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Multiscale Image Enhancement Techniques with Shrinkage Denoising based on Characteristics of Human Visual System

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***Abstract*— Image enhancement is basically improving the interpretability or perception of information in images to provide better input for automated image processing techniques. In this paper, multi-scale image enhancement algorithm based on a new parametric contrast measure is presented which supports both luminance masking and contrast masking characteristic of the human visual system. The implementation of the new contrast measure can be adapted for any multi-scale decomposition scheme. Here, it is exemplified using Laplacian pyramid, discrete wavelet transform(DWT), stationary wavelet transform, and dual-tree complex wavelet transform which yields human visual system-inspired multi-scale transforms. Since enhancement procedure may also amplify noise, a noise suppression step is added. This paper compares different multi scale decomposition techniques with a suitable algorithm and a denoising method to produce the best enhanced image. Performance is compared on the basis of PSNR (Peak signal to noise ratio), entropy and SSIM (Structural similarity index). DT-CWT gives better performance adjusts overall brightness and achieves dynamic range compression. The proposed enhancement technique is applicable to real images and standard images.**

Keywords*— Image Enhancement, Denoising Human Visual System, Luminance Masking, Contrast Masking, Multiscale Transforms

I. Introduction

Image enhancement is a process which improves the visual quality of an image [14].The main goal of the image enhancement is to improve the visual appearance of the image. There is no specific set of criteria which can universally define an ideal enhancement for all circumstances or requirements, so many image enhancement techniques have been proposed. The methods of enhancement algorithms can be classified into two types:

- Indirect image enhancement methods.
- Direct image enhancement methods.

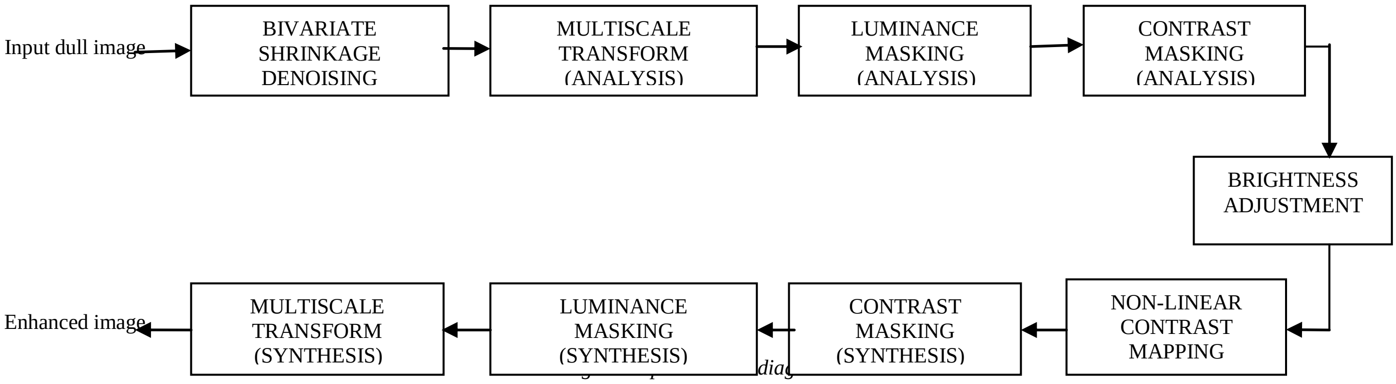
Indirect image contrast enhancement methods enhance the image without measuring the contrast.Histogram equalization (HE), basic pixel transformations, and contrast stretching operations belong to indirect methods of enhancement and can often yield inadequate detail preservation or over-enhancement.On the other hand, direct enhancement techniques establish a criterion of contrast measure in spatial or transform domain and enhance the images by improving the contrast measurement directly by linear or non-linear means [2].Multiscale enhancement algorithms helps to measure image contrast at different scales and can be enhanced

Laine[1] did multiscale analysis technologies for mammogram contrast enhancement where three multiscale representations including dyadic wavelet transform, ϕ-transform and hexagonal wavelet transform were investigated to perform feature analysis. The results showed that wavelet-based image processing algorithms could play an important role in improving the imaging performance of digital mammography and proved to be better than the other two multiscale enhancement algorithms.

