# AUTOMATIC SEGMENTATION OF COMMON CAROTID ARTERY IN TRANSVERSE MODE ULTRASOUND IMAGES

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## ABSTRACT

We consider the problem of carotid artery segmentation and develop an automated outlining technique based on the active disc formalism that we recently introduced. The outlining problem is posed as one of optimization of a locally defined contrast function with respect to the affine transformation parameters that characterize the active disc. It turns out that standard techniques based on gradient-descent minimization can be used to carry out the optimization, although more sophisticated optimizers could also be deployed. For the initialization, we use a matched filter with a template size chosen based on an estimate of the average size of the carotid artery. We report results of experimental validation on Brno university's signal processing (SP) lab database, which contains 971 transverse mode ultrasound images of the carotid artery. The images in the database are manually annotated using a circle with center and radius explicitly specified in pixels, which serves as the reference. The circular annotation is also a good match with the active disc template considered in this paper. The proposed method results in an average detection accuracy of 95.5% and an average Dice similarity measure of 87.36% and takes only a few seconds of processing time per image. Comparisons with other state-of-the-art techniques are also reported.

***Index Terms***— Common carotid artery (CCA), segmentation, atherosclerosis, active disc, ultrasound (US) images

## 1. INTRODUCTION

The common carotid artery (CCA) is a major blood vessel in the neck that supplies oxygenated blood to the large front part of the brain where thinking, speech, personality, sensory, and motor functions reside. Carotid atherosclerosis, a carotid artery disease, which is due to the build-up of plaque inside the arteries hampers the blood flow to the brain that leads to "stroke" [1]. Stroke (brain attack) was the second leading cause of mortality and morbidity behind heart attack in 2013, accounting for 11.8% of total deaths globally [2]. Stroke is the leading preventable cause of disability, if detected in the early stages. Carotid ultrasound (US) imaging is a popular, inexpensive, and noninvasive screening test to diagnose atherosclerosis. CCA detection and segmentation in US images is an important first step in evaluating the severity of atherosclerosis causing stroke [3]. The CCA manual marking on an US image is shown in Fig.1 The CCA delineation for quantitative analysis and diagnosis of the carotid atherosclerosis is a challenging, difficult, and laborious task. Several efforts have been made to develop an automated technique for reliable segmentation and diagnosis.

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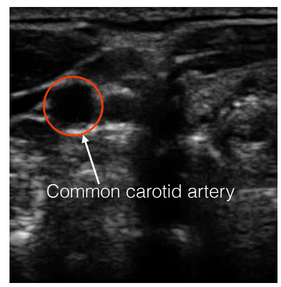


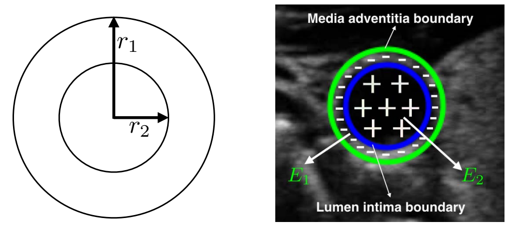

**Fig. 1**. [Color online] An ultrasound image of the common carotid artery and the manual outline specified using a circular template. Image courtesy: SP Lab Database, Brno University.

### 1.1. Related work

A number of studies in the past have addressed the problem of CCA segmentation. Mao et al. [4] proposed a semi-automatic method based on a deformable model, which is initialized with a single seed point placed by the user. Hamou et al. [5] proposed a method based on histogram equalization, Canny edge detection, and morphology. They have achieved precise segmentation by tuning the Canny edge detection scheme. Adbel-Dayem et al. [6] proposed a method based on watershed segmentation. Hamou et al. [7] presented a modified dynamic programming snake algorithm based CCA segmentation that utilizes a modified Canny edge detector and a priori knowledge about the carotid artery. Stoitsis et al. [8] proposed an active-contour-based CCA segmentation technique. Their method combines active contours with the Hough transform for automatic initialization. A method suggested by Yang et al. [9] uses self-adaptive histogram equalization, non-linear filtering, Canny edge detector, and morphology methods for automated CCA segmentation. A hybrid method comprising mathematical morphology and gradient-vector-field snake to evaluate atherosclerosis was proposed by Xin Yang et al. [10]. Riha et al. [11] proposed a method using the Viola-Jones detector specially adapted for efficient detection of the CCA in transverse US images. A team of researchers at Brno University of Technology, Signal Processing laboratory (SP lab) created a database of US transverse mode CCA images specifically for the measurement of static and dynamic parameters of the arteries and subsequently released for use by other researchers [12]. Yang et al. [13] presented a segmentation method based on active shape model to outline CCA for carotid atherosclerosis computer-aided evaluation and diagnosis. Ukwatta [14] et al. presented a semi-automated algorithm based on the level-set method to segment the *media adventitia* boundary and *lumen intima* boundary of the carotid arteries for computing the volume of the carotid arterial wall.

