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A joint ROI extraction filter for computer aided lung nodule detection [1]

Zhenghao Shi [a,*], Binxin Xu [a], Minghua Zhao [a], Jinwei Zhao [a], Yinghui Wang [a], Yonghong Liu [c], Ming Zhang [b], Lifeng He [d] and Kenji Suzuki [e]

[a] *School of Computer Science and Engineering, Xi'an University of Technology, Xi'an, 710048, China*
[b] *First Affiliated Hospital of School of Medicine,Xi'an Jiaotong University, Xi'an, 710061, China*
[c] *Xianyang Hospital,Yan'an University, Xianyang, 712000, China*
[d] *School of Information Science and Technology, Aichi Prefectural University, Nagakute, Aichi 4801198,Japan*
[e] *Department of Electrical and Computer Engineering, Illinois Institute of Technology,Chicago,IL 60616-3793,USA*

Abstract. Extraction of regions of interest plays an important rule in computer aided lung nodules detection. However, because of the complex background and structure, accurate and robust extraction of ROIs in medical image still remains a problem. Aim at this problem, a two-stage operations joint filter: Hessian-LoB, is proposed. The first stage is blobs (which being taken as candidate ROIs) detection and the second stage is ROIs extraction. In the first stage, the derivatives of a Hessian matrix at multiple scales are convolved with input images to localize blobs. Then in the second stage, Laplacian of bilateral filter (LoB) is convolved with the detected blobs to extract the final ROIs. Experiments show that the proposed filter can deal with images with noise and low brightness contrast, and is effectively in ROI extraction for lung nodule detection.

Keywords: Region of interesting(ROI), extraction, hessian matrix, $Laplacian$ of Bilateral (LoB)

1. Introduction

Region of interest (Region of Interest, ROI) is the most interested region in an image for observers, it contains the main imaging information that an observer need to know. For a medical image, ROIs contain the main information of pathological changes of patients, such as cancer, calcification, and inflammation and so on. Quantitative analysis of the shape and properties of ROI could provide reliable data for diagnosing disease and the follow-up treatment planning. Therefore, extraction of ROI plays a crucial role in medical image analysis [1].

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[*]Corresponding author: Zheng-hao Shi, School of Computer Science and Engineering, Xi'an University of Technology, Xi'an 710048, China. Tel.: +1 029 8231 2231; Fax: +1 029 8231 2231;E-mail: ylshi@xaut.edu.cn.

In this work, we focus on extracting ROIs for lung cancer in Thoracic Computed Tomography (Computed Tomography, CT). Thoracic Computed Tomography is a common imaging tool for lung cancer diagnosis currently. In the early stage of lung cancer, it often appears as a solitary pulmonary nodule, which is a region in lung fields with a spherical structure [2]. Therefore, to extract ROIs for lung cancer Thoracic Computed Tomography, we can conceive it as a filtering process that searches for any region that has a spherical structure Thoracic Computed Tomography. To address such problems, inspired by [2–4], a joint filter, Hessian-LoB, is proposed in this paper. The proposed filter consists of two major operations: candidate regions of interesting (ROI) detection based on Hessian matrix and ROI extraction using Laplacian of bilateral filter (LoB) filter. Experiments show that the proposed filter is effectively in ROI extraction.

The remainder of this paper is organized as follows: Section 2 gives a brief review of related works. Section 3 describes the proposed method in detail, and Section 4 provides experimental materials for this study firstly and then details the experimental results. Finally, the paper is concluded in Section 5.

2. Related works

Many ROI extraction methods have been developed in past years, such as template matching [5], Thresholding [6], Region growing [7] and mathematical morphology method [8]. Template matching method is on the whole image matching using the traversal designed templates to find the best matching region in which. It is simple and easy to implement, but has high computational load, it is also difficult to select a template; the threshold based segmentation method is by selecting a threshold or multiple thresholds to classify all the pixels of the image into two classes or multi-classes, the key is to determine a threshold. This kind of method is easy to understand and implement, however, it is sensitive to noises. Region growing is a commonly used method for region of interest extraction. The main idea of it is to start from a seed point and expand according to the growth rule around a pre-defined seed until meet the growth conditions. The key problems and difficulties of this method are to select the seed points.

