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Contrast enhancement of dark images using stochastic resonance

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Abstract: Two stochastic resonance (SR)-based techniques are introduced for enhancement of very low-contrast images. In the proposed SR-based image enhancement technique-1, an expression for optimum threshold has been derived. Gaussian noise of increasing standard deviation has been added iteratively to the low-contrast image until the quality of enhanced image reaches maximum. A quantitative parameter 'distribution separation measure (DSM)' is used to measure the enhancement quality. In order to reduce the required number of iterations in the second enhancement technique the author's have derived an expression for optimum noise standard deviation σ_{optimum} that maximises signal-to-noise ratio (SNR). Image enhancement is obtained by iterating only with few noise standard deviations around σ_{optimum}. This reduces number of iterations drastically. Comparison with the existing methods shows the superiority of the proposed method.

1 Introduction

Some features are hardly detectable from very low-contrast image by human eyes. Therefore it is needed to enhance the contrast before display. This can be done by many methods like adaptive histogram equalisation, un-sharp masking, constant variance enhancement, homomorphic filtering, high-pass, low-pass filtering etc. [1, 2]. It has been observed that each method is restricted to some kind of images and for some particular enhancement application. For example, the method based on log transforms given in [3] is used for mainstream digital cameras for capturing high dynamic scenes. Methods based on wavelet transform described in [4, 5] are used for enhancement of medical images like mammography. The strengths and weaknesses of these methods were also pointed out. It has also been mentioned that the log transforms increases the contrast very well at low intensity range but compresses the contrast at high intensity range. In histogram equalisation brightness of an image can be changed, which is mainly because of the flattening property of the histogram equalisation. Wavelet-based algorithms offer the capability of modifying/enhancing image components adaptively based on their spatial-frequency properties. The dynamic range and local contrast in wavelet domain is not adjusted properly. The Retinex method is efficient for dynamic range compression, but does not provide good tonal rendition [6]. The multi-scale Retinex combines several single-stage Retinex outputs to produce a single output image which has good dynamic range compression, good tonal rendition [6] and colour constancy [7]. In addition to these existing techniques for enhancement, stochastic resonance (SR) is also applied for contrast enhancement of very low-contrast images [8–14].

In recent time the surveillance systems are in demand for security and safety. The problems of remote surveillance have received growing attention, especially in the context of public infrastructure and monitoring. For surveillance application, in the night time at the harbour or at the line of control, SR algorithm is useful to enhance very low-contrast images (approximately dark image). SR-based contrast enhancement has two advantages over the other enhancement techniques. First, it is able to enhance very low-contrast images. This is because, in this approach random noise is added to all pixels of very low-contrast image and then thresholded the noisy image. Since the added noise is random, so, the thresholded image for individual random noise is different. Now, multiple noisy threshold images are averaged, which is basically non-linear averaging. The error generated owing to non-linearity (threshold) (in one noisy image) is minimised by averaging of different thresholded noisy images. Hence, it enhances specially those regions where pixels information are very very less. Second, there is no blocking or spot kind of artefacts introduced in SR-enhanced image. This is because of averaging operation or linearity operation of multiple thresholded images.

In this paper two novel enhancement techniques are investigated. Both these techniques are based on conventional SR phenomenon. The experimental results of both these enhancement techniques are compared to the existing techniques such as histogram equalisation, gamma correction, frequency selective modified high-pass filtering, Retinex and multi-Retinex.

To reduce the time complexity of the enhancement algorithm, a new SR-based enhancement algorithm is proposed. The new method is based on goodness of the noisy low-contrast image, which is a statistical approach. This approach focuses on finding the overall goodness of noisy image, which describes the optimal noise standard deviation for enhancement of very low-contrast images. Since, the optimal noise intensity is known approximately, the number of iterations with different noise intensities are less and hence the computation time is significantly reduced.

Rest of the paper is organised as follows. Section 2 introduces the basics of non-linear non-dynamic SR. Section 3 describes the proposed SR phenomenon in a mixture of n sinusoids. Section 4 elaborates the proposed SR-based enhancement method-1. Section 5 provides proposed method-2 for enhancement of low-contrast images. Simulation results are given in Section 6. The final Section 7 concludes the paper.

2 Non-linear non-dynamic SR

SR is classified into three categories. These are non-linear dynamic SR [15], non-linear non-dynamic SR [15, 16] and suprathreshold SR [17]. The general block diagram of non-linear non-dynamic SR phenomenon is shown in Fig. 1. It consists of input signal, random noise and threshold. Moss *et al.* [15] and Jung *et al.* [16] described non-linear non-dynamic SR phenomenon, and set a rule which can be seen in Fig. 2.

The rule is the following: whenever sum of signal and noise crosses the threshold a rectangular pulse is obtained as shown in Fig. 2*a* and *b*, respectively. The pulse indicates the unidirectional threshold crossing of the combination of signal and noise. This type of non-dynamic SR is called threshold-based SR. The power spectrum of rectangular pulse train is a sinc function. Moss *et al.* [15] and Jung [16] derived an expression for signal-to-noise ratio (SNR) in a threshold-based SR system as discussed below.

