Lung Disease Identification and Segmentation in Medical Images

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Abstract:
The classification and identification of the disease in medical images were helpful in biomedical applications. The process of segmentation of the diseased portion in the lung lobe images were done based on Toboggan algorithm. The lung lobes were segmented from the input images based on gradient estimation following original Toboggan algorithm. If the segmented lung lobes were disease affected means then the identification of disease location is done. The classification process is employed using SVM classifier with the help of features extracted from lung lobes using texture identification. From the gradient estimated lung lesion inside the segmented lung lobes were extracted based on the improved Toboggan algorithm. Contours were extracted over the identified lung lesion regions. The overall performance of the process were measured based on the performance metrics.

Keywords: *Lung cancer, SVM, Lung lesion, Computed Tomography.*

I. INTRODUCTION

Lung lesion extraction becomes the crucial part in the lung cancer diagnosis. The accurate segmentation of lung lesion from computerized tomography scans is important for lung cancer diagnosis and research. In older days, the lung lesion segmentation can be carried out by experts with experience such as Radiologists define the lesion manually. It is a difficult task to obtain robust and efficient results for various reasons. The experts may underestimate or overestimate the lesion volume. Different manual delineations are also varying from one to another. Then the time consumption limits change the CT images to undetectable data due to fading, therefore a robust, high efficient and automatic lung lesion segmentation approach is required immediately.

However, accurate segmentation of lung lesions by an automatic method is also a difficult process because of the various type and characteristics of the lesions. Due to the diversity of lung lesions, current segmentation accuracy is inadequate. The intensity, shape, and location of lung lesions change greatly because of the time and the severity of the lesions. The intensity of lung lesions is sometimes close to the intensity of vessels, fissures or chest wall. But other times it is close to the intensity of lung fields, such as ground-glass opacity (GGO), which is not detected on CT scans that indicate a partial filling of air spaces as well as lung wall thickening or partial damage of lung alveoli. Moreover, the influence of the inherent noise in CT images can also be significant. All these facts render that it is very challenging to achieve the precise delineation of lung lesions automatically.

II. RELATED WORK

In the work developed by Pu et al. (2008a) the authors use adaptive borders algorithms to delimit the area of the juxta pleural nodules without selecting lung external tissue together with the region of interest. The methodology is divided into two steps. The first one is the image pre-processing. The second one corrects the defects caused by the exclusion of juxta pleural nodules. The experiments used 20 datasets and obtained an accuracy of 90%. This work uses an Adaptive Border Marching method to segments the lung region, reducing the over-segmentation problem. However, this algorithm, although adaptive, requires some parameters, assigned arbitrarily in this work.

The methodology proposed by Shen, Bui, Cong, and Hsu (2015) presents a lung nodule segmentation method, focused on juxta pleural nodules. The authors separated the methodology into three steps. First, the image pre-processing generates one initial mask with an adaptive threshold. Secondly, the inflexion point detection (horizontally and vertically) is realized using chain-code algorithm, to find inflexion points. Lastly, correction of the lung edge is done using SVM. The methodology achieved an accuracy of 92.6%. The chain-code technique to detect inflexion points is highly sensitive to noises, which is the main challenge of this work. Depending on the scans quality, this technique strongly depends on the adaptive threshold method and SVM performance to not raise the over-segmentation and under-segmentation ratios.

Tan, Deklerck, Jansen, Bister, and Cornelis (2011) presents a CAD system to detect lung nodules in CT images using nodule and vessel enhancement filters and a computed divergence feature for cluster the nodules. To classify, invariant features were extracted, defined on a gauge coordinates system that separates nodules from non-nodules structures, using SVM and Artificial Neural Network. This methodology reached a sensitivity of 87.5%. 235 cases of LIDC database were selected for evaluation.

The work of Pu, Zheng, Leader, Wang, and Gur (2008) proposes a method to achieve lung nodule detection based on geometric analysis of the signed distance field in CT images. The methodology achieved a maximum sensitivity of 95.1%. The methodology was evaluated with 52 low-dose screening CT exams. The related works have been described with their highlights and shortcomings.

