Contrast Enhancement of Dark Images using Stochastic Resonance in Wavelet Domain

Rajlaxmi Chouhan, C. Pradeep Kumar, Rawnak Kumar, and Rajib Kumar Jha

***Abstract*—In this paper, a dynamic stochastic resonance (DSR)-based technique in discrete wavelet transform (DWT) domain is presented for the enhancement of very dark grayscale and colored images. Generally in DSR, the performance of an input signal can be improved by addition of external noise. However in this paper, the intrinsic noise of an image has been utilized for the purpose of contrast enhancement. The DSR procedure iteratively tunes the DWT coefficients using bistable system parameters. The DSR-based technique significantly enhances the image without introducing any blocking, ringing or spot artifacts. The algorithm has been optimized and made adaptive. Performance of the given technique has been measured in terms of distribution separation measure (DSM), target-to-background enhancement measure based on standard deviation (TBEs) and target-to-background enhancement measure based on entropy (TBEe). When compared with the existing enhancement techniques such as histogram equalization, gamma correction, single-scale retinex, multi-scale retinex, modified high-pass filtering and Fourier-based DSR, the DWT-based DSR technique gives better performance in terms of visual information, color preservation and computational complexity of the enhancement process.**

***Index Terms*—Dynamic stochastic resonance; contrast enhancement; discrete wavelet transform; noise1.**

I. Introduction

Image enhancement is required for better visualization of dark images to improve visual perception, interpretability and feature identification. Many images have very low dynamic range of the intensity values due to insufficient illumination and therefore need to be processed before being displayed. A large number of techniques have focused on the enhancement of gray level images in the spatial domain. These methods include histogram equalization, gamma correction, high pass filtering, low pass filtering, homomorphic filtering, etc. [1, 2]. Jobson et al. [3] has reported single-scale retinex theory that also leads to good contrast enhancement of an image. However, their technique is computationally intensive as it requires filtering with multi-scale Gaussian kernels and post-processing stages for adjusting colors. Techniques have also been reported in *R-G-B* space that uses equalization of the 3-D histograms [4].

The above mentioned enhancement techniques are based on spatial-domain. In particular, DCT domain provides the spectral separation, and due to this property it is possible to enhance features by treating different frequency components differently. Many algorithms can be found in literature that has been designed for both colored and gray-scale images in block DCT domain [5, 6, 7]. 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. Discrete wavelet transform has also found application in contrast enhancement of images [8].

Recently, a concept of physics called Dynamic Stochastic Resonance (DSR) has been used in image enhancement. Most of the de-noising algorithms suppress noise from the signal. The noise is usually thought to be a nuisance which disturbs the system. Stochastic resonance, on contrary, is a phenomenon in which noise can be used to enhance rather than *hinder* the system performance. Stochastic resonance is one such nonlinear phenomenon where the output signals of some nonlinear systems can be amplified by adding noise to the input.

First experiment of stochastic resonance for image visualization was noticed in [9]. They reported the outcome of a psychophysics experiment which showed that the human brain can interpret details present in an image contaminated with time varying noise and the perceived image quality is determined by the noise intensity and its temporal characteristics. In 2000 Piana *et al.* [10] described two experiments related to the visual perception of noisy letters. The first experiment found an optimal noise level at which the letter is recognized for a minimum threshold contrast [9]. In the second experiment, they demonstrated that a dramatically increased ability of the visual system in letter recognition occurs in an extremely narrow range of noise intensity. Qinghua *et al.* have used SR phenomenon for image enhancement of low contrast sonar images [11]. In this work, they have reported the image enhancement technique which showed that an additional amount of noise besides the noise of the image itself would be helpful to enhance low contrast images. In 2007 Peng *et al.* [12] reported a novel preprocessing approach to improve the low contrast medical images using stochastic resonance. The enhancement is improved by adding some suitable noise to

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the input image.

