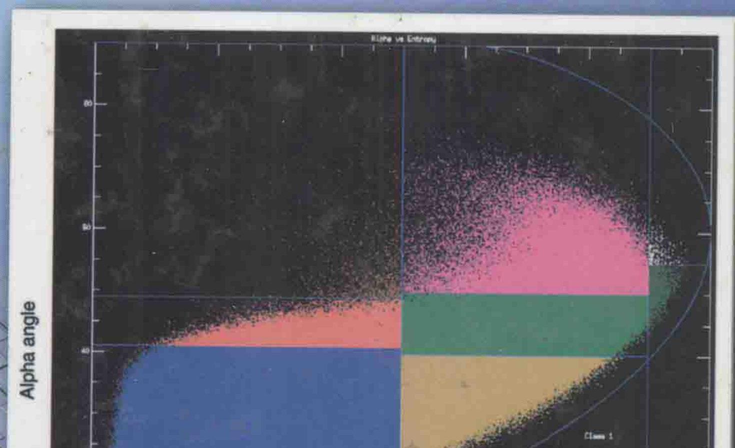
IMAGE PROCESSING FOR REMOTE SENSING



EDITED BY

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CRC Press
Taylor & Francis Group

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CRC Press
Taylor & Francis Group
Boca Raton London New York

CRC Press is an imprint of the
Taylor & Francis Group, an **informa** business

The material was previously published in *Signal and Image Processing for Remote Sensing* © Taylor and Francis 2006.

CRC Press
Taylor & Francis Group
6000 Broken Sound Parkway NW, Suite 300
Boca Raton, FL 33487-2742

Printed in the United States of America on acid-free paper
10 9 8 7 6 5 4 3 2 1

International Standard Book Number-13: 978-1-4200-6664-7 (Hardcover)

Library of Congress Cataloging-in-Publication Data

Image processing for remote sensing / [edited by] C.H. Chen.
p. cm.
Includes bibliographical references and index.
ISBN-13: 978-1-4200-6664-7
ISBN-10: 1-4200-6664-1
1. Remote sensing--Data processing. 2. Image processing. I. Chen, C.H. (Chi-hau), 1937- II. Title.

G70.4.I44 2008
621.36'78--dc22 2007030188

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Preface

This volume is a spin-off edition derived from *Signal and Image Processing for Remote Sensing*. It presents more advanced topics of image processing in remote sensing than similar books in the area. The topics of image modeling, statistical image classifiers, change detection, independent component analysis, vertex component analysis, image fusion for better classification or segmentation, 2-D time series modeling, neural network classifications, etc. are examined in this volume. Some unique topics like accuracy assessment and information-theoretic measure of multiband images are presented. An emphasis is placed on the issues with synthetic aperture radar (SAR) images in many chapters. Continued development on imaging sensors always presents new opportunities and challenges on image processing for remote sensing. The hyperspectral imaging sensor is a good example here. We believe this volume not only presents the most up-to-date developments of image processing for remote sensing but also suggests to readers the many challenging problems ahead for further study.

Original Preface from *Signal and Image Processing for Remote Sensing*

Both signal processing and image processing have been playing increasingly important roles in remote sensing. While most data from satellites are in image forms and thus image processing has been used most often, signal processing can contribute significantly in extracting information from the remotely sensed waveforms or time series data. In contrast to other books in this field which deal almost exclusively with the image processing for remote sensing, this book provides a good balance between the roles of signal processing and image processing in remote sensing. The book covers mainly methodologies of signal processing and image processing in remote sensing. Emphasis is thus placed on the mathematical techniques which we believe will be less changed as compared to sensor, software and hardware technologies. Furthermore, the term "remote sensing" is not limited to the problems with data from satellite sensors. Other sensors which acquire data remotely are also considered. Thus another unique feature of the book is the coverage of a broader scope of the remote sensing information processing problems than any other book in the area.

The book is divided into two parts [now published as separate volumes under the following titles]. Part I, *Signal Processing for Remote Sensing*, has 12 chapters and Part II [comprising the present volume], *Image Processing for Remote Sensing*, has 16 chapters. The chapters are written by leaders in the field. We are very fortunate, for example, to have Dr. Norden Huang, inventor of the Huang–Hilbert transform, along with Dr. Steven Long, to write a chapter on the application of the transform to remote sensing problem, and Dr. Enders A. Robinson, who has made many major contributions to geophysical signal processing for over half a century, to write a chapter on the basic problem of constructing seismic images by ray tracing.