HVS (Human visual system)acts as a multiscale device and an excellent image processor which is capable of detecting and recognizing image information[5]. HVS helps to attain more consistent results while reducing the time required for the enhancement process. The effectiveness of a direct enhancement procedure is based on the formulation of a suitable contrast measure which is consistent with the psycho visual laws of the HVS. Existing direct multi-scale enhancement algorithms are based on multi-scale contrast defined in terms of only absolute luminance changes.. HVS is sensitive to relative luminance changes of background intensities.[13] This phenomenon is known as the luminance masking (LM). Laine's [10] and Tang's [4] algorithms are able to enhance the contrast of some of the image structures, but cannot equalize or provide the necessary brightness. Linear mappings will enhance already visible strong edge structures. Compared to linear mappings non-linear mappings prove to be efficient [9].

Main characteristic of HVS is that it is sensitive to relative changes in contrast, that is the visual hiding of one signal due to other. This characteristic is called contrast masking. The idea of a single scale edge detection algorithm[3] which includes both luminance and contrast masking features of HVS is used for image enhancement. In this paper a new parametric contrast measure is proposed, incorporating both LM and CM phenomenon of the HVS.This method generalizes existing contrast measures. The HVS inspired contrast coefficients are mapped non-linearly. A direct means of achieving dynamic range compression and global brightness adjustment is also implemented. Proposed method is extended to pyramidal schemes such as the Laplacian pyramid (LP) [6], and wavelet-based decomposition schemes such as the Discrete Wavelet Transform (DWT)[7],Stationary Wavelet Transform (SWT), and Dual-

Tree Complex Wavelet Transform (DT-CWT) [8]. This paper is organized as follows. Section II deals with HVS characteristics and phenomena.



In Section III shrinkage denoising is formulated. This is followed by multiscale transforms in section IV and the proposed method in section V.Results and performance measure in section VI. Finally, conclusion remarks are given in Section VII.

II. HVS MULTISCALE CHARACTERISTICS AND PHENOMENA

HVS (Human visual system) acts as a multiscale device and an excellent image processor which is capable of detecting and recognizing image information [5].It consists of two functional parts, the eye and (part of the) brain. The brain does all of the complex image processing, while the eye functions as the biological equivalent of a camera.. The eye have two types of photoreceptors: rods and cones. The rods are abundant, about 100 million in a human eye, and spread evenly about the retina.The fovea is the area of the retina where our vision is sharpest. Cones are responsible for high resolution vision which helps in resolving fine details. Rods gives general idea of the field of view. No photoreceptors are found at the point where the optic nerve attaches to the eye called blind spot. Since rods are more responsive to light than cones we can identify three types of vision, depending on the amount of light that reaches the eye. Under dark circumstances,practically only the rods are active.Under daylight circumstances, the cones are most active, and experience photopic or day vision. [11].HVS response is classified into dark,Devries-Rose,Weber, and saturation regions.Each defines the dependency of perceived contrast with background illumination. The minimum change required for HVS to perceive contrast is a function of background illumination and can be closely approximated with three regions.Weber region quantifies the minimum change required for the HVS to perceive contrast and models the threshold for properly illuminated area.

III. BIVARIATE SHRINKAGE DENOISING

Degradation of images comes from blurring and noise due to electronic and photometric sources. Noise is unwanted signal that interferes with the original signal and degrades the visual quality of digital image. The main source of noise in digital image is due to problem with data acquisition process

So image denoising step is a preprocessing step for restoring the original image.Here,denoising is done by a local adaptive algorithm.Let$y_k=w_k+n_k$.k=1,2,……..,no of wavelet coefficients,$w_k=(w_{1k},w_{2k})$,$y_k=(y_{1k},y_{2k})$,$n_k=(n_{1k},n_{2k})$.MAP estimator [15] for w,given the corrupted observation

$$\hat{w}(y)=\arg ax[p_n(y-w).p_w(w)] \quad (1)$$

Non-gaussian bivariate pdf for coefficients and parents are

$$Pw(w) = \frac{3}{2\pi\sigma 2}\exp\left(-\frac{\sqrt{3}}{\sigma}\sqrt{{w_1}^2+{w_2}^2}\right) \quad (2)$$

