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From Particle Mechanics to Pixel Dynamics: Utilizing Stochastic Resonance Principle for Biomedical Image Enhancement

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1. Introduction

There is a noteworthy analogy between the statistical mechanical systems and the digital image processing systems. We can make pixel gray levels of an image correspondence to a discrete particles under thermodynamic noise (Brownian motion) that transits between binary state transition from a weak- signal state to a strong-signal state whereas a noisy signal to the enhanced signal in digital imaging systems. One such phenomenon in the physical systems is stochastic resonance (SR) where the signal gets enhanced by adding a small amount of mean-zero Gaussian noise. A local change is made in the image based upon the current values of pixels and boundary elements in the immediate neighborhood. However, this change is random, and is generated by the sampling from a local conditional probability distribution. These local conditional distributions are dependent on the global control parameter called "temperature" in physical systems (Geman & Geman, 1984). At low temperature the coupling between the particles is tighter means that the images appear more regular and whereas at higher temperature induce a loose coupling between the neighboring pixels and the image appears noisy or blurred image. At particular optimum temperature these particles comes much closer fashion and similarly the pixels of an image got arranged in much closer and leads to noise degradation and further enhances the signal. In this chapter, we discuss the application of the physical principle of stochastic resonance in biomedical imaging systems. Some of the applications of stochastic resonance are signal detection and signal transmission, image restoration, enhancement of noisy or blurred images and image segmentation.

Stochastic resonance (SR) is a phenomenon of certain nonlinear systems in which the synchronization between the input signal and the noise occurs when an optimal amount of additional noise is inserted into the system (Gammaitoni et al., 1998). Stochastic resonance is a ubiquitous and conspicuous phenomenon. The climatic model addressing the apparently periodic occurrences of the ice ages by the weak, periodic external signal was thought to be the first theoretical model of stochastic resonance phenomenon, from which the concept of stochastic resonance was put forward (Benzi et al., 1981). Since after the discovery by Benzi, there has been increasingly attracting applications of stochastic resonance in various fields like physics (Gammaitoni et al., 1998), (Anishchenko et al., 1999), chemistry (Horsthemke & Lefever, 2006), biology and neurophysiology (Moss et al., 2004), biomedical (Morse & Evans,

1996), engineering systems (Hongler et al., 2003), and signal processing applications (Badzey & Mohanty, 2005). Usually noise is the hindrance to any system but in some cases, a little extra amount of noise will help, rather than hinder, the performance improvement of the system by maximizing or minimizing the chosen performance measure, such as output signal-to-noise ratio (SNR) (Gammaitoni et al., 1998), or mutual information (Deco & Schrmann, 1998).

Stochastic resonance can be characterized as a resonant synchronization phenomenon, resulting from the combined action of noise and forcing signals. If the noise intensity and the system parameters are tuned properly, synchronization will happen between the noise and the signal, yielding the "enhancement" of the signal (Gammaitoni et al., 1998). The basic components required for SR phenomenon is the input signal, threshold and the system outputs with different noise intensities (Marks et al., 2002). In stochastic resonance systems, noise can be converted into a positive fact in the improvement of system performance when the synchronization between the input signal and noise occurs. Usually, there are two approaches to realize this synchronization between the input signal and noise. The first one is the traditional stochastic resonance. It realizes the stochastic resonance effect by adding an optimal amount of additional noise into the systems. The second approach is called parameter-induced stochastic resonance. It is discovered that the synchronization can also be realized by tuning the parameters of stochastic resonance systems without adding noise (Xu et al., 2004).

The plot between input noise intensity versus signal-to-noise ratio is shown in figure 1. From figure 1, we can notice that the output signal-to-noise ratio will be maximized or stochastic resonance phenomenon occurs for optimal noise intensity. It is obvious that the output signal will start to change at the same frequency as the input signal when an optimal amount of noise is inserted into the system. One way of showing the SR phenomenon is the frequency domain, where the information can be recovered from the response recording using Fourier analysis. First, we compute the discrete Fourier transform of the recording at discrete values of the frequency. The power spectral density (PSD) at each frequency can be calculated as twice the square of the Fourier transform at that frequency. The PSD provides the distribution of power over frequency in the recorded response. If a periodic signal is detected it will show as a peak in the PSD at the frequency of the signal.

