Undecimated Balanced GHM Multiwavelet Transform based Contrast Enhancement Technique for Dark Images using Dynamic Stochastic Resonance

S. Deivalakshmi
Assistant Professor
National Institute of Technology
Tiruchirappalli - 620015

P. Palanisamy
Associate Professor
National Institute of Technology
Tiruchirappalli - 620015

ABSTRACT
The main aim of this paper is to propose a technique for enhancing contrast of the dark images using Undecimated Balanced GHM multi wavelet transform (UMWT) and Dynamic Stochastic Resonance (DSR). The DSR based approach utilizes the inherent noise of an image for enhancement. Darkness due to inadequate illumination is treated as noise, and is used to yield a noise induced adjustment of the image from a state of low to high contrast. The stochastic resonance is stimulated in the approximation and detail coefficients of undecimated multiwavelet transformed dark image in an iterative manner. This results intensification in contrast of the coefficient distribution. The desired response is validated by the performance metrics such as Relative Contrast Enhancement Factor (F), Perceptual Quality Measures (PQM) and Color Enhancement Factor (CEF). The results shows that the proposed technique offers good performance in terms of above mentioned metrics, perceptual quality as well as colourfulness.

General Terms
Contrast enhancement, Performance metrics, Wavelet decomposition

Keywords
Dynamic stochastic resonance, Undecimated Multi Wavelet Transform (UMWT), Relative Contrast Enhancement Factor (F), Perceptual Quality Measures (PQM), Color Enhancement Factor (CEF)

1. INTRODUCTION
In general noise is considered as an undesirable signal that reduces the performance of a system. On the other hand, stochastic resonance is a phenomenon in which noise can be exploited to enhance instead of debasing the system performance. Generally, though the noise is considered as an undesired factor in digital images, sometimes it can be used to play beneficial role in specific image processing applications. The first work on stochastic resonance was reported in [1]. Recently some of the applications based on stochastic resonance for grayscale image or edge enhancement have been reported in literatures [2-8]. The presence of darkness due to insufficient illumination, image enhancement is required for better visualization of dark images that are having low dynamic range intensity values.

Many spatial domain contrast enhancement techniques are reported in literatures [9-12]. Though many algorithms available in literature have been designed in block DCT domain for both colored and grayscale images [13-16] there are some drawbacks in processing images using block DCT. Using these algorithms processing the blocks independently is difficult due to the presence of blocking artefacts in the processed data. Due to the sharp discontinuities of the intensity distribution, sometimes superfluous edges may appear at the image boundaries. For that reason, in this work, Undecimated Balanced Multi Wavelet Transform (UMWT) based contrast enhancement technique has been suggested so as to avoid blocking artefacts. By following a Dynamic Stochastic Resonance (DSR) model, low and the high frequency informations are processed simultaneously. In Undecimated Multi wavelet transform based DSR technique (UMWT-DSR) one can able to achieve better performance metrics and visual quality compared to Discrete Wavelet Transform (DWT) based DSR technique (DWT-DSR).

In this paper we worked on Hue Saturation Value (HSV) color model instead of brightness, contrast and original color composition. While computing the performance metrics such as contrast enhancement, perceptual quality and color enhancement for the enhanced image it is observed that the proposed DSR based enhancement technique in undecimated multi wavelet transform domain surpasses the performance of the DSR based enhancement method in DWT domain. Conventionally, by addition of external noise, the performance of a nondynamic stochastic resonance based system is upgraded. The work proposed in this paper is completely different from nondynamic stochastic resonance based techniques. The technique proposed in [17] and [18] use the conception of nondynamic stochastic resonance that adds N parallel frames of independent and identically distributed (i. i. d.) gaussian noise and addition of external noise. The technique deals with edge detection using vibrating noise is reported in [3]. The technique reported in [4] for sonar image enhancement suggests the addition of external noise on bi-leveled images. The techniques described in [19, 20] based on suprathreshold stochastic resonance deal with noise induced contrast enhancement of dark images. But all these methods are functioning in spatial domain. Former applications of Stochastic Resonance (SR) for contrast enhancement is done by addition of external noise and the performance metrics were chosen based on experimentation. However in the proposed technique, the intrinsic noise (darkness) present in an image due to low illumination has been utilized to enhance the contrast of an image. Proper preservation of color is achieved by processing on intensity vector of hue saturation model. In the proposed technique, an analogy to Benzi's double well model for recurrence of ice ages [21] has been presented in the Undecimated Balanced Multi Wavelet domain. The DSR based approach has been explored to utilize the nature of approximation and detail coefficients of first level UMWT decomposition, and has been found to enhance and preserve the color accurately. The proposed technique selects double well parameters by maximization of SNR, and also relates the DSR parameters with the statistical properties of the poorly illuminated image itself.

This paper is organized as follows. Section 2 reviews the undecimated multiwavelet transform. Section 3 briefs the concept of DSR and its mathematical formulation. Section 4 presents the proposed enhancement algorithm. The experimental results are discussed in section 5. Concluding remarks are given in section 6.

