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HESSIAN-*LoG*: A NOVEL DOT ENHANCEMENT FILTER

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Abstract. *In order to make regions appearing as dots on a chest radiograph more clearly in visual, a novel filtering method, Hessian-LoG filter, is developed in this paper. The proposed filter consists of two major operations. First, using the eigenvalues of Hessian matrix detects dot points in chest radiography.The derivatives of a Hessian matrix at multiple scales are convolved with an input image at each pixel.To determine the local shape of structures at pixels in each scale, the eigenvalues of Hessian matrix are analyzed at each pixel in the resulting image.The diameter of the detected dot is equal to the kernel size with the highest classifier value.Finally, dot images are convolved with the Laplacian of Gaussian (LoG) operator.Experiments show that the proposed enhancement filter can simultaneously enhance dot-like objects and suppress line-like structures, and thus improve the sensitivity of nodule detection.*
Keywords: Dot enhancement, Hessian matrix, *Laplacian* of Gaussian (LoG), Chest radiography

1. **Introduction.** As one of basic image preprocess techniques, image enhancement does a great effect on improving the visual of chest radiography, and a series smooth filters have been reported in recent years[1],e.g. adaptive unsharp masking, the *Laplacian* filtering and local normalization (LN) filtering. These works have been extremely positive and helpful to improve radiologist performance in nodules diagnosis. However, adaptive unsharp masking is less efficient for images containing a wide range of features because of its single scale properties. The major drawback of the *Laplacian* filtering is the absence of explicit noise suppression model that can cause amplification of the noise or artifacts. By local normalization (LN) filtering, a global equalization of contrast throughout an image is achieved, but edge strength normalized too. More even, it should be noticed that all enhancement methods mentioned above work on whole chest radiography. As a result, not only nodules, but also other anatomic structures such as ribs, blood vessels,

and airway walls are enhanced in the same time, this will lead to a large number of false positives in lung nodule detection [2].

Multi-scale analysis of the Hessian matrix, i.e. second derivatives in orthogonal directions at each location, is widely used for enhancement or detection of line-like structures in two-dimensional images recently [3]. Based on the eigenvalues of the Hessian matrix, a local pattern is classified as plate-like, line-like or dot-like structures. The method was further developed by Lorenz et al.[4] and Frangi et al.[5] for the purpose of vessel enhancement. Li et al. [6] developed a selective enhancement filter based on the eigenvalues of the Hessian matrix, and generalized their filter for enhancing nodules, vessels, and airway walls . However, one known problem of Hessian-based filters is sensitive to local intensity variations due to second-order derivatives. Furthermore, by relying on principal curvatures alone, Hessian matrix based filters are incapable of distinguishing between nodules and vessel junctions, and are incapable of handling cases in which nodules touch vessels.

Motivated by the biological mechanisms of the human visual system reported in [7], approaches using *Laplacian* of Gaussian (LoG) filter [8] and its modification [9] for enhancing lung nodule-like pattern on chest radiograph were investigated in our previous works. Although experiments show the promising of these filters in enhancing lung nodule on chest radiographs, lung nodule enhancement remains an ongoing research topic. One of the major problems is too much blurring can occur during the multi-scale smoothing lead to false detections, especially for close-by structures.

To make problems mentioned above tractable, a novel dot enhancement filter, Hessian-*LoG* filter, is proposed in this paper. Different from conventional filters, the proposed filter consists of two operations: first, dots are detected using Hessian matrix where an input image is convolved with the derivatives of a Hessian matrix at multiple scales firstly, and then the Hessian matrix is analyzed at each pixel in the resulting image to determine the local shape of the structures. Next, the dots image is convolved with the *LoG* operator. This can effectively enhance the contrast between dots and their surrounding and make the dots more clearly in visual and more easily be detected by human visual perception. Experiments show the proposed filter is effectively.

2. **Proposed Method.**

Our dot enhancement filter consists of two major operations. First, the Hessian matrix is employed to detect dots. Next, the dots are convolved with the *LoG* operator. Details of each operation are described as bellows.