2. Types of stochastic resonance models

2.1 Nonlinear systems

Many kinds of nonlinear systems have demonstrated stochastic resonance phenomena, such as static systems (Chapeau-Blondeau & Godivier, 1997), dynamic systems (Gammaitoni et al., 1998), (Wellens et al., 2004), discrete systems (Zozor & Amblard, 1999), and coupled systems (Jung et al., 1992). The traditional stochastic resonance requires the information-carrying signal to be weak and periodic (Gammaitoni et al., 1998). Now, aperiodic (Barbay et al., 2001) and suprathreshold signals can also be the input of certain stochastic resonance systems, in terms of aperiodic stochastic resonance (Park et al., 2004), (Sun et al., 2008) and suprathreshold stochastic resonance (Stocks, 2001) respectively.

The stochastic resonance paradigm is compatible with single-neuron models or synaptic and channels properties and applies to neuronal assemblies activated by sensory inputs and perceptual processes as well. In literature, the landmark experiments including psychophysics, electrophysiology, functional MRI, human vision, hearing and tactile

functions, animal behavior, single/multiunit activity recordings have been explored. Models and experiments show a peculiar consistency with known neuronal and brain physiology (Moss et al., 2004). A number of naturally occurring 'noise' sources in the brain (e.g. synaptic transmission, channel gating, ion concentrations, membrane conductance) possibly accounting for stochastic resonance phenomenon.

2.2 Suprathreshold systems
 Suprathreshold stochastic resonance can operate with signals of arbitrary amplitude and has been reported in the transmission of random aperiodic signals (Stocks, 2001). Noise is an essential part of stochastic resonance systems and will improve the system performance when synchronization between noise and input signals happens. The most common and extensively studied noise is the additive zero-mean white Gaussian noise (Wang, 2008). The noise, however, is no longer limited to white Gaussian noise and even it can be colored (Nozaki et al., 1999), or non-Gaussian noise (Kosko & Mitaim, 2001), (Rousseau, et al., 2006). In some cases, chaotic signals can replace the stochastic noise and generate the stochastic resonance effect. In order to describe SR phenomena quantitatively and reveal the synchronization between signals and noise, different manners to characterize stochastic resonance phenomena have been advanced over the years. For periodic signals, the most commonly used quantifier is signal-to-noise ratio (Gammaitoni et al., 1998). For aperiodic signals, cross-correlation measures (Collins et al., 1996), and information-based measures, such as mutual information (Deco & Schrmann, 1998), can be used instead. The theoretical analysis of stochastic resonance systems is often very difficult, because of the complexity of the systems. Approximation models and approaches have been adopted in these cases. Some of the useful tools for the theoretical analysis are two-state model (Ginzburg, & Pustovoit, 2002), Fokker-Planck equation (Hu et al., 1990), and linear-response theory (Casado-Pascual et al., 2003). The noise-enhanced feeding behavior of the paddle fish is an example of stochastic resonance phenomena in biological systems and Schmitt trigger in engineering systems (Gammaitoni et al., 1998).

2.3 Excitable systems
Another example of a system, often found in neuronal circuits, that exhibits SR is an excitable system. Unlike the double well bistable system discussed below, this system has a single rest state and an unstable excited state that is reached by crossing a barrier. An excitable system behavior of SR is shown in figure 2. The system has an inbuilt threshold and monitors (over time) whether an input crosses this threshold. If, when the receiver is looking at the input it lies above the threshold, a pulse is emitted figure 2(b) and (c). If, on the other hand, the input lies below the threshold, no pulse is emitted. The pattern of pulses can be used by the detector to determine frequency information about the signal. Again, when the whole signal lies below the threshold, no pulses are emitted and it will not be detected. If noise is added to this sub-threshold signal it may push the input above the threshold, this is most likely to happen at the peaks of the signal (Rousseau et al., 2005). Information about the signal frequency is contained in the emitted pulse train and can be recovered by the detector.

2.4 Bistable systems
Another typical example of the stochastic resonance system is the nonlinear bistable double-well dynamic system, which describes the overdamped motion of a Brownian particle in a symmetric double-well potential in the presence of noise and periodic forcing as shown in

