Remote Sensing Application of Image Processing

R K Samantaray

REC, Bhubaneswar, Odisha, India
samantaray.ranjan75@gmail.com

Abstract: Remote sensing image processing is nowadays a mature research area. The techniques developed in the field allow many real-life applications with great societal value. For instance, urban monitoring, fire detection or flood prediction can have a great impact on economical and environmental issues. To attain such objectives, the remote sensing community has turned into a multidisciplinary field of science that embraces physics, signal theory, computer science, electronics, and communications. From a machine learning and signal/image processing point of view, all the applications are tackled under specific formalisms, such as classification and clustering, regression and function approximation, image coding, restoration and enhancement, source unmixing, data fusion or feature selection and extraction. This paper serves as a survey of methods and applications, and reviews the last methodological advances in remote sensing image processing.

[R K Samantaray. **Remote Sensing Application of Image Processing.** Researcher. 2013;5(3): 68-72]. (ISSN: 1553-9865). http://www.sciencepub.net. 11

Keywords: Remote sensing, machine learning, signal and image processing, survey, applications.

1. Introduction

Of all the various data sources used in GIS, one of the most important is undoubtedly that provided by remote sensing. Through the use of satellites, we now have a continuing program of data acquisition for the entire world with time frames ranging from a couple of weeks to a matter of hours. Very importantly, we also now have access to remotely sensed images in digital form, allowing rapid integration of the results of remote sensing analysis into a GIS. The development of digital techniques for the restoration, enhancement and computer-assisted interpretation of remotely sensed images initially proceeded independently and somewhat ahead of GIS. However, the raster data structure and many of the procedures involved in these Image Processing Systems (IPS) were identical to those involved in raster GIS. As a result, it has become common to see IPS software packages add general capabilities for GIS, and GIS software systems add at least a fundamental suite of IPS tools. IDRISI is a combined GIS and image processing system that offers advanced capabilities in both areas. Because of the extreme importance of remote sensing as a data input to GIS, it has become necessary for GIS analysts. Remote sensing can be broadly defined as the collection and interpretation of information about an object, area, or event without being in physical contact with the object. Aircraft and satellites are the common platforms for remote sensing of the earth and its natural resources. Aerial photography in the visible portion of the electromagnetic wavelength was the original form of remote sensing but technological developments has enabled the acquisition of information at other wavelengths including near infrared, thermal infrared and microwave. Collection of information over a large numbers of wavelength bands is referred to as multispectral or hyperspectral data. The development and deployment of manned and unmanned satellites has enhanced the collection of remotely sensed data and offers an inexpensive way to obtain information over large areas. The capacity of remote sensing to identify and monitor land surfaces and environmental conditions has expanded greatly over the last few years and remotely sensed data will be an essential tool in natural resource management. Attending to the type of energy resources involved in the data acquisition, remote sensing imaging instruments can be passive or active. Passive optical remote sensing relies on solar radiation as illumination source. The signal measured at the satellite by an imaging spectrometer is the emergent radiation from the Earth-atmosphere system in the observation direction. The radiation acquired by a (airborne or satellite) sensor is measured at different wavelengths and the resulting spectral signature (spectrum) is used to identify a given material. The field of spectroscopy is concerned with the measurement, analysis, and interpretation of such spectra [1]. Some examples of passive sensors are infrared, charge-coupled de- vices, radiometers, or multi and hyperspectral sensors [2]. In active remote sensing, the energy is emitted by an antenna to- wards the Earth's surface and the energy scattered back to the satellite is measured [3]. Radar systems, such as Synthetic Aperture Radar (SAR), are examples of systems for active re- mote sensing. In these systems, the time delay between emission and return is measured to establish the location, height, speed and direction of objects. The diversity of platforms and sensors implies a diversity and very articulated research area in which machine learning, signal and image processing are very active. In fact, from a machine learning and signal/image processing viewpoint, all the applications are tackled under specific formalisms, such as classification and clustering or regression and function approximation. However, the statistical characterization of re- mote sensing images turns to be more difficult than in grayscale natural images because of pixel's higher dimensionality, particular noise and uncertainty sources, the high spatial and spectral redundance, and their inherently non-linear nature. It is worth to note that all these problems also depend on the sensor and the acquisition process. Consequently the developed methods for processing remote sensing images need to be carefully designed attending to these needs.

Even if scientific production is high, the cross-fertilization between the remote sensing and the image processing com- munities is still far from being a reality. In order to boost communication paths, this paper presents a survey of related methods and applications in both fields, and revises the hot topics and last methodological advances in remote sensing image processing.

