TECHNIQUES FOR LUNG NODULE EXTRACTION IN MEDICAL IMAGES: A REVIEW

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ABSTRACT:

The classification and identification of the disease in medical images were useful for computer aided diagnosis, medical research, radiotherapy, evaluations of surgery and biomedical applications. The accurate segmentation of lung lesions from computed tomography (CT) images is of great importance for image-driven lung cancer study and screening processes. Due to the heterogeneity of lung lesions and the presence of similar various pictorial characteristics between lesions and their surrounds make it difficult for robust segmentation of lesions in medical images. This work provides a comprehensive review of the existing automatic techniques of identifying pulmonary nodules present in thorax CT scans. In this work, the information regarding size of lesions, characterization and 2D or 3D techniques is also fused. All the automated lung lesion extraction schemes roughly involve some common procedures including image acquisition, pre-processing, lung or lesion segmentation, feature extraction and classification and reduction of false positives. The techniques developed to perform all the intermediate procedures are briefly described. This work presents the comparison of the recent techniques in terms of the standard parameters employed by the researchers.

KEYWORDS:

Image segmentation, Computed tomography, thorax, lung lesions, computed tomography, lung cancer, benign, malignant.

INTRODUCTION:

Cancer is a most important public fitness problem in the world. Lung cancer is currently the principal cause of cancer related deaths worldwide and is the second leading cause of death in terms of the report collected from the World Health Organization(WHO) [2]. In developed countries, patients detected with this type of pathology have a survival rate of five-years between 10 and 16% [1]. However, in cases where lung tumour is diagnosed in early stages, the five-years survival rate increases to 70%. Sex differences in lung cancer trends to reflect historic differences in use of tobacco. Women took up smoking and at older ages than men, but were slower to quit, including recent rises in smoking occurrence in some birth cohorts [115], [116]. There is potential for lung cancer to be identified at an earlier stage using screening with low-dose computed tomography, which has been shown for reducing lung cancer mortality by up to 20% among former and current and smokers with a smoking history of 30 or more pack-years [119].

Treatment therapy monitoring and lung lesion analysis using CT images are important procedures for early lung cancer treatment and survival of patients. In these strategies, accurate lung nodule segmentation is necessary that can affect the analysis results. Specifically, given fact of growing volumes of clinical data, developed a data-driven segmentation model is of great clinical importance to avoid tedious manual processing and reduce inter-observer variability [138]. Despite development of techniques for lung nodule segmentation in current years [30], [138], attaining accurate segmentation performance continues to require attention due to the heterogeneity of lung nodules on CT images. The occurrence of similar visual and pictorial characteristics between nodules and their surroundings poses a technical challenge for developing robust segmentation models.

Since the introduction of helical multi slice technology CT has become the most sensitive imaging modality for the exposure of small lung nodules [12]. More recently, one of the hopes to change the scenario of late diagnosis has been conducted by monitoring programs with low-dose CT, particularly applied to risk groups such as smokers [119].

After the identification of a pulmonary nodule through CT, the surgeon is asked about its malignancy. During the examination, the radiologist must list the diagnostic possibilities and offer a result based on the analysis of the nodule morphology and clinical context. This diagnosis may have no treatment, no follow up, or may recommend surgical resection. However, it should always seek a cost benefit trade-off analysis of treatment strategies by not allowing a potentially malignant nodule to continue evolving, by limiting unnecessary invasive investigations and radiation from repeated CT scans as well as containing patient anxiety. The chosen strategy should follow traditional recommendations and incorporate the recent extensive and fast changing research found in the literature. The nodule imaging features and the role of the radiologist are essential to the definition of this diagnosis [49] and [23].

A lung nodule is a small mass of tissues in the lung. It appears as round, white shadows on a computerized tomography scan or a chest X-ray. Typically, lung nodules are approximately 0.2 inch to 1.2 inches in size. A bigger lung nodule of up to 30 millimetres is more likely to be cancerous than a smaller lung nodule.

The term “micronodule” is reserved for opacities less than 3 mm in diameter and the term “mass” is used for opacities which are greater than 30 mm. The accuracy in calculating the nodule diameter is critical because the nodule size is related to malignancy. Lung nodules are categorized as benign lung nodules, nodules from inflammation, and fibrosis and malignant lung nodules. A benign nodule usually does not spread to other areas. However, their presence, especially if they are big, may cause health problems. There are two types of benign nodules which include granulomas and hamartomas. Lung nodules caused by infections are classified as bacterial infections. Conditions that lead to inflammation and fibrosis can make one susceptible to benign lung nodules.

A study of the existing journals on pulmonary nodule detection exposes that a proper effort to categorize the existing nodule detection methods based on their operation principles has not been made. This work formulates the generic structure for lung nodule detection scheme that can be used to categorise majority of the previous methods. It consists of a few mechanisms which includes acquisition, pre-processing, lung segmentation, nodule detection, and false positives reduction. Various algorithms have been employed to realise each component in different systems. These algorithms are revised in this paper. In addition, this work provides a comparison of the performance of the existing methods making it easier for the reader to establish an understanding of the applicability of the studied approaches.

REVIEW OF EXISTING NODULE DETECTION METHODS:

Nodules are the principal cause of cancer; however, the timely detection of these nodules can greatly aid in improving the survival rate of cancer patients. Nodules are usually identified manually by radiologists. However, discriminating malignant nodules from benign nodules by visual analysis varies from radiologist to radiologist. The presence of calcification or fat is normally an indicator of benign nodules, whereas features such as irregular margins and assorted attenuation have been associated with malignant nodules. Due to inter-reader variability, some genuine nodules may sometimes be misclassified, particularly when the huge amount of available CT scan data is put into consideration. Therefore, CAD offers a second opinion that may validate radiologists’ assessment.

Solid nodules are easier to detect due to harmonized intensity. But, due to nonuniform interior structure subsolid nodule detection posture challenge to researchers, that is why little research has been witnessed that particularly focuses on subsolid nodule detection.

Figure 1 shows the General Structure of Lung Nodule Extraction System in CT Images. The process includes CT scan image acquisition, pre-processing, lung or candidate nodule ROI segmentation, feature extraction, feature vector size reduction and classification or false positive reduction.

General Structure of Lung Nodule Detection System in CT Images:

Lung image acquisition

Pre-processing

Classification

Feature Reduction

Feature Extraction

Lung/Nodule segmentation

If feature reduction required

Normal lung

If nodules present

Nodule extraction

 yes

 no

 yes

 no

Fig. 1. General Structure of Lung Nodule Extraction System

LUNG IMAGE ACQUISITION:

 Image acquisition is the process of retrieving image from an imaging modality. Several imaging modalities exist for example, radiographs, Magnetic Resonance Images (MRI) and CT scans. CT scan images are better to show contrast difference among nodules and adjacent structures. Few publicly available databases aid as a reference source to facilitate the development, training and assessment of CAD algorithms. They contain thorax scans with marked annotated lesions. Some of the publicly available databases are Early Lung Cancer Action Program (ELCAP) Public Lung Image Database, ELCAP Public Lung Database to Address Drug Response, Lung Image Database Consortium (LIDC) in National Imaging Archive, Medical Image Database, and Lung Image Database Consortium image collection (LIDC-IDRI). Various researchers have acquired databases of research institutes and private hospitals. The nodule detection algorithms are evaluated on the public databases and private databases collected from the private sectors.

# PRE-PROCESSING:

Pre-processing aims to increase the visualization of the CT scan images, thereby reducing the noise and other artefacts introduced during image acquisition process probably due to CT scan machine resolution or other environmental factors. Semi-automated approaches entail cropping annotated image area. One such approach cropped 31x31 pixel area with annotated centroid in the middle. Nascimento used histogram Equalization to enhance the contrast of the images. Chip level; a user defined maximum is imposed on the height of local histogram which rules out the possibility of over-enhancement of noise simultaneously minimizing edge shadowing effect. To improve image contrast and deal with noise, the author combined CLAHE algorithm with Wiener filter. Ashwin [80] adopted CLAHE algorithm to pre-process the images.

