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# Image Enhancement and Feature Extraction Based On Low Resolution Satellite

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#### Abstract:

The purpose of this study is to investigate the sensitivity of contrast-based textural measurements and morphological characteristics that derive from high-resolution satellite imagery (three-band SPOT-5) when diverse image enhancements techniques are piloted. The general framework of the application is the built-up/non-built-up detection. In the existence of a low-resolution reference layer, we apply supervised learning that indirectly reduces the uncertainty and improves the quality of the reference layer. Based on the new class label assignments, the image histogram is adjusted suitably for the computation of contrastbased textural/morphological features. A case study is presented where we test a mixture of image enhancement operations like linear and decor relation stretching and assess the performance through ROC against available analysis building footprints. Experimental results demonstrate that spectral band combination is the key factor that conditions the contrast of grayscale images. Contrast adjustment (before or after the band combination and merging)supports considerably the extraction of informative features from a low-contrast image; in case of a well-contrasted image, the improvement is marginal.

#### I. INTRODUCTION:

In the context of contrast-based feature extraction from high-resolution satellite imagery, image enhancement techniques are utilized to modify the band intensities and decrease the noise that covers significant information. Typical image enhancement techniques are as follows: linear contrast adjustment, decor relation stretching, histogram equalization, and adaptive filtering [1]-[4] classified as pixel/spatial-based approaches. Fourier decomposition, wavelet transform, and discrete cosine transform [2], [5], [6] are alternative approaches that belong to the frequency-domain techniques. The majority of the aforementioned techniques aims at improving the visual inspection of the image and usually involves manual parameter tuning. The proposed approach constitutes a data preparation phase just before the feature extraction. It attempts to improve the quality of the textural/morphological characteristics while retaining the computational burden in low levels. Generally speaking, it moves inside the concept of synergy between machine learning and image processing; one contiguous application has been presented recently in [13].

### II. SCHEMA DEFINITION:

#### A. Image Features:

The textural measurements we are interested in are estimated through the Haralick's measure for the intensity contrast between a pixel and its neighbors [14]. The factors (quantization, length, and orientation) and the operators like fuzzy composition are defined in [15]; the produced textural layer is known as PANTEX. Regarding the morphological features, we included in our tests a recently introduced index named morphological building index (MBI) [16], [17]. It is a quite accurate indicator that considers the characteristics of buildings (brightness, size, contrast, directionality, and shape) by integrating multi-scale and multidirectional morphological operators.

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Note that both PANTEX and MBI are automatic indices and their operation is not based on statistical learning and training samples.

#### **B. Syllogism:**

Apart from directly using the up-sampled SSL as reference layer, we elaborated the process of downscaling the layer in a statistical fashion. The simple idea we introduce in this paper is to seek for the hyper-plane that separates tuples of spectral values, derived from the input images, into two groups (BU/NBU) according to the reference layer in its original (low) resolution. For this purpose, we employ a powerful classification technique like the SVM which draws the optimal hyper plane that linearly discriminates the two classes BU/NBU into a highdimensional feature space H without using an explicit mapping. This can be achieved by means of the kernel trick [18], [19]. Support vectors (SVs) are the closest tuples of measurements to the hyper plane with respect to H; consequently, they contain the critical information for the class separation. In our application, having as fact that the reference layer does not constitute an accurate template mainly due to its low spatial resolution, the meaning of SVs matches with the concept of uncertainty that is inherent along the class boundaries. Thereafter, three options are deemed for the SVs usage.

- To totally remove their respective class labels from the reference layer: this decision targets at the increase in both intra-class similarity and interclass dissimilarity; however, it has high risk due to the loss of potentially useful information for the discrimination of the classes.
- 2) To set the SVs of BU class to the NBU class and change accordingly the respective class labels in the reference set: this is a biased decision having its basis on the fact that when the reference layer is projected into the spatial resolution of the input image (2.5 m), it represents an optimistic version of the BU reality: it introduces commission errors by having pixels in BU class, while the

corresponding spectral signature fits better with NBU class.

3) To remove all SVs and build another SVM by using the remaining vectors as training set: the hypothesis behind this choice is that the second batch of SVs is expected to have fewer and more reliable vectors, i.e., to act as a confidence set for the separation of the two classes.

#### C. Generating Reference Sets:



#### **D.** Contrast Adjustment:

The last processing stage refers to the adjustment of the image histogram. At this point, we explore two scenarios. (C1) The original image is converted to grayscale, and then, the contrast adjustment takes place. (C2) The histogram adjustment is done separately for each band of the original image (multichannel histogram stretching), and then, the bands are merged to form a grayscale image. Fig. 1 displays the two experimental scenarios using flow charts. In both cases, the operation occurs in the spatial domain of size  $m \times n$ .



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#### **DISCUSSION:**

This section analyzes the results of the experimental process. Some interesting findings are listed as follows.

- 1. The contrast adjustment seems to have more influence on the extraction of textural measurements rather than on the morphological characterization. In this application, the texture is determined uniquely by the density of thedetected corners. The probability of a pixel to represent a corner increases proportionally to the distinction level between this pixel and its neighborhood. That is, a contrast adjustment that sharpens enough the grayscale imagehas the potentiality to boost the derivation of prominent textural characteristics. The morphological features instead, and especially those that derive from multi-scale analysis, turn out to be more stable against the contrastvariations. The successive use of structural elements of increasing size and the subsequent process of differentiating between objects detected dissimilar scales somehow manage at to compensate the influence of a moderate contrast. Besides, the morphological characterization has to do, not only with brightness and contrast but also takes into consideration the size and the shape of the objects to be detected.
- 2. The feature extraction as described herein requires agrayscale image as input. The typical approach for the calculation of both PANTEX and MBI is to provide as input an image consisting of the maximum values of the RGB triplet. However, the experimental results show that there are other band combinations (like the luma, with or without decorrelation stretching) that, in many cases, lead to a better contrast. Selecting the right band combination seems to be a key factor especially for the extraction of, good textural measurements.



