Automated Identification of Vessel Contours in Coronary Arteriograms by an Adaptive Tracking Algorithm

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Abstract—A tracking algorithm for identification of vessel contours in digital coronary arteriograms was developed and validated. Given an initial start-of-search point, the tracking process was fully automated by exploiting the spatial continuity of the vessel’s centerline, orientation, diameter, and density. The incremental sections along a major vessel were sequentially identified, based upon the assumption of geometric similarity and continuation between adjacent incremental sections. The algorithm consisted of an extrapolation-update process which was guided by a matched filter. The filter parameters were adapted to the measured lumen width. The tracking process was robust and extremely efficient as indicated by test results on synthetic images, digital subtraction angiograms, and cineangiograms. The computational time on a microcomputer averaged 1.83 s per vessel (SD = 0.53 s, n = 21, vessel length = 274 ± 77 pixels). To quantify the accuracy of measuring vessel lumen width over a broad range of image quality and stenosis severity, the algorithm was further evaluated by use of computer simulated images of stenotic vessels. The algorithm provided accurate measurement of lumen width (SEE = 0.51 pixels) and percent stenosis (SEE = 1.7 percent), relatively invariant to the vessel’s orientation, dynamic range, background variation, and degree of blurring. The performance of the algorithm degraded for images of signal-to-noise ratio of less than 6 dB or stenotic lumen width of less than 3 pixels. The algorithm should be useful for automating angiographic analyses of blood vessels.

I. INTRODUCTION

Computer-assisted procedures can improve quantitative analysis of coronary arteriograms in two respects. First, automation reduces the interobserver and intraobserver variation for determining the severity of coronary artery stenosis [23], [24]. Second, efficient computer algorithms are essential to analysis procedures of high computational demand, such as determination of coronary blood flow from sequential frames of arteriograms [4], [29] and reconstruction of three-dimensional vascular structures from biplane angiograms [14], [20].

Unfortunately, the spatial resolution of the state-of-the-art computer imaging systems is not sufficient to support complete automation of the analysis of coronary arteriograms. Without a priori knowledge regarding stenosis location, the entire coronary angiographic frame digitized to 512 × 512 pixels has a pixel density in the order of one pixel per mm². The resulting digital coronary arteriograms frequently contain vessel sections of only a few pixels wide. By comparison, in various diagnostic procedures, higher imaging spatial resolution is required and frequently obtained by digitizing a small region of interest on a cineangiographic frame. Nichols et al. [16] computed the percent area stenosis by cinevideodensitometric analysis with a pixel density in the order of 10⁵ pixels/mm². Brown et al. [6] studied the recanalization process during intracoronary infusion of streptokinase in selectively magnified angiograms with a 0.1 mm resolution. While it is unlikely that, in the near future, linear spatial resolution of the imaging systems can be increased by an order of magnitude, development of appropriate computer algorithms can contribute in: 1) automatic detection of the coronary artery stenosis; and 2) exploration of the subpixel resolution by exploiting the spatial continuity properties of the blood vessels [28].

The spatial continuity properties of the vessel have, either explicitly or implicitly, been used to improve the accuracy of vessel boundary estimation. Pappas and Lim [19] in 1983 presented a parametric model to fit the vessel cross-sectional density profile. Using model parameters obtained from adjacent boundary estimations, their method was more accurate than the traditional maximum slope method for boundary estimation. Graphic theory and dynamic programming techniques have also been applied to the vessel boundary estimation problem [9], [27]. These methods are semiautomatic and computation-demanding. To guide the edge detection process, a tentative vessel centerline or vessel orientation must be manually specified.

Fully automated methods for the identification of coronary artery contours have been studied. Eichel and Delp in 1986 [7] reported a sequential tree searching method in which an optimal path of vessel edges was identified by hypothesizing long edge paths and a Markov-chain model for linking the edge paths. The lumen width was then determined by scanning the edge information. In contrast, Nguyen and Sklansky [17] implemented scanning operations first to extract both the edge and ridge points, and then a tracking operation to delineate the vessels. These methods, however, also suffered from a relatively long computational time. Other reported tracking approaches either required a priori knowledge of the vessel’s orientation [15], [21] or were not sufficiently robust [10], [18].
In particular, premature termination of the tracking operation may occur at vessel sections where a coronary artery stenosis is present.

The purpose of this study is to develop an automated, robust, accurate, and computationally efficient algorithm for identifying artery contours in coronary arteriograms. To accomplish this, the continuity constraints of vessel centerline, width, orientation, and density are mathematically formulated in a tracking algorithm. Heuristics regarding the search path are also incorporated into the algorithm. Matched filtering and adaptive filtering techniques are employed whereby the contour of a major artery segment is delineated by its incremental sections without any \textit{a priori} assumption on the vessel’s local orientations.

