

Acknowledgements

I wish to express deep sense of gratitude and sincere thanks to my thesis supervisor Prof. Rajiv Gupta, Dean, Engineering Service Division, Birla Institute of Technology and Science, Pilani, Rajasthan, India, for his valuable guidance, encouragement and moral support. It has been a great pleasure to be associated with him on this work.

Gratitude is also accorded to B.I.T.S., Pilani for providing all the necessary facilities to complete the research work. My special thanks go to Prof. L. K. Maheshwari, Vice-Chancellor, B.I.T.S., Pilani for giving me an opportunity to do research at the Institute. I also thank Prof. K. E. Raman Deputy Director (Administration), Prof. G Raghurama, Deputy Director (Academic), Prof. S. Bhanot, Unit Chief and Group Leader, Instrumentation Unit and Prof. A. K. Sarkar, Dean Instruction Division and FD-I of the institute for providing the necessary infrastructure and other facilities.

I also express my heartfelt gratitude to Prof. Ravi Prakash, Dean, Research and Consultancy Division for his kind and affectionate enquiries about the work and continuous encouragement for making this work as a success.

I am deeply indebted to Prof. Rashmi Ranjan Misra and Prof. S. Balasubramaniam who are the members of Doctoral Advisory Committee, for their valuable suggestions and moral support.

I also express my gratitude for the kind and affectionate enquiries about the work and the encouragement given by Research and Consultancy Division staff.

Special thanks are also extended to all of senior faculties of EEE & Instrumentation Group and my colleagues for their kind inspiration.

Finally, but most deeply, the author thanks his parents, his wife, his daughter, his son and other family members for their love and moral support during the entire period of this research work with which this work is successfully completed.

Abstract

Image denoising has always been one of the standard problems of the image analysis and processing community. It is motivated by itself or by some practical application such as preprocessing for e.g. remote sensing applications, medical image diagnosis; the goal is to reduce noise. The successful image denoising algorithms are mainly based on transforms. Recent research in transform based image denoising has stressed on the wavelet transform due to its superior performance over other transforms such as Fourier, Karhunen-Loeve transform, Discrete cosine transform. It is applied to image processing successfully for last two decades. It has been shown in several papers that wavelet-based methods arise naturally for image denoising.

The first part of this thesis is for additive noise. The proposed algorithms use local adaptivity based on static of neighboring pixels in wavelet domain. These statistics consist of energy and variance in different scales that capture certain statistical regularities of natural images. The existing methods are limited because they make at least one of the following three assumptions: i) the wavelet coefficients are independent; ii) the signal component of the wavelet coefficient distribution follows a specified parametric model; and iii) the wavelet representation of all signal of interest has same level of sparsity. We propose two methods namely locally adaptive energy (LAE) and locally adaptive variance (LAV), based on locally adaptivity that addresses each of these issues. The algorithm uses Discrete Wavelet Transform (DWT) to extract information about sharp features in multiresolution images and applies shrinkage function adapting the local statistics of the image. The shrinkage function depends on standard deviation or

energy of neighboring pixels, whereas in standard wavelet methods, the empirical wavelet coefficients shrink pixel by pixel, on the basis of their individual magnitude. The algorithms use very few and intuitive parameter. The parameters are first chosen by heuristic approach then it is optimized. The cost function used for the optimization process is to minimize the mean square error.

To assess the performance of our methods, we have compared it with several standard wavelet-based denoising algorithms on a number of benchmark natural images. A very important aspect of all the denoising methods and proposed methods is to the accurate estimation of the noise level. Therefore this topic is treated in detail to review noise estimation methods. Two methods are implemented and assessed thoroughly, one in spatial domain and other in wavelet domain.

The second part of this thesis is for multiplicative noise. The noise is reduced to detect geographical features in synthetic aperture radar (SAR). SAR images are corrupted by speckle noise which is multiplicative in nature. Existence of this noise may hide details and thus, reduce resolution of these images. The speckle degrades the quality of the image and makes difficult to interpret, analysis and classification of the SAR images. This noise is signal dependent and different from additive noise used in natural images. In this thesis, speckle is reduced by multiscale analysis in wavelet domain. The SAR image is first despeckled then the features are detected by wavelet filter.

The third part is devoted to image enhancement method using image regularity. Enhancement often includes a denoising and a deblurring or sharpening step. It has been shown that the Holder regularity is decreased with additive white Gaussian noise. The

regularity is estimated by wavelet coefficient in different scale then it is increased as perceived by a human observer.