2. The Framework of Remote Sensing Image processing

From acquisition to the final product delivered to the user, a remotely sensed image goes through a series of image processing steps, starting with efficient compression strategies and ending with accurate classification routines (Fig. 1). Each step is detailed in the next sections.

2.1. Image Coding

Along with the increasing demand of hyperspectral data, the sensor technology used to capture these images has been significantly developed, improving, among others, the spatial and spectral resolution.

Such improvement on quality leads to an increasing demand on storage and bandwidth transmission capabilities. Both lossy and lossless image coding have been investigated extensively in hyperspectral images [4]. The lossy coding systems in the Consultative Committee for Space Data Systems (CCSDS) [http://public.ccsds.org] recommendation are based on a transform stage, where data is decorrelated in the spatial domain using a wavelet transform (plus a bit plane encoder stage), thus following the latest standard JPEG2000 for grayscale images. Other well known wavelet-based cod- ing system used for hyperspectral data are SPIHT-3D and SPECK-3D [5]. In order to improve the coding performance, a common strategy is to decorrelate first the image in the spectral domain [6].

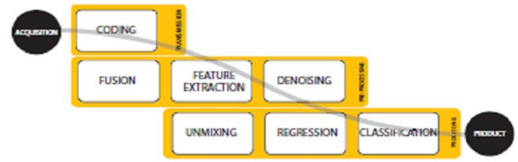

Fig. 1. Remote sensing image processing chain.

For feature selection, either filters or wrappers are proposed [7]. Although filters have been extensively studied in remote sensing [8], the recent advances focus on wrappers, which guarantees that the selected feature subset is iteratively optimized. SVM-based recursive feature elimination [9] and genetic algorithms [10] are some examples of recent successful applications of wrappers in remote sensing. Regarding feature extraction, the use of linear methods such as PCA is quite common. Recently, advances in embedding using nonlinear methods have been proposed such as local lin - ear embedding or isometric mapping [11]. Also, multivariate kernel-based feature extraction methods have been presented recently to cope with nonlinearities in the data [12].

2.3. Restoration and Denoising

Image restoration is an important step in the image processing chain. Several problems are encountered in this application: different noise sources and amounts are present in the data and scattered either in the spatial or specific spectral bands. This makes necessary appropriate spatial smoothing per band. Note also that applying PCA captures second-order statistics only, and has no information about noise variance. A nice alternative is the widely used minimum noise fraction (MNF) algorithm [13]. The method performs nicely in multispectral imagery and moderate noise levels. In hyperspectral images the noise covariance estimation is a more challenging problem and other techniques have been recently proposed, such as anisotropic diffusion [14], wavelet shrinkage [15], or kernel multivariate methods [12]. In radar signal processing, the main problem is about removing speckle noise in SAR images. Latest advances propose specific wavelet forms [16] and to include spatial information through Markov random fields [17]. Assessment of the obtained filtered images is another hot topic in the area [18]. A common problem is also found in removing the registration noise, with critical impact in change detection applications [19].

2.4. Image Fusion and Enhancement

Spatial resolution of sensors is often limited with respect to their spectral resolution. Multi- or hyperspectral sensors give a unique amount of spectral information, but they often lack the spatial detail necessary for the application. On the contrary, panchromatic sensors provide information with higher level of spatial detail, but lack spectral information. Since the design of a high resolution sensor in both spectral and spatial domains would be extremely costly and challenging in terms of engineering, image fusion methods are often employed to create an image taking advantage of both panchromatic and multi- or hyperspectral sensors. Classical IHS or PCA methods are inadequate when applied to remote sensing images. Therefore specific approaches based on Laplacian Pyramids [20], wavelets [21], geostatistics [22], and Bayesian Maximum Entropy [23], have been proposed recently.

2.5. Signal Unmixing

An important problem in remote sensing is the development of automatic extraction of spectral end members directly from the input hyperspectral data set. With these pure pixels in the image identified, all pixels can be synthesized as a linear (or non-linear) combination of them, and this, in turn, allows subpixel detection [2] or mineral mapping [24]. Some classic techniques for this purpose include the N-FINDR algorithm [25], the vertex component algorithm (VCA) in [26], and an orthogonal subspace projection (OSP) technique in [27], among others [28]. Selection of the free parameters and inclusion of spatial information in the unmixing process are key issues nowadays [29]. Recently support vector domain description (SVDD) has been also used [12].

