Noise ain't that bad!

Utilizing noise in image processing

FEB 15, 2016

Students' Reading Group
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Organization of the talk

- What is Stochastic Resonance?
- SR Applications in Image Processing
- Stochastic resonance-based Image Enhancement
- Stochastic resonance-based Watermark Extraction
- Challenges and Future scope

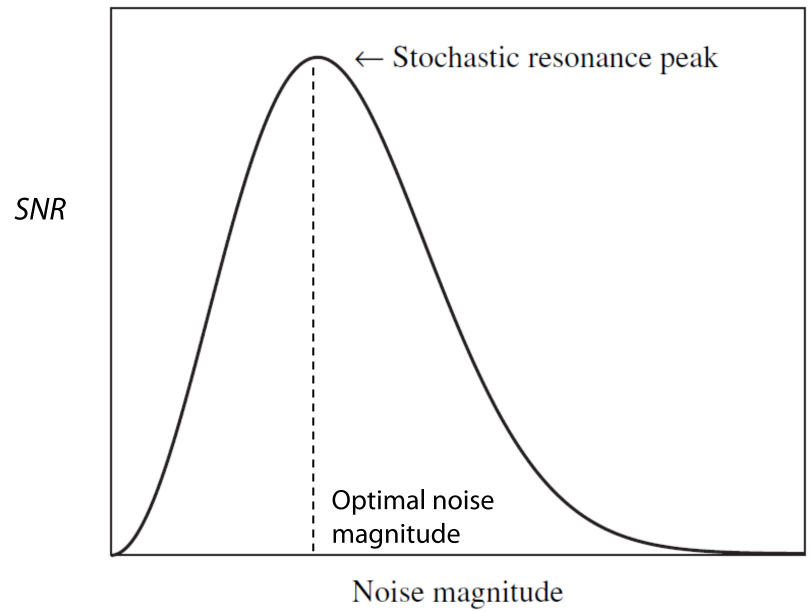
Introduction

Stochastic Resonance

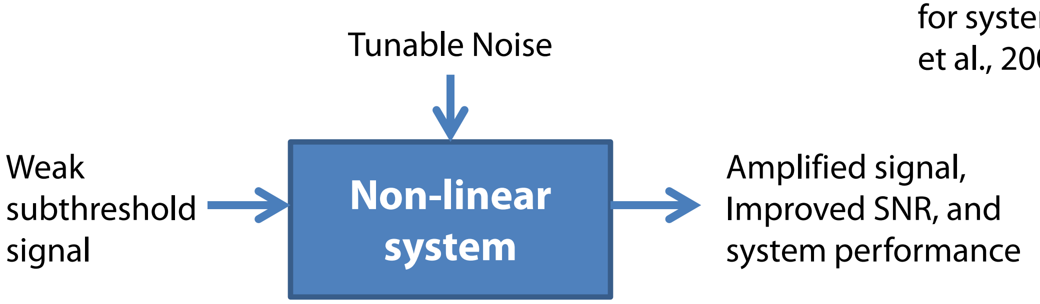
Stochastic Resonance (SR) is a phenomenon in which **the addition of an optimal amount of noise** can be used to enhance the performance of a non-linear system.

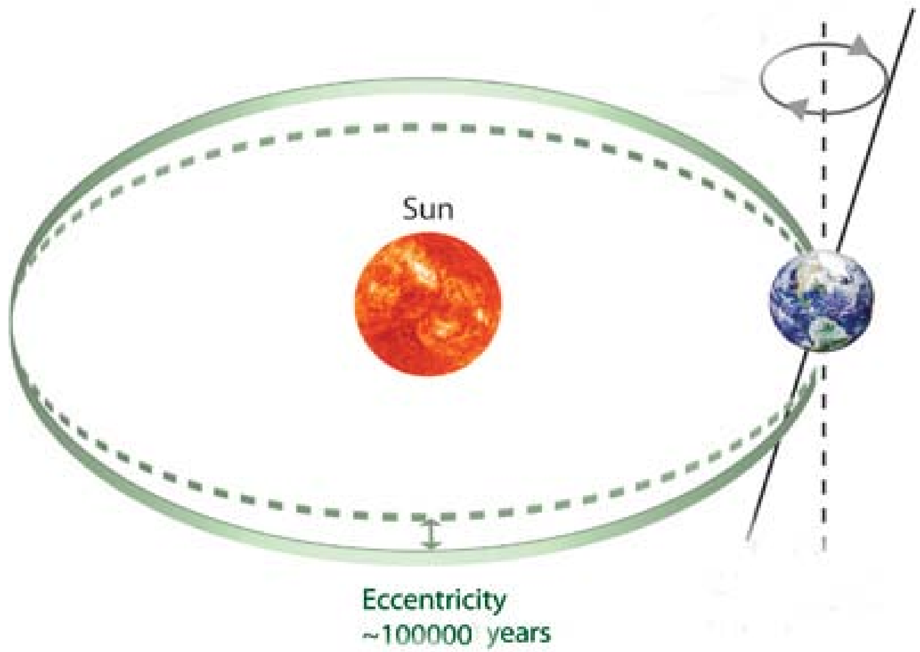
SR can be viewed as a noise-induced enhancement of the response of a *nonlinear system* to a weak input signal.

Noise-induced resonance



Typical curve of output SNR vs. input noise magnitude, for systems capable of stochastic resonance [McDonnell et al., 2008]





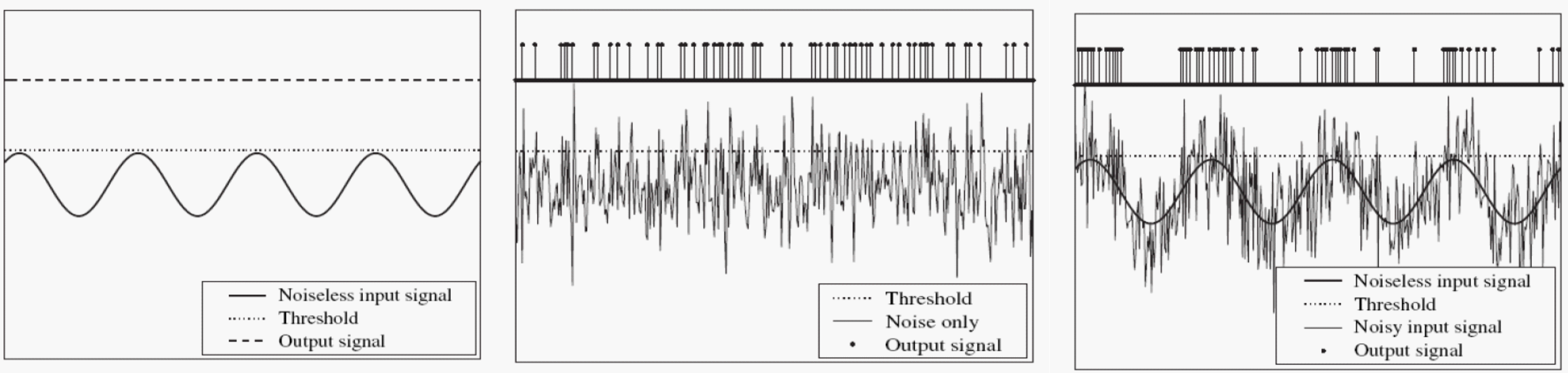
- The concept of **stochastic resonance (SR)** was developed in 1981−82 in the context of the evolution of the earth's climate.
- Change in earth's climate is attributed to the change in eccentricity of the earth's orbit.
- However, current theories suggest that the eccentricity alone is not enough to cause such dramatic changes in climate.
- Benzi *et al*. (1981) – and, independently, Nicolis (1981, 1982) – suggested that

  "**it is the combination of stochastic perturbations (like short-term fluctuations in solar radiation) in the Earth's climate, along with the changing eccentricity, which is behind the ice age cycle.**"

- Later SR was found to be exhibited in Schmidt trigger and bidirectional ring laser.

Non-dynamic Stochastic Resonance

- Non-linearity due thresholding
- A subthreshold signal crosses a threshold on addition of optimum amount of noise