2. UNDECIMATED BALANCED MULTIWAVELET TRANSFORM (UMWT)

Wavelets are obtained from single prototype called mother wavelet ψ(t) by dilations and shifting. Wavelets gained wide acceptance in image compression, signal processing because of its multi resolution nature. This results in use of wavelet coding schemes in applications where tolerable degradation and scalability are important. Scalar wavelets have a single scaling function ϕ(t) and wavelet function ψ(t), whereas multiwavelets may have two or more wavelet and scaling functions [22] [23]. There are two types of multiwavelets. They are Balanced multi wavelets and Unbalanced multi wavelets. In Unbalanced multiwavelets due to the application of the filter coefficients on the images in which the boundaries are not treated properly and they have dissimilar spectral characteristics of sub bands. Therefore the pre-processing step is required to treat the image boundaries properly before applying the filter coefficients [24]. This pre filter (pre-processing filter) may destroy the properties that a multiwavelet basis is designed to have [25]. Balanced multiwavelet eliminates the use of pre-filtering and they are computationally more efficient than unbalanced multiwavelet. Multiwavelet iterates on the low-frequency components generated by the previous decomposition level. In UMWT, down sampling and an up sampling process is absent during wavelet decomposition of an image.

L_0L_0	L_0L_1	L_0H_0	L_0H_1
L_1L_0	L_1L_1	L_1H_0	L_1H_1
H_oL_o	H_oL_1	H_oH_o	H_oH_1
H_1L_o	H_1L_1	H_1H_o	H_1H_1

Fig 1: Sub band distribution structure for undecimated MWT

After first level scalar wavelet decomposition, single low frequency sub band is present, whereas in multiwavelet decomposition, r^2 low frequency sub bands are present with each of size same as original image. The second level decomposition is obtained by applying the UMWT on the low frequency components of first level decomposition (L_0L_0, L_0L_1, L_lL_o, L_1L_1). In this situation, when r=2, a structure of 4(3*J+1) sub bands can be generated after J^{th} decomposition, and when J=1 the decomposition is as shown in figure1. In general '*r*' scaling functions can be written using the following vector notation.

$$\Phi(t) = [\Phi_1(t)\Phi_2(t)\Phi_3(t)......\Phi_r(t)]^T$$

Where ϕ (t) is called as multi scaling function. In the same way, '*r*' wavelet functions can be represented as follows. $\psi(t)=[\psi_1(t) \quad \psi_2(t) \quad \psi_3(t)........ \psi_r(t)]^T$. In general a scalar wavelet is represented with r=1. Most of the developed multiwavelet transforms use two scaling and wavelet functions but theoretically r can take any value. Similar to scalar wavelets, for *r*=2, the multi scaling function satisfies the following two scale equation:

$$\phi(t) = \sqrt{2}\sum_{-\infty}^{\infty} H_k \phi(2t-k) \tag{1}$$

$$\psi(t) = \sqrt{2}\sum_{-\infty}^{\infty} G_k \phi(2t-k) \tag{2}$$

Where H_k and G_k are 2x2 matrix filters defined as:

$$H_K = \begin{pmatrix} h_0(2k) & h_0(2k+1) \\ h_1(2k) & h_1(2k+1) \end{pmatrix}$$

$$G_K = \begin{pmatrix} g_0(2k) & g_0(2k+1) \\ g_1(2k) & g_1(2k+1) \end{pmatrix}$$

The matrix elements provide more degrees of freedom than a traditional scalar wavelet. These extra degrees of freedom is used to incorporate the useful properties into the multiwavelet filters, such as symmetry, orthogonality and high order of approximation. The undecimated multiwavelet transform is implemented through a filter bank structure as shown in figure 2. Where $L_0(z)$ and $L_1(z)$ are the transforms of the two low pass branch filters L_0 and L_1. Similarly, $H_0(z)$ and $H_1(z)$ are the transforms of the two high pass branch filters H_0 and H_1. In the time-varying filter bank implementation, the coefficients of the two low-pass and high-pass filters are simply interleaved at the output. However, in the 2-D transform case with r=2, sixteen sub bands are obtained instead of the usual four sub bands with scalar wavelet transforms. For second level decomposition one should apply UMWT over four low frequency sub bands which were obtained after first level decomposition.

3. DYNAMIC STOCHASTIC RESONANCE AND ITS MATHEMATICAL FORMULATION

In general there is an assumption that noise degrades the performance of a system. But recent studies have shown that in nonlinear systems, noise can be used for amplification of weak signals and in turn increases signal to noise ratio. SR occurs when SNR and input/output correlation have maximum value at certain noise level. This concept is well explained in [26]. Any system to exhibit stochastic resonance, it should possess the following three properties like, non linearity in terms of threshold, sub threshold signals like signals with small amplitude and a source of additive noise. This phenomenon occurs frequently in bi stable systems [26]. For lower noise intensities, weak signal is unable to cross the threshold results in low SNR and for higher noise intensities the output is dominated by noise which again results in low SNR. Whereas at moderate noise intensities noise allows the signal to cross the threshold results in maximum SNR at an optimum noise level as shown in figure 3a. A classic one dimensional nonlinear system that exhibits stochastic resonance is modeled with the help of Langevien equation of motion given below