Tan et al., [131] used isotropic re-sampling of lung images, while Messay et al., [79] changed orientation of slices and down sampled them so to make the slice spacing equal to that of training data followed by Local Contrast Enhancement. Cascio et al., [34] proposed isotropic interpolation in pre-processing step to convert voxels into 3D Cartesian coordinate grids with uniform 3D spatial resolution. All the slices were rescaled to 221x221 size employing Lanczos interpolation; the resized matrix was reproduced thrice to reproduce RGB image as used by Over Feat feature extractor in Ciompis method. Gaussian and Gabor filters are also employed for image enhancement. Gabor function is a bandpass filter which improves contrast among nodule and surrounding areas. Quadratic Enhancement was applied by Filho et al., [133] to selectively enhance contrast of the images. This enhances noise content as well, which was eliminated by Gaussian filter and median filter.

## **LUNG SEGMENTATION:**

Lung Segmentation is the process of classifying the lung lobe region and eliminating the rest of the image (Fig. 2). Segmentation of the lung is frequently performed as a significant pre-processing step for quantitative analysis of chest CT imaging. Segmentation is used for partitioning the input image into multiple segments. Segmenting lungs from adjacent structures significantly reduces the execution time of lung nodule detection schemes and help improve its efficiency. It plays a vital role in pulmonary nodule detection by increasing the accuracy, reliability, precision, and decreasing computational cost of detection.

Segmentation is the process which is important for Lung Nodule classification and detection. For example, juxta-pleural nodules have an intensity like that of lung wall; therefore, they are difficult to distinguish using intensity values only. Similarly, non-solid nodules such as ground-glass opacity (GGO) possess a challenge since a simple morphological action is not suitable due to low intensity contrast in CT data [61].



1. (b)

**Fig. 2.** Sample segmented lung image: (a) original image and (b) segmented image

Fig.3. 2D based segmentation methods

Figure 3 shows the overview of 2D based segmentation methods. Various semi-automatic and automatic approaches have been presented for lung or nodule segmentation. Semi-automated procedures were primarily formulated to obtain candidate nodule ROI from observations by experts.

3D based segmentation

Mathematical morphology

Region-based methods

Model-based methods

Thresholding methods

Deformable models

Region growing

Graph based methods

Graph-cut

Dynamic programming

Fig 4. 3D-based segmentation techniques for lung CT images

Figure 4 shows the overview of 3D based segmentation techniques used for lung CT images. Great contrast exists among lungs and adjacent organs in the thorax CT scan, segmenting lungs by using intensity based approaches were initially proposed to segment lung parenchyma ([33], [34], [35]). Intensity-based methods using mathematical morphological operation [136], [79] and region growing [61], [138] have been considered. Energy optimization techniques including level set [30] and graph cut [82] were also researched for pulmonary nodule segmentation. Though, the robustness is still challenging particularly for segmenting juxta-pleural nodules. For example, in morphology-based methods, the morphological template size is difficult to generalize with nodules of various diameters [138]. Sophisticated methods can process juxta-pleural nodules by applying a shape constraint [30], [124] or depend on user interactive parameter settings [79]. However, it may not be suitable for irregular shaped nodules where the shape hypothesis can be violated. In addition, user interactive constraints such as well centralized seed point [79] or stroke are tough to tune for different types of nodules. Fan Zhang [129] utilises the thresholding segmentation. The limitations of directly applying raw intensity value for segmentation recommend the need of innovative solutions for capturing high-level, nodule-sensitive features from CT volumes.

Authors [47], [54] proposed vector quantization method to segment lung; the method envisaged detecting and segmenting nodules simultaneously and addressed the weakness of global thresholding method. The authors [27], [39] presented wave-front simulation to refine the results achieved using Region Growing algorithm. Connected Component Labelling and contour correction based on chain code analysis was applied [28] to extract and refine lung area. Quick Shift clustering algorithm [32] has also been applied to divide the data into clusters. Zhang [129] and Fan et. al. [62] proposed adaptive patch based image representation to cluster lung area, where Super pixel labelling assigns unique labels to foreground and background labels. Rolling Ball Algorithm was used [25] to refine results of initial lung extraction so that the nodules are not erroneously missed during segmentation stage. Watershed transform [37], a region-based segmentation method has been employed for lung segmentation. Followed by watershed transform [37], used median filter and morphological operations to remove post-segmentation noise. Author [132] combined thresholding and Marker Controlled Watershed Transform to obtain better results.

**FEATURE EXTRACTION**

Feature extraction deals with the image intensity, texture, and gradient. For feature extraction process MR8(Maximum Response), LBP (Local Binary Patterns), MHOG (Multi orientation Histogram of Oriented Gradients) and Sift descriptor are used. Four class SVM (Support Vector Machine) is used for feature extraction process. Generally, 128-dimensional feature set is used for the computational process.

Template based models have been employed during the recent years. Many 2D schemes neglect the nodules attached to vessels, hence decreasing the number of true positives and failing the classification performance of CAD system. 3D schemes have an edge over 2D schemes in that they better identify the nodules attached to vessels. Farag et al. [30] extracted texture features using Daugman coding and SIFT descriptor. Tsallis and Shannon entropy measurements were used by Santos et al. [12] to extract texture information. True nodules possess high concentration of gradient vector as they grow from centre to surrounding, hence, Cao et. al. [81] used gradient distribution features to discriminate nodules from surrounding structures. Intensity based features mean, contrast, entropy and standard deviation have been most popular types of features for candidate nodule detection. Farag [30] used SURF (Speeded-Up Robust Features) algorithms to extract texture features; this approach is better than SIFT in terms of execution time. Authors in [47], [48] employed dot enhancement filter. Hessian filter and iris filter are used to highlight spherical objects and suppress vessel like structures.

Jacobs et. al. [113] used comprehensive feature set including texture, shape, wavelet features and Local binary patterns. Combination of geometric and context features such as elongation and Cube Compactness were used in [28] and [14]. Cascio et al. [34] proposed intensity features in conjunction with 3D mass-spring model [12]. Texture and shape features including homogeneity, momentum, spherical disproportion, spherical density, weighted radial distance, Boyce-Clark radial shape index, density of solitary pulmonary nodules, presence of spicules and caverns have been described by several authors [16], [25], [44], [27], [6], [38]. Lee [27] used Fourier descriptors. Orozco [121] used Daube chis wavelet features.

**FEATURE REDUCTION**

Use of numerous features result in overfitting of classifier. Feature reduction is done to utilize appropriate features to provide optimum classification results, and enhancing the computational efficiency of CAD systems. Lee [27] achieved feature reduction via ensemble-learning and used GA ensemble to analyse the features. Wu et al. [19] used LASSO (Least Absolute Shrinkage and Selection Operator).

**CLASSIFICATION**

Classification is final yet certainly the most significant phase in nodule detection process. The feature extraction procedure yields candidates that are fed to the classifier; the classifier finally categorizes them as either nodules or non-nodules. Classification stage trains the classifier to make them learn features computed using training data and classify the input candidates or test data as nodule or non-nodule. Feature extraction phase generates several candidates that have likelihood of being recognized correctly or not.

Fig. 5. An overview of Nodule classification methods

Figure 5 shows the overview of Nodule classification methods. Variants of neural network classifier are a prominent choice of researchers. BP Neural Network was used in another scheme [19]. Artificial Neural Networks were used [12], [17], [69] for false positive reduction. Kuruvilla [125] and Cerello [29] used feed forward neural network for classifying the candidates into nodules and non-nodules. Nearest Neighbour Classifier [51] and k-nearest neighbour classifier [35] have also been used in the classification approaches.

