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Medical Imaging and Computer-Aided Diagnosis

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Unsharp Masking with Local Adaptive Contrast Enhancement of Medical Images

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Outline

- Introduction
- Algorithms Description
- Experimental Results
- Conclusion

Introduction

- Role of the contrast in medical imaging - [1, 2, 3]
- Recent studies
  - Prediction of contrast enhancement [4] – Deep Learning, class activation, combining of gradient-weight, saliency and backpropagation maps to new map for prediction; accuracy – over 90%, higher specificity for the saliency map, clearer voxel visualization (CT-images)
  - Discrete wavelet approach, by Kallel and Hamida [5] – DWT + SVD for adaptive gamma correction, SVD from LL with factoring and classification to low and average contrast, further gamma correction (CT-images)
  - Clustering-based algorithm [6] – 1D column-wise separation, sorting and clustering and labeling, faster execution (CT-images)

Introduction (2)

- Multiscale contrast enhancement, Irrera et al. [7] – patch-based filtering, parameter-based noise estimation, limited contrast enhancement up to corrupting free image contrast increase (X-ray images)
- Morphological operators for contrast enhancement, Kushol et al. [8] – top-hat & bottom-hat operations, adaptive parameter estimation of structuring element from intensity gradients, better than CLAHE (X-ray images)
- CLAHE + high-pass filter [9] - few tunable parameters, >48% test images higher subjective quality given by medical personnel (X-ray images)

Introduction (3)

- Aim of the study – evaluation of the performance of histogram equalization, image adjustment and CLAHE over CT and X-ray images for unsharp masking
- Evaluation aspects:
  - Root-mean square contrast
  - Sharpness
  - Overall distortion – PSNR and SSIM
  - Visual inspection

Algorithms description (1)

