

Nonlinear Filtering for Enhancing Prostate MR Images via Alpha-Trimmed Mean Separation

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Abstract—This paper introduces a new enhancement algorithm for prostate MR images using a new nonlinear filtering operation and an alpha-trimmed Mean Separation. A new enhancement measure is also introduced to measure and assess the enhanced results. Experimental results show that the presented algorithm can significantly improve the contrast of prostate MR images. It has a potential application in prostate cancer detection.

Keywords— MR image enhancement, nonlinear filtering, alpha-trimmed mean, prostate cancer detection

I. INTRODUCTION

Prostate cancer is the single most common cancer in men in the United States. The latest American Cancer Society estimates that about 192,280 new cases of prostate cancer will be diagnosed and 27,360 men will die of prostate cancer in the United States in 2009 [1]. Treatment of prostate cancer is most successful in its early stage [2]. Magnetic resonance imaging (MRI) is a common technique and plays an important role for pretreatment evaluation of prostate cancer [3]. However, there are some limitations of the MRI evaluation for prostate cancer such as the lack of information on tumor grade or vascularity to predict patient diseases [4]. Image enhancement is a useful tool to improve the visual quality of prostate MR images, making easier for radiologists to detect and diagnose prostate cancer. Several algorithms have been developed for MRI image enhancement in computer-aided prostate cancer detection systems. Examples include multi-wavelet grading [5] and dynamic contrast enhancement [6].

Traditionally, the alpha-trimmed mean is used as a nonlinear filtering operation to reduce noise in image processing [7]. In this paper, we introduce a new enhancement algorithm for prostate MR images by combining image decomposition and nonlinear filtering. The new algorithm uses the alpha-trimmed mean as a threshold for image decomposition and a new nonlinear filtering operator for image enhancement. To evaluate the performance of the enhancement algorithm, a new enhancement measure called the second-derivative-like measure of enhancement (SDME) is also proposed.

The rest of this paper is organized as followed. Section II introduces the new enhancement algorithm for prostate MR images. Section III introduces the new SDME measure for

quantitative evaluation of the image enhancement. Section IV presents several computer simulation results and compares the enhancement performance of the new algorithm with other existing enhancement methods. Section V draws a conclusion.

II. NEW ENHANCEMENT ALGORITHM

In this section, we introduce a new enhancement algorithm for prostate MR images by integrating the nonlinear filtering operation with the image decomposition which uses the alpha-trimmed mean as the threshold.

A. Alpha-Trimmed Mean

The alpha-trimmed mean filter is widely used for image processing. Here, we use the alpha-trimmed mean for image decomposition.

For an image with size of $M \times N$, let $K = M \times N$ and a single index x_1, x_2, \dots, x_K indicate the sorted values of all pixels of the image such that $x_1 \leq x_2 \leq \dots \leq x_K$. Let $T_\alpha = \lceil \alpha K \rceil$ (the nearest integer greater than or equal to αK) is the number of the smallest and largest pixel values to be trimmed or discarded from the sorted sequence, x_1, x_2, \dots, x_K . The alpha-trimmed mean of the image is defined by,

$$X_\alpha = \frac{1}{K - 2T_\alpha} \sum_{i=T_\alpha+1}^{K-T_\alpha} x_i \quad (1)$$

where $0 \leq \alpha < 0.5$ is the percentage of the trimmed samples.

The alpha-trimmed mean will be different when the parameter α changes. For example, it will be the mean value of the image for $\alpha = 0$ and the median value of the image if α is close to 0.5. Taking this advantage, we use the alpha-trimmed mean as the threshold for image decomposition.

B. New Enhancement Algorithm

To improve the visual quality of the prostate MR images, we integrate nonlinear filtering with the image decomposition technique described above and introduce a new algorithm for enhancing prostate MR images for prostate cancer detection. The algorithm is shown in Fig. 1.

The algorithm first separates the original MR image $I(m, n)$ into two sub-images. The threshold value of the image

decomposition is the alpha-trimmed mean of the input MR image defined in equation (1).