Few researchers in [59], [70], [8], [71], [23], [10], [41] used Support Vector Machine. Particle Swarm optimization was used by Cao et. al [81] to optimize Cost Sensitive SVM. Zhu [39] used SVM with Gaussian kernel function and Zhang used [129] polynomial kernel. The authors in [15] and [44] used RBF kernel functions. Wang [22] combined Minimum Within-Class Scatter SVM with higher order tensor technology to improve classification accuracy.

Farag et al., [30] created templates using AAM template matching approach and combined rotation variations in template matching which improved classification results. Few authors [37] and [16] used RBF, polynomial function and Minkowski distance function as kernel functions. Assefa invented templates possessing Gaussian-like intensity distribution in which circular templates were used for identifying nodules inside the lung region and semi-circular templates for nodules at lung border.

The computational classifiers that are used for the reduction of false positives are indicated in Table 3.

|  |  |  |
| --- | --- | --- |
| Authors | Year | Classifier used |
| Ashwin et al. [80] | 2012 | Artificial neural networks (ANN) |
| Wang et al. [33] | 2013 | SVM |
| El-Baz et al. [30] | 2013 | Bayesian supervised |
| Gurcan et al. [105] | 2002 | Rule based |
| Lin et al. [103] | 1996 | Artificial neural networks (ANN) |
| Camarlinghi et al. [106] | 2012 | Feed Forward Neural Networks (FFNN) |
| Bellotti et al. [104] | 2007 | Artificial neural networks (ANN) |
| Suiyuan and Junfeng [37] | 2012 | Invariant moments |
| Namin et al. [40] | 2010 | Fuzzy k-NN classifier |
| Cascio et al. [34] | 2012 | Artificial neural networks (ANN) |
| Armato III et al. [99] |  | Linear discriminant analysis (LDA) |
| Ozekes and Osman [45]  | 2008 | Feed forward neural networks (FFNN) |
| Matsumoto et al. [43]  | 2008 | Rule based |

Table 1: Computational classifiers used for the reduction of false positives

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| Authors | Year | Acquisition of data | Pre-processing | Lung Segmentation | Nodule detection | FPreduction |
| Santos et al. [12] | 2014 | Yes | No | Yes | Yes | Yes |
| Badura and Pietka [26] | 2014 | Yes | No | Yes | Yes | Yes |
| El-Baz et al. [30] | 2013 | Yes | No | Yes | Yes | Yes |
| Choi and Choi [32] | 2014 | Yes | No | Yes | Yes | Yes |
| Wang et al. [33] | 2013 | Yes | No | Yes | Yes | Yes |
| Cascio et al. [34] | 2012 | Yes | Yes | Yes | Yes | Yes |

Table 2: Processing stages included in each of the selected works.

The stages considered by each of the selected works for the automatic detection of lung nodules in lung CT images are indicated in Table 2.

## PERFORMANCE MEASURES:

This section gives the comparison of the recent nodule detection schemes. The majority authors have used few common parameters for evaluating their schemes such as accuracy, sensitivity, specificity, and area under ROC curve. The information regarding type, number and size of nodules is also incorporated to facilitate the reader in better differentiating the techniques. Comparison of existing techniques and their performance is summarized in table 3 that shows the results in organized form. Tae [16] used 2D and 3D geometric, texture features along with SVM. They reported 95.28% sensitivity with 2.27 false positives/ scan and 97.61% accuracy. SVM classifier was used in the research works [4], [8], [25] [39]. Zhu et al. [39] utilized SVM and texture feature to discriminate malignant and benign nodules and accomplished AUC 0.844. Rodrigo [25] used histogram-based, geometric, gradient and spatial features along with SVM and obtained 95.21% accuracy, 84.84% sensitivity, and 96.15% specificity.

Orozco [121] used 61 scans (36 scans with cancerous nodules and 25 scans without nodules) for training and 45 (23 with cancerous nodules and 22 scans without nodules) for testing. The technique using Daubechis wavelet features results 82% accuracy, 90.9% sensitivity and 73.91% specificity. Nodules having diameter between 2 mm and 30 mm are correctly classified. Lin et al. [59] using fractal geometry and SVM gained 88.82% accuracy, 93.92% sensitivity, 82.9% specificity, and 0.9019 area under ROC curve. Roy [74] used combination of Fuzzy Inference System and SVM and shown 94.12% accuracy.

Song [32] achieved 97.9% recall, 82.7% precision and AUC 0.9705 using SVM and conditional random fields. Huang [71] used SVM together with fractional Brownian motion model to achieve accuracy of 83.11% and Area under ROC of 0.8437. Teramoto [83] used SVM and cylindrical nodule enhancement filter and spotted 80% nodules with 4.2FP/case. Authors claim to achieve detection speed being 4-36 times faster than the previous methods.

The sensitivity of the system can be given as:

Sensitivity = $\frac{TP}{TP+FN}$ (1)

where TP (true positive) is when the system gives a positive result for a sample that has disease, and FN (false negative) is when the system a gives an output as negative for a sample that has disease.

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Author | Data | 2D/3D | Classifier | Nodule size | Results |
| Filho [133] | 140 exams from LIDCIDRI | 3D | SVM with RBF | 3mm to 30 mm | Sensitivity 85.91 specificity97.7% and accuracy 97.55%  |
| Tan[131] | LIDC 360 CT scans | 3D | Phased Searching with NEAT | Nodules with diameter greater than or equal to 3 mm | Detection sensitivity of 83+9.7%  |
| Keshani [124] | 63 scans including 8 clinical sets, 5 datasets from ANODE 50 sets by LIDC | 2D/ 3D | SVM | Solid, non-solid and cavitary nodules greater than 5mm | Detection rate of 89% with 7.3FP/scan |
| Cao et. al [81] | Private database, 165 CT scans containing 192 solid nodules, 5 datasets from ANODE50 sets by LIDC | 3D | Hybrid probabilistic sampling combined with diverse random subspace ensemble | 3 mm to 30 mm | Sensitivity 83.17 %, G-mean84.69% AUC 85.7% |
| Choi[32] | Private database containing 165 CT scans with 192 nodules | 2D/ 3D | Genetic Programmingbased classifier | 3 mm to 30 mm | 5.45 FP rate/ scan and 94.1% sensitivity |
| Lin et. al. [71] | Private database 107 CT scans including 48 benign and 59 malignant |  | SVM | 8.5mm both malignant and benign nodules | Accuracy 88.82%, sensitivity 93.92%, specificity 82.9%, positive predictive value 87.3%, negative predictive value 90.2%, area under ROC curve 0.9019 |
| Messay[79] | LIDC database consisting of 84 CT scans containing 143 nodules 1.3 and 3.0 mm in size | 2D/ 3D | Quadratic classifier and Fisher Linear Discriminant classifier | 3 mm to 30 mm Vascular nodules,Pleural nodules | Sensitivity 82.66% with average of 3FPs per scan/ case |
| Wang[33] | Private database Test data contains 196 scans that consist of 8428 sections (108 nodules | 3D | SVM  | 5mm-30 mm isolated,attached to vessels and attached to pleura | 98.2% with 9. IFPs/scan, AUC0.995 |
| Cascio [34] | LIDC 84 scans and 148 nodules | 3D | Double Threshold cut and neural network | 3 mm - 50 mm juxta-pleural nodules | 97.66% sensitivity with 6.1 FPs/case 88% sensitivity with 2.5 FPs/ scan |

Table 3. Comparison of existing techniques and their performance

CONCLUSION:

 This work gives an overview of the current and existing lung nodule extraction techniques used for CT images that may help researchers when choosing a given method. Certainly, lung analysis techniques have been improved over the last decade. However, there are issues to be solved such as innovating novel and improved techniques for contrast enhancement and selecting better criteria for performance evaluation is also required.