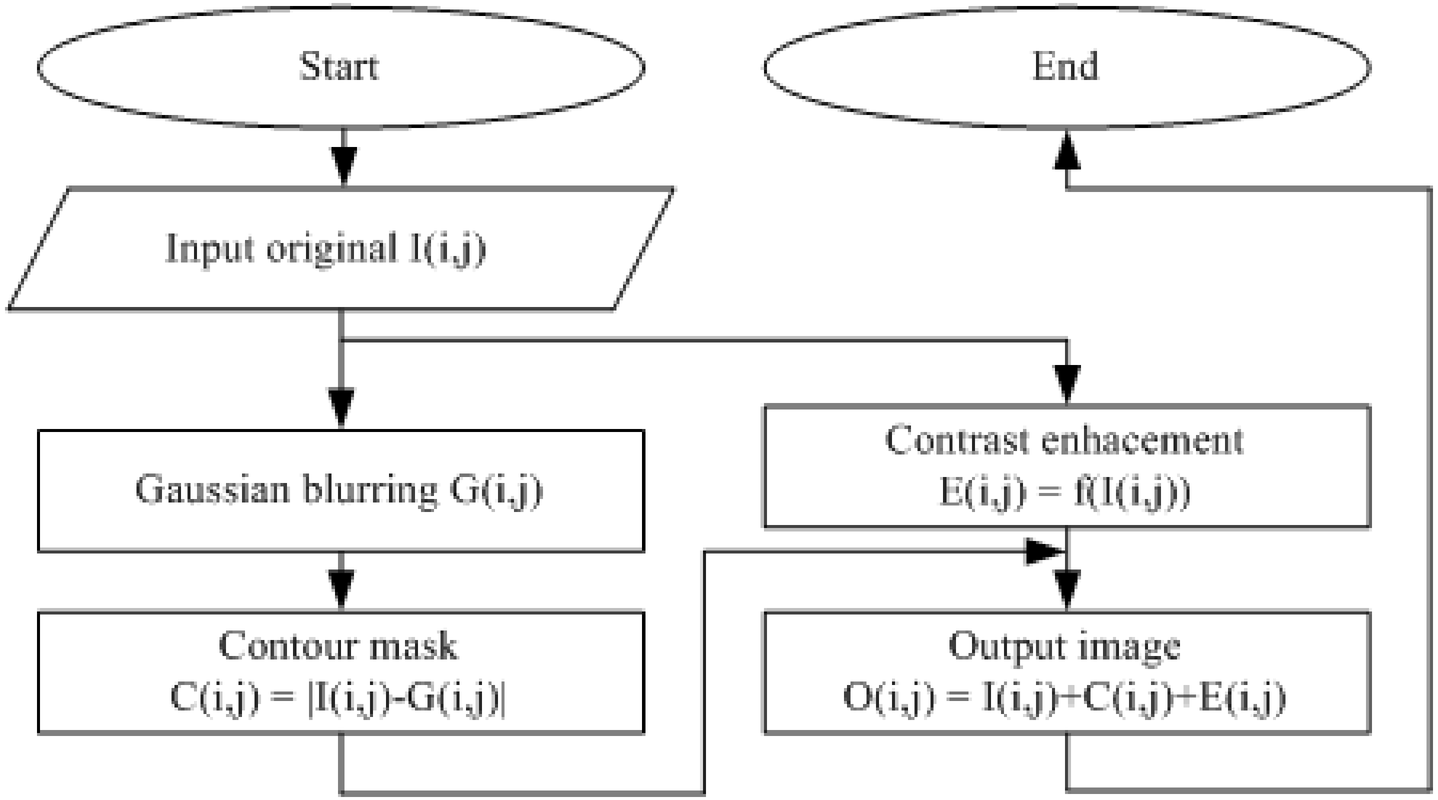

Fig.1. General unsharp masking scheme

Algorithm description (2)

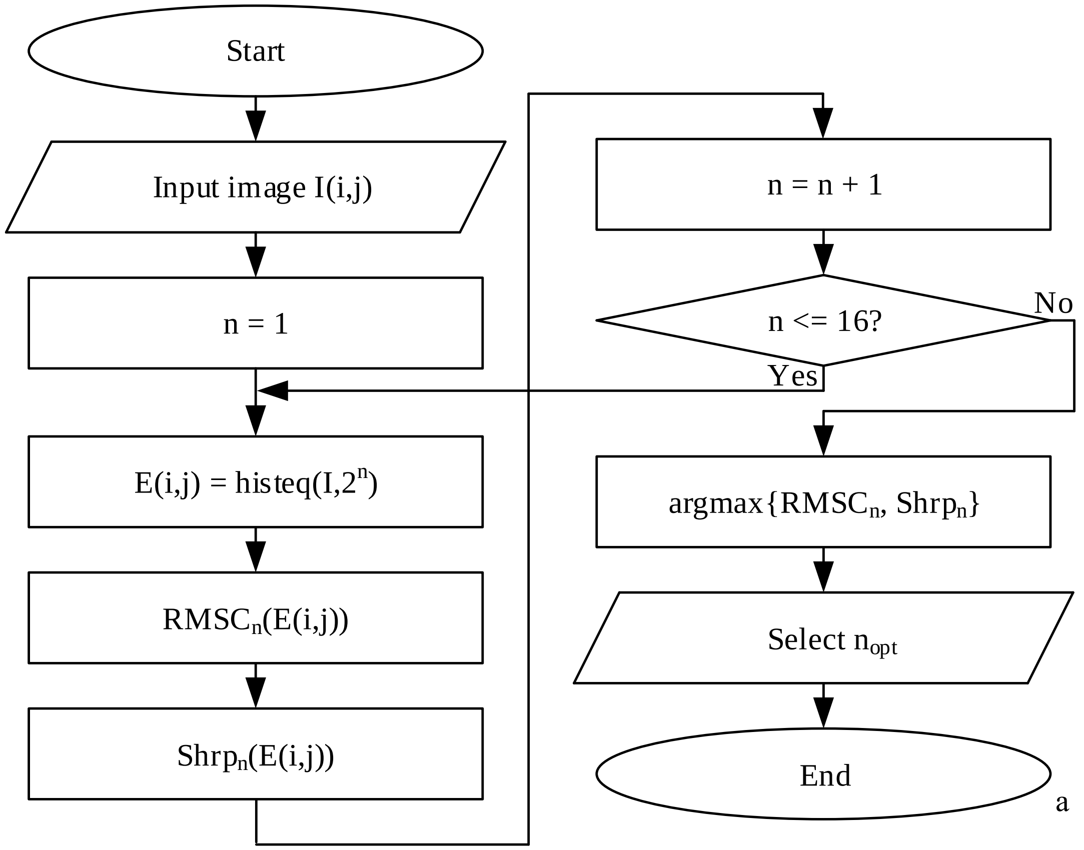

Fig. 2.a. Finding optimal parameters for histogram equalization (a)