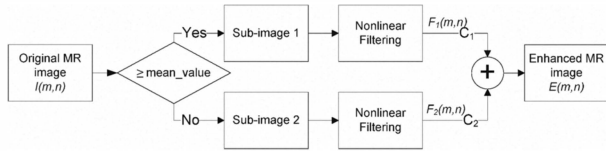


Figure 1. Block diagram of the MSNLF scheme

The two sub images are then filtered by a nonlinear filtering operation individually to obtain the filtered images $F_1(m,n)$ and $F_2(m,n)$. The filtering operation is defined by,

$$F(m,n) = w_0 Y_0 + w_1 Y_1 + w_2 Y_2 \quad (2)$$

where

$$Y_0 = I^{2\alpha_0}(m,n)$$

$$Y_1 = I^{2\alpha_1}(m-1,n) + I^{2\alpha_1}(m+1,n) + I^{2\alpha_1}(m,n-1) + I^{2\alpha_1}(m,n+1)$$

$$Y_2 = I^{2\alpha_2}(m-1,n-1) + I^{2\alpha_2}(m+1,n-1) + I^{2\alpha_2}(m+1,n+1) + I^{2\alpha_2}(m-1,n+1)$$

and constants w_i , α_i are weight coefficients, $i = 0,1,2$.

Finally, the output enhanced image is defined by,

$$E(m,n) = C_1 F_1(m,n) + C_2 F_2(m,n) \quad (3)$$

where constants C_1, C_2 are the scaling factors.

Since the alpha-trimmed mean value is dependent on alpha, the decomposed sub-images contain different background intensities when the alpha value changes. The nonlinear filter then enhances sub-images with different intensity values. Therefore, the presented algorithm enhances images while preserving the background intensity at different levels.

The nonlinear filter is embedded in two filters specified by w_0, w_1, w_2 and $\alpha_0, \alpha_1, \alpha_2$ separately. These two filters can be designed as two different types of linear or nonlinear filters. For example, the coefficients w_0, w_1, w_2 can be designed as a highpass filter and $\alpha_0, \alpha_1, \alpha_2$ can be chosen as a weighted mean filter. The nonlinear filtering process can suppress noise and keep sharp details unchanged while enhancing the contrast of fine details in prostate MR images. All these make the presented new algorithm more robust for different applications.

III. NEW ENHANCEMENT MEASURE

Since image enhancement is intended to improve image contrast, the enhancement measure is usually based on a contrast measure. To quantitatively assess the enhancement performance of the presented algorithm, we introduce a new enhancement measure using an image contrast measure based on the concept of the second derivative. It is called the second-derivative-like measure of enhancement (SDME) which is defined by,

$$SDME = -\frac{1}{k_1 k_2} \sum_{l=1}^{k_1} \sum_{k=1}^{k_2} 20 \ln \left| \frac{I_{\max;k,l} - 2I_{\text{center};k,l} + I_{\min;k,l}}{I_{\max;k,l} + 2I_{\text{center};k,l} + I_{\min;k,l}} \right| \quad (4)$$

where an image is divided into $k_1 \times k_2$ blocks. $I_{\max;k,l}, I_{\min;k,l}$ are the maximum and minimum values of the pixels in each block separately, and $I_{\text{center};k,l}$ is the center pixel value in each block.

Thus, the size of blocks should be odd number such as 3×3 . Each block contains an odd number of pixels.

IV. ENHANCEMENT RESULTS AND ANALYSIS

The original prostate MR images are obtained from Department of Radiology at Memorial Sloan-Kettering Cancer Center in New York, NY. These images are cropped into images with smaller sizes in order to minimize the dark background and also remove the text records of patient's information. Our algorithm is then used to enhance these images.

The presented algorithm has been successfully applied to more than 30 different MR images with prostate cancer. In this section, we provide several enhanced results to show its performance. We also compare the presented algorithm with some existing enhancement methods.

A. Parameter Selection

To find the best parameters of the coefficients in the nonlinear filtering operator for achieving the better enhanced results, we set: $\alpha_1 = \alpha_2 = h$, $w_1 = w_2 = -w$, $\alpha_0 = 4h$, $w_0 = 4w$, $C_1 = C_2 = 1$ and $0 < h, w \leq 1$. The prostate MR image in Fig. 3(a) is enhanced by the presented algorithm when these coefficients changes as different h, w values within $(0,1]$. The enhanced images are then measured by the SDME respectively. The measure results are plotted in Fig. 2. The parameter to achieve the best enhanced image is located at the local extremum in the SDME curve.