(a) Subthreshold periodic input signal

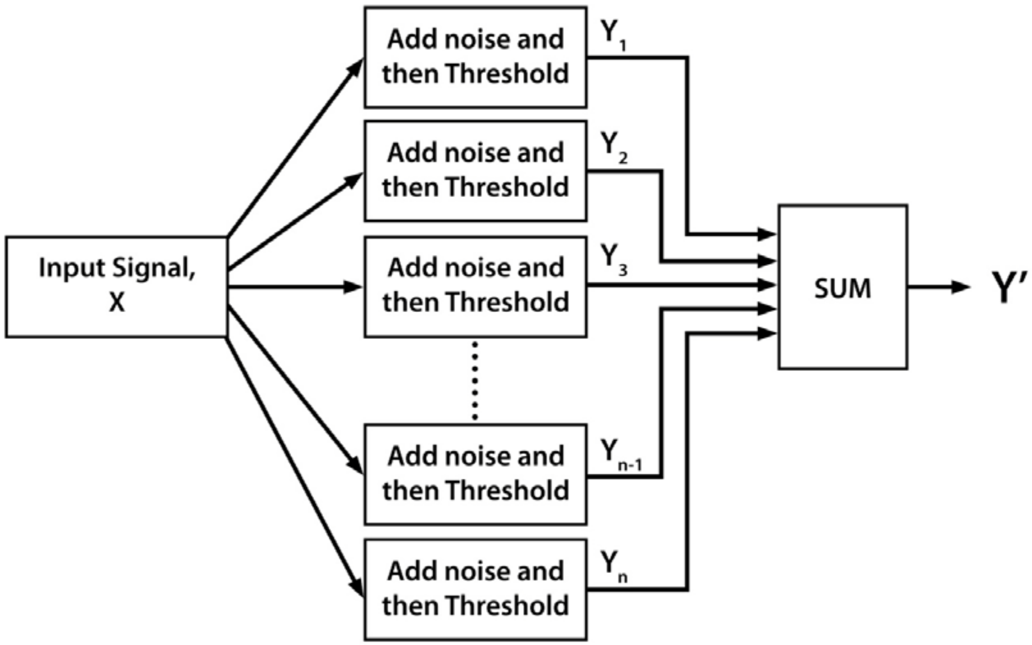
(b) Noise only

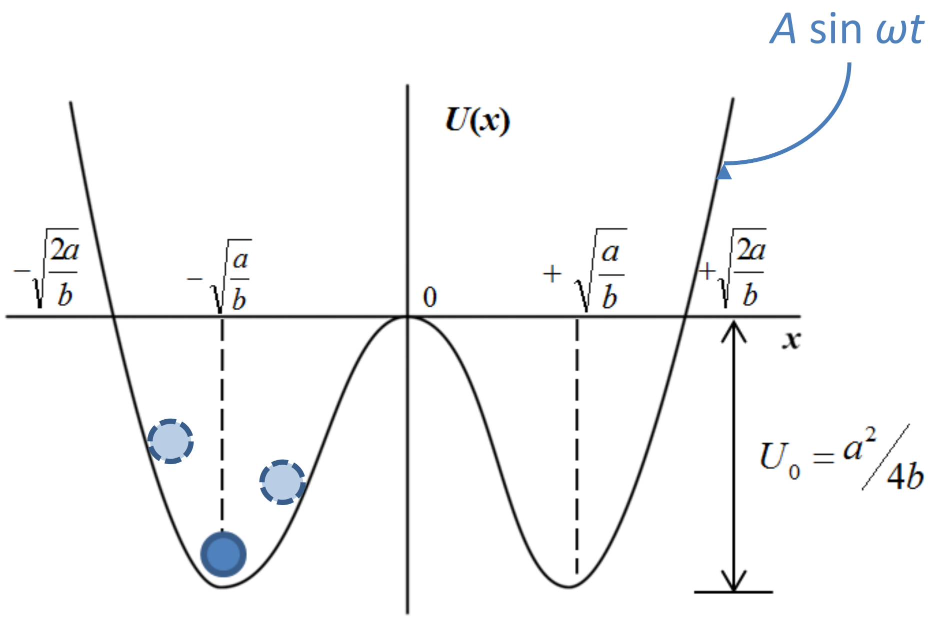
(c) Subthreshold but noisy periodic input signal

[McDonnell et al, 2008]

Suprathreshold Stochastic Resonance [N. G. Stocks, 2000]

- Each individual threshold device receives the same signal, but is subject to independent additive random noise.
- The output of each device is a binary signal, which is unity when the input is greater than the threshold value, and zero otherwise.
- The overall output of the SSR model is the sum of the individual binary signals.





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

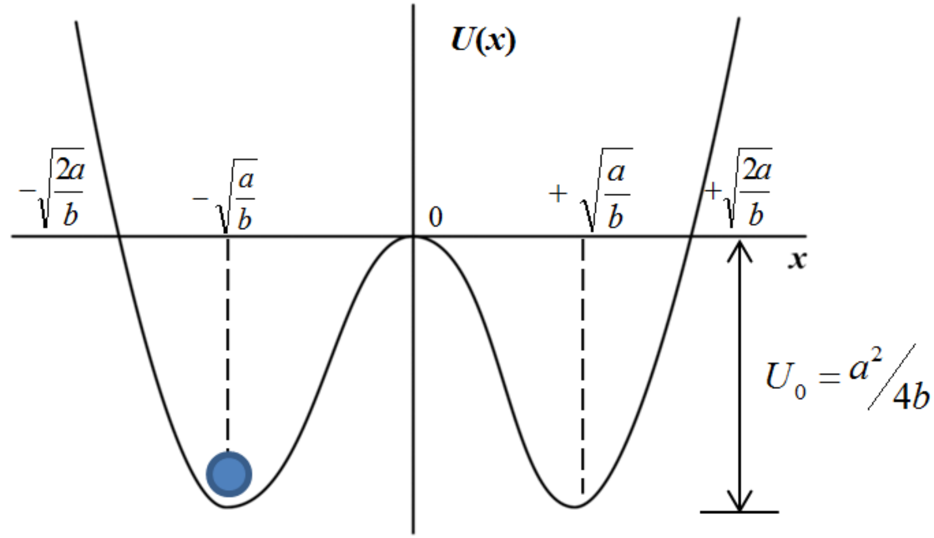
Dynamic Stochastic Resonance (DSR) may be explained using motion dynamics of a particle oscillating in a **bistable double-well system**, in the presence of a **weak signal** and **noise**.

Input	:	Weak periodic signal
Output	:	Position of particle, x

Stochastic resonance occurs when period of inter-well transitions (Kramer's rate) match the period of the signal.

Demo
"Stochastic Resonance" from the Wolfram Demonstrations Project http://demonstrations.wolfram.com/StochasticResonance/

In the presence of a weak periodic signal, ***A sin ωt***, and noise of intensity, ***D***, the double well gets tilted back and forth, asymmetrically [Duffing's equation].



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

The equation of motion after substitution of quartic potential becomes:

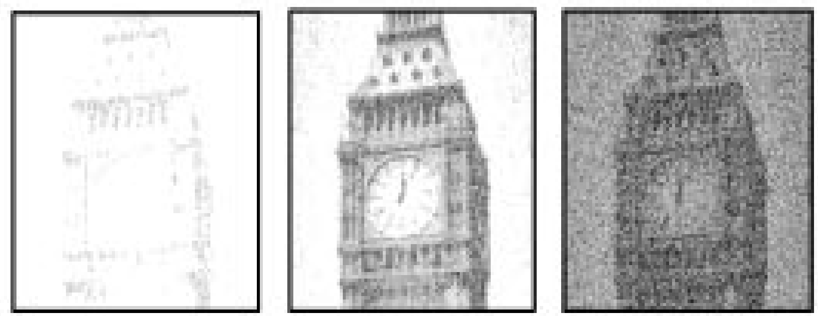
$$\frac{dx(t)}{dt} = \left[ax - bx^3\right] + A\sin(\omega t) + \sqrt{D}\xi(t)$$

$$\Rightarrow \quad x_{n+1} = x_n + \Delta t\left[ax_n - bx_n{}^3 + \textbf{\textit{Signal}} + \textbf{\textit{Noise}}\right]$$

Applications

Stochastic Resonance in Image Processing

1997 **Simonotto et al.** - the ***first to report an experiment on use of stochastic resonance for image visualization***. Their psychophysics experiment showed that the human brain can interpret details present in an image contaminated with time varying noise.



2000 **Piana et al. -** Two experiments related to the ***visual perception of noisy letters***. First - found an optimal noise level at which the letter is recognized for a minimum threshold contrast. Second – demonstrated a dramatically increased ability of the visual system in letter recognition in an extremely narrow range of noise intensity.

2003 **Hongler et al.** reported the use of ubiquitous presence of random vibrations in vision systems for ***edge detection***.

Ye et al. used SR phenomenon for ***line detection from noisy images*** based on Radon transform. They have shown that the bistable stochastic resonance-based Radon transform can easily extract weak lines from noisy images.

2004 **Ye et al.** used dynamic SR for ***image enhancement*** of low-contrast sonar images and proposed the **input-output statistics-dependent (IOS) parametric selection**

2006 **Histace et al.** - Constructive action of noise for ***impulsive noise removal*** from noisy images - based on the restoration process of Perona and Malik (1990) in which a Gaussian noise is purposely added.

Guangchun et al. - A novel ***watermarking scheme*** based on SR - the watermark is viewed as a weak binary signal.

Janpaiboon and Mitiam showed that addition of a small amount of noise can improve the accuracy of ***color object segmentation.***

2007 **Peng et al.** reported a novel preprocessing approach using SR to improve ***the low-contrast medical images***.

2008 **V. P. S. Rallabandi** reported stochastic resonance-based techniques in ***wavelet domain for the enhancement of diagnostic ultrasound images***; images are enhanced by fusing a constructive interaction of noise (small amount of Gaussian noise) and signal to improve the image quality.

Rallabandi and Roy - SR-based ***tomographic transform for enhancement*** of noisy or indistinct computer-assisted tomographic images of the brain lesions for radiological diagnosis.

Sun et al. - An ***aperiodic stochastic resonance signal processor*** for communication systems based on bistable dynamic mechanism. Here, the DCT coefficients of the watermarked image were viewed as the input weak signal and as noise in the watermark detection process

2010 **Jha et al**. report the application of ***non-dynamic stochastic resonance for image enhancement and watermark detection***

2011 **Ryu et al. -** a new approach for enhancing feature extraction from low quality fingerprint images using SR.

2011 **Chouhan et al.** report a new **input statistics-dependent SR (ISSR) parametric model for *enhancement of dark images*** in various domains

Chouhan et al. propose the use of ISSR model **to *watermark extraction and detection*** in various domains

2013 **Peng and Varshney** reported a novel **noise-refined image enhancement algorithm using multi-objective optimization**

2014 **Chouhan and Biswas** report a new **intensity-specific value dependent SR (IVSR)** model for ***dynamic range compression*** in images with dark and bright regions.

Applications

Stochastic Resonance-based Contrast Enhancement

Contrast Enhancement

Contrast is the difference in luminance or colour that makes an object (or its representation) in an **image** or display distinguishable.

Human visual system is more sensitive to contrast than absolute luminance.

Images acquired in poor illumination need enhancement for better visualization.