$$\frac{dx(t)}{dt} = -\frac{dU(x)}{dx} + \sqrt{D}\xi(t) \tag{3}$$

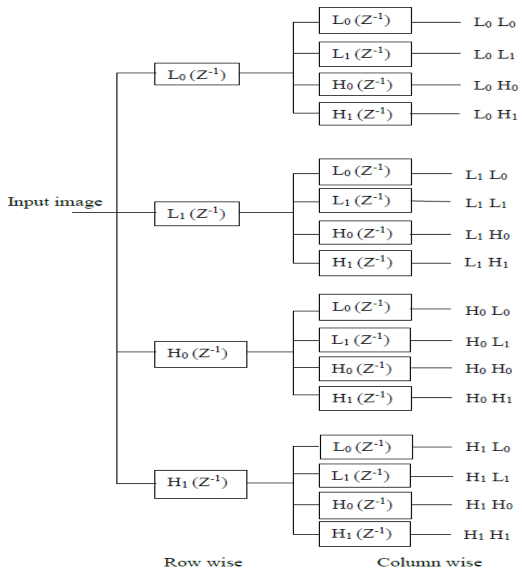

Fig 2. Undecimated MWT decomposition

In equation (3) U(x) is bi stable potential as shown in figure 3b and is given in the following equation. ξ(t) is additive zero mean stochastic fluctuation and D is the noise variance.

$$U(x) = -\frac{ax^2}{2} + \frac{bx^4}{4} \tag{4}$$

From the above equation, a and b are double well parameters. The double well system is stable at

$x = \pm\frac{\sqrt{a}}{b}$ separated by barrier of height $\Delta U = \frac{a^2}{4b}$, where $\xi(t) = 0$. Addition of periodic input signal $B\sin(\omega t)$ makes the bistable system time dependent such that its dynamics are governed by the following equation.

$$\frac{dx(t)}{dt} = -\frac{dU(x)}{dx} + B\sin(\omega t) + \sqrt{D}\xi(t) \tag{5}$$

where ω and B are frequency and amplitude of an input signal. It is assumed that small amplitude of signal is not enough so that in the absence of noise it is insufficient to move particle from one well to other. By substituting equation (4) in equation (5) one can get

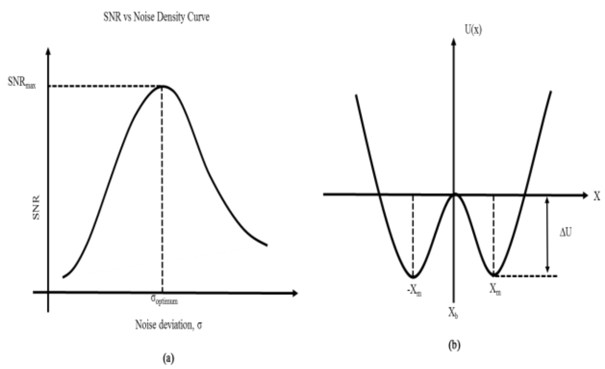

Fig. 3. (a) SNR vs noise standard deviation curve. The SNR is observed to follow a resonant nature (b) Bistable double potential well with two stable states

$$\frac{dx(t)}{dt} = [ax - bx^3] + B\sin(\omega t) + \sqrt{D}\xi(t) \tag{6}$$

The particle fluctuates around its local stable states in the absence of periodic force. The rate of transition of particle (r_k) between potential well under noise driven switching is given by

Kramer's rate [27] as shown in the following equation.

$$r_K = \frac{a}{\sqrt{2\pi}}\exp\left(-\frac{2\Delta U}{D}\right) \tag{7}$$

Noise driven switching between potential well takes place when weak periodic force is applied to unit mass particle in potential well and is synchronized with average waiting time

$$T_K(D) = \left(\frac{1}{r_k}\right)$$

between two noise driven inter well transitions that satisfies the time scale matching between the residence times of the particle in each well and signal frequency ω [28].

$$2T_K(D) = T_\omega \tag{8}$$

where $T\omega$ is the period of periodic force. The most important factor in stochastic resonance is SNR. The expression for SNR in DSR as derived from [29] is given in below equation.

$$SNR = \left[\frac{4a}{\sqrt{2}(\sigma_0\sigma_1)^2}\right]\exp\left(-\frac{a}{2\sigma_0^2}\right) \tag{9}$$

where σ_0 is standard deviation of internal noise of original bi stable system, σ_1 is the standard deviation of added noise in SR based system.

Maximum SNR is obtained when intrinsic parameter of dynamic double well system $a = 2\sigma_0^2$. Other parameter can be obtained from the parameter a, for a weak signal to ensure sub threshold condition required is $b = \frac{4a^3}{27}$. Solving equation (6) using Euler Maruyama's iterative discretized method [30] one can get

$$x(n+1) = x(n) + \Delta t\left[ax(n) - bx^3(n) + input(n)\right] \tag{10}$$

Where $input(n) = B\sin(\omega t) + \sqrt{D}\xi(t)$ denotes sequence of signal and noise. Δt is sampling time taken based on experimentation and initially $x(n) = 0$.

