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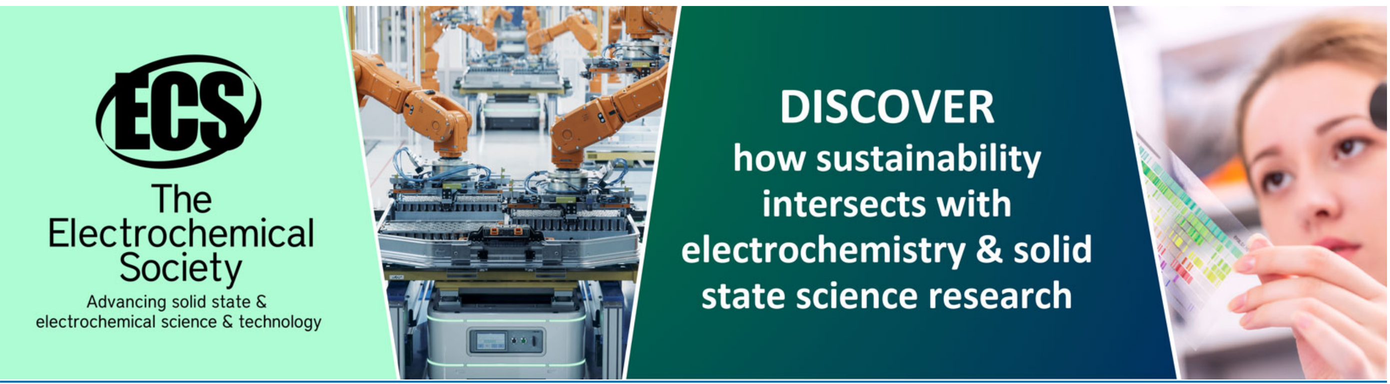

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A vegetation height classification approach based on texture analysis of a single VHR image

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Abstract. Vegetation height is a crucial feature in various applications related to ecological mapping, enhancing the discrimination among different land cover or habitat categories and facilitating a series of environmental tasks, ranging from biodiversity monitoring and assessment to landscape characterization, disaster management and conservation planning. Primary sources of information on vegetation height include in situ measurements and data from active satellite or airborne sensors, which, however, may often be non-affordable or unavailable for certain regions. Alternative approaches on extracting height information from very high resolution (VHR) satellite imagery based on texture analysis, have recently been presented, with promising results. Following the notion that multispectral image bands may often be highly correlated, data transformation and dimensionality reduction techniques are expected to reduce redundant information, and thus, the computational cost of the approaches, without significantly compromising their accuracy. In this paper, dimensionality reduction is performed on a VHR image and textural characteristics are calculated on its reconstructed approximations, to show that their discriminatory capabilities are maintained up to a large degree. Texture analysis is also performed on the projected data to investigate whether the different height categories can be distinguished in a similar way.

1. Introduction

Estimation of canopy structure and vegetation height plays a crucial role in numerous ecological and environmental applications [1, 2]. Furthermore, height is a principal discriminating factor in certain land cover and habitat classification systems. Characteristic examples include the Land Cover Classification System (LCCS) [3], and the recently proposed General Habitat Categories (GHC) [4]. The most accurate way in measuring vegetation height is through hand-held devices, such as hypsometers, during in situ campaigns [5], followed by popular satellite or airborne remote sensing approaches involving Light Detection And Ranging (LiDAR) [6] or, less frequently, Synthetic Aperture Radar (SAR) data [7]. However, such data might be expensive or, particularly for airborne and, to a larger degree, for in situ data, provide restricted area coverage and be time and labour demanding to acquire. Passive sensor satellite data, on the other hand, providing large area coverage often at a reasonable cost, seem to constitute a rational potential alternative. Recent studies have tried to link reflectance characteristics extracted from passive imagery to vegetation height and tree structure properties, either individually [8] or in synergy with active LiDAR or SAR data [2, 9].

A different approach, contrary to focusing on calculation of spectral indices and reflectance characteristics, has recently been developed under the auspices of the BIO_SOS (Biodiversity Multi-SOurce Monitoring System: From Space To Species) European FP7 project, employing texture analysis of satellite passive sensor data to estimate vegetation height [10]. Various texture measures have been calculated on all 4 bands of a very high resolution (VHR) Quickbird image, trying to discriminate between patches with vegetation higher or lower than 2m. The approach was proven particularly promising, with classification accuracies exceeding 90% for certain texture measures.

In this paper, an effort is made to further elaborate on the aforementioned approach by trying to reduce its computational cost. Based on the fact that multispectral image bands may often be highly correlated, dimensionality reduction (DR) techniques are applied. Two distinct pathways are followed: Texture measures are calculated both on the transformed dimensionality reduced data and on reconstructed approximations of the original image, after removing information indicated as redundant. The ability of the texture measures in discriminating between patches with tree and shrubby vegetation higher or lower than 2m is evaluated.

