Declaration

I hereby declare that the work presented in this thesis titled *Enhanced Edge Processing in Noisy Images: Leveraging noise-informed analysis for image denoising and edge detection* submitted to the Indian Institute of Technology Jodhpur in partial fulfillment of the requirements for the award of the degree of Doctor of Philosophy, is a bonafide record of the research work carried out under the supervision of Dr. Rajlaxmi Chouhan. The contents of this thesis in full or in parts, have not been submitted to, and will not be submitted by me to any other Institute or University in India or abroad for the award of any degree or diploma.

Deepak
P16VSS001

Certificate

This is to certify that the thesis titled *Enhanced Edge Processing in Noisy Images: Leveraging noise-informed analysis for image denoising and edge detection*, submitted by *Deepak* (P16VSS001) to the Indian Institute of Technology Jodhpur for the award of the degree of *Doctor of Philosophy*, is a bonafide record of the research work done by him under my supervision. To the best of my knowledge, the contents of this report, in full or in parts, have not been submitted to any other Institute or University for the award of any degree or diploma.

Dr. Rajlaxmi Chouhan
Ph.D. Thesis Supervisor

Abstract

This thesis aims to advance the research and development in image processing with a focus on edges of a noisy image by leveraging the noise itself. Edges occur where there is an abrupt change in the intensity in an image, and they act like boundaries or demarcations separating distinct objects in an image. Further, edges help enunciate the inner detailing present within an object. Since the very nature of edges is separating the boundary between two objects, it is highly desirable that the edges are definite and pixel-level accurate. Handling edges is challenging not only for developing an algorithm but also for extraction of ground truth.

Some major contributions of this thesis include edge-preserving image denoising, enhanced edge detection, and modular plug-and-play edge post-processing. This thesis has also attempted to open new avenues by presenting how to analyze discontinuities (corners, lines, and edges) in real noisy environments, and how the noise (which is considered undesirable) can be used to improve the performance of a system at hand. The various analyses presented in this thesis go to the pixel-level details, with the objective to gain better insights that can be extended to diverse applications.

Our first contribution deals with edge-preserving image denoising. It is well known that denoising through averaging typically reduces the sharpness of the edges and the details present in the denoised image. We proposed an *edge-preserving* image denoising algorithm where we extend the non-local means (NLM) algorithm by enhancing its most crucial part—the similarity weights. These similarity weights are enhanced, or in other words, rearranged, using the concept of stochastic resonance (SR). This iterative SR-based processing ensures that weights of similar patches are high and those of dissimilar patches are low. Through the lens of image attributes, the proposed work can be understood as iterative processing, and thereby enhancing, the similarity weights in a non-linear fashion using the modified and discretized Duffing's equation. The proposed algorithm is tested for a wide range of AWGN noise, and benchmarked on the popular SET12 and BSD68 datasets. For a high noise (sd 50), the cumulative effect is reflected as an improvement (in PSNR) of 14.5% and 12.1% over that of NLM for SET12 and BSD68 datasets. As compared to the NLM, the proposed algorithm produces images with better visual quality, better edge preservation, and negligible artifact generation, especially at high noise.

Our second contribution deals with discontinuity detectors and the noise behavior in real smartphone images. As smartphone cameras are the most popular photography devices in today's era, we analyze how the discontinuity detectors like corner, line, and edge detectors behave when the image is corrupted by the real smartphone noise. On deeper analyses, it is observed and demonstrated that these discontinuity detectors exhibit SR in cameraphone noisy environment. The behavior of these detectors with changing noise as well with changing threshold is demonstrated. The pixel-level demonstrations presents how these detectors can take advantage of the presence of noise.

Our third contribution is an application derived from the previous contribution and deals with improvement of popular Canny Edge Detector. Even the latest popular DL-based edge/boundary detectors produce thick grayscale edges (instead of thin binary edges), and struggle to achieve high pixel-level accuracy. Canny is a popular edge detector that gives thin binary edges, but it suffers from two major problems—broken edges and noisy structures. We propose an enhanced edge detector (SR-TW-CED) that improves the core of the Canny using SR-guided threshold maneuvering and window mapping. The whole image is partitioned into

windows, and mapped according to the underlying content, which decides how the threshold is to be maneuvered to obtain better edges. The proposed edge detector jointly addresses the two-fold problem of broken edges and noisy structures of the Canny edge detector. We also propose a novel measure of efficient edge detection; a unique, efficient way of edge content extraction and its combination for various channels; and a framework to handle repercussion of the randomness of the noise. Benchmarking on the BIPED dataset gives the human-level performance ($F1$ score 0.79), which is appreciable considering that it is a non-DL–based algorithm.

Our fourth contribution is an application that derives its premise from the edge detection measures proposed in the previous contribution and does not directly use iterative SR processing. Most of the edge detectors in the research community are stand-alone edge detectors. With this contribution, we propose a post-processing filter that can simply be plugged in at the output of essentially any edge detector to suppress the detection of false edges, improve accuracy, and boost the precision of detection. A traditional edge detector suffers highly from false-positive edge detection, and the problem is so prevalent that the falsely detected edges often outnumber the true-positive detected edges. While this significantly limits the capabilities of non-DL–based edge detectors for typical images, it also creates a serious bottleneck in the performance of DL-based edge detectors particularly for images that contain texture or mesh. To address this, we have designed a novel framework, called the 'triple-window patch-debias broken-hysteresis' framework. We also use the eigen-based measures as the filtering units in this framework to create a precision-boosting filter, called PBEdgeFilter. The proposed filter is a modular filter that requires minimum or, in most cases, no external inputs, and can be used in a plug-and-play manner. When tested on the BIPED dataset, PBEdgeFilter is observed to boost the precision of Canny by 89%, SMED by 102%, and LoG by 93.5%. When applied over the latest DL-based edge detector, DexiNed, the precision is observed to be boosted by 57.7% for the specific case of input images having mesh regions.