There are two major assumptions for deriving SNR for non-dynamic system. (i) signal frequency $\omega \ll \langle v \rangle$, where $\langle v \rangle$ is the mean threshold crossing rate of Gaussian noise,

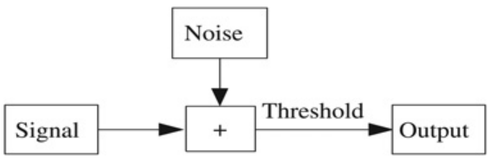

Fig. 1 *Block diagram of non-dynamic SR*

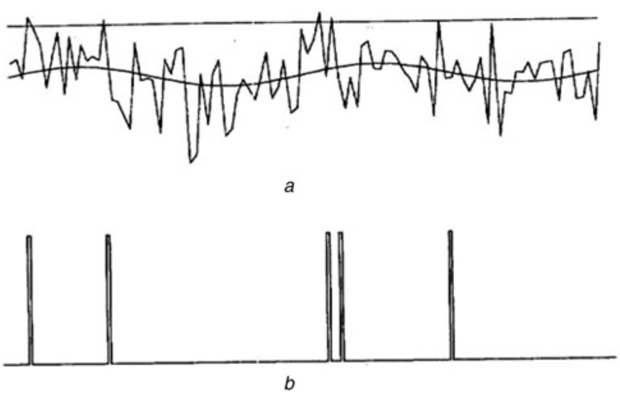

Fig. 2 *Threshold realisation of stochastic resonance*

a Sub-threshold signal ($B\sin\omega t$), threshold (straight line) and random noise
b Rectangular pulses which mark the threshold crossing of signal and noise

and (ii) the width of the pulses τ is narrow, that is, $\tau \ll \langle v \rangle^{-1}$. The theory of non-dynamic SR begins with a classical formula given by Rice [18], for mean threshold crossing rate of Gaussian noise with cut-off frequency f_0 as given in (1)

$$\langle v \rangle = \exp\left[-\frac{\Delta^2}{2\sigma^2}\right]\sqrt{\frac{\int_0^\infty f^2 S(f)\mathrm{d}f}{\int_0^\infty S(f)\mathrm{d}f}} \tag{1}$$

In (1), Δ is the threshold, σ is the standard deviation of noise and $S(f)$ is the power spectral density of Gaussian noise. The individual threshold crossing event is marked by a small rectangular pulse of width τ and height A. Under the above-mentioned assumptions the power spectrum of the pulse train corresponding to Gaussian noise is defined by the Campbell's pulse noise theorem [15, 19], which is given by

$$P_\mathrm{n}(f) \cong \frac{1}{2}A^2\tau^2\langle v \rangle = \frac{1}{2}A^2\tau^2\frac{f_0}{\sqrt{3}}\exp\left(-\frac{\Delta_0^2}{2\sigma^2}\right) \tag{2}$$

where τ is the pulse width, A is the pulse amplitude and σ is the standard deviation of the Gaussian noise.

This is the noise spectra at low-frequency or no frequency modulation. So, the mean amplitude of the random pulse train is given by

$$\langle V \rangle = [A\tau\langle v \rangle] = \left[A\tau\frac{f_0}{\sqrt{3}}\right]\exp\left(-\frac{\Delta^2}{2\sigma^2}\right) \tag{3}$$

The pulse sequence is generated in the threshold-based system as the sum of Gaussian noise and sinusoidal signal $B\sin(\omega t)$ of frequency ω crosses the threshold Δ. So, if a sub-threshold signal $B\sin(\omega t)$ is added to the Gaussian noise, then Moss *et al.* [15] have shown that the power spectrum of the output pulse train is given by

$$P_\mathrm{s}(f) = \frac{A^2\tau^2 f_0^2}{3}\left[\left(\frac{\Delta_0 B}{\sigma^2}\right)^2\delta(\omega) + \left(\frac{B}{4\sigma^2}\right)^2\delta(2\omega)\right]\exp\left(-\frac{\Delta_0^2}{\sigma^2}\right) \tag{4}$$

From (2) and (4), they computed the SNR as

$$\mathrm{SNR} = \frac{P_\mathrm{s}(f)}{P_\mathrm{n}(f)} = \frac{2f_0\Delta_0^2}{\sqrt{3}\sigma^4}[B^2]\exp\left(-\frac{\Delta_0^2}{2\sigma^2}\right) \tag{5}$$

where P_s is the signal power, P_n is the noise power, B is the signal amplitude, σ^2 is the noise variance and Δ_0 is the threshold value, where $\Delta = \Delta_0 + B\sin(\omega t)$

3 Proposed SR phenomenon in a mixture of *N* sinusoids

Any random signal can be represented by sum of its sinusoidal components of different frequency, amplitude and phase. Same is true in case of images also. Hence, we discuss in this section the SR phenomenon in a mixture of N sinusoidal signals of different frequency, amplitude and phase.