figure 3(a) and the particle in the double-well potential crossing the barrier from a weak-signal state to a strong-signal state as shown in figure 3(b). The bistable double-well systems have found several applications in signal processing (Leng et al., 2007) and fault diagnosis (Tan et al., 2009). It has been used to amplify the coherent signals (Badzey & Mohanty, 2005). We can make pixel gray levels of an image correspondence to a discrete particles under Brownian motion that transits between binary state transition whereas a noisy image to an enhanced image in digital imaging systems. The assignment of an energy function in the states of atoms or molecules in the physical system is determined by its Boltzmann's or Gibbs distribution. Because of the Gibbs distribution, markov random field (MRF) equivalence, this assignment also determines MRF image model (Geman & Geman, 1984). Similarly, the threshold-crossing rate of the stochastic resonator occurs only at the Kramer's frequency. In physical systems, at low temperature the coupling between the particles is tighter means that the images appear more regular and whereas at higher temperature induce a loose coupling between the neighboring pixels and the image appears noisy or blurred image. At particular optimum temperature these particles comes much closer and analogous the pixels of an image got arranged in much closer and leads to noise reduction and enhances the signal.
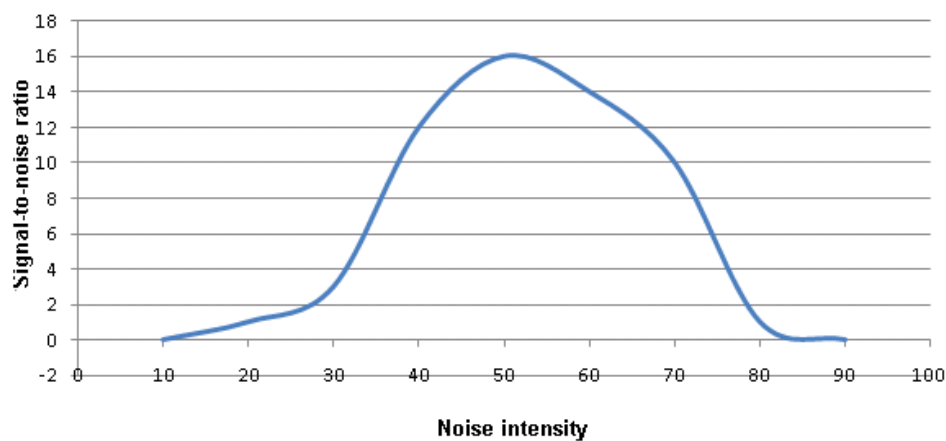

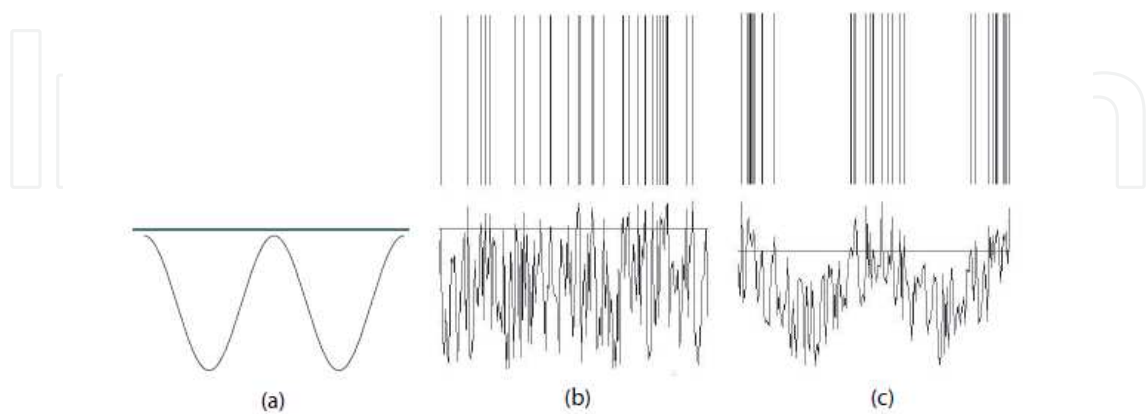Fig. 1. Signal-to-noise ratio maximum peak occurs at an optimum level of noise intensity

Fig. 2. An excitable system (a) A periodic signal lying below the threshold (b) If only noise is added to the system, threshold crossings are random and no information is contained in the pulse train, (c) If both the noise and signal are added to the system, the threshold crosses and hence the pulse train corresponds to peak of signal and information can be recovered.

In this chapter, we focuses on the phenomenon of stochastic resonance application in various medical imaging systems like computed tomography (CT) and magnetic resonance imaging (MRI).We investigate the applications of stochastic resonance techniques in medical image processing based on systematic and theoretical analysis, rather than only based on simulations. We develop a totally new formulation of two-dimensional parameter-induced stochastic resonance for nonlinear image processing. We reveal it is feasible to extend the concept of one-dimensional parameter-induced stochastic resonance to two-dimensional and use it for image processing. Compared with current SR-based methods, the current approach based on two-dimensional SR technique can eliminate the noise on the addition of noise into images, which can be used as a nonlinear filter for image processing. Here, we first propose a new two dimensional bistable stochastic resonance system in their respective integral transforms such as Radon and Fourier transforms respectively for CT and MR imaging.
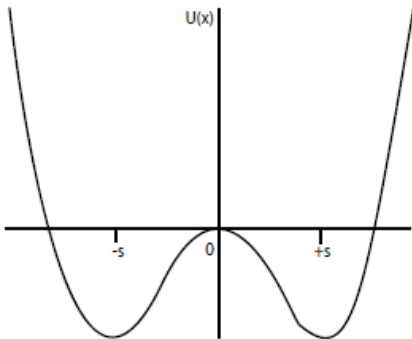

