PROBABILISTIC BRANCHING NODE DETECTION USING HYBRID LOCAL FEATURES

Haibin Ling[1], Michael Barnathan[2], Vasileios Megalooikonomou[2], Predrag R. Bakic[3], Andrew D.A. Maidment[3]

[1]Center for Information Science and Technology, [2]Data Engineering Laboratory (DEnLab), Department of Computer and Information Sciences, Temple University, 1805 N. Broad St. Philadelphia, PA 19122, USA

[3]Department of Radiology, University of Pennsylvania, 3400 Spruce St., Philadelphia, PA 19104, USA

ABSTRACT

Probabilistic branching node inference is an important step for analyzing branching patterns involved in many anatomic structures. We propose combining machine learning techniques and hybrid image statistics to perform branching node inference, using a support vector machine as a probabilistic inference framework. Then, we use local image statistics at different image scales for feature representation, including the Harris cornerness, the Laplacian, and the eigenvalues of the Hessian. The proposed approach is applied to a breast imaging dataset. Despite the challenge of the task, our approach achieves very encouraging results, which are helpful for further analysis of the breast ducts and other branching structures.

Index Terms— Branching Structure, Breast Imaging, Support Vector Machine.

1. INTRODUCTION

Branching structures are present in a variety of biomedical contexts, including the vascular, nervous, bronchial, and lactiferous networks of the human body. Patterns of properties such as branching topology, length, spatial distribution, and tortuosity have been analyzed in the literature [1]; alterations in these patterns have been associated with altered function and/or pathology [2, 3]. For example, regional changes in vessel tortuosity have been used to identify early tumor development in the human brain [4]. Moreover, studies have associated morphological variability of the breast ductal network with subsequent development of breast cancer; these studies suggest that analysis of branching structures within the human breast can assist in diagnosing malignancy or estimating cancer risk [5].

However, although branching structures frequently occur in nature and the rules of their development have been well studied over a great length of time, many challenges exist in the segmentation and analysis of such structures: images of natural and biomedical branching structures often include complex surroundings that may partially or completely occlude the branching structures. Projections of 3-dimensional branching structures may also induce overlaps between branches due to the loss of depth. Furthermore, the modalities for acquiring images of natural branching structures differ in their degree of sensitivity in visualizing the tree. In certain imaging modalities, such as unenhanced mammography, the branching topology of a tree structure may be barely visible or even absent from an image, but still contributes to the image texture of its surroundings [6]. Such examples are shown in Figure 1. The maximum depth of tree-branching that is captured in the image may also vary, depending on a modality's ability to extract a branching structure from its complex surroundings. Modalities which offer visualization of higher levels of branching are usually more prohibitive in terms of cost, health hazard, or comfort. Alternatively, modalities that can capture only the indirect effects of the presence of a branching structure on its complex surroundings are more easily available.

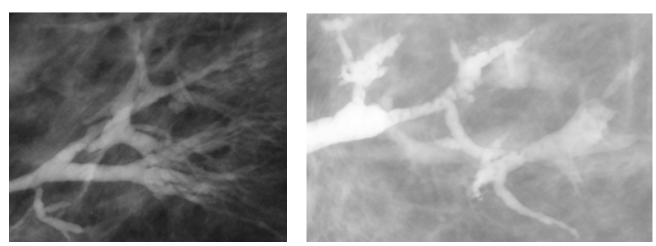


Fig. 1: Two examples of breast imaging with ductal systems.

Motivated by these challenges, we have previously investigated novel approaches for studying branching structures [7], their branching patterns [3] and their influence on corresponding texture in medical images [6]. In this paper, we propose combining machine learning techniques and hybrid local features for probabilistic branching node inference and detection.