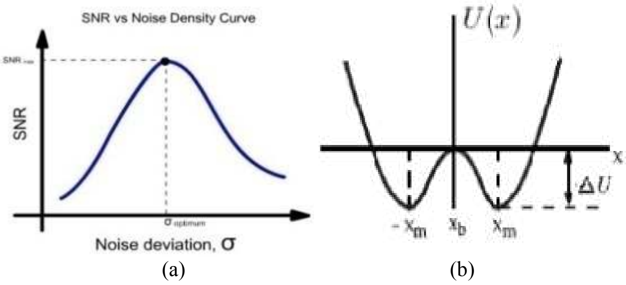
Recently, a stochastic resonance based technique in Fourier and wavelet domain for the enhancement of unclear diagnostic ultrasound and MRI images respectively is reported by Rallabandi [13, 14]. These methods can readily enhance the image by fusing a unique constructive interaction of noise and signal, and enable improved diagnosis over conventional methods [1, 2]. The approach well illustrates the novel potential of using a small amount of Gaussian noise to improve the image quality. Ryu *et al.* [15] has developed a new approach for enhancing feature extraction from low quality fingerprint images using stochastic resonance. Dynamic SR-based contrast enhancement of dark images in DCT and singular domain have been reported by [16] and [17] respectively.

In this paper, we have used a DSR-based adaptive algorithm in discrete-wavelet transform domain for enhancement of very dark images. This algorithm optimizes the bistable system parameters and maximizes performance by an iterative procedure.

II. Dynamic Stochastic Resonance

It was traditionally believed that the presence of noise can only make a system worse. However, recent studies have convincingly shown that in non-linear systems, noise can induce more ordered regimes that cause amplification of weak signals and increase the signal-to-noise ratio.

In order to exhibit stochastic resonance (SR), a system should possess three basic properties: a 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 bistable systems or in systems with threshold-like behavior [18]. The general behavior of SR mechanism shows that at lower noise intensities the weak signal is unable to cross the threshold, thus giving a very low SNR. For large noise intensities the output is dominated by the noise, also leading to a low SNR. But, for moderate noise intensities, the noise allows the signal to cross the threshold giving maximum SNR at some optimum additive noise level. Thus, a plot of SNR as a function of noise intensity shows a peak at an optimum noise level as shown in Fig. 1 (a).



(a) (b)

Fig. 1. (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.

A. Mathematical Formulation of DSR for Contrast Enhancement

A classic one-dimensional nonlinear dynamic system that exhibits stochastic resonance is modeled with the help of Langevin equation of motion given in [18, 19] in the form of (1) given below.

$$\frac{dx(t)}{dt} = -\frac{dU(x)}{dx} + \sqrt{D}\xi(t) \tag{1}$$

where U(x) is a bistable potential given in (2). D is the noise variance and *ξ(t)* is the noise.

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

Here, a and b are positive bistable double-well parameters. The double-well system is stable at $x_m = \pm\sqrt{\frac{a}{b}}$ separated by a barrier of height $\Delta U = \frac{a^2}{4b}$ when the *ξ(t)* is zero. Addition of a periodic input signal $[B\,sin(\omega t)]$ to the bistable system makes it time-dependent whose dynamics are governed by (3).

$$\frac{dx(t)}{dt} = -\frac{dU(x)}{dx} + Bsin(\omega t) \tag{3}$$

where B and ω are the amplitude and frequency of the periodic signal respectively.

It is assumed that the signal amplitude is small enough so that in the absence of noise it is insufficient to force a particle of unit mass (as shown in (4)) to move from one well to another. It, therefore, fluctuates around its local stable states.

$$\frac{dx(t)}{dt} = -\frac{dU(x)}{dx} + Bsin(\omega t) + \sqrt{D}\xi(t) \tag{4}$$

When a weak periodic force and noise are applied to the unit mass particle in the bistable potential well, noise-driven switching between the potential wells takes place only at some ‘resonant’ value of noise. This noise-induced hopping is synchronized with the average waiting time, between two noise-driven inter-well transitions that satisfies the time-scale matching between signal frequency and the residence times of the particle in each well [18]. Maximum SNR is achieved when $a = 2\sigma_0^{\,2}$. Thus SNR has maximum value at an intrinsic parameter, a, of the dynamic double well system. The other parameter b can be obtained using parameter a. For weak input signal, condition $b = 4a^3/27$. is required to ensure sub threshold condition [17].