The marginal variance is dependent on wavelet coefficient index k.[15]Using (1) and (2) the MAP estimator is derived to

$$\hat{w} = \frac{\sqrt{{y_1}^2+{y_2}^2}-\frac{\sqrt{3}\sigma_n^2}{\sigma}}{\sqrt{{y_1}^2+{y_2}^2}} + y1 \quad (3)$$

To estimate the noise variance a median estimator is used from the finest wavelet coefficients.

$$\sigma_n^2 = \frac{median\,(|y_i|)}{0.6745} \quad (4)$$

y_i ϵ subband HH.Also, where is the marginal variance of noisy observation estimated by

$$\hat{\sigma}_y^2 = \frac{1}{M}\sum y_i^2 \quad (5)$$

where y_i ϵ N(k).N(k) is defined as all coefficients within a square shaped window is estimated as

$$\hat{\sigma} = \sqrt{\sigma_y^2+\sigma_n^2} \quad (6)$$

The algorithm is to first calculate noise variance using (4).For each wavelet coefficient k=1,…,.number of wavelet coefficients:

(a) Calculate $\hat{\sigma}$ using (6).

(b) Calculate $\hat{\sigma}_y^2$ using (5).

Estimate each coefficient using $\hat{\sigma}$ and ${\sigma_n}^2$ in (3). We apply this denoising technique to multiscale transforms namely Laplacian pyramid,DWT,SWT and 2-D dual tree complex wavelet transform which combines HVS characteristics. This technique of denoising is effective for HVS and when compared to BayesShrink and AdaptShrink.

IV.MULTISCALE TRANSFORMS

TABLE I.
Analysis and synthesis stages of proposed HVS-multiscale transforms

		HVS-LP	HVS-DWT	HVS-SWT	HVS-DT-CWT
Analysis	LM	$C_{LM}^{(n)} = \frac{y_1^{(n)}}{a1 + \lvert \bar{y}_0^{(n+1)} \rvert^{\gamma 1}}$	$C_{LM}^{(n)} = \frac{y_i^{(n)}}{a1 + \lvert y_0^{(n)} \rvert^{\gamma 1}}$	$C_{i,LM}^{(n)} = \frac{y_i^{(n)}}{a1 + \lvert y_0^{(n)} \rvert^{\gamma 1}}$	$C_{i,LM}^{(n)} = \frac{y_i^{(n)}}{a1 + \lvert y_0^{(n+1)} \rvert^{\gamma 1}}$
	CM	$C_{LCM}^{(n)} = \frac{C_{LM}^{(n)}}{a2 + \lvert C_{LM}^{(n+1)} \rvert^{\gamma 2}}$	$C_{LCM}^{(n)} = \frac{C_{i,LM}^{(n)}}{a2 + \lvert \bar{C}_{i,LM}^{(n+1)} \rvert^{\gamma 2}}$	$C_{i,LCM}^{(n)} = \frac{C_{LM}^{(n)}}{a2 + \lvert C_{i,LM}^{(n+1)} \rvert^{\gamma 2}}$	$C_{i,LCM}^{(n)} = \frac{C_{LM}^{(n)}}{a2 + \lvert C_{i,LM}^{(n+1)} \rvert^{\gamma 2}}$
Synthesis	CM	$C_{LM}^{(n)} = C_{LCM}^{(n)} . [a2 + \lvert C_{LM}^{(n+1)} \rvert^{\gamma 2}]$	$C_{i,LM}^{(n)} = C_{i,LCM}^{(n)} . [a2 + \lvert \bar{C}_{i,LM}^{(n+1)} \rvert^{\gamma 2}]$	$C_{i,LM}^{(n)} = C_{i,LCM}^{(n)} . [a2 + \lvert C_{i,LM}^{(n+1)} \rvert^{\gamma}$	$C_{i,LM}^{(n)} = C_{i,LCM}^{(n)} . [a2 + \lvert C_{i,LM}^{(n+1)} \rvert^{\gamma}$
	LM	$y_1^{(n)} = C_{LM}^{(n)} . [a1 + \lvert \bar{y}_0^{(n+1)} \rvert^{\gamma 1}]$	$y_i^{(n)} = C_{i,LM}^{(n)} . [a1 + \lvert y_0^{(n)} \rvert^{\gamma 1}]$	$y_i^{(n)} = C_{LM}^{(n)} . [a1 + \lvert y_0^{(n)} \rvert^{\gamma 1}]$	$y_i^{(n)} = C_{LM}^{(n)} . [a1 + \lvert y_0^{(n+1)} \rvert^{\gamma 1}]$