The work of Mousa and Khan (2002) uses manually segmented nodules and non-nodules candidates, in contrast of the proposed methodology. The nodules candidates are segmented using markers by the radiologists and the non-nodules are obtained from Carvalho Filho et al. (2014) methodology, since the non-nodule separation in this work is automatically generated.

Jing et al. (2010) and Namin et al. (2010) presented a sensitivity reduction due to the irregular shapes of the nodules candidates. Our work uses extraction methods fully based on texture to overcome this situation. Lee et al. (2010) and Pu et al. (2008a) their approaches utilize techniques that require parameterization, empirically obtained. The original AC method was adapted in this work to not need any parameterization, as well as RD method. Finally, Tartar et al. (2013) and Zhang et al. (2013) methods are adapted to extract features from two-dimensional slices from the CT exams. This may reduce the natural characteristics of the lung nodules; if the chosen slices do not com- prise all information necessary to recognize the object. This work uses all the three-dimensional properties of the CT scans in both proposed techniques.

III. PROPOSED METHODOLOGY

The proposed method consists of original Toboggan algorithm, Classification and Disease Identification by Improved Toboggan algorithm. The detailed flow chart gives thorough knowledge about the entire system. It involves mainly four phases a) seed point location b) Gradient Extraction c) Region Growing d) Segmentation. This technique is found to be more efficient than before.

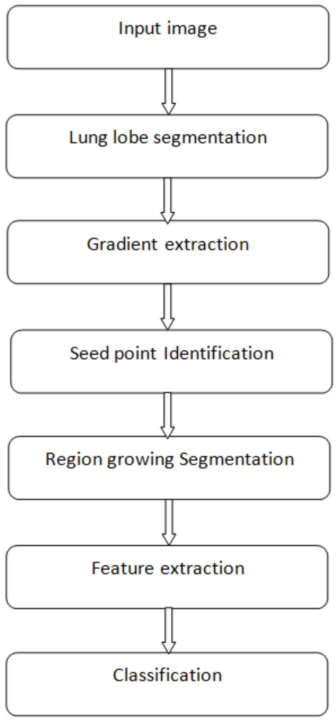

Fig.1. Block diagram of proposed method

The input of this algorithm is a slice of CT image containing lung lesion(s). The lung lobe segmentation process is employed based on Toboggan algorithm. In Toboggan algorithm the neighbours of each pixel were examined and the steepest downward direction in the sliding list is recorded. Then region growing process is employed in order to find the shortest paths from each inner pixel in the non-local-minimum flat regions to its lower boundary. The remaining empty sliding lists belong to the local-minimum flat regions. The connected components were used for recognizing local minimum flat regions. Finally a topological sort is applied by taking the pixels as the vertices and the corresponding pixels in the sliding list as the targets of the directed edges.

From the segmented lobes features were extracted based on eXtended Center-Symmetric Local Binary Pattern (XCS-LBP) process. The texture patterns can be extracted from the images based on XCS-LBP process. The extracted texture patterns acts as the features for the images. The extracted texture features were classified using Support Vector Machine classifier in order to find whether the lobes are normal or disease affected. The SVM classifier is based on the kernel functions employed for the matching of the test image features with the training features. If the lung lobes were identified to be abnormal then segmentation process is employed.

The diseased portions in the lung images were identified based on improved toboggan algorithm. By the improved toboggan method, the highlighted vessels, tracheal wall and other noise in the gradient image will be moved into the lung field while the lesion remains at a higher value. Therefore, the other tissues would be dimmed and the lesion could be enhanced in the label image for the subsequent automatic seed point selection. The improved toboggan algorithm is based on improving the gradient obtained from the lung lobes. The area and the perimeter for the different diseased locations in the images were set and by comparing with those values the diseased locations were segmented from the images. From the gradient estimated lung lesion inside the segmented lung lobes were extracted based on the improved Toboggan algorithm. Contours were extracted over the identified lung lesion regions.

IV. PERFORMANCE MEASURES

The performance of the process is measured by measuring the accuracy of the process. The accuracy is measured by comparing with the ground truth images.