Solving the stochastic differential equation given in eq. (4) after substituting *U(x)* from (2) using the stochastic version of Euler-Maruyama’s iterative discretized method as follows [14].

$$x(n+1) = x(n) + \Delta t\,[\,ax(n) - bx^3(n) + Input\,(n)] \tag{5}$$

where $Input(n) = Bsin(\omega t) + \sqrt{D}\xi(t)$ denotes the sequence of input signal and noise, with the initial condition being x(0) = 0. Here Δt is the sampling time, taken as 0.015 experimentally.

Considering the image enhancement scenario, one can imagine that the x-axis corresponds to the normalized pixel intensity value with respect to the threshold value that is defined as *x*=0, while proper selection of parameters *a, b* gives the strong signal state or enhanced images. The objective is to add stochastic fluctuation or noise to the pixel value of the weak signal state so that the pixel particle is activated, jumps over the detector threshold and transits to strong signal state or enhanced state.

B. Discrete Wavelet Transform

The 2-D Discrete Wavelet Transform (DWT) separates an image into a lower resolution approximation image (LL) as well as horizontal (HL), vertical (LH) and diagonal (HH) detail components. The process can then be repeated to compute multiple "scale" wavelet decomposition. Multi-resolution analysis analyzes the signal at different frequencies giving different resolutions. Wavelet transform decomposes a signal into a set of bases functions called *wavelets*. Wavelets are obtained from a single prototype wavelet $\psi(t)$ called mother *wavelet* by *dilations* and *shifting* [2]. One of the many advantages over the wavelet transform is that it is believed to more accurately model aspects of the HVS as compared to the FFT or DCT. The wavelet transform (WT) has gained widespread acceptance in signal processing and image compression. Because of their inherent multi-resolution nature, wavelet-coding schemes are especially suitable for applications where *scalability* and *tolerable degradation* are important. In this paper, we have explored the nature of DWT coefficients and their behavior to improve contrast of a dark image.

III. Proposed Adaptive DSR-based Algorithm

The proposed optimization algorithm for enhancement of dark images is as follows. Bistable parameters *a, b* and Δt are optimized with respect to each other and then number of iterations is optimized by an adaptive procedure. Note that $Input(n) = \ Bsin(\omega t) + \sqrt{D}\xi(t)$ in the iterative equation (5) denotes the sequence of input signal and noise, with the initial condition being $x_0 = 0$. This de-notion can be done keeping in view that the low contrast image is a noisy image containing internal noise due to lack of illumination. This noise is inherent in its DWT coefficients and therefore, the DWT coefficients can be viewed as containing signal (image information) as well as noise. The final stochastic simulation is obtained after optimum number of iterations.

A. Quantitative Characterization : Performance metrics

To gauge the quality of the DSR-based enhanced image, three quantitative measures such as distribution separation measure (DSM), target to back-ground contrast enhancement measure based on standard deviation (TBE_S), target to background contrast enhancement measure based on entropy (TBE_E) are used [20].

Other 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. These measures require distortion free image or reference image. Such images are not available in the current application. The mathematical expression for (DSM), (TBE_S) and (TBE_E) are given in (6)-(8).

$$DSM = (\mid \mu_T^E - \mu_B^E \mid) - (\mid \mu_T^O - \mu_B^O \mid) \tag{6}$$

$$TBE_S = \frac{\left(\frac{\mu_T^E}{\mu_B^E} - \frac{\mu_T^O}{\mu_B^O}\right)}{\frac{\sigma_T^E}{\sigma_T^O}} \tag{7}$$

$$TBE_E = \frac{\left(\frac{\mu_T^E}{\mu_B^E} - \frac{\mu_T^O}{\mu_B^O}\right)}{\frac{e_T^E}{e_T^O}} \tag{8}$$

where μ_T^E, μ_B^E, μ_T^O, μ_B^O represent the mean of the selected target and background region of the enhanced and original images respectively. σ_T^E, σ_T^O, e_T^E, e_T^O are respectively the standard deviations and entropies of target region of enhanced and original images. It is observed by Sameer *et al.* [20] that better the quality of the image more the DSM value. Other parameters (TBE_S) and (TBE_E) should be positive for good enhancement.

