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An Adaptive Enhancement Algorithm for CT Brain Images

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Abstract – **We present an adaptive smoothing filter aiming to improve the visibility and detectability of the obscuration of the lentiform nucleus, which is one of the early signs of acute cerebral artery infraction, in CT brain images. The proposed method is able to enhance image data by removing noise without significantly blurring the structures in the images. This method is tested both on computer-simulated image data and on clinical CT brain images. Moreover, a comparison of the proposed method to two commonly used techniques is made. Preliminary results demonstrate the superiority of the proposed method and its usefulness for detecting the obscuration of the lentiform nucleus, which could not be detected previously without using the proposed method.**

I. Introduction

Noise and resolution are two major factors to influence medical image quality. Images with low noise and high resolution are desirable in medical diagnosis of diseases. In order to acquire the desired image quality, many image enhancement algorithms have been developed and published in the literature. Currently, computed tomography (CT) is widely accepted as the imaging modality for acute cerebral artery infraction (ACAI) investigation. The obscuration of the lentiform nucleus is one of early signs of ACAI in CT images [1-3]. However, the detection of obscure lenticular nuclei is considerably difficult. To overcome this problem, image processing for enhancement is required. However, conventional enhancement algorithms reduce image noise at the expense of blurring of lines and edges of the image. To cope with this issue, some techniques such as adaptive Wiener filters [4,5] and anisotropic adaptive filtering [6,7] have been proposed. Nevertheless, most of these adaptive filters are useful for specific applications. Moreover, these techniques are extreme time consuming resulting in precluding their use in real-time application.

In the present study we propose an adaptive smoothing filter aiming to improve the visibility and detectability of the lentiform nucleus. The proposed technique can enhance image data by removing noise without significantly blurring the structures in the image. The advantage of this approach is its simplicity of processing, which in turn reduces computation time. In this method we also use two reference values, *i.e.*, standard deviation and slope ratio of the image of interest, to respectively describe the extent of noise reduction and edge blurring of the images enhanced by the proposed technique. By measuring the standard deviation and slope ratio, the optimal conditions used for our proposed image-enhancement algorithm can be determined. To validate the clinical effectiveness of the proposed method, CT images with the ACAI were used for evaluation.

II. Methods and Materials

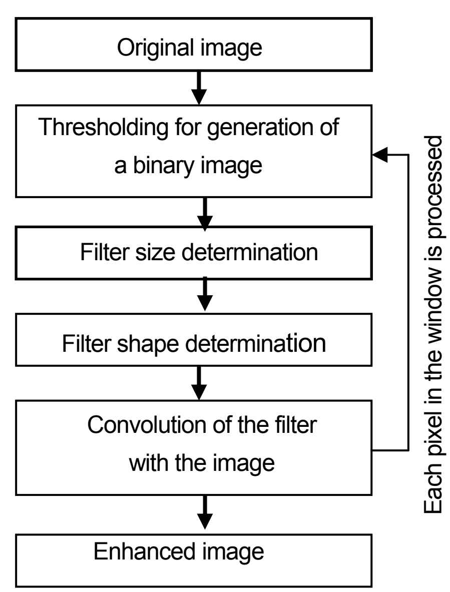


Fig. 1. Flow chart of the main steps of the proposed image-processing technique.

We devised an adaptive smoothing filter (ASF), which is a specially designed filter used to perform local smoothing using a variable filter size and shape. The approach to thresholding employed in the ASF partly refers to a report related to adaptive neighborhood contrast enhancement [8]. Fig. 1 shows the flow chart of the technique's main steps and they are as follows.

(1) After applying a 5×5 averaging filter to the original image, each pixel (i,j) of the image I is assigned an upper window W_{max} centered on it whose size is smaller than the original image, where W_{max} is an odd number.

(2) Let T be a given threshold. Pixel (k,l) within W_{max} is assigned a binary mask value 0 if $|I(k,l) – I(i,j)|>T$, else it is assigned a binary mask value1. This results in constructing a binary image. Fig. 2 shows an example in the case of T=5 and W_{max}=9.

(3) For each window size C×C [C=3,5,…., W_{max}], the percentage P_0 of zeros is computed over the region of external area of C×C window. Let C_0 be the upper C value beyond which the percentage P_0 is greater than 60%. Then the pixel (i,j) is assigned the window with a size of W= $C_0 \times C_0$. The value of 60% was chosen because beyond this limit, we may consider too many 0 pixels are surrounding the inner area and so the notion of neighborhood with the central pixel pixel (i,j) in terms of gray levels is no longer satisfactory [8].