In recent years, multi-scale analysis of the Hessian matrix is widely used in image processing [9–20]. The method was originated by Koller et al.[9] and was further developed by Lorenz et al.[10] and Frangi et al.[11–14] for the purpose of vessel enhancement. Su et al.[15] selected candidate junction points through a new measurement which combines Hessian information and correlation matrix. Sato et al. [16,17] developed blob enhancement filters based on the eigenvalues of the Hessian matrix. In [18–20], Hessian analysis with multi-scale blob detection was applied for the detection of tumors. One known problem of this kind of method is noises will be amplified in a multi-scale iterative process, of them will produce too many candidate points, increasing the computational cost for the blob detection.

Gaussian fitting has also been used to locate ROIs. For example, in [21] Gaussian has been used for locate pulmonary nodules, and other studies have shown that the characteristic scale of a Laplacian of Gaussian (LoG) agreed well with radiologistsąŕ estimates of nodule size [22,23]. Kong et al.[24] propose a generalized Laplacian of Gaussian (LoG) (gLoG) filter for detecting general elliptical blob structures in images,Miao et al.[25] used rank order LoG filter for interest point detection, and Shi et al.[2] proposed a dot enhancement filter by combining Hessian matrix and LoG filter. One problem of LoG based method is too much blurring can occur during the multi-scale smoothing lead to false detections, especially for close-by structures.

3. Proposed filter

This proposed filter is an improvement of what described in [2], it consists of two major operations: Blobs detection based on Hessian matrix analysis, and ROIs extraction using LoB.

Blobs refer to bright regions on dark backgrounds or viceversa [17]. Hessian detector employs the Hessian matrix to analyze the second order derivatives of image intensity [11]. The idea behind the Hessian eigenvalues analysis is to extract the principal direction of the image features according to eigenvalues[18]. The trace and the determinant of this matrix are used to detect blobs in a single scale. Details for blobs detection based on Hessian matrix analysis can be referred to [2]. In the following, we focus on ROIs extraction using LoB.

In our previous work [2], Laplacian of Gaussian (LoG) filter was employed for dot enhancement. However, one drawback of the LoG filter in extracting blobs is that spurious local extrema are produced around the blobs, and this leads to too much false positives remain. What leads to this? The reason is that the intuitions for LoG filter. LoG filter is a convolution of two functions, the Laplacian function and Gaussian function, where Gaussian is for smoothing and Laplacian is for differentiation. To smooth image noises, the intuition for Gaussian function is that images typically vary slowly over space, however, the assumption of slow spatial variations fails at image edges.

Aim at this problem, bilateral filter is employed to instead of Gaussian function of the LoG filter in this work. We term this new joint filter as Laplacian of bilateral filter, simply (LoB). The bilateral filter [12] is a nonlinear edge-preserving smoothing filter, and usually defined as:

$$B_x = \frac{1}{k(x)} \sum_{\xi \in \Omega} c(\xi, x) s(I_\xi, I_x) I_\xi \tag{1}$$

where B_x is the output of bilateral filter, and Ω denotes the neighboring pixels locations including the current location $x.c(\xi, x)$ and $s(I_\xi, I_x)$ are Gaussian functions that measure the geometric closeness and photometric similarity between the neighborhood center x and a nearby point ξ . I_ξ represents the intensity value of ξ. $k(x)$ is a normalized factor that is defined by:

$$k(x) = \sum_{\xi \in \Omega} c(\xi, x) s(I_\xi, I_x) \tag{2}$$

By means of a nonlinear combination of nearby image values, the bilateral filter smoothes images while preserving edges.

After bilateral filtering, Laplacian filtering followed. In this work, the following 3×3 Laplacian template is employed:

$$\begin{bmatrix} -1 & -1 & -1 \\ -1 & 8 & -1 \\ -1 & -1 & -1 \end{bmatrix} \tag{3}$$

In summary, the joint filter is shown as bellows:

Input:

Original image I

Scale factor σ
Iteration step-length t
Output:
Extracted ROIs I_R

Stage 1: blobs detection based on Hessian matrix
1).Create a pixel matrix form the input image;
2).Initialize the spatial scale σ;
3).For each pixel I(x, y) in image I, repeat from 4) to 9);
4).Loop according to Iteration step-length t;
5).Calculate convolution of I(x, y) with the second derivative of Gaussian function;
6).Create Hessian matrix H, and calculate the eigenvalues of H;
7).Calculate module of Hessian matrix in current scale;
8).Hessian filtering outputting according to Eq.(5);
9).If ęÒ satisfies the termination conditions, exit the loop;
10).Select the maximum values of Hessian filtering output as the detected blobs pixels;
11).Traverse all pixels and get the detected blobs image J;
Stage 2: ROI extraction using LoB operator
12).Initialize the parameters of LoB filter;
13).For each blob pixel J(x, y) in image J, repeat from 14) to 15);
14).Calculate convolution of J(x, y) with bilateral filter according to Eq.(9);
15).Calculate convolution of J(x, y) with Eq. (11) to extracted ROIs from above detected blobs;
16).Travers all blobs and get the extracted blobs image I_R.

3.1. Computational complexity

Given an image I, suppose its size is $N \times N$. The computational complexity to compute Hessian matrix is $O(N^2)$. The time complexity to compute LoB for blob i is linear to the total number of detected blobs. In general, this number is $O(1)$ because the detected blobs are usually limited. Hence, to perform the joint filter, the computational complexity is approximately $O(N^2)$.

4. Experiments

To evaluate the performance of the proposed filter, several experiments have been conducted on three image sets: synthetic image set and CT set, respectively. The experiment was designed to compare the overall performance between the proposed filter, Li's filter [3] that is a selective filter based on hessian features for detecting nodules, and Schilham's filter [26] that uses LoG for detecting dot like patterns, also with our previous work [2], including qualitative and quantitative evaluations. All experiments are coded using Matlab 2011 and run on a 2.8GHz Pentium Dual with 2.0GB of RAM.

4.1. Materials

Two data sets were used in this study, synthetic image set and CT set. The synthetic image set consists of ten images that are designed to contain several idealized dots of different sizes and lines of different types. The radius of the dots is in [1, 12] pixels, the width of the lines is in [1, 6] pixels.

The CT set were acquired with a MDCT scanner (GE Light-Speed Ultra, Milwaukee, WI, USA) with 120kVp and 100 mA in the medical school of Xiąŕan Jiao tong University. Our database consists of 23 scans, including a total of 883 2D slice images, with the number of slices per scan ranging from 28 to 62 (a mean of 38 slices per scan). Each CT slice has an image matrix of 512 by 512 (16 bits depth) pixels. Pixel size ranges between 0.625 mm and 0.742 mm, with a mean value of 0.692 mm, depending on the physical size of the patient.

A qualified physician confirmed the absence and presence of nodules both in CR and in CT.

4.2. Qualitative experiment

Figure 1 and 2 show part experimental results on synthetic images, respectively. In these experiments, dots of different sizes in synthetic images are defined as ROIs and should be extracted. In Figure 1, we compare our filter with Liąŕs work [3],with Schilham's method [26],and with our previous work [2]. It can be seen from figure 1 that all filters can extract ROIs while suppress lines. However, the proposed filter in this work presents a more accurate description of ROIs in high-intensity contrast(show in Figure 1(e)). Compared with the filter proposed in this work, output images of li's method is too dim to see(show in Figure 1(b)),Schilham's method has over extracted ROIs, and contains too much dot like patterns(show in Figure 1(c)). In the output image of our previous work, some non-blob structures are not well eliminated, and meanwhile, some blobs structure are a little blur (show in Figure 1(d)).

In Figure 2, we test the performances of the filters with respect to noises. Figure 2(a) is the original images that were polluted with salt and pepper noise of 0.01, Figure 2(b) is results with Li's filter, Figure 2(c) is results with our previous method, Figure 2(d) is results with this proposed filter. It is apparent that all three filters successfully extract the isolated blobs even noise is added. However, for noises disturb, if blobs are very close to line-like structures, our previous work fails to extract them, many points in line-like structures also being extracted, noises are also significantly much.

