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Automatic Detection and Segmentation of Lymph Nodes Using NonMaximal Suppression Algorithm From CT Data

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Abstract— Image segmentation is a difficult task in all medical imaging process. The major issue deals with the segmentation time needed for each organ. This paper presents a robust learning-based method for automatic detection and segmentation of solid lymph nodes from CT data.Lymph node is an oval-shaped organ of the immune system, which is difficult to identify in most cases and is distributed widely throughout the body so that they are having high clinical significance.The proposed approach first uses a classifier to train the lymph nodes to extract haar and self aligning features.Second, it presents a Nonmaximal suppression algorithm for the lymph node detection inorder to identify the most relevant lymph nodes.Third, it uses a segmentation based on Delaunay triangulation to segment the detected lymph nodes. The method is evaluated for abdominal and pelvic LN detection containing 371 LN, yielding a 84.0% detection rate with 1.0 false positive per volume.

***Keywords*:** Delaunay, Haar, LymphNodes, Nonmaximal suppression

INTRODUCTION

LYMPH node (LN) analysis is a difficult task that accounts for a significant part of daily clinical work in radiology. Lymph node is an oval-shaped organ of the immune system, which is difficult to identify in most cases and is distributed widely throughout the body including the armpit and stomach and linked by lymphatic vessels. They act as filters or traps for foreign particles and are important in the proper functioning of the immune system.Lymph nodes also have clinical significance. They become inflamed or enlarged in various conditions, which may range from trivial, such as a throat infection, to life-threatening such as cancers.When the cancer treatment becomes successful they gradually reduce in size and comes to normal size.However the main problem concerns with detecting the lymph nodes from other particles in the abdominal regions.Lymph nodes nearby primary cancer regions are routinely assessed by clinicians to monitor disease progress and effectiveness of the cancer treatment. The assessment is usually based on 3-D computed tomography (CT) data.Since finding the lymph nodes is time consuming and highly dependent on the observer's experience, a system for automatic lymph node detection and measurement is desired. For follow-up studies, the system could further report the size change[2] for each major lymph node. In this paper, we introduce a non maximal suppression algorithm for the automatic detection and segmentation of solid lymph nodes. Enlarged lymph nodes with a solid interior are of particular clinical interest since they are believed to have a higher probability of being malignant than lymph nodes that for example have a fatty core.Only those measurable lesions will be considered as so-called target lesions to be recorded and tracked over time across follow-up exams during therapies. Following these guidelines[8], our method is targeted for detecting clinically relevant (and possibly malignant) lymph nodes of size at least 10 mm. For speed and accuracy, regions of interest (two axillary and one pelvic in our experiments) are extracted automatically as described. A number of lymph node center candidates are generated for each region using a two-stage detectors.Earlier work appeared focused only on axillary LN detection. This work follows the same basic algorithm, and presents a more thorough evaluation of the LN detection on a larger axillary dataset as well as on another dataset focused on the pelvic/abdominal area. Moreover, we present an evaluation of the segmentation accuracy of the proposed approach.

I. RELATED WORKS

There is a limited amount of work directed to automatic lymph node detection [4]–[8].These works target mediastinal,abdominal, pelvic ,or neck lymph nodes.Our work targets axillary and pelvic+abdominal lymph nodes. While the work in [4] uses multiple MR sequences and special contrast, our work addresses lymph node detection in CT images. The proposed approach could in principle be adapted to other modalities such as MR or 3-D ultrasound images. A special filter was used in Automated extraction of lymph nodes from 3-D abdominal CT images using 3-d minimum directional difference filter[3]by T. Kitasaka, Y. Tsujimura to detect lymph node centers.This minimum directional difference filter is constructed with the assumption that lymph nodes have uniform intensity and are spherical. The approach obtained a 57% detection rate with about 58 false positives per volume. The Min-DD filter work inAutomatic detection of pelvic lymph nodes using multiple MR sequences was improved by adding a Hessian-based blobness measure for reducing false positives. Our work also combines segmentation with object detection

II. ALGORITHM FOR LN DETECTION

Input: 2D CT of abdominal and pelvic regions.

