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Detection of Lung Nodule on Temporal Subtraction Images Based on Artificial Neural Network

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Abstract

The temporal subtraction technique as one of computer aided diagnosis has been introduced in medical fields to enhance the interval changes such as formation of new lesions and changes in existing abnormalities on deference image. With the temporal subtraction technique radiologists can easily detect lung nodules on visual screening. Until now, two-dimensional temporal subtraction imaging technique has been introduced for the clinical test. We have developed new temporal subtraction method to remove the subtraction artifacts which is caused by mis-registration on temporal subtraction images of lungs on MDCT images. In this paper, we propose a new computer aided diagnosis scheme for automatic enhancing the lung nodules from the temporal subtraction of thoracic MDCT images. At first, the candidates regions included nodules are detected by the multiple threshold technique in terms of the pixel value on the temporal subtraction images. Then, a rule-base method and artificial neural networks is utilized to remove the false positives of nodule candidates which is obtained temporal subtraction images. We have applied our detection of lung nodules to 30 thoracic MDCT image sets including lung nodules. With the detection method, satisfactory experimental results are obtained. Some experimental results are shown with discussion.

Keywords: Lung Nodule, Computer Aided Diagnosis, Temporal Subtraction Technique, Statistical Features, Class-featuring information compression

1. Introduction

Lung cancer has become the primary cause relate to the cancer deaths in the world. Its diagnosis and detection are important to improve the survival rate. Therefore, the chance of receiving the diagnostic imaging has been increased to detect abnormalities on the visual screening as a diagnostic imaging tool by use of multiple detector-row computed tomography (MDCT) images in the last few years. By setting a multi detectors and obtaining more slices simultaneously, the MDCT scan could get higher quality images and more information than X-ray. Using the MDCT, the radiologists can detect the lung cancer with high accuracy. But, the workload increasing to the radiologists turns into a problem. Because, they must interpret a large number of MDCT images without mistake in a limited time. So we develop the computer aided diagnosis (CAD) systems to improve precision and the efficiency of the medical examination.

CAD [1-3] is one of useful tools to support on visual screening on medical fields. As one of the techniques to suppose CAD (Computer Aided Diagnosis) systems, the temporal subtraction technique has been introduced in the medical fields [4-8]. This technique can emphasize the interval changes on medical images by removing the most of the normal background structures such as blood vessels and airways on the thoracic CT images. Also there are many report concern with the temporal subtraction techniques [9, 10]. Fig.1 shows an example of temporal subtraction image which is subtracted from the two images using the subtraction technique. However, the subtraction artifacts due to the mis-registration still exist on the temporal subtraction images [11-14]. It cause the false positives of lung nodules when the detection on temporal subtraction images. Therefore, we need to distinguish the lung nodules from artifacts by image processing.

In this paper, we develop a method for automatic detection of lung nodules based on temporal subtraction images in MDCT images of chest. First, candidate regions are detected by using of multiple threshold technique based on the pixel value on the temporal subtraction images. Next, candidate regions are calculated and marked on the current CT images. Finally, the false positives are removed by rule-based method and CLAFIC (Class-featuring information compression) method. We evaluated our proposed method using 11 of statistical features. We applied our computerized scheme to 30 abnormal chest MDCT cases including 31 lung nodules. Our scheme for detecting lung nodules provided sensitivity of 87.1 [%] for lung nodules with 2.07 FP (false positive) per a scan.

2. Method

This section introduces our new approach to detect lung nodules in MDCT images. Fig.2 shows the overall scheme for

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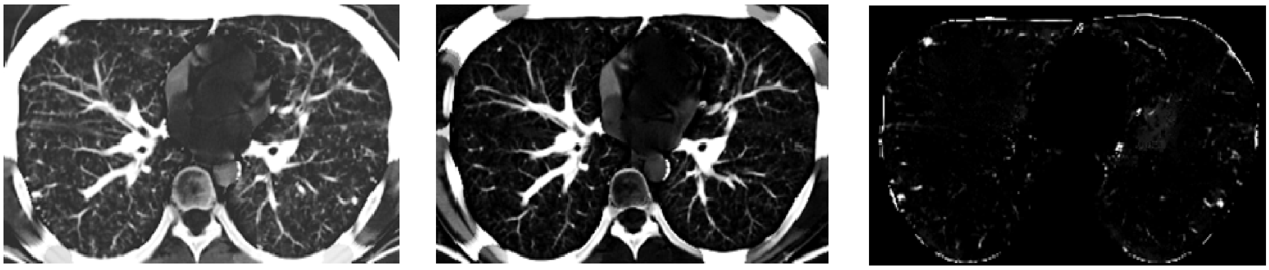

