SPECTRAL ANALYSIS OF ASTER AND HYPERION DATA FOR GEOLOGICAL CLASSIFICATION OF VOLCANO TEIDE

Piscini A. and Amici S.

INTRODUCTION

This work is an evaluation, to which degree geological information can be obtained from modern remote sensing systems like the multispectral ASTER or the hyperspectral Hyperion sensor for a volcanic region like Teide Volcano (Tenerife, Canary Islands). To account for the enhanced information content these sensors provide, hyperspectral analysis methods, incorporating for example Minimum Noise Fraction-Transformation (MNF) for data quality assessment and noise reduction as well as Spectral Angle Mapper (SAM) for supervised classification, were applied. Ground Truth reflectance data were obtained with a FieldSpec Pro measurements campaign conducted during later summer of 2007.

GEOLOGICAL SETTING OF THE STUDY AREA

The Canarian Arcipelago is made up of seven islands that represent different stages of geologic evolution [4]. Tenerife is the central island of archipelago and has developed the complex formed by the rifts and Teide-Pico Veio (T-PV) (Lat 28° 16' 30" Lon -16°38' 42") stratovolcanoes that reach a height of 3718m, 7500 above the ocean floor. It is an active shield though quiescent volcano (http://en.wikipedia.org/wiki/Volcano) that last erupted in 1909.

The sub aerial history of the island began in the late Miocene Plio-Quaternary, post-shield volcanism on Tenerife and has been characterized by the cyclic development of petrologically evolved eruptive centers. The most recent eruptive cycle has produced the twin strato-volcanoes Pico Teide (PT) and Pico Viejo (PV), and numerous flank-vent systems, whose products collectively form the PT/PV formation [1]. Like previous cycles, PT/PV volcanism has involved central activity and persistent eruptions from prominent rifts. The recent output of the central part of the system includes significant volumes of photolytic magmas.

REMOTE SENSING DATA AND PREPROCESSING

The multispectral 'Advanced Spaceborne Thermal Emission and Reflection Radiometer' (ASTER) onboard the TERRA satellite has three bands in the VNIR (15 m) and six bands in the SWIR (30 m) wavelength region

(Fujisada, 1995). In particular, the SWIR bands were intended for the discrimination of minerals or rock types. For the spectral analysis, AST_07 reflectance product scene (‘Surface Reflectance’) from April 4, 2007 was acquired [2]. The preprocessing of the ASTER data comprised the resample of VNIR bands to 30 m spatial resolution and the combination of the VNIR and SWIR instrument data to a 9 bands imagecube.

The Hyperion sensor, onboard NASA's EO-1 platform, is the first spaceborne imaging spectrometer covering the wavelength region from 0.4 to 2.5 µm with 220 bands of 10 nm spectral resolution and 30 m spatial resolution. For the current study, L1R-Data ('at-sensor radiance') of November 13, 2003 was acquired. Due to signal-to-noise issues and other radiometric detractions only 198 bands are calibrated in this data product (for further details see [10]). As a result, only a subset of 196 bands, still containing bands with radiometric interferences, was maintained for further analysis. We applied a scaling factor to convert dataset in radiometric units, georeferenced data from ASTER image and finally computed calibration in reflectance using ENVI’s Fast Line-of-sight Atmospheric Analysis of Spectral Hypercubes (FLAASH) [6].

METHODS

Due to the increased number of bands hyperspectral sensors like Hyperion or even modern multispectral sensors like ASTER provide, new analysis methods have become available in recent years [9] [5] [11]. To account for the improved information content of the new generation sensors, hyperspectral analysis techniques were chosen for the study for both datasets. These methods are based on the fact that every material exhibits a unique spectral signature in the electromagnetic spectrum. If sufficient bands are available in the remote sensing data, these signatures can be reconstructed. Thus, for mapping the surface composition, image derived reflectance spectra of the pictured earth surface are compared to known reference spectra of materials, also referred to as endmembers [3]. Endmembers can be obtained from different sources like field measurements, spectral libraries (e.g. ASTER spectral library: http://speclib.jpl.nasa.gov) or from the image data itself. In the latter case, surface type identification can be achieved e.g. by comparing the image spectra with spectra of known areas or with library spectra.

