GENERIC REBOOTING SCHEME AND MODEL-BASED PROBABILISTIC PRUNING ALGORITHM FOR TREE-LIKE STRUCTURE TRACKING

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ABSTRACT

Tree-like vessel structures are an information-rich source for many image analysis tasks. Hence tracking algorithms extracting such structures have wide applicability. However, due to image artifacts and the minute nature of vessels, these algorithms face several challenges; two of the most common ones are 1) *early termination*, where tracking stops before the structure ends and 2) *leaking*, where tracking leaks into nearby closed organs or irrelevant structures. To address these issues, this paper makes two main contributions: a generic rebooting scheme that identifies early terminations and then restarts tracking to track objects in their entirety and a model-based pruning algorithm that uses global optimization to identify and mitigate leaking. The performance of the proposed algorithm is demonstrated by tracking coronary arteries on 3D cardiac Computed Tomography Angiography (CTA) data from 28 human subjects. Our methods dramatically improve tracking results by detecting and recovering from early terminations and identifying and removing leaking in 98% (63 of 64) branches, with a single erroneously removed valid branch.

Index Terms— vessel segmentation, early termination, leaking control, model-based pruning, probabilistic tracking

1 Introduction

Detection and analysis of vessel structures is of great importance in many clinical applications. For example, blood vessel delineation on medical scans is essential for further diagnosis of vessel pathologies such as stenosis and calcification. Multiple algorithms have been proposed for vessel segmentation including threshold-based approaches [1], region growing techniques [2], model-based methods [3], and tracking schemes [4]. See [5] for a detailed review. Different methods are typically specialized for specific segmentation criteria depending on the imaging modality, vessel characteristics and the amount of user interaction and no single method works under all circumstances. However there are several challenges that these methods share, the two most prevalent being *early termination* where tracking stops before the structure of interest actually ends and *leaking* where the final segmentation includes nearby irrelevant structures. Most methods address these issues in a task- and algorithm-dependent manner, wherein modifications are added to the original algorithm to improve results. For instance, an algorithm-specific directional jump growing scheme is proposed in [6] and leakage detection in [7] depends on task-specific characteristics of the initial segmentation unique to lung airways.

Here, we propose a generic framework to recover from early terminations and to remove leakages. For the former (dubbed 'rebooting'), a local search method is employed to first identify potential vessel segments compatible with the tracked vessel within a disconnected region and the tracking algorithm is then restarted along these segments. The latter (dubbed 'pruning') uses a model-based approach to assign a probabilistic score to each candidate vessel segment quantifying its likelihood of being a valid vessel. Models are built using features that can discriminate between valid vessels and leakage in training data. Finally a global optimization scheme is used to prune leaks and reconstruct the vessel tree.

Recently Zhao and Bhotika [8] developed a robust and accurate probabilistic coronary artery tree tracking method. The rebooting and pruning methods introduced here are layered over the tracking results of [8] to further improve 3D coronary artery tree tracking and extraction from 28 human cardiac CTA exams. Cardiac CTA is a non-invasive procedure to study coronary artery disease. Consequently, coronary tree tracking methods that require minimum human interaction are of great clinical importance.

2 Generic Rebooting

As mentioned previously many tracking algorithms are plagued by *early termination* due to sharp changes in the vessel orientation and low contrast gap regions (Fig. 1) among other reasons. While there is a vast body of literature on vessel structure delineation [5], the specific task of early termination has received little attention. Further most available methods are closely coupled to a single underlying segmentation framework [6]. Here we propose a generic 'identify and reboot' scheme, applicable to different tracking algorithms, to robustly recover from early terminations.

Our proposed 'reboot' scheme consists of two parts, 1) detection of potential candidate segments followed by starting

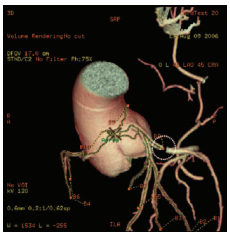


Fig. 1: Gap region (within circle), tracking stops before the gap while actual structure continues

point and vessel direction estimation and 2) reinitialization of the tracking process. As shown in Fig. 2, at every termination point, we first perform a local search for potential vessel segment candidates. For this purpose, a binary vessel map that marks all voxels potentially belonging to a vessel structure is investigated within a certain neighborhood of the termination point. After candidate selection, we estimate the starting point and direction for each new potential vessel segment and reboot the tracking. Finally, updated tracking results are obtained by adding the new tracked branches to the original vessel tree.