In Part I, following Chapter 1 by Drs. Long and Huang, and my short Chapter 2 on the roles of statistical pattern recognition and statistical signal processing in remote sensing, we start from a very low end of the electromagnetic spectrum. Chapter 3 considers the classification of infrasound at a frequency range of 0.001 Hz to 10 Hz by using a parallel bank neural network classifier and a 11-step feature selection process. The >90% correct classification rate is impressive for this kind of remote sensing data. Chapter 4 through

Chapter 6 deal with seismic signal processing. Chapter 4 provides excellent physical insights on the steps for construction of digital seismic images. Even though the seismic image is an image, this chapter is placed in Part I as seismic signals start as waveforms. Chapter 5 considers the singular value decomposition of a matrix data set from scalar-sensors arrays, which is followed by independent component analysis (ICA) step to relax the unjustified orthogonality constraint for the propagation vectors by imposing a stronger constraint of fourth-order independence of the estimated waves. With an initial focus of the use of ICA in seismic data and inspired by Dr. Robinson's lecture on seismic deconvolution at the 4th International Symposium, 2002, on Computer Aided Seismic Analysis and Discrimination, Mr. Zhenhai Wang has examined approaches beyond ICA for improving seismic images. Chapter 6 is an effort to show that factor analysis, as an alternative to stacking, can play a useful role in removing some unwanted components in the data and thereby enhancing the subsurface structure as shown in the seismic images. Chapter 7 on Kalman filtering for improving detection of landmines using electromagnetic signals, which experience severe interference, is another remote sensing problem of higher interest in recent years. Chapter 8 is a representative time series analysis problem on using meteorological and remote sensing indices to monitor vegetation moisture dynamics. Chapter 9 actually deals with the image data for digital elevation model but is placed in Part I mainly because the prediction error (PE) filter is originated from the geophysical signal processing. The PE filter allows us to interpolate the missing parts of an image. The only chapter that deals with the sonar data is Chapter 10, which shows that a simple blind source separation algorithm based on the second-order statistics can be very effective to remove reverberations in active sonar data. Chapter 11 and Chapter 12 are excellent examples of using neural networks for retrieval of physical parameters from the remote sensing data. Chapter 12 further provides a link between signal and image processing as the principal component analysis and image sharpening tools employed are exactly what are needed in Part II.

With a focus on image processing of remote sensing images, Part II begins with Chapter 13 [Chapter 1 of the present volume] that is concerned with the physics and mathematical algorithms for determining the ocean surface parameters from synthetic aperture radar (SAR) images. Mathematically Markov random field (MRF) is one of the most useful models for the rich contextual information in an image. Chapter 14 [now Chapter 2] provides a comprehensive treatment of MRF-based remote sensing image classification. Besides an overview of previous work, the chapter describes the methodological issues involved and presents results of the application of the technique to the classification of real (both single-date and multitemporal) remote sensing images. Although there are many studies on using an ensemble of classifiers to improve the overall classification performance, the random forest machine learning method for classification of hyperspectral and multisource data as presented in Chapter 15 [now Chapter 3] is an excellent example of using new statistical approaches for improved classification with the remote sensing data. Chapter 16 [now Chapter 4] presents another machine learning method, AdaBoost, to obtain robustness property in the classifier. The chapter further considers the relations among the contextual classifier, MRF-based methods, and spatial boosting. The following two chapters are concerned with different aspects of the change detection problem. Change detection is a uniquely important problem in remote sensing as the images acquired at different times over the same geographical area can be used in the areas of environmental monitoring, damage management, and so on. After discussing change detection methods for multitemporal SAR images, Chapter 17 [now Chapter 5] examines an adaptive scale–driven technique for change detection in medium resolution SAR data. Chapter 18 [now Chapter 6] evaluates the Wiener filter-based method, Mahalanobis distance, and subspace projection methods of change detection, with the change detection performance illustrated by receiver operating characteristics (ROC) curves. In recent years, ICA and related approaches have presented many new potentials in remote sensing information processing. A challenging task underlying many hyperspectral imagery applications is decomposing a mixed pixel into a collection of reflectance spectra, called endmember signatures, and the corresponding abundance fractions. Chapter 19 [now Chapter 7] presents a new method for unsupervised endmember extraction called vertex component analysis (VCA). The VCA algorithms presented have better or comparable performance as compared to two other techniques but require less computational complexity. Other useful ICA applications in remote sensing include feature extraction, and speckle reduction of SAR images. Chapter 20 [now Chapter 8] presents two different methods of SAR image speckle reduction using ICA, both making use of the FastICA algorithm. In two-dimensional time series modeling, Chapter 21 [now Chapter 9] makes use of a fractionally integrated autoregressive moving average (FARIMA) analysis to model the mean radial power spectral density of the sea SAR imagery. Long-range dependence models are used in addition to the fractional sea surface models for the simulation of the sea SAR image spectra at different sea states, with and without oil slicks at low computational cost.