Low-contrast Image

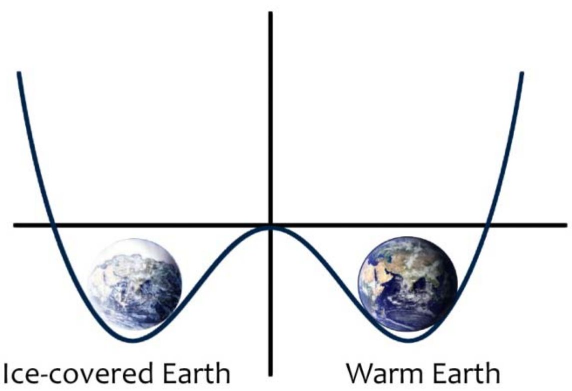
Contrast-enhanced Image

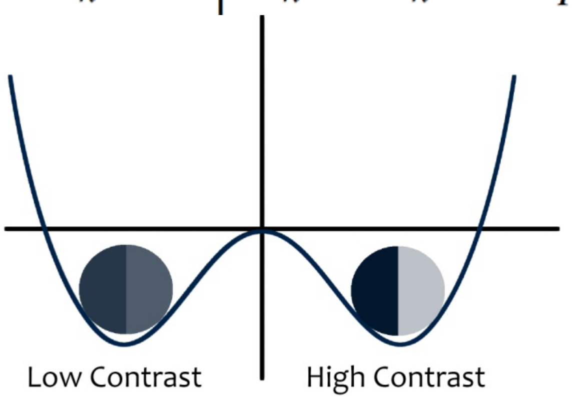
Contrast Enhancement using Dynamic SR

Analogy of Benzi *et al.*'s Climate Model to Image enhancement

Double-well System	Analogy for recurrence of ice ages [Benzi et al., 1981]	Analogy for Image Enhancement [Chouhan et al., 2011]
Double well	Global climate	Image contrast or quality
Weak signal	Small modulation of earth's orbital eccentricity	Input image / coefficients
Noise	Short-term climatic fluctuations in solar system (solar perturbations)	Noise inherent in a dark image due to lack of sufficient illumination
Position of particle	State of earth's climate	State of image / coefficients
Two stable states (minima)	Temperatures corresponding to a largely ice-covered earth and a warm earth, respectively	Contrast / quality corresponding to low-contrast and enhanced-contrast, respectively

$$x_{n+1} = x_n + \Delta t\left[a x_n - b {x_n}^3 + Input\right]$$





Step 1 Color model conversion (H-S-V) and transformation (if required)

Step 2 Application of the SR iterative equation using *internal noise*

$$x_{n+1} = x_n + \Delta t\left[ax_n - bx_n^{\,3} + Input\right]$$

Here, ***Input* = *Signal* + *Noise***. Here, ***Input*** indicates the values (or coefficients) of the input image. This denotation can be made because a low-contrast image contains visual information (signal) as well as noise due to lack of illumination (noise).

Step 3 Back-projection to produce image in spatial domain

Compute performance metrics

Terminate iteration when target performance metrics are achieved

Termination Criteria

1. **Contrast Enhancement Factor (*F*)**
   Ratio of contrast qualities of enhanced image and input low-contrast image. Contrast quality of image (here) defined as variance/mean of an image.

2. **Perceptual Quality Measure (*PQM*)**
   A no-reference metric to quantify visual quality of an image based on its blurriness, average absolute difference, zero-crossing etc. [**Wang et al., 2002**]. According to the model, for best perceptual quality, *PQM* should be closest to 10.

Example (Spatial Processing)

$\Delta t = 0.005$

Input

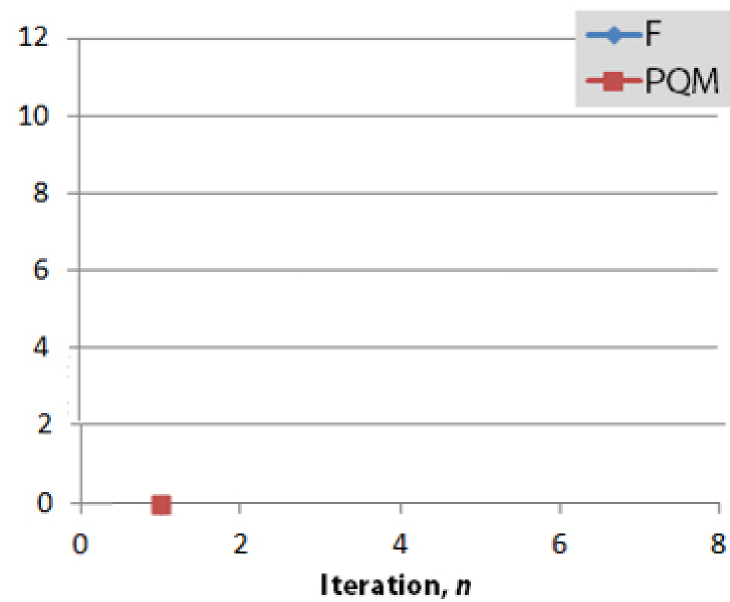
$n = 0$

Example (Spatial Processing)

$\Delta t = 0.005$

Input

$n = 1$

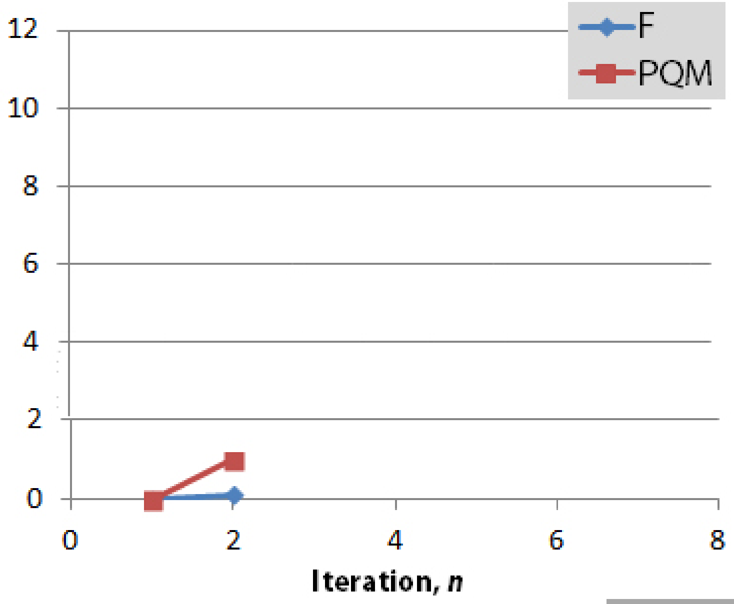


Example (Spatial Processing)

$\Delta t = 0.005$

Input

$n = 2$

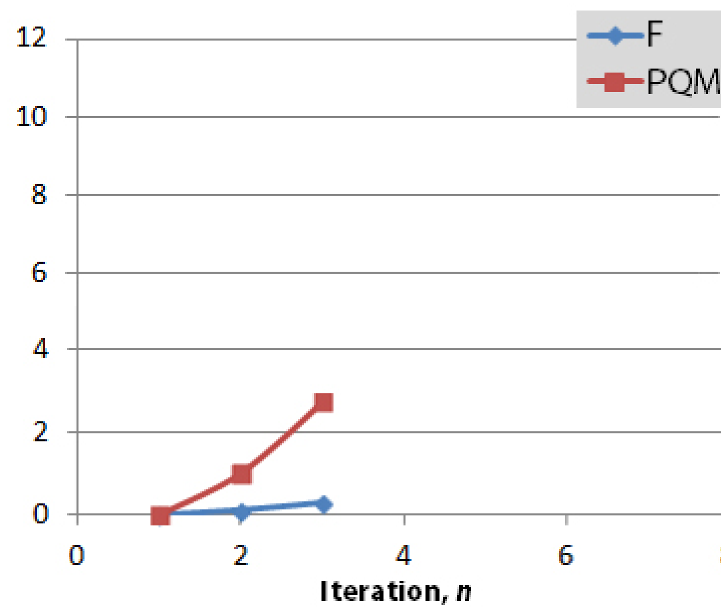


Example (Spatial Processing)