II. \textbf{Rationale}

Two different strategies have been employed for identification of vessel contours, i.e., scanning and tracking. Scanning is typically a two-pass operation [1], [17]. First, extraction of edge or ridge pixels is accomplished by an enhancement-detection process. The desirable image features points are enhanced by convolving a mask-type operator with the entire image, and extracted by threshold detection. Second, recognition of the vascular tree structure is accomplished by chaining centerline points into vessel segments while excluding points resulting from either random or structural noise. In contrast, a tracking operation begins at an \textit{a priori} known position on the image plane [21], [30]. In a single-pass operation, extraction of the image features and recognition of the vessel structure are simultaneously accomplished by exploiting the continuity properties of the vessel. In this study the tracking approach is considered due to its inherent efficiency in computation. The robustness and accuracy of tracking are improved by exploiting the following continuity properties of a blood vessel.

1) \textit{Continuity of Position}: The centerline and edge pixel positions vary continuously along a vessel segment on the image plane.

2) \textit{Continuity of Curvature}: The vessel direction varies continuously along a vessel segment.

3) \textit{Continuity of Diameter}: The lumen width varies continuously along a vessel segment. However, abrupt changes of lumen width or irregular shapes of lumen cross section may be observed at a stenotic section.

4) \textit{Continuity of Density}: Although the image background may present abrupt changes in density, the dynamic range (i.e., the signal magnitude above the background level) of the cross-sectional density profile varies relatively continuously along a vessel segment.

The optimal design of a tracking algorithm would require the \textit{a priori} information regarding the probability distributions and spatial frequency characteristics of position, curvature, diameter, and density functions. The problem is further complicated by the variation in imaging quality, resolution, and calibration process. While such information is unavailable at present to facilitate an overall optimal design, a combined mathematical and heuristic approach is developed in this study.

The tracking algorithm developed here has an extrapolation-update structure similar to that of a Kalman filter [8]. Given the estimation of centerline, width, and orientation for the current incremental section of the vessel, the next incremental section is extrapolated along the current vessel direction. A matched filter locates the next centerline position based upon the vessel cross-sectional density profile at a \textit{look-ahead} distance away. In the update process, the vessel direction, width, and centerline position for the next incremental section are determined. The \textit{look-ahead} distance and the search window size are adapted to the current vessel width. The tracking process is actuated by the operator’s input which defines a start-of-search point and an initial search direction in the digital coronary arteriogram.

III. \textbf{Algorithm}

\textbf{Centerline Identification}

Each point of the centerline has three attributes: position, direction, and width. As shown in Fig. 1, the centerline pixel position is denoted by the position vector \( p_k \), which has two components \( p^x_k \) and \( p^y_k \) (the x and y components, respectively). Subscript \( k \) is used to specify the current iteration in the tracking process; \( k \) is also the distance (in pixels) along the centerline measured from the start-of-search point. The local orientation of the vessel at \( p_k \) is defined by a unit vector \( \hat{u}_k \). This orientation vector has length equal to one pixel; its x and y components are denoted by \( u^x_k \) and \( u^y_k \), respectively.

Given the current centerline point, the position of the centerline point at a distance of \( d \) pixels ahead is detected by use of a matched filter. The look-ahead distance \( d \) is adapted to the current radius, or half width (R), of the vessel lumen. The heuristic-based adaptation scheme will be described later. We first extrapolate the current centerline to a point \( \hat{p}_{k+d} \), which is at \( d \) pixels away, along the current centerline direction \( \hat{u}_k \). The extrapolated centerline pixel is located at

\[
\hat{p}_{k+d} = p_k + d\hat{u}_k. \tag{1}
\]

Centered at this position a density profile vector \( \hat{g} \) is obtained by resampling, where \( g \) denotes a vector containing the \( 2w+1 \) pixel gray-scale values along a line segment, i.e., \( g = [g[1] \ g[2] \ \cdots \ g[2w+1]]^T \). The width of the search window \( 2w+1 \) is also adapted to the lumen width. The density profile is obtained along a scanline perpendicular to the current centerline direction. Because position (\( \hat{p}_{k+d} \)) and direction (\( \hat{u}_k \)) of the centerline point are known, resampling is simply done by: 1) computing the position of each point in the scanline; and 2) assigning the gray-scale value of the nearest pixel in the original image to this point. The \( i \)th element in the density profile vector \( \hat{g}_{k+d} \) is given by

\[
\hat{g}_{k+d}[i] = G[\hat{p}_{k+d} + (i - w - 1)\hat{u}_k, \rho_{k+d}^x, \rho_{k+d}^y - (i - w - 1)\hat{u}_y] \tag{2}
\]
where $G[\cdot, \cdot]$ denotes the gray-scale value of the resampled pixel and is taken as the gray-scale value of the pixel closest to the specified position by rounding off.

