Automated Lymph Node Labeling System

Atilla P. Kiraly[1], Benjamin J. Odry[1], David P. Naidich[2], and Carol Novak[1]

[1] Siemens Corporate Research, Princeton, NJ 08540, USA
[2] New York University Medical Center, New York, NY, 9999, USA

Abstract. Lung cancer staging typically requires locating, measuring, and labeling lymph nodes to determine affected nodes. Until recently, automation and workflow reduction has focused on the first two tasks. According to the classification scheme recommended by the American Joint Committee on Cancer and the Union Internationale Contre le Cancer, pulmonary lymph nodes are divided into four groupings with two to four stations per grouping. We present a system that automatically assigns proper group and station labels to lymph node locations within contrast enhanced chest CT images. The airways and aortic arch are automatically segmented to obtain an anatomic model of the patient. The model provides spatial features, such as distance and angle, used by a support vector machine to automatically provide a label for any given location. The model also provides interactive visual feedback, allowing the user to understand the relationship between the nodes and nearby anatomy for verification and for surgical planning.

1 Introduction

Recently the concept of automatically labeling lymph nodes has been presented to assist in cancer staging [1]. Previous automation approaches mainly focused on lymph node segmentation to assist in evaluation [2,3]. During cancer staging, lymph nodes are evaluated based upon condition and location. The cancer severity not only depends on the condition of the lymph node, but also on its anatomical location. According to the American Joint Committee on Cancer and the Union Internationale Contre le Cancer, pulmonary lymph nodes are divided into four groupings, each with several stations [4]. A scoring or evaluation of a patient involves assessing lymph nodes within each grouping.

We present a demonstration system for automated lymph node labeling and visualization. The user can select any lymph node and receives the label associated with that location. The labeling algorithm is independent of lymph node detection and segmentation methods and can be applied soon after the data is loaded. The topic of assisted labeling was later explored in [5] with a Bayesian approach to define station regions as discussed in [1]. However, not all components used in station definitions were acquired.

2 Method

The method proceeds by first obtaining a physical centerline and surface model of the airways and aorta in the given image. A user input of a lymph node location then produces several physical features relative to the models such as angles and distances that are used as a feature vector on a trained support vector machine (SVM) to produce a label. Further details are described below with complete details in [1].

2.1 Airway and Aortic Arch Modeling

The centerline and surface of the airways are obtained by an adaptive region growing method followed by skeletonization and refinement. The model describes the hierarchy of the airway tree and its physical location. The carina and left and right main bronchus can be determined from the model. The aortic arch is obtained by a tracking process focusing on a 3D response image. The top most region of the arch is then determined. These anatomical features are based on those used to define labels in the staging system.

A user input in a form of a 3D coordinate then produces a feature vector encoding relative distances, angles, and vectors relating the location to specific locations on the airway and aortic arch models. This vector is then passed to the SVM.

2.2 SVM classification

An SVM with a radial basis function is used to determine the label from the feature vector. The SVM was trained and evaluated on a total of 10 images with 86 labeled nodes. The labels in the ground truth were assigned by an experienced radiologist and then verified for by a second reader.

The SVM was first used to test and train on all of the datasets to determine the best features. A total of 8 features both from the airways and aorta were selected to be the most discriminating with the angle in relation the carina deemed the most important feature. The other features included the nearest distance to the airway tree and the distance to the top of the aortic arch.

In order to evaluate the method with the 8 selected features, round-robin testing was performed where all but one image was used to train the classifier with the remaining image used for testing. This procedure was repeated for each image. The results were 100% accuracy for group labeling and 76% for station labeling [1].

Even with a 76% accuracy for stations, staging scores rely more on the group labeling than station labeling to determine severity. Hence, the current method can still serve for automatic group labeling and assist in scoring.

3 System

Figure 1 shows the application. A patient dataset is loaded and the airway and aortic arch models are automatically determined. The user can click on any slice views (transverse, sagittal, coronal) and then have the label automatically generated. Since only a label is generated, the core labeling components of the system are portable and can be easy incorporated into dictation systems to provide further assistance with workflow. In this system, any user specified locations can be saved and documented into a case study. The determined label is automatically added to this case study.

Conversely, since the system has regions associated with station labels, the user can also focus on a particular region of the image given a specific station that they are interested in pursuing.