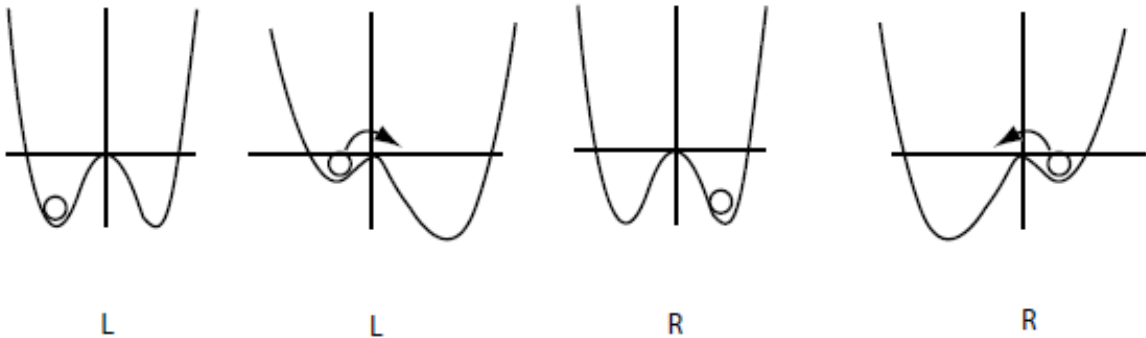Fig. 3. (a) Bistable double well potential

Fig. 3. (b) Particle in double well potential crossing the barrier when signal reaches peak

3. Mathematical framework

We now elaborate the bistable SR model in the theoretical form that is conventionally used by the physicists. We now ask how an image pixel would transform if mean-zero Gaussian fluctuation noise $\eta(t)$ is added, so that the pixel is transferred from a weak-signal state to a strong-signal state, i.e. a binary-state transition occurs. Actually, such a discrete image pixel under noise can be modeled by a discrete particle under Brownian motion, the particle

transits between two binary states L and R, separated by a threshold (figure 3b). The theory of stochastic Brownian model is well known in statistical physics and thermodynamics, and the initial investigations on stochastic transition by (Kramers, 1940) and on the bistability theory of stochastic resonance by (McNamara, 1989). The transition of a Brownian particle between two-states (Gammaitoni et al., 1998), having a bistable potential, $U(x)$, is given by

$$U(x) = \frac{-a}{2}x^2 + \frac{b}{4}x^4 \tag{1}$$

where x is the particle's normalized position in the state parameter axis centred on the origin at $x = 0$ (figure 3a). We can obtain the equation of motion of the particle by delineating that its velocity $\dot{x}(t)$ as the algebraic resultant of the two causative factors of motion, namely the sinusoidal signal force term and the damping force term, the latter being the (negative) first differential of the potential, $U'(x)$ and hence given by:

$$\dot{x}(t) = -U'(x) + A_0 \cos(\Omega t + \phi) \tag{2}$$

where A_0, Ω and ϕ are respectively the signal amplitude, modulation frequency and phase. In order to occur the stochastic resonance phenomenon, we need to add small amount of mean-zero white Gaussian noise $\eta(t)$ to the particle, which causes the particle to move from one state to the other state, jumping and crossing over the threshold that has a threshold potential, ΔU as shown in figure 3b. As already mentioned earlier, each particle of the physical system above, corresponds to a pixel of the image, from a signal processing perspective. Note that $\eta(t)$ is the stochastic noise administered, having the mean or expected value of zero, i.e.

$$\xi[\eta(t)] = 0$$

with the autocorrelation function $\eta(t)$ being that of a Gaussian white noise, given by

$$\langle \eta(t)\eta(0) \rangle = 2 D \, \delta(t)$$

Here $\delta(\tau)$ and D are the delta function and noise intensity respectively.
Mathematically, one can represent the random motion of the particle in a bistable potential in the presence of noise and periodic forcing can be given by:

$$\dot{x}(t) = -U'(x) + A_0 \cos(\Omega t + \phi) + \eta(t) \tag{3a}$$

where $U'(x) = -ax + bx^3$.
Since our aim is to obtain a maximal signal, we let the cosine term attain its maximum value i.e. unity, and substitute $U'(x)$ as obtained by differentiating eq. (1), we get from eq. (3a):

$$\dot{x}(t) = ax(t) - bx^3(t) + A_0 + \eta(t) \tag{3b}$$

The threshold-crossing rate of the stochastic resonator occurs at the Kramer's frequency

$$r_k = \frac{a}{\sqrt{2\pi}} \exp\left(-\frac{\Delta U}{D}\right) \tag{4}$$

Being reciprocal of Kramer's frequency, the periodicity or waiting time of the stochastic transition between two noise-induced inter-well transition which is given by $T_k(D) = 1/r_k$.