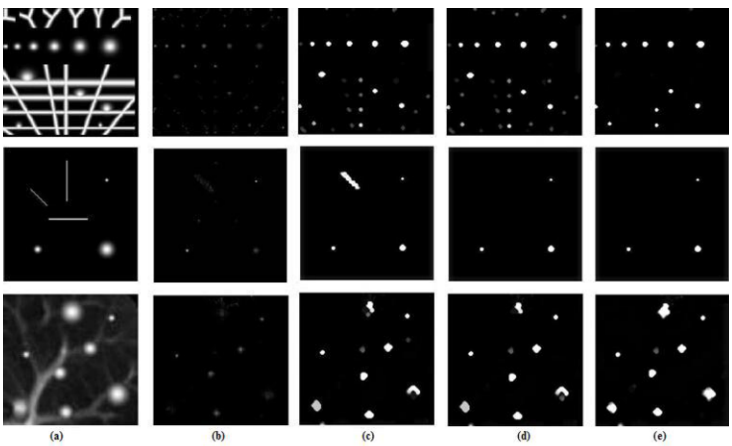

Fig. 1. Comparison of different ROI extraction filters on synthetic images. a) Original images; b) Li's filter;c) Schilham's filter; d) Our previous work; e) The proposed filter in this work.

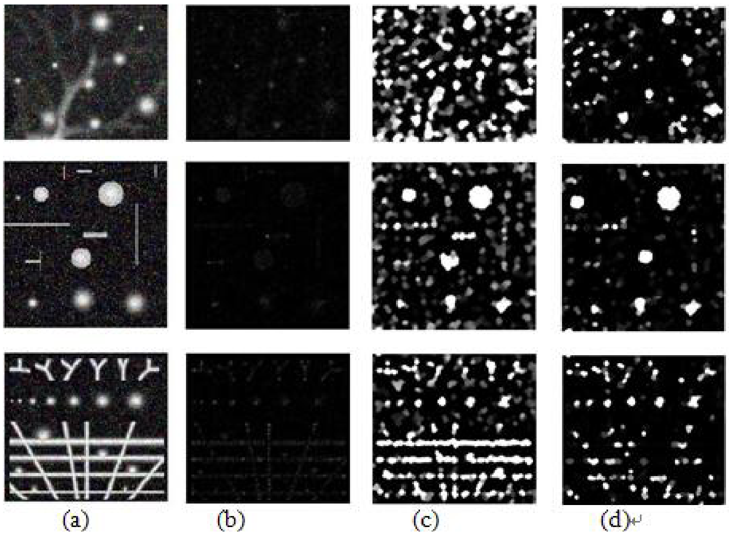

Fig. 2. Comparison of different ROI extraction filters on synthetic images with noises. a) Original images; b) Li's filter; c) Our previous work; d) The proposed filter in this work.

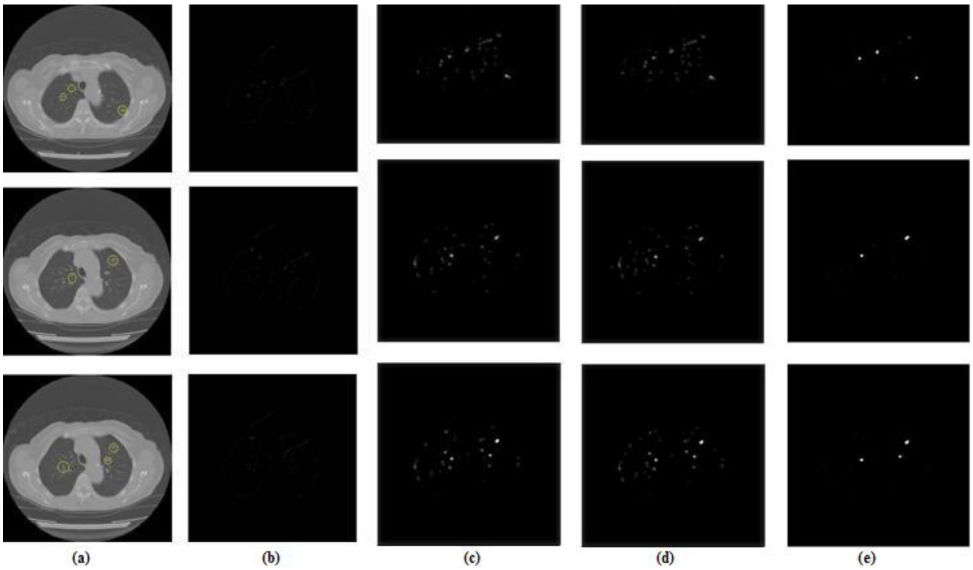

Fig. 3. Comparison of different ROI extraction filters on Thoracic Computed Tomography. a) Original images; b) Li's filter;c) Schilham's filter; d) Our previous work; e) The proposed filter in this work.