# REFERENCES:

1. R. Siegel, Kimberly D. Miller, A. Jemal, “Cancer Statistics, 2017”, CA: A cancer journal for clinicians, 2017.
2. W. H. Organization, “Description of the global burden of NCDs, their risk factors, and determinants”, Geneva, Switzerland: World Health Organization, 2011.
3. ELCAP public lung image database. Vision and Image Analysis Group (VIA) and International Early Lung Cancer Action Program (I-ELCAP) Labs, Cornell University. http://www.via.cornell.edu/lungdb.html (2007)
4. Public lung database to address drug response. Vision and Image Analysis Group (VIA) and International Early Lung Cancer Action Program (I-ELCAP) Labs, Cornell University. http://www.via.cornell.edu/crpf.html (2007)
5. Lung Imaging Database Consortium (LIDC). <http://imaging>.cancer.gov/programs and resources/Information Systems/LIDC.
6. Medical image database. Med Pix. <http://rad.usuhs.edu/medpix/> index.html (2007)
7. <http://www.ncbi.nlm.nih.gov/entrez/query.fcgi>.
8. http://imaging.cancer.gov/programsandresources/InformationSystems/LIDC/page10.
9. Nascimento LB, de Paiva AC, Silva AC., “Lung nodules classification in CT images using Shannon and Simpson diversity indices and SVM”, Machine Learning and Data Mining in Pattern Recognition: Springer, 2012, pp. 454-466.
10. N. Camarlinghi, “Automatic detection of lung nodules in computed tomography images: training and validation of algorithms using public research databases”, The European Physical Journal Plus vol.128, no. 9, 2013.
11. S. Diederich, M. G. Lentschig, T. R. Overbeck, D. Wormanns, W. Heindel, “Detection of pulmonary nodules at spiral CT: comparison of maximum intensity projection sliding slabs and single-image reporting”, European Radiology vol.11 no.8, 2011, pp.1345–1350.
12. A. M. Santos, A. O. de Carvalho 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 entropy and SVM”, Engineering Applications of Artificial Intelligence vol. 36, 2014, pp. 27–39.
13. M. Lederlin, M. Revel, A. Khalil, G. Ferretti, B. Milleron, F. Laurent, “Management strategy of pulmonary nodule in 2013”, Diagnostic and Interventional Imaging, vol. 94 no.11, 2013, pp. 1081–1094.
14. D. M. Hansell, A. A. Bankier, H. MacMahon, T. C. McLoud, N. L. Muller, J. Remy, Fleischner Society: “glossary of terms for thoracic imaging”, Radiology 246 (3), 2008, pp. 697–722.
15. ELCAP, ELCAP public lung image database, 2015. URL <http://www.via.cornell.edu/lungdb.html>
16. C. I. Henschke, D. I. McCauley, D. F. Yankelevitz, D. P. Naidich, G. McGuinness, O. S. Miettinen, D. M. Libby, M. W. Pasmantier, J. Koizumi, N. K. Altorki, J. P. Smith, “Early Lung Cancer Action Project: overall design and findings from baseline screening”, Lancet 354 (9173), 1999, pp. 99–105.
17. M. Revel, A. Bissery, M. Bienvenu, L. Aycard, C. Lefort, G. Frija, “Are two-dimensional CT measurements of small noncalcified pulmonary nodules reliable?”, Radiology 231 (2) ,2004, pp. 453–458.
18. L. B. Lusted, “Logical analysis in roentgen diagnosis”, Radiology 74, 1960, pp. 178–193.
19. W. J. Tuddenham, “Visual search, image organization, and reader error in roentgen diagnosis. Studies of the psycho-physiology of roentgen image perception”, Radiology 78,1962, pp. 694–704.
20. H. L. Kundel, G. Revesz, “Lesion conspicuity, structured noise, and film reader error”, AJR. American journal of roentgenology 126 (6), 1976, pp. 1233–1238.
21. K. S. Berbaum, E. A. Franken, D. D. Dorfman, S. A. Rooholamini, M. H. Kathol, T. J. Barloon, F. M. Behlke, Y. Sato, C. H. Lu, G. Y. El-Khoury, “Satisfaction of search in diagnostic radiology”, Investigative Radiology 25 (2), 1990, pp. 133–140.
22. D. L. Renfrew, E. A. Franken, K. S. Berbaum, F. H. Weigelt, M. M. Abu-Yousef, “Error in radiology: classification and lessons in 182 cases presented at a problem case conference”, Radiology 183 (1), 1992, pp. 145– 150.
23. N. Petrick, B. Sahiner, S. G. A. Iii, A. Bert, L. Correale, S. Delsanto, M. T. Freedman, D. Fryd, D. Gur, L. Hadjiiski, Z. Huo, Y. Jiang, L. Morra, V. Raykar, F. Samuelson, R. M. Summers, G. Tourassi, H. Yoshida, C. Zhou, H.-p. Chan, B. Zheng, “Evaluation of computer aided detection and diagnosis systems”, Medical Physics 639, 2007.
24. Z. Ma, J. M. R. S. Tavares, R. M. N. Jorge, “A review on the current segmentation algorithms for medical images, in: 1st International Conference on Imaging Theory and Applications (IMAGAPP)”, INSTICC Press, February 5-8, Lisboa, Portugal, 2015, pp. 135–140.
25. Z. Ma, J. M. R. S. Tavares, R. N. Jorge, T. Mascarenhas, “A review of algorithms for medical image segmentation and their applications to the female pelvic cavity”, Computer Methods in Biomechanics and Biomedical Engineering 13 (2), 2010, pp. 235–246.
26. P. Badura, E. Pietka, “Soft computing approach to 3D lung nodule segmentation in CT”, Computers in Biology and Medicine 53, 2014, pp. 230–243.
27. S. L. A. Lee, A. Z. Kouzani, E. J. Hu, “Automated detection of lung nodules in computed tomography images: A Review”, Machine Vision and Applications 23 (1), 2012, pp. 151–163.
28. K. Suzuki, “A review of computer-aided diagnosis in thoracic and colonic imaging”, Quantitative imaging in medicine and surgery 2 (3), 2012, pp. 163–176.
29. L. H. Eadie, P. Taylor, A. P. Gibson, “A systematic review of computer assisted diagnosis in diagnostic cancer imaging”, European Journal of Radiology 81 (1), 2012, pp.70–76.
30. A. El-Baz, A. Elnakib, M. Abou El-Ghar, G. Gimel farb, R. Falk, A. Farag, “Automatic Detection of 2D and 3D Lung Nodules in Chest Spiral CT Scans”, International Journal of Biomedical Imaging, 2013.
31. M. Firmino, A. H. Morais, R. M. Mendo¸ca, M. R. Dantas, H. R. Hekis, R. Valentim, “Computer-aided detection system for lung cancer in computed tomography scans: review and future prospects”, Biomedical engineering online 13 (2014).
32. W.-J. Choi, T.-S. Choi, “Automated pulmonary nodule detection based on three-dimensional shape-based feature descriptor”, Computer Methods and Programs in Biomedicine 113 (1), 2014, pp.37–54.
33. Q. Wang, W. Kang, C. Wu, B. Wang, “Computer-aided detection of lung nodules by SVM based on 3D matrix patterns”, Clinical Imaging 37 (1), 2013, pp. 62–69.
34. D. Cascio, R. Magro, F. Fauci, M. Iacomi, G. Raso, “Automatic detection of lung nodules in CT datasets based on stable 3D mass-spring models”, Computers in Biology and Medicine 42 (11), 2012, pp. 1098–1109.
35. B. Chen, T. Kitasaka, H. Honma, H. Takabatake, M. Mori, H. Natori, K. Mori, “Automatic segmentation of pulmonary blood vessels and nodules based on local intensity structure analysis and surface propagation in 3D chest CT images”, International Journal of Computer Assisted Radiology and Surgery 7 (3), 2012, pp. 465–482.