Accuracy = (TP+TN) / (TP+FP+FN+TN)

Sensitivity = TP / (TP+FN)

Specificity= TN / (TN+FP)

- TP = True positive = correctly identified
- FP = False positive = incorrectly identified
- TN = True negative = correctly rejected
- FN = False negative = incorrectly rejected

V. RESULTS AND COMPARISON

By using the Toboggan algorithm, the lung lobe images are segmented and the disease is identified and detected more efficiently. Modification process is adapted here such as seed point selection, gradient extraction, region growing through contour extraction and segmentation. When the input CT image is given then it undergoes gradient extraction through Toboggan algorithm. Further, the gradient image gets feature extracted by using XCSLBP. The image then goes classification process through SVM classifier which identifies whether the lung is disease affected or not. If no damage is traced out then it comes out of the process as normal lung. If any disease is identified then it goes into Improved Toboggan algorithm. The overall performance is measured by using performance metrics.

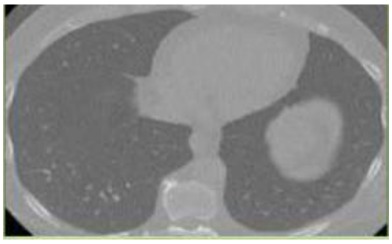

Fig.2. Input image

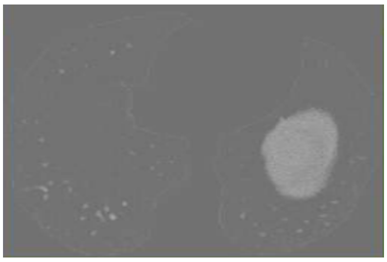

Fig.3. Segmented lung lobes

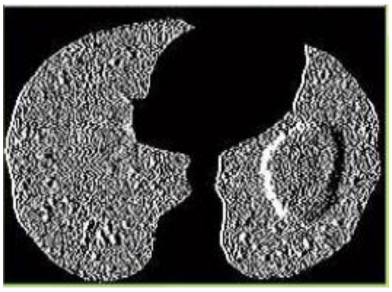

Fig.4.Gradient extracted

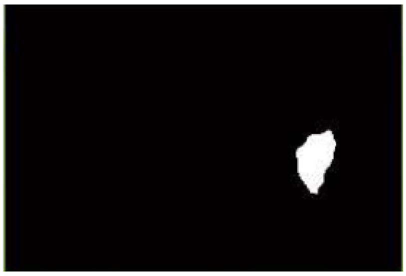

Fig.5. Selected Seed Region

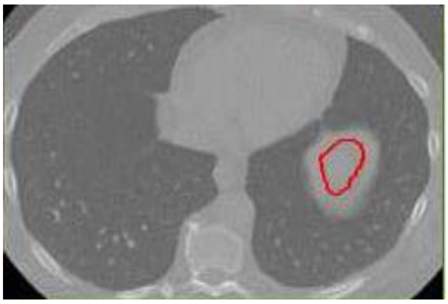

Fig.6.Contour Growing

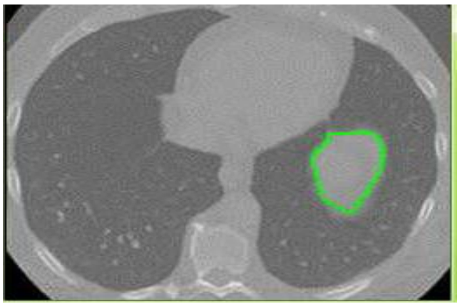

Fig.7. Contour Growing

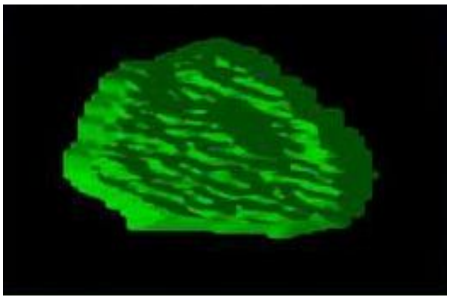

Fig.8. Tumor region

Table1. Performance measures

Performance Metrics	Existing system	Proposed Approach
Accuracy	96.145	99.745
Sensitivity	84.7	100
Specificity	83.8	84.8
True Positives	12540	61850
True Negatives	1263	3126
False Positives	360	560
False Negatives	0	0

