of stenosed anastomoses can be corrected if errors are detected by intraoperative anastomosis quality assessment. Here, coronary angiography is considered the gold standard but it is not normally available in the operation room [2]. Other approaches such as transit time flow measurement and intraoperative flourescence imaging are less accurate compared to coronary angiography and only reliabily detects stenosis degrees $>$75%. [2]

Epicardial ultrasound (EUS) has been suggested as an alternative approach for quality assessment of anastomoses and has shown promising results in ex-vivo and post surgery analysis studies. [3, 4] To use EUS during surgery a quantitative assessment of anastomotic stenotic rates (fig. 1) has to be made by automatic extraction of the maximum area in the anastomotic sites from in vivo EUS sequences obtained on the beating heart. Stenotic rates of the heel and toe site can be evaluated if vessel structures are detected and segmented in transversal EUS images. To determine the maximum area of the anastomotic sites the vessel structures has to be segmented throughout EUS sequences as the area changes during the cardiac cycle. However segmentation of the vessel lumen in EUS sequences is complicated as sudden translations of the vessel lumen can occur in the scan plane in between frames due to cardiac motion and the quality of the vessel information may be inhibited by motion artifacts.

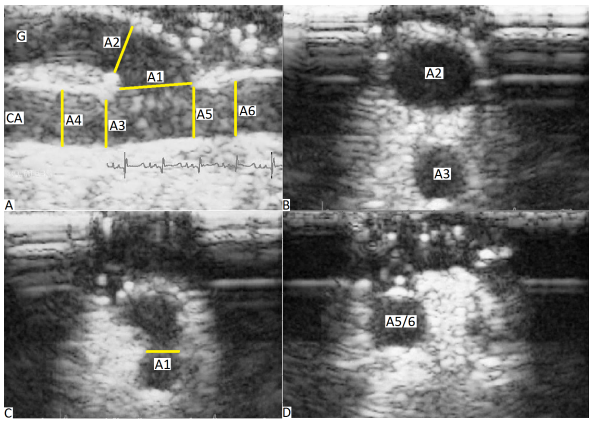

Figure 1. EUS images of an anastomosis. (A) is the longitudinal view. A1-6 denote where the area of the anastomotic orifice, graft (G), coronary artery (CA) at the heel site, reference CA proximal to the heel site, CA at the toe site and reference CA distal to the toe site of the anastomosis can be determined using transverse images respectively. A1, A2, A3, and A5 have to be as least as large as A4 and A6 to have a fully patent anastomosis. (B), (C) and (D) shows the transverse view of the heel, midway heel/toe, and toe/reference CA sites respectively.

Previous studies has worked with tracking and segmentation of transversal vessel structures in ultrasound sequences [5–7]. However these algorithms either uses manual initialization [5] or has been implemented in ultrasound

sequences with a different appearance [7], less complex vessel movement and motion artifacts compared to in vivo EUS images [5, 6].

We present an automatic vessel tracking and segmentation framework that can detect, track, and segment vessels in transversal in vivo EUS sequences of the heel- and toe-sites of porcine end-to-side anastomoses.

2. Vessel Tracking and Segmentation Framework

The vessel tracking and segmentation framework consists of vessel detection, vessel segmentation, quality control of the segmentations, and contour alignment. The vessel detection is used to automatically assess if a vessel is present in a EUS frame in the start of the sequence or if tracking of a vessel is lost. When a vessel is detected the vessel segmentation is used to segment the vessel lumen. The quality control is used to assess if a poor vessel segmentation was made or if vessel information is low e.g. due to motion artifacts. If the segmentation is approved it can be used to quantify the area of the vessel lumen otherwise the segmentation is discarded and vessel detection is used in the next frame. The contour alignment is used to track the vessel lumen by estimating the size of vessel lumen translations in between frames and align the initial contour for the vessel segmentation in the next frame. The approved segmentations are used as an initial contour for the vessel segmentation in the next frame, as it is assumed the area of the vessels does not change significantly in between subsequent frames.

2.1. Vessel detection

The vessel detection is used to determine if vessels are present in a frame. It consist of a vessel candidate segmentation followed by a vessel candidate classification. The vessel candidate segmentation is based on the fact that vessel lumen is darker than the surrounding tissue. It consist of a watershed segmentation [8] followed by an adaptive thresholding. The watershed segmentation is used to extract vessel candidate regions where a vessel could be present. It is performed on an image preprocessed with a morphological closing (disc, radius = 20 pixels) and a Gaussian low pass filter (standard deviation (σ) = 20) to merge small gaps in between structures and only obtain gross anatomical details respectively. As the watershed segmentation often overestimate the vessel lumen the adaptive thresholding is used to extract a possible vessel lumen region. The adaptive threshold is performed on an image filtered with a median filter (kernel = 30x30) followed by a Gaussian low pass filter (σ = 4) to obtain a uniform vessel lumen region. The threshold was set to 20% of the dynamic range inside the watershed region added to the minimum intensity value in the same region. Pixels below the threshold were defined as possible lumen pixels.