2. BACKGROUND

To analyze the branching anatomic structures, the first step is to detect or localize them. These are important problems in medical imaging [8, 9, 10, 11, 12, 18, 19]. Early works usually involve manual or semi-manual efforts, often combined with vessel specific enhancement techniques. Many previous studies use lower-level processing for pixel-wise labeling. For example, correlation-based enhancement filters are used for vessel tree reconstruction in thoracic CT scans [8]. A similar approach is applied for retinal vessel segmentation in [9]. Machine learning techniques play important roles in some recent systems for vessel anatomy study [11]. In [11], Adaboost [13] is applied on features for classification of lung bronchovascular anatomy. Tracking-based approaches have also been applied for vessel detection [14, 10]. A thorough survey on vessel detection is given in [15].

Unlike previous works that focus on manual or semi-manual tree structure detection, we are interested in an automatic solution. This task is very challenging because anatomic tree-like structures are usually very complex in both topology and pattern of appearance. Furthermore, the imaging process often introduces more obstacles, such as blurring, noise (in some modalities), and the vessel occlusion and intersection caused by 3D to 2D projection.

Branching nodes and leaf nodes in tree-structures are the key components for tree localization as well as topology building. Therefore, node detection is a very important first step towards fully automatic tree-structure segmentation. In addition, the node statistics themselves can be used for medical analysis. For these reasons, we focus on node detection in this paper.

3. METHODOLOGY

3.1. Problem formulation

The goal of this paper is to investigate a learning-based framework for branching node inference. In other words, instead of directly detecting branching nodes, we are interested in the probability of any given location being a branching node. Specifically, we start with an normalized input image $I : D \rightarrow [0,1]$, where $D=[1..m]\text{x}[1..n]$ is the lattice on which I is defined. For any $(x,y)\in D$, the intensity $I(x,y)$ is normalized from the original image by

$$I(x,y) = (I(x,y) - I_{\min}) / (I_{\max} - I_{\min}) ,$$

where $I_{\max}$ and $I_{\min}$ are the maximum and minimum intensities over all original un-normalized images. Our task is to find a node probability estimation $P(x,y;I) : D\rightarrow[0,1]$, such that for any (x,y) in D, $P(x,y)$ measures the probability that a tree node exists at pixel (x,y).

Note that function P is more general than the commonly used detection function that provides a binary output. The probabilistic output of P is very flexible. It provides a local confidence that can be fused in the future steps involving semantic (usually global) information. Second, as shown in the following sections, it can be used for candidate node detection.

We use a learning-based approach to automatically build function P. This involves two issues: probabilistic branching node inference framework and feature representation.

3.2. Probabilistic branching node inference

We use a support vector machine (SVM) for this task. In this framework, let $z= f\ (x,y;I)$ be the feature vector extracted from image I at location (x,y). The classification boundary is then defined by the following equation,

$$\sum_{i=1..n_s} \alpha_i l_i K(s_i, z) + b = \Delta ,$$

where n_s is the number of support vectors s_i, l_i are the labels of corresponding support vectors, α_i and b are parameters estimated by the learning procedure, and Δ is the threshold that will be adjusted for trading off the false positive and false negative rates. A radial basis function (RBF) kernel K is used

$$K(s,z) = \exp(-\gamma \, \| s - z \|^2) ,$$

where γ is a parameter determining the size of RBF kernels (γ =100 is used in all our experiments).

Since our goal is a probability function that measures the likelihood of a given pixel being a node, we use the probabilistic output of SVM. In particular, a confidence output (or margin) from the learnt SVM model is converted to a probability using a sigmoid function.

3.3. Hybrid local features

To find local feature representation $z= f\ (x,y;\ I\ )$, we use three kinds of image statistics: Harris cornerness [16] $h(x,y)$, Laplacian $l(x,y)$, and eigenvalues ($\lambda_1(x,y)$, $\lambda_2(x,y)$) of the Hessian matrix $H(x,y)$.