The original image is decomposed into subbands by using the pyramidal scheme such as Laplacian pyramid (LP)[6] and wavelet based decomposition scheme such as DWT,Dual Tree complexWavelet Transform (DT-CWT), Stationary Wavelet Transform (SWT).These multiple transforms measure the luminance and contrast coefficients. Each transform will generate an approximation coefficient subband $y_0^{(n)}$ and a set of detail coefficients $y_i^{(n)}$,i=1,2,3,…,i_{sb} at level of decomposition n.The transforms are characterized by their bases,the number of detail coefficient sub-bands at each analysis stage ,their orientation,dimension of approximation and detail coefficient sub-band of same scale and relative dimension of approximation coefficient sub-bands at successive scales.

In Laplacian pyramid (LP) [6] the image is filtered with a small kernel. In each filter step,the previous low-pass image is smoothed by the small kernel and sub-sampled by a factor of two to give the next low-pass image The sequence of low-pass images is termed a Gaussian Pyramid while,Laplacian pyramid uses differences between successive scales of a Gaussian pyramid to provide a multi-scale representation for an image *I*. In our paper LM contrast is given by $C_{LM}^{(n)}$ of scale n. This luminance masked coefficient is obtained by dividing the detail coefficients of scale n with the approximation coefficient of scale n+1. Where a1 is a small positive constant,γ_1 is parameter that controls the degree to which luminance masked contrast is affected by background luminance and ȳ is an expansion function. Multi-scale LCM contrast is defined as $C_{LCM}^{(n)}$ of scale n.

2D DWT uses set of 1D analysis filters, and synthesis filters, to provide multiresolution with added directionality.It applies the analysis filters to the rows of an image. This produces two new images, where one image is set on coarse row coefficients, and the other a set of detail row coefficients. Then applied to the columns of each new image, to produce four subbands. The SWT is a shift-invariant and it reduces artifact effects of the DWT by upsampling the analysis filters rather than down-sampling the approximation coefficient sub-bands at each level of decomposition and it is more memory intensive.

DTCWT is implemented using two DWTs in parallel and is 2-times expansive. The subband signals of the upper DWT can be interpreted as the real part of a complex wavelet transform, and lower DWT can be interpreted as the imaginary part. In general, the DTCWT has the following properties:

(1) Good directionality in 2-dimensions and high.

(2) Reconstruction is perfect and shift invariant.

(3) No artifacting problem

V. PROPOSED ALGORITHM

1. Observed dull image that contains noise is denoised using bivariate shrinkage denoising.
2. Generate an N+1 level Laplacian pyramid(or other multiscale transform) of denoised image using (7) and (9).
3. Measure LM contrast of denoised image. Measure LCM contrast of luminance masked denoised image.
4. Adjust brightness using $\acute{y}_0^{(N)} = y_0^{(N)})+L$. The brightness adjustment parameter is set by L = 255-mean $(y_0^{(N)})$.
5. Calculate the enhanced LCM contrast by a non– linear mapping.

$$\lambda_i^{(n)}(x) = \begin{cases} k_1^{(n)}.x & x \le T_i^{(n)} \\ k_2^{(n)}.x + \left(k_1^{(n)} - k_2^{(n)}\right) T_i^{(n)} & x \ge T_i^{(n)} \end{cases} \quad (7)$$

$$\acute{C}_{LCM}^{(n)} = \mathrm{sgn}(C_{LCM}^{(n)})\, \lambda_i^{(n)}\left(\lvert C_{LCM}^{(n)} \rvert\right) \quad (8)$$

Where $T_i^{(n)} = \frac{median(\lvert y_i \rvert)}{0.6745}$

(9)

For our HVS based approach, we set gain factors as $k_1^{(1-2)}=2$, $k_1^{(3-4)}= 1.5$,$k_1^{(5-6)}=0.8$,$k_2^{(n)}=\max(1,k_1^{(n)})$ and $\gamma 1 = 1$, and $\gamma 2 = 0.52$ (variable parameter) for all results, with $a1 = 0$ and $a2 = 1$.