Next, matched filtering is performed on $g$ to identify a new centerline point $p'$. The expected pattern for the voxel cross-sectional density profile $h$ is assumed to be rectangular in shape with width equal to $2R + 1$. This assumption is based upon the following rationale. First, a rectangular pattern with appropriate width generally results in correct identification of the centerline position provided that the shape of the cross-sectional density profile is unimodal. Second, the assumption of a rectangular pattern significantly reduces computation in the matched filtering as shown below. The $i$th element in $h$ is given by

$$h[i] = \begin{cases} 1, & |i| \leq R \\ -1, & R < |i| \leq w \\ 0, & \text{otherwise} \end{cases}$$

The vector resulting from convolution between $g$ and $h$ is denoted by $r$, with the $i$th element equal to

$$r[i] = \sum_{j=1}^{2w+1} g[j] h[i-j]$$

where $i = R + 1, R + 2, \cdots, 2w - R + 1$. By substituting (3) into (4) we obtain

$$r[i] = \sum_{j=i-R}^{i+R} g[j] - \left( \sum_{j=1}^{R-1} g[j] + \sum_{j=i+R+1}^{2w+1} g[j] \right).$$

Notice that the convolution reduces to a simple summation. Next, the maximum of the convolution result $r[m]$ is determined; the $m$th pixel location on the density profile $g$ corresponds to the maximum output of the matched filter. The updated centerline position is located at

$$p_{k+d}^r = \left[ \hat{p}_{k+d}^r + (m - w - 1) u_{\hat{p}_{k+d}^r} \right] \left[ \hat{p}_{k+d}^r - (m - w - 1) u_{\hat{p}_{k+d}^r} \right].$$

**Edge Detection and Stopping Criterion**

The updated centerline position $p_{k+d}^r$ is identified by use of the direction vector $u_{\hat{p}_{k+d}^r}$ which represents the vessel orientation at a distance of $d$ pixels behind. If not corrected, this would become a potential source of error in determining the centerline position and, consequently, the tracking path. To improve accuracy, first, the direction vector is updated according to

$$u_{\hat{p}_{k+d}^r} = \frac{p_{k+d}^r - p_k}{\|p_{k+d}^r - p_k\|}$$

where $\| \cdot \|$ denotes the norm of a vector. The resulting direction vector remains normalized. Next, the updated density profile $g_{k+d}$ is reassembled along a line segment perpendicular to the updated direction vector $u_{\hat{p}_{k+d}^r}$. Signal level $s_{k+d}$ is determined by the average gray level of the $2R + 1$ pixels centered around $p_{k+d}^r$

$$s_{k+d} = \frac{1}{2R+1} \sum_{i=-R}^{R} g_{k+d}[i].$$

The remaining pixel values in the search window are averaged to determine a background level $b_{k+d}$

$$b_{k+d} = \frac{1}{2(w-R)} \left( \sum_{i=1}^{w-R} g_{k+d}[i] + \sum_{i=w-R+1}^{w} g_{k+d}[i] \right).$$

The signal and background levels relative to the density profile $g$ are illustrated in Fig. 2 (left). The two edge points are identified by searching for the roll-off point at a density level equal to or less than $(s_{k+d} + b_{k+d})/2$ on either side of the updated centerline point. This point roughly corresponds to the inflection point for a typical vessel cross-sectional density profile. Because the roll-off point is determined by an averaging process and using information of the entire density profile, this edge detection scheme should be less sensitive to high frequency noise than a maximum slope method which employs a differentiation process. Once the edge points are identified, the vessel half width $(R)$ is updated. The final centerline position $p_{k+d}$ is adjusted to the midpoint between the edges as shown in Fig. 1. To identify the contour for the entire incremental section, the resampling and edge detection process is repeated for every scanline from $k+1$ to $k+d$. The direction vector at each point is kept the same as $u_{\hat{p}_{k+d}^r}$. While the position of a centerline point is not confined to the image pixel grid, the distance between any two adjacent centerline points is always one pixel.
puted for each cross-sectional density profile according to
\[ \gamma_k = \frac{S_k - B_k}{B_k} \times 100 \text{ percent.} \quad (10) \]

This parameter is used to identify the condition when density of the X-ray contrast material along the vessel is approaching the background level. A threshold for the percent dynamic range \( \gamma_i \) is set a priori based upon the imaging quality. A stopping criterion \( '\gamma_k < \gamma_i' \) is constantly checked in the tracking process. The tracking process iterates the detection of incremental vessel sections until the stopping criterion is met.