4. THE PROPOSED ENHANCEMENT ALGORITHM USING DSR AND UMWT

The various steps involved in the proposed method are as follows.

Step 1. The low contrast colour input image is projected into

HSV color space to ensure inherent colour preservation of the image and to minimize the computation complexity.

Step 2. The Value vector (V) is decomposed into sixteen sub bands (approximation and detail) using the analysis filter coefficients of undecimated balanced multi wavelet transform as given in Table 1.

Step 3. SR parameters are computed from all sixteen sub bands by assuming initial values for m, n and Δt. i.e. x(0)=0, Δt=0.15 for gray images and $1 \le \Delta t \le 5$ for color images, $a_s=k\times2\sigma_o^2$, $b_s=m\times4(a_s^3)/27$, where s ϵ L_0L_0, L_0L_1, L_0H_0, L_0H_1, L_1L_0, L_1L_1, L_1H_0, L_1H_1, H_oL_o, H_oL_1, H_oH_o, H_oH_1, H_1L_o, H_1L_1, H_1H_o, H_1H_1. The bistable parameters a_s and b_s are computed for each of the sixteen sub bands using its local variance (σ_0^2s). Here m is a factor much less than 1 to ensure sub threshold condition of the signal. k is a factor which denotes image region dullness and is given as (inverse of (variance × dynamic range)).

Step 4. Using dynamic stochastic resonance parameters, the tuned undecimated balanced multi wavelet transform sub band coefficients are found for all sixteen sub bands iteratively using equation given in (16).

$$x(n+1) = x(n) + \Delta t\left[ax(n) - bx^3(n) + UMWT_{coeff.}\right] \tag{11}$$

Step 5. Inverse UMWT is found for every iterated tuned set of UMWT coefficients using the synthesis filter coefficients.

Step 6. The conversion of HSV color space to RGB is performed on the synthesized image to obtain the contrast enhanced image.

Step 7. Compute F, PQM and CEF for the contrast enhanced image.

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 ± 2. For enhancing low contrast gray scale images the above steps are followed except step 1 and 6 and therefore UMWT is directly applied on it. The block diagram representation of the above proposed algorithm is also given in figure 4. For measuring the Peak Signal to Noise Ratio (PSNR) and Mean Square Error (MSE), distortion free image is required. Since such images are not available here, one cannot use such metrics for analysing the performance of the proposed enhancement technique. Therefore to analyse the performance of the proposed technique, relative contrast enhancement factor (F), perceptual quality metric (PQM) and color enhancement factor (CEF) were computed. Contrast enhancement (F) is based on global variance and mean of the original and enhanced images [7]. Image quality index has been used in calculating F. where image quality index Q is given as $Q = \frac{\sigma^2}{\mu}$. where σ and μ are standard deviation and mean of the image. Contrast enhancement factor is defined as the ratio of the quality index of the post enhanced image (Q_A) and the quality index of pre enhanced image (Q_B). In this work, no reference metric is used for judging the image quality termed as Perceptual Quality Metric (PQM) [31]. For good perceptual quality, PQM should be close to 10 ± 2. If the image is colored, one can measure the color enhancement of image using the metric called color enhancement factor (CEF). For typical color and contrast enhancement, the values of CEF and F should be greater than 1.

Table 1. Scaling and Wavelet filter coefficients

L_0	L_1	H_0	H_1
0.01513026672650	0.00044873488326	0.00666766359674	-0.00044873488326
-0.10232198801947	0.01089896516162	0.10321945778598	-0.01089896516162
0.10232198801947	-0.00303467520953	0.04509164359067	0.00303467520953
0.69197651446004	-0.07370681580507	-0.069804586487911	0.07370681580507
0.69197651446004	0.07415555068833	0.069804586487911	0.13138589511713
0.10232198801947	0.69924249123446	-0.04509164359067	-0.69077988810469
-0.10232198801947	0.69924249123446	-0.10321945778598	0.69077988810469
0.01513026672650	0.07415555068833	-0.00666766359674	-0.13138589511713
0	-0.07370681580507	0	-0.07370681580507
0	-0.00303467520953	0	-0.00303467520953
0	0.01089896516162	0	0.01089896516162
0	-0.00044873488326	0	-0.00044873488326