### 1.2. The proposed method

We introduce a novel, automated, active-disc-based CCA segmentation method. The segmentation comprises two major stages: automatic initialization of the active disc on the carotid artery using a matched filter [15], and segmentation and outlining of the CCA contour using active discs. The matched filter template requires prior knowledge of the average size of the carotid artery, which a clinician would be able to provide. We introduced the active disc in [16] for segmenting the optic disc in fundus images. The methodology is based on the formulation of Pediredla and Seelamantula [17], who generalized the specific solution presented in [18]. In the process of segmentation, the disc is evolved from a specified initialization towards the boundary of the CCA by minimizing a local energy function, which measures the local contrast. The disc evolution is based on a restricted affine transformation that allows for translation (two parameters that are the coordinates of the center) and isotropic scaling (one parameter along both $x$ and $y$). In this way, the end result would still be a circle, which is what the clinicians use for outlining. Since we are restricting the contour to be circular, rotations need not be considered. The three parameters are optimized for using a standard gradient-descent optimizer [19]. We use Green's theorem [20] to make the calculations computationally efficient. Finally, the algorithm performance is assessed by comparing clinician outlining with the algorithm outlining. For quantitative comparison, we use the Dice index as the similarity measure [21].




(a) (b)

**Fig. 2**. [Color online] (a) An active disc template; and (b) Optimal active disc fit on an ultrasound image of the carotid artery. The green and blue contours outline the *media adventitia* and *lumen intima*, respectively.

## 2. ACTIVE DISC DESIGN AND OPTIMIZATION

An active disc template consists of a pair of concentric circles as the template, and subject to a restricted affine transformation that allows for only translations and isotropic scaling. The translation and scaling parameters are chosen to optimize a local contrast function. In [16], we introduced the active discs technique to segment the optic disc in retinal fundus images. In this paper, we use the active disc formulation to perform CCA segmentation in US images of the carotid artery.

### 2.1. Template parametrization

A pair of concentric circles with center at the origin are parameterized by the equations: $x_i(t) = r_i \cos t$ and $y_i(t) = r_i \sin t$ for $i = 1, 2$, and $\forall t \in (0, 2\pi]$; $r_1$, and $r_2$ denote the radii of the outer and inner circles, respectively. In the active disc formulation, we chose the parameters $r_1 = 1$ and $r_2 = 1/\sqrt{2}$. An example of such a circular template is shown in Fig. 2 (a). For brevity of notation, we denote $(x_i(t), y_i(t))$ with $(x_i, y_i)$.

### 2.2. Restricted affine transformation of the template

An active disc is obtained from the template by means of the following transformation $X_i = Rx_i + x_c$ and $Y_i = Ry_i + y_c$, $i = 1, 2,$; $(X_1, Y_1)$, and $(X_2, Y_2)$ are the outer and inner contours, respectively, of the active disc. The center of the active disc is at $(x_c, y_c)$; $R$ is the scale parameter.

### 2.3. Active disc energy

We consider the region enclosed by the inner circle as the foreground (denoted as $\mathcal{R}_2$) and that in the annulus between the inner and outer circles as the immediate surrounding or background (denoted as $\mathcal{R}_1 - \mathcal{R}_2$, where $\mathcal{R}_1$ is the region enclosed by the outer circle). The disc energy is defined as the normalized contrast function: $E = \frac{1}{R}(E_1 - 2E_2)$, where $E_i = \iint_{R_i} f_I(X,Y)\,\mathrm{d}X\,\mathrm{d}Y$, $f_I$ being the given two-dimensional function (which in the present case is the image, histogram-equalized and inverted on the gray scale). By minimizing the energy $E$ with respect to $R$, $x_c$ and $y_c$, the active disc can be made to lock on to the CCA. The normalization by $R$ ensures that among all competing candidates with the same contrast $E_1 - 2E_2$, the tightest fit outline is obtained. An example of an optimal active disc with corresponding regional energies indicated is shown in Fig. 2 (b).