B. Algorithm

Step 1. Compute 1-level DWT decomposition of the input dark image.

Step 2. Application of DSR to DWT approximation coefficients

(a) Initialize x(0) = 0, $a = k \times 2\sigma_0{}^2$, $b = m \times 4a^3/27$. Here k is a number chosen experimentally initially, while m is a number less than 1 to ensure subthreshold condition of the signal. The value of k has been later inferred to be related to statistics of the input image itself.

(b) Using iterative equation given in (5) compute tuned DWT coefficients.

$$x(n+1) = x(n) + \Delta t\,[\,ax(n) - bx^3(n) + DWT\,coeff.] \tag{9}$$

(c) Repeat steps 2 (a)-(b) for three detail coefficient-sets LH, HL, HH.

(d) Compute inverse DWT from these enhanced coefficient sets to give enhanced image after *(n+1)^th* iteration. To make the algorithm adaptive, DSM is computed for output after every iteration. If DSM no longer increases and starts decreasing, that value of iteration is taken as optimum number. If the image is truecolor, repeat the above steps for all color bands.

Optimization of parameters *a, b* and Δt can be done by initializing some values of factors *k, m,* Δt and *n* and then varying one of them to reach highest DSM while keeping the other three parameters constant. In this way, optimized values of *a, b* and Δt can be obtained which later becomes a part of the adaptive iterative process.

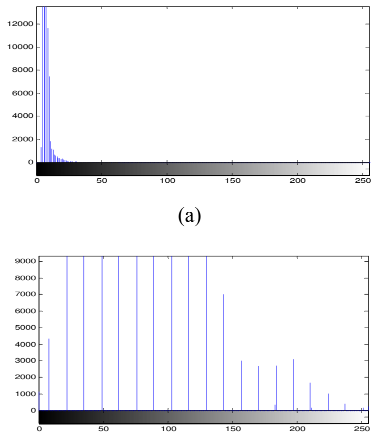
IV. Experimental results

Results obtained using proposed optimization based DWT-based DSR technique on very dark grayscale (Test 1-2, Test 5-6) and colored images (Test 3-4) have been shown in Fig. 2. All results were obtained by simulation of DSR-based technique on biorthogonal spline wavelet (9/7 filter bank) using MATLAB™ v.7.0.4. Test 1-4 are naturally dark images captured using Sony DSC H9 in poor illumination. Test 5 and 6 were obtained from the Internet and then edited to be made dark. Comparison with existing DFT-based DSR technique and non-DSR contrast enhancement techniques like histogram equalization (HE), gamma correction (GC), single-scale retinex (SSR), multi-scale retinex (MSR) and modified high-pass filtering (MHPF) have been displayed in Fig. 2. Graphs showing optimization of parameters *k, m,* Δt and iteration *(n)* have been displayed in Fig 3. Table 1 shows DSM values attained by DWT-based DSR technique and those obtained by other existing contrast enhancement techniques.

Fig. 2. Comparison of output enhanced image with other enhancement techniques. Test 1, 2, 5 and 6 are grayscale images. Test 3 and 4 are colored images.

TABLE I: DSM (AND ITERATION VALUES, N FOR DSR-BASED) FOR DWT-DSR AND OTHER EXISTING CONTRAST ENHANCEMENT TECHNIQUES

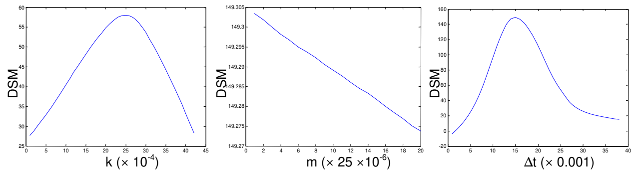
Tech-nique	Metric	Test 1	Test2	Test 3	Test 4	Test 5	Test 6
DWT-DSR	**DSM**	**56.97**	**5.5896**	**144.2**	**51.52**	**11.02**	**84.08**
	n	**50**	**250**	**450**	**400**	**350**	**100**
DFT-DSR	DSM	32.03	4.5758	92.50	8.012	4.463	88.40
	n	8000	8000	8000	8000	8000	8000
HE	DSM	55.77	4.9920	90.85	16.41	7.737	67.36
GC γ=1.5	DSM	45.98	9.04	116.8	24.26	11.61	83.4
SSR	DSM	28.61	3.6846	85.50	12.27	4.413	78.15
MSR	DSM	5.910	0.3910	20.11	6.771	1.156	13.14
MHPF	DSM	21.71	7.2688	63.18	12.83	1.546	56.94