(4) Finally, the processed image I' is obtained from I' (i, j) = M (i, j), where M (i, j) is the mean value in image I of pixels labeled as the binary mask value 1 in the window $C_0 \times C_0$ around pixel (i,j).

31	36	41	43	45	45	45	36	46
32	35	35	35	36	36	34	35	45
31	36	36	33	34	33	35	50	45
29	35	35	36	33	34	50	50	50
25	34	34	35	**35**	34	50	51	51
32	35	33	32	34	33	51	35	50
39	25	34	35	34	45	46	45	45
25	24	25	32	20	20	21	20	43
24	25	31	32	32	20	45	43	41

(a)

1	1	0	0	0	0	0	1	0
1	1	1	1	1	1	1	1	0
1	1	1	1	1	1	1	0	0
0	1	1	1	1	1	0	0	0
0	1	1	1	1	1	0	0	0
1	1	1	1	1	1	0	1	0
1	0	1	1	1	0	0	0	0
0	0	0	1	0	0	0	0	0
0	0	1	1	1	0	0	0	0

(b)

Fig. 2. Adaptive neighborhood selection with a threshold value T=5. Pixel (k,l) within W_{max} is assigned a binary mask value 0 if $|I(k,l) – I(i,j)|>T$, else it is assigned a binary mask value 1. (a) W_{max} window around bold-faced pixel value 35; (b) mask values associated to test pattern in (a).

However, it is noted that the quality of the processed image depends on the threshold value T. Determination of optimal threshold value is, therefore, required to make the ASF having best performed. To this end, the standard deviation and slope ratio of the image are used as two criteria for measuring the performance of the ASF. To conduct the measurement of the performance, a series of composite images were generated by adding a computed-simulated lentiform-nucleus like object (LN) to each uniform phantom image obtained from a 4-slice CT scanner.

In this study, the standard deviation of the pixel values in a specified area, which is used to quantify the degree of noise reduction, was obtained from a region of interest in the composite images. Low standard-deviation value means that high reduction of noise can be obtained by the ASF.

To investigate the extent of edge blurring, slope ratio was calculated from a profile of pixel values, which was measured at the right angle with respect to the edge of LN. In this work, the slope ratio (SR) is defined as the ratio of the profile slope of the processed image to that of the original image, and can be given as

$$SR(\%) = (\Delta P_{pr} / \Delta x)/(\Delta P_{org} / \Delta x) \times 100 \quad , \qquad (1)$$

where $(\Delta P_{pr} / \Delta x)$ and $(\Delta P_{org} / \Delta x)$ are the profile slope of the processed image and that of the original image, respectively (Fig.3). Low slope-ratio value means that high edge blurring occurs resulting from the ASF.

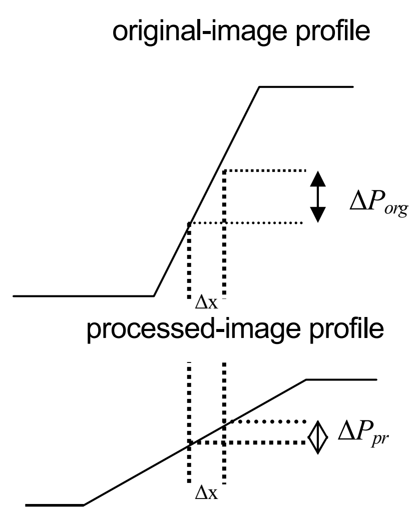


Fig. 3. Slope ratio is defined as the ratio of the profile slope of the processed image $(\Delta P_{pr} / \Delta x)$ to that of the original image $(\Delta P_{org} / \Delta x)$.

III. Results And Discussion

The effect of threshold-value determination on the standard deviation of the composite images was calculated and the results are shown in Fig. 4. It is noted that the standard-deviation value decreases with the increase of threshold value and maintains constant when the threshold value is higher than 3.0. Therefore, noise reduction can be effectively achieved if the threshold value is set at T=3.0. In this case, the standard-deviation value of the original image is 2.5 and that of the processed image is 0.6. As a result, a 76% of the noise reduction can be obtained against the original image.

The variation of the slope ratio with the threshold value used in the ASF for LN-contained composite image was also investigated and the results are shown in Fig. 5. The slope ratio is at approximately 60% for the threshold values ranging from 0 to 3.0 and gradually declines when the threshold value is greater than 3.0. Recall that low slope-ratio value shows high edge blurring. Therefore, the edge blurring of the LN-contained composite image can be suppressed if the threshold value is set at 3.0 or less. From the two experimental results, it is reasonable to conclude that T=3.0 is the optimal value used in the ASF for image improvement in noise reduction.

