Wavelet-based Contrast Enhancement of Dark Images using Dynamic Stochastic Resonance

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ABSTRACT

In this paper, a dynamic stochastic resonance (DSR)-based technique has been proposed for contrast enhancement of dark and low contrast images in discrete wavelet transform (DWT) domain. Traditionally, the performance of a stochastic resonance (SR)-based system is improved by addition of external noise. However, in the proposed DSR-based approach, the *internal noise* of an image has been utilized for the purpose of contrast enhancement. The degradation due to inadequate illumination is treated as noise, and is used to produce a noise-induced transition of the image from a low-contrast state to a high-contrast state. Stochastic resonance is induced in the approximation and detail coefficients in an iterative fashion, producing an increase in variance and mean of the coefficient distribution. Optimal output response is ensured by selection of optimal of bistable system parameters. An iterative algorithm is followed to achieve target value of performance metrics, such as relative contrast enhancement factor (F), perceptual quality measures (PQM), and color enhancement factor (CEF), at minimum iteration count. When compared with the existing SR-based and non SR-based enhancement techniques in spatial and frequency domains, the proposed technique is found to give noteworthy performance in terms of contrast enhancement, perceptual quality, as well as colorfulness.

Keywords

Dynamic stochastic resonance, colored images, contrast enhancement, discrete wavelet transform, noise, stochastic resonance

1. INTRODUCTION

Conventionally, noise is thought to be a nuisance that deteriorates the performance of a system. Stochastic resonance, on the contrary, is a phenomenon in which noise can be *utilized* to *enhance* rather than hinder system performance. Stochastic resonance (SR) is a counter-intuitive phenomenon where the presence of noise in a non-linear system is essential for optimal system performance. Though traditionally noise is considered undesirable in digital images, it can sometimes be made to play a constructive role in various image processing applications. The first experimental work on visualization of stochastic resonance was reported by [16]. Recently some of the works on application of stochastic resonance for grayscale image or edge enhancement that have been reported in literature are [22, 4, 23, 12, 13, 14, 15, 6]. Many images have very low dynamic range of the intensity values due to insufficient illumination, and need to be processed before being displayed. Enhancement of images is required for better visualization of dark images so as to improve visual perception. Many techniques for contrast enhancement that operate in spatial domain exist in literature [10], [3], [9], [20]. Many algorithms available in literature have been designed for both colored and grayscale images in block DCT domain [2], [17], [11], [18]. However, there are some disadvantages in processing images using block DCT. Due to independent processing of blocks, as in most of the cases, the presence of blocking artifacts may become more visible in the processed data. Sometimes superfluous edges may appear at the image boundaries due to the sharp discontinuities of the intensity distribution. Therefore, in this paper, a contrast enhancement technique based in wavelet-domain has been proposed so as to avoid blocking artifacts. Low frequency and high frequency information are simultaneously processed following a dynamic stochastic resonance (DSR) model.

Recently, other stochastic resonance-based techniques in wavelet and fourier domains for the enhancement of unclear diagnostic ultrasound and MRI images respectively have been reported [13], [14]. These methods can readily enhance the image by fusing a unique constructive interaction of noise and signal, and enable improved diagnosis over conventional methods [10], [3]. The approach well-illustrated the novel potential of using a small amount of Gaussian noise to improve the image quality. Ryu *et al.* [15] have developed a new approach for enhancing feature extraction from low quality fingerprint images using stochastic resonance.

In this paper, we have investigated the use of *stochastic fluctuation* (also called 'noise') for image enhancement. The unique feature of this technique is use of *internal noise* instead of externally added noise and an adaptive processing to reach target optimal performance. The motivation of this study was to reduce the noise due to lack of illumination and enhance the dark regions of an image following a double-well model analogous to that developed by Benzi *et al.* [1]. Here, noise itself is used to counter the effect of noise. In other words, in DSR-based enhancement, a small amount of extra noise rearranges the intrinsic noise that is already present in the image. Our approach is to maximize the performance of our algorithm in terms of contrast and color enhancement while assuring good perceptual quality (visual information).