**The Tracking Process**

To demonstrate how the algorithm functions, intermediate results of the tracking process, when applied to a human coronary arteriogram, are shown. The three panels in Fig. 2 (left to right) show typical density profiles taken from a normal section, bifurcation, and distal end of a vessel, respectively. In each panel the resampled density profile \( g \) is plotted across a scanline as shown at the top. The midpoint on \( g \) corresponds to the extrapolated centerline position \( p \). The second and third curves are, respectively, for the expected vessel cross-sectional pattern \( h \) and for the result of convolution \( r \) between \( g \) and \( h \). The updated centerline position \( p' \) is determined by the matched filter output, i.e., the maximum point of \( r \). The update process produces a new direction vector and, based upon the new direction, a resampled density profile \( g \). Once the two edge points are identified based upon \( g \) (shown by the two vertical dashed lines), the final centerline position \( p \) is adjusted to the midpoint between the edges.

As shown in the middle panel of Fig. 2, upon bifurcation the path of the tracking process follows whichever vessel branch presents the strongest signal. In this example, due to the mechanism of direction update, the updated intensity profile \( g \) no longer shows the double-peak pattern as the original density profile \( g \) does. This mechanism provides a clean breakaway of the tracking path at a bifurcation point. At the distal end (Fig. 2, right) the decreased dynamic range signals the termination of the tracking process.

**Spatial Averaging**

The tracking process generates an \( N \)-point description of the vessel contour \( \{ C_k; k = 1, 2, \ldots, N \} \). Each entry is depicted by the triplet \( \{ \text{centerline position, direction, half width} \} \)

\[ C_k = \{ p_k, u_k, R_k \}. \quad (11) \]

Sandor et al. [25] suggested that, if properly implemented, averaging adjacent scan profiles can enhance the precision of the vessel diameter measurements. In this study a low-pass digital filter is used to explore the subpixel resolution in the measurements based on the assumption of spatial continuity. Without a priori knowledge concerning the frequency characteristics of the vascular structural changes, the following empirical formula is used to implement an equally weighted moving average filter

\[ \overline{C}_k = \frac{1}{2l + 1} \sum_{j=-l}^{l} C_{k+j} \]

where \( C_k \) denotes the triplet of the vessel contour description after averaging. The filter does not introduce any spatial phase shift due to its symmetrical structure. The length of the average buffer and, consequently, the spatial cutoff frequency are controlled by the heuristically determined parameter \( l \).

**Heuristics and Adaptation Schemes**

A common problem associated with heuristical approaches is concerned with the assignment of empirical parameters in an algorithm. Such empirical parameters may include the orders and coefficients of filters used, dimensions of search windows, and thresholds used in detection processes. Without appropriate schemes to adapt these parameters to variations in the imaging resolution, field of view, and noise level, the algorithm may easily loose its generality and, consequently, its application value.

In this study, one of the adaptation schemes is based on the heuristic that the winding pattern and the relative diameter variation along a blood vessel should be independent to the imaging resolution. Moreover, a small vessel is more likely to exhibit abrupt changes in its orientation than a large vessel is. Thus, the look-ahead distance and the search window size in the algorithm are adjusted in proportion to the lumen width in terms of pixels. In addition, a deliberate effort has been made to reduce the number of empirical parameters in the algorithm, and to implement adaptation schemes whenever appropriate. The empirical parameters in this algorithm are limited to the following five:
1) $R_0$—initial expected half width (pixels) of the vessel lumen;
2) $K_v$—proportionality constant for look-ahead distance ($d$), where $d = K_v R$ (pixels);
3) $K_v$—proportionality constant for search window ($w$), where $w = K_v R$ (pixels);
4) $\gamma$—threshold for percent dynamic range (percent) of the density profile; and
5) $l$—one-sided length of the moving average buffer.

IV. PERFORMANCE EVALUATION

The algorithm was implemented on an IBM PC/AT based imaging system. The performance of the algorithm was evaluated based upon: 1) the ability of the algorithm to track vessels with winding patterns in both synthetic and real arteriograms; and 2) the accuracy of measuring vessel lumen width over a broad range of image quality and stenosis severity.