The vessel candidate segmentations are used in the vessel candidate classification consisting of a preliminary candidate removal and a weighted voting classifier. In the preliminary candidate removal candidate regions with an unrealistic area of the possible vessel lumen (< 18000 pixels) determined from the data is excluded. The weighted voting classifier is used to calculate a vessel probability in the remaining vessel candidates. It consist of two classifiers: A Parzen Window Classifier and a Bayes Classifier. Eight features are extracted in the vessel candidates: intensity standard deviation in the watershed region, mean intensity, compactness, signed y-distance from image center to the centroid, absolute x-distance from the image center to the centroid, mean boundary gradient, intensity variance, and aspect ratio of the possible lumen region. Features where the feature data cannot be transformed into a normal distribution is used in the Parzen Window Classifier. Features that are or can be transformed into a normal distribution is used in the Bayes Classifier. The vessel probability (VP) for a candidate region is calculated by:

$$VP_i = \sum_j w_j d_{ji} \text{ where } w_j \geq 0, \sum_j w_j = 1 \qquad (1)$$

where i is the classification sample, d is the classifier, w the weight of d and j is the number of classifiers. One feature (signed y-distance from image center to the centroid) could not be normally distributed. Therefore w for the Bayes Classifier and Parzen Window Classifier was set to $\frac{7}{8}$ and $\frac{1}{8}$ respectively so each feature in the classification has equal weight. When a vessel has been detected the possible vessel lumen segmentation is used as an initial contour for the vessel segmentation.

2.2. Vessel segmentation

The vessel segmentation is based on active contours (snakes) which are energy-minimizing contours guided by internal and external forces to evolve the contour to features of interest [9]. To robustly reduce the risk of locating a false gradient when using the contour from frame k in frame $k + 1$ a multi-scale coarse to fine approach using Gaussian low pass filters is used [10]. To cope with vessel deformation during the cardiac cycle in between frames no inward or outward motion is preferred in the internal or external energies. The formulation of the snake is: [9–11]

$$\begin{aligned} E_{snake} &= \int_0^1 E_{cont}(\mathbf{v}(s)) + E_{rigidity}(\mathbf{v}(s)) \\ &\quad - E_{gradient}(\mathbf{v}(s))ds \end{aligned} \qquad (2)$$

E_{cont} is implemented as in [11] and encourage equal spacing between points on the contour to make the snake robust

in detecting changes in shape. $E_{rigidity}$ is implemented as in [9] to avoid abnormal shapes of the contour. $E_{gradient}$ is implemented as a multi scale gradient as in [10]. The energy of the active contour is minimized using dynamic programming [12]. The parameters used for the snake can be seen in table 1. α and β were determined to be between 1 and 0. To achieve a more robust segmentation as more spurious edges appear in the fine scales due to speckle γ is reduced and β is increased from the coarse to fine scales.

2.3. Quality control

The quality control consists of a contour gradient analysis in the left, right, top and bottom segments of an interpolated contour. The gradient intensity in each contour point is used calculate the mean gradient magnitude in the segments. If the mean gradient magnitude in a segment is below a threshold, ϖ, the segmentation is not approved. The contour gradient analysis is obtained from the gradient of a Gaussian low pass filtered image (σ = 5). ϖ is set to 1.5 which was determined as a level of low vessel information.

2.4. Contour alignment

The contour alignment consist of a weighted centroid mean shift procedure to cope with sudden vessel translations in between frames due to cardiac motion. It is a variation of the kernel based object tracking described by Comaniciu et al. [13] therefore does not assume any model in estimating the motion of the vessel lumen. The vessel segmentation in frame k is initialized in frame $k+1$ and is used as the spatial mask in the motion estimate. By assuming the vessel lumen (target model) is homogeneous and that bright intensities from the tissue appear inside the target candidate in frame $k+1$ when a vessel translation has occurred the vessel translation (VT) is estimated by:

$$VT_{\mathbf{v}(s)} = c_{\mathbf{v}(s)} - wc_{\mathbf{v}(s)} \quad (3)$$

$\mathbf{v}(s)$ denote vertices on the contour, s denote the position on the contour by $0 \leq s \leq 1$ where 0 is the start and 1 is the end, (c) is the centroid of the spatial mask and (wc) is the weighted centroid of the intensity content inside the spatial mask. The contour from frame k is moved according to $VT_{\mathbf{v}(s)}$ iteratively until $VT_{\mathbf{v}(s)}$ is below a threshold, ϵ which is set to an absolute movement of one pixel.