Algorithm description (3)

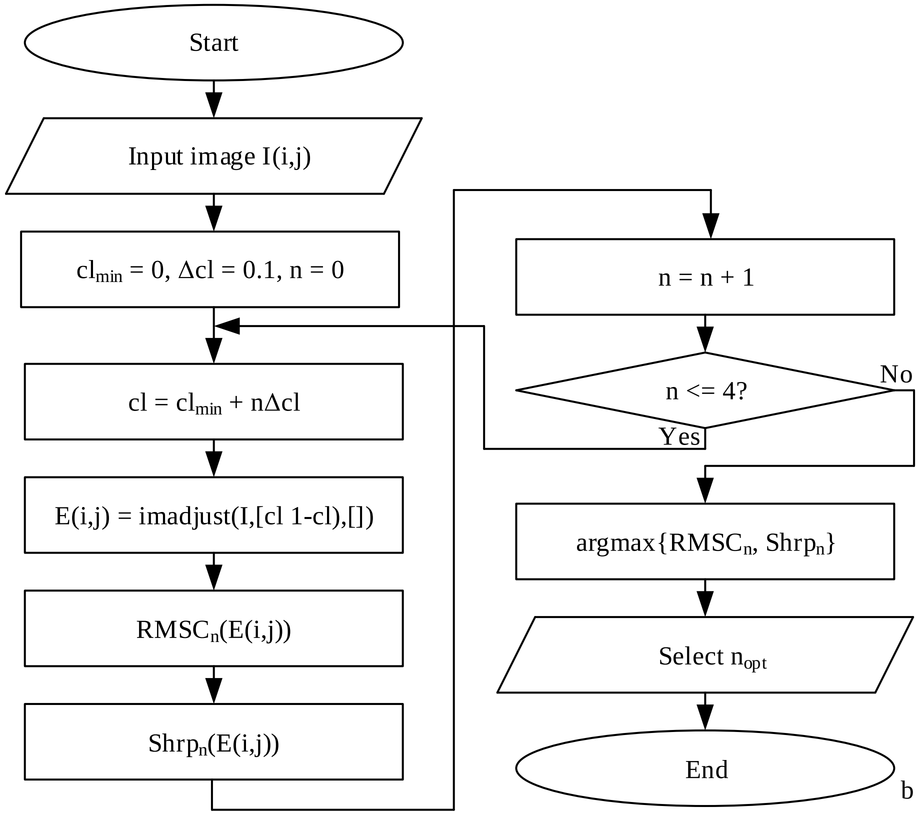

Fig. 2.b. Finding optimal parameters for image adjustment (b)

Algorithm description (4)