(a)

(b)

Fig. 3. (a) Histogram of dark input image (Test1) (b) Histogram of DSR-enhanced image. The histogram of input dark image is narrow and accumulated at the darker end while that of enhanced output is more uniform and broad in distribution.



(a) (b) (c)

Fig. 4. Graph of (a) DSM vs. k (b) DSM vs. m (c) DSM vs. Δt (d) DSM vs. n for image Test 5. DSM is observed to be maximum at k=25 × 10^{-4}, m=10^{-6} and Δt=0.015. These are the optimum values of bistable parameters.

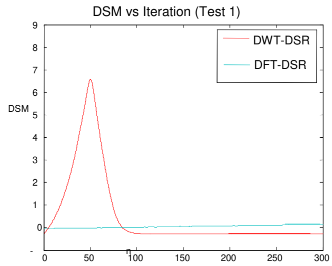


Fig. 5. Computational complexity of DWT-DSR technique w.r.t. existing DFT-DSR technique for Test 1 image. Note that DSM for DFT-DSR increases very slowly (almost zero) till 2000 iterations.

V. OBSERVATIONS

Output enhanced images obtained using the DWT-based DSR technique shows remarkable improvement in contrast and visual quality as shown in Fig. 2.

- All the curves of DSM versus bistable parameters are observed to be of resonant nature, i.e. increasing and reaching a peak, and then gradually decreasing.
- The DSM values of DSR on DWT coefficients are found to be higher than those obtained from other techniques. Optimized values of *k, m and Δt* are found to be 25 × 10^{-4}, 10^{-6} and 0.015 respectively for maximum DSM.
- Smoother output without any artifacts are observed using DWT-DSR enhancement technique.
- Computational complexity (number of iterations needed to reach a particular DSM value) of DWT-based technique is much lesser than that of DFT. For DFT-based technique, number of iterations is unacceptably high (as high as 8000) to reach a sensible perceptual quality.
- Optimum number of iterations is obtained respectively for all the images. For image Test 1, it is found to be 50.
- DWT-based DSR-technique is also observing d to retain color while DFT-based technique is found to lose all color information when applied to colored images.

VI. DISCUSSION

The mechanism of contrast enhancement can be attributed to the modification of DWT coefficient distribution with DSR iterations.

- This algorithm can similarly be used for 2 or higher level DWT but DSR should be applied to approximation coefficients only at one of the levels, preferably at level 1 as that has best resolution.

- Application of DSR to approximation coefficients affects both brightness and contrast of image in totality. DSR on detail coefficients is conducive to enhancement of edges. If DSR is applied to higher levels, due to successive decrease in resolution, the computational complexity decreases, but best output is obtained on level-1 approximation coefficients.
- All most all available wavelet filter banks were tested and found to give good results on application of DSR.
- The value of k can be initialized to be of the order of inverse of global variance of the dark input image.

VII. Conclusions

The adaptive DWT-based DSR technique can be used to give excellent enhancement of very dark images. This DSR-based technique used inherent noise (due to lack of illumination) of a dark image for implementing DSR. By adjusting the bistable system parameters a, b and Δt, remarkable enhancement can be obtained at minimum computational complexity. For both grayscale and colored dark images, it is found to give better visual perception and contrast quality than existing contrast enhancement techniques. When compared with existing DSR-based technique using DFT, DWT-based technique is observed to give colored output with much less computational complexity. This technique can therefore be considered highly suitable for contrast enhancement of very dark grayscale and colored images.

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