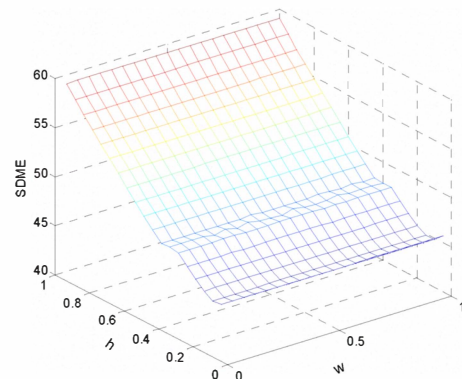


Figure 2. SDME results of the enhanced MR images for parameter optimization.

B. Enhancement Analysis

Fig. 3 shows the enhanced images by using this parameter. The contrast of the original MR image and the visual quality of the fine details are significantly improved.

More enhanced examples are shown in Fig. 4 and Fig. 5. The first row shows the original prostate MR images. The second and third rows show the enhanced MR images by the presented algorithm respectively. The SDME is used to measure all the enhanced images. The measure results are plotted in Fig. 6. The larger SDME values indicate better enhancement performance. These SDME results quantitatively demonstrate that the presented algorithm shows excellent enhancement performance in prostate MR images.

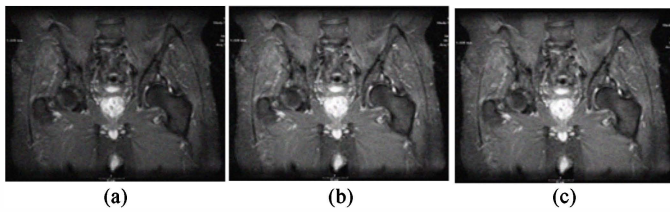


Figure 3. Prostate MR image Enhancement. (a) The original prostate MR image; (b) The image enhanced by the presented algorithm, $\alpha=0$; (c) The image enhanced by the presented algorithm, $\alpha=0.5$.

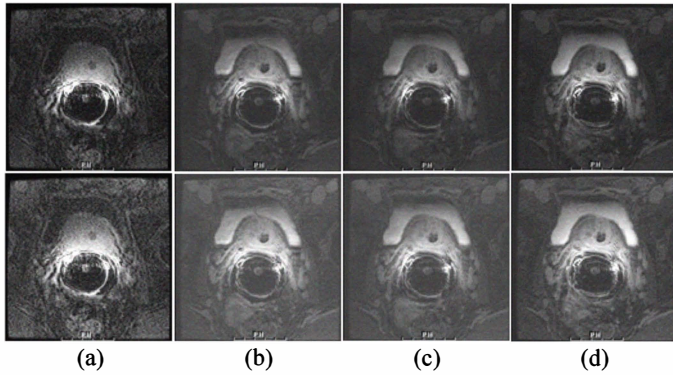


Figure 4. Prostate MR images enhanced by the presented algorithm. (a)-(d) The top row shows the original prostate MR images; the bottom row shows the enhanced prostate MR images, $\alpha=0$.

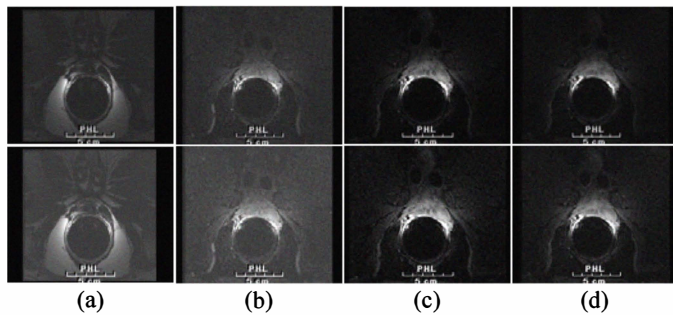


Figure 5. Prostate MR images enhanced by the presented algorithm. (a)-(d) The top row shows the original prostate MR images; the bottom row shows the enhanced prostate MR images, $\alpha=0.49$.