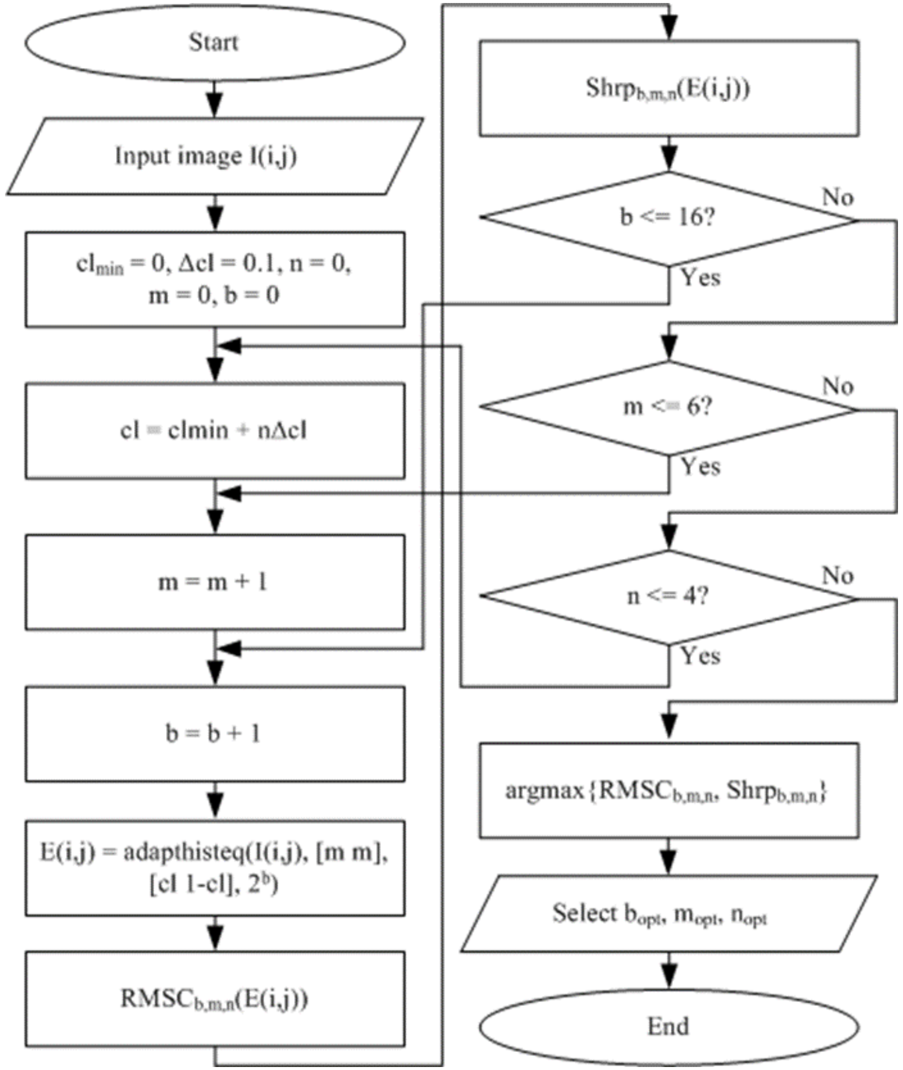

Fig. 3. Finding optimal parameters for contrast-limited adaptive histogram equalization

Algorithm description (5)

- Evaluating parameters
  - Root Mean Square Contrast RMSC:

$$RMSC = \sqrt{\frac{1}{MN}\sum_{i=0}^{M-1}\sum_{j=0}^{N-1}(O(i,j) - \bar{O})^2} \quad , \quad (1)$$

O – output image, $\bar{O}$ - average intensity of the output image, M and N – number of pixels by columns and rows, respectively, i and j – pixel coordinates by rows and columns, respectively

Sharpness $Shrp_d$:

$$Shrp_d = \frac{1}{P}(T_1 - T_2)\sum_{p=1}^{P} S_p^2 \quad , \quad (2)$$

T_1 and T_2 – maximum and minimum densities of an area of the image over which $Shrp_d$ is calculated, S_p – change of the intensity profile (slope), P – number of points through which S_p is calculated

Additionally, the peak signal-to-noise ratio (PSNR) and structural similarity index (SSIM) are used as limiting parameters to adjust the boundaries of RMSC and $Shrp_d$ when rising unstoppably.

Experimental results (1)

- Test database – 103 CT image from DeepLesion [14], 512x512 pixels, 16 bpp, and 105 X-ray images from ChestX-ray8 [15], 1024x1024 pixels, 8 bpp
- Testing environment – Intel Core i5 x64 4-cores CPU @ 3.1 GHz, 12 GB RAM, Linux Ubuntu LTS 14.04, Matlab R2016A
- Histeq algorithm – finding only the optimal number of bins of the histogram 2^n -> n_{opt} = ?
- Image adjust – finding the optimal clip limit -> cl_{opt} = ?
- CLAHE – finding the optimal number of bins for the histogram, clip limit and tile size -> n_{opt} = ?, cl_{opt} = ?, m = ? (tile 2^mx2^m pixels)
- Optimal standard deviation for the Gaussian filter from the unsharp masking stage – σ_{opt} = ? for CT images, σ_{opt} = ? for X-ray images

Experimental results (2)