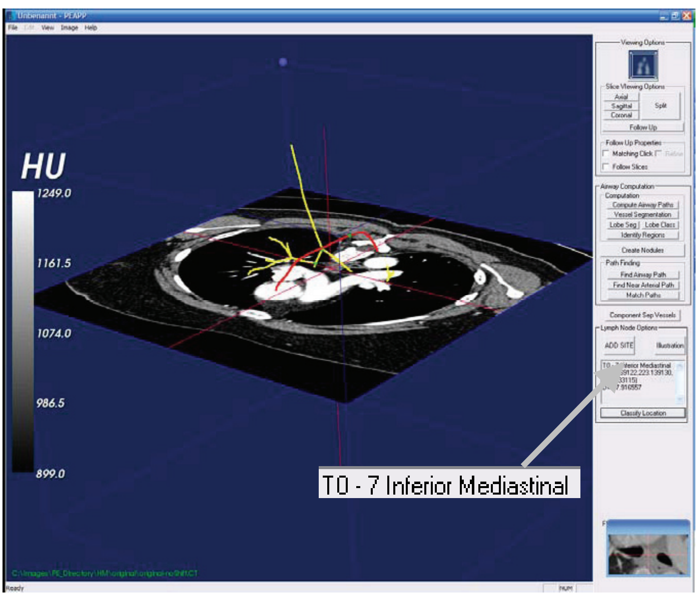

Fig. 1. The demonstration system for automatic lymph node labeling. In this example, the user has selected a location on the axial slice. The "Classify Location" button is pressed to produce the label associated with given lymph node location. This process is then repeated for each lymph node found. The labeled node and its location are then saved into the patient's case study for future reference.

4 Conclusions

We have demonstrated a prototype system for automated lymph node labeling. The interface is simple in that the user simply selects a location to immediately obtain a station label. Also, knowing a specific station, the region bounded by that station can also be obtained. The display of the models obtained allow for verification and better spatial understanding of the station label.

The labeling method is open to different labeling systems and image modalities since it based on physical features. In addition to benefiting the user, the regions defined by the method can be used as precursor inputs to lymph node detection and segmentation methods to help limit search regions.

The evaluation with the SVM provided a 76% accuracy for nodal station labels. Without an accurate model of the brachiocephalic artery, pulmonary artery, or pulmonary ligament, it is difficult to exactly model the labeling system. These are future components that must be incorporated to allow for a label determination on a Bayesian level. Without these components, an SVM allows us to maximize the accuracy with the available models and offer accurate group labels.

The system will be more complete with the incorporation of these additional models. However, the SVM would still be of use in determining useful features to help validate and even possibly improve existing lymph node station schemes. Valuable clues can be garnered to provide a more intuitive boundary description.

References

1. A.P. Kiraly, D.P. Naidich, L. Guendel, L. Zhang, and C.L. Novak, "Novel method and applications for labeling and identifying lymph nodes," SPIE Medical Imaging 2007, vol. 6511, Feb. 2007.
2. J. Dornheim, H. Seim, B. Preim, I. Hertel, and G. Strauss, "Segmentation of Neck Lymph Nodes in CT Datasets with Stable 3D Mass-Spring Models," Medical Image Computing and Computer-Assisted Intervention – MICCAI 2006, Volume 4191/2006, pp. 904-911.
3. G. Unal , G. Slabaugh , A. Ess , A. Yezzi , T. Fang , J. Tyan , M. Requardt , R.Krieg , R.Seethamraju , M. Harisinghani , and R. Weissleder, "Semi-Automatic Lymph Node Segmentation in LN-MRI," Proceedings of the IEEE Int. Conf. Image Processing, 2006.
4. J.P. Ko, E.A. Drucker, J.A. Shepard, C.F. Mountain, C. Dresler, B. Sabloff, and T.C. McLoud, "CT depiction of regional nodal stations for lung cancer staging," AJR Am J Roentgenol. 2000 Mar;174(3):775-82.
5. Lu, K., Merritt, S.A., Higgins, W.E., "Extraction and Visualization of the Central Chest Lymph-Node Stations," SPIE Medical Imaging 2008, Feb. 2008.
6. C. Cortes and V. Vapnik, "Support-Vector Networks," *Machine Learning*, vol. 20, no. 3, 1995, p. 273-297.