2.6. Regression and Model Inversion

In remote-sensing data analysis, the estimation of biophysical parameters is of special relevance in order to better understand the environment dynamics at local and global scales [1]. The inversion of analytical models introduces a higher level of complexity, induces an important computational burden, and sensitivity to noise becomes an important issue. Consequently, the use of empirical models adjusted to learn the relationship between the acquired spectra and actual ground measurements has become very attractive. Parametric models have some important drawbacks, which typically lead to poor prediction results on unseen data. As a consequence, *nonparametric* and potentially *non-linear* regression techniques have been effectively introduced for the estimation of biophysical parameters from remotely sensed images. Different models and architectures of neural networks have been considered for the estimation of biophysical parameters [30]. Recently the use of support vector regression (SVR) has yielded good results in modeling some biophysical parameters [31].

2.7. Image Classification

Classification maps are probably the main product of remote sensing image processing. Important applications are urban monitoring, catastrophe assessment, change or target detection. Broadly speaking, classification methods can be divided in three families. Unsupervised methods aim at clustering the image pixels into a pre-defined number of groups by measuring their similarity. One of the main applications for such methods is change detection, where the method should be able to recognize changes in real time [32, 33]. Supervised methods use labeled information to train a model capable to recognize pre-defined classes. At present, this field is probably the most active in remote sensing image processing. The most successful methods are neural networks [34] and sup- port vector machines [35]. The latter have been applied in a wide range of domains, including object recognition [36], multi-temporal classification [37] and urban monitoring [38]. Finally, semi-supervised methods join the (typically few) labeled data and the information about the wealth of unlabeled samples. In remote sensing, the data manifold has been modeled with either graphs [39, 40] or cluster kernels [41] algorithms. Also, the transductive SVM has been applied [42].

Table 1. A taxonomy for remote sensing methods and applications

Topic	Fields & Tools	Objectives & Problems	Examples	Methods & Techniques
Coding	Transform coding and vision computing	Compress the huge amount of acquired data	Transmission of data to Earth station, avoid redundancy and errors, realistic quick-looks	PCA, DCT, Wavelets, SPIHT
Feature Sel./Extract.	Filters/Wrappers	Ranking and channel selection	Efficient transmission, model development, compression.	PCA, SFFS, RFE, Network pruning, GA.
Restoration	Denoising, deblurring	interpretation, feat. extract.	Rem. acq. noise, transmission	Wiener, wavelets, advanced de-noising
Data fusion	Image/Signal Proc.	Different sensors, temporal acquisitions, resolutions	Multi-temp., change detection	Multi-resolution, fusion
Signal Unmixing	Signal Processing and machine learning	Independizing the mixture of spectra, restoration, classification with pure pixels	Unmixing and subpixel techniques	ICA, linear/non-linear unmixing, kernels and pre-images.
Model inversion	Regression	Monitoring Earth's Cover at a local/global scale	Water quality, desertification, vegetation indexes, T, biomass, ozone, ...	Linear regression, statistical approaches, neural networks, SVR.
Classification	Pattern recognition	Monitoring evolution and changes of Earth's cover	Urban monitoring, mineral detection, change detection, ...	*k*-NN, LDA, neural nets, kernel methods

3. Conclusion

The fields of remote sensing and image processing are constantly evolving in the last decade, but cross-fertilization is still needed. This paper serves as a survey of methods and applications and highlights the hot topics and latest methodological advances in remote sensing image processing. The literature has been revised under the specific machine learning and signal processing paradigms, and attention has been paid to classification, regression, image coding, restoration, source unmixing, data fusion, feature selection and extraction.