$n_{opt} = 6$
for histeq

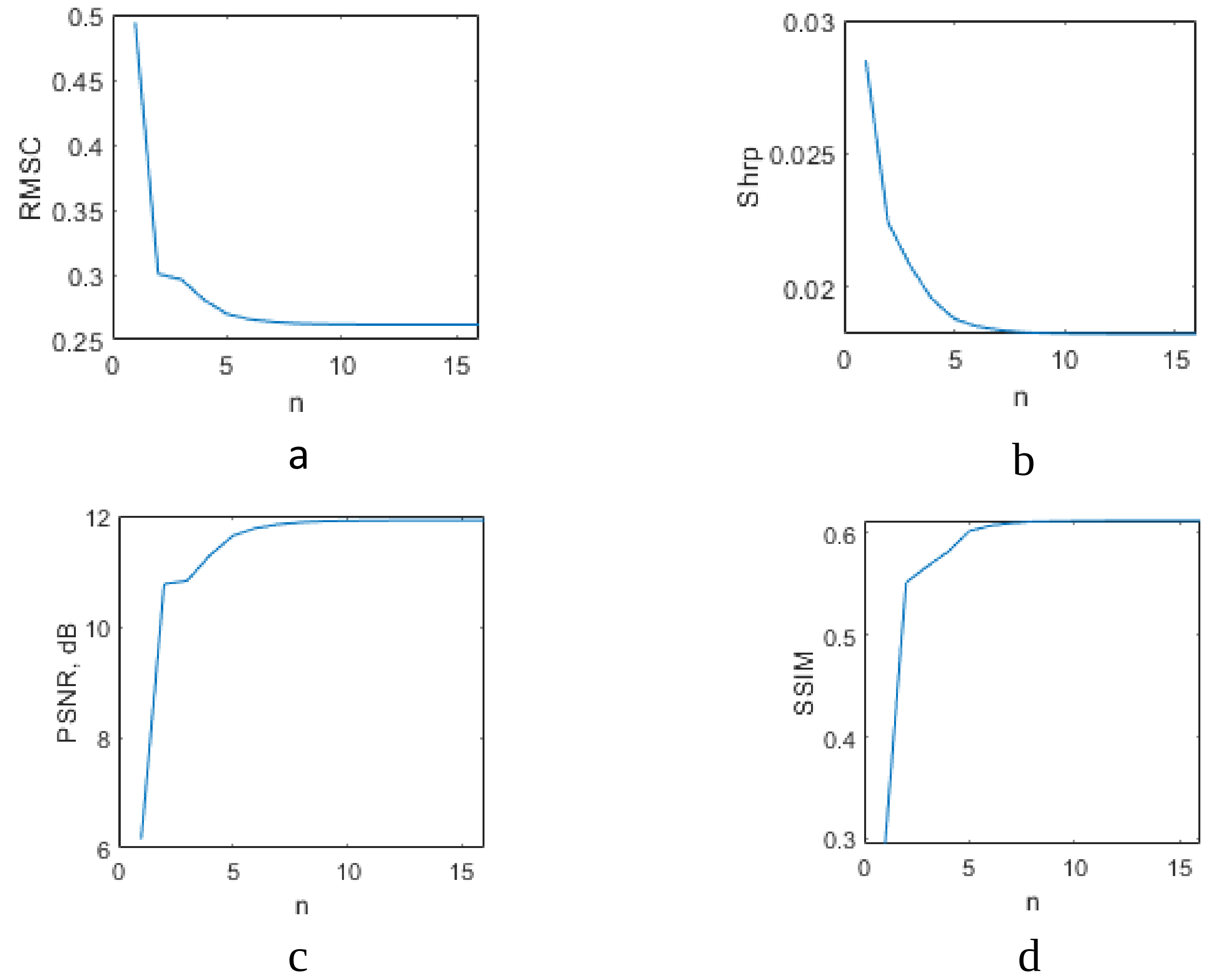

Fig. 4. Finding the optimal number of bins for the histogram processed by histeq

Experimental results (3)

