ISSN No: 2348-4845
International Journal & Magazine of Engineering, Technology, Management and Research
A Peer Reviewed Open Access International Journal

Feature Extraction and Image Enhancement for Low Resolution Satellite Images

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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 contrast-based textural/morphological features. A case study is presented where we test a mixture of image enhancement operations like linear and decorrelation stretching and assess the performance through ROC analysis against available

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

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B. Syllogism:

Apart from directly using the up-sampled SSL as referencelayer, 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 hyperplane that linearly discriminates the two classes BU/NBU into a high-dimensional feature space H without using an explicit mapping. This can be achieved by means of the kernel trick [18], [19]. Supportvectors (SVs) are the closest tuples of measurements to the hyperplane 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.

1) To totally remove their respective class labels from thereference layer: this decision targets at the increase in both intra-class similarity and inter-class 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:

Algorithm 1. *Generate Reference Images* Pseudocode

$I \leftarrow$ Input multiband image
$Ref \leftarrow$ Binary image $(-1, 1)$ used as reference
$X \leftarrow$ Downsample(I) according to Ref dimensions
Train SVM(X,Ref)
$SV = \{x_v : v \in V\}$
Generate new reference $Y \leftarrow$ Ref:
Option (i) : Set 0 to the pixels of Y that correspond to the support vectors of SV
Option (ii) : Set -1 to the pixels of Y that correspond to the support vectors of SV
Option (iii): Train SVM$(X \backslash SV, Y\{y_j, j \in V\})$
$SV_1 = \{$new support vectors$\}$
$Y = \text{SVMclassify}(I, SV_1)$
Output Y

Output Y

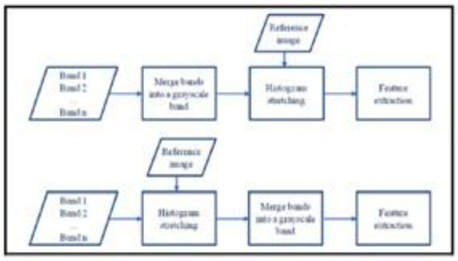

Fig. 1. Two experimental configurations.

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 × n.

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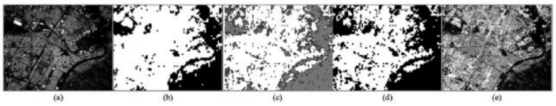

Fig. 2. Reference layers at 2.5-m spatial resolution: (a) City of Torino: building footprints covered an area of 6.5 × 8.24 km; (b) $SSL^{(1)}$; (c) $SSL^{(2)}$; (d) $SSL^{(3)}$; and (e) $SSL^{(4)}$. The images in (b), (c), and (d) have been resized via *nearest neighbor* interpolation to match the resolution of the input image. In (c), the darker pixels have been omitted completely.

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 at dissimilar scales somehow manage 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.

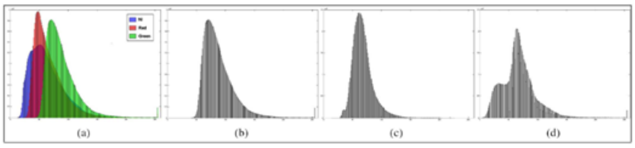

Image histogram and contrast stretching:

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 low-resolution 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.

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