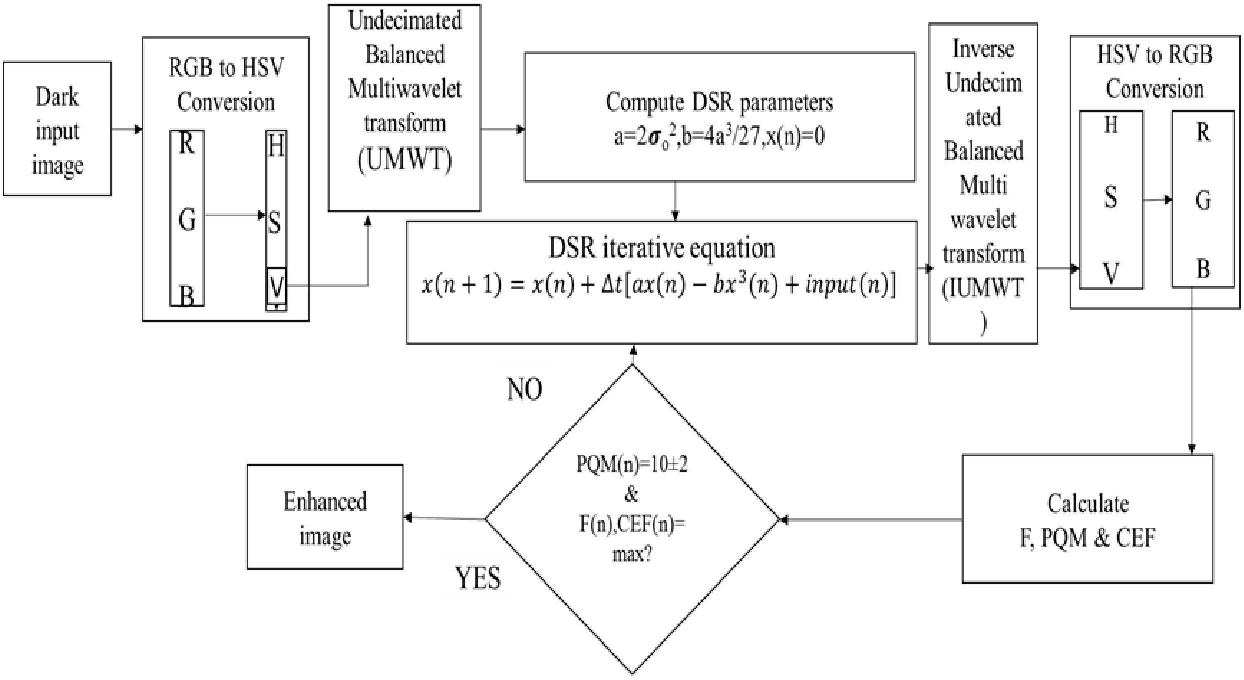

Fig 4. Block diagram of the Proposed algorithm

5. THE EXPERIMENTAL RESULTS AND DISCUSSION

The proposed method is implemented as an algorithm and tested on very dark gray level and colored images. Results obtained using proposed undecimated MWT based DSR technique on colored and very dark grayscale images have been compared with the results obtained for various enhancement techniques such as DWT based DSR technique (DWT-DSR) [32], DSR [19], Histogram equalization (HEQ), Gamma correction [10], Multiscale retinex (MSR) [33] and Retinex [11]. Figure 5 and 6 shows the results obtained using the proposed Undecimated MWT based DSR technique (UMWT-DSR) and the existing enhancement techniques for different dark gray and color images. Table. 2 shows the values of performance metrics obtained by proposed UMWT-DSR technique and by existing techniques for different color and dark gray images. The results show that the use of the undecimated multi wavelet transform gives significantly better results than the ones obtained with real scalar wavelets. Visual quality of the enhanced image by UMWT-DSR technique is significant. The reason behind this performance is that UMWT operates over more number of low frequency sub bands compared to scalar DWT. Further the size of the each sub band is same as that of the size of the original image.

The reason behind the reduction in computational complexity in UMWT based DSR is that the usage of more low frequency information. That is the availability of four low frequency sub bands in case of first level UMWT decomposition. The performance metrics obtained and computational complexity involved in first level UMWT based DSR are lesser compared to first level DWT based DSR and other existing techniques. The reason is, again as number of approximation sub bands are four and more information is available in approximation sub bands, F and PQM converges with lesser number of iteration (n).

The mechanism of contrast enhancement can be credited to the modification of UMWT coefficient distribution with DSR iterations. Likewise this algorithm can be used for second or higher level UMWT decomposition. Application of DSR to approximation coefficients affects both brightness and contrast of an image. DSR on detail sub band coefficients are helpful to enhance edges. If DSR is applied to higher levels, due to successive decrease in resolution, the computational complexity decreases, but best output is obtained only for first level decomposition. Therefore in this work results were presented only for first level decomposition.

The time taken for execution of UMWT based DSR is less compared to DWT based DSR and other techniques. As the number of iterations required for image enhancement is less in UMWT based DSR which results in reduction of number of multiplications and additions. For an image of size M×N the number of multiplications and additions for UMWT- DSR and DWT- DSR and other existing methods are given in the Table. III for the following system configuration. Processor: Intel (R) Core (TM) i3-4005U CPU @ 1.70GHz, Installed Memory (RAM): 4.00GB, System type: 64-bit Operating System, x64- based processor. where the term ‘n’ in Table. 3 represents the number of iterations. As the visual quality of the non wavelet based enhancement techniques are not so good, here no need to bother the time required for execution of those methods. For the implementation of DWT-DSR method, db1 wavelet is considered in this work.