$\Delta t = 0.005$

Input

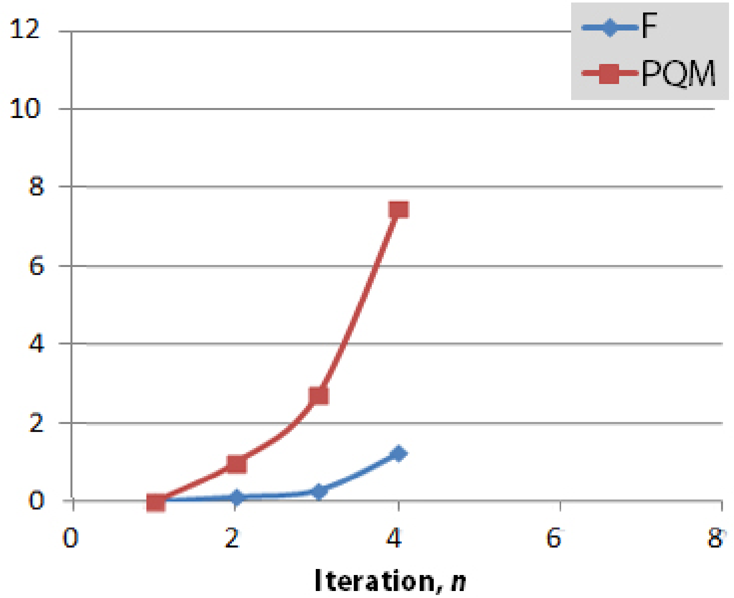
$n = 3$



$\Delta t = 0.005$

Input

$n = 4$

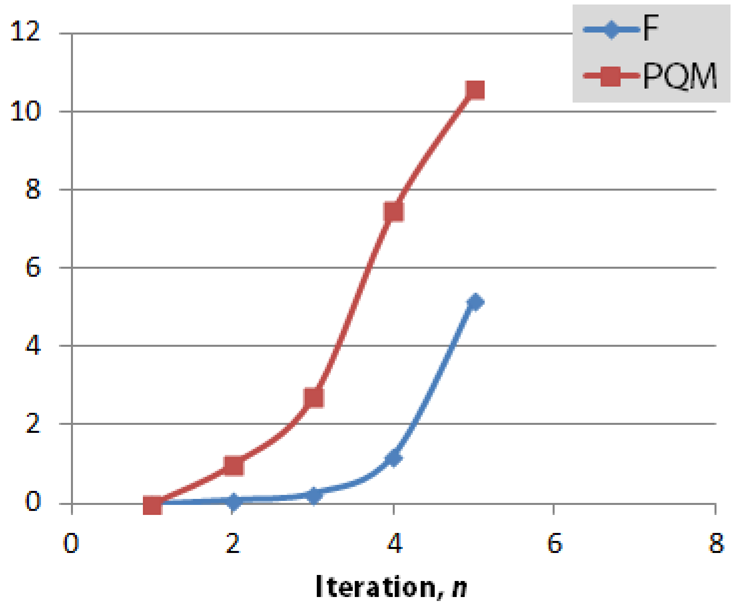


Example (Spatial Processing)

$\Delta t = 0.005$

Input

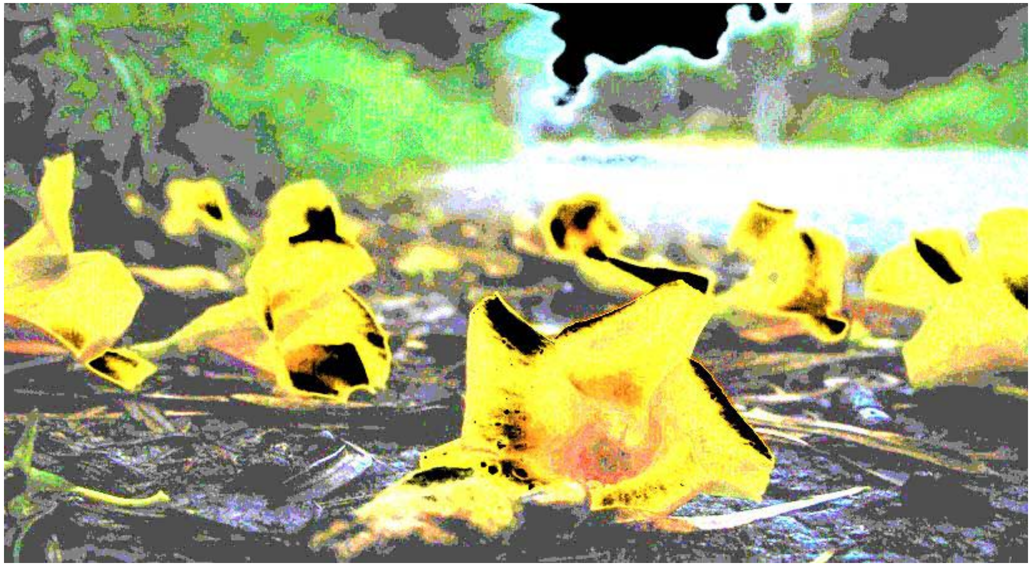
$n = 5$



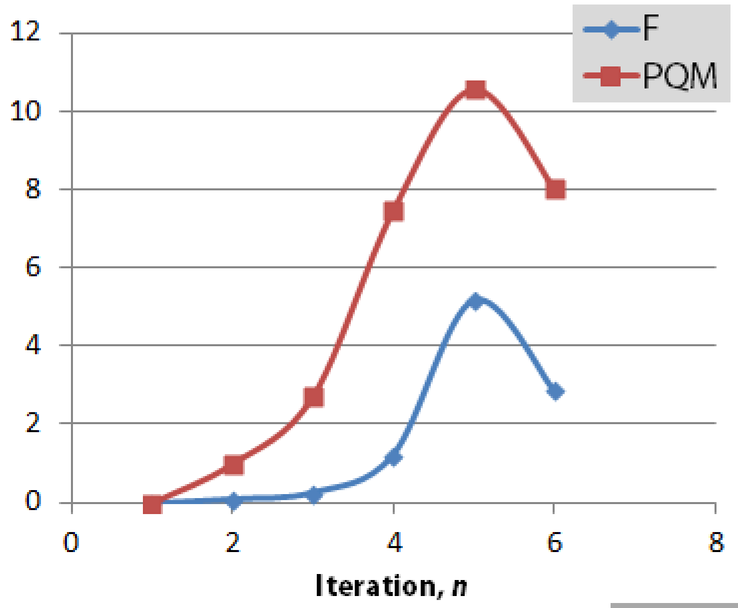
Example (Spatial Processing)

$\Delta t = 0.005$

Input



$n = 6$

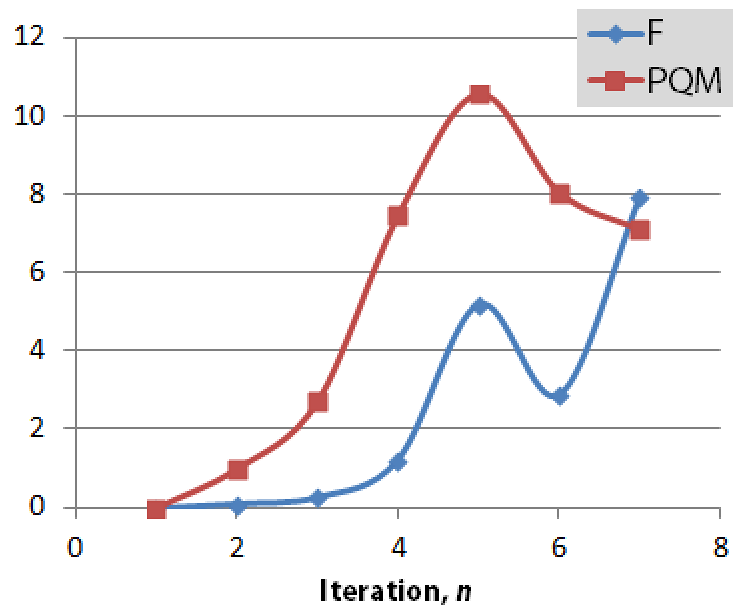


Example (Spatial Processing)

$\Delta t = 0.005$

Input

$n = 7$

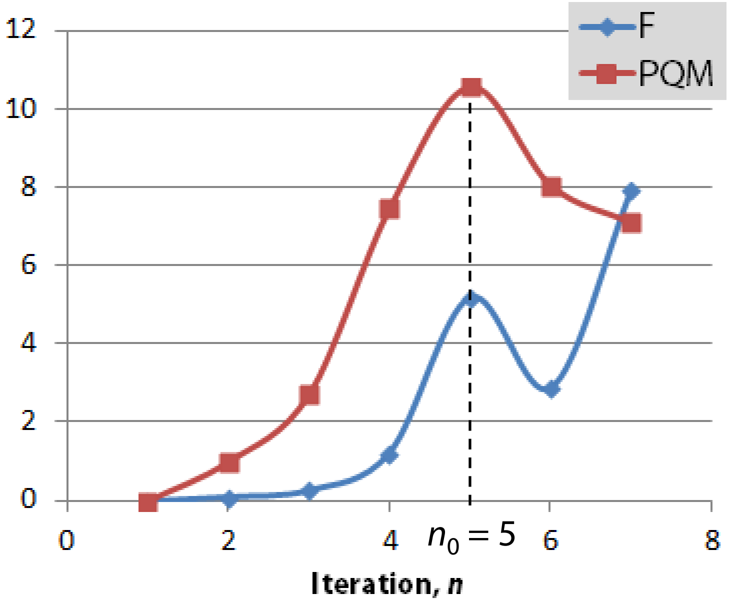


Example (Spatial Processing)

$\Delta t = 0.005$

Input

$\boldsymbol{n_0 = 5}$



Dynamic SR Models
for Contrast Enhancement

An SR Model is defined by

- Processing equation
- Parameter selection

Some SR models for image enhancement

1. Input-output statistics dependent SR (IOSSR) model [**Ye et al., 2004**]
2. Input Statistics-dependent SR (ISSR) model [**Chouhan et al., 2011**]
3. Intensity-specific value-dependent SR (IVSR) model [**Chouhan et al., 2014**[1]]

Contrast Enhancement using Suprathreshold Stochastic Resonance[2]

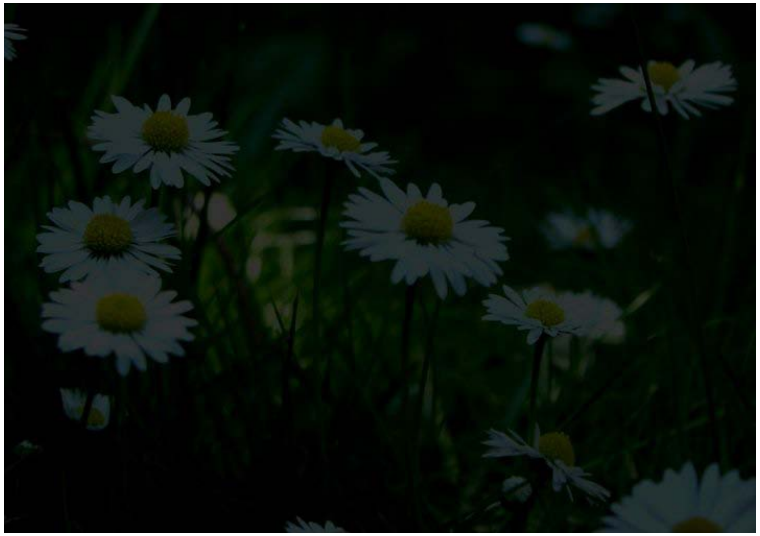
[1] R. Chouhan and P. K. Biswas, “Image enhancement and dynamic range compression using novel intensity-specific stochastic resonance-based parametric image enhancement model,” in Proc. 2014 *IEEE International Conference on Image Processing* (*ICIP* 2014), October 27 – 30, 2014, Paris, France, pp. 4532-4536

[2] R. K. Jha, R. Chouhan, and P. K. Biswas, “Noise-induced contrast enhancement of dark images using non-dynamic stochastic resonance,” in *Proc. National Conference on Communications,* 2012, pp. 1–5, doi: 10.1109/NCC.2012.6176793.