6. Calculate enhanced LM contrast by

$$\acute{C}_{LM}^{(n)} = \acute{C}_{LCM}^{(n)} . [a2 + \lvert \acute{C}_{LM}^{(n+1)} \rvert^{\gamma 2}] \quad (10)$$

7. Calculate enhanced detail coefficients by

$$\acute{y}_0^{(n)} = \acute{y}_1^{(n)} + EXPAND[\acute{y}_0^{(n+1)}] \quad (11)$$

8. Reconstruct the enhanced image.

VI. RESULTS AND PERFORMANCE MEASURES

The effectiveness of the presented image enhancement algorithms is validated through MATLAB simulations. While the enhancement results in each transform domain have their own subtle difference, the enhancement procedure can effectively enhance the image both locally and global in each of the transform domains. Quantitative and qualitative assessment is done using entropy,PSNR amd SSIM.

(a)Entropy

It is used to evaluate information quantity contained in an image, defined as

$$E=\sum P*\log_2 P \tag{12}$$

Where M is the maximum allowed intensity value and p is the probability distribution of pixel intensities.

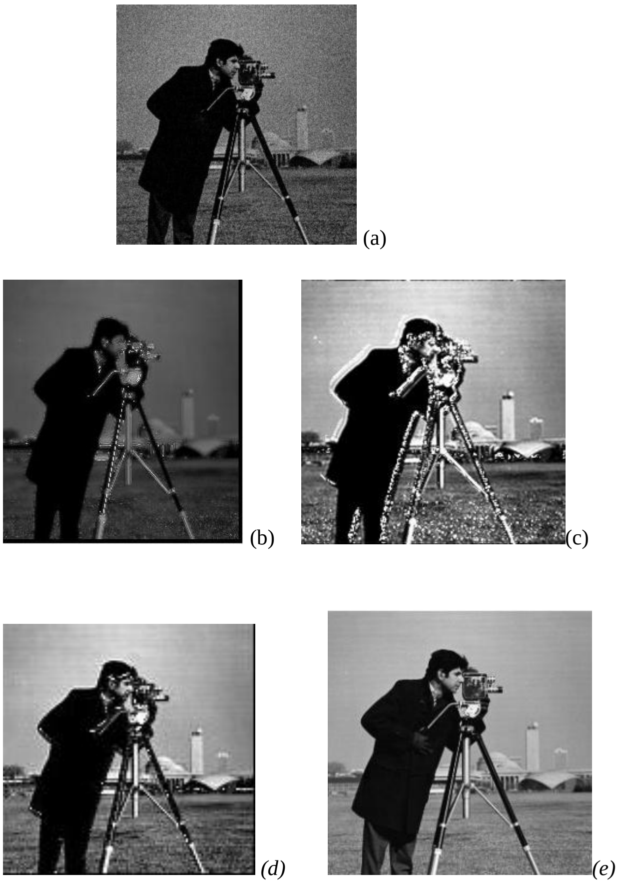


Fig 2.(a) Original noisy dull 'cameraman' image enhancement using (b)HVS-LP,(c)HVS-DWT and (d)HVS-SWT(e)HVS-DTCWT

(b)PSNR

It is usually expressed in terms of the logarithmic decibel scale. A low value for MSE denotes less error and an improvement in PSNR denotes how effectively the denoising is performed.

(c) Structural SIMilarity (SSIM) index

It is a method for measuring the similarity between two images. The SSIM index can be viewed as a quality measure of one of the images being compared with other.The proposed enhancement approach achieves both global and local enhancements simultaneously [12] and these parameters work sufficiently with many test images.

