SEGMENTATION OF PATHOLOGICAL LUNGS FROM CT CHEST IMAGES

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This is a short description of our framework used for lung segmentation. Our paper is currently under submission. The full paper will replace this document once the review process finished.

This work proposes an accurate and automated framework for the segmentation of pathological lung tissues from computed tomography (CT) images. The proposed segmentation methodology is based on a novel 3D joint Markov-Gibbs random field (MGRF) model of the CT images and its Gaussian scale space generated data. The proposed image model integrates three image features: (*i*) a novel adaptive soft shape model of the lung guided by the appearance of the CT image, (*ii*) the first–order visual appearance model of the CT images, and (*iii*) the global appearance features of the Gaussian scale space (GSS) filtered CT images, using a joint MGRF image model. The first–order appearance model describes the empirical distribution of image signals using a linear combination of discrete gaussians (LCDG) with positive and negative components. The second order spatial interaction model describes the relation between the CT image signals using a pairwise MGRF spatial model of independent image signals and interdependent region labels. **The whole segmentation process is represented in Algorithm 1.**

1 Results

We tested our framework on multiple CT data sets that were acquired using different scanners and acquisition protocols and contains different types of pathologies. Particularly, our approach is tested on our locally acquired data (30 data sets) involving a wide-variety of pathologies, including tumors, ground glass opacity, pleural effusion, consolidation, fibrosis,

and cavities. As well as on three publically availably CT databases, namely 55 data sets from the LOLA11 MICCAI challenge, 60 data sets from the EMPIRE 2010 MICCAI challenge, and 20 data sets from the VESSEL ISBI 2012 challenge. Segmentation accuracy, for our locally acquired, EMPIRE and VESSEL data sets, has been evaluated using the Dice similarity coefficient (DSC), the 95-percentile modified bidirectional Hausdorff distance (BHD), and absolute lung volume difference (ALVD). The accuracy on the LOLA11 has been blindly evaluated by the challenge organizers.

2 Conclusions

This paper presents a novel methodology for the segmentation of lung tissues from 3D computed tomography (CT) images. The proposed approach shows high performance in segmenting different pathological lungs (e.g., pulmonary fibrosis, pleural effusion, consolidation, and cavities) of CT data acquired using different scanners and protocols. This is due to taking the advantage of integrating first- and second-order visual appearance features of the CT images with a novel adaptive appearance-based shape model using an improved MGRF model. Validation results of different CT data confirm the advantages and privileges of our approach over other state-of-the-art approaches, which is documented by the ROC curves and by both the area-based (Dice coefficient and volume difference) and distance-based (bidirectional Hausdroff distance) error metrics. Experimental results are acquired from running the proposed framework on Dell Precision T7500 server with four Intel DualCore 3.33 GHz CPU with 72 GB of RAM.

Algorithm 1 The Proposed Lung Segmentation Algorithm

- **Input:** Read the original 3D CT data
- **Appearance-based Adaptive Shape Creation:**
  1. Register the test subject to the training database to get the deformation fields for each voxel.
  2. Generate the Gaussian scale space (GSS) data.
  3. Perform a cross correlation similarity between the test subject and each subject in the training database and select the most similar subjects.
  4. Estimate the appearance-based shape model by calculating the value of the shape prior probability at each voxel using the following steps **for the original and GSS data**:
     (a) Transform each voxel in the test subject to the training database domain using the calculated deformation field.
     (b) Initialize an $N_{1i} \times N_{2i} \times N_{3i}$ search space centered at the mapped voxel.
     (c) Find the voxels within the search space that is close to the voxel's Hounsfield value within $\pm\tau$.
     (d) If no corresponding voxels are found, increase the search space size and repeat Step 3-(b, and c) until a correspondence is found or the predefined maximum search space size is reached.
     (e) If no correspondences are found, increase the tolerance with a predefined value $\Delta\tau$ and repeat Step 3-(b,c, and d) until a correspondence is found.
     (f) Calculate the label probabilities for each voxel based on the relative occurrence of each label in the found voxel's correspondences search results.
- Lung Segmentation **for the original and GSS data:**
  1. Find an initial map by voxelwise Bayesian MAP classification of a given CT image using the estimated appearance-based shape probabilities.
  2. Estimate the conditional intensity model by identifying the LCDG models of signals of each object class represented by one of the dominant modes.
  3. Use the initial region map to identify the MGRF model of region maps.
  4. Perform the final Bayesian segmentation of the lung regions using the joint MGRF model..
- **Output:** Obtain the final segmentation of the lung regions using majority voting of individual segmentation of the original and GSS data.