36. S. Soltaninejad, M. Keshani, F. Tajeripour, “Lung nodule detection by KNN classifier and active contour modelling and 3D visualization”, The 16th CSI International Symposium on Artificial Intelligence and Signal Processing (AISP 2012), IEEE, May 2-3, Shiraz, Fars, Iran, 2012, pp. 440–445.
37. W. Suiyuan, W. Junfeng, “Pulmonary Nodules 3D Detection on Serial CT Scans”, Third Global Congress on Intelligent Systems, IEEE, November 6-8, Wuhan, China, 2012, pp. 257–260.
38. A. Riccardi, T. S. Petkov, G. Ferri, M. Masotti, R. Campanini, “Computer-aided detection of lung nodules via 3D fast radial transform, scale space representation, and Zernike MIP classification”, Medical Physics 38 (4), 2011, pp. 1962–1971.
39. Y. Liu, J. Yang, D. Zhao, J. Liu, “A Study of Pulmonary Nodule Detection in Three-Dimensional Thoracic CT Scans”, Second International Conference on Computer Modeling and Simulation, Vol. 1, IEEE, January 22-24, Sanya, China, 2010, pp. 481–484.
40. S. Taghavi Namin, H. Abrishami Moghaddam, R. Jafari, M. EsmaeilZadeh, M. Gity, “Automated detection and classification of pulmonary nodules in 3D thoracic CT images”, IEEE International Conference on Systems, Man and Cybernetics, IEEE, October 10-13, Istanbul, Turkey, 2010, pp. 3774–3779.
41. Q. Wang, K. Wang, Y. Guo, X. Wang, “Automatic Detection of Pulmonary Nodules in Multi-slice CT Based on 3D Neural Networks with Adaptive Initial Weights”, International Conference on Intelligent Computation Technology and Automation, Vol. 1, IEEE, May 11-12, Changsha, China, 2010, pp. 833–836.
42. J. Yang, Y. Liu, W. Li, D. Zhao, “A Three-Dimensional Method for Detection of Pulmonary Nodule”, 2nd International Conference on Biomedical Engineering and Informatics, IEEE, October 17-19, Tianjin, China, 2009, pp. 1–4.
43. S. Matsumoto, Y. Ohno, H. Yamagata, D. Takenaka, K. Sugimura, “Computer-aided detection of lung nodules on multidetector row computed tomography using three-dimensional analysis of nodule candidates and their surroundings”, Radiation Medicine 26 (9), 2008, pp. 562– 569.
44. J. Wang, R. Engelmann, Q. Li, “Computer-aided diagnosis: a 3D segmentation method for lung nodules in CT images by use of a spiral scanning technique”, Medical Imaging 2008: Computer-Aided Diagnosis, International Society for Optics and Photonics, February 19-21, San Diego, California, USA, 2008, pp. 69151H–69151H–8.
45. S. Ozekes, O. Osman, “Computerized Lung Nodule Detection Using 3D Feature Extraction and Learning Based Algorithms”, Journal of Medical Systems 34 (2), 2008, pp. 185–194.
46. S. Ozekes, O. Osman, O. N. Ucan, “Nodule detection in a lung region that’s segmented with using genetic cellular neural networks and 3D template matching with fuzzy rule based thresholding”, Korean Journal of Radiology 9 (1), 2008, pp. 1–9.
47. M. Yang, S. Periaswamy, Y. Wu, “False Positive Reduction in Lung GGO Nodule Detection with 3D Volume Shape Descriptor”, IEEE International Conference on Acoustics, Speech and Signal Processing ICASSP ’07, Vol. 1, IEEE, April 15-20, Honolulu, Hawaii, USA, 2007, pp. I–437–I–440.
48. Y. Zheng, K. Steiner, T. Bauer, J. Yu, D. Shen, C. Kambhamettu, “Lung Nodule Growth Analysis from 3D CT Data with a Coupled Segmentation and Registration Framework”, IEEE 11th International Conference on Computer Vision, IEEE, October 14-21, Rio de Janeiro, Brazil, 2007, pp. 1–8.
49. J. Wang, R. Engelmann, Q. Li, “Segmentation of pulmonary nodules in three-dimensional CT images by use of a spiral-scanning technique”, Medical Physics 34 (12), 2007, pp. 4678–4689.
50. A. A. Farag, A. El-baz, G. Gimel, R. Falk, “Appearance Models for Robust Segmentation of Pulmonary Nodules in 3D LDCT Chest Images”, 9th International Conference on Computing and Computer-Assisted Intervention, October 1-6, Copenhagen, Denmark, 2006, pp. 662–670.
51. T. W. Way, L. M. Hadjiiski, B. Sahiner, H.-P. Chan, P. N. Cascade, E. a. Kazerooni, N. Bogot, C. Zhou, “Computer-aided diagnosis of pulmonary nodules on CT scans: segmentation and classification using 3D active contours”, Medical Physics 33 (7), 2006, pp. 2323–2337.
52. X. Zhang, G. McLennan, E. A. Hoffman, M. Sonka, “3D segmentation of non-isolated pulmonary nodules in high resolution CT images”, Medical Imaging 2005: Image Processing, International Society for Optics and Photonics, February 12, San Diego, California, USA, 2005, pp. 1438–1445.
53. Z. Ge, B. Sahiner, H.-P. Chan, L. M. Hadjiiski, P. N. Cascade, N. Bogot, E. A. Kazerooni, J. Wei, C. Zhou, “Computer-aided detection of lung nodules: False positive reduction using a 3D gradient field method and 3D ellipsoid fitting”, Medical Physics 32 (8), 2005, pp. 2443–2454.
54. S. Matsumoto, Y. Ohno, H. Yamagata, H. Asahina, K. Komatsu, K. Sugimura, “Diminution index: A novel 3D feature for pulmonary nodule detection”, International Congress Series 1281, 2005, pp. 1093–1098.
55. T. Hara, M. Hirose, X. Zhou, H. Fujita, T. Kiryu, R. Yokoyama, H. Hoshi, “Nodule detection in 3D chest CT images using 2nd order autocorrelation features”, Engineering in Medicine and Biology 27th Annual Conference, Vol. 6, September 1-4, Shanghai, China, 2005, pp. 6247–6249.
56. Z. Ge, B. Sahiner, H.-P. Chan, L. M. Hadjiiski, J. Wei, N. Bogot, P. N. Cascade, E. A. Kazerooni, C. Zhou, “Computer-aided detection of lung nodules: false positive reduction using a 3D gradient field method”, Medical Imaging 2004: Image Processing, International Society for Optics and Photonics, February 14, San Diego, California, USA, 2004, pp. 1076–1082.
57. K. Okada, D. Comaniciu, A. Krishnan, “Robust 3D Segmentation of Pulmonary Nodules in Multislice CT Images”, 7th International Conference on Medical Image Computing and Computer-Assisted Intervention, September 26-29, St. Malo, France, 2004, pp. 881–889.
58. C. Fetita, R. Preteux, C. Beigelman-Aubry, P. Grenier, “3D Automated Lung Nodule Segmentation in HRCT”, 6th International Conference on Medical Imaging Computing and Computer-Assisted Intervention, November 15-18, Montr´eal, Canada, 2003, pp. 626–634.
59. Y. Mekada, T. Kusanagi, Y. Hayase, K. Mori, J.-i. Hasegawa, J.-i. Toriwaki, M. Mori, H. Natori, “Detection of small nodules from 3D chest X-ray CT images based on shape features”, International Congress Series 1256, 2003, pp. 971–976.
60. J. Debmeshki, M. Valdivieso, M. Roddie, J. Costello, “Shape based region growing using derivatives of 3D medical images: application to automatic detection of pulmonary nodules”, 3rd International Symposium on Image and Signal Processing and Analysis, Vol. 2, IEEE, September 18-20, Rome, Italy, 2003, pp. 1118–1123.