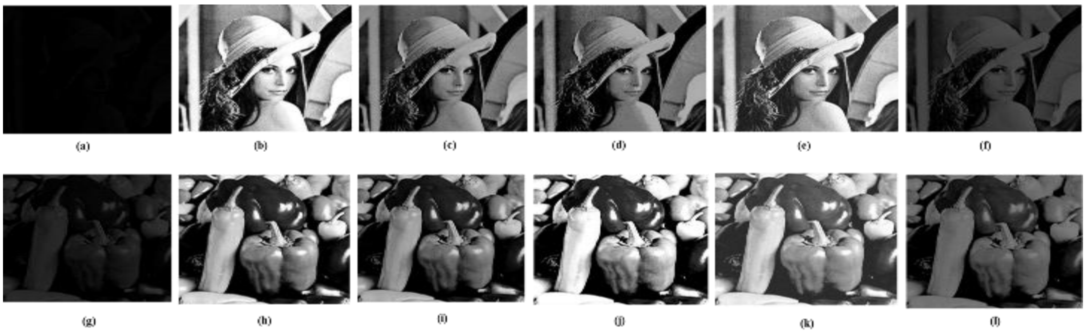

Fig. 5. Comparison of proposed method result with existing enhancement technique results for different dark gray images. (a), (g) -Input images, (b), (h) Proposed UMWT-DSR method, (c), (i) DWT-DSR technique, (d), (j) DSR technique (e), (k) HEQ technique, (f), (l) Gamma correction