2. Materials

2.1. Study area

The area of interest is a Natura 2000 protected site, lying on the Adriatic side of the south eastern part of Apulia region, Italy, called Le Cesine (figure 1). It is one of the oldest protected sites in Apulia, covering an area of approximately 3.48km^2. The area is characterized by a complex of coastal lagoons, various canals, marshes and humid grasslands. Helophytic, halophilous and dry therophytic vegetation species alternate, creating interesting mosaics and including species such as *Cladium mariscus*, *Pinus halepensis*, *Quercus ilex* and *Erica forskalii*.

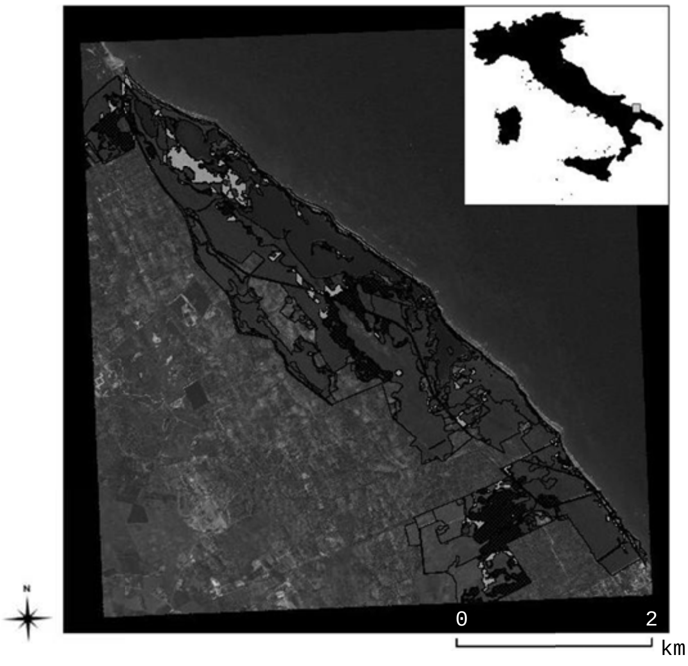

Figure 1. Quickbird image of Le Cesine site (SE Italy, Europe) with LPH/MPH and TPH habitats.

2.2. Data

A VHR multispectral Quickbird image, acquired in mid July 2005, serves as the only available data source to retrieve vegetation height information. The spatial resolution of the image is 2.4m and its four bands lie on the blue (450–520nm), green (520–600nm), red (630–690nm) and near-infrared (760–900nm) regions of the spectrum. To validate the proposed approach, a habitat map of the area, from the same period, is used. The habitat categories depicted on the map comply with the tree-structured GHC classification scheme, which distinguishes a total of 160 habitat classes [4]. Vegetation height is the principal—if not the only—feature that discriminates certain classes with similar appearance and spectral characteristics, from an earth observation point of view, but different underlying ecological properties and functions. This paper focuses on the distinction between two indicative tree and shrub GHC classes, namely low and mid phanerophytes (LPH/MPH) and tall phanerophytes (TPH), having a height of less and more than 2m, respectively. In figure 1, the boundaries of the protected area are marked on the green band of the Quickbird image drawn in greyscale. LPH/MPH habitats are depicted as white dotted patches, while TPH habitats as dark dotted ones. For the rest of the habitats, as extracted from the habitat map, no marking is used.

3. Methods

The main objective of this study is to investigate whether DR performed on the VHR image is able to maintain the discriminatory power of the employed texture measures to similar levels as when calculated on the original image. DR is applied to the Quickbird image and texture measures are calculated on both the transformed data and the reconstructed versions of the image and evaluated.

3.1. Dimensionality reduction

Two of the most popular and widely used linear DR methods are applied to the original image, namely Principal Component Analysis (PCA) and Singular Value Decomposition (SVD) [11]. In both approaches, the pixels of the image are considered as vectors with 4 feature values, i.e. their intensity values in the 4 bands of the Quickbird image. In many multispectral, and in a larger extent in hyperspectral, images, these feature values present a high degree of correlation.

The goal of PCA is to apply a linear transform—Karhunen-Loève transform—to the original data, in order to generate mutually uncorrelated features. After converting the data to be zero mean, pixel vectors are sorted in lexicographic ordering, forming a $4 \times N$ matrix X, where N stands for the number of the image pixels. Eigendecomposition is applied on the correlation matrix of X, in order to extract its orthonormal eigenvectors. Projection of the original data onto the produced eigenvectors

$$Y = A^{\mathrm{T}} X, \tag{1}$$

where A stands for the 4×4 matrix of the eigenvectors, written in decreasing order of the respective eigenvalues, while Y stands for the $4 \times N$ projected data and T denotes matrix transpose, results in pixels/vectors with mutually uncorrelated features. In order to reconstruct the original image, the data need to be re-projected to the original feature space, following the inverse process. DR is achieved depending on the number of the transformed features, or *principal components*, selected to be re-projected to the original space. It has been proven that eigenvectors whose respective eigenvalues are very small or zero, can be omitted during the reconstruction without influencing the final result. Therefore, selecting only the eigenvectors whose respective eigenvalues are significant, DR is achieved without practically compromising the accuracy of the reconstructed data. In this study, reconstruction was attempted using only the first one, two or three out of the four components, i.e. approximately 1/4, 2/4 and 3/4 of the initial amount of data, respectively, resulting in the respective approximations of the original image.