For the first part, the algorithm was tested with synthetic images ($n = 7$), digital subtraction angiograms ($n = 7$), and cineangiograms ($n = 7$). All images were quantized to 256 x 256 pixels with 8-bit gray-scale level. The synthetic images were obtained by imaging hand-drawn patterns of complex vascular tree structures via a video camera. White Gaussian noise of known variance was added to the images such that the resulting signal-to-noise ratio was 10 dB. Digital subtraction angiograms (DSA) were taken from a 256 x 256 window at the center of 512 x 512 original DSA's which were obtained by use of an ADAC DPS-4100 system (ADAC Laboratories, San Jose, CA). Both the DSA's and cineangiograms were acquired in a human catheterization laboratory by use of a Siemens radiographic system. The performance of the algorithm was evaluated on the basis of segmenting the major vessel correctly and without premature termination in the tracking process. The computational time of the algorithm was measured.

For the second part, computer simulations were performed to assess the accuracy of the algorithm in determining vessel dimensions. In order to quantitate the quality of the image, computer simulated images of stenotic vessels were mathematically generated. Each image was synthesized with three components: 1) a stenotic vessel segment with known dimensions, dynamic range, and orientation; 2) an additive white Gaussian noise of known variance; and 3) a linear background variation of known gradient. To simulate spatial blurring caused by scatter, glare, or extended focal spot in a digital radiographic system, smoothing of various degrees was applied to the synthetic images. The measured lumen width and percent stenosis were compared to their true values as the percent stenosis, signal-to-noise ratio, image resolution, dynamic range, vessel orientation, background variation, and degree of blurring were systematically varied.

Synthesis of the stenotic vessel images is described as follows. The boundaries of a stenotic segment are given by two bell-shaped curves as shown in Fig. 3 (top). A signal level ($S$) is assigned to the region between the two curves, and a background level ($B$) to the region outside

$$G[x', y'] = \begin{cases} 
S, & \text{if } (R_s - R_e)(1 - e^{-x^2/\sigma^2}) - R_i \leq y' \leq (R_a - R_s) \\
R_i(1 - e^{-x^2/\sigma^2}) + R_s, & \text{otherwise} 
\end{cases}$$

(13)

where $G[x', y']$ denotes the pixel value at position $(x', y')$, $R_a = \text{half width of the normal vessel lumen}$, $R_i = \text{half width of the narrowest point}$, $\sigma$ is related to the length of the stenosis and assigned the value of 2 $R_a$. The minimum lumen width is denoted by $W_s$, where $W_s = 2R_a$. The pattern of the stenotic vessel is then shifted to the center of the image frame and rotated by an angle of $\theta$ degrees as shown in Fig. 3 (bottom). White Gaussian noise of variance $V_{noise}$ is added to the image. The signal-to-noise ratio ($S/N$) of the resulting image is given by

$$S/N = 10 \log_{10} \frac{D^2}{V_{noise}}$$

(14)

where the image dynamic range $D = S - B$. A linear background variation with a slope of $\beta_{ Gry}$ (gray-level change per pixel in percent) is also added to the image. The gradient of the background variation is along the $x$-axis of the image. Finally, the image is blurred by convolving with a $3 \times 3$ equally weighted mask. The degree of blurring ($\phi_{blur}$) is defined by the number of repetitive convolutions with the $3 \times 3$ moving average mask. Thus, the quality of the synthetic stenosis images is characterized by a set of five parameters: signal to noise ratio.
(S/N), background variation (β_vent), degree of blurring (σ_blur), imaging spatial resolution (related to R_v), and dynamic range (D). In addition, because the gradient of background variation in the synthetic images is always along the x-axis, the vessel orientation (θ) may also affect the result of tracking.

V. RESULTS

Tracking Ability

The default parameters \{R_0, K_d, K_w, γ_v, L\} = \{5, 2, 2, 0.5 percent, 2\} were used in 13 of the 21 images for evaluation of the tracking ability. The algorithm showed better performance in three cases with a wider search window and a longer look-ahead distance, i.e., \{K_d, K_w\} = \{3, 3\}; in three cases with \{K_d, K_w\} = \{1, 3\}; and in two cases with \{K_d, K_w\} = \{3, 2\}. The other three parameters, namely the initial vessel width R_0, the stopping threshold γ_v, and the averaging buffer half length L, had minor effects on performance of the algorithm and were kept constant in this study.

In Fig. 4 the tracking result for a typical digital subtraction angiogram is shown. The framed region in the original image (Panel A) is magnified by 8 times and shown in Panel C. The segmentation of a major coronary artery by the algorithm (Panels B and D, respectively, for the original and magnified image) shows that the centerline and direction function are relatively continuous and qualitatively agreeable to human perception.