Image histogram and contrast stretching:

#### **CONCLUSION:**

Image enhancement and contrast adjustment play a substantial role for the extraction of trustworthy textural and morphological characteristics. In order to investigate and measure the sensitivity of those features against variations in contrast, a series of tests were carried out; different scenarios were examined regarding mainly the image bands' combination and the image histogram adjustment guided by lowresolution reference data. From the reported results, a number of approaches can be distinguished for improving the image contrast and for instructing effectively the feature extraction. Future work includes tests with adaptive histogram adjustment, usage of different reference layers, and application of radiometric feature selection and transformation techniques. The presented work is in experimental phase and still remains to be scaled up and adapt to the conditions of the operational mode.

#### **REFERENCES:**

[1] F. Y. Shih, Image Processing and Pattern Recognition-Fundamentals andTechniques. Hoboken, NJ, USA: Wiley, 2010.

[2] R. C. Gonzalez and R. E. Woods, Digital Image Processing, 2nd ed. Englewood Cliffs, NJ, USA: Prentice Hall, 2002.

[3] S. Kim, W. Kang, E. Lee, and J. Paik, "Waveletdomain color image enhancement using filtered directional bases and frequency-adaptive shrinkage," IEEE Trans. Consum. Electron., vol. 56, no. 2, pp. 1063–1070, May 2010.

[4] A. R. Gillespie, A. B. Kahle, and R. E. Walker, "Color enhancement of highly correlated images. I.



A Peer Reviewed Open Access International Journal

Decorrelation and HSI contrast stretches,"Remote Sens. Environ., vol. 20, no. 3, pp. 209–235, Dec. 1986.

[5] H. Demirel, C. Ozcinar, and G. Anbarjafari, "Satellite image contrast enhancement using discrete wavelet transform and singular value decomposition," IEEE Geosci. Remote Sens. Lett., vol. 7, no. 2, pp. 333–337, Apr. 2010.

[6] G. Srilekha, V. K. Kumar, and B. Jyothi, "Satellite image resolution enhancement using DWT and contrast enhancement using SVD," Int. J.Eng. Res. Technol. (IJERT), vol. 2, no. 5, pp. 1227–1230, May 2013.

[7] [Online]. Available:

http://cidportal.jrc.ec.europa.eu/copernicus/services/we bviewer/core003

[8] S. Ferriet al., "A new map of the European settlements by automatic classification of 2.5m resolution SPOT data," in Proc. IEEE Int. Geosci.Remote Sens. Symp. (IGARSS), Quebec City, QC, Canada, Jul. 2014, pp. 1160–1163.

[9] A. Burger, G. Di Matteo, and P. J. Åstrand, "Specifications of view services for GMES Core\_003 VHR2 coverage," European Commission, JRC Tech. Rep., 2012, doi: 10.2788/21898.

[10] M. Pesaresiet al., "A global human settlement layer from optical HR/VHR RS data: Concept and first results," IEEE J. Sel. Topics Appl.

Earth Observ. Remote Sens., vol. 6, no. 5, pp. 2102–2131, Oct. 2013.

[11] [Online]. Available: http://www.eea.europa.eu/articles/urban-soilsealing-ineurope

[12] G. Maucha, G. Büttner, and B. Kosztra, "European validation of GMES FTS soil sealing enhancement data," European Environment Agency, Final draft, Jun. 2010. [13] G. K. Ouzounis, V. Syrris, and M. Pesaresi, "Multiscale quality assessmentof global human settlement layer scenes against reference data using statistical learning," Pattern Recognit. Lett., vol. 34, no. 14, pp. 1636–1647, Oct. 2013.

[14] R. M. Haralick, K. Shanmugan, and I. Dinstein, "Textural features for image classification," IEEE Trans. Syst. Man Cybern., vol. 3, no. 6, pp. 610–621, Nov. 1973.

[15] M. Pesaresi, A. Gerhardinger, and F. Kayitakire, "A robust built-up area presence index by anisotropic rotation-invariant textural measure," IEEEJ. Sel. Topics Appl. Earth Observ. Remote Sens., vol. 1, no. 3, pp. 180–192, Sep. 2008.

[16] X. Huang and L. Zhang, "A multidirectional and multiscale morphological index for automatic building extraction from multispectral GeoEye-1 imagery," Photogramm.Eng. Remote Sens., vol. 77, no. 7, pp. 721–732, 2011.

[17] X. Huang and L. Zhang, "Morphological building/shadow index forbuilding extraction from high-resolution imagery over urban areas,"IEEE J. Sel. Topics Appl. Earth Observ. Remote Sens., vol. 5, no. 1, pp. 161–172, Feb. 2012.

[18] V. Vapnik, Statistical Learning Theory. Hoboken, NJ, USA:Wiley, 1998.

[19] C. Cortes and V. Vapnik, "Support vector networks," Mach. Learn., vol. 20, pp. 273–297, 1995.

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Page 1769