If we input a small periodic forcing term to the particle, stochastic switching and jumping occurs between the potential wells and the switching may become synchronized with the input. This stochastic synchronization happens if the mean waiting time satisfies the time-scale matching requirement (Gammaitoni et al., 1998)

$$T_\Omega = 2 \ T_k(D)$$

where T_Ω is the period of the input periodic forcing term.

Stochastic resonance occurs if the signal-to-noise level of a system increases with the values of noise intensity. For lower noise intensities, the signal does not affect the system to cross threshold, so little signal is passed through it. For large noise intensities, the output is dominated by the noise, also leading to a low signal-to-noise ratio. For moderate optimal intensity level, the noise allows the signal to reach threshold, and increases the signal-to-noise ratio of a system. SR occurs at the maximum response of the signal i.e. signal-to-noise ratio. (SNR) and the alteration of the response of the signal due to stochastic resonator is given by

$$SNR = \frac{4a}{\sqrt{2}(\sigma_0 \sigma_1)^2} \exp\left(\frac{-a}{2\sigma_0^{\ 2}}\right) \tag{5}$$

With respect to figure 3a, the potential minima are located at $s = \pm\sqrt{(a/b)}$, while the height of the threshold potential barrier between the two states is $\Delta U = \left(a^2/4b\right)$. Considering the image enhancement scenario, one can posit that the x-axis corresponds to the normalized pixel intensity value with respect to the detector threshold value that is defined as $x = 0$, where it is analogous to noisy image to enhanced image.

Based on the power spectral density of a one dimensional signal or the coefficient of variance (CV) of an image, which is the contrast enhancement index defined as the performance measure of nonlinear bistable dynamic systems with fluctuating potential functions can be further enhanced by adding noise and tuning system parameters at the same time, if the input signal is Gaussian-distributed. Then, we extend these results to hazy or noisy images. The relative enhancement of the contrast of an image means the ratio of the coefficient of variance between the input noisy image and the output SR enhanced image. Therefore, we suggest a potential application of this mechanism in the recovery of weak signals corrupted by noise to biomedical imaging.

4. Application of stochastic resonance in biomedical imaging

4.1 SR-based Integral transform

In this section, we discuss the application of the bistability stochastic resonance model for the enhancement of commonly used medical images such as computed tomography and magnetic resonance imaging. Due to the fact that CT image reconstructed using Radom transform (Deans, 1983), whereas MR image formation corresponds to the Fourier transform (Lauterbur & Liang, 2001), we propose a bistable SR system operating in the spatial domain

of the two-dimensional integral transforms. Let us consider the 2D spatial representation of an object as a function $\psi(x,y)$, which can be the image intensity or a 2D projection of a CT image, pixel gray value in T_1-weighted MR image where the pixel brightness respectively depend on the tissue relaxation rate or the spin density. The generalized MR or CT imaging equation in projective imaging case can be given by

$$I(x,y) = \int_{z=-\infty}^{\infty} \psi(x,y,z)dz$$

Since we consider a single slice of 3-D volume, and the 2-D image $\hat{I}(x,y)$ can be formed using respective Fourier integral transform (eq. 6a) and Radon transform (eq. 6b) which is given by (Rallabandi & Roy, 2008):

$$\hat{I}(k_x,k_y) = \int_{x=-\infty}^{\infty} \int_{y=-\infty}^{\infty} I(x,y).e^{-i2\pi(k_x x + k_y y)}dk_x dk_y \qquad (6a)$$

$$\hat{I}(\rho,\theta) = \int_{x=-\infty}^{\infty} \int_{y=-\infty}^{\infty} I(x,y).\delta(x\cos\theta + y\sin\theta - \rho)d\rho d\theta \qquad (6b)$$

where $\delta(.)$ is a dirac-delta function given for the plane of projection which is equal to 1 if $x=0$ and 0 otherwise.