The thesis contains denoising algorithms for two types of noises: additive noise and multiplicative noise. Two methods are proposed for additive noise. The geographical feature detection method is proposed for SAR images which are affected by multiplicative noise. The enhancement algorithm is applied for denoising when the type of noise is unknown.

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LIST OF SYMBOLS

f	True Image
f'	Noisy image
$E[.]$	expected value
\hat{f}	Estimated image
η	Holder exponent
σ_n^2	Noise variance (contaminated)
$\hat{\sigma}_n^2$	Estimated noise variance
$\phi(\cdot)$	Scaling function
$\phi_{j,k}(\cdot)$	Translated and dilated Scaling function
$\psi(\cdot)$	Wavelet function
$\psi_{j,k}(\cdot)$	Translated and dilated wavelet function
ξ_B	Homogeneity measure of block B
\hat{m}_k	Expected k^{th} moment of data
λ	Threshold value
λ_{univ}	Universal threshold value
$\lambda_{soft}, \lambda_{hard}$	Soft and hard threshold value
Δ	Sobel operator
A	Approximate subband image
D	Diagonal subband image
G	Gradient amplitude

g	Gradient amplitude
H	Horizontal subband image
h	Histogram
J	Largest level of decomposition
j	Decomposition level
L	Number of gray levels
m_k	k^{th} moment of data
M_k	Normalized moment of data
$m_{l,n}$	Holder exponents
N	Noise
R	Number of gray levels
t	Time or unitless index
$T(.,.)$	Threshold operator
V	Vertical subband image
$Var\{.\}$	Variance operator
V_j	Approximate subspace at scale j
W_j	Detail subspace at scale j

LIST OF ABBREVIATIONS

<i>1-D</i>	One dimensional signal
<i>2-D</i>	Two dimensional signal
<i>ABE</i>	Amplitude-scale-invariant Bayes estimator
<i>AR</i>	Autoregressive
<i>ASIC</i>	Application-specific integrated circuits
<i>ATR</i>	Automatic target recognition
<i>AWGN</i>	Additive white Gaussian Noise
<i>bpp</i>	bits per pixel
<i>CDF</i>	Cumulative distribution function
<i>COI</i>	Cone of influence
<i>CWT</i>	Continuous wavelet transform
<i>dB</i>	Decibels
<i>db2</i>	Daubechies Wavelet basis 2
<i>DCT</i>	Discrete cosine transform
<i>DWT</i>	Discrete wavelet transform
<i>EM</i>	Expectation Maximization
<i>ENL</i>	Equivalent number of looks
<i>FIR</i>	Finite impulse response
<i>GGD</i>	Generalized Gaussian Distribution
<i>GMM</i>	Gaussian mixture model
<i>GSM</i>	Gaussian Scale mixture
<i>HMC</i>	Hidden Markov Chain

<i>HMT</i>	Hidden Markov Tree
<i>ICA</i>	Independent Component Analysis
<i>iid</i>	Independent, identically distributed
<i>IPSNR</i>	Incremental peak signal to noise ratio
<i>IV</i>	Image variance
<i>LMMSE</i>	Linear minimum mean square error
<i>LMS</i>	Least mean square
<i>LSI</i>	Linear shift invariant
<i>MAD</i>	Mean absolute difference
<i>MAE</i>	Mean absolute error
<i>MAP</i>	Maximum A Posteriori
<i>mips</i>	Millions instructions per second
<i>MNSS</i>	Multiplicatively non-stationary speckle
<i>MRA</i>	Multiresolution analysis
<i>MRF</i>	Markov random field
<i>MSE</i>	Mean squared error
<i>MSS</i>	Multiplicatively stationary speckle model
<i>pdf</i>	Probability distribution function
<i>PSNR</i>	Peak signal to noise ratio
<i>RAM</i>	Random access memory
<i>ROM</i>	Read only memory
<i>SURE</i>	Stein's unbiased risk estimator
<i>SWT</i>	Stationary wavelet transform

<i>Sym4</i>	Symlet wavelet basis 4
<i>UDWT</i>	Undecimated discrete wavelet transform
<i>WCAE</i>	Worst case absolute error
<i>WP</i>	Wavelet Packets
<i>WSS</i>	Wide-Sense stationary
<i>WT</i>	Wavelet Transform
<i>WTMM</i>	Wavelet transform modulus maxima

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