Returning to the image classification problem, Chapter 22 [now Chapter 10] deals with the topics of pixel classification using Bayes classifier, region segmentation guided by morphology and split-and-merge algorithm, region feature extraction, and region classification.

Chapter 23 [now Chapter 11] provides a tutorial presentation of different issues of data fusion for remote sensing applications. Data fusion can improve classification and for the decision level fusion strategies, four multisensor classifiers are presented. Beyond the currently popular transform techniques, Chapter 24 [now Chapter 12] demonstrates that Hermite transform can be very useful for noise reduction and image fusion in remote sensing. The Hermite transform is an image representation model that mimics some of the important properties of human visual perception, namely local orientation analysis and the Gaussian derivative model of early vision. Chapter 25 [now Chapter 13] is another chapter that demonstrates the importance of image fusion to improving sea ice classification performance, using backpropagation trained neural network and linear discrimination analysis and texture features. Chapter 26 [now Chapter 14] is on the issue of accuracy assessment for which the Bradley–Terry model is adopted. Chapter 27 [now Chapter 15] is on land map classification using support vector machine, which has been increasingly popular as an effective classifier. The land map classification classifies the surface of the Earth into categories such as water area, forests, factories or cities. Finally, with lossless data compression in mind, Chapter 28 [now Chapter 16] focuses on information-theoretic measure of the quality of multi-band remotely sensed digital images. The procedure relies on the estimation of parameters of the noise model. Results on image sequences acquired by AVIRIS and ASTER imaging sensors offer an estimation of the information contents of each spectral band.

With rapid technological advances in both sensor and processing technologies, a book of this nature can only capture certain amount of current progress and results. However, if past experience offers any indication, the numerous mathematical techniques presented will give this volume a long lasting value.

The sister volumes of this book are the other two books edited by myself. One is *Information Processing for Remote Sensing* and the other is *Frontiers of Remote Sensing Information Processing*, both published by World Scientific in 1999 and 2003, respectively. I am grateful to all contributors of this volume for their important contribution and, in particular, to Dr. J.S. Lee, S. Serpico, L. Bruzzone and S. Omatu for chapter contributions to all three volumes. Readers are advised to go over all three volumes for a more complete information on signal and image processing for remote sensing.

C. H. Chen

Editor

Chi Hau Chen was born on December 22nd, 1937. He received his Ph.D. in electrical engineering from Purdue University in 1965, M.S.E.E. degree from the University of Tennessee, Knoxville, in 1962, and B.S.E.E. degree from the National Taiwan University in 1959.

He is currently chancellor professor of electrical and computer engineering at the University of Massachusetts, Dartmouth, where he has taught since 1968. His research areas are in statistical pattern recognition and signal/image processing with applications to remote sensing, geophysical, underwater acoustics, and nondestructive testing problems, as well as computer vision for video surveillance, time series analysis, and neural networks.

Dr. Chen has published 25 books in his area of research. He is the editor of *Digital Waveform Processing and Recognition* (CRC Press, 1982) and *Signal Processing Handbook* (Marcel Dekker, 1988). He is the chief editor of *Handbook of Pattern Recognition and Computer Vision*, volumes 1, 2, and 3 (World Scientific Publishing, 1993, 1999, and 2005, respectively). He is the editor of *Fuzzy Logic and Neural Network Handbook* (McGraw-Hill, 1966). In the area of remote sensing, he is the editor of *Information Processing for Remote Sensing* and *Frontiers of Remote Sensing Information Processing* (World Scientific Publishing, 1999 and 2003, respectively).

He served as the associate editor of the *IEEE Transactions on Acoustics Speech and Signal Processing* for 4 years, *IEEE Transactions on Geoscience and Remote Sensing* for 15 years, and since 1986 he has been the associate editor of the *International Journal of Pattern Recognition and Artificial Intelligence.*

Dr. Chen has been a fellow of the Institutue of Electrical and Electronic Engineers (IEEE) since 1988, a life fellow of the IEEE since 2003, and a fellow of the International Association of Pattern Recognition (IAPR) since 1996.

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Contents

1

Polarimetric SAR Techniques for Remote Sensing of the Ocean Surface

Dale L. Schuler, Jong-Sen Lee, and Dayalan Kasilingam

CONTENTS

1.1 Introduction

Selected methods that use synthetic aperture radar (SAR) image data to remotely sense ocean surfaces are described in this chapter. Fully polarimetric SAR radars provide much more usable information than conventional single-polarization radars. Algorithms, presented here, to measure directional wave spectra, wave slopes, wave–current interactions, and current-driven surface features use this additional information.