We now derive a transformed image $I'(k_x,k_y)$ by subtracting the mean-zero noise image $I(k_x,k_y)$ image from the original image $\hat{I}(k_x,k_y)$ such that

$$I'(k_x,k_y) = \hat{I}(k_x,k_y) - <I(k_x,k_y)> \qquad (7)$$

where $< >$ denotes the spatial average value of pixel intensity of the original image $\hat{I}(k_x,k_y)$ .Now convoluting the stochastic resonator SR on the transformed image $I'(k_x,k_y)$, thereby obtaining the stochastically enhanced image $I''(k_x,k_y)$ which is given by:

$$I''(k_x,k_y) = \int_{x=-\infty}^{\infty} \int_{y=-\infty}^{\infty} SR \left[I'(k_x,k_y).e^{2\pi i(k_x x + k_y y)}dk_x dk_y \right] \qquad (8)$$

Here SR is operated on the magnetic resonance image I as given in eq.3 (b) such that SR phenomenon occurs at maximum SNR given in eq.(5).

Now we need to solve the stochastic differential equation given in eq. (3b) using stochastic version of Euler-Maruyama's method using the iterative method as follows [Gard, 1998]:

$$x_{n+1} = x_n + k(ax_n - bx_n^3 + s_n) \qquad (9)$$

in which $s_n = A_0 + \sigma w_n$, denotes the sequence of input signal and noise with the initial condition being $x_0 = x(0)$, i.e. the initial value of x being 0. Observe that the zero-mean stochastic noise sequence $\{w_n\}$ has unit variance, $\sigma_w^2 = 1$. We discretize the stochastic simulation in terms of 'k' steps as shown in eq. (9).

4.2 Selection of optimal parameters

Note that it is necessary to select the optimal bistability parameters of 'a' and 'b', we consider the output SNR as a function of noise intensity given in eq. (5) such that the pixel maps (Ω_0, σ_0) and (Ω_1, σ_1) have the relationship (Ye et al., 2003):

$$\frac{a}{b} = \left(\frac{\sigma_1^2}{\sigma_0^2} \right) \tag{10}$$

where (Ω_0, Ω_1) are respectively the signal frequencies of the input image and SR-enhanced image, while (σ_0, σ_1) are respectively the standard deviation of noise in the input image and SR-enhanced image. Our approach has been adapted and modified from the usual methodology of using the bistability-based stochastic resonance effect to enhance input noisy image based on the integral transform of the input image (Rallabandi & Roy, 2010). In our case, we fix one of the bistability parameters 'a' at a particular value, and estimate the other parameter 'b' according to the relation given in eq.(10). However, the choice of parameters 'a' and 'b' are selected for CT and MRI using the relationship given in eq. (10).

To furnish a readily obtainable quantitative index of image upgradation, we plot the gray-level histograms of the input image and the optimal enhanced image. As a ready approximation, it is known that as an image is enhanced and there is more finer or clearer heterogenous structuration obtained, this enhancement can be characterized by an increase in the image quality contrast parameter, which is the coefficient of variance (CV) of an image, that is, the ratio of variance to the mean of the image histogram given by $Q = \left(\sigma^2 / \mu \right)$.

Further, we can estimate the relative image enhancement factor due to SR by means of the ratio of the pre-enhancement (Q_A) and post-enhancement (Q_B), values of image quality index given by (Rallabandi & Roy, 2010)

$$F = \left(\sigma_B^2 \mu_A / \sigma_A^2 \mu_B \right) \tag{11}$$

The general illustration of using SR approach for CT/MRI images is shown in figure 4. We consider the noisy CT axial image so that the image became indistinct, which caused the obliteration of the lesion and its edema, and the midline falx cerebri (figure 5a). To this indistinct image, the SR-based Radon transform is applied (the resultant output image is shown in Figure 5b). Note that the noise in the image has been reduced, whereas clearer visibility has been attained by the representation of the edema, falx, and lesion, with an inner central core reminiscent of a calcified scolex blob inside (arrow; figure 5b).

We consider the T_1-weighted MR image of the malignant brain tumor, glioblastoma multiforme having mass effect in both the hemispheres, contraction of the ventricles and involvement of the splenium of the corpus callosum. Noise was added to this image so that it becomes indistinct; the gray matter, white matter and the lesion region cannot be distinguished and the sulci and gyri become obliterated (figure 6a). We then apply the SR enhancement process in Fourier domain and the resultant enhanced image is given in figure 6b. One may easily observe that the noise in the image has reduced, while the representation of the lesion, sulci, gyri, white and gray matter has appreciably restored with clearer demarcation. To enable a quantitative comparison, the image histograms are constructed, and are displayed to the right of the respective images. Figures 6c and 6d are the image histograms of figures 6a and 6b respectively.