VI. CONCLUSION

CT Lung images were taken as the input. The true positives, False Negatives, Area under Curve, Accuracy, Sensitivity and Specificity of the classifiers were calculated. The lobes were segmented from the CT lung images based on Toboggan algorithm. XCS-LBP is employed for the extraction of texture features from the images. The extracted features were then classified using SVM classifier in order to find whether the lung lobes were disease affected or not. The performance of the process is measured based on the performance metrics.

REFERENCES

[1] D.B. Hassen and H.Taleb, "Automatic detection of lesions in lung regions that are segmented using spatial relations", Clinical Imaging, vol.37.pp. 498-503, 2013.

[2] L.Wang, H.Lin, X.Huang, B.Wang, Y.Chen, "A 3D segmentation and visualization scheme for solid and non-solid lung lesions based on Gaussian filtering regularized level set", International conference on 3D vision, pp.67-73,2014.

[3] A M Santos, A O de C Filho, A C Silva, A C de Paiva, R A Nunes, M Gattass, "Automatic detection of small lung nodules in 3D CT data using Gaussian mixture models, Tsallis entrophy and SVM", Engg. Apllications of AI, vol. 36, pp. 27-39, 2014.

[4] F.Rossi, A.A.Abd.Rahni, "Combination of low level processing and active contour techniques for semi-automated volumetric lung lesion segmentation from thoracic CT images", IEEE Trans. On Biomedical engineering and sciences, vol. 15, pp. 26-30, 2015.

[5] Lim J. Seelan L. Padma Suresh, S H K Veni, "Automatic extraction of lung lesion by using optimized toboggan based approach with feature normalization and transfer learning methods", IEEE Trans. on emerging tech. trends, vol. 16, pp. 18-27, 2016.

[6] Yosefina Finsensia Riti, Hanung Adi Nugroho, Sunu Wibirama, Budi Windarta,Lina Choridah, "Feature extraction for lesion margin characteristic classification from CT scan lungs Image", IEEE Trans. on 2016 1st International Conference on Information Technology, Information Systems and Electrical Engineering, vol. 16, pp. 54-58, 2016.

[7] D. M. Campos, A. Simões, I. Ramos, A. Campilho, "Feature-Based Supervised Lung Nodule Segmentation", pp. 23-26, 2014.

[8] S. Diciotti, S. Lombardo, M. Falchini, G. Picozzi, M. Mascalchi, "Automated segmentation refinement of small lung nodules in CT scans by local shape analysis", IEEE Trans. Biomed. Eng., vol. 58, no. 12, pp. 3418-3428, 2011.

[9] S. Candemir, S. Jaeger, K. Palaniappan, J. P. Musco, R. K. Singh, Z. Xue, A. Karargyris, S. Antani, G. Thoma, C. J. McDonald, "Lung segmentation in chest radiographs using anatomical atlases with nonrigid registration", IEEE Trans. Med. Imaging, vol. 33, no. 2, pp. 577-590, 2014.

[10] A. a Farag, H. E. A. El Munim, J. H. Graham, A. a Farag, "A novel approach for lung nodules segmentation in chest CT using level sets.", IEEE Trans. Image Process., vol. 22, no. 12, pp. 5202-5213, 2013.

[11] Vigneshwar. R, Karthic.K, Karthick.A and Senthamizhselvi.R "Lung Lesion Extraction Using Improved Toboggan Based Algorithm" ,International Journal of Advance Research, Ideas and Innovations in Technology,Volume3, Issue2, pg. no.774-779, 2017.

[12] S. Sun, Y. Guo, Y. Guan, H. Ren, "Juxta-Vascular Nodule Segmentation Based on the Flowing Entropy and Geodesic Distance Feature", Scientia Sinica(Informationis), vol. 61, pp. 1136-1146, 2013.