To evaluate the selected methodology and the classification results that can be achieved with ASTER and Hyperion data, two different methods for the selection of endmembers were applied in this study. The first method is mainly based on the 'Spectral Hourglass' processing scheme (Kruse et al. 2003) which is implemented in the Software ENVI (Research Systems Inc. 2005). This Procedure includes the generation of Minimum Noise Fraction-Images

(MNF) for data dimensionality estimation and reduction by decorrelating the useful information and separating noise [7], Pixel Purity Index-Mapping (PPI) for the determination of the purest pixels in an image (as potential endmembers) utilizing the (uncorrelated) MNF-images and finally the extraction of endmembers (referred to as n-D-endmembers in the following) utilizing the n-Dimensional-Visualizer tool (n-D-Vis). The extracted endmembers were then compared to known spectra from spectral libraries for identification. Subsequently, an alternative endmember selection was performed with ground truth data from campaign conducted during last summer 2007. In this case, locations regarded as representative for a surface type, were marked as Regions-of-Interest (ROI) in the ASTER and Hyperion images as sources for the extraction of endmembers as well (ROI-endmembers).

For the mapping of the surface composition the Spectral Angle Mapper (SAM) was chosen. SAM is a physically based classification algorithm that compares the spectral similarity between surface reflectance image spectra and reference spectra, treating them as vectors in a space with the dimensionality equal to the number of bands [8]. Image spectra are assigned to the reference spectrum class that yields the smallest calculated angle.

RESULTS AND DISCUSSION

Results showed that the endmembers derived with the Spectral Hourglass methodology were not able to reveal the information content of both (ASTER & Hyperion) datasets. Therefore, this we concentrated on the analysis results using the roi-endmembers.

The classification results show that detailed information can be extracted from the data, which were compared with the Geological Map of Teide crater. Regarding the data quality, the analysis revealed that the Hyperion scene was strongly affected by system induced radiometric interferences. As a result, a considerable amount of bands had to be discarded to allow satisfying results. Therefore, although similar surface types were discriminated with the ASTER and the Hyperion results, the ASTER data allowed a more detailed classification of the surface composition of the study area however SAM classification is not be able to distinguish the differentiated lavas characterizing the Teide crater. In the future we intend to improve analysis using methods of classification like Support Vector Machine (SVM).

REFERENCES

[1] Ablay, G.J. Martì, J. (2000). Stratigraphy, structure, and volcanic evolution of the Pico Teide-Pico Viejo formation, Tenerife, Canary Islands. Journal of Volcanology and Geothermal Research 103(2000) 175-208.

[2] Abrams, M., 2000. The Advanced Thermal Emission and Reflection Radiometer (ASTER): data products for the high spatial resolution imager on NASA's Terra platform. *International Journal of Remote Sensing*, 21(5), pp. 847-859.

[3] Adams, J.B. and Gillespie, A.R., 2006. *Remote Sensing of Landscapes with Spectral Images. A Physical Modeling Approach*. Cambridge, New York.

[4] Carracedo, J. C., El Volcan Teide Volcanologia Interpretacion De Paisajes E Itinerarios Comentados, 2007 CajaCanarias.

[5] Chang, Ch.-I., 2003. *Hyperspectral Imaging. Techniques for Spectral Detection and Classification*. New York.

[6] *EO-1 User Guide 2003*, USGS Earth Resources Observation System Data Centre (EDC).

Fujisada, H., 1995. Design and performance of ASTER instrument. *Proceedings of SPIE*, 2583, pp. 16-25.

[7] Green, A.A., Berman, M., Switzer, P. & Craig, M.D., 1988. A Transformation for Ordering Multispectral Data in Terms of Image Quality with Implications for Noise Removal. *IEEE Transactions on Geoscience and Remote Sensing*, 26(1), pp. 65-74.

[8] Jenson, J.R., 2005. Introductory Digital Image Processing. A Remote Sensing Perspective. Pearson, Prentice Hall, Upper Saddle River.

[9] Kruse, F.A., Boardman, J.W. & Huntington, J.F., 2003. Comparison of Airborne Hyperspectral Data and EO-1 Hyperion for Mineral Mapping. *IEEE Transactions on Geoscience and Remote Sensing*, 41(6), pp. 1388-1400.

[10] Pearlman, J.S., Barry, P.S., Segal, C.C., Shepanski, J., Beiso, D. & Carman, S.L., 2003. Hyperion, a Space-Based Imaging Spectrometer. *IEEE Transactions on Geoscience and Remote Sensing*, 41(6), pp. 1160-1173.

[11] Van der Meer, F.D., De Jong, S. M. & Bakker, W., 2003. Imaging Spectrometry: Basic Analytical Techniques. In: Van Der Meer, F. D. & De Jong, S. M. (eds.): *Remote Sensing and Digital Image Processing. Vol. 4. Imaging Spectrometry. Basic Principles and Prospective Applications*. Dordrecht, London.