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The display of a color image depends upon three important factors, namely (i) brightness, (ii) contrast, and (iii) original color composition. In this paper, we have chosen to work on Hue-Saturation-Value (HSV) color model, and have computed performance parameters to assess contrast enhancement, perceptual quality and color enhancement of output image. We have observed that the DSR-based enhancement technique surpasses the conventional methods of image enhancement in both spatial and frequency transform domains. In this paper, all the three mentioned important factors have been considered while designing a simple computationally-efficient iterative algorithm that enhances a dark image using DSR.

2. KEY CONTRIBUTION

The work proposed in this paper is uniquely different from the state-of-the-art SR-based techniques in the aspects mentioned as follows. The technique reported in [4] deals with edge detection using vibrating noise. The technique reported in [12] used *non-dynamic* stochastic resonance to improve the performance of adaptive histogram equalization by using stochastic resonance. The technique reported in [23] for sonar image enhancement suggests *addition of externally added noise* on bi-leveled images. Both [12] and [15] use the concept of *non-dynamic SR* that adds N parallel frames of independent and identically distributed (i.i.d.) gaussian noise, and use *addition of externally added noise*. Techniques on suprathreshold stochastic resonance [5], [7] deal with noise-induced contrast enhancement of dark images. All these techniques are in spatial domain.

Earlier application of stochastic resonance in contrast enhancement [13], [14] tested its applicability using externally added noise and selected parameters experimentally. However, in the proposed technique, intrinsic noise present due to low illumination has been uniquely utilized without using any externally added noise. Preservation of color has been implicitly maintained due to processing on the intensity vector of HSV color model. In the proposed technique, an analogy to Benzi's double well model for recurrence of ice ages [1] has been presented in the wavelet domain. The DSR-based approach has been explored to exploit the nature of approximation and detail coefficients of one-level DWT decomposition, and has been found to implicitly enhance and preserve color accurately. The proposed technique selects double-well parameters by maximization of SNR, and also relates DSR parameters with the statistical properties of the poorly illuminated image itself.

3. MATHEMATICAL FORMULATION OF THE DWT-BASED DSR FOR IMAGE ENHANCEMENT

It has been observed in one dimensional signals that at an optimum "resonant" value of noise, the signal crosses the threshold and transits into another (enhanced) state. To establish the principles of SR in applications of image processing, the discrete image pixels are incisively treated as discrete particles, whereby the gray value of an image pixel corresponds to a specific kinetic parameter of a physical particle in Brownian motion. For mathematical formulation of theory of dynamic stochastic resonance, readers are advised to refer to [6] where an analogy to Benzi *et al.*'s double-well model for global climate in the context of image enhancement has been reported.

At optimum intrinsic noise density (or optimum number of oscillations) the particle makes a transition into the other well. In the proposed analogy, this optimum amount of noise is reached by stochastic approximation using a corresponding discrete iterative equation.

$$x(n+1) = x(n) + \Delta t \left[ax(n) - bx^3(n) + Input\right] \qquad (1)$$

Note that $Input = B\sin(\omega t) + \sqrt{D}\xi(t)$ denotes the sequence of input signal and noise. As described in [6], this denotation can be done with the view that a low contrast image is a noisy image containing internal noise due to lack of illumination. This noise is inherent in its overall description (approximation) and detail coefficients, and therefore, the DWT coefficients can be considered to be comprising signal (image information) as well as noise. The final stochastic simulation is obtained after number of iterations. Here, Δt is the discrete time sample applied to the system, or individual iteration time used in numerical simulation. Finally, the image is reconstructed in the spatial domain by applying inverse wavelet operation.

By differentiation of the SNR equation for dynamic stochastic resonance w.r.t a, optimum value of a for maximum SNR is found to be a=$2{\sigma_0}^2$ (as derived in [6]). Another condition is needed to ensure that the maximum allowable force on the bistable well maintains its stability, i.e. the periodic input signal is less than or equal to maximum restoring force or gradient of potential function. This is ensured by the condition $b < \frac{4a^3}{27}$.