Although the result of the tracking process is insensitive to the operator’s choice of the initial search direction, the initial start-of-search position occasionally influenced the tracking path. This usually occurs at a bifurcation point that spawns two branches, both presenting comparable signal level to the matched filter. As shown in Fig. 5, the tracking path followed one of the four major vessel segments in this cineangiogram when different parameters were set in the algorithm. The parameters \{K_d, K_w\} = \{2, 2\} were used for both tracking paths shown in Panel A and in Panel B, respectively. The initial start-of-search point in Panel A was defined few pixels proximal to that in Panel B. After the first bifurcation point on the upper right corner of the cineangiogram, different vessel segments were tracked as a result of difference in the start-of-search position. Another different path shown in Panel C was tracked with \{K_d, K_w\} = \{1, 2\}, and in Panel D with \{K_d, K_w\} = \{3, 3\}.

Computational Time

The algorithm was coded in Fortran. All computation utilized 16-bit integer arithmetics except for the vector normalization in (7), in which square-root function and floating-point division were performed. The centerline position and vessel width were represented by scaled integers in terms of 1/100 pixel. This scaled integer representation provided high efficiency and sufficient precision for the vessel width computation. The x-y components of the vessel orientation vector are also integers in terms of 1/100 pixel. The resulting precision for measuring vessel direction was 0.3°.

The computational time (T) depends on the length (N) of the identified vessel, the look-ahead distance (L), the search window size (W), and the half length of the averaging buffer (L). In Table I statistics of the computational time and numbers of centerline pixels are summarized. The tracking time includes the iteration time for the tracking procedure (1)-(10) to identify the entire vessel segment. The time for image input/output and operator’s specification of the start-of-search point is not included.
The average time is the time to perform the moving average filtering (12). The computational time was an average 1.01 s per vessel for tracking plus 0.82 s for averaging. The vessel length was on average 274 pixels. Linear regression analysis of the total computational time ($T$) versus the vessel length ($N$) resulted in the expression: $T = 0.01N + 0.10$ s; with $r = 0.74$, and $n = 21$ samples.

Table I

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Mean*</th>
<th>S.D.</th>
<th>Range</th>
</tr>
</thead>
<tbody>
<tr>
<td>Tracking Time (s)</td>
<td>1.01</td>
<td>0.36</td>
<td>0.55-2.03</td>
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<tr>
<td>Average Time (s)</td>
<td>0.82</td>
<td>0.24</td>
<td>0.49-1.27</td>
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<tr>
<td>$T$: Total Computational Time (s)</td>
<td>1.83</td>
<td>0.53</td>
<td>1.04-3.01</td>
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<tr>
<td>$N$: Number of Centerline Pixels</td>
<td>274</td>
<td>77</td>
<td>166-429</td>
</tr>
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</table>

*n = 21 samples.

Measurements of Lumen Width

There were two parts in the computer simulation. First, the lumen width function was measured by the algorithm as the severity of stenosis varied from 0 to 100 percent. The quality of the synthetic images was set at $S/N = 10$ dB, $\beta_{\text{rand}} = 0$, $R_{\text{m}} = 1.8$ pixels, $\phi_{\text{blur}} = 1$, $D = 60$ gray levels, and $\theta = 45^\circ$. The choice of these parameters resulted in images of reasonable quality, and was otherwise arbitrary. The measured versus true values are plotted in Fig. 6 (left) for minimum vessel width, and in Fig. 6 (right) for percent stenosis. The algorithm generated accurate estimates except for two cases when minimum width $\leq 3$ pixels (corresponding percent stenosis $\geq 90$ percent). The standard error of estimate (SEE) for the minimum width measurement was 0.95 pixel when all samples were considered and 0.45 pixel without the 90 and 100 percent stenosis samples. The measured and true quantities were highly correlated (all correlation coefficients $r > 0.99$) as shown in Fig. 6.

Next, the image quality was systematically varied. The performance of the algorithm was qualitatively evaluated by using the accuracy of measuring a 75 percent stenosis as an index. The choice of this performance index was based upon the following rationale. It has been shown that, due to an autoregulatory mechanism in the coronary circulation, coronary artery stenoses less than 75 percent have minimal effect on coronary reserve and blood flow [11]. In addition, as shown in Fig. 6 (right), the 75 percent stenosis roughly corresponds to the critical point where the performance of the algorithm begins to deteriorate for the chosen image quality. In all, 55 images of a 75 percent stenotic vessel were generated over a broad range of image quality. Each quality parameter was adjusted independently towards the low and high extremes until either tracking became difficult or performance of the algorithm reached a steady state. The measured percent stenosis is plotted in Fig. 7 (Panels A-F) versus the variation of $S/N$, $\beta_{\text{rand}}$, $\phi_{\text{blur}}$, $W_{\text{m}}$, $D$, and $\theta$, respectively. The stenotic section with overlapped tracking result is shown in Fig. 8 (Panels A-D) for synthetic images of different $S/N$.