The image in Figure 2(a),3(a) has many visually poor elements.Overall, the image is dark. Figure 2(b)(c)(d) and 3(b)(c)(d) (both size 512 x 512 with noise variance 25),illustrates that the proposed enhancement algorithm can indeed be carried out in any of the HVS-based multi-scale transform domains. Table-2, illustrates the quantitative and qualitative image enhancement assessment via entropy,SSI(Structural Similarity Index) and PSNR. Higher values of entropy suggest higher visual quality.

While the enhancement results in each transform domain have their own subtle difference, the enhancement procedure can effectively enhance the image both locally and global in each of the transform domainsIt was found that the use DT-CWT resulted in improved entropy,PSNR and SSIM when compared to other multiscale techniques. DT-CWT retains the original picture information but reduces the noise. Results obtained using various images are shown.

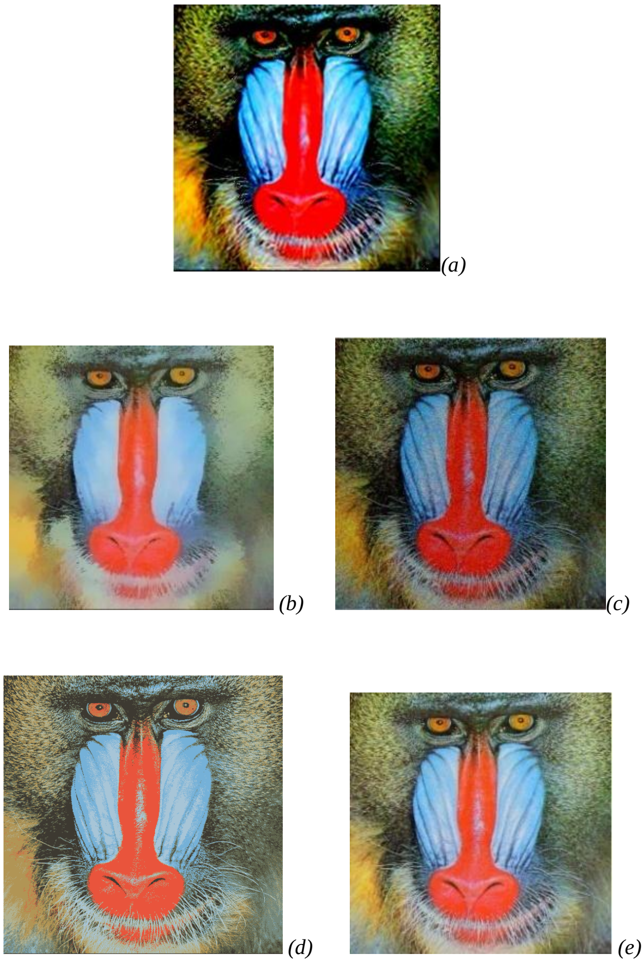


Fig 3.(a) Original noisy dull 'baboon' image enhancement using (b)HVS-LP,(c)HVS-DWT and (d)HVS-SWT(e)HVS-DTCWT

Table 2 illustrates different values of entropy,SSIM and PSNR.The transform DTCWT gives better results for real and standard images and results are bold faced.

TABLE II

Quantitative And Qualitative Image Enhancement Assessment Via Entropy,PSNR and SSIM

IMAGE	METHOD ENTROPY	HVS-LP	HVS-DWT	HVS-SWT	HVS-DTCWT
GRAY	Cameraman	6.0663	6.5419	7.0753	7.68
	Lena	6.0244	6.4543	6.9981	7.4563
	Harbor	6.2432	6.6751	7.2311	7.4551
COLOR	Lena	6.2331	6.5433	7.3341	7.4778
	Baboon	5.8772	6.2322	6.5543	6.9921

IMAGE	METHOD PSNR	HVS-LP	HVS-DWT	HVS-SWT	HVS-DTCWT
GRAY	Cameraman	21.037	23.897	25.075	27.682
	Lena	21.024	23.454	24.998	26.456
	Harbor	21.243	24.675	25.231	28.455
COLOR	Lena	21.233	23.543	24.334	26.477
	Baboon	20.877	22.232	24.554	27.992