cl_{opt} = 0.01
for imadjust

n = 8
cl_{opt} = 0.01
m = 1
for adapthisteq

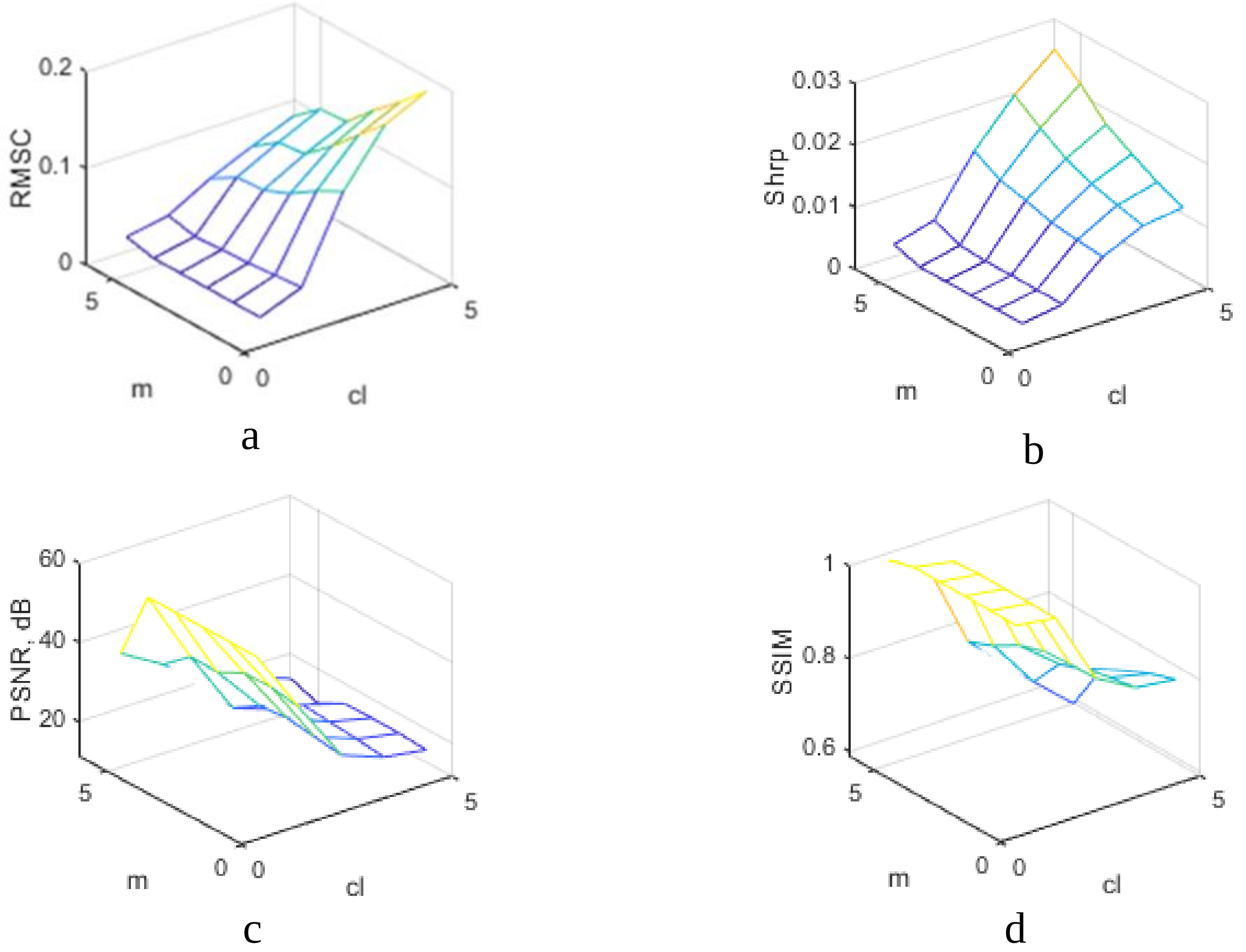

Fig. 5. Finding the optimal clip limit and tile size for the adapthisteq

Experimental results (4)

Table 1. Average performance for histeq, imadjust and adapthisteq alone

	CT images			X-ray images		
Algorithm	RMSC	Shrp	Time, s	RMSC	Shrp	Time, s
Input images	0.0084	0.0005	N/A	0.2320	0.0099	N/A
histeq	0.2656	0.0185	0.0026	0.2926	0.0142	0.0071
imadjust	0.0210	0.0012	0.0012	0.2363	0.0101	0.0029
adapthisteq	0.1850	0.0108	0.0159	0.2832	0.0156	0.0183

Experimental results (5)

Table 2. Unsharp masking average evaluating parameters

	CT images			X-ray images		
Algorithm	RMSC	Shrp	Time, s	RMSC	Shrp	Time, s
Input images	0.0084	0.0005	N/A	0.2320	0.0099	N/A
histeq	0.1220	0.0086	0.0087	0.2232	0.0118	0.0207
imadjust	0.0155	0.0011	0.0076	0.1992	0.0102	0.0196
adapthisteq	0.0851	0.0051	0.0076	0.2162	0.0125	0.0191

Gaussian filter standard deviation - σ_{opt} = 10 for CT images, σ_{opt} = 0.8 for X-ray images

Experimental results (6)