2.1. **Dots detection using hessian matrix.**

Assume that a pixel in a 2-D image is denoted by I(x,y), and its four second derivatives are represented by I_{xx},I_{yy},I_{xy} and I_{yx}, where I_{xy}=I_{yx}. Then the Hessian matrix H of the pixel I(x,y) in the original 2-D image can be constructed as

$$H = \begin{pmatrix} I_{xx} & I_{xy} \\ I_{yx} & I_{yy} \end{pmatrix} \tag{1}$$

Let the eigenvalues of the Hessian matrix be λ_1 and λ_2 ($|\lambda_1| \geq |\lambda_2|$). The eigenvalues λ_1 and λ_2 of the Hessian matrix can be calculated through the following equation:

$$\Delta(H - E * \lambda) = 0 \tag{2}$$

where E is the identity matrix and λ is the set of eigenvalues λ_1 and λ_2. The two eigenvalues of λ_1 and λ_2 give information about the shape of the considered area. Let $R_\sigma^\lambda = \frac{|\lambda_2|}{|\lambda_1|} e^{-\frac{R_c^2}{2}}$ with $R_c^2 = k - 2\sigma$ [6] be the ratio for distinguishing between dot-like and line-like structures. Apparently, the index of R_σ^λ has a value of 1 for a dot, a value of 0 for a line, and a value between 0 and 1 for a quasi-dot. Here, we assume that the detected object is bright with respect to it background.

Because the goal of our study is to enhance dot-like circular objects and to suppress line-like elongated objects, so in case of 2D filter, the eigenvalues λ_1 and λ_2 of Hessian matrix should satisfy the following condition:

$$Dot : \lambda_1 = \lambda_2 << 0 \tag{3}$$

$$Line : \lambda_1 << 0, \lambda_2 = 0 \tag{4}$$

Because nodules in chest radiography can appear in different size and scale, for preventing the lost detection of the positive nodules, it is important to measure them in different scale. To deal with this problem, also to reduce the second derivatives sensitivity to image noise, a Gaussian kernel is convolved with the original image before the calculation of Hessian matrix. The Gaussian kernel for 2-D images is defined as:

$$G(x, y, \sigma) = \frac{1}{2\pi\sigma^2} e^{-(\frac{x^2+y^2}{2\sigma^2})} \tag{5}$$

where the parameter of σ is the standard deviation of the Gaussian kernel, it controls the scale and the smoothing effect. For nodule enhancement, this value should be fitted to the nodule density distribution. In this study, method proposed in [6] was employed to calculate the standard deviations of a series Gaussian smoothing filters.

For finding the right diameter of a dot in chest radiography, the ratio of R^λ_σ for distinguishing between dot-like and line-like structures is analyzed at different scale σ of Gaussian kernel. The algorithm starts at an area of interest with the smallest kernel for the convolution. Then the kernel is incrementally extended. For every kernel size the eigenvalues are calculated. Finally, ratios of R^λ_σ at different scales are integrated to obtain the final measure of dot likeness. For the best fitting kernel size the ratio of R^λ_σ has the highest value at one scale, as described in equation (6).

$$R^\lambda_{max} = max R^\lambda_\sigma, \sigma \in [\sigma_{min}, \sigma_{max}] \tag{6}$$

This means that the detection can be stopped if the value of the classifier R^λ_σ begins to decrease, and at which the Gaussian kernel will approximately matches the size of the dot to be detected. The detected dot point $I_B(x, y)$ can be expressed as

$$I_B(x, y) = \begin{cases} 1, if : R^\lambda_{max} \\ 0, \text{others.} \end{cases} \tag{7}$$

2.2. **Interesting dots enhancement using *LoG* operator.** The *Laplacian* of Gaussian (LoG) operator of an image with pixel intensity values I(x, y), centered on zero, has the following form:

$$LoG_\sigma(x, y) = \frac{1}{\pi\sigma^4}(1 - \frac{x^2 + y^2}{2\sigma^2})e^{-\dfrac{x^2+y^2}{2\sigma^2}} \tag{8}$$

where the meaning of parameter σ is the same as that in equation(4). Figure 1 illustrates a perspective plot of *LoG* operator with $\sigma = 1$. As it can be seen from Figure 1(a), the *Laplacian* of Gaussian filter is a circular-symmetric filter and has a high central lobe which can provoke a high intensity transmission, and make the *LoG* filter acts as a probe that calculates the difference in contrast within and outside the region of interest. The difference in contrast between the two regions will be high if we apply this kernel over a nodule since nodules have high values at the center (bright) and low values in its surrounding region (dark), as shown in Figure 1(b). This reveals that the *LoG* operator emits low and high frequencies (those close to the origin, and those far away from the origin).

This profile closely mimics the response of the spatial receptive field found in biological vision [7]. Biological receptive fields have been shown to have a circularly symmetric impulse response, with a central excitory region surrounded by an inhibitory band.