61. J. Dehmeshki, X. Ye, J. Costello, “Shape based region growing using derivatives of 3D medical images: application to semi-automated detection of pulmonary nodules”, International Conference on Image Processing, Vol. 1, IEEE, September 14-18, Barcelona, Catalonia, Spain, 2003, pp. 1085–1088.
62. L. Fan, J. Qian, B. L. Odry, H. Shen, D. Naidich, G. Kohl, E. Klotz, “Automatic segmentation of pulmonary nodules by using dynamic 3D cross-correlation for interactive CAD systems”, Medical Imaging 2002: Image Processing, International Society for Optics and Photonics, February 23, San Diego, California, USA, 2002, pp. 1362–1369.
63. S. G. Armato III, M. L. Giger, H. MacMahon, “Analysis of a three-dimensional lung nodule detection method for thoracic CT scans”, Medical Imaging 2000: Imaging Processing, International Society for Optics and Photonics, February 12, San Diego, California, USA, 2000, pp. 103–109.
64. A. Delegacz, S. B. Lo, H. Xie, M. T. Freedman, J. J. Choi, “Three-dimensional visualization system as an aid for lung cancer detection”, Medical Imaging 2000: Image Display and Visualization, International Society for Optics and Photonics, February 12, San Diego, California, USA, 2000, pp. 401–409.
65. S. G. Armato III, M. L. Giger, J. T. Blackburn, K. Doi, H. MacMahon, “Three-dimensional approach to lung nodule detection in helical CT”, Medical Imaging 1999: Image Processing, International Society for Optics and Photonics, February 20, San Diego, California, USA, 1999, pp. 553–559.
66. B. Zhao, A. Reeves, D. Yankelevitz, C. Henschke, “Three-dimensional multi criterion automatic segmentation of pulmonary nodules of helical computed tomography images”, Optical Engineering 38 (8), 1999, pp.1340– 1347.
67. B. van Ginneken, C. M. Schaefer-Prokop, M. Prokop, “Computer-aided diagnosis: how to move from the laboratory to the clinic”, Radiology 261 (3), 2011, pp. 719–732.
68. W. D. Bidgood, S. C. Horii, F. W. Prior, D. E. Van Syckle, “Understanding and using DICOM, the data interchange standard for biomedical imaging”, Journal of the American Medical Informatics Association 4 (3), 1997, pp. 199–212.
69. S. Tangaro, R. Bellotti, F. De Carlo, G. Gargano, E. Lattanzio, P. Monno, R. Massafra, P. Delogu, M. E. Fantacci, A. Retico, M. Bazzocchi, S. Bagnasco, P. Cerello, S. C. Cheran, E. Lopez Torres, E. Zanon, A. Lauria, A. Sodano, D. Cascio, F. Fauci, R. Magro, G. Raso, R. Ienzi, U. Bottigli, G. L. Masala, P. Oliva, G. Meloni, A. P. Caricato, R. Cataldo, “MAGIC-5: an Italian mammographic database of digitised images for research”, La Radiologia Medica 113 (4), 2008, pp. 477–485.
70. M. F. McNitt-Gray, S. G. Armato, C. R. Meyer, A. P. Reeves, G. McLennan, R. C. Pais, J. Freymann, M. S. Brown, R. M. Engelmann, P. H. Bland, G. E. Laderach, C. Piker, J. Guo, Z. Towfic, D.P.-Y. Qing, D. F. Yankelevitz, D. R. Aberle, E. J. R. van Beek,H. MacMahon, E. A. Kazerooni, B. Y. Croft, L. P. Clarke, “The Lung Image Database Consortium (LIDC) data collection process for nodule detection and annotation”, Academic Radiology 14 (12), 2007, pp. 1464– 1474.
71. H. Lin, Z. Chen, W. Wang, “A Pulmonary Nodule View System for the Lung Image Database Consortium (LIDC)”, Academic Radiology 18 (9), 2011, pp. 1181–1185.
72. S. G. Armato, G. McLennan, L. Bidaut, M. F. McNitt-Gray, C. R. Meyer, A. P. Reeves, B. Zhao, D. R. Aberle, C. I. Henschke, E. A. Hoffman, E. A. Kazerooni, H. MacMahon, E. J. R. Van Beeke, D. Yankelevitz, A. M. Biancardi, P. H. Bland, M. S. Brown, R. M. Engelmann, G. E. Laderach, D. Max, R. C. Pais, D. P. Y. Qing, R. Y. Roberts, A. R. Smith, A. Starkey, P. Batrah, P. Caligiuri, A. Farooqi, G. W. Gladish, C. M. Jude, R. F. Munden, I. Petkovska, L. E. Quint, L. H. Schwartz, B. Sundaram, L. E. Dodd, C. Fenimore, D. Gur, N. Petrick, J. Freymann, J. Kirby, B. Hughes, A. V. Casteele, S. Gupte, M. Sallamm, M. D. Heath, M. H. Kuhn, E. Dharaiya, R. Burns, D. S. Fryd, M. Salganicoff, V. Anand, U. Shreter, S. Vastagh, B. Y. Croft, “The Lung Image Database Consortium (LIDC) and Image Database Resource Initiative (IDRI): a completed reference database of lung nodules on CT scans”, Medical Physics 38 (2), 2011, pp. 915–931.
73. Cancer Imaging Archive, Lung image database consortium image collection, accessed: 2015-05-27 (2014). URL https://wiki.cancerimagingarchive.net/display/Public/ LIDC-IDRI
74. Y. Ru Zhao, X. Xie, H. J. de Koning, W. P. Mali, R. Vliegenthart, M. Oudkerk, “NELSON lung cancer screening study”, Cancer Imaging 11, 2011, pp. S79–S784.
75. Consortium for Open Medical Image Computing, Automatic nodule detection, accessed: 2015-05-27 (2009). URL <http://anode09.grand-challenge.org/>
76. B. van Ginneken, S. G. Armato, B. de Hoop, S. van Amelsvoort-van de Vorst, T. Duindam, M. Niemeijer, K. Murphy, A. Schilham, A. Retico, M. E. Fantacci, N. Camarlinghi, F. Bagagli, I. Gori, T. Hara, H. Fujita, G. Gargano, R. Bellotti, S. Tangaro, L. Bolan˜os, F. De Carlo, P. Cerello, S. Cristian Cheran, E. Lopez Torres, M. Prokop, “Comparing and combining algorithms for computer-aided detection of pulmonary nodules in computed tomography scans: The ANODE09 study”., Medical Image analysis 14 (6), 2010, pp. 707–722.
77. W. Choi, T. Choi, “Genetic programming-based feature transform and classification for the automatic detection of pulmonary nodules on computed tomography images”, Information Sciences 212, 2012, pp. 57–78.
78. Y. Liu, J. Yang, D. Zhao, J. Liu, “A method of pulmonary nodule detection utilizing multiple support vector machines”, International Conference on Computer Application and System Modeling, IEEE, October 22-24, Taiyuan, China, 2010, pp. V10–118–V10–121.
79. T. Messay, R. C. Hardie, S. K. Rogers, “A new computationally efficient CAD system for pulmonary nodule detection in CT imagery”, Medical Image Analysis 14 (3), 2010, pp. 390–406.
80. S. Ashwin, J. Ramesh, S. A. Kumar, K. Gunavathi, “Efficient and reliable lung nodule detection using a neural network based computer aided diagnosis system”, International Conference on Emerging Trends in Electrical Engineering and Energy Management, IEEE, December 13-15, Chennai, Tamil Nadu, India, 2012, pp. 135–142.
81. H. Shao, L. Cao, Y. Liu, “A detection approach for solitary pulmonary nodules based on CT images”, 2nd International Conference on Computer Science and Network Technology, IEEE, Dec 29-31, Changchun, China, 2012, pp. 1253–1257.
82. X. Ye, X. Lin, J. Dehmeshki, G. Slabaugh, G. Beddoe, “Shape-based computer-aided detection of lung nodules in thoracic CT images”, IEEE Transactions on Bio-medical Engineering 56 (7), 2009, pp. 1810–1820.
83. A. Teramoto, H. Fujita, “Fast lung nodule detection in chest CT images using cylindrical nodule-enhancement filter”, International Journal of Computer Assisted Radiology and Surgery 8, 2013, pp. 193–205.