4. References

[1] T. M. Lillesand, R.W. Kiefer, and J. Chipman, Rem. Sens. And Image Interpretation, J. Wiley & Sons, NY, 2008.
[2] G. Shaw and D. Manolakis, "Signal processing for hyperspectral image exploitation," IEEE Signal Processing Magazine, vol. 50, pp. 12–16, Jan 2002.
[3] H. Mott, Remote Sensing with Polarimetric Radar, J. Wiley & Sons, NY, 2007.
[4] G. Motta, F. Rizzo, and J. A. Storer, Hyperspectral data compression, Springer Berlin, 2006.
[5] X. Tang and W. A. Pearlman, Hyperspectral Data Compression, chapter Three-Dimensional Wavelet-Based Compression of hyperspectral Images, pp. 273–308, Springer, NY, 2006.
[6] B. Penna, T. Tillo, E. Magli, and G. Olmo, "Transform coding techniques for lossy hyperspectral data compression," IEEE Trans. Geosci. Rem. Sens, vol. 45, no. 5, pp. 1408–1421, 2007.
[7] I. Guyon, S. Gunn, M. Nikravesh, and L. A. Zadeh, Feature extraction: foundations and applications, Springer, 2006.
[8] L. Bruzzone and S.B. Serpico, "A technique for features selection in multiclass problems," Int. J. Rem. Sens., vol. 21 (3), pp. 549–563, 2000.
[9] R. Archibald and G. Fann, "Feature selection and classification of hyperspectral images with support vector machines," IEEE Geosc. and Rem. Sens. Lett., vol. 4 (4), pp. 674–679, 2007.
[10] M. Pal, "Support vector machine-based feature selection for land cover classification: a case study with dais hyperspectral data," Int. J. Rem. Sens., vol. 27 (14), pp. 2877–2894, 2006.
[11] C.M. Bachman, T.L. Ainsworth, and R.A. Fusina, "Improved manifold coordinate representations of large-scale hyperspectral scenes," IEEE Trans. Geosc. Rem. Sens., vol. 44 (10), pp. 2786–2803, 2006.
[12] G. Camps-Valls and L. Bruzzone, Kernel Methods for Remote Sensing Data Analysis, J. Wiley & Sons, 2009.
[13] U. Amato, R.M. Cavalli, A. Palombo, S. Pignatti, and F. Santini, "Experimental approach to the selection of the components in the minimum noise fraction," IEEE Trans. Geosc. Rem. Sens., vol. 47, no. 1, pp. 153–160, Jan. 2009.
[14] J. Mart´ın-Herrero, "Anisotropic diffusion in the hypercube," IEEE Trans. Geosc. Rem. Sens., vol. 45, no. 5, pp. 1386–1398, May 2007.
[15] H. Othman and Shen-En Qian, "Noise reduction of hyperspectral imagery using hybrid spatial-spectral derivative-domain wavelet shrinkage," IEEE Trans. Geosc. Rem. Sens., vol. 44, no. 2, pp. 397–408, Feb. 2006.
[16] S. Solbo and T. Eltoft, "Homomorphic wavelet-based statistical despeckling of SAR images," IEEE Trans. Geosc. Rem. Sens., vol. 42, no. 4, pp. 711–721, April 2004.
[17] D. Gleich and M. Datcu, "Wavelet-based despeckling of SAR images using Gauss-Markov random fields," IEEE Trans. Geosc. Rem. Sens., vol. 45, no. 12, pp. 4127–4143, Dec. 2007.
[18] E. Trouve, Y. Chambenoit, N. Classeau, and P. Bolon, "Statistical and operational performance assessment of multitemporal SAR image filtering," IEEE Trans. Geosc. Rem. Sens., vol. 41, no. 11, pp. 2519–2530, Nov. 2003.
[19] J. Inglada, V. Muron, D. Pichard, and T. Feuvrier, "Analysis of artifacts in subpixel remote sensing image registration," IEEE Trans. Geosc. Rem. Sens., vol. 45, no. 1, pp. 254–264, 2007.
[20] B. Aiazzi, L. Alparone, S. Baronti, and A. Garzelli, "Contextdriven fusion of high spatial and spectral resolution images based on oversampled multiresolution analysis," IEEE Trans. Geosc. Rem. Sens., vol. 40 (10), pp. 2300–2312, 2002.
[21] X. Otazu, M. Gonzalez Audicana, O. Fors, and J. Nu nez, "Introduction of sensor spectral response into image fusion methods. applications to wavelets-based methods," IEEE Trans. Geosc. Rem. Sens., vol. 43 (10), pp. 2376–2385, 2005.
[22] E. Pardo-Igoezquiza, M. Chica-Olmo, and P. M. Atkinson, "Downscaling cokriging for image sharpening," Remote Sensing of Environment, vol. 102 (1-2), pp. 86–98, 2006.
[23] D. Fasbender, J. Radoux, and P. Bogaert, "Bayesian data fusion for adaptable image pansharpening," IEEE Trans. Geosc. Rem. Sens., vol. 46 (6), pp. 1847–1857, 2008.
[24] N. Keshava and J. F. Mustard, "Spectral unmixing," IEEE Signal Processing Magazine, vol. 19, no. 1, pp. 44–57, 2002.
[25] M. E. Winter, "N-FINDR: an algorithm for fast autonomous spectral end-member determination in hyperspectral data," Proc. SPIE Im. Spectr. V, vol. 3753, pp. 266–277, 2003.

