An Unbiased Technique for Automatic Estimation of Vessel Contours in Angiograms.

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Abstract— **Accurate and fully automatic assessment of artery dimensions in angiograms has been sought as a diagnostic tool, in particular for coronary heart disease. We propose a new technique to estimate vessel borders in angiographic images. Unlike in previous approaches, the obtained edge estimates are unbiased, this being of primordial importance since quantitative analysis is the goal. Another important feature of the proposed estimator is that no constant background is assumed, making it well suited for non-subtracted angiograms. The key aspect of our approach is that the smoothness constraint is not used to smooth or in some other way modify the estimates directly derived from the image (which would introduce bias) but rather elect (without modifying) candidate estimates. As a result, the selected points, if correct, are unbiased estimates. Even at low contrast segments and in the vicinity of artifacts, the true border points still correspond to (possibly faint) local maxima of the edge operator, which can be correctly chosen if the surrounding context is taken into account. Robustness against unknown background is provided by the use a morphological edge detector rather than some linear operator such as a matched filter which assumes flat background.**

I. Introduction

Accurate automatic assessment of vessel dimensions in digital (or digitized) angiographic images is a valuable and clinically important diagnostic tool. Objective, verifiable, and reproducible quantitative analysis has been the goal of much research effort, in particular for coronariography [1], [2]. Underlying this search is the need to accurately assess the severity of coronary disease which reveals itself by vessel narrowings. It is clear that automatic border location is a crucial first step of any quantitative coronary analysis (QCA) system, for which several techniques have been proposed.

II. Previous Work

To cope with the difficulties which are inherent to the vessel contour estimation problem (unknown image background, faint contrast, unknown vessel shape) most approaches use prior knowledge/constraints about vessel continuity and smoothness. Recent examples include: dynamic programming type search, like in [3], [4], and [5]; and extended Kalman filter type prediction-correction tracking, as proposed in [6]. By adopting smoothness constraints these techniques achieve robustness and yield smooth vessel edges at the cost of introducing bias. Take as an example, the case of a very short but very pronounced narrowing (stenosis) which can be severely underestimated if smooth edges are fitted to it. This may be a serious problem if quantitative analysis is to be performed with the obtained border estimates. Note that vessel diameters in a typical coronariography can be as small as a few pixels, with a one pixel deviation being a serious relative error. This is in contrast with the ventricular boundary estimation problem in which the much larger dimensions involved give sense to simple smoothness constraints, as we adopted in [7]. Other approaches such as those in [8], and [9], are inadequate for coronary arteriograms because they assume constant (or known) background and several projections.

An exception to the smoothness assumption trend is the work reported in [10], in which each vessel cross section is analyzed separately. However, this work presents (from our point of view) some problems: the vessel and background models are simplistic and unrealistic (e.g. the background is modelled as a low order polynomial); by performing section-by-section independent analysis, they avoid the smoothness bias but throw away the robustness that is typical of global approaches (i.e. in which all the border points are jointly estimated).

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III. Proposed Method

A. Rationale

We propose a technique aiming at producing unbiased contour estimates, and which does not demand any background flatness assumptions. This last characteristic makes the method well suited both for digital subtracted images and digitized (unsubtracted) cinefilm images.

The observations and ideas underlying our method are: **a)** Even at low contrast vessel segments (e.g. stenotic areas) and in the vicinity of (possibly stronger) image artifacts (e.g. ribs, other vessels, catheters) any edge operator still presents a (possibly weak) local maximum at the correct border location. **b)** This maximum can still be correctly chosen if the surrounding contextual information is adequately taken into account. **c)** The continuity (or smoothness) constraint should not be used to modify the edge location estimates directly derived from the image; rather, it should be used to elect, among several candidates, the one that best fits into the global contour.

The points just made are valid for any type of edge operator. Here, we adopt the morphological gray-scale edge operator proposed in [11]: the *blur and minimum operator* (BMO). The reason for choosing a morphological operator (non-linear) is that the flat background and white noise assumptions (required by any matched filter type, or derivative based, linear operator) are not guaranteed for angiographic images. The BMO is sensitive to the faster variations associated with the vessel borders, over any slowly varying background, and exhibits high noise immunity. For a detailed description of the BMO (and other morphological edge detectors) see [11]. In Fig. 1(b), we present an example of the application of the BMO to a coronary cross section intensity profile of Fig. 1(a).