Let I be an image of size $M \times N$ where $I(i,j)$ denotes the intensity (pixel value) at pixel coordinates (i,j). The discrete wavelet transform (DWT) of $I(i,j)$ is defined as:

$$W_\phi(l_0,p,q) = \frac{1}{\sqrt{MN}}\sum_{i=0}^{M-1}\sum_{j=0}^{N-1} I(i,j)\phi_{l_0,p,q}(i,j) \qquad (2)$$

$$W_\psi^s(l,p,q) = \frac{1}{\sqrt{MN}}\sum_{i=0}^{M-1}\sum_{j=0}^{N-1} I(i,j)\psi_{l,p,q}^s(i,j) \qquad (3)$$

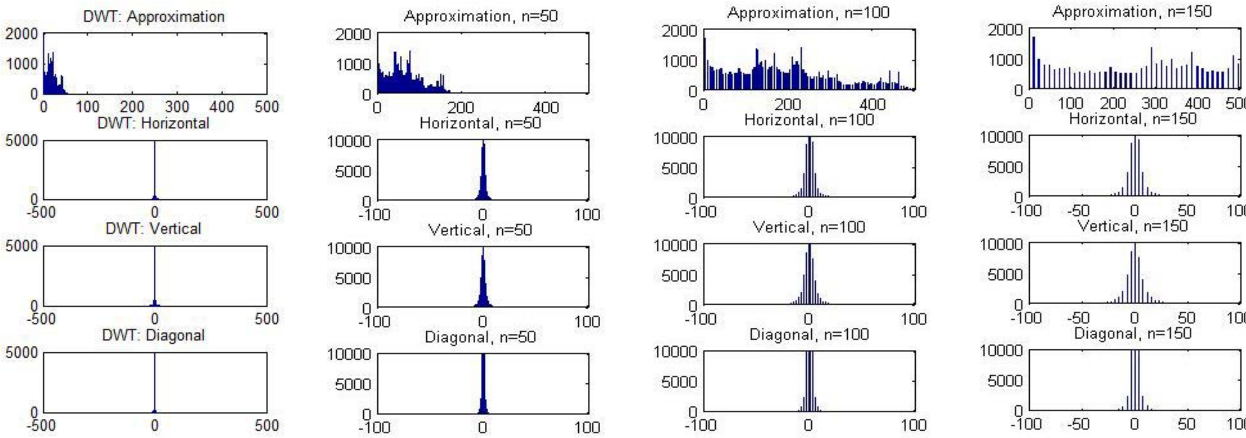
where ϕ is the 2D scaling function and ψ is the 2D wavelet function,
$s\ \epsilon\ H,V,D$ where H,V,D are respectively the Horizontal, Vertical and Diagonal directions. l_0 is an arbitrary starting scale,
$W_\phi(l_0,p,q)$ coefficient define an approximation of $I(i,j)$ at scale l_0, with p,q coordinates of image subband, and
$W_\psi^s(l,p,q)$ are horizontal, vertical and diagonal details for scales $l \geq l_0$.
If $M = N = 2^L$, $l = 0,1,2,\ldots,L-1$ and $p,q = 0,1,2,\ldots,2^L$-1.

Now DSR is applied to the detail and approximation coefficients, thereby obtaining the stochastically enhanced (tuned) coefficients in DWT domain is given as

$$W_\phi(l_0,p,q)_{DSR} = \frac{1}{\sqrt{MN}}\sum_{i=0}^{M-1}\sum_{j=0}^{N-1} DSR\left[I(i,j)\phi_{l_0,p,q}(i,j)\right] \qquad (4)$$

$$W_\psi^s(l,p,q)_{DSR} = \frac{1}{\sqrt{MN}}\sum_{u=0}^{M-1}\sum_{j=0}^{N-1} DSR\left[I(i,j)\psi_{l,p,q}^s(i,j)\right] \qquad (5)$$

where the DSR operation is governed, in discrete equation form, by Eq. 1. Here the noise term $\sqrt{D}\xi(t)$ and the input term $B\sin(\omega t)$ is replaced by DWT subband coefficients of $I(x,y)$, i.e., $W_\phi(l_0,p,q)$