### 2.4. Optimization

In order to optimize $E$ with respect to the parameters $R$, $x_c$, and $y_c$, we use the gradient-descent technique, which requires the corresponding partial derivatives of the energy function. Since the integrals are two-dimensional and the contours are closed, one could compute the partial derivatives using Green's theorem. The details are available in [16]. The final expressions are recalled here:

$$\frac{\partial E}{\partial R} = \frac{1}{R}\left(\int_{t=0}^{2\pi} f_I(X_1,Y_1)\,\mathrm{d}t - \int_{t=0}^{2\pi} f_I(X_2,Y_2)\,\mathrm{d}t - 2E\right),$$

$$\frac{\partial E}{\partial x_c} = \frac{1}{R}\left(\int_{t=0}^{2\pi} (\sqrt{2}f_I(X_1,Y_1)\,\mathrm{d}t - 2f_I(X_2,Y_2))\cos t\,\mathrm{d}t\right),$$

$$\frac{\partial E}{\partial y_c} = \frac{1}{R}\left(\int_{t=0}^{2\pi} (\sqrt{2}f_I(X_1,Y_1)\,\mathrm{d}t - 2f_I(X_2,Y_2))\sin t\,\mathrm{d}t\right).$$

## 3. AUTOMATIC INITIALIZATION

Automatic initialization of the active disc is an important step in the robust detection of CCA in carotid US images and is achieved by matched filtering technique. Matched filtering maximizes the detection signal-to-noise ratio if the object and the template are identical but reflected versions of each other and has been used in several image processing problems [22]. In the present case, the filter template is designed to comprise two concentric circles for which the weights of the inner circle, outer circle, and annulus are considered as positive, negative, and zero, respectively. The given image is then correlated with the template. Since the cross-correlation operation is equivalent to convolving the input image with a conjugated flipped version of the template, the matched filtering operation can be carried out directly in the spatial domain. The matched filter response at $(x_p, y_p)$ is given by $s(x_p, y_p) = \iint f_I(x,y)\,m(x-x_p, y-y_p)\,\mathrm{d}x\,\mathrm{d}y$, where $m(x,y)$ is the filter template. The peak in the cross-correlation corresponds to the best match between the image and the template and is taken as the location for initialization the active disc.

**Table 1**. Performance analysis of the active disc method.

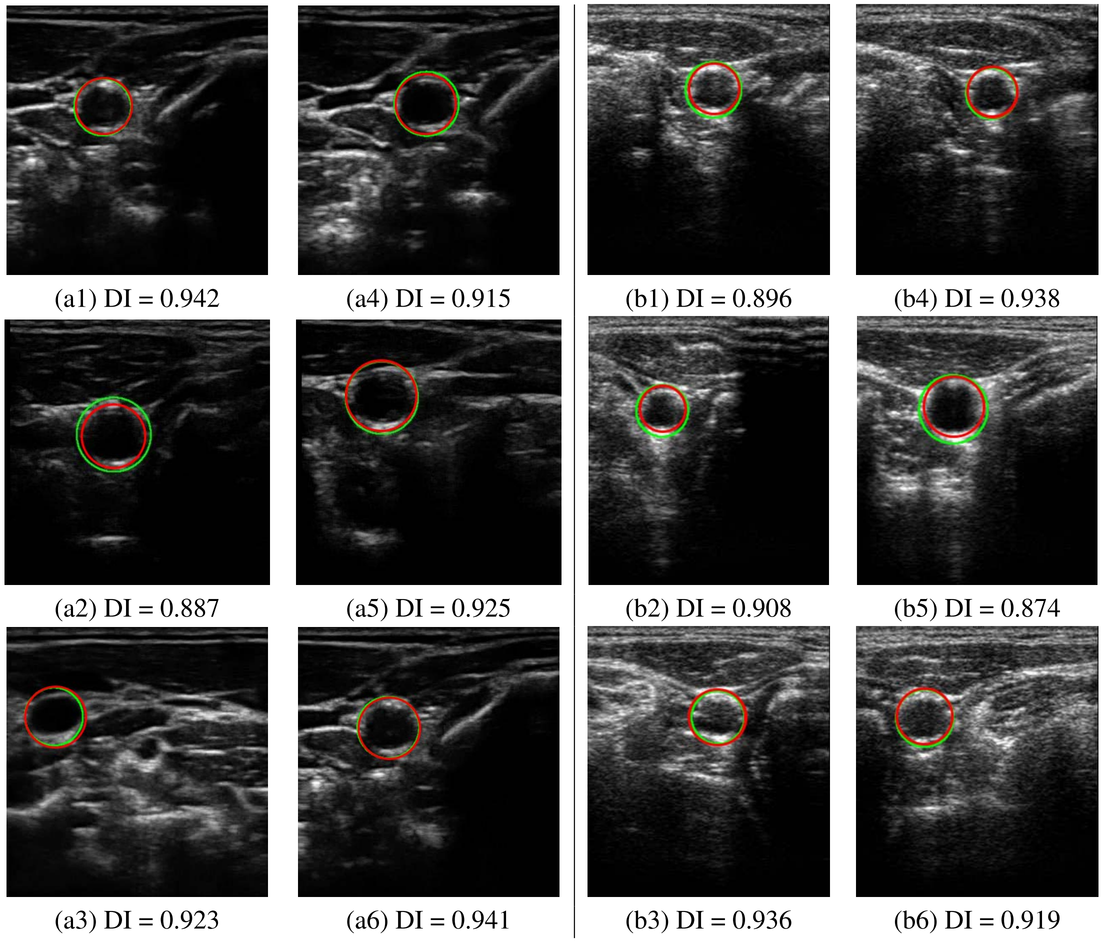
| Database / US machine | Number of US images | DC similarity metric | CCA detection accuracy |
|---|---|---|---|
| SP lab / | | | |
| Ultrasonics | 538 | 86.42% | 96.28% |
| Toshiba | 433 | 88.31% | 94.69% |
| | 971 (Total) | 87.36% (Average) | 95.5% (Average) |