B. Description of the Algorithm

The proposed method, which is supported on the observations and ideas above presented, accomplishes the following design goals: **a)** keep the robustness inherent to global approaches, i.e. do not treat each cross section separately, but rather take advantage of the contextual information provided by the surrounding estimates; **b)** avoid the bias introduced by smoothness constraints.

The algorithm is structured as follows:

- Consider N cross sections of the vessel segment under study. For each section, we define a set of vessel center candidates containing all the local maxima of a 1D *top-hat* operator (THO). The THO operator

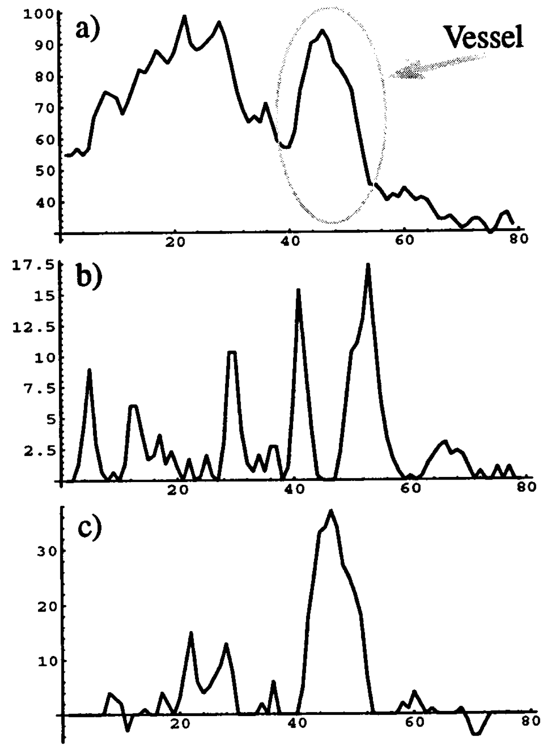

Figure 1: **a) Intensity profile of a true coronary cross section. b)Outcome of the BMO. c) Outcome of the top-hat operator.**

is a morphological operator able to detect local elevations on arbitrary background [12]. The result of applying a THO operator to the intensity profile of Fig. 1(a) is shown is Fig. 1(c). The center candidates obtained from the vessel segment presented in Fig. 2 as just described are presented in Fig. 3(a).

- A minimum cost path along the vessel is then obtained by using dynamic programming [13] to choose one candidate from each section. This yields the so called vessel *skeleton* which is defined by a set of vessel center points $\mathcal{S} = \{c_i, i = 1, 2, ..., N\}$. The adopted cost function combines a term favoring continuity with another term depending on the candidates strength,

$$\mathrm{Cost}(\mathcal{S}) = \sum_{i=1}^{N} \alpha d(c_i, c_{i-1}) + \beta T(c_i) \qquad (1)$$

where $d(c_i, c_{i-1})$ is the distance between the two consecutive center points c_i and c_{i-1}, $T(c_i)$ is the strength of the THO operator at the location of point c_i, and parameters α and β are wheighting factors. In Fig. 3(b), the vessel skeleton obtained ob-

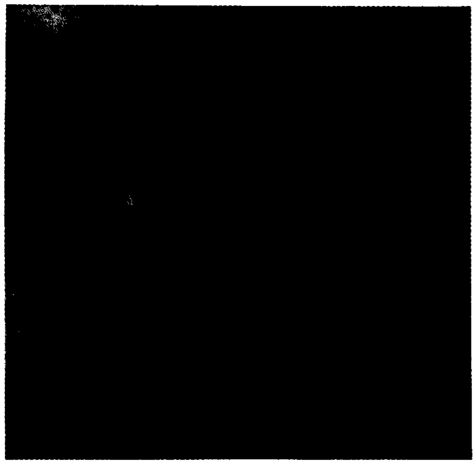

Figure 2: **Angiographic image of a portion of the coronary tree; notice the very pronounced and short stenosis.**

tained from the candidates of Fig. 3(a) is presented. Note that although some candidates outside the vessel presented higher THO response, the contextual information allowed the correct ones to be chosen. Notice also that some candidates were generated by background structures (such as other vessels) while some others were caused by noise.

- For each of the N cross sections, two sets of candidates to border points are created, each containing all the maxima of the BMO applied to each side of the skeleton. Fig. 4(a) shows all the border candidates so obtained, superimposed on the vessel image.