The thesis includes image processing algorithms derived directly from or informed by the concept of SR or noise-enhanced iterative processing. While the first contribution, i.e. SR-enhanced NLM, directly utilizes the noise-aided iterative processing in a noisy environment, other contributions are broadly informed by the dynamics of signals (edges, in this case) in noisy and non-noisy environments. These contributions do not directly utilize SR-based processing but are designed with the rationale of signal behavior in different image regions.

With the above contributions, an attempt has been made to contribute towards the knowledge base of edge processing in noisy environments.

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List of Symbols

Symbol	Description
Acc	Accuracy
A	Amplitude of signal
ω_s	Angular frequency of signal
k	a constant
$\in$	Belongs to (set operation)
$\mathcal{O}(.)$	Big-O notation
$D[.]$	Detector specific image operation
$det(.)$	Determinant of a matrix
Δt	Discretized steps
a, b	Double-well parameters; Two parameters of NLF
$e_{measure}$	e measure (elongation)
λ	eigenvalue
$\widehat{\{.\}}$	Estimated quantity
$d(B(.), Q(.))$	Euclidean distance between two patches B and Q
$F1$	F1 measure
h	Filtering parameter
M	Harris matrix
$v(.)$, $x[.]$	Intensity of noisy image
$u(.)$, $s[.]$	Intensity of pristine image
n, n_{iter}	iteration count
T_l, T_h	Low-threshold and high-threshold
m	Mass of a particle
μ	Mean of AWGN
D	Noise variance
$\mathcal{N}(.)$	Normal distribution
C	Normalization constant
n_{opt}	Optimum iteration count
$p_{measure}$	p measure (plus)
P	Patch window height/width; Precision
i, p	Pixel location
$\mathcal{P}(.)$	Poisson distribution
x	Position of particle; State of system
$U(.)$	Potential function
R	Research window height/width; Recall; Cornerness
$\mathcal{T}(n)$	Running time
η_p	Signal-dependent noise component
η_g	Signal-independent noise component
$W_{\{.\}}$	Similarity distance
w	Similarity weight
$B(p, f)$	Square neighborhood of pixels centered at p and sized $(2f+1) \times (2f+1)$
σ	Standard deviation of AWGN

Symbol	Description
$\xi(.)$	Stochastic noise
$T[.]$	Threshold operation
$trace(.)$	Trace of a matrix
σ^2	Variance of AWGN
γ	Viscous force
$w(B,Q)$	Weight between patches B and Q

List of Abbreviations

Abbreviation	Full form
2D	2 Dimensional
AWGN	Additive White Gaussian Noise
AP	Average Precision
BSDS500	Berkeley Segmentation Data Set 500
BDCN	Bi-Directional Cascade Network
CED	Canny Edge Detector
COCO	Common Objects in Context
CNN	Convolutional Neural Network
dB	Decibel
DL	Deep Learning
DexiNed	Dense EXtreme Inception Network for Edge Detection
DCR	Detection Common Rate
DSR	Dynamic Stochastic Resonance
FFT	Fast Fourier Transform
GAN	Generative Adversarial Network
gPb	Globalized Probability of Boundary
HMM	Hidden Markov Model
HDR	High Dynamic Range
HED	Holistically-Nested Edge Detection
HSI	Hue Saturation Intensity
i.i.d.	Independently and Identically Distributed
LCC	Largest Connected Components
LTI	Linear Time Invariant
ML	Machine Learning
MRI	Magnetic Resonance Imaging
MRF	Markov Random Field
NN	Neural Network
NLF	Noise Level Function
NLM	Non-Local Means
NMS	Non-Max Suppression
ODS	Optimal Dataset Scale
OIS	Optimal Image Scale
OFET	Organic Field-Effect Transistor
PLGFM	Pattern of Local Gravitational Force Magnitude
PSNR	Peak Signal-to-Noise Ratio
FOM	Pratt's Figure Of Merit
PBEdgeFilter	Precision-Boosting Edge Filter
PCA	Principal Component Analysis
PC	Principal Components
PWM	Processed Window Map
QPSO	Quantum Particle Swarm Optimization

Abbreviation	Full form
RWM	Raw Window Map
RCF	Richer Convolutional Features
SMED	Scale Multiplication Edge Detection
SNR	Signal to Noise Ratio
SVD	Singular Value Decomposition
SIDD	Smartphone Image Denoising Dataset
SR-TW-CED	SR-guided enhanced Canny Edge Detector using Thresholding maneuvering and Window mapping
sd	Standard deviation
SOTA	State Of The Art
SR	Stochastic Resonance
SSIM	Structural SIMilarity index measure
SE	Structured Edge Forest
TP	True positive