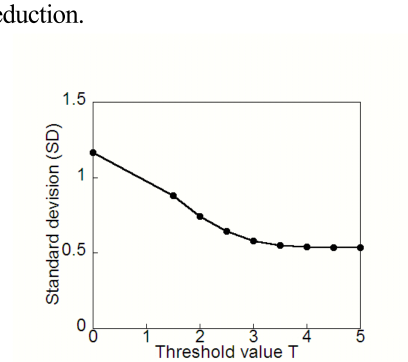


Fig. 4. A plot of the standard deviations computed by varying the threshold value T.

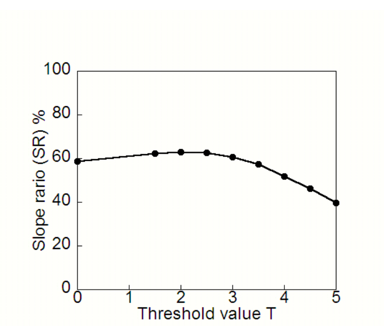
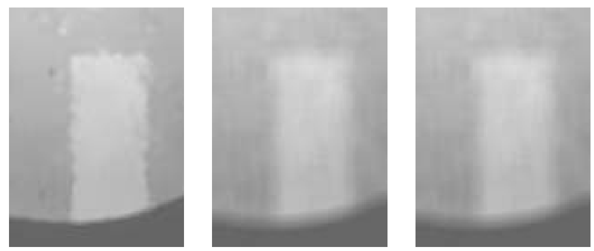


Fig. 5. A plot of the slope ratios computed by varying the threshold value T.

TABLE I

Slope Ratios Evaluated On The Composite Images After Applying The ASF, Averaging Filter, And Median Filter.

Filter	Standard Deviation	Slope Ratio (%)
ASF	0.59	59.9
Averaging	0.60	21.3
Median	0.61	31.2



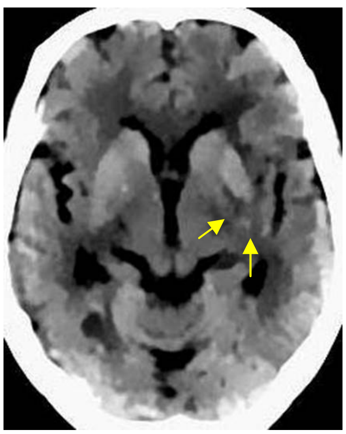
(a) (b) (c)

Fig. 6. Results obtained from the composite image after applying (a) the ASF, (b) the averaging filter, and (c) the median filter.

In order to demonstrate the superiority of the ASF, we also applied two commonly used smoothing filters, *i.e.*, the averaging filter and the median filter, to the composite images for comparison. The SD and SR were used for performance assessment. We tried to keep the value of SDs at nearly the same and then to compare the values of SR which is considered as an index for expressing the edge blurring of the images caused by image processing. The results are summarized in Table I. The results indicate that the performance of the proposed method is superior to the other two filters. Fig. 6 shows the results obtained by applying the three processing methods to the same composite image. It is visually evident that the ASF enhance image data by removing noise without significantly blurring the structures in the image as compared to the averaging and median filters do.

The ASF with the pre-determined optimal condition of thresholding T=3.0 was applied to three un-enhanced CT images obtained at 2 hours after stroke onset demonstrating obscured outline of the left lentiform nucleus. Fig. 7 illustrates an experimental result. Our experimental results showed that the visibility and detectability of the lentiform nucleus were much improved by the proposed method.

original image



enhanced image

Fig. 7. The ASF was applied to an un-enhanced CT image obtained at 2 hours after stroke onset demonstrating obscured outline of the left lentiform nucleus *(arrows)*. The proposed method improved the visibility of the right normal lentiform nucleus and the detectability of the obscuration of the left lentiform nucleus.

IV. CONCLUSIONS

In this study we have proposed an adaptive smoothing filter aiming at improving the visibility and detectability of the obscuration of the lentiform nucleus. Moreover, in order to obtain the optimal thresholding value used in this filter, we have measured the standard deviation and slope ratio of the image of interest, which are respectively used to describe the degree of noise reduction and edge blurring of the images enhanced by the proposed method. Our preliminary results have demonstrated that the visibility and detectability of the obscuration of lentiform nucleus are much improved by our proposed method. The results also showed that the proposed ASF performed well and clinically useful. In particular our proposed method could be a strong strategy for determining eligibility for thrombolytic therapy in ischemic stoke.

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