- Again using dynamic programming, two minimum cost paths are obtained which are the final vessel borders estimates. These vessel edges are represented by two sets of border points, one for each side of the skeleton, $\mathcal{B}_a = \{a_i, i = 1, 2, ..., N\}$, and $\mathcal{B}_b = \{b_i, i = 1, 2, ..., N\}$. As before, the cost functions includes continuity and edge strength terms,

$$\mathrm{Cost}(\mathcal{B}_a, \mathcal{B}_b) = \mathrm{Cost}(\mathcal{B}_a) + \mathrm{Cost}(\mathcal{B}_b) \qquad (2)$$

with

$$\mathrm{Cost}(\mathcal{B}_a) = \sum_{i=1}^{N} \gamma d(a_i, a_{i-1}) + \eta\, \mathrm{BMO}(a_i) \qquad (3)$$

(and a similarly for $\mathrm{Cost}(\mathcal{B}_b)$), where $\mathrm{BMO}(a_i)$ is the intensity of the BMO response at the location of border point a_i. Fig. 5 contains the final vessel borders obtained by the procedure described.

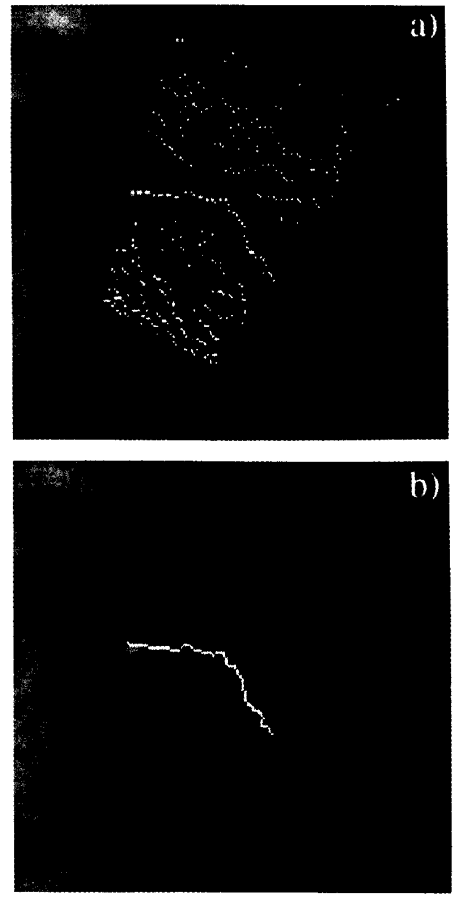

Figure 3: **(a) Vessel center candidates. (b) Vessel skeloton obtained as the minimum cost path through the candidates.**

The method was implemented and tested on a conventional workstation where it runs in less than 3 seconds, thus perfectly compatible with routine use.

In some mentioned references [3], [4], and [5] (see also [14]) dynamic programming is also used, although in a fundamentally different way: minimum cost paths are found not among sets of candidates but among all the pixels in an edge intensity image. Thus, the selected points may not be maxima of the edge operator and are possibly biased estimates. In our algorithm, continuity is used only to select among candidates, without modifying their values, i.e. estimates are unbiased. Notice that the short but very sharp narrowing present in the coronary vessel of Fig. 2. The extracted contours shown in Fig. 4(b) capture this stenosis correctly; any smoothing of the borders would lead to a seriously underestimated stenosis severity.

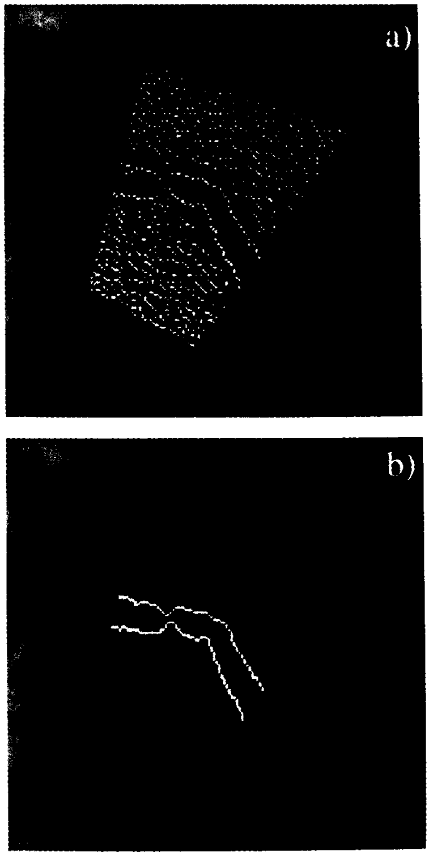

Figure 4: (a) Vessel border candidates. (b) Vessel borders obtained as minimum cost paths through the candidates.

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