(a) A current MDCT image (b) A previous MDCT image (c) A temporal subtraction image

Fig.1. Example of temporal subtraction image

detection of lung nodules. Our algorithms consist of three main steps. Firstly temporal subtraction images are created from current MDCT images and previous one. Then, we detect the candidate regions of lung nodules on temporal subtraction images. Finally, we remove the false positives in candidate regions by the CLAFIC method. The temporal subtraction technique algorithms consists of global rigid registration and local non-rigid registration offered by generalized gradient vector flow (GGVF) [15] and voxel matching technique [11] .

2.1. First Candidate Regions of Lung Nodules

We conduct sampling of object on the temporal subtraction i mages by use of multiple threshold technique to detect candidat e regions of lung nodules. And, it conducts segmentation of the candidate region by binarization based on the pixel value on t he current MDCT images. The multiple threshold technique for detection of lung nodules from temporal subtraction images is applied based on observation that nodules newly appearing in the current MDCT image must have a high CT value on the te mporal subtraction image. In the multiple threshold technique, t he thresholds are taken from the CT values corresponding to th e top 0.5, 1.0, 1.5, 2.0, and 2.5 percentages of histogram in the t emporal subtraction image.

2.2. Calculation of Statistical Features

We calculate the characteristics on the volume of interests (VOIs) on the current MDCT image. In this paper, adopted characters consists of 4 luminance features (average, standard deviation, maximum, average of ranked tetrad), 5 shape features (circularity, elongation, irregularity, sphericity, cross correlation), and 2 features based on output of 2-dimentional adaptive ring filter. Here, the VOIs are placed at the center of the candidate region, with the sizes of 51[pixel] ×51[pixel] ×51[pixel].

<Cross Correlation>

Generally, the lung nodule should be similar to a globular in 3-dimensional space. Therefore, if the candidate region is the true positive, the correlation calculated in 3 areas of the candidate region (axial, sagittal, and coronal) has the value of 1 approximately. Otherwise, the correlation has a lower value. The cross correlation C is given by the function (1), (2) below,

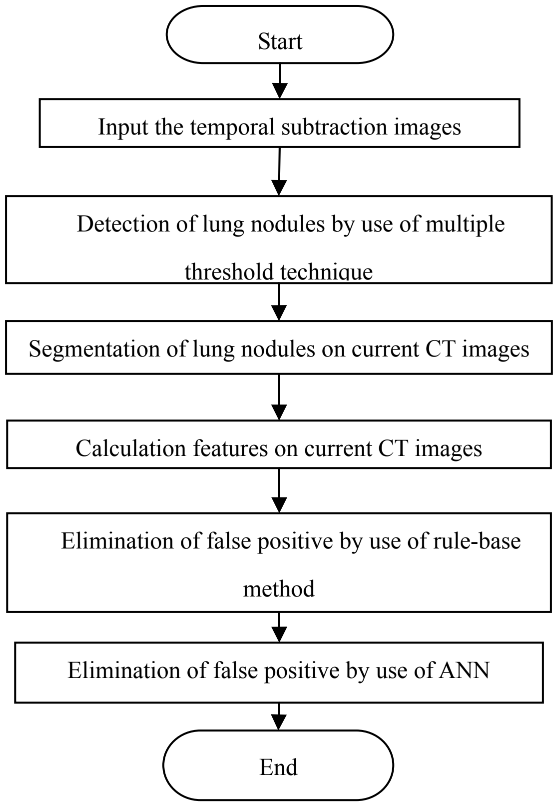

Fig.2 Overall scheme for detection of lung

$$C = \frac{1}{3}(m_{axical} + m_{sagittal} + m_{coronal}) \qquad (1)$$

$$m = \frac{\sum\sum\left(f(x,y)-\bar{f}\right)\left(g(x,y)-\bar{g}\right)}{\sqrt{\sum\sum\left(f(x,y)-\bar{f}\right)^2\left(\sum\sum g(x,y)-\bar{g}\right)^2}} \qquad (2)$$

<2-Dimentional Adaptive Ring Filter [16], [17]>

The 2-dimentional adaptive ring filter is a numerical method in a vector convergence index that is average a cosine of an angle between a directional vector from near field region to attention point and a gradient vector of near field region. So, if the correlation in the two vectors directions has a higher value, the vector convergence index shows high values.