Following the approach of Moss *et al.* [15] we have derived the expression for SNR when the sub-threshold input signal is a mixture of sinusoids of different frequencies, amplitudes

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and phases. Thus the input signal in this case is given by

$$\sum_{i=1}^{N} B_i \sin(\omega_i t - \phi_i) \tag{6}$$

For simplicity, we consider only two sinusoids for derivation of SNR expression. As the Gaussian noise modulated by input signal (6), crosses threshold Δ_0 produces a sequence of output pulses. Thus, according to the modulation theory, the present problem can be viewed as a level crossing problem of the pure noise modulated by input signal (6) of the threshold level Δ_0. In case of two input sinusoids the new threshold will be

$$\Delta_{\text{new}} = \Delta_0 + B_1 \sin(\omega_1 t + \phi_1) + B_2 \sin(\omega_2 t + \phi_2)$$

This modulates the mean threshold crossing rate ν at signal frequencies. Since, mean amplitude of the pulse train $V(t)$ depends on mean-threshold crossing rate ν, and so, $V(t)$ will also get modulated. The mean amplitude of the pulse trains $\langle V\rangle(t)$ is given by

$$\begin{aligned}
\Rightarrow \langle V\rangle(t) &= A\tau\langle\nu\rangle \\
&= \frac{A\tau f_0}{\sqrt{3}} \exp\left[-\frac{[\Delta_0 + B_1\sin(\omega_1 t + \phi_1) + B_2\sin(\omega_2 t + \phi_2)]^2}{2\sigma^2}\right] \\
&= \frac{A\tau f_0}{\sqrt{3}} \exp\left[-\frac{\Delta_0^2}{2\sigma^2}\right] \\
&\quad \times \exp\left[-\frac{B_1^2\sin^2(\omega_1 t + \phi_1) + B_2^2\sin^2(\omega_2 t + \phi_2)}{2\sigma^2}\right] \\
&\quad \times \exp\left[-\frac{2\Delta_0 B_1\sin(\omega_1 t + \phi_1) + 2\Delta_0 B_2\sin(\omega_2 t + \phi_2)}{2\sigma^2}\right] \\
&\quad \times \exp\left[-\frac{2B_1B_2\sin(\omega_1 t + \phi_1)\sin(\omega_2 t + \phi_2)}{2\sigma^2}\right] \\
&= \frac{A\tau f_0}{\sqrt{3}} \exp\left[-\frac{\Delta_0^2}{2\sigma^2}\right]\left[1 - \frac{B_1^2}{4\sigma^2} - \frac{B_2^2}{4\sigma^2}\right] \\
&\quad + \left[\frac{B_1^2}{4\sigma^2}\cos 2(\omega_1 t + \phi_1)\right] + \left[\frac{B_2^2}{4\sigma^2}\cos 2(\omega_2 t + \phi_2)\right] \\
&\quad + \left[\frac{\Delta_0 B_1 \sin(\omega_1 t + \phi_1)}{\sigma^2}\right] + \left[\frac{\Delta_0 B_2 \sin(\omega_2 t + \phi_2)}{\sigma^2}\right] \\
&\quad - \left[\frac{B_1B_2}{\sigma^2}\cos[(\omega_1 - \omega_2)t + \phi_1 - \phi_2]\right. \\
&\quad \left. + \cos[(\omega_1 + \omega_2)t + \phi_1 + \phi_2]\right]
\end{aligned}$$

The power corresponding to this amplitude is the square of the modulus of Fourier transform of $\langle V\rangle(t)$

$$\begin{aligned}
\Rightarrow P_s = &\left[\frac{A^2\tau^2 f_0^2}{3}\exp\left(-\frac{\Delta_0^2}{\sigma^2}\right)\right]\left(\frac{\Delta_0 B_1}{\sigma^2}\right)^2 \delta(\omega - \omega_1)\ldots\ldots \\
&+ \left(\frac{\Delta_0 B_2}{\sigma^2}\right)^2 \delta(\omega - \omega_2) + \left(\frac{B_1 B_2}{\sigma^2}\right)^2 \\
&\times [\delta(\omega - (\omega_1 - \omega_2))\ldots\ldots + \delta(\omega - (\omega_1 + \omega_2))] \\
&+ \left(\frac{B_1^2}{4\sigma^2}\right)^2 \delta(\omega - 2\omega_1) + \left(\frac{B_2^2}{4\sigma^2}\right)^2 \delta(\omega - 2\omega_2)
\end{aligned}$$

In the above expression, total number of frequency components are six. Considering only the fundamental frequencies ω_1 and ω_2, output SNR is given below

$$\text{SNR} = \frac{2f_0\Delta_0^2}{\sqrt{3}\sigma^4}[B_1^2 + B_2^2]\exp\left(-\frac{\Delta_0^2}{2\sigma^2}\right) \tag{7}$$

The phase term of the input sinusoids only add to the phase part, amplitudes remain the same. Generalising (7) for N sinusoids as input signal, we obtain a generalised SNR expression given below

$$\text{SNR} = \frac{2f_0\Delta_0^2}{\sqrt{3}\sigma^4}[B_1^2 + B_2^2 + B_3^2 + \cdots + B_N^2]\exp\left(-\frac{\Delta_0^2}{2\sigma^2}\right) \tag{8}$$

If the input signal is a combination of N different sinusoids with different amplitudes, phase and frequency, the total number of spikes in the frequency spectrum will be $[N + {}^{N+1}C_2 + {}^{N}C_2]$. The number of fundamental frequency components will be equal to the number of input sinusoids.