In Figure 3, we compare our approach (Figure 3(c)) with Liąŕs work [3],with Schilham's method [26],and with our previous work [2] on thoracic computed tomography. As can be seen that all filters can successfully extract blobs in the image while suppress lines. However, Comparing the detected blob to the reference one by radiologists (indicated by a circle as show in Figure 3(a)), it appears that Liąŕs filter gives good results with large ROIs but fails to extract small ones compared with the references indicated by radiologists (labeled by a circle, as show in Figure 3(a)),Schilham's method identified some rib-crossing areas as suspected areas(Figure 3(b)),the extracted blobs in our previous work looks dim, and its edges are blur. Whereas the proposed filter in this work can well extracted all ROIs labeled by radiologists with few other anatomical structures, edges of the extracted blobs are more clear, and this closely match the discernible by radiologists.

4.3. Quantitative experiment

The quantitative performance is measured with receiver operating characteristic (ROC) curves which are shown in Figure 4. An ROC curve plots the rate of blobs correctly extracted as ROIs (i.e., true positive rate or sensitivity) against the rate of blobs incorrectly extracted as ROIs (i.e., false positive rate or specificity). The rates are obtained with all possible threshold choices. Each discrete threshold value produces a (sensitivity, specificity) pair corresponding to a single point in the curve. The closer the curve approaches the top and left corner, the better, the better the filter performs. For this experiment, forty images, randomly selected from the synthetic image set, CR set and CT set, are used as the test images. For each image, a manually segmented ROI is generated as the background truth. It was apparent from these curves that our filter has the best performance across all the three filters.

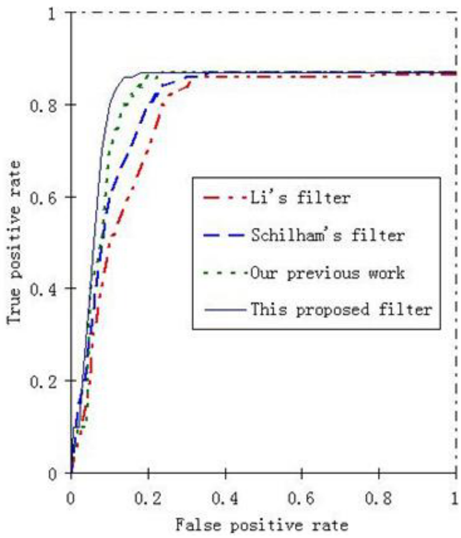

Fig. 4. ROC curve of the ROI extracted filters.

Table 1
Comparison in terms of computational cost of different filters for ROI extraction

Method	Image size(128 × 128)	Image size(512 × 512)
Liąŕs filter	0.7385s	1.2896s
Schilham's method	0.5965s	1.1879s
Our previous work	0.7845s	1.3789s
This proposed filter	0.8078s	1.4165s

Table 1 shows comparison in terms of computational cost of different filters for ROI extraction. As can be seen that under the condition of image size 128×128, our proposed filter in this work processes an image in approximately 0.8078s. In comparison, the filter of Li needs 0.7385s, Schilham requires 0.5965 seconds, the filter of our previous work needs 0.7845 seconds. Under the condition of image size 512×512, our proposed filter in this work processes an image in approximately 1.4165s. In comparison, the filter of Li needs 1.2896s, Schilham requires 1.1879 seconds, the filter of our previous work needs 1.3789 seconds. Though the new proposed filter cost the most computation time, as we analyzed in above section, the new filter has the best ROI extraction result. For this reason, we think the cost is valuable. In our future work, we will try to reduce the cost of the proposed filter.

5. Conclusion

In this paper, a novel ROI extraction filter for lung nodule, Hessian-LoB filter, is proposed. Experiments show that ROIs for lung nodules can be extracted accurately by our approach. It also show that compared with the existing method, our filter not only accuracy extract specific objects, i.e., ROIs for nodules, but also successfully suppress normal anatomic structures such as rib and vessels. This make the objects, i.e. ROIs for lung nodules, more easily be detected.

However, it should be noticed that the proposed filter needs more computational time than other existing filters. This is next step work that will be taken in future studies.

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