84. H. Arimura, T. Magome, Y. Yamashita, D. Yamamoto, “Computer Aided Diagnosis Systems for Brain Diseases in Magnetic Resonance Images”, Algorithms 2 (3), 2009, pp. 925–952.
85. L. G. Quekel, A. G. Kessels, R. Goei, J. M. van Engelshoven, “Miss rate of lung cancer on the chest radiograph in clinical practice”, Chest 115 (3), 1999, pp. 720–724.
86. F. Li, S. Sone, H. Abe, H. MacMahon, S. G. Armato, K. Doi, “Lung cancers missed at low-dose helical CT screening in a general population: comparison of clinical, histopathologic, and imaging findings”, Radiology 225 (3), 2002, pp. 673–683.
87. K. Suzuki, M. Kusumoto, S.-i. Watanabe, R. Tsuchiya, H. Asamura, “Radiologic classification of small adenocarcinoma of the lung: radiologic-pathologic correlation and its prognostic impact”, The Annals of Thoracic Surgery 81 (2), 2006, pp. 413–419.
88. Q. Li, K. Doi, “New selective nodule enhancement filter and its application for significant improvement of nodule detection on computed tomography”, Medical Imaging 2004: Image Processing, February 14, San Diego, California, USA, 2004, pp. 1–9.
89. Y. Lee, T. Hara, H. Fujita, S. Itoh, T. Ishigaki, “Automated detection of pulmonary nodules in helical CT images based on an improved template-matching technique’, IEEE Transactions on Medical Imaging 20 (7), 2001, pp. 595–604.
90. K. Awai, K. Murao, A. Ozawa, M. Komi, H. Hayakawa, S. Hori, Y. Nishimura, “Pulmonary nodules at chest CT: effect of computer aided diagnosis on radiologists’ detection performance”, Radiology 230 (2), 2004, pp. 347–352.
91. M. Tanino, H. Takizawa, S. Yamamoto, T. Matsumoto, Y. Tateno, T. Iinuma, “A detection method of ground glass opacities in chest x-ray CT images using automatic clustering techniques”, Medical Imaging 2003: Image Processing, February 15, San Diego, California, USA, 2003, pp. 1728–1737.
92. K. Murphy, A. Schilham, H. Gietema, M. Prokop, B. van Ginneken, “Automated detection of pulmonary nodules from low-dose computed tomography scans using a two-stage classification system based on local image features”, Medical Imaging 2007: Computer-Aided Diagnosis, International Society for Optics and Photonics, February 17, San Diego, California, USA, 2007, pp. 651410–1–651410–12.
93. N. Yamada, M. Kubo, Y. Kawata, N. Niki, K. Eguchi, H. Omatsu, R. Kakinuma, M. Kaneko, M. Kusumoto, H. Nishiyama, N. Moriyama, “ROI extraction of chest CT images using adaptive opening filter”, Medical Imaging 2003: Image Processing, International Society for Optics and Photonics, February 15, San Diego, California, USA, 2003, pp. 869–876.
94. K. Kanazawa, Y. Kawata, N. Niki, H. Satoh, H. Ohmatsu, R. Kakinuma, M. Kaneko, N. Moriyama, K. Eguchi, “Computer-aided diagnosis for pulmonary nodules based on helical CT images”, Computerized Medical Imaging and Graphics 22 (2), 1998, pp. 157–167.
95. F. Mao, W. Qian, J. Gaviria, L. P. Clarke, “Fragmentary window filtering for multiscale lung nodule detection: preliminary study”, Academic Radiology 5 (4), 1998, pp. 306–311.
96. P. R. S. Mendon¸ca, R. Bhotika, S. A. Sirohey, W. D. Turner, J. V. Miller, R. S. Avila, “Model-based analysis of local shape for lesion detection in CT scans”, Medical Image Computing and Computer Assisted Intervention, October 26-29, Palm Springs, California, USA, 2005, pp. 688–695.
97. D. Paik, C. Beaulieu, G. Rubin, B. Acar, R. Jeffrey, J. Yee, J. Dey, S. Napel, “Surface Normal Overlap: A Computer-Aided Detection Algorithm with Application to Colonic Polyps and Lung Nodules in Helical CT”, IEEE Transactions on Medical Imaging 23 (6), 2004, pp. 661–675.
98. G. Agam, S. Armato, “Vessel tree reconstruction in thoracic CT scans with application to nodule detection”, IEEE Transactions on Medical Imaging 24 (4), 2005, pp. 486–499.
99. S. G. Armato, M. L. Giger, C. J. Moran, J. T. Blackburn, K. Doi, H. MacMahon, “Computerized detection of pulmonary nodules on CT scans”, Radio graphics 19 (5), 1999, pp. 1303–1311.
100. S. Saita, T. Oda, M. Kubo, Y. Kawata, N. Niki, M. Sasagawa, H. Ohmatsu, R. Kakinuma, M. Kaneko, M. Kusumoto, K. Eguchi, H. Nishiyama, K. Mori, N. Moriyama, “Nodule detection algorithm based on multislice CT images for lung cancer screening”, Medical Imaging 2004: Image Processing, International Society for Optics and Photonics, February 14, San Diego, California, USA, 2004, pp. 1083–1090.
101. K. Suzuki, S. G. Armato, F. Li, S. Sone, K. Doi, “Massive training artificial neural network (MTANN) for reduction of false positives in computerized detection of lung nodules in low-dose computed tomography”, Medical Physics 30 (7), 2003, pp. 1602–1617.
102. H. M. Orozco, O. O. V. Villegas, L. O. Maynez, V. G. C. Sanchez, H. d. J. O. Dominguez, “Lung nodule classification in frequency domain using support vector machines”, 11th International Conference on Information Science, Signal Processing and their Applications, IEEE, July 2-5, Montreal, Canada, 2012, pp. 870–875.
103. J. S. Lin, S. B. Lo, A. Hasegawa, M. T. Freedman, S. K. Mun, “Reduction of false positives in lung nodule detection using a two-level neural classification”, IEEE Transactions on Medical Imaging 15 (2), 1996, pp. 206–217.
104. R. Bellotti, F. De Carlo, G. Gargano, S. Tangaro, D. Cascio, E. Catanzariti, P. Cerello, S. C. Cheran, P. Delogu, I. De Mitri, C. Fulcheri, D. Grosso, A. Retico, S. Squarcia, E. Tommasi, B. Golosio, “A CADsystem for nodule detection in low-dose lung CTs based on region growing and a new active contour model”, Medical Physics 34 (12), 2007, pp. 4901–4910.
105. M. N. Gurcan, B. Sahiner, N. Petrick, H.-P. Chan, E. a. Kazerooni, P. N. Cascade, L. Hadjiiski, “Lung nodule detection on thoracic computed tomography images: Preliminary evaluation of a computer-aided diagnosis system”, Medical Physics 29 (11), 2002, pp. 2552–2558.
106. N. Camarlinghi, I. Gori, A. Retico, R. Bellotti, P. Bosco, P. Cerello, G. Gargano, E. L. Torres, R. Megna, M. Peccarisi, M. E. Fantacci, “Combination of computer-aided detection algorithms for automatic lung nodule identification”, International Journal of Computer Assisted Radiology and Surgery 7 (3), 2012, pp. 455–464.
107. K. Suzuki, “A supervised lesion-enhancement filter by use of a massive training artificial neural network (MTANN) in computer-aided diagnosis (CAD)”, Physics in Medicine and Biology 54 (18), 2009, pp. S31–S45.
108. A. S. Iwashita, J. P. Papa, A. N. Souza, A. X. Falca˜o, R. A. Lotufo, V. M. Oliveira, V. H. C. de Albuquerque, J. M. R. S. Tavares, “A pathand label-cost propagation approach to speed up the training of the optimum-path forest classifier”, Pattern Recognition Letters 40, 2014, pp. 121–127.