A plot of SNR against noise strength (noise standard deviation) ($\Delta_0 = 0.45$) is shown in Fig. 3. Plot is drawn for two different cases, with a single sinusoid as input signal and with sum of two sinusoids as input. In both the cases it is observed that SNR value reaches a peak for optimal noise strength ($\sigma = 0.60$).

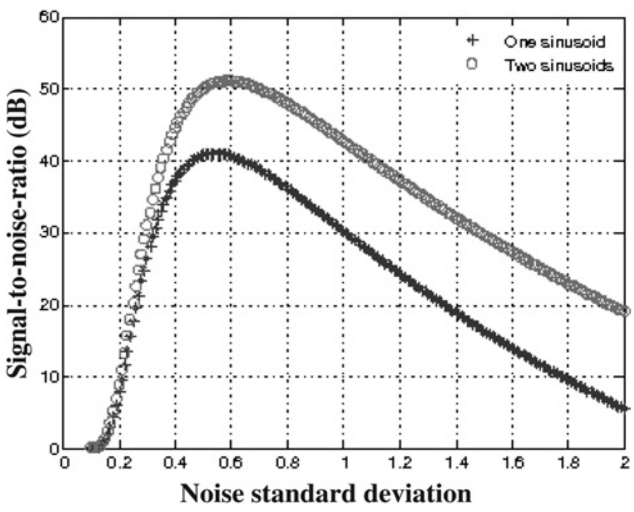

Fig. 3 *SNR for a sinusoidal signal and combination of two sinusoidal signals under different noise standard deviation*

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4 SR-based image enhancement technique-1

This section discusses the first proposed technique for enhancement of images. In Section 3 it was mentioned that any random signal can be represented as sum of sinusoidal components of different frequency, amplitude and phase. Same is true for images also. When a Gaussian noise of standard deviation σ is added to the image and the noise added image is thresholded the SNR of output signal is given by (8) which is of the form

$$\mathrm{SNR} = \frac{P_s(f)}{P_n(f)} = \frac{2f_0\Delta_0^2}{\sqrt{3}\sigma^4}\sum_{i=1}^{N}[B_i^2]\exp\left(-\frac{\Delta_0^2}{2\sigma^2}\right) \quad (9)$$

where B_i is the amplitude of ith sinusoidal component of input signal.

Fig. 3 demonstrates that SNR value reaches a peak for a specific value of σ. This observation motivates us to use SR phenomenon for image enhancement.

Equation (9) is used to obtain the threshold expression (Δ_0) for image enhancement. The SNR expression given in (9) is derived for a train of identical pulses, which is similar to neural action potentials determined by a combination of random and weakly coherent processes [15, 20, 21]. The theory is based on the power spectrum of the pulse train and it suggests that the brain may make use of a similar computation while processing noisy images. Simonotto *et al.* [22] reported the outcome of a psychophysics experiment which showed that the brain can interpret details present in a stationary image contaminated with time varying noise and the perceived image quality is strongly determined by noise intensity and its temporal characteristics.

To obtain an expression for threshold we replace P_n in (9) by $P_n = \sigma^2/f_0$ leading to (10) as given below

$$\Rightarrow \sqrt{3}P_s\sigma^2 = 2\Delta_0^2\sum_{i=1}^{N}(B_i^2)\exp\left(-\frac{\Delta_0^2}{2\sigma^2}\right) \quad (10)$$

Expanding the exponential of (10) to obtain

$$\Rightarrow \sqrt{3}P_s\sigma^2 = 2\Delta_0^2\sum_{i=1}^{N}(B_i^2)\left[1-\frac{\Delta_0^2}{2\sigma^2}+\frac{\Delta_0^4}{4\sigma^4}+\cdots\right] \quad (11)$$

As $\Delta_0 \ll \sqrt{2}\sigma$ we can neglect the higher order terms to obtain a simplified expression (12)

$$\Rightarrow \sqrt{3}P_s\sigma^2 = 2\Delta_0^2\sum_{i=1}^{N}(B_i^2)\left[1-\frac{\Delta_0^2}{2\sigma^2}\right] \quad (12)$$

Ignoring the negative value, the solution for Δ_0 is given by

$$\Rightarrow \Delta_0^4 - 2\Delta_0^2\sigma^2 + \frac{\sqrt{3}P_s\sigma^4}{\sum_{i=1}^{N}(B_i^2)} = 0 \quad (13)$$

$$\Rightarrow \Delta_0 = \pm\sigma\sqrt{1\pm\sqrt{1-\frac{\sqrt{3}P_s}{\sum_{i=1}^{N}(B_i^2)}}} \quad (14)$$

Considering only the positive value of Δ_0 we obtain two solutions

$$\Rightarrow \Delta_{01} = \sigma\sqrt{1-\sqrt{1-\frac{\sqrt{3}P_s}{\sum_{i=1}^{N}(B_i^2)}}} \quad (15)$$

$$\Rightarrow \Delta_{02} = \sigma\sqrt{1+\sqrt{1-\frac{\sqrt{3}P_s}{\sum_{i=1}^{N}(B_i^2)}}} \quad (16)$$

In our simulation for enhancement, Δ_{01} is considered as it fulfils $\Delta_{01} \ll \sqrt{2}\sigma$ criteria. The threshold expression of (15) depends on the external noise standard deviation, input signal power and sum of squares of amplitudes of sinusoidal signal of low-contrast image.