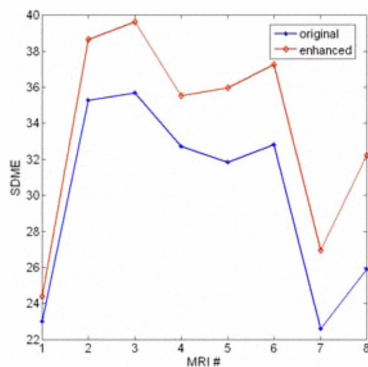


Figure 6. SDME plot of the prostate MR image enhancement in Fig. 4-5.

Fig. 7 shows some examples for region enhancement. The regions shown in the top row in Fig. 7 are cropped from the original prostate MR images. They are enhanced by the

presented algorithm individually. The enhanced results are shown in the bottom row in Fig. 7. The region contrast is greatly improved. This shows that the presented algorithm has potential applications for enhancing the fine details or specific regions in images.

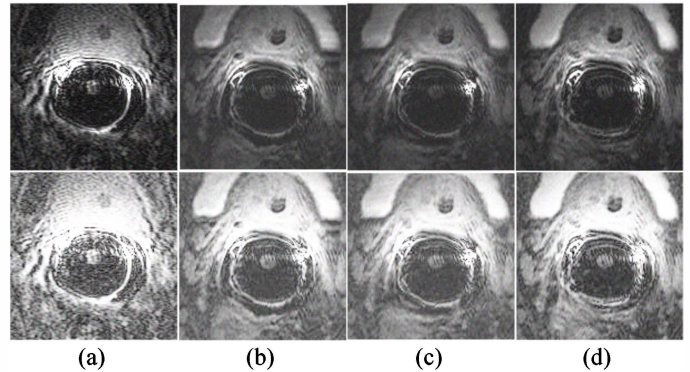


Figure 7. Regions enhanced by the presented algorithm. Top row: The regions cropped from the original prostate MR images; Bottom row: The corresponding enhanced regions.

C. Performance Comparison

The presented algorithm is compared with the rational unsharp masking method [8] for several prostate MR images. The presented algorithm shows better enhancement performance. One example is shown in Fig. 8. The algorithm not only enhances the contrast of prostate cancer regions but also improve the visual quality of the images.

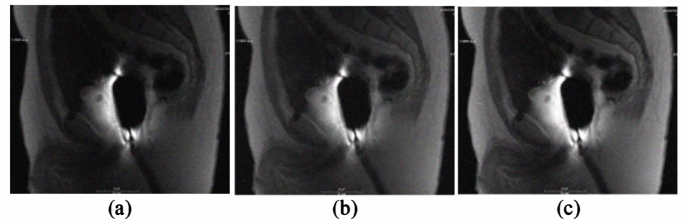


Figure 8. Comparison of prostate MR image enhancement. (a) The original prostate MR image; (b) The image enhanced by the presented algorithm; (c) The image enhanced by the rational unsharp masking.

D. Visualization

Fig. 9 shows an example of the negative representation of the prostate MR images. This provides an alternative method for radiologists to diagnose and determine the prostate cancer.

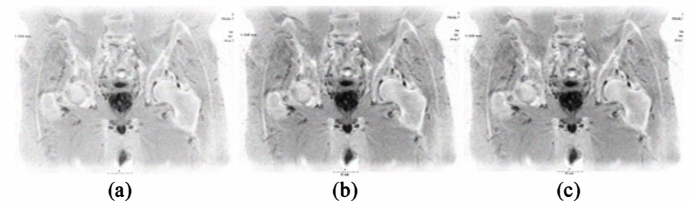


Figure 9. Negative representation of prostate MR image Enhancement. (a) The negative photo of the original prostate MR image; (b) The negative photo of the image enhanced by the presented algorithm, $\alpha=0$; (c) The negative photo of the image enhanced by the presented algorithm, $\alpha=0.49$.

The human visual system (HVS) based image decomposition has been employed for edge detection [9] and image enhancement [10]. Since the HVS-based image

decomposition separates images based on the background intensity and the rate of information change, we extend its application for image visualization. Fig. 10 shows the HVS-based decomposition results of a prostate MR image. The observation shows that some specific regions in the prostate MR image are contained within a decomposed sub-image. This feature is useful for prostate cancer detection because we can use the HVS-based image decomposition to automatically separate the cancer regions from the prostate MR images.