(a) Input Distribution (b) n=50 (c) n=100 (d) n=150

(e) Input Image (f) n=50 (g) n=100 (h) n=150

Figure 1: *(a) shows distribution of coefficients of a dark low contrast input image. (b)- (d) show the probability density function (pdf) of DWT subband coefficients of a dark low contrast image after 50, 100 and 150 iterations respectively. (e) shows the input dark low contrast image. (f)-(h) show output image after 50, 100 and 150 iterations respectively*

and $W_\psi^s(l,p,q)$ respectively. This would effectively lead to four such iterative equations, each corresponding to a particular subband.

In terms of wavelet coefficients, if X_ϕ and X_ψ^s denote the stochastically tuned set of approximation and detail coefficients W_ϕ and W_ψ^s respectively, then

$$X_\phi(n+1) = X_\phi(n) + \Delta t\left[(aX_\phi(n) - bX_\phi(n)^3) + W_\phi\right] \quad (6)$$

$$X_\psi^s(n+1) = X_\psi(n)^s + \Delta t\left[(aX_\psi^s(n) - b\left(X_\psi(n)^s\right)^3 + W_\psi^s\right] \quad (7)$$

where X_ϕ and X_ψ^s are initialized as zero matrices for mathematical simplicity.

The tuned (enhanced) set of wavelet coefficients are obtained by Eq. 6 and Eq. 7. The enhanced image in spatial domain can be obtained by inverse discrete wavelet transform (IDWT) of the tuned coefficient sets.

3.1 Choice of Discrete Wavelet Transform domain

The mechanism of DSR for contrast enhancement is attributed to the way it tunes the DWT coefficients of intensity values. Fig. 1 shows how the distribution of coefficients varies with DSR iterations.

The nature of approximation coefficients has been observed to be very similar to the distribution of intensity values of the input (histogram). This is obvious because the approximation coefficients contain low-pass information of the image, and contain an overall general description of the image. This is why the distribution of approximation coefficients of a dark, low contrast image is narrow and concentrated at the lower end of the values. When DSR is applied to these LL coefficients, it is found that the distribution shifts towards the higher end, broadening and flattening at the same time. In other words, both the mean (denoting average brightness) and the variance (denoting contrast) of the approximation coefficients are observed to increase with DSR iterations (Fig. 1). It can be clearly observed from Fig. 1 that application of DSR leads to increase in overall contrast and brightness of the input image. However, with too many iterations, the distribution of approximation coefficients becomes nearly uniform and further flattens leading to a segmented image. The increase in variance, and corresponding energy of detail coefficients, should also theoretically reflect an increase in sharpening of the image.

3.2 Quantitative Characterization

There is a need to quantify the quality of enhanced image to gauge the performance of the DWT-DSR technique. Performance measures such as peak signal-to-noise-ratio $(PSNR)$, mean-square-error (MSE), structural similarity index measure $(SSIM)$, quality index etc. are *not* suitable for our purpose as they require distortion-free image or reference image. Metric of contrast enhancement (F) is based on global variance and mean of original and enhanced images [14]. Therefore, a descriptor called Image quality index Q has been used such that $Q = \sigma^2/\mu$, where σ and μ are respectively

(a) Low contrast image (b) DWT-DSR enhanced image, n=50 (c) Performance characterization

Figure 2: *Input image has been made low-contrast by modification of the original image, courtesy of Sajan Pillai. Enhanced output shows enhanced background without losing information in the already lit area. Performance metrics show target PQM and maximal enhancement around n=50.*

(a) Low contrast image (b) DWT-DSR enhanced image, n=32 (c) Performance characterization