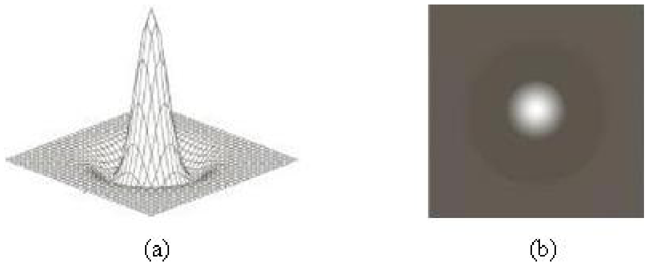

FIGURE 1. Illustration of a *Laplacian* of Gaussian (*LoG*)filter ($\sigma = 1$). a) A three dimensional illustration of the *LoG* operator.b) A two dimensional profile the *LoG* operator

What mentioned above are just the motivation of using *LoG* operator for enhancing dot-like structures on chest radiograph in this study. The *LoG* filtered image is represented by

$$I_E(x, y) = I_B(x, y) * LoG_\sigma(x, y) \tag{9}$$

where $I_E(x, y)$is the enhanced dot image, $I_B(x, y)$is the input image, and $*$ indexes the convolution operator. By a property selection of the standard deviation and kernel size of *LoG* filter, pixels within a spherical structure (where a potential nodule may happen to occur) in a chest radiograph image are of higher intensity, on average, than pixels that are part of a non-spherical structure.

3. **Experiments.** In this section, experiments have been performed with both synthetic images and real radiographies to verify the performance of the proposed enhancement filter in comparison with the filters introduced by Li Qiang [6] which are considered as the standard techniques, comparison with our previous work [9] is also given.

3.1. **Experiment on synthetic images.** Figure 2 shows the results of a synthetic image which is designed to contain three idealized dots of different sizes and three lines of different types. The radius of the three dots is 3, 6, and 12 pixels, respectively. The width of the three lines is 3, 4, and 6 pixels, respectively.

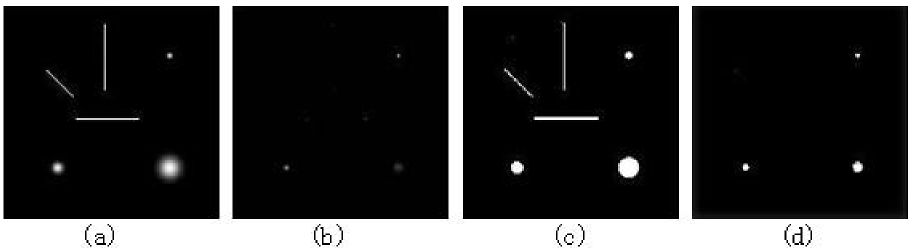

FIGURE 2. Comparison of different dot enhancement filters. a) Original images; b) Li's filter; c) Shi's filter; d) Filter proposed in this study.

Figure 2(d) shows the enhancement result with our proposed dot enhancement filter. As it can be seen that the proposed dot enhancement filter successfully enhanced all dots in the image while suppress the lines. Figure 2(b) and (c) show the enhancement image with Li's enhancement filter [6] and Shi's enhancement filter [9] on the synthetic image, respectively. As it can be seen that Li's enhancement filter (show in Figure.2 (b)) and our filter (shown in Figure 2(d)) successfully enhanced ideally dots and suppress lines simultaneously, while Shi's filter not only enhanced ideally dots but also enhanced ideally lines in the image. By comparing Figure 2(b) (enhanced with Li's filter) with Figure 2(d) (enhanced with our filter), it can be seen that, the dots in Figure 2(d) is more clearly than that in Figure 2(b).

3.2. **Experiment on noise sensitivity.** To compare the performances of the filters with respect to noise, we construct a series of testing data by adding various levels of white noise to images, and then apply the three filters on those images. Figure 3 shows sample enhancement results for the data with Gaussian white noise of 0.05. As we can see that the proposed filter and Li's filter outperforms the Shi's filter for the noise image. Specifically, compared to the Li's filter, it generates much better enhancement result in case of low noise. This result indexes that the proposed filter is least sensitive to noise among the three filters.