3. Test setup

Eight anesthetized pigs underwent coronary artery bypass graft surgery and one end-to-side anastomosis was performed on each pig. 10 independent in vivo EUS sequences, consisting of 40 - 112 frames, were obtained of the heel and toe site in each anastomosis using a GE Vivid 4 echo machine (General Electric) and a 13-MHz, i13L GE ultrasound transducer (General Electric, Schenectady, NY) mounted in a novel ultrasound transducer positioning device, Echoclip [14]. The dynamic range was set to 70 dB, gain to 70 and imaging depth to 1 cm.

Table 1. *Show the parameters used for the multi-scale snake at each scale of the Gaussian low pass filtering.*

Scale (σ)	E_{cont} (α)	$E_{rigidity}$ (β)	$E_{gradient}$ (γ)
10	1	0.5	70
5	1	0.6	40
2	1	1	30
0	1	1	20

The mean sensitivity, specificity and overall accuracy of the vessel detection classifier in detecting vessels was assessed using an eight-fold cross validation of the classifier where regions with a vessel probability >80% was selected to be vessel regions. Feature data for the Bayes Classifier that was not normally distributed were transformed using a box-cox transformation. For each subject 18 frames with vessels fully included within the acoustic range of the transducer were randomly selected from separate sequences to avoid bias from using similar frames from the same sequence. At each eight-fold feature data from a separate subject was used as the test data and feature data from the remaining subjects was used to train the classifier.

To test the tracking and segmentation framework one heel site and one toe site EUS sequence were randomly selected from each subject. The tracking and segmentation framework was applied from the first frame in the sequences to each vessel (24 in total). The vessel detection classifier was trained as in the vessel detection test for each subject. Prior to the test the number of vessels fully included within the acoustic range of the transducer in the sequences was assessed. The percentage of these vessels that was approved by the quality control was determined. The approved segmentations were assessed by a non-expert user in an a posteriori manual visual validation to determine the percentage of correct segmentations.

4. Results

The eight-fold cross validation of the vessel detection classifier showed a mean sensitivity of 88.44%, specificity of 98.68%, and an overall accuracy of 92.82% in detecting vessels.

Results from the tracking and segmentation framework test can be viewed in table 2 and an example of the performance is shown in fig. 2. 94.11% of the vessels had an approved segmentation. The a posterori visual validation showed that 78.51% of the vessel segmentations approved

Table 2. *Results of the tracking and segmentation framework test.*

Vessels fully included within the acoustic range	Vessels with an approved segmentation [%]	Approved segmentations assessed as correct [%]
1493	94.11	78.51

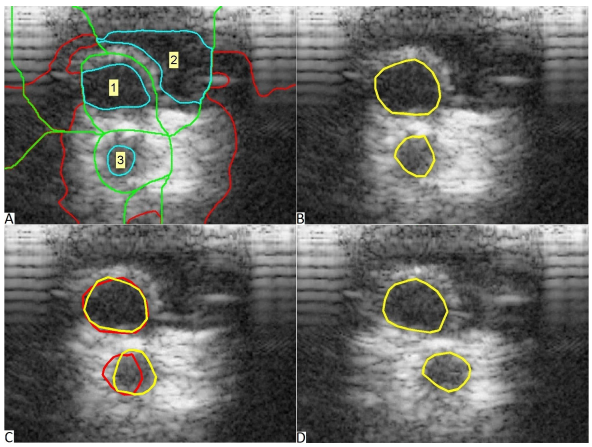

Figure 2. Shows an example of the tracking and segmentation framework. (A) show the vessel detection segmentations. Green lines are the watershed candidate regions, red lines are possible lumen regions of preliminary eliminated candidate regions, and cyan contours are possible lumen regions of candidates which is assessed by the classifier. Object 1, 2, and 3 has a vessel probability of 94.86%, 2.63% and 99.18% respectively. (B) shows the vessel segmentation of detected vessels. (C) shows the result of the segmentations (yellow contour) in frame $k+1$. The red contours are the segmentations from frame k. (D) is the final segmentation in frame $k+2$.

by the quality control were segmented correct.

5. Discussion

We have presented an automatic tracking and segmentation framework to detect, track and segment vessels using transverse in vivo EUS sequences of the heel and toe sites in anastomoses. 78.51% of the vessel segmentations were assessed as correct. This may be improved by increasing the threshold, ϖ, in the quality control or by improving the vessel segmentation to not only rely on gradient based information. It was shown that it was possible to detect and track vessels in EUS sequences with a high accuracy.

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Address for correspondence:

Alex Skovsbo Jørgensen
Department of Health Science and Technology
Fredrik Bajers Vej 7C1 - DK-9220 Aalborg - Denmark
asj@hst.aau.dk