Enhancement of dark images

Input

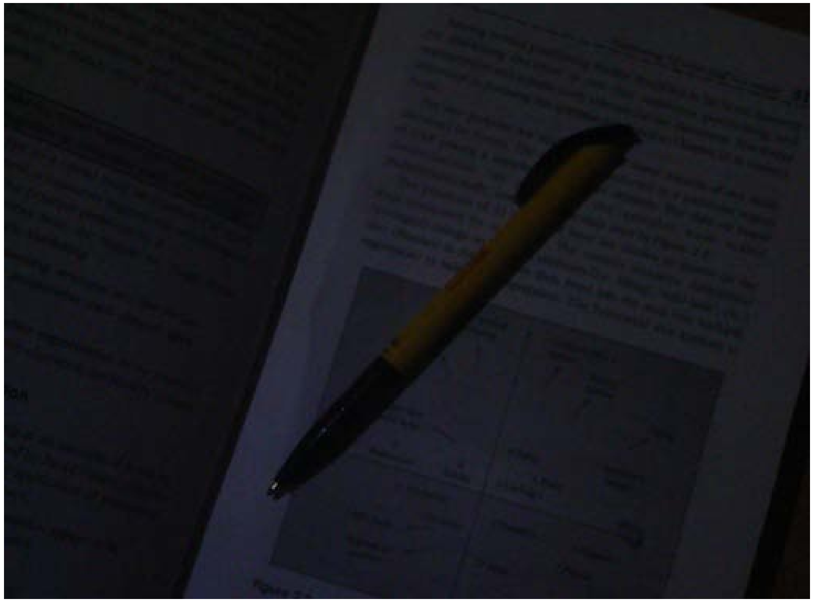
DFT-DSR Enhanced, n_0=13, F = 4.9, PQM = 9.8



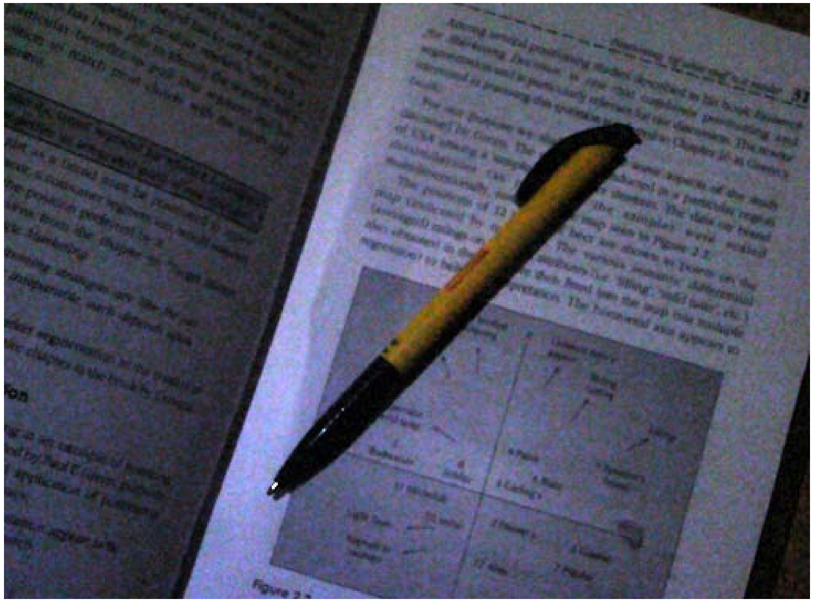
Input

DFT-DSR Enhanced, n_0=13, F = 3.2, PQM = 6.8

R. Chouhan, P. K. Biswas, and R. K. Jha, "**Enhancement of low-contrast images by internal noise-induced Fourier coefficient rooting**," *Signal, Image and Video Processing* (*Springer*), 2015, DOI: 10.1007/s11760-015-0812-2



Input



DFT-DSR Enhanced Image
n_0=17, F = 4.2, PQM = 11.8

R. Chouhan, P. K. Biswas, and R. K. Jha, "**Enhancement of low-contrast images by internal noise-induced Fourier coefficient rooting**," *Signal, Image and Video Processing* (*Springer*), 2015, DOI: 10.1007/s11760-015-0812-2

(a) Input, *Watch*, PQM=12.1

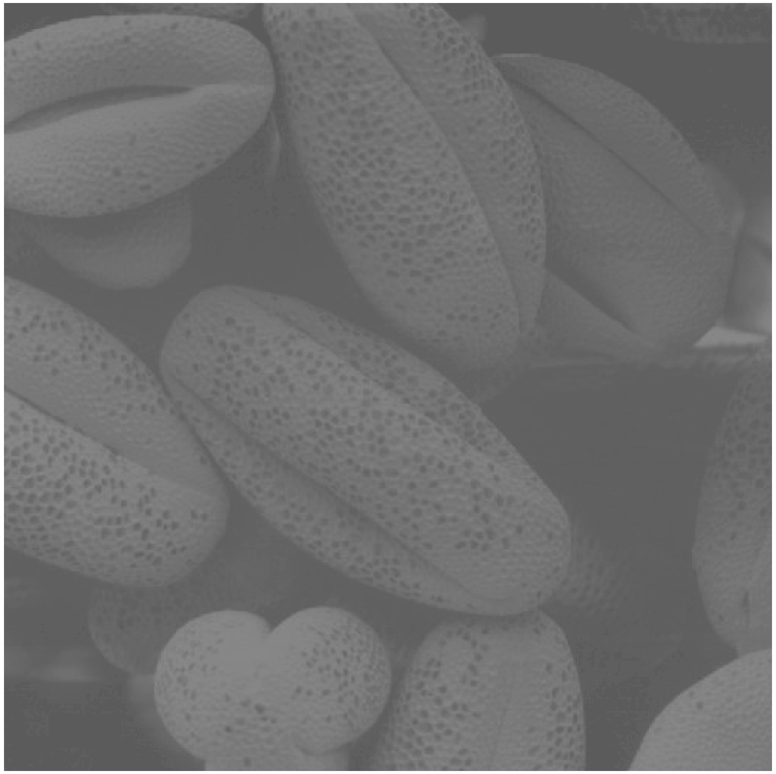
(b) SV-DWT, n=36, F=4.1, PQM=7.5

(c) SV-DCT, n=8, F=5.3, PQM=7.6

(d) DCT-DWT, n=20, F=5.1, PQM=9.0

ISSR Model in hybrid domains

R. Chouhan**,** P. K. Biswas, and R. K. Jha, "**Hybrid domain analysis of noise-aided contrast enhancement using stochastic resonance**," *Journal of Signal Processing Systems* (*Springer*), 2015 (Accepted)



Input

DFT-DSR Enhanced Image
n_0=34, F = 44.2, PQM = 7.2

IOSSR Model

R. Chouhan, P. K. Biswas, and R. K. Jha, "**Enhancement of low-contrast images by internal noise-induced Fourier coefficient rooting**," *Signal, Image and Video Processing* (*Springer*), 2015, DOI: 10.1007/s11760-015-0812-2

Input

DFT-DSR Enhanced Image
n_0=15, F = 28.1, PQM = 6.8

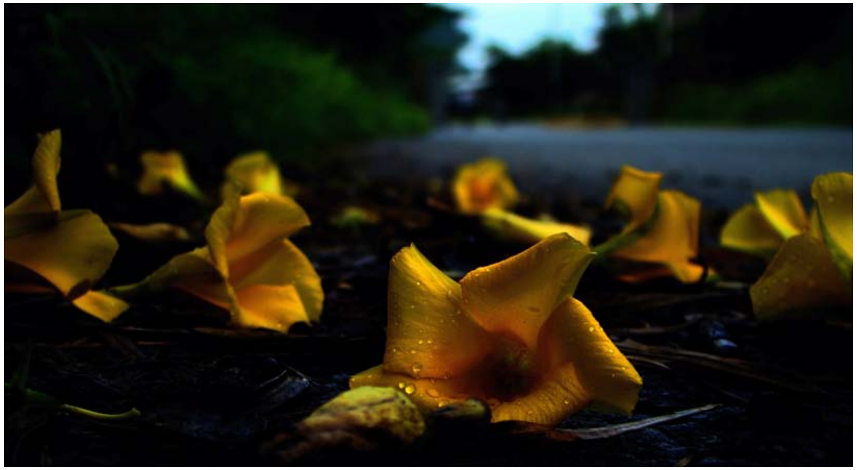
IOSSR Model

R. Chouhan, P. K. Biswas, and R. K. Jha, "**Enhancement of low-contrast images by internal noise-induced Fourier coefficient rooting**," *Signal, Image and Video Processing* (*Springer*), 2015, DOI: 10.1007/s11760-015-0812-2