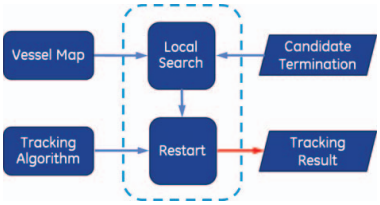


Fig. 2: Flowchart for generic rebooting algorithm

For candidate detection, we utilize a binary vessel map to identify voxels belonging to vessel structure. Such a vessel map is a superset of the final tracking. It can be generated by various methods such as region growing with liberal settings or a *vesselness* measurement followed by thresholding. Here, we employed the Sato vesselness measure [9]. In detail, the first step is to generate an ROI around the termination point of each tracked vessel (Fig. 3(a)), then several vessel segments can be extracted by grouping connected voxels in the binary vessel map using a connected component algorithm (Fig. 3(b)). Next, small components are regarded as noise and removed while large groups are labeled as potential vessel segment candidates (Fig. 3(c)). Finally, centerlines of each group are examined for radius and directional compatibility with the tracked vessel. Child candidates showing strong agreement are selected (Fig. 3(d)) and start points and child segment directions are estimated simultaneously. The tracking algorithm is now rebooted along the direction of the child segment centerline, starting from the point on the child centerline nearest to the termination point on the parent vessel segment.

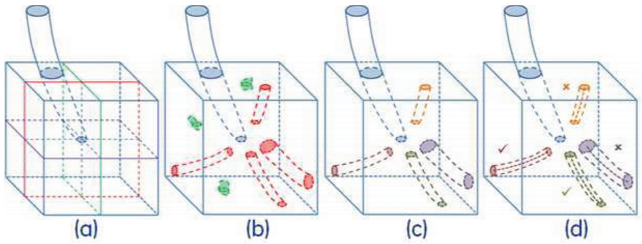


Fig. 3: Illustration of rebooting algorithm: (a) generate ROI around termination point; (b) find candidate vessel segments with connected component; (c) label each segment and remove small groups (noise); (d) extract centerline for each group and test compatibility with tracked vessel to select candidate segments.

3 Model-Based Probabilistic Pruning

Leaking which results in an erroneous labeling of irrelevant adjacent regions as vessels, is another major challenge in selectively extracting vessel structures. For example, in the case of coronary artery tree estimation, the tracking process may enter a neighbouring vein or other anatomy. There are several causes that lead to leaking: First, due to image artifacts and noise, there are often regions where the vessel lumen has a low contrast-to-background. Second, due to the bad timing of image acquisition, closed arteries may be similar in intensity to neighbouring veins. Last, vessel trees are usually surrounded by complex organs with a similar appearance.

Currently, most algorithms focus on preventing leaks by intrinsically adding components to or adjusting the tracking process. For example, in airway tree segmentation with region growing, the volume and directional change can be monitored to detect and stop leakage [7].

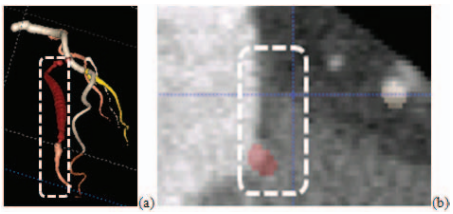


Fig. 4: Leakage to adjacent anatomy during coronary artery tracking: (a) 3D rendering of vessel tree with a leaking branch (within the rectangle), (b) a slice with leaking region labeled.

Such prevention techniques are often unable to identify and remove all leaks given that leak detection relies only on local information without any global contextual knowledge. Also, it is usually difficult to achieve a good balance between sensitivity and specificity to vessels with limited local information. To remedy this, we propose a model-based probabilistic pruning algorithm as a post processing step *after* an initial extraction of the whole vessel tree. This allows us to leverage non-local contextual information and use global optimization to reliably detect and remove leaks.