4.1 Quantitative measures for enhanced image

To determine the quality of the SR-based enhanced image, three quantitative measures such as distribution separation measure (DSM), target to background-contrast enhancement measure based on standard deviation ($\mathrm{TBE_S}$), target to background-contrast enhancement measure based on entropy ($\mathrm{TBE_E}$) are used [23]. Other performance measures such as peak signal-to-noise-ratio, mean-square-error, structural similarity index measure, 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, $\mathrm{TBE_S}$ and $\mathrm{TBE_E}$ are given in equations: (17)–(19)

$$\mathrm{DSM} = (|\mu_T^E - \mu_B^E|) - (|\mu_T^O - \mu_B^O|) \quad (17)$$

$$\mathrm{TBE_S} = \left(\frac{(\mu_T^E/\mu_B^E) - (\mu_T^O/\mu_B^O)}{\sigma_T^E/\sigma_T^O}\right) \quad (18)$$

$$\mathrm{TBE_E} = \left(\frac{(\mu_T^E/\mu_B^E) - (\mu_T^O/\mu_B^O)}{e_T^E/e_T^O}\right) \quad (19)$$

Here, μ_T^E, μ_B^E, μ_T^O, μ_B^O, σ_T^O, σ_T^E, e_T^O, e_T^E represent the mean of the selected target region of the enhanced image, mean of the selected background region of the enhanced image, mean of the selected target region of the original image, mean of the selected background region of the original image, standard deviation of the target region of the original and enhanced image and entropy of the target region of the original and enhanced image, respectively. It is observed by Sameer *et al.* [23] that better the quality of the image more the DSM value. Other parameters ($\mathrm{TBE_S}$) and ($\mathrm{TBE_E}$) should be positive for good enhancement.

4.2 Simulation steps

The simulation steps of adaptive SR-based image enhancement technique is given below.

- *Step-1.* Very low-contrast image $I(x, y)$ is taken as an input image. Set $\sigma = M/2$ where M is average image intensity value. DSM = 0.10.
- *Step-2.* Gaussian random noise, $\xi(x, y)$, of mean zero and different standard deviation, σ is added to the low-contrast image $I(x, y)$. N different noisy low-contrast images are generated for single noise standard deviation.

• *Step-3*. Each noisy image is thresholded using the threshold value obtained using (15) as given below

$$I'(x, y) = \begin{cases} 255, & \text{if } I(x, y) + x(x, y) \geq \Delta_{01} \\ 0, & \text{if } I(x, y) + x(x, y) < \Delta_{01} \end{cases} \quad (20)$$

• *Step-4*. The N thresholded images are averaged to obtain the enhanced image. In our simulation $N = 30$ is considered which is experimentally obtained number. If more than 30 noisy frames are taken, there is not appreciable improvement in quality, (DSM), of the enhanced image. If less than 30 noisy frames are taken then quality, (DSM), of the enhanced image reduced.

• *Step-5*. To make enhancement algorithm adaptive, DSM [23] of the individual output enhanced image is calculated. If DSM value is more than previous DSM value the algorithm from *Step-2–Step-4* are repeated with noise standard deviation $\sigma = (M/2) + 1$ till DSM value starts decreasing. The image with maximum DSM value is the final enhanced image.

Fig. 4 *Comparative results on very low-contrast test-1 colour image*

a Very low-contrast test-1
b SR enhanced
c Histogram equalised (HE)
d Gamma correction (Gamma)
e Retinex (Retinex)
f Modified high pass filtered (MHPF)

5 SR-based image enhancement technique-2

In the SR-based enhancement technique presented in Section 4, number of iterations required is quite high as the enhancement operation is to be tried with increasing noise strength until DSM value reaches the peak. This increases the computation time. To reduce computation time a second approach, SR-based image enhancement technique-2, is presented in this section. In this approach we try to estimate an optimum noise strength (noise standard deviation) which needed to be added to the low-contrast image for proper enhancement. The estimation of optimum noise strength is discussed below.

5.1 Optimum noise strength estimation

SR-based enhancement technique works on the principle of addition of noise to the signal and subsequently thresholding it. Averaging of a large number of such thresholded frames gives the enhanced image. The basic purpose of image enhancement is to increase the dynamic range of intensity values. So, any enhancement technique tries to push the higher intensity values towards maximum

Fig. 5 *Comparative results on very low-contrast Lena image*

a Very low-contrast Lena
b SR enhanced
c Histogram equalised (HE)
d Gamma correction (Gamma)
e Retinex (Retinex)
f Modified high pass filtered (MHPF)

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and lower intensity values towards minimum. Let us consider the following situation:

$I(x, y)$ is the input low-contrast image and μ is the average intensity value of $I(x, y)$. We partition the pixels in $I(x, y)$ in two groups $I_l(x, y)$ and $I_h(x, y)$. $I_l(x, y)$ contains those pixels from $I(x, y)$ whose intensity values are less than μ and $I_h(x, y)$ contains those pixels from $I(x, y)$ whose values are more than μ. As discussed before enhancement operation should push the intensity values in $I_h(x, y)$ towards maximum. In SR-based technique, as random noise $\xi(x, y)$ is added to the image, we can have the following two situations

$$I_h(x, y) + \xi(x, y) > \Delta \tag{21}$$

$$I_l(x, y) + \xi(x, y) > \Delta \tag{22}$$

where Δ is the considered as $[\max[I_h(x,y)] + \max[I_l(x,y)]]/2$. Equation (21) leads to enhancement, whereas (22) introduces error. To judge the performance of enhancement technique we define a parameter called overall quality Q as follows

$$Q = P[I_h(x, y) + \xi(x, y) > \Delta] - P[I_l(x, y) + \xi(x, y) > \Delta] \tag{23}$$

$P[I_h(x, y) + \xi(x, y) > \Delta]$ indicates the probability that image intensity plus noise is more than threshold. Equation (23) can be written using probability distribution function $F(x)$ of a Gaussian noise. If Gaussian noise standard deviation is considered as σ, the required equation will be

$$Q(\sigma) = F\left[\frac{\Delta + I_h(x, y)}{\sigma}\right] - F\left[\frac{\Delta + I_l(x, y)}{\sigma}\right] \tag{24}$$

Our aim is to find an optimum σ that maximises over all quality Q. So, differentiating Q with respect to σ and

Fig. 6 *Comparative results on very low-contrast Lena colour image*

a Very low-contrast Lena colour
b SR enhanced
c Histogram equalised (HE)
d Gamma correction (Gamma)
e Retinex (Retinex)
f Modified high pass filtered (MHPF)

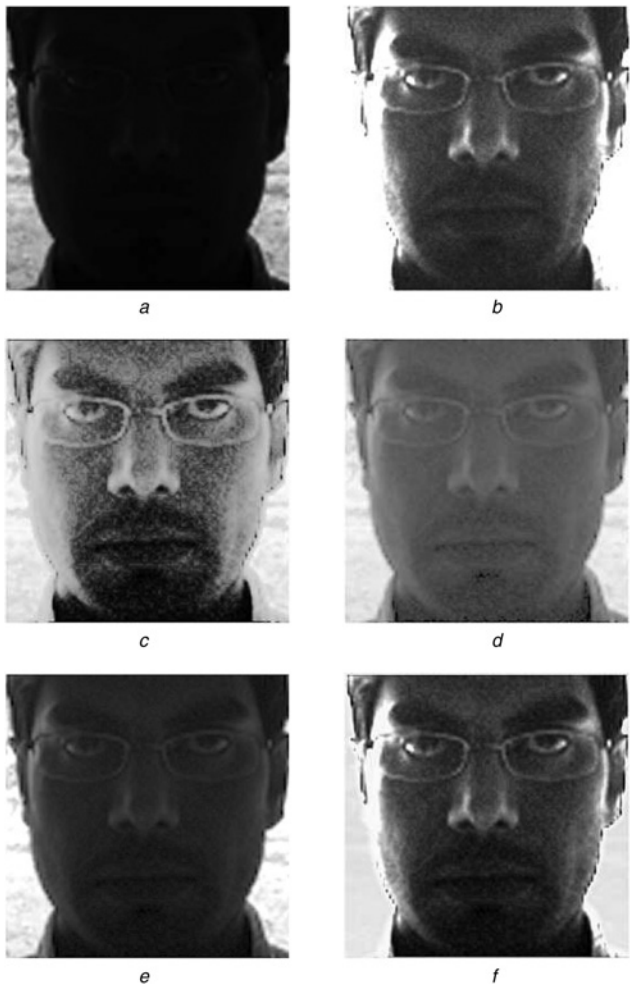

Fig. 7 *Comparative results on very low-contrast test-2 image*

a Very low-contrast test-2
b SR enhanced
c Histogram equalised (HE)
d Gamma correction (Gamma)
e Retinex (Retinex)
f Modified high pass filtered (MHPF)

equating to zero we obtain the following expression

$$\frac{dQ(\sigma)}{d\sigma} = \frac{1}{\sigma^2}\left[[\Delta + I_h(x, y)]f\left(\frac{[\Delta + I_h(x, y)]}{\sigma}\right) - [\Delta + I_l(x, y)]f\left(\frac{[\Delta + I_l(x, y)]}{\sigma}\right)\right] = 0 \quad (25)$$

$$\frac{f[\Delta + I_h(x, y)/\sigma]}{f[\Delta + I_l(x, y)/\sigma]} = \frac{\Delta + I_l(x, y)}{\Delta + I_h(x, y)} \quad (26)$$

where $f(x)$ is the probability density function, that is, $dF(x)/dx$. Expanding the probability density function, $f(x)$, for Gaussian noise

$$\exp\left[\frac{[\Delta^2 + I_l^2(x,y) + 2\Delta I_l(x,y)] - [\Delta^2 + I_h^2(x,y) + 2\Delta I_h(x,y)]}{2\sigma^2}\right] = \left[\frac{\Delta + I_l(x,y)}{\Delta + I_h(x,y)}\right] \quad (27)$$

Solving (27) we get

$$\sigma_{\text{optimal}} = \sqrt{\frac{[I_h(x, y) - I_l(x, y)][I_h(x, y) + I_l(x, y) + 2\Delta]}{2\ln[\Delta + I_h(x, y)/\Delta + I_l(x, y)]}} \quad (28)$$

This is the required expression of optimum noise standard deviation for enhancement of very low-contrast images using SR technique. In the simulation, I_h and I_l are taken as the highest value from respective partitions.