Input, $PQM = 11.88$

DSR-enhanced
$n_0 = 5$, $F = 5.2$, $PQM = 10.57$

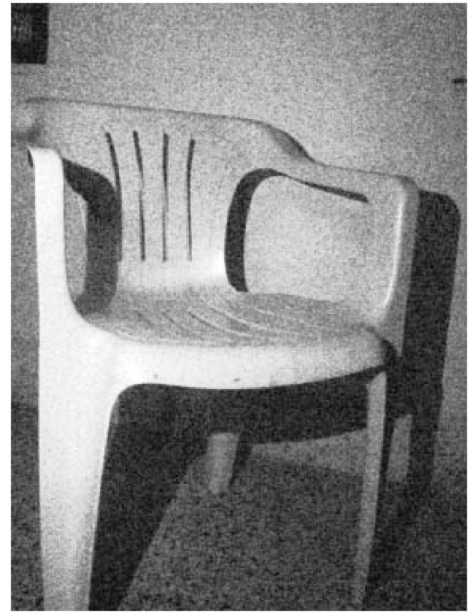
Histogram Equalization
$F = 6.7$, $PQM = 11.75$



Photoshop Autocontrast
$F = 6.7$, $PQM = 10.45$

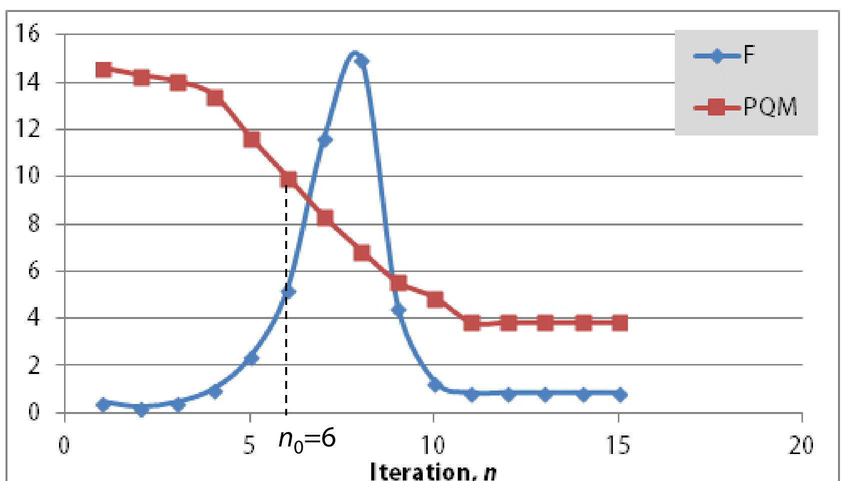
Input
$PQM = 12.2$

DSR-enhanced
$n_0 = 6$, $F = 5.3$, $PQM = 9.9$



Histogram Equalization
$F = 21.3$, $PQM = 6.9$

Photoshop Autocontrast
$F = 7.1$, $PQM = 8.2$



Results in various domains

(a) Input

(b) DFT-DSR

(c) SV-DWT-DSR

(d) SV-DCT-DSR

(e) DCT-DWT-DSR

(f) SVD-DSR

(g) DCT-DSR

(h) DWT-DSR

(i) Intensity-DSR

(j) SSR

Results in various domains

(a) Input, *Grass*

(b) DFT-DSR, n=13

(c) SV-DWT-DSR, n=10

(d) SV-DCT-DSR, n=3

(e) DCT-DWT-DSR, n=23

(f) DCT-DSR, $n = 15$

(g) DWT-DSR, $n = 95$

(h) SVD-DSR, $n = 14$

(i) Intensity-DSR, $n = 6$

(j) SSR

Results in various domains

(a) Input

(b) DFT-DSR

(c) SV-DWT-DSR

(d) SV-DCT-DSR

(e) DCT-DWT-DSR

(f) DCT-DSR

(g) DWT-DSR

(h) SVD-DSR

(i) Intensity- DSR

(j) SSR

Input Image (with bright and dark regions)

IVSR-enhanced image (with dark regions enhanced, and bright regions preserved)

Applications

Stochastic Resonance-based Watermark Extraction

Watermark Embedding

Watermark embedding refers to embedding an imperceptible secret signal (watermark) in the original (cover) data.

Watermark Extraction

Watermark extraction refers to retrieval of embedded data for verification and authentication of owner from a possibly tampered/corrupted watermarked image.

A good watermark should be

- Perceptually invisible
- Robust to attacks (such as geometrical distortions, noise addition, compression, enhancement, filtering)

General Watermarking Algorithm

Cover image

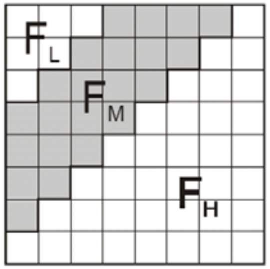
Binary logo

Step 1

Cover image

Discrete Wavelet Transform

Discrete Cosine Transform



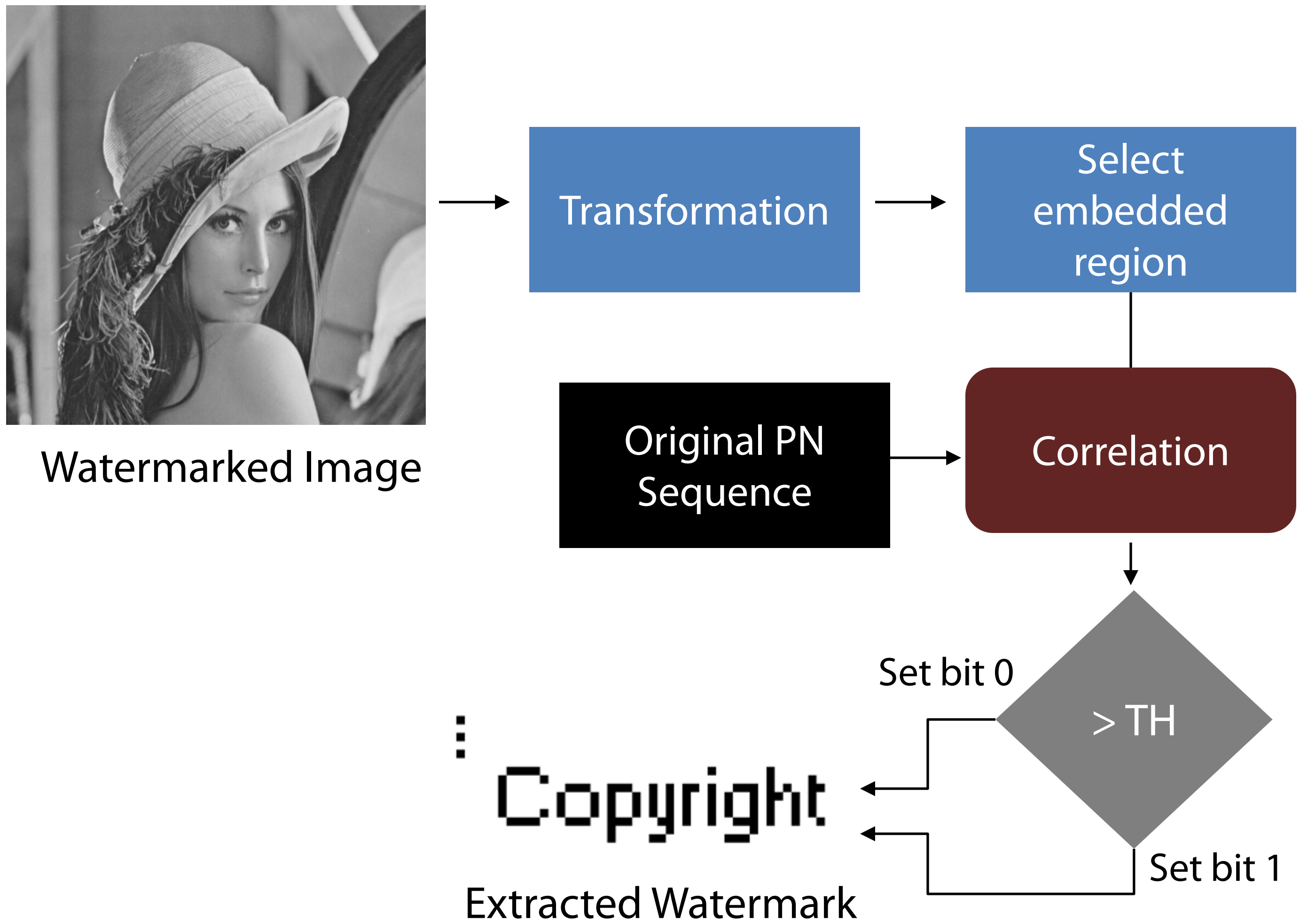
DCT Midband

Step 2 Generate pseudorandom sequence(s) and add to the selected coefficients (after multiplication with a weight)

$$I_i = W_i + \alpha P N_0$$

Step 3 Reconstruction using Inverse DWT / IDCT

Binary Watermark Extraction



Example: *SVD domain*

Embedding

- Singular value decomposition of watermark
- Addition of weighted singular values of watermark to cover image
- Reconstruction

Extraction

- Singular value decomposition of watermarked image
- Extraction of singular values
- Reconstruction of watermark

Challenges in robust watermark extraction

- Large value of watermarking weight is needed to achieve good robustness
- Small value of watermarking weight is needed to achieve perceptual transparency (less degradation in watermarked image)
- A trade-off between perceptual quality and robustness has to be achieved. Therefore, one of them has to be compromised with.