Our leakage removal algorithm consists of three parts:
a) Tree structure construction: the tracked result is first reorganized in a proper tree structure based on parent-children branch relationships.
b) Feature extraction and offline model training: features that are useful in differentiating leaks from valid vessel structures are extracted from each individual branch. Then based on training data with labeled true valid branches and leaks, a likelihood model for branch validity can be generated with each feature as a model parameter.
c) Branch scoring and optimization: during the online testing stage, each candidate branch is assigned a likelihood score based on its compatibility with the branch validity model. A positive score implies that the candidate is more likely to be a valid branch. Finally, global optimization based on these likelihood scores is performed to produce the final tree.

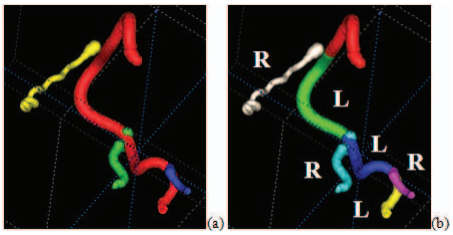


Fig. 5*:* Tree structure construction: (a) 3D rendering of a tracked vessel branch with several bifurcations found by the probabilistic tracking algorithm [8], different colors represent different branches (b) Branches get segmented at bifurcation points to form a binary tree with left and right child nodes shown.

For our coronary artery tree tracking application, the original output is shown in Fig. 5(a). As can be observed, a main branch can have several bifurcations. To construct a regular binary tree that can be easily processed, we first break each tracked branch at bifurcation points into several segments, so that each segment can be considered to be an individually (as shown in Fig. 5(b)). A binary tree can be constructed as follows: each branch is broken down into two segments at every bifurcation point, and every single branch segment is a node in the tree. A node can at most have two child nodes connected to it. The left child is defined as the one more compatible with the parent; for most cases, the left child and parent belong to the same branch before bifurcation detection. On the other hand, the right child is the less compatible one and is usually a bifurcation from the original branch.

Once the binary tree is constructed, a branch validity likelihood model can be built using suitable features. Here we have employed both inter- and intra- branch features that contain a mix of application-specific features and generic application independent features. In our implementation generic inter-branch features include differences in radii, ratio between radii and differences in vessel directions for the child branch with respect to the parent branch. Features such as the likelihood value given by the initial probabilistic tracking algorithm are also incorporated to further enhance the performance of our algorithm. Based on the selected features, a comprehensive multivariate Gaussian validity likelihood model is trained:

$$f(\mathbf{x}) = \frac{1}{(2\pi)^{k/2}|\Sigma|^{1/2}} \exp\left(-\frac{1}{2}(\mathbf{x}-\boldsymbol{\mu})'\Sigma^{-1}(\mathbf{x}-\boldsymbol{\mu})\right)$$

Here $\mathbf{x}$ is the feature vector; we can compute the mean $\boldsymbol{\mu}$ and covariance matrix Σ for the model based on the training set. The likelihood score of each incoming candidate branch can be estimated by testing its feature vector for compatibility with the model. Finally, global optimization is performed using dynamic programming to solve a tree partitioning problem. Specifically, let current graph T represent the tracked vessel tree consisting of multiple segments $T = S_1, S_2, ..., S_N$. Each segment is assigned a validity likelihood score $V(S_i), i = 1, 2, ...N$. Our objective is to extract a sub tree $T_s \subseteq T$ that retains valid vessel segments and removes leaks. For this tree partitioning problem, we need to effectively obtain values for a set of flags $F = F_{S_1}, F_{S_2}, ..., F_{S_N}$ that serve as validity switches for every node of T satisfying the criterion that if segment S_k is excluded from the final tree, i.e. $F_{S_k} = 0$, all its children should also be excluded. Mathematically our problem is to find the optimal sub tree T_s such that the corresponding validity flag set F is given by

$$F = \arg\max \sum_{i=1}^{N} F_{S_i} V(S_i)$$

Dynamic programming has been shown to be an efficient mechanism to solve the above problem. The solution involves two phases: first, each node is visited in a bottom-up manner so that the maximum achievable score of the sub tree rooted at every candidate node is computed; then the tree is revisited in a top-down manner so that all negative sub trees get removed (flag set to 0), resulting in the optimal tree T_s.