## 4. EXPERIMENTAL RESULTS

We developed an ImageJ [23] plugin to implement the proposed method and an associated batch-processing ImageJ macro to handle an entire database (comprising close to a thousand images) for automated CCA segmentation. The validation of the method has been carried out on SP lab publicly available carotid artery database [12, 24]. SP lab database contains 538 and 433 US carotid artery test images taken using Ultrasonix and Toshiba US devices, respectively. All test images were coupled with labeling information containing the ground-truth coordinates of the center and radius of the circle. Automatic initialization of the active disc is performed on the histogram-equalized and grayscale-inverted CCA images using matched filtering technique. The grayscale inversion is needed because the carotid artery is of very low intensity and when the active disc energy function is maximized, the active disc locks on to bright regions. Alternatively, one could avoid grayscale inversion and minimize the energy function instead of maximizing for CCA outlining. The histogram equalization step is a standard preprocessing step and was found to boost the automatic detection of the CCA. Figures 3 (a1)–(a6) and 3 (b1)–(b6) show the CCA outlining results (green color) on SP lab Ultrasonix images and SP lab Toshiba images, re-

**Table 2**. Comparative analysis of various algorithms; SA: semi-automated; A: automated.

| Method | # images | Dice index (%) | Time (min.) | Type |
|---|---|---|---|---|
| Mao et al. [4] | 07 | 83.3 | 0.8 | SA |
| Yang et al. [9] | 180 | 70.5 | — | A |
| Yang et al. [10] | 110 | 90.3±3.5 | — | A |
| Yang et al. [13] | 68 | 92.8±3.3 | 4.3±0.5 | SA |
| Ukwatta et al. [14] | 231 | 92.8±3.2 | 2.1±0.3 | SA |
| Active discs | 971 | 87.36 | $< 0.4$ | A |



(a1) DI = 0.942 (a4) DI = 0.915 (b1) DI = 0.896 (b4) DI = 0.938

(a2) DI = 0.887 (a5) DI = 0.925 (b2) DI = 0.908 (b5) DI = 0.874

(a3) DI = 0.923 (a6) DI = 0.941 (b3) DI = 0.936 (b6) DI = 0.919

**Fig. 3**. [Color online] CCA outlines: active disc – green color, expert outlines – red color; (a1)–(a6): SP lab Ultrasonix images; (b1)–(b6): SP lab Toshiba images.

spectively. For comparison, manual outlines are also shown (red color). The performance of the method has been quantified using the Dice index (DI), which measures the degree of similarity between two regions. For perfect segmentation, the index should be 100%. In Table 1, we present the CCA detection accuracy and Dice index values. The CCA is said to be detected if the initialization estimated using the matched filter method falls anywhere within the manual outline given by the expert. The CCA detection accuracy is estimated as the percentage of images in which the CCA has been successfully detected in a given database. The proposed method achieves a CCA detection accuracy of 96.28% and 94.69% on SP lab Ultrasonix images and SP lab Toshiba images, respectively. Table 2 lists the performances of various algorithms measured using the Dice index on respective databases as reported by the authors. The proposed active disc method has a comparable Dice index to the state-of-the-art methods and over a much larger dataset. The results show that the proposed method is reliable and has a high degree of agreement with the expert outlines over several hundred images.

## 5. CONCLUSIONS

We proposed an active-disc-based segmentation technique for delineating CCA in transverse mode US images, which is a precursor and important step in the automated diagnosis of atherosclerosis. The initialization of the active disc is automated using the matched filtering technique. The translation and scale parameters of the active disc are optimized with the local contrast as the energy function. The optimization is carried out using gradient descent and the partial derivatives are evaluated using Green's theorem. The segmentation performance was found to be consistent with the expert outlines over a large number of images. The computational time taken per image is also much less than the competing methods. The proposed method could be adapted to delineate the CCA in the longitudinal mode as well by suitably designing the active shape template. An automated diagnosis system based on the proposed outlining method and corresponding analysis in terms of the sensitivity and specificity would be the next steps for our research.

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