The stochastic resonance imaging approach has advantages like that it can recover the image from noise and also enhance the selected region of tumor image. The proposed method can be used to distinguish boundaries between gray matter, white matter, and CSF and also delineate edematous zones, vascular lesions and proliferative tumor regions. This method would be of considerable use to clinicians since SR enhanced images, under a suitable choice of 'a' and 'b' parameters. One can reiterate that the advantage of SR procedure is that the process can adapt to the local image texture by altering these stochastic bistability parameters, so that the enhancement process is suitably optimized.

4.3 Contrast sensitivity

Stochastic resonance inherently is a process that is well tuned to enhance the contrast sensitivity and decrease the neurophysiological threshold of the human visual system, which have been well demonstrated experimentally when stochastic fluctuation of pixel intensity is administered to visual images on a computer screen observed by a subject (Simonotto et al; 1997). In other words, it may be emphasized that the development of a high performance contrast enhancement algorithm must hence attempt to enhance the contrast in the image, based not only on the local characteristics of the image but also on some basic human visual characteristics, especially those properties related to contrast. The development of a high-performance contrast enhancement algorithm must thus attempt to enhance the contrast in the image based not only on the local characteristics of the image but also on some basic human visual characteristics, especially those properties related to
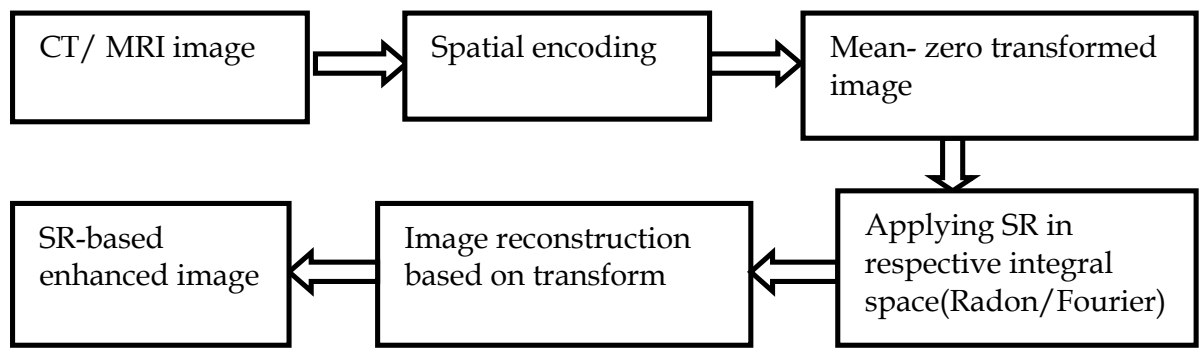
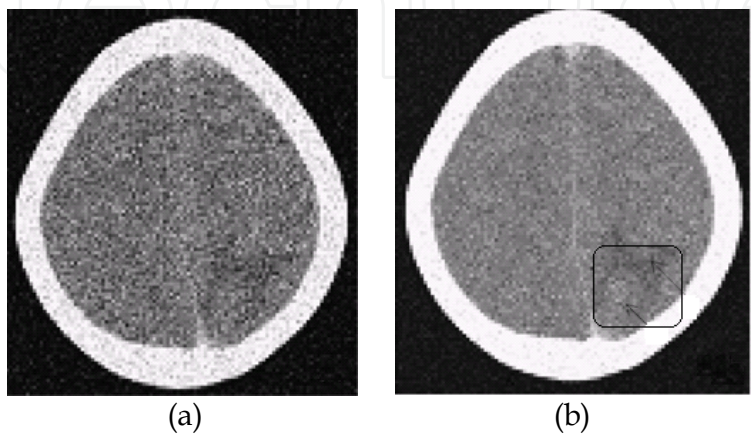Fig. 4. Illustration of Stochastic Resonance in Radon/Fourier integral domain