Output: Set of detected and segmented lymph nodes
.
1: Extract subvolume(s) of interest from the CT data
2: **for** each subvolume V **do**
3: Obtain initial set of candidates C0 as all locations with intensity in HU
4: Of the candidates C0, keep the candidates C1 that pass the 5: Of the candidates C1, keep the candidates C2 that pass the self-aligning detector
6: **for** each ci=(xi,yi) **do**
7: Obtain a segmentation Si with center Ci
8: Obtain a score Pi from the detector based on segmentation features extracted
9: **end for**

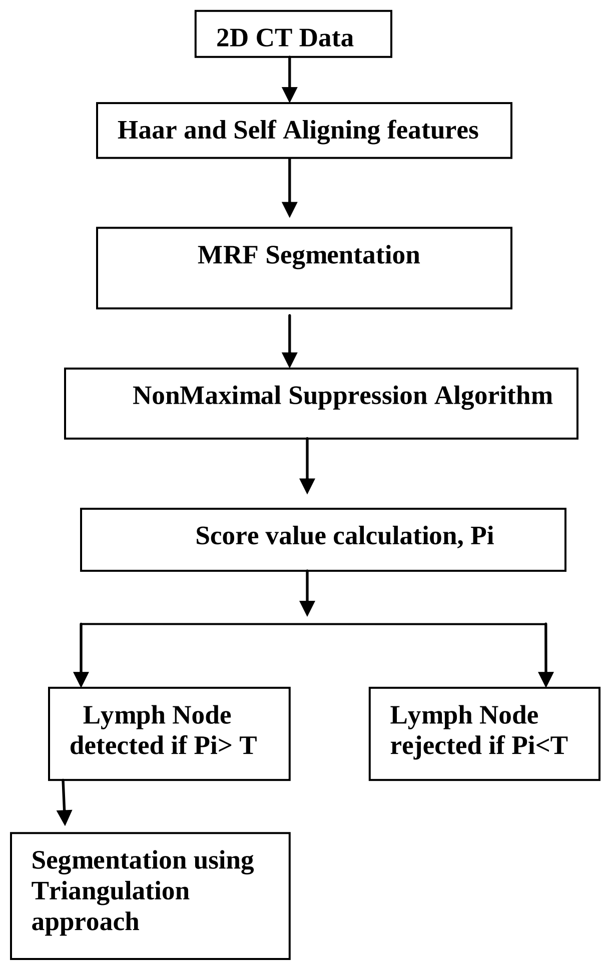

FIG1:RERRESENTATION OF OVERALL PROCESS

III. CANDIDATE LYMPH NODE DETECTION USING NONMAXIMAL SUPPRESSION ALGORITHM

Lymph node center candidates are detected in the cropped subvolumes ignoring the lymph node size

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and shape,making use of non maximal suppression algorithm.The algorithm detects the clinically relevant lymph nodes having a size greater than 10mm. The lymph nodes containing CT data are first trained using a classifier such as SVM classifier and the corresponding features are extracted using appropriate detectors.The detectors used here are haar and self aligning detectors. The LN sizes and shapes are then obtained using the LN segmentation approach

1) Haar Detector: The first detector is a cascade of Adaboost classifiers trained using 92000 3-D Haar features. For each candidate location, the Haar features are extracted from a window of size 23 x23x 23 voxels centered at that location. This window size guarantees that most lymph nodes (up to 35 mm diameter) will be inside the window. A cascade of detectors is trained using these features

2) Self-Aligning Detector: The second detector uses a set of features that are self-aligned to high gradients. The self-alignment insures that the feature values will be consistent for different lymph nodes independent of their size and shape

The proposed self-aligning gradient features are the following.

• Each of the 24 point features for the detected lymph node is computed at each of the first three local maxima for each direction ,threshold , and scale .

• Each of the 24 features types described above is computed half way between the candidate location and each of the first three local maxima, for each .

• The differences between distances to the corresponding first three local maxima in any combination of two different directions di,dj

The detection process can be refined by making use of a score value calculation.The score value can be calculated combing haar and self aligning features of the detected candidates.Again a threshold based on the size is set inorder to identify only the clinically relevant defective lymph nodes.The score value calculation can be obtained using the below equation

$$Pi = \sum_{i=1}^{n} H(f) + \sum_{i=1}^{n} S(f)$$

Where pi is the score value,h(f) is the corresponding haar features,s(f) is the corresponding self aligning features and n represents the number of lymph nodes identified.