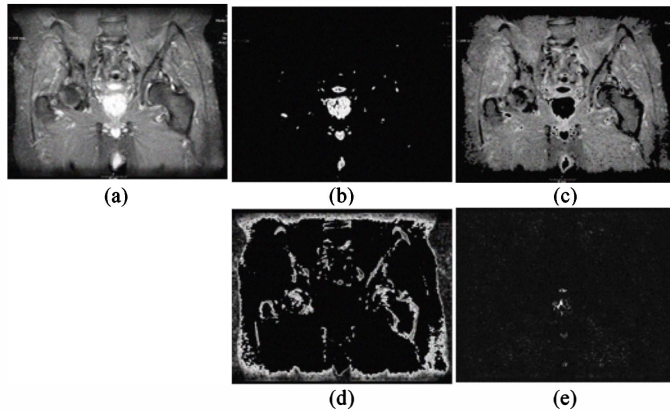


Figure 10. HVS-based decomposition of the enhanced prostate MR image. (a) The prostate MR image enhanced by the presented algorithm, $\alpha=0$; (b) The first sub-image; (c) The second sub-image; (d) The third sub-image; (e) The fourth sub-image.

V. CONCLUSION

We have introduced a new enhancement algorithm to improve the visual quality of prostate MR images in this paper. A new contrast measure has also been introduced to measure and evaluate the enhancement performance of the presented new algorithm.

The new algorithm uses the alpha-trimmed mean as a threshold to decompose images into sub-images. Different decomposition results can be obtained by changing the value of alpha. The new nonlinear filter can be designed as a combination of two different types of linear or nonlinear filters. This offers the user design flexibility for meeting more complex and specific requirements in practical applications.

Simulation results and comparisons have demonstrated that the presented algorithm can significantly improve visual quality of images and show better enhancement performance in prostate MR images. The presented algorithm has the potential application for prostate cancer detection.

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REFERENCES

- [1] "What Are the Key Statistics About Prostate Cancer?," http://www.cancer.org/docroot/CRI/content/CRI_2_4_1X_What_are_the_key_statistics_for_prostate_cancer_36.asp.
- [2] A. Madabhushi, et al., "Automated detection of prostatic adenocarcinoma from high-resolution ex vivo MRI," *Medical Imaging, IEEE Transactions on*, vol. 24, pp. 1611-1625, 2005.
- [3] L. Wang, et al., "Prediction of Seminal Vesicle Invasion in Prostate Cancer: Incremental Value of Adding Endorectal MR Imaging to the Kattan Nomogram," *Radiology*, vol. 242, pp. 182-188, 2007.
- [4] A. R. Padhani, et al., "Dynamic Contrast Enhanced MRI of Prostate Cancer: Correlation with Morphology and Tumour Stage, Histological Grade and PSA," *Clinical Radiology*, vol. 55, pp. 99-109, 2000.
- [5] K. Jafari-Khouzani and H. Soltanian-Zadeh, "Multiwavelet grading of pathological images of prostate," *Biomedical Engineering, IEEE Transactions on*, vol. 50, pp. 697-704, 2003.
- [6] L. Lemaitre, et al., "Dynamic contrast-enhanced MRI of anterior prostate cancer: morphometric assessment and correlation with radical prostatectomy findings," *European Radiology*, vol. 19, pp. 470-480, Feb 2009.
- [7] R. Oten and R. J. P. de Figueiredo, "Adaptive alpha-trimmed mean filters under deviations from assumed noise model," *Image Processing, IEEE Transactions on*, vol. 13, pp. 627-639, 2004.
- [8] G. Ramponi and A. Polesel, "Rational unsharp masking technique," *Journal of Electronic Imaging*, vol. 7, pp. 333-338, 1998.
- [9] E. Wharton, S. Agaian, and K. Panetta, "A logarithmic measure of image enhancement," in *Mobile Multimedia/Image Processing for Military and Security Applications*, Orlando, FL, USA, 2006, pp. 62500P-12.
- [10] K. A. Panetta, E. J. Wharton, and S. S. Agaian, "Human Visual System-Based Image Enhancement and Logarithmic Contrast Measure," *Systems, Man, and Cybernetics, Part B, IEEE Transactions on*, vol. 38, pp. 174-188, 2008.