Objective

Improving the robustness of the extraction process without any compromise in perceptual quality of watermarked image

- This may be achieved by using DSR in **extraction** process, while a low watermarking weight is used in the embedding stage to ensure good visual quality of watermarked image.
- Here, the watermark signal is considered a weak force (since it is statistically and perceptually invisible after embedding)
- Noise comprises the degradation introduced due to attacks on the watermarked image (in the environment where watermark is embedded)
- Tested in domains
  - DCT-based Binary watermarking [1]
  - SVD-based Grayscale watermarking [2]
  - SVD-DCT-based Grayscale watermarking [3]

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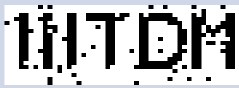
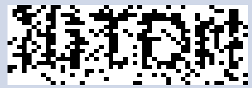
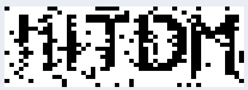
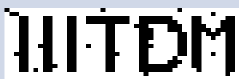
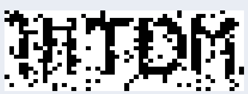
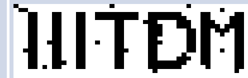
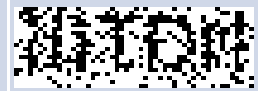
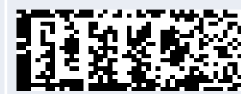
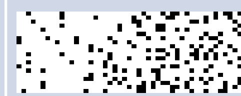
[1] R. Chouhan, R. K. Jha, M. Shrivastava, A. Chaturvedi, "Improved watermark extraction using Dynamic Stochastic Resonance," *Proc. IEEE Recent Advances in Intelligent Computational Systems*, Cochin, India, September 52-24, 2011, pp. 280-285

[2] R. Chouhan, R. K. Jha, A. Chaturvedi, T. Yamasaki, K. Aizawa, "Robust watermark extraction using SVD-based dynamic stochastic resonance," in *Proc. IEEE International Conference on Image Processing* (*ICIP*), Brussels, Belgium, September 11-14, 2011, vol. 11, pp. 2801-2804.

[3] R. K. Jha and R. Chouhan, "Dynamic Stochastic Resonance-based Grayscale Logo Extraction in Hybrid SVD-DCT Domain," *Journal of The Franklin Institute (Elsevier*), vol. 351, pp. 2931-2965, 2014

Binary Watermark (DCT domain)

Attack	With DSR	Without DSR
Salt and pepper		
Speckle		
Gaussian		
Rotation		
Cropping		

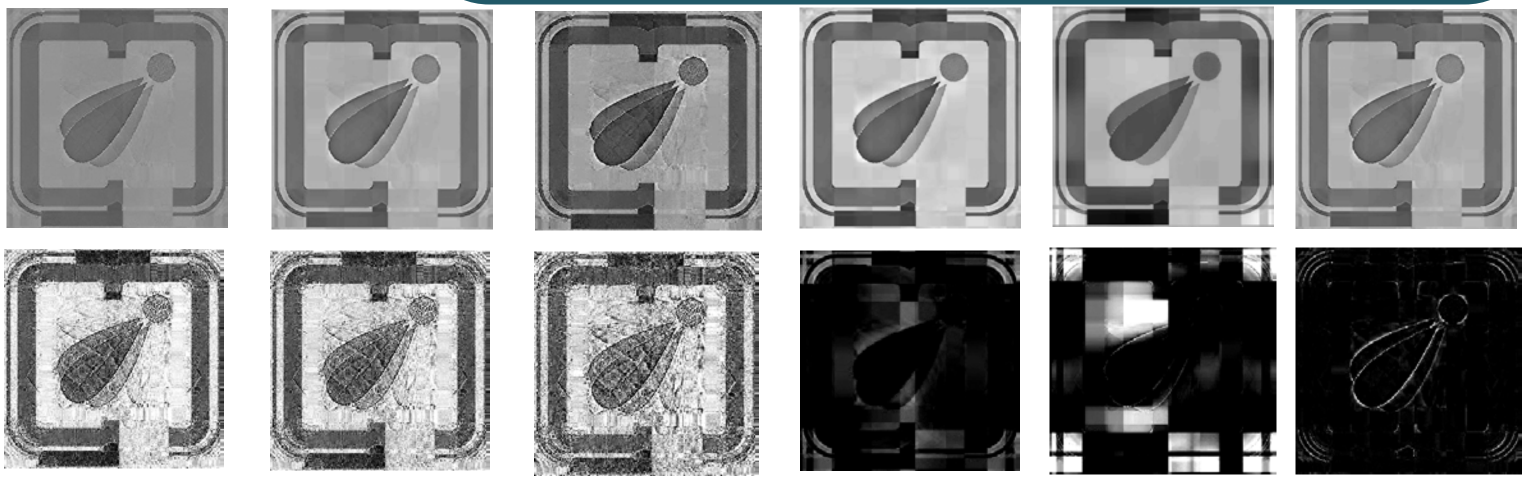
Attack	With DSR	Without DSR
Scaling		
Histogram equalization		
Low pass filtering		
High pass filtering		
JPEG compression		

R. K. Jha, R. Chouhan, K. Aizawa, “Dynamic Stochastic Resonance-based Improved Watermark Extraction in DCT Domain,” *Computers and Electrical Engineering* (*Elsevier*), vol. 52, number 6, pp. 1917-1929, August 2014

Extracted Watermarks (in presence of attacks)
SVD-based Watermarking

DSR-based Extraction

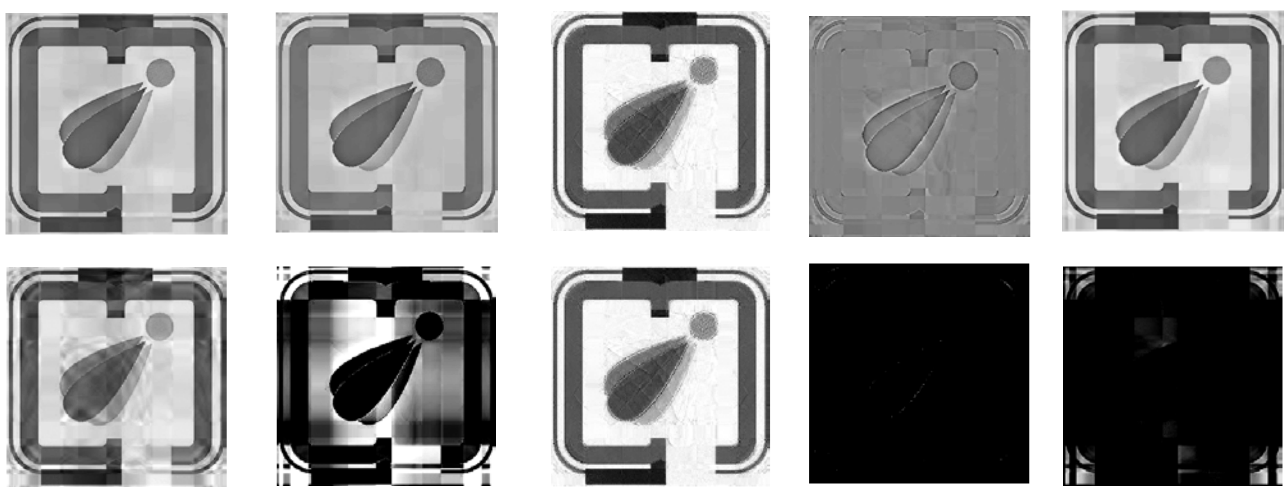
Extraction without DSR



Salt & Pepper Noise (σ = 0.04) | Speckle Noise (σ = 0.04) | Gaussian Noise (σ = 0.04) | Rotation (10 deg) | Cropping (35%) | Scaling (2:1:2)

DSR-based Extraction

Extraction without DSR

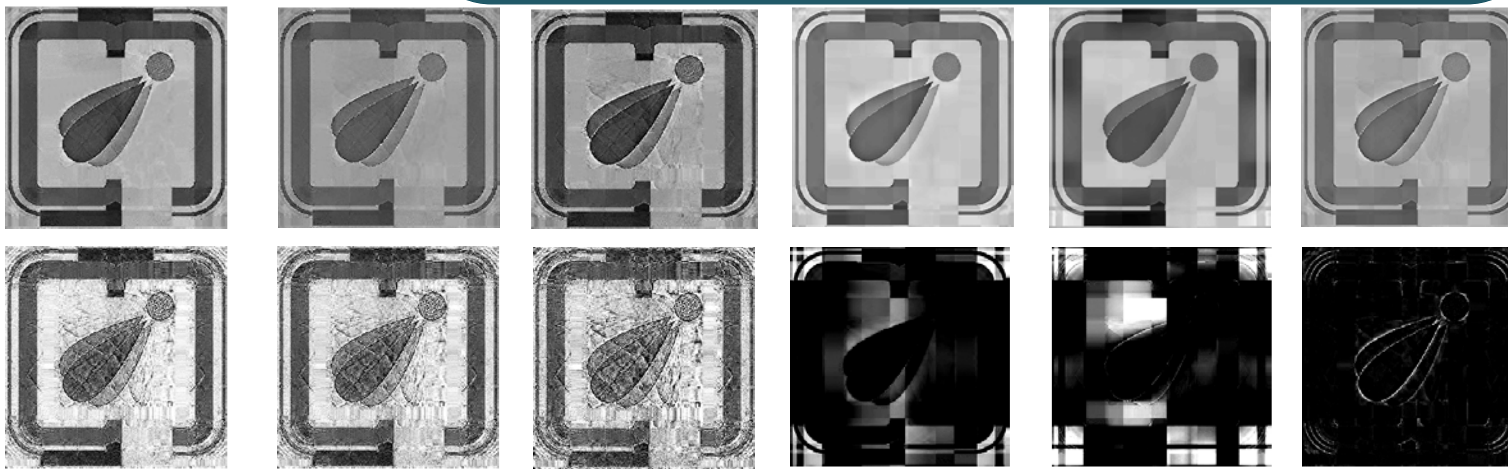


Warping | Hist. Eq. | LPF (9 x 9 Avg) | HPF (3 x 3 Sobel) | JPEG (Q=5)