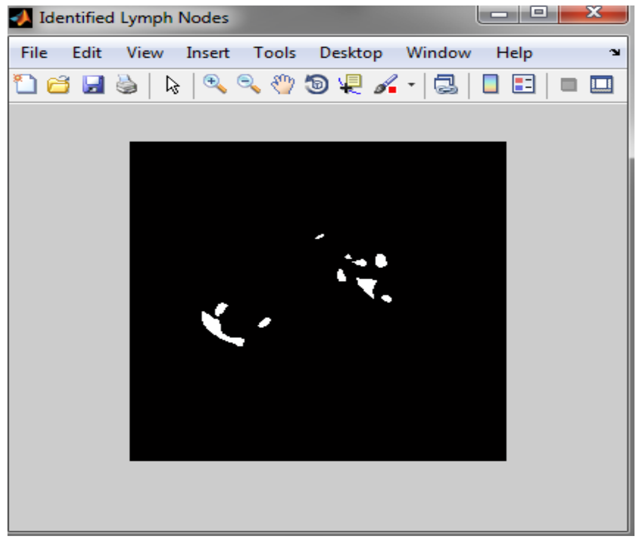

Fig 2:Identified lymph Node by applying a threshold greater than 10mm

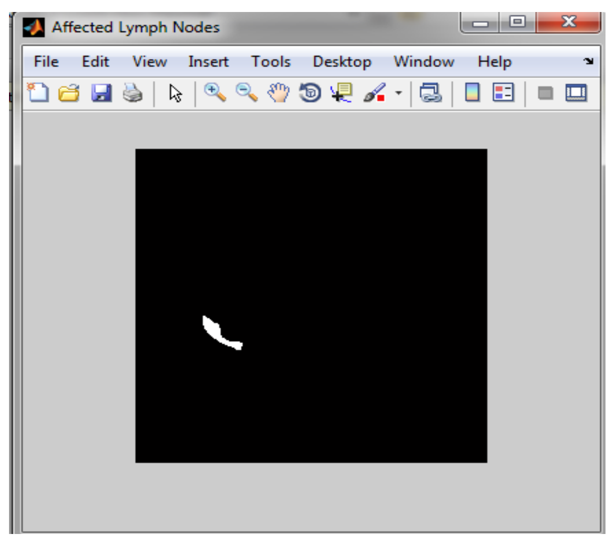

Fig 3:Detected lymph Node using Nonmaximal Suppression algorithm

IV. CANDIDATE LYMPH NODE SEGMENTATION

The segmentation algorithm is specially designed for detecting clinically highly relevant solid lymph nodes. The solid lymph nodes have a blob-like shape that can be described by using a Delaunay triangulation approach. This is a novel method for decomposing the detected lymph using high-level geometric constraints that are derived from low-level features of maximum curvature computed along the contour of each ilmph. Points of maximum curvature are used as vertices for Delaunay triangulation(DT).In this work, the lymph nodes has been discretized using a triangulation with 162 vertices, 480 edges, and 320 triangles inorder to balance the speed and accuracy for handling large lymph nodes. Alternatively, triangulations with 1280 or more triangles could also be used at a larger computational cost. The edges of this triangulation induce a neighborhood structure between the vertices. Two vertices are considered neighbors if there is a triangulation edge connecting them. This shape representation can accurately describe blob-like shapes even when they are not convex. It has some difficulty representing the extremities of very elongated shapes (with aspect ratio at least 4:1. However, out of the more than 900 solid lymph nodes that have been manually segmented using this representation. Instead of a PCA model, we adopt a Gaussian MRF shape prior to constrain the shape of the obtained segmentation.To find the segmentation vector we propose an approach similar to the active shape models but using a robust data cost, gradient optimization and a Gaussian MRF shape prior.The Gaussian MRF prior that encourages the neighboring vertices to have similar radii. The robust data term ensures that the segmentation is robust to any sporadic outliers in the measurements