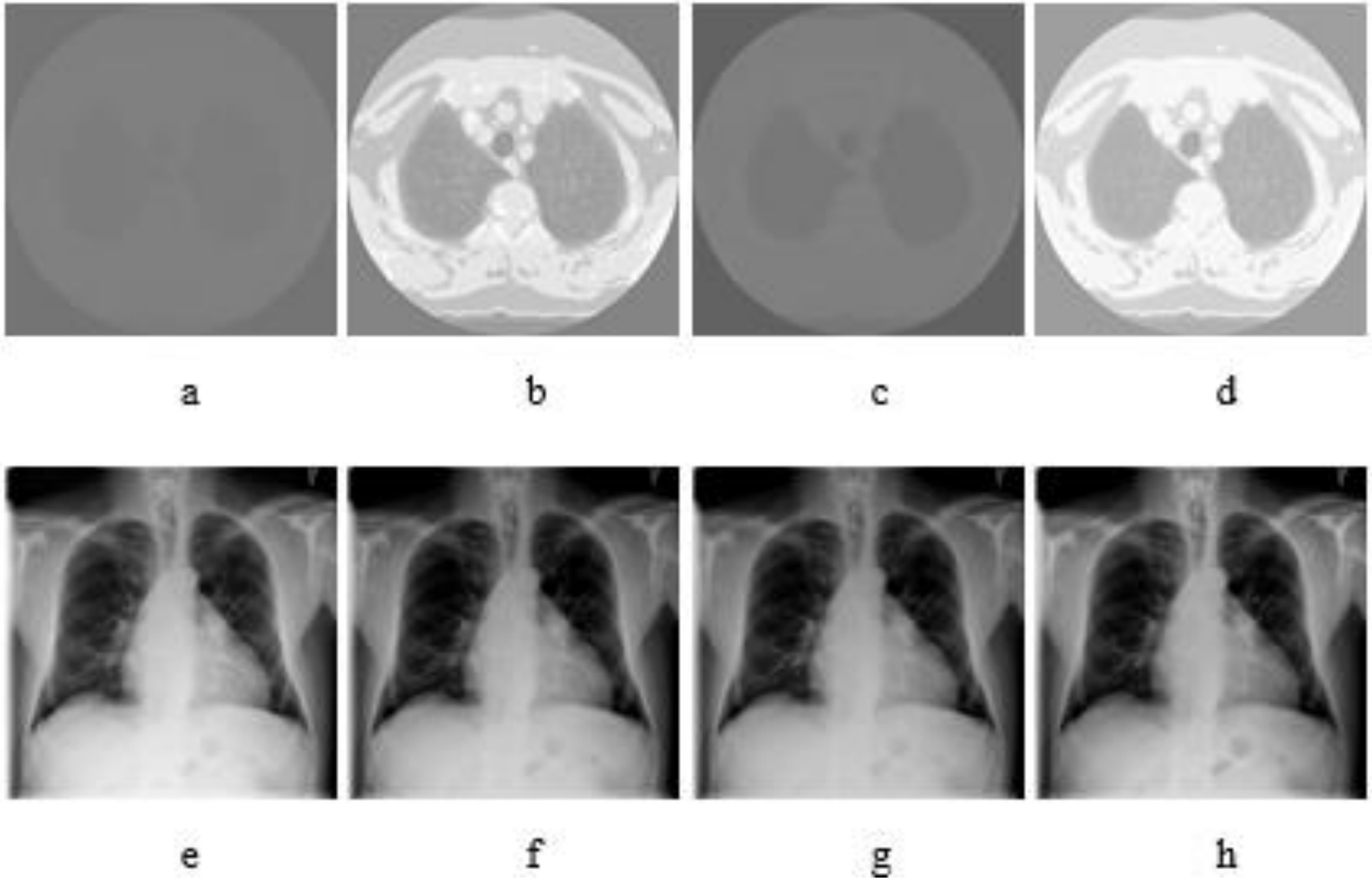

Fig. 6. Original – a (CT), e (X-ray), and processed by histeq – b, f, imadjust – c, g, and adapthisteq – d, h images

Conclusion

- Simple optimization procedure is proposed in this study for the histeq, imadjust and CLAHE algorithms
- CLAHE yields more detailed and contrast enhanced images
- Histogram equalization and image adjustment are following in terms of evaluating parameters
- The implementations of the latter two from the testing environment demand more computational time
- All three contrast enhancing algorithms are applicable within the unsharp masking procedure with CLAHE leading to the most satisfying result

THANKS FOR YOUR ATTENTION!