[26] J. M. P. Nascimento and J. M. Bioucas-Dias, “Vertex Component Analysis: A Fast Algorithm to Unmix Hyperspectral Data,” IEEE Trans. Geosc. Rem. Sens., vol. 43, no. 4, pp. 898–910, 2005.
[27] J. C. Harsanyi and C.-I Chang, “Hyperspectral image classification and dimensionality reduction: An orthogonal subspace projection,” IEEE Trans. Geosc. Rem. Sens., vol. 32, no. 4, pp. 779–785, 1994.
[28] A. Plaza, P. Martinez, R. Perez, and J. Plaza, “A quantitative and comparative analysis of endmember extraction algorithms from hyperspectral data,” IEEE Trans. Geosc. Rem. Sens., vol. 42, no. 3, pp. 650–663, 2004.
[29] A. Plaza and C.-I Chang, “Impact of initialization on design of endmember extraction algorithms,” IEEE Trans. Geosc. Rem. Sens., vol. 44, no. 11, pp. 3397–3407, 2006.
[30] B. Dzwonkowski and X.-H. Yan, “Development and application of a neural network based colour algorithm in coastal waters,” Intl. J. Rem. Sens., vol. 26, no. 6, pp. 1175–1200, 2005.
[31] G. Camps-Valls, L. Bruzzone, J.L. Rojo-´Alvarez, and F. Melgani, “Robust support vector regression for biophysical parameter estimation from remotely sensed images,” IEEE Geosc. Rem. Sens. Lett., vol. 3, no. 3, pp. 339–343, 2006.
[32] F. Bovolo and L. Bruzzone, “A split-based approach to unsupervised change detection in large size multitemporal images: application to tsunami-damage assessment,” IEEE Trans. Geosc. Rem. Sens., vol. 45 (6), pp. 1658–1671, 2007.
[33] F. Bovolo, “A multilevel parcel-based approach to change detection in very high resolution multitemporal images,” IEEE Geosc. and Rem. Sens. Lett., vol. 6 (1), pp. 33–37, 2009.
[34] F. Del Frate, F. Pacifici, G. Schiavon, and D. Solimini, “Use of neural networks for automatic classification from highresolution images,” IEEE Trans. Geosc. Rem. Sens., vol. 45 (4), pp. 800–809, 2007.
[35] G. Camps-Valls and L. Bruzzone, “Kernel-based methods for hyperspectral image classification,” IEEE Trans. Geosc. Rem. Sens., vol. 43, pp. 1351–1362, 2005.
[36] J. Inglada, “Automatic recognition of man-made objects in high resolution optical remote sensing images by SVM classification of geometric image features,” ISPRS Journal of Photogrammetry Rem. Sens., vol. 62, pp. 236–248, 2007.
[37] G. Camps-Valls, L. G´omez-Chova, J. Mu˜noz-Mar´ı, J. Luis Rojo-´Alvarez, and M. Mart´ınez-Ram´on, “Kernel-based framework for multi-temporal and multi-source remote sensing data classification and change detection,” IEEE Trans. Geosc. Rem. Sens., vol. 46 (6), pp. 1822–1835, 2008.
[38] M. Fauvel, J.A. Benediktsson, J. Chanussot, and J.R. Sveinsson, “Spectral and spatial classification of hyperspectral data using svms and morphological profiles,” IEEE Trans. Geosc. Rem. Sens., vol. 46, no. 11, pp. 3804–3814, Nov. 2008.
[39] G. Camps-Valls, T.V. Bandos Marsheva, and Zhou D., “Semisupervised graph-based hyperspectral image classification,” IEEE Trans. Geosc. Rem. Sens., vol. 45, pp. 3044–3054, 2007.
[40] L. G´omez-Chova, G. Camps-Valls, J. Mu˜noz-Mar´ı, and J. Calpe-Maravilla, “Semi-supervised image classification with Laplacian support vector machines,” IEEE Geosc. Rem. Sens. Lett., vol. 5, no. 3, pp. 336–340, 2008.
[41] D. Tuia and G. Camps-Valls, “Semi-supervised remote sensingimage classification with cluster kernels,” IEEE Geosc. And Rem. Sens. Lett., vol. 6, no. 2, 2009.
[42] L. Bruzzone, M. Chi, and M. Marconcini, “A novel transductive SVM for semisupervised classification of remote sensing images,” IEEE Geosc. And Rem. Sens. Lett., vol. 6, no. 2, 2009.

2/20/2013