6 Simulation results

The proposed SR enhancement is simulated on Linux platform using C language. The enhancement technique was tested on four low-contrast images namely test-1, Lena Grey, Lena Colour and test-2 images. Each of these images are of size 512 × 512 and are shown in Figs. 4*a*, 5*a*, 6*a* and 7*a*, respectively. The images test-1 and test-2 shown in Figs. 4*a* and 7*a* are captured using SonyCybershot Model-DSC-W80 during night time under poor lighting. Whereas the images Lena grey and Lena colour shown in Figs. 5*a* and 6*a* have been generated by editing (using Paint shop Pro 7.0) the original images to make them low contrast.

For SR-based enhancement of these low-contrast images, in each iteration zero mean Gaussian noise of a particular noise standard deviation was added to each image. For each image and for each noise standard deviation 30 noisy images were generated. Each of these noisy images were thresholded (threshold value Δ_0 depends on added noise standard deviation) and average of 30 threshold image were taken as the enhanced image. If the DSM value of the current enhanced image was found to be greater than the DSM value of the image obtained in previous iteration; then the noise standard deviation was incremented by one and next enhanced image was obtained repeating the same iterative steps but with increased noise standard deviation. The simulation terminated when DSM value started falling. In the first iteration noise standard deviation was taken as half of the average intensity value of the low-contrast image.

To compare the performance of proposed SR-based enhancement technique over histogram equalisation, gamma correction, single-scale Retinex, multi-scale Retinex, and modified high-pass filtering-based enhancement, we have implemented histogram equalisation, gamma correction, single-scale Retinex, multi-scale Retinex and modified high-pass filtering-based enhancement techniques on Matlab 7.4 platform. The results are presented in Table 1 for low-contrast test-1 colour image and Lena grey scale image and Table 2 for Lena colour image and test-2 grey scale image, respectively.

Table 1 Comparative performance of the proposed technique with various existing techniques using three parameters on test images

Methods	Test-1 colour image			Lena grey image		
	DSM	TBE_S	TBE_E	DSM	TBE_S	TBE_E
SR	29.40	0.027	0.192	41.94	0.076	0.176
HE	16.46	0.077	0.117	23.43	0.006	0.014
Gamma	8.32	0.018	0.136	22.63	0.001	0.003
Retinex	14.70	0.012	0.146	31.70	0.0007	0.002
MSR	24.91	0.018	0.154	31.71	0.0007	0.0021
MHPF	22.88	0.025	0.033	44.14	0.0011	0.0034

Table 2 Comparative performance of the proposed technique with various existing techniques using three parameters on test images

Methods	Lena colour image			Test-2 grey image		
	DSM	TBE_S	TBE_E	DSM	TBE_S	TBE_E
SR	54.73	0.017	0.0215	10.59	0.0735	0.4591
HE	32.85	0.0001	0.0007	2.83	0.1125	0.2864
Gamma	33.55	0.0025	0.0142	1.51	0.0997	0.3584
Retinex	56.87	0.0001	0.0084	2.50	0.1413	0.4816
MSR	63.65	0.0012	0.0126	2.63	0.0778	0.6962
MHPF	54.62	0.0007	0.0055	7.88	0.085	0.41

Table 3 Comparative performance of two proposed enhancement technique in terms of noise standard deviations and number of iteration

	Stochastic resonance technique-1			Stochastic resonance technique-2		
	Range of std. dev.	Std. dev. at best o/p	Iterations	σ_{optimum}	Std. dev. at best o/p	Iterations
test-1 colour	11–20	20	10	19.43	18	4
Lena grey	14–21	21	8	24.13	26	6
Lena colour	20–30	30	11	35.74	36	5
test-2 grey	7–17	17	11	19.84	21	6

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Tables 1 and 2 illustrate the quantitative performance of all the techniques on test images using parameters like DSM, TBE_S and TBE_E. DSM value should be high for good-contrast images and TBE_S and TBE_E value should be positive for good-contrast images. It is observed from these Tables 1 and 2 that these parameters have highest value for SR-enhanced images compared to the five existing techniques.

For subjective evaluation of colour and grey scale test images using proposed approach and existing enhancement approach, the enhanced output images from different algorithms are shown in the figures: Figs. 4–7. It can be observed that the results of the proposed approach is better than the results obtained using histogram equalisation and gamma correction methods and comparable to the results obtained using Retinex-based enhancement, multi-scale Retinex-based enhancement and modified high-pass filtering-based enhancement techniques. The point to be highlighted here is that the output of the proposed approach has no blocking artefact, no spot, no degradation in the enhanced image. Other images have blocking artefacts and loss of colour in colour-enhanced images.

To reduce the number of iteration we have proposed the second technique where optimum noise standard deviation (σ_{optimum}) is estimated using (28). The iteration starts with initial noise standard deviation ($\sigma_{\text{optimal}} - 3$). In every iteration step noise standard deviation is incremented by one. As the initial noise standard deviation is taken as close to (σ_{optimum}) so the number of iteration is expected to be less. Table 3 shows the results.