Polarimetric techniques that measure directional wave slopes and spectra with data collected from a single aircraft, or satellite, collection pass are described here. Conventional single-polarization backscatter cross-section measurements require two orthogonal passes and a complex SAR modulation transfer function (MTF) to determine vector slopes and directional wave spectra.

The algorithm to measure wave spectra is described in Section 1.2. In the azimuth (flight) direction, wave-induced perturbations of the polarimetric orientation angle are used to sense the azimuth component of the wave slopes. In the orthogonal range direction, a technique involving an alpha parameter from the well-known Cloude–Pottier entropy/anisotropy/averaged alpha ($H/A/\bar{\alpha}$) polarimetric decomposition theorem is used to measure the range slope component. Both measurement types are highly sensitive to ocean wave slopes and are directional. Together, they form a means of using polarimetric SAR image data to make complete directional measurements of ocean wave slopes and wave slope spectra.

NASA Jet Propulsion Laboratory airborne SAR (AIRSAR) P-, L-, and C-band data obtained during flights over the coastal areas of California are used as wave-field examples. Wave parameters measured using the polarimetric methods are compared with those obtained using *in situ* NOAA National Data Buoy Center (NDBC) buoy products.

In a second topic (Section 1.3), polarization orientation angles are used to remotely sense ocean wave slope distribution changes caused by ocean wave–current interactions. The wave–current features studied include surface manifestations of ocean internal waves and wave interactions with current fronts.

A model [1], developed at the Naval Research Laboratory (NRL), is used to determine the parametric dependencies of the orientation angle on internal wave current, wind-wave direction, and wind-wave speed. An empirical relation is cited to relate orientation angle perturbations to the underlying parametric dependencies [1].

A third topic (Section 1.4) deals with the detection and classification of biogenic slick fields. Various techniques, using the Cloude–Pottier decomposition and Wishart classifier, are used to classify the slicks. An application utilizing current-driven ocean features, marked by slick patterns, is used to map spiral eddies. Finally, a related technique, using the polarimetric orientation angle, is used to segment slick fields from ocean wave slopes.

1.2 Measurement of Directional Slopes and Wave Spectra

1.2.1 Single Polarization versus Fully Polarimetric SAR Techniques

SAR systems conventionally use backscatter intensity-based algorithms [2] to measure physical ocean wave parameters. SAR instruments, operating at a single-polarization, measure wave-induced backscatter cross section, or sigma-0, modulations that can be developed into estimates of surface wave slopes or wave spectra. These measurements, however, require a parametrically complex MTF to relate the SAR backscatter measurements to the physical ocean wave properties [3].

Section 1.2.3 through Section 1.2.6 outline a means of using fully polarimetric SAR (POLSAR) data with algorithms [4] to measure ocean wave slopes. In the Fourier-transform domain, this orthogonal slope information is used to estimate a complete directional ocean wave slope spectrum. A parametrically simple measurement of the slope is made by using POLSAR-based algorithms.

Modulations of the polarization orientation angle, θ, are largely caused by waves traveling in the azimuth direction. The modulations are, to a lesser extent, also affected by range traveling waves. A method, originally used in topographic measurements [5], has been applied to the ocean and used to measure wave slopes. The method measures vector components of ocean wave slopes and wave spectra. Slopes smaller than 1° are measurable for ocean surfaces using this method.

An eigenvector or eigenvalue decomposition average parameter $\bar{\alpha}$, described in Ref. [6], is used to measure wave slopes in the orthogonal range direction. Waves in the range direction cause modulation of the local incidence angle ϕ, which, in turn, changes the value of $\bar{\alpha}$. The alpha parameter is "roll-invariant." This means that it is not affected by slopes in the azimuth direction. Likewise, for ocean wave measurements, the orientation angle θ parameter is largely insensitive to slopes in the range direction. An algorithm employing both ($\bar{\alpha}$, θ) is, therefore, capable of measuring slopes in any direction. The ability to measure a physical parameter in two orthogonal directions within an individual resolution cell is rare. Microwave instruments, generally, must have a two-dimensional (2D) imaging or scanning capability to obtain information in two orthogonal directions.

Motion-induced nonlinear "velocity-bunching" effects still present difficulties for wave measurements in the azimuth direction using POLSAR data. These difficulties are dealt with by using the same proven algorithms [3,7] that reduce nonlinearities for single-polarization SAR measurements.