[13] Y. Gu, V. Kumar, L. O. Hall, D. B. Goldgof, C. Y. Li, R. Korn, C. Bendtsen, E. R. Velazquez, A. Dekker, H. Aerts, P. Lambin, X. Li, J. Tian, R. A. Gatenby, R. J. Gillies, "Automated delineation of lung tumors from CT images using a single click ensemble segmentation approach", Pattern Recognition, vol. 46, no. 3, pp. 692-702, 2013.

[14] C. Bendtsen, M. Kietzmann, R. Korn, P. D. Mozley, G. Schmidt, G. Binnig, "X-Ray computed tomography: Semi automated volumetric analysis of late-stage lung tumors as a basis for response assessments", Int. J. Biomed. Imaging, 2011.

[15] T. Kubota, A. K. Jerebko, M. Dewan, M. Salganicoff, A. Krishnan, "Segmentation of pulmonary nodules of various densities with morphological approaches and convexity models", Med. Image Anal., vol. 15, no. 1, pp. 133-154, 2011.

[16] A. Mansoor, U. Bagci, Z. Xu, B. Foster, K. N. Olivier, J. M. Elinoff, "A generic approach to pathological lung segmentation", IEEE Trans Med Imaging, vol. 33, pp. 2293-2310, Dec. 2014.

[17] R. Siegel, D. Naishadham, A. Jemal, "Cancer statistics 2017", CA Cancer J Clin, vol. 63, pp. 11-30, Jan. 2017.

[18] J. Song and C. Yang et al, "A New Quantitative Radiomics Approach for Non- Small Cell Lung Cancer (NSCLC) Prognosis", The 101ndInt. Conf. Radiological Society of North America, Chicago, Illinois, November 29– December 2015.

[19] H. J. W. L. Aerts, E. R. Velazquez, R. T. H. Leijenaar, C. Parmar, P.Grossmann, S. Cavalho, J. Bussink, R. Monshouwer, B. Haibe-Kains,D. Rietveld, F. Hoebers, M. M. Rietbergen, C. R. Leemans, A. Dekker,J. Quackenbush, R. J. Gillies, and P. Lambin, "Decoding tumourPhenotype by noninvasive imaging using a quantitative radiomics Approach." Nat. Communes., vol. 5, pp. 4006, 2014.

[20] Bian and Zijian et al., "Accurate airway centerline extraction basedOn topological thinning using graph-

theoretic analysis", Bio-medical Materials and engineering, vol. 24, no. 6, pp. 3239–3249, 2014.

[21] Caiyum Yang,Li Fan , Kun Wang ,Feng Yang,shiyuan Liu, and Jie Tian, "Lung lesion extraction using a toboggan based growing automatic segmentation approach", IEEE Transactions on medical imaging, vol.35 no.1, January 2016.

[22] D. M. Campos, A. Simões, I. Ramos, and A. Campilho, "Feature-Based Supervised Lung Nodule Segmentation", pp. 23–26, 2014.

[23] S. Candemir, S. Jaeger, K. Palaniappan, J. P. Musco, R. K. Singh, "Lung segmentation in chest radiographs using anatomical atlases with Non rigid registration", IEEE Trans. Med. Imaging, vol. 33, no. 2, pp. 577–590, 2014.

[24] B. Lassen, E. M. Van Rikxoort, M. Schmidt, S. Kerkstra, B. Van Ginneken and J. M. Kuhnigk, "Automatic segmentation of the pulmonary Lobes from chest CT scans based on Fissures, Vessels, Bronchi", IEEE Trans. Med. Imaging, vol. 32, no. 2, pp. 210–222, 2013.

[25] M. Nakata, H. Saeki, I. Takata, Y. Segawa, H. Mogami, K. Mandai, andK. Eguchi, "Focal ground-glass opacity detected by low-dose helical CT", Chest, vol. 121, no. 5, pp. 1464–1467, 2002.

[26] W. H. Organization, "Description of the global burden of NCDs, their Risk factors and determinants," Geneva, Switzerland: World Health Organization, 2011.