IMAGE	METHOD SSIM	HVS-LP	HVS-DWT	HVS-SWT	HVS-DTCWT
GRAY	Cameraman	0.7876	0.8543	0.8876	0.9772
	Lena	0.7955	0.8455	0.8845	0.9754
	Harbor	0.7832	0.8566	0.8644	0.9877
COLOR	Lena	0.7999	0.8457	0.8488	0.9855
	Baboon	0.7877	0.8375	0.8475	0.9875

VII. CONCLUSION

The new image enhancement algorithm is capable of adjusting the appropriate brightness level of the image directly, and used a non-linearly mapping to contrast coefficients at each scale. This mapping was capable of providing both dynamic range compression and contrast enhancement, and brightness control. The proposed image enhancement algorithm was able to achieve local and global enhancements simultaneously within a direct enhancement framework. DT-CWT retains the original picture information but reduces the noise. DT-CWT thus resulted in improved PSNR and SSI when compared to other multiscale techniques. Results illustrated the improved performance of the proposed method via quantitative and qualitative assessment. This can be extended to enhancement of mammogram images.

REFERENCES

[1] Laine *et al.*, “Mammographic feature enhancement by multiscale analysis,” *IEEE Trans. Med. Imag.*, vol. 13, no. 4, pp. 725–740, Apr.1994.

[2] J. Tang, E. Peli, and S. Acton, “Image enhancement using a contrast measure in the compressed domain,” *IEEE Signal Process. Lett.*, vol. 10, no. 10, pp. 289–292, Oct. 2003.

[3] F. Yang, Y. Chang, and S.Wan, “Gradient-threshold edge detection based on the human visual system,” *Opt. Eng.*, vol. 44, no. 2, p. 020205,Feb. 2005.

[4] J. Tang, X. Liu, and Q. Sun, “A direct image contrast enhancement algorithm in the wavelet domain for screening mammograms,”*IEEE Sel. Topics Signal Process.* vol. 3, no. 1, pp. 74–80, Nov. 2009.

[5] M. T. H. Romeny, *Front-End Vision and Multiscale Image Analysis:Introduction to Scale-Space Theory*. Norwell, MA, USA: Kluwer, 1997.

[6] P. J. Burt and E. Adelson, “The Laplacian pyramid as a compact image code,” *IEEE Trans. Commun.*, vol. 31, no. 4, pp. 532–540, Apr. 1983.

[7] S. G. Mallat, “A theory for multiresolution signal decomposition:The wavelet representation,” *IEEE. Trans. Pattern Anal. Mach. Intell.*,vol. 11, no. 7, pp. 674–693, Jul. 1989.

[8] O. Rockinger, “Image sequence fusion using a shift-invariant wavelet transform,” in *Proc. IEEE Int. Conf. Image Process.*, Oct. 1997,pp. 288–291.

[9] S. Dippel, M. Stahl, R. Wiemker, and T. Blaffert, “Multiscale contrast enhancement for radiographies: Laplacian pyramid versus fast wavelet transform,” *IEEE Trans. Med. Imaging*, vol. 21, no. 4, pp. 343–353,Apr. 2002.

[10] Laine, J. Fan, and W. Yang, “Wavelets for contrast enhancement of digital mammography,” *IEEE Eng. Med. Biol.Mag.*, vol. 14, no. 5,pp. 536–550, Oct. 1995.

[11] S. Agaian, K. P. Panetta, and A. M. Grigoryan, “Transform based image enhancement algorithms with performance measure,” *IEEE Trans. ImageProcess.*, vol. 10, no. 3, pp. 367–380, Mar. 2001

[12] S. Nercessian, K. Panetta, and S. Agaian, ―Non-linear direct multi-scale image enhancement based on the luminance and contrast masking characteristics of human visual system,‖ *IEEE Trans. Image Process.*, vol. 22, no. 9, pp.3549-3561, Sep. 2013.

[13] M. K. Kundu and S. K. Pal, “Thresholding for edge detection using human psychovisual phenomena,” *Pattern Recognit. Lett.*, vol. 4, no. 6, pp. 433–441, 1986.

[14] Rafael C Gonzalez,Richard E woods,Digital Image Processing,3rd edition.

[15] Bivariate Shrinkage With Local Variance Estimation,Levent S¸endur and Ivan W. Selesnick.,