Extracted Watermarks (in presence of attacks)
SVD-DCT-based Watermarking

DSR-based Extraction

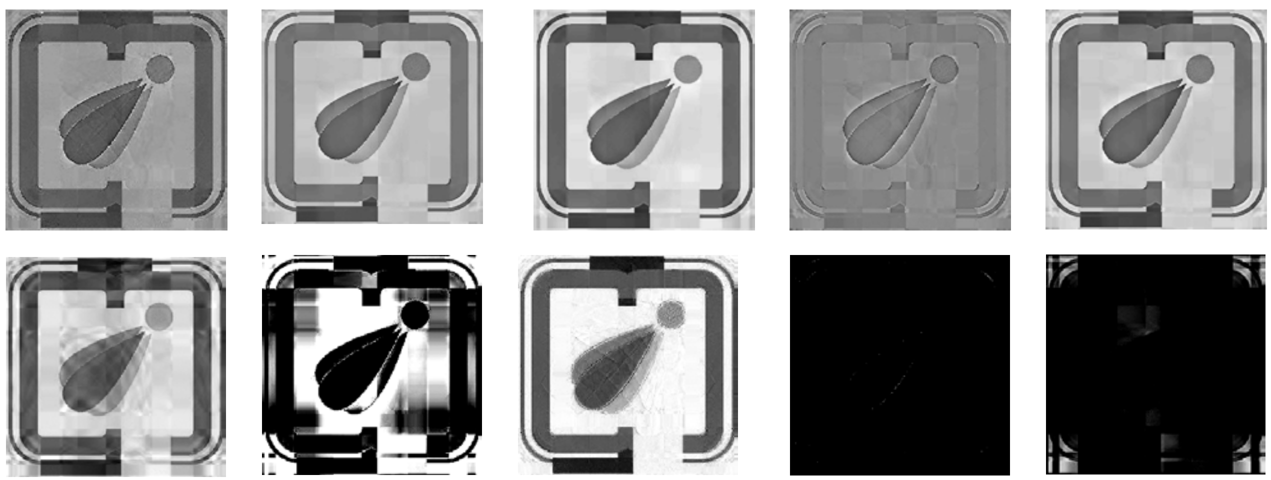
Extraction without DSR



Salt & Pepper Noise (σ = 0.04) | Speckle Noise (σ = 0.04) | Gaussian Noise (σ = 0.04) | Rotation (10 deg) | Cropping (35%) | Scaling (2:1:2)

DSR-based Extraction

Extraction without DSR



Warping | Hist. Eq. | LPF (9 x 9 Avg) | HPF (3 x 3 Sobel) | JPEG (Q=5)

Robustness (in terms of correlation coefficient)

	DSR-SVD-DCT		SVD-DCT	DSR-SVD		SVD	DSR-DCT		DCT
Attacks	ρ	n	ρ	ρ	n	ρ	ρ	n	ρ
Salt and pepper (noise density = 0.04)	**0.9869**	**80**	0.5457	0.9299	300	0.5457	0.5912	300	0.5912
Gaussian noise (mean = 0, variance = 0.04)	**0.8424**	**225**	0.3506	0.8439	300	0.3497	0.3323	500	0.3323
Speckle noise variance= 0.04	**0.9206**	**175**	0.4961	0.9218	330	0.4926	0.6104	350	0.6104
Rotation (10 degrees)	**0.9822**	**300**	0.8028	0.9809	295	0.6527	-0.0208	400	-0.0208
Cropping (35 %)	**0.9769**	**200**	0.2807	0.9656	250	0.5027	0.7434	500	0.7434
Scaling (2 1 2)	**0.9741**	**250**	0.9127	0.9613	300	0.1757	0.4598	460	0.4598
Warping	**0.9774**	**40**	0.9851	0.9811	300	0.9656	0.0406	400	0.0406
Histogram equalization	**0.9760**	**300**	0.7532	0.9760	350	0.7921	0.9930	500	0.9930
Low-pass filtering (Average 9×9)	**0.9874**	**100**	0.9584	0.9868	300	0.9584	-0.0372	300	-0.0372
High-pass filtering (Sobel)	**0.6136**	**500**	0.5082	49.4345	250	-0.8651	-0.4725	400	-0.4725
JPEG compression (Quality = 5)	**0.9905**	**50**	0.9922	0.9817	300	0.3555	-0.0093	350	0.0093

R. K. Jha and R. Chouhan, "Dynamic Stochastic Resonance-based Grayscale Logo Extraction in Hybrid SVD-DCT Domain," *Journal of The Franklin Institute (Elsevier)*, vol. 351, pp. 2931-2965, 2014

Stochastic Resonance

Challenges

Addressing **oversaturation**

Modeling *internal* degradation **due to lack of illumination**

Contextual interpretation of dynamics of a double-well system

Possible applications of the SR Models for image enhancement

- Enhancement of real-life images
- Preprocessing of medical images (E.g. low-contrast retinal images)
- Remote sensing images
- Night surveillance

The counterintuitive nature of stochastic resonance and utilization of noise can be studied for various image processing problems:

- Image denoising
- Image restoration (by utilizing the internal degradation)

Other Applications

Sensory neurobiology

Signal processing and analysis (dithering, detection and enhancement)

Medicine (medical devices for enhancing sensory and motor functions)

Audio processing

Suprathreshold SR in cochlear implants

Optical applications

Electronic and Magnetic Systems

Suggested Reading

Stochastic Resonance
L. Gammaitoni, P. Hanggi, P. Jung, F. Marchesoni
Reviews of Modern Physics (**1998)**

Tuning in to noise
A. R. Bulsara, L. Gammaitoni
Physics Today **(1996)**

Noise-Enhanced Information Systems
Hao Chen, Lav R. Varshney, Pramod K. Varshney
Proceedings of the IEEE (2014)

Takeaway?

- Noise ain't that bad after all !
- Stochastic resonance -
  counter-intuitive phenomenon
- Noise-aided image enhancement
- Robust watermark extraction
- Unexplored vista of applications

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S. Aghagolzadeh and O. K. Ersoy, “Transform image enhancement,” *Optical Engineering,* vol. 31, pp. 614–626, Mar. 1992.

V. P. S. Rallabandi, “Enhancement of ultrasound images using stochastic resonance based wavelet transform,” *Computerized Medical Imaging and Graphics*, vol. 32, pp. 316–320, 2008.

V. P. S. Rallabandi and P. K. Roy, “Magnetic resonance image enhancement using stochastic resonance in fourier domain,” *Magnetic Resonance Imaging,* vol. 28, pp. 1361–1373, 2010.

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A. R. Rivera, B. Ryu, and O. Chae, “Content-aware dark image enhancement through channel division,” *IEEE Transactions on Image Processing*, vol. 21, no. 9, pp. 3967–3980, Sep. 2012.

R. Chouhan, R. K. Jha, P. K. Biswas, “Enhancement of Dark and Low Contrast Images using Stochastic Resonance,” *IET Image Processing,* vol. 7, no. 2, p. 174 – 184, March 2013.

Thank you

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Contrast Enhancement Factor, *F*

$$\text{Contrast Enhancement Factor } (F) = \frac{\text{Contrast Quality of enhanced image}}{\text{Contrast Quality of input image}}$$

Contrast Quality (Q) $$Q = \frac{\sigma^2}{\mu}$$ [Rallabandi and Roy, 2010]

where σ and μ, respectively, are the standard deviation and mean of the image(s)

Back

Perceptual Quality Measure, *PQM*

There are many different ways to combine features to constitute a good no-reference quality quality assessment model. One such model proposed by [Wang et al, 2002] is:

$$PQM = \alpha + \beta B^{\gamma_1} A^{\gamma_2} Z^{\gamma_3}$$

where α, β, γ_1, γ_2, γ_3, are model parameters.

$(\alpha = \text{-}245.9,\ \beta = 261.9,\ \gamma_1 = \text{-}0.0240,\ \gamma_2 = 0.0160 \text{ and } \gamma_3 = 0.0064)$

- *B* is the average blockiness, estimated as the average differences across block boundaries for horizontally and vertically.
- The activity is measured using two factors. The first is the average absolute difference between in-block image samples, *A*.
- The second activity measure is the zero-crossing (ZC) rate, *Z*

For best perceptual quality as assessed by this model, *PQM* should be closest to 10 [Mukherjee and Mitra, 2008]

Back

Input Output Statistics-dependent SR (IOSSR) Model

Double-well parameters in DFT domain for the iterative procedure have been selected by an approach adapted and modified from that proposed by [Ye *et al.*, 2004].

$$\frac{a}{b} = \frac{\sigma_1^2}{\sigma_0^2}$$

where σ_1 and σ_0 respectively denote the standard deviation of noise in the input image and SR-enhanced image.

Back

Input Statistics-dependent SR (ISSR) Model

The double-well parameter, ***a,*** can be obtained by maximization of the SNR expression (by differentiation w.r.t. *a*).

The SNR is maximum when

$$a = 2\sigma_0^2$$

Parameter, ***b***, is selected by ensuring the condition of subthreshold input. This is done by setting a constraint indicating the maximum possible value of the a periodic force that can be applied to the double-well without making it unstable (or without allowing inter-well transition).

This subthreshold condition is ensured when

$$b < \frac{4a^3}{27}$$

Parameter **Δ*t*** is chosen arbitrarily, subject to application requirements.

R. Chouhan, R. K. Jha, P. K. Biswas, "Enhancement of Dark and Low Contrast Images using Stochastic Resonance," *IET Image Processing*, vol. 7, no. 2, p. 174 – 184, March 2013

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