Figure 3: *Input image has been made low-contrast by modification of the original image, courtesy of Sajan Pillai. The DSR enhanced output shows reasonable improvement in darker regions without any artifacts. Performance metrics reach a target PQM and maximal enhancement around n=32.*

the standard deviation and mean of the image. Relative contrast enhancement factor, F, is computed as the ratio of values of Quality index post-enhancement (Q_B) and pre-enhancement (Q_A). For evaluation of perceptual quality, we have used a no-reference metric for judging the image quality which we shall refer to as perceptual quality metric (PQM) [19, 11], where for good perceptual quality, PQM should be close to 10. Here, perceptual quality is calculated from a model [19] taking into account the activity, blurriness and blockiness of an image. If the image is colored, one would also interested to observe the quality in terms of colorfulness, and therefore, a metric for color enhancement factor (CEF) [11] has been used. For good color and contrast enhancement, respective values CEF and F should be greater than 1.

4. ALGORITHM

DSR-processing of approximation band (LL) would increase the average contrast and brightness, while processing of detail coefficients should lead to boosting of edges. The proposed DSR-based algorithm for contrast enhancement consists of the following steps.

Step 1 Color model conversion and DWT decomposition: The input image is projected into HSV color space. The Value vector (V) is decomposed into approximation and detail (horizontal, vertical and diagonal) coefficients using 1-level discrete wavelet transform (here, biorthogonal CDF filter bank, 9×7 tap).

Step 2 Computing SR parameters: Assuming an initial value of bistable parameters Δt, m and n the coefficients from all four subbands are tuned using dynamic stochastic resonance as follows.

Assuming $\Delta t = 0.015$, $a_s = k \times 2{\sigma_{0s}}^2$, $b_s = m \times (4a_s^3)/27$ where $s \in A, H, V, D$. Bistable parameters a_s and b_s *for each subband* are computed using its local variance (σ_{0s}^2) as obtained from **Step 2**.

Here, k is a factor denoting image region dullness (given by inverse of ($variance \times$ dynamic range)) and m is a factor much less than 1 (so that b is less than its maximum value to ensure that input is weak signal, and is eligible for application of DSR).

Step 3 SR tuning of DWT Coefficients: Initializing four matrices of tuned subbands as zero.

Using the bistable dynamic stochastic resonance parameters tune the DWT subband coefficients according to Eq. 6 and Eq. 7. Inverse DWT is computed for the tuned set of coefficients. This is the general step of the application of DSR.

To make this step adaptive, iteration is continued until the sum of $F(n) + CEF(n)$ becomes maximum in the nearest possible vicinity of PQM = 10, say 10 ± 0.1.

5. EXPERIMENTAL RESULTS AND DISCUSSION

Results of software simulation and performance characteristics of the proposed algorithm have been shown in Fig. 2 to Fig. 5, stating their respective required iteration count. Fig. 1(e), Fig. 5(b), Fig. 5(e) and Fig. 5(h) are phantom images obtained by manipulation of contrast and brightness in original standard images for

(a) Low contrast image (b) DWT-DSR enhanced image, n=95 (c) Low contrast image (d) DWT-DSR enhanced image, n=40

Figure 4: *Input images have been made low-contrast by modification of the original images, courtesy of Sajan Pillai. The DSR-enhanced output shows reasonable improvement in visual information.*

investigation of iterative SR on DWT coefficients. Fig. 3(a), 4(a), 4(c) and have been made dark by contrast/brightness reduction in original images (after permission). Fig. 6(a) is naturally dark and has been captured under poor illumination.

Performance characteristics for the corresponding outputs have been shown in Fig. 2 and Fig. 3, showing the performance characterization of the proposed technique in terms of contrast enhancement factor (F), color enhancement factor (CEF) and perceptual quality measure (PQM), with respect to iteration count. Target output is obtained in the close vicinity of PQM=10, i.e. say 10 ± 0.1.