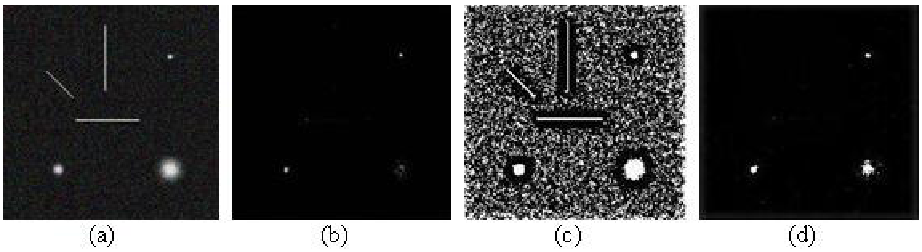

FIGURE 3. A sample of enhancement results on noise image.a) An image with Gaussian white noise of 5%;b) Li's filter; c) Shi's filter; d) Filter proposed in this study.

3.3. **Experiment on real radiographies.** The database used in this study consisted of 52 posterior anterior chest radiographs selected from the Japanese Standard Digital Image (JSRT) Database [10] developed by the Japanese Society of Radiological Technology, which is available publicly. The absence and presence of nodules in the chest radiographs were confirmed by use of CT examinations. In this study, the lungs were first segmented from chest radiography and the background was removed by using a threshold technique.

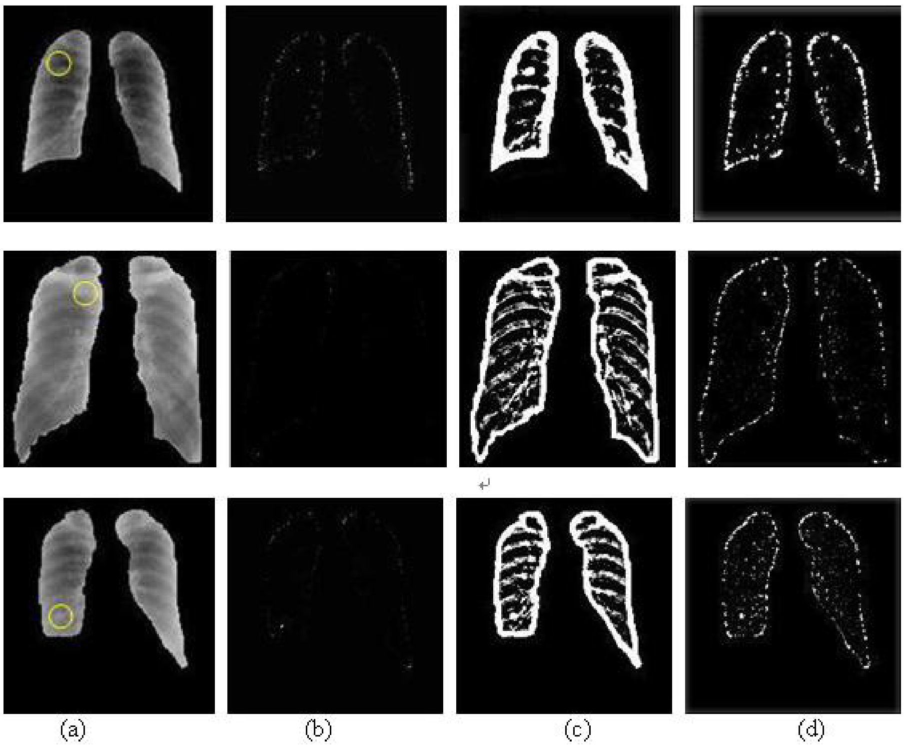

FIGURE 4. Comparison of nodule enhancement a) Original images; b) Li's filter, c) Shi's filter, d) Filter proposed in this study.

Figure 4(a) shows the segmented lung image with one true positive nodule indicated by a circle. Figure 4 (b), (c), and (d) show the enhanced nodules in lung area by applying Li's filter, Shi's filter, and filter described in this paper on the segmented lung image, respectively. Five smoothing scales of 4, 6, 8, 10, and 12 pixels were utilized in all three filters. As can be observed, Li's filter (as shown in Figure 4 (b)) gives good results with large dots but fails to enhance small ones while Shi's (as shown in Figure 4 (c)) is able to enhance small dots but unfortunately enhances other non-dot-like structures (i.e. ribs, vessels) also. Conversely, the proposed filter (As shown in Figure 4 (d)) can enhance small dots while suppress most other normal anatomical structures such as ribs, vessels, and this closely match the discernible by our eyes.

4. **Conclusions.** In this paper, a novel dot enhancement filter, Hessian-LoG filter, is proposed in this paper. Compared with the existing enhancement filters in computer-aided diagnostic schemes, our filter not only enhance specific objects, i.e., nodules, but also successfully suppress normal anatomic structures such as rib and vessels. This make the objects, i.e. dots, more easily be detected by human visual perception.

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