109. E. J. S. Luz, T. M. Nunes, V. H. C. de Albuquerque, J. P. Papa, D. Menotti, “ECG arrhythmia classification based on optimum-path forest”, Expert Systems with Applications 40 (9), 2013, pp. 3561–3573.
110. T. M. Nunes, A. L. Coelho, C. A. Lima, J. P. Papa, V. H. C. de Albuquerque, “EEG signal classification for epilepsy diagnosis via optimum path forest – A systematic assessment”, Neurocomputing 136, 2014, pp. 103–123.
111. J. P. Papa, A. X. Falca˜o, V. H. C. de Albuquerque, J. M. R. Tavares, “Efficient supervised optimum-path forest classification for large datasets”, Pattern Recognition 45 (1), 2012, pp. 512–520.
112. F. P. M. Oliveira, J. M. R. S. Tavares, “Medical image registration: a review”, Computer Methods in Biomechanics and Biomedical Engineering 17 (2), 2014, pp. 73–93.
113. J. M. R. S. Tavares, “Analysis of biomedical images based on automated methods of image registration”, Advances in Visual Computing, Lecture Notes in Computer Science, Vol. 8887, Springer, 2014, pp. 21– 30.
114. R. S. Alves, J. M. R. S. Tavares, “Computer image registration techniques applied to nuclear medicine images”, Computational and Experimental Biomedical Sciences: Methods and Applications, Lecture Notes in Computational Vision and Biomechanics, Vol. 21, Springer, 2015, pp. 173–191.
115. Harris JE. “Cigarette smoking among successive birth cohorts of men and women in the United States during 1900-80”, J Natl Cancer Inst. 1983, 71:473-479.
116. Jemal A, Ma J, Rosenberg PS, Siegel R, Anderson WF. “Increasing lung cancer death rates among young women in southern and midwestern states”. J Clin Oncol. 2012, 30: pp. 2739-2744.
117. National Lung Screening Trial Research Team, Aberle DR, Adams AM, et al., “Reduced lung-cancer mortality with low dose computed tomographic screening”, Engl J Med. 2011, 365: 395-409.
118. Marcus PM, Doria-Rose VP, Gareen IF, et al., “Did death certificates and a death review process agree on lung cancer cause of death in the National Lung Screening Trial?”, Clin Trials. 2016;13: 434-438.
119. Doria-Rose VP, White MC, Klabunde CN, et al., “Use of lung cancer screening tests in the United States: results from the 2010 National Health Interview Survey”, Cancer Epidemiol Biomarkers Prev. 2012, 21: 1049-1059.
120. Jacobs C, Snchez CI, Saur SC, Twellmann T, de Jong PA, van Ginneken B., “Computer-aided detection of ground glass nodules in thoracic CT images using shape, intensity and context features”, Medical image Computing and Computer-Assisted Intervention MICCAI 2011: Springer, 2011, pp. 207-214.
121. Orozco HM, Villegas OOV, Snchez VGC, Domnguez HdJO, Alfaro MdJN, “Automated system for lung nodules classification based on wavelet feature descriptor and support vector machine”, Biomedical engineering online, vol. 14, no. 1, 2015.
122. Lee SLA, Kouzani AZ, Hu EJ, “Automated detection of lung nodules in computed tomography images: a review”, Machine vision and applications, vol. 23, no. l, pp. 151-163, 2012.
123. Li Q, “Recent progress in computer-aided diagnosis of lung nodules on thin-section CT”, Computerized Medical Imaging and Graphics, vol. 31, no. 4, pp. 248-257, 2007.
124. Keshani M, Azimifar Z, Tajeripour F, Boostani R., “Lung nodule segmentation and recognition using SVM classifier and active contour modeling: A complete intelligent system”, Computers in biology and medicine, vol. 43, no. 4, pp.287-300, 2013.
125. Kuruvilla J, Gunavathi K., “Lung cancer classification using neural networks for CT images”, Computer methods and programs in biomedicine, vol. 113, no. 1, pp. 202-209, 2014.
126. Krewer H, Geiger B, Hall LO, Goldgof DB, Gu Y, Tockman M, et al., editors., “Effect of texture features in computer aided diagnosis of pulmonary nodules in low-dose computed tomography”, Systems, Man, and Cybernetics (SMC), 2013 IEEE International Conference, 2013.
127. Hawkins SH, Korecki JN, Balagurunathan Y, Gu Y, Kumar V, Basu S, et al., " Predicting Outcomes of Nonsmall Cell Lung Cancer Using CT Image Features, Access, IEEE, vol. 2, pp. 1418-1426, 2014.
128. Madero Orozco H, Vergara Villegas, de Jesus Ochoa Dominguez H, Cruz Sanchez VG, editors, “Lung Nodule Classification in CT Thorax Images Using Support Vector Machines”, Artificial Intelligence (MICAI), 2013 12th Mexican International Conference, 2013.
129. Zhang F, Song Y, Cai W, Zhou Y, Shan S, Feng D, “Context curves for classification of lung nodule images”, Digital Image Computing: Techniques and Applications (DICTA), 2013 International Conference, 2013.
130. Nascimento LB, de Paiva AC, Silva AC., “Lung nodules classification in CT images using Shannon and Simpson diversity indices and SVM”, Machine Learning and Data Mining in Pattern Recognition: Springer, 2012, pp. 454-466.
131. Tan M, Deklerck R, Jansen B, Bister M, Cornelis J., “A novel computer aided lung nodule detection system for CT images”, Medical physics, vol. 38, no. 10, pp.5630-45, 2011.
132. Kanitkar SS, Thombare N, Lokhande S, editors., “Detection of lung cancer using marker-controlled watershed transform”, Pervasive Computing (ICPC), 2015 International Conference; 2015: IEEE, 2015.
133. de Carvalho Filho AO, de Sampaio WB, Silva AC, de Paiva AC, Nunes RA, Gattass M., " Automatic detection of solitary lung nodules using quality threshold clustering, genetic algorithm and diversity index," Artificial intelligence in medicine, vol.60, no. 3, 2014, pp. 165-77.
134. Choi W-J, Choi T-S., “Automated pulmonary nodule detection system in computed tomography images: A hierarchical block classification approach”, Entropy, vol. 15, no. 2, 2013, pp.507-523.
135. <http://medical.nema.orgS.&http://anode09.isi.uu.nlS>.
136. Stefano Diciotti, Simone Lombardo, Massimo Falchini, Giulia Picozzi, Mario Mascalchi. “Automated segmentation refinement of small lung nodules in CT scans by local shape analysis.” IEEE Transactions on Biomedical Engineering, 58(12):3418–28, 2011.
137. T. Kubota, A. Jerebko, M. Salganicoff,M. Dewan, and A. Krishnan, “Robust segmentation of pulmonary nodules of various densities: from ground-glass opacities to solid nodules,” in Proceedings of the International Workshop on Pulmonary Image Processing, pp. 253–262, 2008.
138. T. Kubota, A. K. Jerebko, M. Dewan, M. Salganicoff, and A. Krishnan, “Segmentation of pulmonary nodules of various densities with morphological approaches and convexity models,” Medical Image Analysis, vol. 15, no. 1, pp. 133–154, 2011.
139. ELCAP public lung image database. [www.via.cornell.edu/databases/lungdb.html](http://www.via.cornell.edu/databases/lungdb.html).
140. Y. Liu, J. Yang, D. Zhao, “Computer Aided Detection of Lung Nodules Based on Voxel Analysis utilizing Support Vector Machines”, International Conference on Future Bio Medical Information Engineering, 2009.