The algorithm accurately measured the percent stenosis and was relatively insensitive to background variation, dynamic range, and vessel orientation. As expected from
the previous analysis, the algorithm deteriorated for S/N < 6 dB or minimum vessel width < 3 pixels. In the case of low degree of blurring (Φblur = 1–4), the accuracy of percent stenosis measurement was within ±2 percent. The effect of spatial averaging of white noise by blurring in fact resulted in better accuracy as compared to the case of Φblur = 0. Further increasing the degree of blurring showed a slowly increasing underestimation of percent stenosis as a result of overestimation of the minimum lumen width. The standard error of the estimate (SEE) was calculated and used to assess the accuracy. The analysis was performed on two data sets: 1) all samples (n = 55); and 2) excluding the samples with either S/N < 6 dB or W ≤ 3 pixels (n = 51). The result is summarized in Table II.

VI. DISCUSSION

In summary, a novel method was developed for fully automated identification of vessel contours in coronary arteriograms. By a combined mathematical and heuristical approach the spatial continuity properties of the vessel's position, orientation, and width were incorporated in an adaptive tracking algorithm. The tracking process was fast and robust as indicated by the test results on hand-drawn vessel patterns, digital subtraction coronary arteriograms, and cineangiograms. The algorithm accurately measured the vessel lumen width over a broad range of image quality and stenosis severity as indicated by the computer simulation result.

The algorithm is aimed at providing a descriptive con-
Table II

<table>
<thead>
<tr>
<th>Data Set</th>
<th>Percent (mean)</th>
<th>Stenosis (percent)</th>
<th>W (pixels)</th>
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<tbody>
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<td></td>
<td>Mean</td>
<td>S.D.</td>
<td>SEE</td>
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<tr>
<td>n = 55*</td>
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<td>3.8</td>
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<tr>
<td>n = 51†</td>
<td>74.4</td>
<td>1.7</td>
<td>1.7</td>
</tr>
</tbody>
</table>

* all samples.
† excluding samples of S/N < 6 dB or W, < 3 pixels

tour representation so that blood vessel analysis can be quantified and automated. Such an algorithm should be "sensitive, reproducible, accurate, reasonably fast, operator-interactive while minimizing operator subjectivity, and applicable to biplane imagery," as pointed out by Sandor et al. [25]. A major design strategy for this algorithm is the full and sole use of local features in the image, i.e., the continuity properties of blood vessels. Generally speaking, an inherent trade-off by choosing between local and global features is computational speed versus robustness. Computational efficiency is achieved in this algorithm by: 1) identifying direction, scanlines, boundaries, and centerline in a one-pass process; and 2) using information in the vicinity of the vessel instead of scanning the entire image. Nevertheless, computational speed was not necessarily gained at the sacrifice of robustness in this case. Successful tracking of a major vessel was accomplished for all images under investigation including DSA’s, cineangiograms, synthetic vessel images of complex tree patterns, low S/N ratio (0 dB), and discontinuity (100 percent stenosis). The result suggested that the extrapolation-update process developed in this study provides relatively robust and consistent tracking of blood vessels.

Accurate determination of the lumen width function along a vessel segment requires accurate identification of not only boundaries but also centerline and direction. Accuracy of measuring percent lumen width of radiographic phantoms by quantitative angiography was reported: 3–5 percent with a 16 μm/pixel resolution by Brown et al. [5]; 2 percent with a 96 μm/pixel resolution by Reiber et al. [23]; and 0.2–3.4 percent with a 55 μm/pixel resolution by Sandor et al. [25]. Wright et al. [32] showed that, under ideal conditions, noise in a phantom image can be theoretically characterized. White noise is a good approximation of the random noise due to quantum statistics of X-ray absorption. However, under nonideal conditions spatial blurring that colorizes the white noise, nonuniformities of scatter and veiling glare, beam hardening, and structural noise are difficult to model and obviously vary with the characteristics of every component in the chain of a digital radiographic system. The algorithm in this study is designed for blood vessel analysis without the a priori knowledge of the precise vessel direction and stenosis location. Thus, increasing signal-to-noise ratio by spatial or temporal averaging, optimizing resolution by zooming, and histogram equalizing may not be applicable. In order to evaluate accuracy of the algorithm over a broad range of image quality, the algorithm was tested with computer simulated images in which signal-to-noise ratio, background variation, degree of blurring, imaging resolution, dynamic range, vessel orientation, and stenosis severity were systematically varied. The result showed that the algorithm provided an accurate estimate of percent stenosis (SEE = 1.7 percent) and lumen width (SEE = 0.51 pixel) except for signal-to-noise ratio less than 6.
dB or stenosis width less than 3 pixels. By assuming a 3
mm normal lumen width, these data translate into an
accuracy of ±60 µm with a 117 µm/pixel resolution; the
accuracy can be maintained up to ±128 µm with a 250
µm/pixel resolution. The result is comparable to data ob-
tained in phantom studies by other investigators. For low
S/N images, such as arteriograms obtained by intra-
venous injection of a contrast medium, one would expect this
algorithm to become insufficient in both accuracy and
tracking ability. In this case algorithms able to handle low
S/N, such as −6 dB reported by Shmueli et al. [27],
should provide better performance.