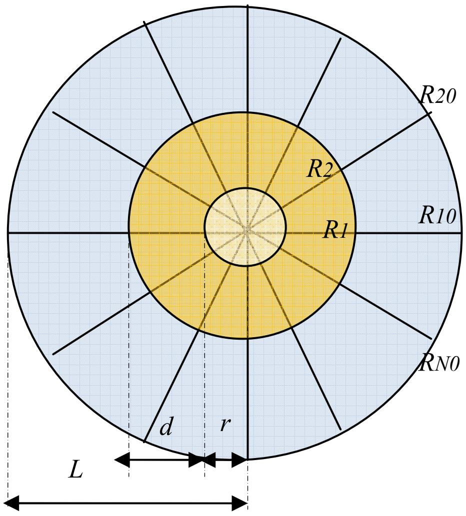

Fig.3 A basic concept of a 2-D adaptive ring filter

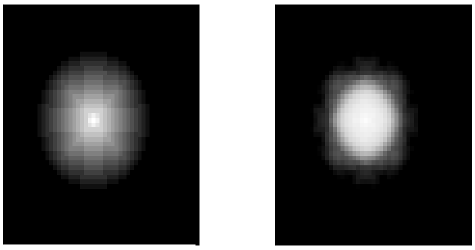
(a) Input image (b) Output image

Fig.4 Output of 2D adaptive ring filter

Fig.3 shows the basic conception of 2-dimentional adaptive ring filter. A near field region R_{i0} is lines passing through a center point x. A length of line is L [pixel]. And, part region R_i is product set region R_{i0} and ring shaped region which is r [pixel] in bore diameter, d [pixel] in width. Here, d is value of fixed, r is value of variable. An output of 2-dimentional adaptive ring filter $c(x)$ is given computing the vector convergence index in region R_i (3), (4).

$$c(x) = \max_{0 \le r \le L-d} \frac{1}{N} \sum_{i=1}^{N} c_i \tag{3}$$

$$c_i = \frac{1}{d} \sum_{j=d+1}^{r+d} \cos\theta_{ij} \tag{4}$$

Fig.4 illustrates the result of globular shape processed by 2-dimentional adaptive ring filter. The pixel value of output ranges from 0 to 1. The biggest value is obtained in center.

By using the maximum of output on the VOI, we can remove the false positive on the temporal subtraction images. Furthermore, operated by the filter the output of the liner areas such as a vessel and bronchi is small. Oppositely, the area with a high output value is judged as the spherical feature, and remarked as candidate region.

<CLAFIC Method>

The CLAFIC method classify unknown pattern according to whether they are similar to subspace by class (the true positive and the false positive).

At first, we make feature vectors of learning data into the subspace by Karhunen-Loeve (KL) method. Next, we calculate the degree of similarity between feature vector of unknown pattern and subspace by class (5), and classify unknown pattern into class that have maximum degree of similarity. Here, $\boldsymbol{x}$ is feature vector of unknown pattern; $\boldsymbol{u_i}$ is orthonormal vector of subspace by class.

$$f(\boldsymbol{x}) = \sum_{j=1} (\boldsymbol{x}^T \boldsymbol{u}_j)^2 \tag{5}$$

Here, learning data and unknown data are provided by a leave one out method.