The Harris cornerness is derived to measure the divergence of local principal directions, which is therefore useful to distinguish branching nodes. It is defined as

$$h(x,y) = \frac{\Phi(I_x^2) g(I_y^2) - \Phi(I_x I_y)^2}{\Phi(I_x^2) + \Phi(I_y^2) + \varepsilon} ,$$

where Φ is a local smoothing function using a Gaussian kernel, ε is used to avoid underflow, and I_x and I_y denote image gradients.

The image Laplacian is defined as $l(x,y)=I_{xx}+I_{yy}$, where I_{xx} and I_{yy} denote second derivatives of image I. The Laplacian is known to relate to local "blob-like" structures such as nodules [17].

The Hessian matrix is often used for vessel analysis [13]. It is defined as

$$H(x,y)=\begin{bmatrix} I_{xx} & I_{xy} \\ I_{xy} & I_{yy} \end{bmatrix},$$

where I_{xx}, I_{yy}, and I_{xy} denote second derivatives of image I.

To combine these hybrid features together, each feature is multiplied by a coefficient for roughly normalization, specifically, we have $l'(x,y)=3l(x,y)$, $\lambda_i'(x,y)=2\lambda_i(x,y)$, and $h'(x,y)=5h(x,y)$.

Furthermore, a hierarchical scheme is used to capture over scale information. In our implementation four scales are used, resulting in a 16-dimensional features space, i.e.,

$$z=f(x,y;I)=(\ldots, l'^{(s)}, \lambda_1'^{(s)}, \lambda_2'^{(s)}, h'^{(s)}, \ldots)^T, \ s=1,\ldots,4,$$

where (s) indicates that the feature is extracted at the image of scale s (image I smoothed by a Gaussian with standard deviation 2^{s-1}), and (x,y) in the feature vectors are omitted for notation simplicity. By this hierarchical scheme, the feature vector implicitly captures neighborhood image statistics at different scales.

4. EXPERIMENTAL RESULTS

4.1. Experimental setup

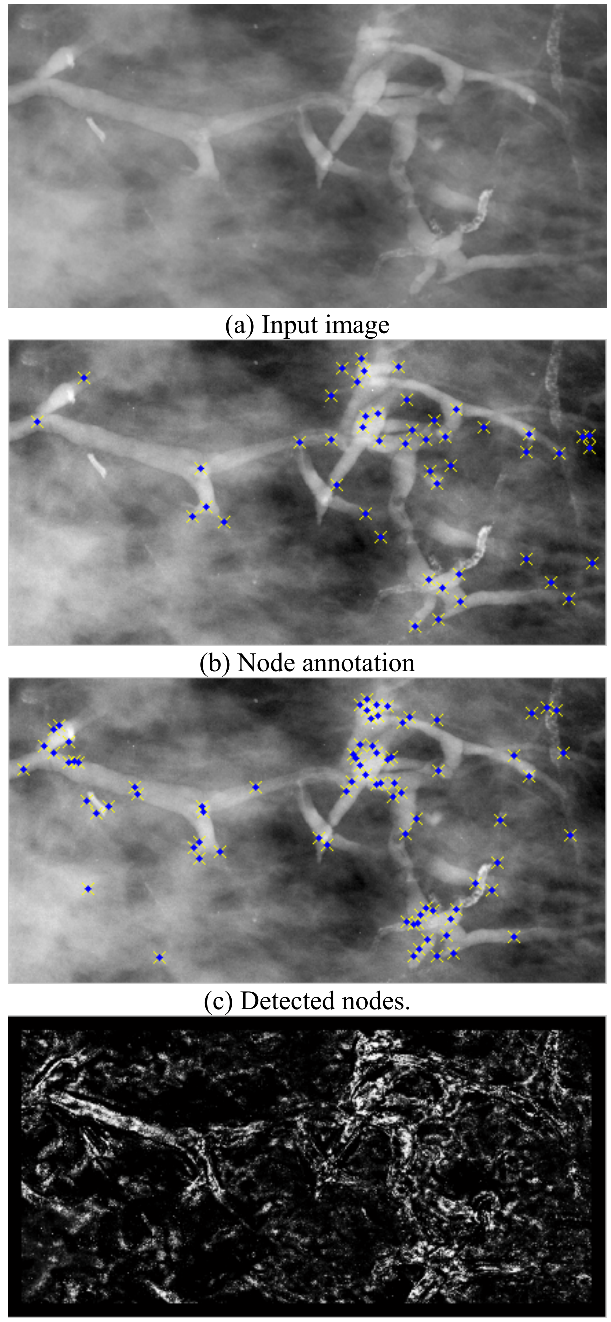
To test the proposed approach, we use a dataset containing seven breast images. Some of these images can be seen in Figures 1 and 2. All the images have been manually annotated by experts; these annotations are used in both training and evaluation. An example annotation is shown in Figure 2 (b). From these figures, we can see the large variation in topology and appearance among breast ductal systems. In addition, some annotated nodes have very similar local appearances to non-node pixels.