As observed in Table 3 that the noise standard deviations corresponding to best output images in both the approaches are very close to each other. As expected, the number of iterations in enhancement technique-2 is significantly less than that in case of enhancement technique-1.

7 Conclusions

Two techniques of image enhancement using SR are presented here. Both techniques depend on noise addition and thresholding. The enhanced images of the proposed techniques are found to be superior to the other existing techniques. There is no artefact, colour loss and spot in the enhanced image. Quantitative performance measures such as DSM, TBE_S and TBE_E of the enhanced images using proposed techniques are higher than or approximately close to the existing techniques. The computational complexity of the two proposed techniques are compared. The qualitative comparisons also demonstrate the effectiveness of the algorithm.

8 References

1 Gonzales, R.C., Woods, R.E.: 'Digital image processing' (Addison Wesley, Reading, MA, 1992)

2 Lim, J.S.: 'Two-dimensional signal and image processing' (Prentice-Hall, Englewood Cliffs, NJ, 1990)

3 Deng, G., Cahill, L.W., Tobin, G.R.: 'The study of logarithmic image processing model and its application to image enhancement', *IEEE Trans. Image Process.*, 1995, **4**, (4), pp. 506–512

4 Laine, A., Fan, J., Sculer, S.: 'A framework for contrast enhancement by dyadic wavelet analysis, digital mammography' (Elsevier, Amsterdam, 1994)

5 Brown, T.J.: 'An adaptive strategy for wavelet based image enhancement', *Proc. IMVIP*, 1998, **5**, pp. 67–81

6 Meylan, L., Susstrunk, S.: 'High dynamic range image rendering with a Retinex-based adaptive filter', *IEEE Trans. Image Process.*, 2006, **15**, (9), pp. 2820–2830

7 Jobson, D., Rahman, Z., Woodell, G.: 'A multiscale Retinex for bridging the gap between color images and the human observation of scenes', *IEEE Trans. Image Process.*, 1997, **6**, (7), pp. 965–976

8 Hongler, M., Meneses, Y., Beyeler, A., Jacot, J.: 'Resonant retina: exploiting vibration noise to optimally detect edges in an image', *IEEE Trans. Pattern Anal. Mach. Intell.*, 2003, **25**, (9), pp. 1051–1062

9 Ye, Q., Huang, H., He, X., Zhang, C.: 'A SR-based Radon transform to extract weak lines from noise images'. Proc. IEEE ICIP, 2003, vol. 5, pp. 1849–1852

10 Ye, Q., Huang, H., He, X., Zhang, C.: 'Image enhancement using stochastic resonance'. Proc. IEEE ICIP, 2004, vol. 1, pp. 263–266

11 Jha, R.K., Biswas, P.K., Chatterji, B.N.: 'Contrast enhancement of digital images using stochastic resonance'. Proc. Tencon-2005, IEEE Region 10 Conf., Melbourne, Australia, 2005, vol. 1, pp. 1–6

12 Jha, R.K., Biswas, P.K., Chatterji, B.N.: 'Image denoising using stochastic resonance'. Proc. ICCR, 2006, pp. 320–325

13 Histace, A., Rousseau, D.: 'Constructive action of noise for impulsive noise removal in scalar images', *IEEE Electron. Lett.*, 2006, **42**, (7), pp. 393–395

14 Subramanyam Rallabandi, V.P.: 'Enhancement of ultrasound images using stochastic resonance based wavelet transform', *Comput. Med. Imaging Graph.*, 2008, **32**, pp. 316–320

15 Moss, F., Pierson, D., O'Gorman, D.: 'Stochastic resonance: tutorial and update', *Int. J. Bifurcation Chaos*, 1994, **4**, (6), pp. 1383–1397

16 Jung, P.: 'Threshold devices: fractal noise and neural talk', *Phys. Rev. E*, 1994, **50**, pp. 2513–2522

17 Stocks, N.G.: 'Information transmission in parallel threshold arrays: suprathreshold stochastic resonance', *Phys. Rev. E*, 2001, **63**, (041114)

18 Rice, S.O.: 'The theory of random noise', *Bell Syst. Tech. J.*, 1944, **23**, p. 282

19 Jung, P., Hanggi, P.: 'Amplification of small signal via SR', *Phys. Rev. A*, 1991, **44**, (12), pp. 8032–8042

20 Gingl, Z., Kiss, L.B., Moss, F.: 'Non dynamical stochastic resonance: theory and experiments with white and various colored noises', *Luglio-Agosto*, 1995, **17**, (7), pp. 795–802

21 Gingl, Z., Kiss, L.B., Moss, F.: 'Non dynamical SR: theory and experiments with white and arbitrarily coloured noises', *Europhys. Lett.*, 1995, **29**, (3), pp. 191–196

22 Simonotto, E., Riani, M., Charles, S., Roberts, M., Twitty, J., Moss, F.: 'Visual perception of stochastic resonance', *Phys. Rev. Lett.*, 1997, **78**, (6), pp. 1186–1189

23 Singh, S., Bovis, K.: 'An evaluation of contrast enhancement techniques for mammographic breast massed', *IEEE Trans. Inf. Technol. Biomed.*, 2005, **9**, (1), pp. 109–119