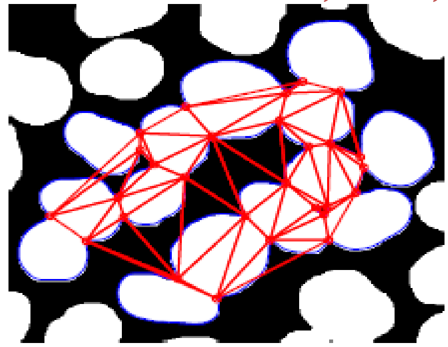

Fig 4:Delaunay triangulation for the detected lymph node

V. LYMPH NODE VERIFICATION

For each of the candidate lymph node centers ,the candidate LN detector with 162 vertices is obtained. The segmentation is used to obtain more discriminative features for the final verification of the lymph node candidates. For each lymph node, a bounding box is extracted from the segmentation and used to measure the LN size. Candidates whose second largest bounding box size is less than 9 mm are automatically rejected purely based on their size since we are interested only in detecting lymph nodes larger than 10 mm. We chose 9 mm instead of 10 mm as the rejection threshold in order to account for small errors in the automatic segmentation.The threshold could be changed accordingly to detect smaller lymph nodes if desired. The LN verification is done using a trained detector based on the following features that are computed from the segmentation result.

• Each of the 24 point features are computed at the 162 segmentation vertices using the directions from the LN center. For each feature, the 162 values are sorted in decreasing order.

• For each of the 24 point features, the 81 sums of feature values at the pairs of opposite vertices are computed and sorted in decreasing order. Two vertices are opposite if the line connecting them passes through the LN center

VI.MANUAL LYMPH NODE SEGMENTATION

For a comprehensive evaluation we manually segmented each lymph node using an interactive segmentation tool. The segmentation tool allows the visualization and interaction with the LN boundary on a number of cutting planes that contain the line that passes through the lymph node center and is parallel to the Z-axis.The LN manual segmentations are also based on the sphere mesh with 162 vertices The interactive segmentation tool allows the user to manually modify the radius of any of the 162 segmentation vertices. After a radius (having direction) has been changed, the LN segmentation is updated by minimizing the energy

VII. RESULTS

Out of the 131 axillary cases, the region extraction failed on the left side of one patient that actually had the left lung removed. The pelvic region extraction was always successful. Non maximal suppression algorithm detected only the lymph node that is having a size greater than 10mm.In the abdominal and the pelvic regions clinically relevant effected lymph node are detected.A score value calculation based on the haar and self aligning detector helped to refine the detection process.A verification step based on segmentation has a great impact on the overall performance of the system.We also evaluated a system in which the segmentation and verification steps are removed and replaced with a lymph node detector that searches the size of the lymph node bounding box.

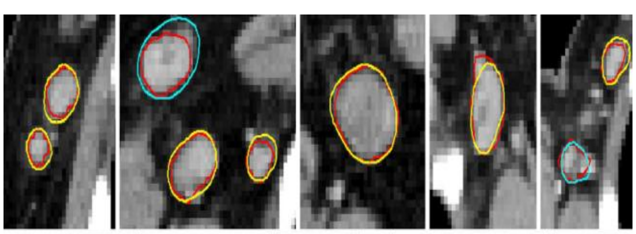

Fig 5:Detected and segmented lymph nodes.

VIII. CONCLUSION

Automatic detection and segmentation of solid lymph nodes from the CT data using Non Maximal Suppression algorithm is proposed. Non Maximal Suppression algorithm detects the lymph nodes with size greater than 10 mm based on the score value calculation. Detected ones are then segmented using triangulation approach from the 2D CT data. The method is fastest since it detects the lymph node automatically ignoring the lymph node shape. A segmentation of the colon, intestines and vessels could in theory improve detection performance for the pelvic area. However, no colon or intestine segmentation has been used in the proposed approach. The axillary lymph nodes are easier to detect than other types of lymph nodes as they are far from airways and intestines, two potential sources of false positives. The evaluation confirms that the detection performance for the axillary region is better than for the pelvic area. The accuracy of the proposed approach for the axillary region could be further improved by using a vessel segmentation, to eliminate many of the systematic false positives.In future the method can be adapted to detect the lymph nodes from MR ultra sound images.

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