Image Analysis, Classification and Change Detection in Remote Sensing, Fifth Revised Edition
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Chapter Abstracts

Chapter 1 Images, Arrays and Matrices

There are many Earth observation satellite-based sensors, both active and passive, currently in orbit or planned for the near future. Laying the mathematical foundation for the image analysis procedures and algorithms forming the substance of the text, Chapter 1 begins in the first two Sections 1.1 and 1.2 with a short description of typical remote sensing imagery in the optical/infrared and synthetic aperture radar (SAR) categories, together with their representations as digital arrays. The multispectral ASTER system and the TerraSAR-X synthetic aperture radar satellite are chosen as illustrations. Then, in Section 1.3, some basic concepts of linear algebra of vectors and matrices are introduced, including linear dependence, eigenvalues and eigenvectors, singular value decomposition and the Python/Numpy/TensorFlow representations. In the final section 1.4 it is shown how to take derivatives of vector functions and find their minima and maxima using Lagrange multipliers. The latter technique is illustrated with the principal components analysis of a multispectral satellite image.

Chapter 2 Image Statistics

In an optical/infrared or a synthetic aperture radar image, a given pixel gray scale value $g(i, j)$, derived from the measured radiation field at a satellite sensor, is never exactly reproducible. It is the outcome of a complex measurement influenced by instrument noise, atmospheric conditions, changing illumination and so forth. It may be assumed, however, that there is an underlying random mechanism with an associated probability distribution which restricts the possible outcomes in some way. Each time we make an observation, we are observing a different possible *realization* of the random mechanism. In Chapter 2, some basic statistical concepts for multi-spectral and SAR images viewed as random mechanisms are discussed. The first Section introduces the notions of random variables, both scalar and vector, and their probability distributions. Section 2.2 addresses the question as to how to estimate the parameters which characterize those distributions by means of random sampling. Section 2.3 focuses on the multivariate distributions which describe optical/infrared and SAR imagery.

Bayes' Theorem and the problem of classification are treated in Section 2.4 and the fundamental idea of testing hypotheses regarding the results of observations is discussed in Section 2.5. The Chapter concludes with the subjects of linear regression and duality (Section 2.6) and entropy (Section 2.7).

Chapter 3 Transformations

In the first two Chapters, multispectral and polarimetric SAR images are represented as three-dimensional arrays of pixel intensities (e.g., columns $\times$ rows $\times$ bands) corresponding, more or less directly, to measured radiances. Chapter 3 deals with other, more abstract representations which are useful in image interpretation and analysis and which play an important role in later Chapters. The discrete Fourier and wavelet transforms, treated, in Sections 3.1 and 3.2 convert the pixel values in a given spectral band to linear combinations of orthogonal functions of spatial frequency and distance. They may therefore be classified as *spatial transformations.* The principal components, minimum noise fraction and maximum autocorrelation factor transformations (Sections 3.3 to 3.5), on the other hand, create at each pixel location new linear combinations of the pixel intensities from all of the spectral bands and can properly be called *spectral transformations.*

Chapter 4 Filters, Kernels and Fields

Chapter 4 is intended to consolidate and extend material presented in the preceding three Chapters and to help lay the foundation for the rest of the book. In Sections 4.1 and 4.2, building on the discrete Fourier transform introduced in Chapter 3, the concept of discrete convolution is introduced and filtering, both in the spatial and in the frequency domain, is discussed. Frequent reference to filtering will be made in Chapter 5 when enhancement and geometric and radiometric correction of optical/infrared and SAR imagery are treated and in the discussion of convolutional neural networks in Chapter 7. In Section 4.3 it is shown that the discrete wavelet transform of Chapter 3 is equivalent to a recursive application of low- and high-pass filters (a filter bank) and a pyramid algorithm for multi-scale image representation is described and programmed in Python. Wavelet pyramid representations are applied in Chapter 5 for panchromatic sharpening and in Chapter 8 for contextual clustering. Section 4.4 introduces so-called *kernelization*, in which the dual representations of linear problems described in Chapters 2 and 3 can be modified to treat non-linear data. Kernel methods are illustrated with a non-linear version of the principal components transformation and they are met again in Chapter 6 when support vector machines for supervised classification are discussed, in Chapter 7 in connection with anomaly detection, and in Chapter 8 in the form of a kernel K-means clustering algorithm. Finally, Section 4.5 describes Gibbs–Markov random fields which are invoked in Chapter 8 in order to include spatial context in unsupervised classification.

Chapter 5 Image Enhancement and Correction

In preparation for the treatment of supervised/unsupervised classification and change detection, the subjects of the final four chapters of the book, Chapter 5 focuses on preprocessing methods. These fall into the two general categories of *image enhancement*: image filter applications (Sections 5.1 and 5.2), panchromatic sharpening (Section 5.3), SAR speckle reduction (Section 5.4) and *geometric correction*: topographic correction (Section 5.5), image-image registration (Section 5.6). Discussion mainly focuses on optical/infrared image data. However polarimetric SAR imagery and the problem of speckle removal are described in some detail.