Comparisons of empirical results of proposed technique with various other SR-based and non-SR based techniques (for Fig. 6(a) and Fig. 4(a)) have been shown in Fig. 6 and Fig. 7. Comparative performance for the same in terms of the metrics has been tabulated in Table 1. Comparative analysis with non-SR-based techniques, like contrast-limited adaptive histogram equalization (CLAHE) [24], gamma correction (Gamma), single-scale retinex (Retinex) [9], multi-scale retinex (MSR) [8], and modified high-pass filtering (MHPF) [21] has been performed. Since the proposed technique is automatic in nature, a comparison has also been made with outputs of 'Auto Contrast' control of Adobe Photoshop $CS2$ (Photoshop). Among SR-based techniques, a comparison with singular-value-based DSR (SVD-DSR) [6] and suprathreshold SR-based technique (SSR) [7] has been made.

It can be observed that though few other techniques achieve higher values of contrast or color enhancement factors, they do so at the cost of visual quality. The proposed technique has been designed to give optimal enhancement while ascertaining good perceptual quality. It is the constraint of optimal perceptual quality that ensures less noise in the output image, with significant enhancement in contrast.

The visual outputs and performance metrics for the proposed DWT-domain technique illustrate noteworthy improvement in the contrast, perceptual quality and colorfulness of the test images. Color preservation is implicit in by processing only the value vector. The improved colorfulness is due to increase in chroma/saturation with increasing value vector (in a conical HSV space-perspective). All the DSR-based techniques give comparable results, better than many of the techniques that they were compared with, in terms of overall enhancement.

An average 512×512 grayscale image takes around 20-30 seconds to reach target (optimal) iteration count on an Intel(R) Core(TM)2 Duo Processor working on 2.53 GHz with 2 GB RAM.

6. CONCLUSION

A technique for contrast enhancement of dark images using noise-induced resonance in wavelet domain was proposed and investigated in this paper. An analogy of a dark image domain to bistable double-well is used to model the state of a wavelet coefficient as the motion of a particle in the double well. Iterative scaling of internal noise due to insufficient illumination is achieved by tuning the approximation and detail coefficient using a parameter-dependent equation. Parameter selection is done by maximizing signal-to-noise ratio of a traditional SR system. Iteration is adaptively terminated on reaching target optimal values of perceptual quality, contrast quality, and colorfulness. Comparison with various SR-based and non-SR based techniques reflects the potential and noteworthy performance of the proposed technique in terms of contrast quality, color enhancement factor and visual information. The approach may further be improved by suitable modifications for application to bright images, and can be extended by adaptive selection of regions for processing.

7. ACKNOWLEDGMENTS

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Table 1: *Comparative performance of the proposed DWT-DSR technique with various existing techniques using three performance metrics F [14], PQM [19] and CEF [11] on three test images.*

	Fig. 2(a)			Fig. 6(a)			Fig. 4(a)		
Method	F	PQM	CEF	F	PQM	CEF	F	PQM	CEF
DWT-DSR	**3.0**	**10.0**	**3.1**	**2.5**	**10.0**	**2.7**	**5.3**	**8.95**	**5.75**
SVD-DSR	5.8	9.4	1.3	3.1	9.7	3.1	5.23	8.40	4.62
SSR	2.2	9.5	6.5	6.1	8.9	5.1	2.51	7.95	6.00
CLAHE	1.9	10.8	0.5	2.2	10.5	1.3	1.98	7.85	2.73
Photoshop	5.4	8.5	1.3	2.1	11.0	1.3	4.69	8.69	4.75
Gamma	9.5	8.5	11.5	1.2	10.9	1.5	5.92	6.92	5.01
Retinex	7.8	8.2	7.1	0.1	12.4	0.2	4.78	6.96	8.37
MSR	1.8	9.5	7.1	0.4	11.7	0.7	1.68	7.18	2.77
MHPF	8.4	8.2	16.8	0.6	11.7	0.8	5.02	9.01	7.21
MCE	1.0	12.2	0.2	1.1	8.8	1.0	1.18	8.77	0.96
MCE-DRC	0.7	11.9	0.2	0.9	11.1	1.0	0.97	9.01	7.21
CES	1.2	11.3	0.3	0.9	10.3	1.5	1.13	8.32	1.58