1.2.2 Single-Polarization SAR Measurements of Ocean Surface Properties

SAR systems have previously been used for imaging ocean features such as surface waves, shallow-water bathymetry, internal waves, current boundaries, slicks, and ship wakes [8]. In all of these applications, the modulation of the SAR image intensity by the ocean feature makes the feature visible in the image [9]. When imaging ocean surface waves, the main modulation mechanisms have been identified as tilt modulation, hydrodynamic modulation, and velocity bunching [2]. Tilt modulation is due to changes in the local incidence angle caused by the surface wave slopes [10]. Tilt modulation is strongest for waves traveling in the range direction. Hydrodynamic modulation is due to the hydrodynamic interactions between the long-scale surface waves and the short-scale surface (Bragg) waves that contribute most of the backscatter at moderate incidence angles [11]. Velocity bunching is a modulation process that is unique to SAR imaging systems [12]. It is a result of the azimuth shifting of scatterers in the image plane, owing to the motion of the scattering surface. Velocity bunching is the highest for azimuth traveling waves.

In the past, considerable effort had gone into retrieving quantitative surface wave information from SAR images of ocean surface waves [13]. Data from satellite SAR missions, such as ERS 1 and 2 and RADARSAT 1 and 2, had been used to estimate surface wave spectra from SAR image information. Generally, wave height and wave slope spectra are used as quantitative overall descriptors of the ocean surface wave properties [14]. Over the years, several different techniques have been developed for retrieving wave spectra from SAR image spectra [7,15,16]. Linear techniques, such as those having a linear MTF, are used to relate the wave spectrum to the image spectrum. Individual MTFs are derived for the three primary modulation mechanisms. A transformation based on the MTF is used to retrieve the wave spectrum from the SAR image spectrum. Since the technique is linear, it does not account for any nonlinear processes in the modulation mechanisms. It has been shown that SAR image modulation is nonlinear under certain ocean surface conditions. As the sea state increases, the degree of nonlinear behavior generally increases. Under these conditions, the linear methods do not provide accurate quantitative estimates of the wave spectra [15]. Thus, the linear transfer function method has limited utility and can be used as a qualitative indicator. More accurate estimates of wave spectra require the use of nonlinear inversion techniques [15].

Several nonlinear inversion techniques have been developed for retrieving wave spectra from SAR image spectra. Most of these techniques are based on a technique developed in Ref. [7]. The original method used an iterative technique to estimate the wave spectrum from the image spectrum. Initial estimates are obtained using a linear transfer function similar to the one used in Ref. [15]. These estimates are used as inputs in the forward SAR imaging model, and the revised image spectrum is used to iteratively correct the previous estimate of the wave spectra. The accuracy of this technique is dependent on the specific SAR imaging model. Improvements to this technique [17] have incorporated closed-form descriptions of the nonlinear transfer function, which relates the wave spectrum to the SAR image spectrum. However, this transfer function also has to be evaluated iteratively. Further improvements to this method have been suggested in Refs. [3,18]. In this method, a cross-spectrum is generated between different looks of the same ocean wave scene. The primary advantage of this method is that it resolves the 180° ambiguity [3,18] of the wave direction. This method also reduces the effects of speckle in the SAR spectrum. Methods that incorporate additional a posteriori information about the wave field, which improves the accuracy of these nonlinear methods, have also been developed in recent years [19].

In all of the slope-retrieval methods, the one nonlinear mechanism that may completely destroy wave structure is velocity bunching [3,7]. Velocity bunching is a result of moving scatterers on the ocean surface either bunching or dilating in the SAR image domain. The shifting of the scatterers in the azimuth direction may, in extreme conditions, result in the destruction of the wave structure in the SAR image.

SAR imaging simulations were performed at different range-to-velocity (R/V) ratios to study the effect of velocity bunching on the slope-retrieval algorithms. When the (R/V) ratio is artificially increased to large values, the effects of velocity bunching are expected to destroy the wave structure in the slope estimates. Simulations of the imaging process for a wide range of radar-viewing conditions indicate that the slope structure is preserved in the presence of moderate velocity-bunching modulation. It can be argued that for velocity bunching to affect the slope estimates, the (R/V) ratio has to be significantly larger than 100 s. The two data sets discussed here are designated "Gualala River" and "San Francisco." The Gualala river data set has the longest waves and it also produces the best results. The R/V ratio for the AIRSAR missions was 59 s (Gualala) and 55 s (San Francisco). These values suggest that the effects of velocity bunching are present, but are not sufficiently strong to significantly affect the slope-retrieval process. However, for spaceborne SAR imaging applications, where the (R/V) ratio may be greater than 100 s, the effects of velocity bunching may limit the utility of all methods, especially in high sea states.