Fig. 5. (a) Noisy or hazy CT image (b) SR-enhanced output image using Radon transform

contrast (Piana et al., 2000). Nevertheless, the majority of enhancement procedures are neither tissue-selective nor tissue-adaptive, since in general the various texture properties in the image are enhanced evenly together. From an ergonomics perspective, the SR approach can be taken to enhance the performance of both aspects of the image visualization process, the radiological image processing device, and the human neurophysiological visual characteristics.
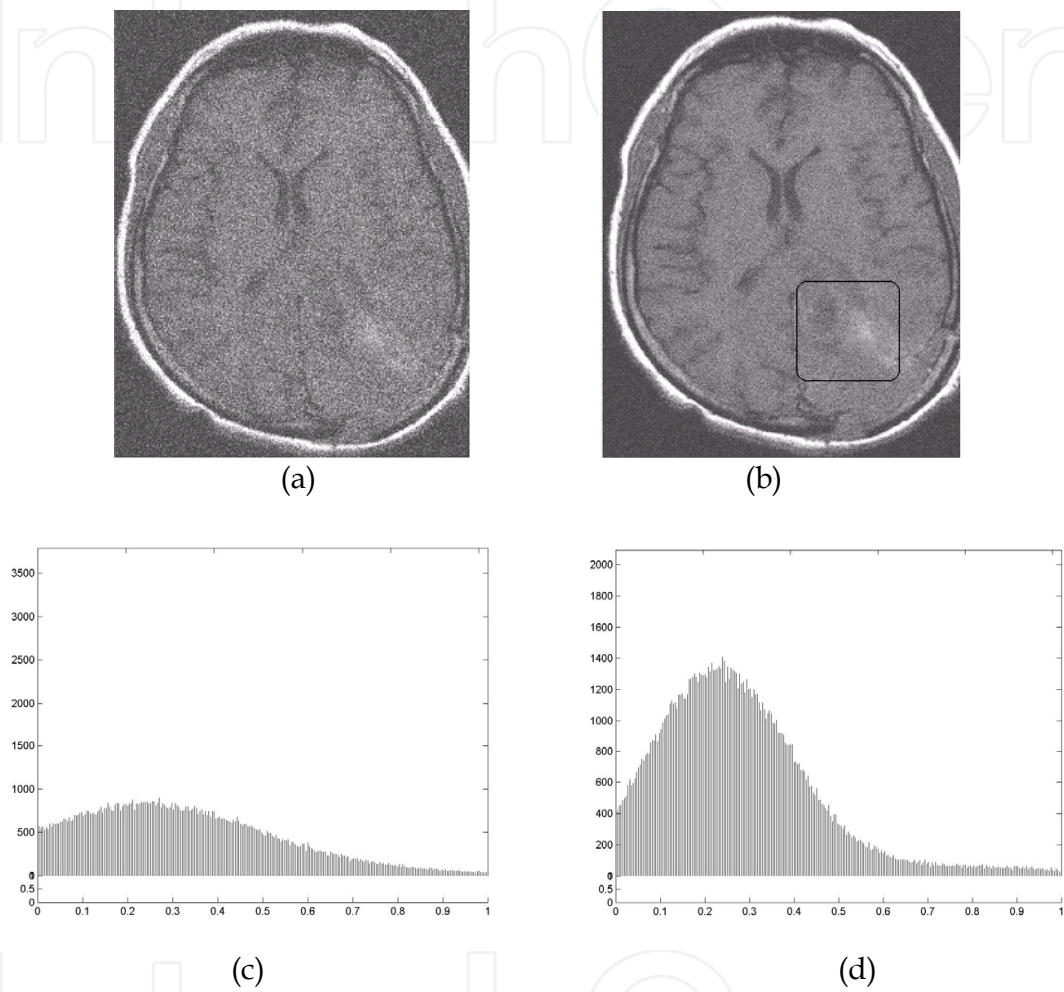

Fig. 6. (a) Noisy MR image (b) SR-enhanced image where the lesion, sulci and gyri are visible (c) & (d) Image histograms of input image of fig.6a and SR-enhanced image of fig.6b.

5. Conclusion

In this chapter, we discuss the phenomenon of stochastic resonance applicable to biomedical image processing, where the discrete image pixels are 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 real-time applications, we can extend our approach for enhancing images which are poor in spatial resolution like positron emission tomography images and low signal-to-noise ratio images like functional MRI. Additionally, we aver that much appreciable scope exists in utilizing the stochastic resonance technique for enhancing higher order noisy images due to various operational conditions during scanning such as electronic device noise, thermal noise or nyquist frequency noise.

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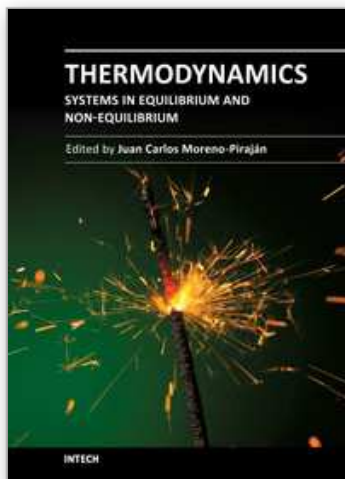
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