4 Experiments and Results

The rebooting and pruning schemes described here were layered on top of an existing probabilistic tracking system [8]. Improvement in the number of additional valid branches detected and leaks removed was measured to evaluate the performance of the proposed algorithms. The effectiveness of the probabilistic coronary tracking algorithm has been previously illustrated in [8] using the Rotterdam coronary artery algorithm evaluation framework [10]. While this framework provides a strong measure of centerline precision, it does not currently evaluate the specificity of the system. Their high resolution ($0.3 \times 0.3 \times 0.4$;mm^3) data are easier to track compared to real clinical data. Here, a more challenging clinical data set of 38 cardiac CTA with $0.5 \times 0.5 \times 0.6$;mm^3 voxels was used to validate the proposed algorithms. Ten datasets with 124 branches were used as a training set to build our

branch validity model. The remaining 28 datasets were used for testing. Fig. 6 shows sample results for one exam following 'rebooting'. In this case, 5 vessel segments missed by the original algorithm were added after rebooting (6(a) and 6(b)). Further Fig. 6 (c) shows that the final result was a correctly relabeled tree without any erroneous leaks. Results following model-based branch pruning are shown in Fig. 7. All the leaks in 7(a) were removed in 7(b) while all valid branches were preserved. Note that some of the junctions within the circle in the final result were originally part of 'false' branches due to leaking. With the help of binary tree decomposition, global optimization and tree reconstruction, we were able to successfully preserve the valid branches and extract the coronary artery tree. Quantitative validation results are listed in Table 1. The original statistical tracking detected 364 valid branches (vessel segments) with 28 false branches or leaks. Utilizing the proposed methods, 'rebooting' added 44 new valid branches but resulted in 36 more leaks. However the 'pruning' algorithm effectively removed 98% (63 out of the resulting 64) leaks. Only a single valid branch was erroneously removed during the pruning stage.

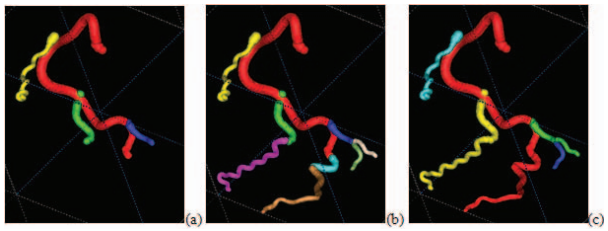


Fig. 6*:* Result for rebooting scheme: (a) original tracking result; (b) tracking result after rebooting; (c) final result after pruning and tree reconstruction.

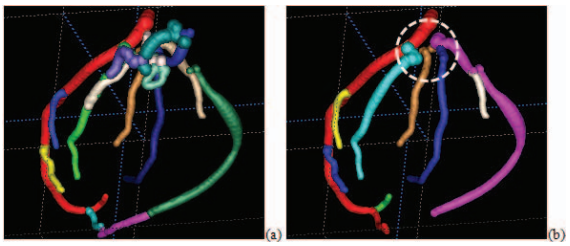


Fig. 7*:* Result for pruning algorithm: (a) original tracking result with rebooting; (b) vessel tree after pruning and tree reconstruction.

Table 1*:* Quantitative result for proposed methods

	Valid Branch	Leaking
Original Result	364	28
Rebooting	408	64
Pruning	407	1

5 Conclusion and Discussion

We have developed methods to enhance the performance of algorithms that track tree-like structures. Our generic 'reboot' scheme accurately locates early terminations and tracks missing vessel segments by jumping local gaps. The probabilistic model-based 'pruning' efficiently removes false vessel segments and the use of a graph based optimization scheme captures global contextual information of the tree, guaranteeing globally optimized pruning results. Application of the methods described here to coronary artery tracking produced promising quantitative results. It may be possible to use more sophisticated machine learning algorithms to further improve the performance of the current model-based pruning scheme.

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