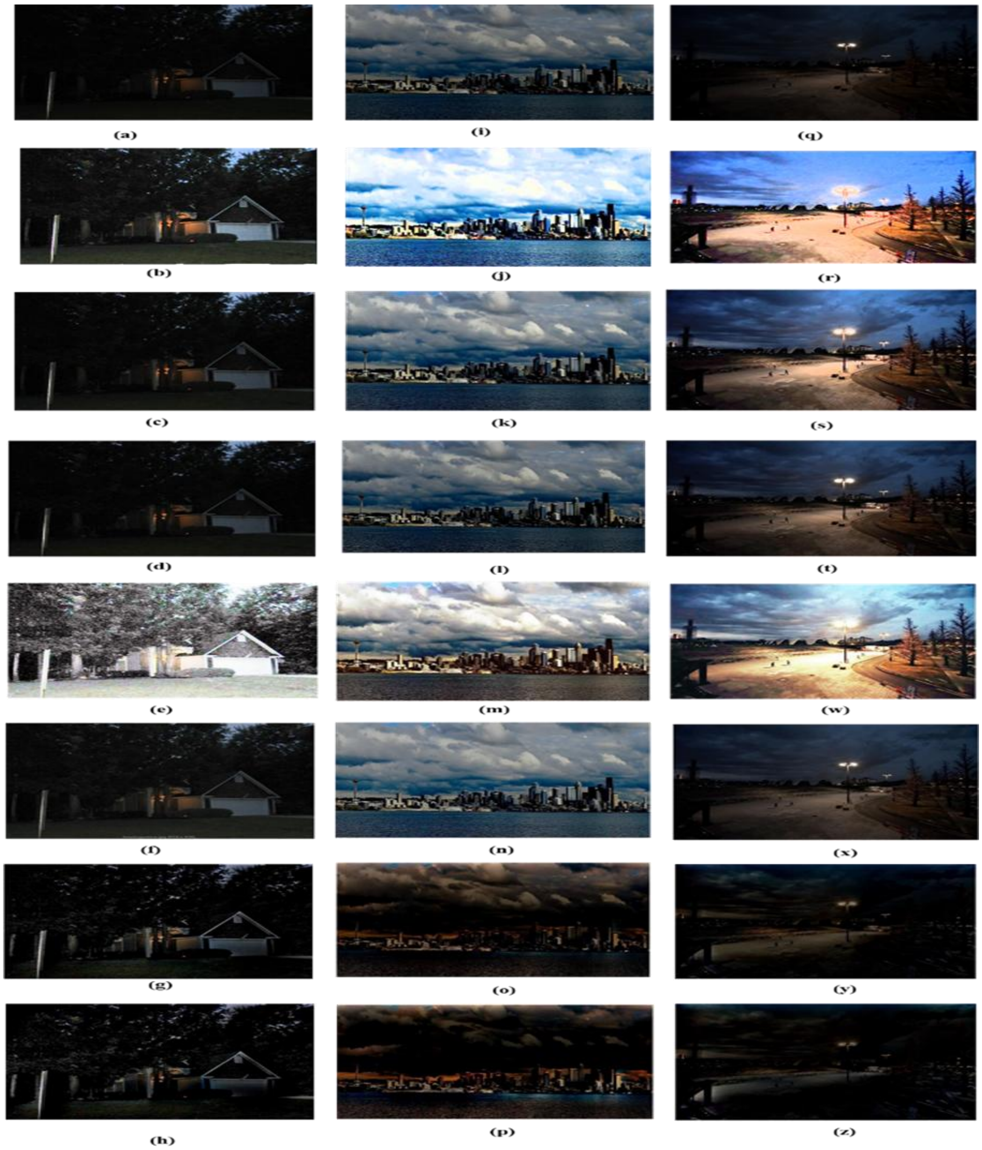

Fig. 6. Comparison of proposed method result with existing enhancement technique results for different color images. (a), (i), (q)- Input images, (b), (j), (r)-proposed method, (c), (k), (s)-DWT-DSR technique, (d), (l), (t)- DSR technique, (e), (m), (u)- HEQ technique, (f), (n), (v)- Gamma correction, (g), (o), (w)- MSR, (h), (p), (x)- Retinex.

Table 2. Performance comparison of proposed method with Existing Techniques

Name of the method	Performance Metrics	House	Sea settle	Foot ball	Lena	Peppers
Proposed UMWT-DSR method	F	2.14	1.85	3.53	10.8	5.0
	PQM	10.8	9.9	10.8	9.9	10.4
	CEF	3.0	2.0	6.48		
	No. of iterations	8	5	13	35	16
	Time taken for execution in seconds	22	5	28	23	18
DWT-DSR	F	1.36	1.34	2.8	8.9	3.72
	PQM	9.01	8.44	9.7	9	10.13
	CEF	1.4168	1.40	4.0		
	No. of iterations	42	29	117	45	17
	Time taken for execution in seconds	46.3	28	93	8.7	4.28
DSR	F	1.3	1.14	2.2	8.9	3.18
	PQM	9.9	9.78	10.9	9	10.48
	CEF	1.3	1.14	2.2		
	No. of iterations	56	42	100	45	14
	Time taken for execution in seconds	60	35	73	8.7	1.48
HEQ	F	2.5	1.8	2.9	9.0	2.74
	PQM	4.9	8.2	9.0	8.5	9.72
	CEF	3.4	1.2	4.5		
Gamma correction	F	0.9	0.9	1.1	3.6	2.22
	PQM	9.0	9.4	11.5	10.7	10.89
	CEF	1.2	1.3	1.5		
MSR	F	2.7	1.7	1.6	2.8	3.75
	PQM	8.1	9.6	11.3	8.7	10.59
	CEF	1.2	0.8	1.1		
Retinex	F	3.6	2.7	2.4	9.8	3.33
	PQM	8.2	9.2	10.9	8.9	11.25
	CEF	1.7	1.1	1.8	8.9	3.72

Table 3. Computations required for UMWT-DSR and DWT-DSR

Name of the method	No. of multiplications	No. of additions
UMWT- DSR	[M/2*N/2*5*16]*n	[M/2*N/2*3*16]*n
DWT- DSR	[M/2*N/2*5*4]*n	[M/2*N/2*3*4]*n

6. CONCLUSION

A technique for contrast enhancement of dark images using Undecimated Multiwavelet transform and dynamic stochastic resonance is proposed and its performance is explored in this paper. From the conducted exhaustive experiments, the results show that the use of the undecimated multi wavelet transform gives significantly better results than the ones obtained with real scalar wavelet based DSR and existing techniques. The reason behind this exceptional performance is that the proposed undecimated MWT based DSR enhancement technique operate over more number of low frequency sub bands compared to real scalar DWT. Addition to that undecimation leads to size of each sub band as the size of original image without any information loss. Comparison with various existing techniques reveals the latent and significant performance of the proposed technique in terms of the contrast quality, the color enhancement factor and the visual information. As a future work it is decided to focus on the enhancement of video.

7. ACKNOWLEDGMENTS

The authors express their gratitude to Mr. Sajan Pillai for providing images for testing the proposed technique. They also thank and acknowledge Rajlaxmi Chouhan for her valuable suggestions and support.

8. REFERENCES

[1] Simonotto, E., Riani, M., Charles, S., Roberts, M.., Twitty,J.., and Moss, F. 1997. Visual perception of stochastic resonance. Phys.Rev. Lett. 78, 1186-1189.

[2] Ye, Q., Huang, H., He, X., and Zhang, C. 2003. A sr-based radon transform to extract weak lines from noise

images. In Proc. IEEE Int. Conf. Image Processing. 5, 1849-1852.

[3] Hongler, M., Meneses, Y., Beyeler, A., and Jacot, J. 2003. Resonant retina: Exploiting vibration noise to optimally detect edges in an image. IEEE Trans. Pattern Analysis and Machine Intelligence. 25, 1051-1062.

[4] Ye, Q., Huang, H., and Zhang, C. 2004. Image enhancement using stochastic resonance. In Proc. IEEE Int. Conf. Image Processing. 1, 263-266.

[5] Peng, R., Chen, H., and Varshney, P. K. 2007. Stochastic resonance: An approach for enhanced medical image processing. In IEEE/NIH Life Science Systems and Applications Workshop. 1, 253-256.