3. Results

This section introduces experimental results applied by our proposed method. Table.1 shows the experiment environment. We try to detect lung nodules automatically in 30 abnormal cases. The results are shown in Table.2. Table.3 shows detail of nodule diameter which is performed in experiment. The true positives and the false positives of detection results on candidate regions are listed on the top. The elimination data of the false positives based on the rule base method are shown in middle. And the eliminations by the CLAFIC method are listed under that. Fig.5 shows the results of elimination using of CLAFIC method by the free-response receiver operating characteristic (FROC) curve. In Fig.5, red line shows results when the thresholding is fix empirically on CLAFIC method. On the other hand, blue lines in Fig.5 illustrates the results based on CLAFIC and rule based method by fix the parameter on threshing without reducing the true positive. Fig.6 to Fig.8 shows some experimental results. Fig.6 shows an example of segmentation results. Fig.7 shows successive slices which is obtained lung nodule (circle area) on temporal subtraction and

Table 1 Experiment environment

CT scanner	**TOSHIBA Aquilion**
Image size	512×512[pixel]
Pixel size	0.625[mm]～0.702[mm]
Slice thickness	2[mm]
CT image sets	30

Table 2 Results of nodule detection

	TP[%]	**FP[/scan]**
Detection of 1st candidate regions	100	143.5
Elimination of the false positive by use of rule base method	87.1	2.17
Elimination of the false positive by use of CLAFIC method	87.1	2.07

Table 3 Detail of nodule diameter which is performed exp erimental data

	Interval[month]	Number of nodules	Diameter[mm]
#1	3	1	9
#2	9	1	3
#3	7	1	16
#4	12	1	7
#5	6	1	15
#6	7	1	6
#7	6	1	9
#8	42	1	12
#9	33	1	5
#10	12	1	16
#11	4	1	10
#12	4	1	6
#13	6	1	5
#14	3	1	8
#15	12	1	18
#16	9	1	16
#17	26	1	7
#18	12	1	11
#19	4	1	12
#20	4	1	7
#21	3	1	10
#22	8	1	10
#23	9	1	7
#24	37	1	5
#25	7	1	4
#26	3	2	2～5
#27	12	1	12
#28	6	1	6
#29	8	1	7
#30	12	1	19

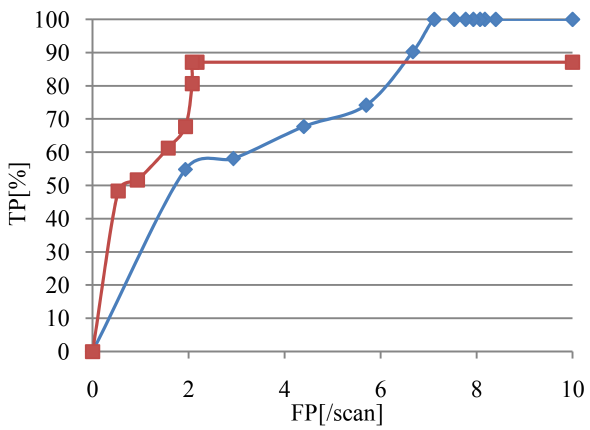

Fig.5 FROC curve

original CT images. In Fig. 7, (a) illustrates original CT images and (b) shows temporal subtraction image, respectively. The nodule is enhanced on temporal subtraction images. Fig.8 and Fig.9 show an example of the true and the false positive respectively.

4. Discussion

In this paper, we proposed a new method for detection of lung nodules using the temporal subtraction images. In the detection of candidate regions of lung nodules from a temporal subtraction image, 100 [%] of the true positive rate was achieved as shown in Tabel.2. But, the true positive rate was come down in a rule base method. This is suspected to be due to segments on current MDCT images. Actually, an example of failure on segmentation in candidate regions is shown in Fig.6. We assume that there is much adverse effect on calculation of shape feature. Fig.5 shows differences of the false positive between TP 87.1 [%] and TP 100 [%] in CLAFIC method and rule base method. Therefore, the accuracy of segmentation needs to be improved in the future.

As shown in Table 2, the CLAFIC method is proved as an effective method to reduce the false positive. To obtain a high accuracy of the true positive, it is necessary to introduce various features on to the CLAFIC method. It is still remain as our future works.

Finally, although the temporal subtraction technique has some advantages on identifying the lung nodules from the similar feature tissues, the subtraction artifacts induced by registration miss still exist on the temporal subtraction images. Therefore, improving the accuracy of registration for the temporal subtraction is necessary, too.