Chapter 6 Supervised Classification Part 1

Land cover classification of remote sensing imagery is an undertaking which falls into the general category of *pattern recognition*. Pattern recognition problems, in turn, are usually approached by developing appropriate *machine learning* algorithms. Broadly speaking, machine learning involves tasks for which there is no known direct, analytic method to compute a desired output from a set of inputs. The strategy adopted is for the computer to "learn" from a set of representative examples. Chapter 6 focuses on the case of supervised classification, which can often be seen as the modeling of probability distributions of the training data. On the basis of representative data for, say, K land cover classes presumed to be present in a scene, the *a posteriori* probabilities for class k conditional on observation $\boldsymbol{g}$, $\Pr(k \mid \boldsymbol{g})$, $k = 1 \dots K$, are "learned" or approximated. (the *training phase*) and then used to classify all of the pixels (the *generalization phase*). Training is achieved through maximizing the probability of observing the training data (Section 6.1) and presupposes data availability and separability (Section 6.2). Parametric and non-parametric statistical classification models are considered in Sections 6.3 and 6.4, neural network and support vector machine approaches are dealt with in Sections 6.5 and 6.6.

Chapter 7 Supervised Classification Part 2

Continuing on the subject of supervised classification, Chapter 7 begins with a discussion of post classification processing methods to improve results on the basis of contextual information (Section 7.1), after which attention is turned to statistical procedures for evaluating classification accuracy and for making quantitative comparisons between different classifiers (Section 7.2). Section 7.3 looks at examples of *ensembles* of classifiers, beginning with the *adaptive boosting* technique, applying it in particular to improve the generalization accuracy of neural networks, and then treats the *random forest* classifier, an ensemble of *binary decision trees*. The remainder of the Chapter examines more specialized forms of supervised image classification, namely as applied to polarimetric SAR imagery (Section 7.4), to data with hyper-spectral resolution (Section 7.5), and, in Section 7.6, to intermediate and high resolution multispectral imagery making use of the deep learning paradigm of *convolutional neural networks*, *transfer learning* and *semantic segmentation*.

Chapter 8 Unsupervised Classification

Supervised classification of remote sensing imagery, the subject of the preceding two Chapters, involves the use of a training dataset consisting of labeled pixels representative of each land cover category of interest in an image. The choice of training areas which adequately represent the spectral characteristics of each category is very important for supervised classification, as the quality of the training set has a profound effect on the validity of the result. Finding and verifying training areas can be laborious, since the analyst must select representative pixels for each of the classes by visual examination of the image and by information extraction from additional sources such as ground reference data (ground truth), aerial photos or existing maps. The subject of Chapter 8, unsupervised classification or *clustering*, requires no reference information at all. Instead, the attempt is made to find an underlying class structure automatically by organizing the data into groups sharing similar (e.g., spectrally homogeneous) characteristics. Often, one only needs to specify beforehand the number of classes present. Based on the simple cost functions of Section 8.1, several common algorithms for their minimization are introduced (and programmed) in Section 8.2. Sections 8.3 and 8.4 treat in detail the powerful Gaussian mixture clustering method, including the integration of spatial context, while Section 8.5 examines a benchmark for a more or less qualitative comparison of all of the techniques introduced. The Chapter concludes with two special unsupervised image classification algorithms, the Kohonen self-organizing map (Section 8.6) and the elegant but computationally expensive mean shift (Section 8.7).

Chapter 9 Change Detection

When comparing multispectral images of a given scene taken at different times, it is desirable to correct the pixel intensities as much as possible for uninteresting differences such as those due to solar illumination, atmospheric conditions, viewing angle, terrain effects or sensor calibration. In the case of SAR imagery, solar illumination or cloud cover play no role, but other considerations are similarly important. If comparison is on a pixel-by-pixel basis, then the images must also be co-registered to high accuracy in order to avoid spurious signals resulting from misalignment. Some of the required preprocessing steps were discussed in Chapter 5. After having performed the necessary preprocessing, it is common to examine various functions of the spectral bands involved (differences, ratios or linear combinations) which in some way bring the change information contained within them to the fore. Large changes are often evident at a glance. However, other changes may have occurred between the acquisition times and require more image processing to be clearly distinguished. Chapter 9 describes in the first two Sections some commonly used techniques for enhancing change signals in bi-temporal satellite images and then, in Section 9.3, focuses attention on the *multivariate alteration detection* (MAD) algorithm for visible/infrared imagery and a powerful iterative implementation. Section 9.4 develops in detail a sequential change statistic for polarimetric SAR data based on the complex Wishart distribution introduced in Chapter 2. The Chapter concludes in Section 9.5 with an "inverse" application of change detection, in which *unchanged* pixels are used for automatic relative radiometric normalization of multi-temporal imagery.