Compared to existing approaches for boundary detec-
tion and segmentation of vascular structures, this algo-
rithm has the following desirable features. First, this
algorithm does not require human specification of a region
of interest, a tentative centerline, or a pair of start-end
points as required by some other semiautomated algo-
rithms [3], [9], [22], [23], [26], [25], nor does it assume
a fixed vessel orientation with scanlines parallel to one
another [15], [19], [27], [28]. Thus, this algorithm pro-
vides automation of a higher degree. Second, compared to
other fully automated algorithms [2], [7], [10], [17],
the computational time of this algorithm (average 1.83 s
per vessel) is at least two orders of magnitude less. Third,
this algorithm provides an effective and high-precision
definition of vessel direction as a function of distance
along the centerline. Accurate direction information is
valuable not only for lumen width measurement [25] but
also for blood flow measurement from arteriograms [4].
Fourth, this algorithm performs tracking and contour
identification in a single-pass process. It is not necessary
to empirically set thresholds for segmentation or to re-
move background by preprocessing as required by some
other algorithms [12], [13].

The algorithm at its present state is insufficient to pro-
vide a complete segmentation when multiple major ves-
sels are present. Furthermore, incorrect segmentation may
occur at the portion of an image where vessel segments
overlap. The cause of this deficiency is twofold. First,
because the tracking process is guided by a matched filter,
the tracking path at a bifurcation point or at a crossover
point of two overlapped vessels follows whichever vessel
presents the strongest signal to the matched filter. Second,
the tracking process uses only local features whereas
global features, such as the distribution of edge and ridges
pixels over the entire image [17], may provide additional
guidance to tracking in the case of multiple major vessels.

To provide complete segmentation and accurate de-
scription of vascular tree structures, this algorithm can be
extended or used as a subsystem in the following ap-
proaches. First, global features of the image may be in-
corporated to initiate multiple tracking processes and to
guide the tracking processes through the setting of the
start-of-search point and the heuristically determined pa-
rameters. The heuristically determined parameters, es-
specially the proportionality constants for the look-ahead dis-
tance and the search window, can be used to adjust the
characteristics of the algorithm, and thus provide limited
control of the tracking path. Generally speaking, increas-
ing the search window size and decreasing the look-ahead
distance enhance the ability to track vessels exhibiting ab-
rupt changes in orientation. Second, our preliminary re-
sult [30] and other research [13] showed that a vascular
tree can be identified in a hierarchical way by detecting
the bifurcation points along a major branch and by recur-
sively implementing the tracking process for each side
branch. The result is an exhaustive breadth-first search for
all the vessel branches spawned from a root node. Third,
most ambiguities of the three-dimensional vascular struc-
ture as observed from a single view arteriogram can be
resolved using information from biplane angiograms. In
addition, because most coronary artery stenoses are ec-
centric, biplane arteriography is necessary to provide a
more accurate assessment to the hemodynamic resistance
of the stenotic lesion [5]. Our preliminary result [31]
showed that the correspondence problem of matching seg-
ment pairs between two orthogonal views can be solved in
an automated way by use of a rule-based method. The
rule-base through which a priori knowledge and human
understanding of arteriograms are incorporated may pro-
vide better guidance to the tracking process. This can be
done in an iterative way such that problems encountered
in the segment-matching phase are fed back to improve
the front-end tracking processes.

In conclusion, the algorithm developed in this study
provides accurate contour identification of a major vessel
in a coronary arteriogram. With this approach automation
for detecting and quantifying coronary artery stenoses in
 coronary arteriograms can be achieved. For future work
the algorithm should be useful for assessing coronary
blood flow and implementing three-dimensional recon-
struktion of vascular structures from biplane angiograms.
The algorithm also provides a framework to investigate
the statistical properties and spatial frequency character-
istics of the centerline, orientation, diameter, density, and
tortuosity functions along the blood vessels.

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