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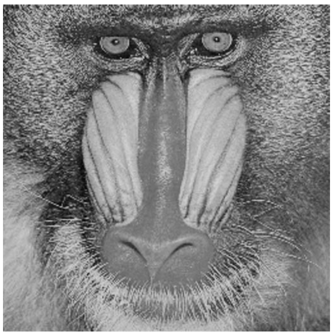
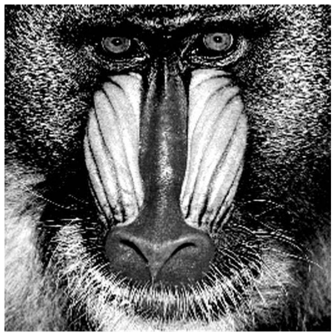


(a) Original *Mandril* Image

(b) Dark *Mandril*



(c) DWT-DSR Enhanced *Mandril*, n=110

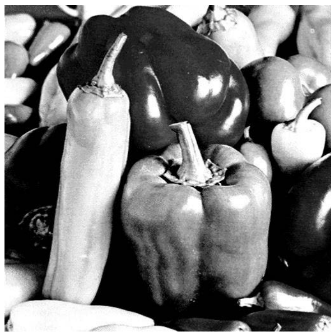
(d) Original *Cameraman* Image

(e) Dark *Cameraman*

(f) DWT-DSR Enhanced *Cameraman*, n=70

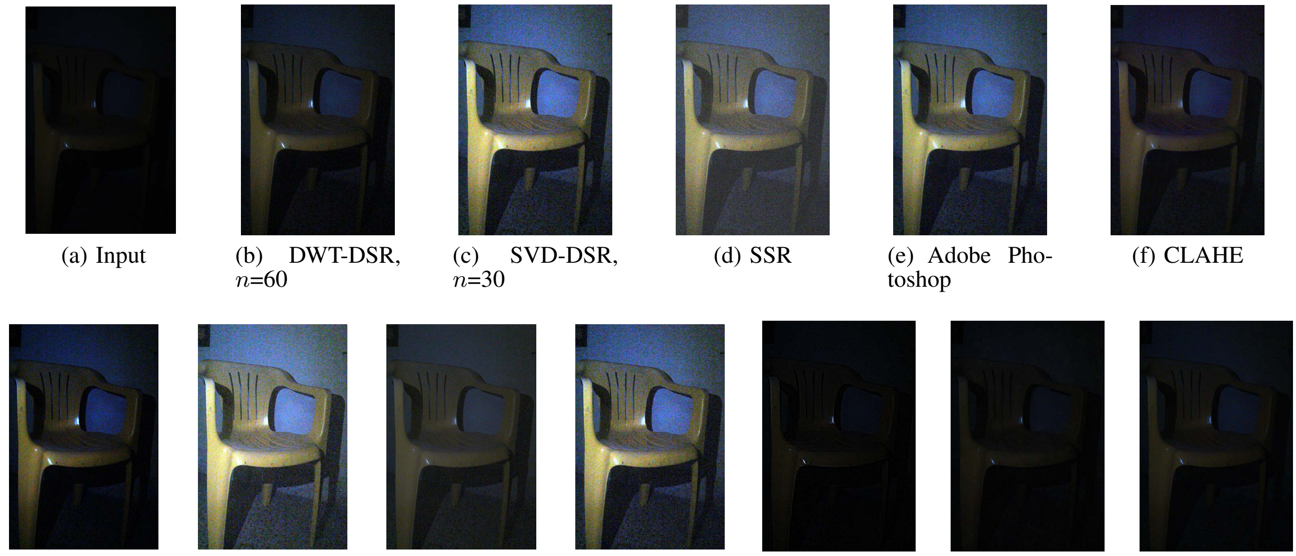
(g) Original *Pepper* Image

(h) Dark *Pepper*



(i) DWT-DSR Enhanced *Pepper*, n=89

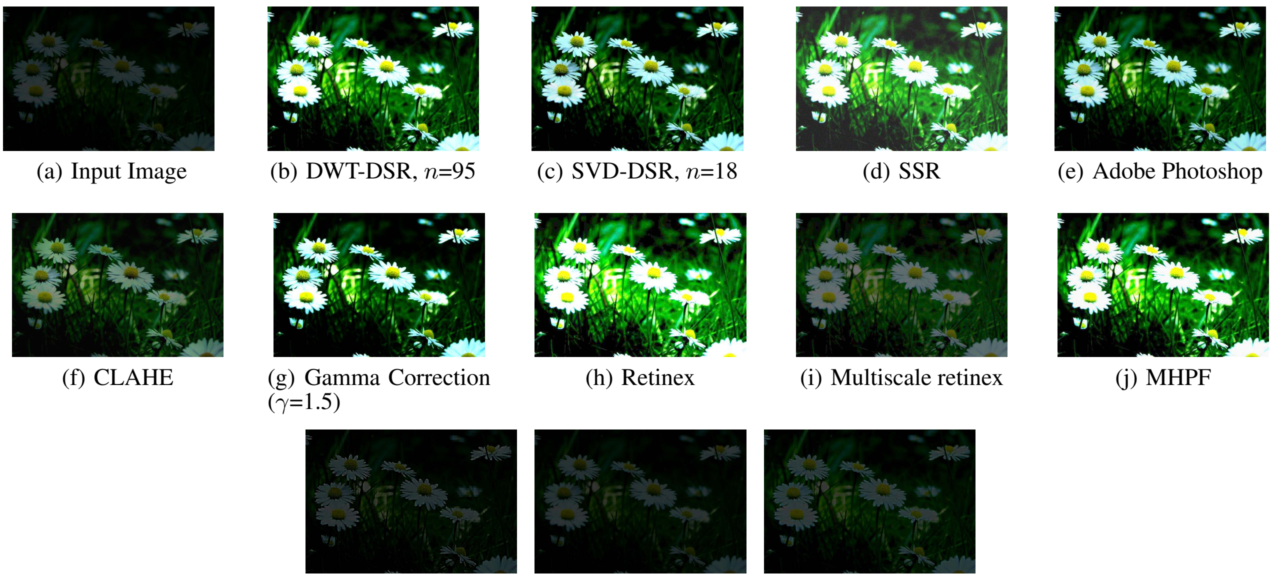
Figure 5: *Contrast of original standard image have been modified to generate dark phantom images. DWT-DSR enhanced images with corresponding iteration count have been displayed.*



(a) Input (b) DWT-DSR, n=60 (c) SVD-DSR, n=30 (d) SSR (e) Adobe Photoshop (f) CLAHE

(g) Gamma Correction (γ=1.5) (h) Retinex (i) Multiscale retinex (j) MHPF (k) MCE (l) MCE-DRC (m) CES

Figure 6: *Enhancement results on an very dark input image using proposed technique and other existing enhancement techniques. Input image, courtesy Sajan Pillai.* MCE*: Multi-contrast Enhancement,* $MCE - DRC$*: multi-contrast enhancement with dynamic range compression,* CES*:Color enhancement by scaling.*



(a) Input Image (b) DWT-DSR, n=95 (c) SVD-DSR, n=18 (d) SSR (e) Adobe Photoshop

(f) CLAHE (g) Gamma Correction (γ=1.5) (h) Retinex (i) Multiscale retinex (j) MHPF

(k) MCE (l) MCE-DRC (m) CES

Figure 7: *Enhancement results on an very dark input image using proposed technique and other existing enhancement techniques. Input image* (a) *has been made low-contrast by contrast/brightness reduction in the original image, courtesy of Sajan Pillai.* MCE*: Multi-contrast Enhancement,* $MCE - DRC$*: multi-contrast enhancement with dynamic range compression,* CES*:Color enhancement by scaling.*