For evaluation, we conduct a leave-one-out experiment on the dataset. In the training stage, the annotated nodes are used as positive samples, and negative samples are randomly selected pixels that are at least eight pixels far from any positive samples. In the testing phase, we applied the learnt SVM model to all image pixels and output their node probabilities.

4.2. Results

The result on one image is shown in Figure 2. In addition to the probability map (Figure 2(d)), we also output the detected top candidates (Figure 2(c)). This is achieved by first finding all local maximums from the probabilistic map, and then picking from these maximums the top 80 with largest probabilities.

For a quantitative study, we output the average (over all images) number of correct nodes among top N candidates picked according to the learned probabilities, for N=20, 40, 60, 80. We compare the hybrid features with other features. The results are summarized in Table 1, which shows the superiority of the proposed approach. From Table 1 we see that about one third of the selected candidates are correct, which can be used for further tree-structure detection steps.



(a) Input image

(b) Node annotation

(c) Detected nodes.

(d) Probability map.

Fig. 2: (a) An example image, (b) its annotation, (c) node detection, and (d) probability map for branching nodes.

The experimental result is very promising considering that only six images are used for training and the large appearance variation among them. We expect that more training samples will boost the performance.

N	20	40	60	80
Hybrid	**7.00**	**14.57**	**20.29**	**26.86**
Laplacian	5.71	11.57	18.43	24.71
Hessian	6.00	12.86	19.71	25.00
Harris cornerness	4.71	9.43	11.86	12.57

Table 1: Average number of correct nodes among top *N* detected candidates.

5. CONCLUSION

We propose combining machine learning tools with hybrid local features for branching node inference. The learning based framework enables us to design an automatic solution for probabilistic node detection. The proposed approach demonstrates promising results on a dataset containing seven breast images.

6. ACKNOWLEDGMENTS

This work was supported in part by NSF Research Grant IIS-0237921. The funding agency specifically disclaims responsibility for any analyses, interpretations and conclusions.

7. REFERENCES

[1] Uppaluri, R., Hoffman, E.A., Sonka, M., Hunninghake, G.W, McLennan, G., Interstitial Lung Disease: A Quantitative Study Using the Adaptive Multiple Feature Method, Am. J. Respiratory Crit Care Med,159 519-525, 1999.

[2] K Horsfield and A Thurlbeck, Relation between diameter and flow in branches of the bronchial tree, Bulletin of Mathematical Biology, 43 (6), 681-691, 1981.

[3] V. Megalooikonomou, M. Barnathan, D. Kontos, P. R. Bakic, A. D.A. Maidment, " A Representation and Classification Scheme for Tree-like Structures in Medical Images: Analyzing the Branching Pattern of Ductal Trees in X-ray Galactograms," IEEE Transactions on Medical Imaging, Vol. 28, No, 4, pp. 487-493, April 2009.