[6] Rallabandi, V. P. S., 2008. Enhancement of ultrasound images using stochastic resonance based wavelet transform. Computerized medical imaging and graphics. 32, 316-320.

[7] Rallabandi, V. P. S., and Roy, P. K., 2010. Magnetic resonance image enhancement using stochastic resonance in Fourier domain. Computerized medical imaging and graphics. 28, 1361-1373.

[8] Ryu, C., Konga, S. G., and Kimb, H. 2011. Enhancement of feature extraction for low-quality fingerprint images using stochastic resonance. Pattern Recognition Letters. 32, 107-113.

[9] Lim, J. S., 1990. Two-Dimensional Signal and Image Processing. Englewood Cliffs. NJ: Prentice-Hall.

[10] Gonzales, R. C., and Woods, E., 1992. Digital Image Processing. Addison-Wesley.

[11] Jobson, D. J., Rahman, Z. and Woodell, G. A. 1997. Properties and performance of a center/surround retinex. IEEE Trans. Image Process. 6, 451- 462.

[12] Wolf, S., Ginosar, R., and Zeevi, Y. 1998. Spatio-chromatic image enhancement based on a model of human visual information system. J. Vis. Commun. 9, 25-37.

[13] Bockstein, I., 1986. Color equalization method and its application to color image processing. J. Opt. Soc. Amer. 3, 735-737.

[14] Mukherjee, J., and Mitra, S. K. 2008. Enhancement of color images by scaling the DCT coefficients. IEEE Transactions on Image Processing. 17, 1783-1794.

[15] Strickland, R. N., Kim, C. S., and McDonnell, W. F. 1987. Digital color image enhancement based on the saturation component. Opt. Eng., 26, 609-616.

[16] Tang, J., Peli, E., and Acton, S. 2003. Image enhancement using a contrast measure in the compressed domain. IEEE Signal Process. Lett. 10, 289-292.

[17] Peng, R., Chen, H., and Varshney, P. K. 2007. Stochastic resonance: An approach for enhanced medical image processing. In IEEE/NIH Life Science Systems and Applications Workshop. 1, 253-256.

[18] Ryu, C., Konga, S. G., and Kimb, H. 2011. Enhancement of feature extraction for low-quality fingerprint images using stochastic resonance. Pattern Recognition Letters. 32, 107-113.

[19] Jha, R. K., Biswas, P. K., and Chatterji, B. N. 2012. Contrast enhancement of dark images using stochastic resonance. IET Journal of Image Processing. 6, 230-237.

[20] Jha, R. K., Chouhan, R., and Biswas, P. K. 2012. Noise-induced contrast enhancement of dark images using non-dynamic stochastic resonance. In Proc. National Conference on Communications. 1-5.

[21] Benzi, R., Sutera, A., and Vulpiani, A. 1981. The mechanism of stochastic resonance. J. Phys. A, 14, 453-457.

[22] Strela, V., Heller, P. N., Strang, G., Topiwala, P., and Heil, C. 1999. The Application of Multiwavelet Filter Banks to Image Processing. IEEE Trans. on Image Processing. 8.

[23] Vasily Strela. 1996. Multiwavelets Theory and Applications. Moscow institute of physics and technology.

[24] Lahouari Ghouti, Ahmed Bouridane, Ibrahim, M. K., and Said Boussakta. 2006. Digital Image Watermarking Using Balanced Multiwavelets. IEEE Transactions on signal processing. 54.

[25] Selesnick, I. W. 2000. Balanced Multiwavelet Bases Based on Symmetric FIR Filters. IEEE Transactions on signal processing. 48.

[26] Gammaitoni, L., Hanggi, P., and Marchesoni, F. 1998. Stochastic resonance. Rev. Mod. Phys. 70, 223-270.

[27] Risken, H. 1984. The Fokkar Plank equation. Springer Verlag, Berlin.

[28] Jung, P., and Hanggi, P. 1991. Amplification of small signal via stochastic Resonance. Phys. Rev. A, 44, 8032-8042.

[29] Ye, Q., Huang, H., He, X., and Zhang, C. 2003. A SR-based radon transform to extract weak lines from noise images. Proc. IEEE Int. Conf. on Image Processing. Barcelona, Spain, 5, 1849-1852.

[30] Gard, T. C. 1998. Introduction to stochastic differential equations. Marcel-Dekker, New York.

[31] Wang, Z., Sheikh, H.R., and Bovik, A.C. 2002. No-reference perceptual quality assessment of jpeg compressed images. In Proc. IEEE Int. Conf. Image Processing, 1, 477-480.

[32] Rajlaxmi Chouhan, Pradeep kumar, C., Rawnak Kumar and Rajib Kumar Jha. 2012. Contrast Enhancement of Dark Images using stochastic Resonance in Wavelet Domain. International Journal of Machine learning and Computing, 2 711-715.

[33] Jobson, D. J., Rahman, Z., and Woodell, G. A. 1997. A multi-scale retinex for bridging the gap between color images and the human observation of scenes. IEEE Trans. Image Process. 6, 965-976.