5. Conclusion

The subtraction image can make by image registration technique from a previous to current image set. Radiologist analyzes abnormalities by using the previous, current CT image and temporal subtraction images. In this paper, we developed a new method for detection of lung nodules on the MDCT images which is obtained temporal subtraction. As the detection of lung nodules method, candidate regions are limited by using of multiple threshold technique based on the pixel value in the temporal subtraction images. As well, the candidate regions are calculated and marked on the current CT images. Finally, the false positives are removed by rule-based method and CLAFIC method. Our scheme for detecting lung nodules provided sensitivity of 87.1 [%] for lung nodules with 2.07 FP per scan. As future work, the improvement of segmentation to improve of the true positive rate and the introduction of varied features to remove of the false positive become the task. Some problems still remained. One of the problems is that high accuracy is required to use the system on visual screening. To overcome this problem, we are developing a non-rigid image registration technique now.

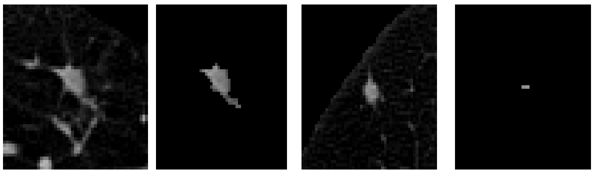

Fig.6 Results of nodule segmentation

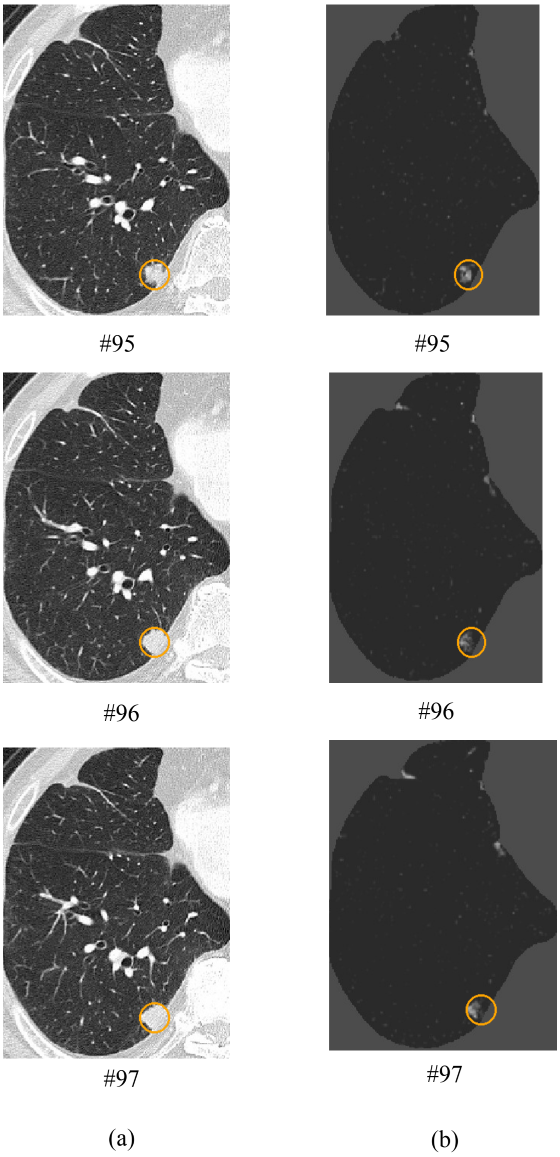

Fig.7 Obtained lung nodules on successive slices

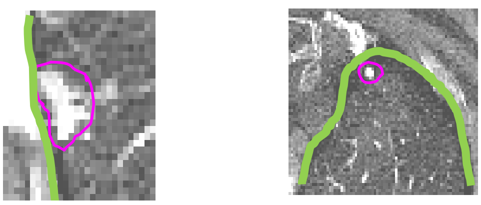

Fig.8 Examples of the true positive

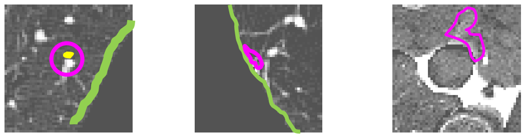

Fig.9 Examples of the false positive

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