[4] Bullitt, E., Zeng, D., Gerig, G., Aylward, S., Joshi, S., Smith, J.K., Lin, W., Ewend, M. G.: Vessel Tortuosity and Brain Tumor Malignancy: A Blinded Study. Academic Radiology, vol. 12, pp. 1232-1240, 2005.

[5] H. P. Dinkel, A. Trusen, A. M. Gassel, M. Rominger, S. Lourens, T. Muller, and A. Tschammler, “Predictive value of galactographic patterns for benign and malignant neoplasms of the breast in patients with nipple discharge,” Brit. J. Radiol., vol. 73, pp. 706–714, 2000.

[6] M. Barnathan, J. Zhang, D. Kontos, P. Bakic, A. Maidment, V. Megalooikonomou, “Analyzing Tree-Like Structures in Biomedical Images Based on Texture and Branching: An Application to Breast Imaging”, Proceedings of the International Workshop on Digital Mammography (IWDM), Tucson, AZ, Digital Mammography, Lecture Notes in Computer Science, Vol. 5116, pp. 25-32, 2008.

[7] D. Kontos, Bakic, P.R., Maidment, A.D.A., "Analysis of Parenchymal Texture Properties in Breast Tomosynthesis Images," SPIE Medical Imaging: Computer Aided Diagnosis, San Diego, USA, 2007.

[8] Agam, G, Armato, SG, Wu C. Vessel Tree Reconstruction in Thoracic CT Scans With Application to Nodule Detection, IEEE Transactions on Medical Imaging, 24(4): 486-499 (2005), 2005

[9] Chang-Hua Wu, Gady Agam, Peter Stanchev: A Hybrid Filtering Approach to Retinal Vessel Segmentation. ISBI 2007: 604-607

[10] Charles Florin, Nikos Paragios, James Williams: Globally Optimal Active Contours, Sequential Monte Carlo and On-Line Learning for Vessel Segmentation. ECCV (3) 2006: 476-489

[11] Robert A. Ochs, Jonathan G. Goldin, Fereidoun Abtin, Hyun J. Kim, Kathleen Brown, Poonam Batra, Donald Roback, Michael F. McNitt-Gray, Matthew S. Brown, Automated classification of lung bronchovascular anatomy in CT using AdaBoost, Medical Image Analysis, Volume 11, Issue 3, June 2007, Pages 315-324.

[12] Michal Sofka, Charles V. Stewart: Retinal Vessel Centerline Extraction Using Multiscale Matched Filters, Confidence and Edge Measures. IEEE Trans. Med. Imaging 25(12): 141-126 (2006)

[13] Yoav Freund, Robert E. Schapire: A Decision-Theoretic Generalization of On-Line Learning and an Application to Boosting. J. Comput. Syst. Sci. 55(1): 119-139 (1997)

[14] Carrillo J.F., Hernández Hoyos M., Dávila E.E., Orkisz M., Recursive tracking of vascular tree axes in 3D medical images, International Journal of Computer Assisted Radiology and Surgery, 2007, 2:6, 331-339

[15] Kirbas, C. and Quek, F. 2004. A review of vessel extraction techniques and algorithms. ACM Comput. Surv. 36, 2 (Jun. 2004), 81-121.

[16] Harris, C. and Stephens, M., A combined corner and edge detector, Alvey Vision Conference, 8-13, 1988.

[17] Okada, K., Comaniciu, D., and Krishnan, A. Robust anisotropic Gaussian fitting for volumetric characterization of Pulmonary nodules in multislice CT. IEEE Trans. Med. Imaging 24(3): 409-423, 2005.

[18] Prasad, M., Sowmya, A. Detection of Bronchovascular pairs on HRCT Lung Images, IEEE International Symposium on Biomedical Imaging, pp. 1135 – 1138, IEEE, USA, 2004.

[19] Prasad, M., Sowmya, A. Automatic detection of bronchial dilatation in HRCT lung images, Journal of Digital Imaging, 2007.