The powerful linear algebra algorithm of SVD decomposes matrix X into the form

$$X = UYV^{\mathrm{T}}, \tag{2}$$

where U and V are unitary matrices of dimensions 4×4 and $N \times N$ containing the eigenvectors of XX^{T} and $X^{\mathrm{T}}X$, respectively, and Y is a matrix of dimensions $4 \times N$, having the square roots of the respective eigenvalues (same for both XX^T and X^TX), known as *singular values*, in its main diagonal and all its other elements zero. The number of non-zero singular values equals the rank of X. DR may be performed by selecting to use certain singular values and the respective eigenvectors from U and V for the reconstruction of X, or through selection of specific components of the projected data of X to the new space indicated by the SVD transformation, U^TX ($U^TX = YV$). It has been proven that reconstructing a matrix X using its larger n singular values results in its best possible n-rank approximation in the Frobenius norm sense [11]. Similar to PCA, the largest one, two and three singular values were used in this study for the reconstruction of the initial image.

3.2. Texture analysis
A number of texture measures is calculated on reconstructed versions of the original data and on the projected data, after re-arranging all pixels from the lexicographic order to the initial image array format. The selected texture measures are the ones suggested in [10], based on local variance, entropy, local binary patterns and proposed variations. For each specific texture measure, a texture value is calculated locally for each pixel from its surrounding pixels in a specified window and is assigned to the pixel; then, the values of all pixels belonging to the same patch are averaged, notating the patch with a single value for the specific texture measure and the band/feature under study. Since in areas with short and shrubby vegetation the texture of the image appears more homogeneous than in areas with high vegetation, where vegetation canopy, tree trunks and bare ground alternate, it is expected that TPH have significantly larger values than LPH/MPH patches, reflecting their larger heterogeneity.

3.3. Experiment design
In total, 52 LPH/MPH and 99 TPH patches were considered, as delineated on the available habitat map. The texture measures described in [10] were calculated on approximations of the original Quickbird image after applying PCA and SVD, as well as on components of the transformed data, in an effort to evaluate whether the projected data themselves can offer vegetation height information under this texture analysis approach. Among others, the local variance was calculated using a 3×3 pixel window around each central pixel (LE); local entropy was calculated using a 9×9 pixel window, after quantizing its pixel values in 8 bins (LH); local entropy ratio was calculated considering 13×13 and 21×21 pixel windows as internal and external ones, respectively, excluding the pixels of the internal window from the entropy calculation of the external one (LHR); rotation invariant (LBP1) and rotation variant (LBP2) local binary patterns were calculated for radius 1; rotation variant local ternary patterns were calculated for radius 1 (LTP) and local binary patterns with range for radius 2 (LTBP). For a specific image, each measure was calculated on a per pixel basis for every patch and then averaged for the pixels of the patch. 30 LPH/MPH and 50 TPH patches were randomly selected to train a pruned decision tree classifier based on the CART (Classification And Regression Tree) methodology [12], while the rest were used as the validation set. The classification was repeated 50 times, with different training and validation sets randomly selected each time, to ensure that the classification results were unbiased, and the average accuracy from all tests was considered.

4. Results and discussion
Figure 2 presents the classification accuracy, i.e. the ratio of the correctly classified patches to the total number of validation set patches, for the texture measures discussed in section 3.3 and applied on data generated using PCA, in comparison with the respective results obtained from the original Quickbird image (QB). Reconstructions of the original image using the principal components corresponding to the largest one (PCA_1/4), two (PCA_2/4) and three (PCA_3/4) eigenvalues are considered. The green band is used for analysis and demonstration as the highest performing, according to [10]. Projected data on the first (PCA_proj1) and third (PCA_proj3) principal eigenvectors are also shown, indicatively. The same results for SVD are drawn in figure 3.

As seen in figure 2, PCA_1/4 lead to accuracies around 10–15% lower than the ones achieved by the original data (QB), with the exception of the LHR measure. The amount of stored data was reduced to approximately 1/4, but this had an important impact in accuracy. On the other hand, even though PCA_3/4 results slightly outperformed the ones derived by PCA_2/4, it seems that both data sets have resulted in classification accuracies comparable to QB. This is a crucial observation, stating that, using PCA, the amount of data, i.e. the data storage and memory requirements, necessary to perform height discrimination may be reduced to half, after identifying and removing redundant information, without practically compromising the achieved classification accuracy. The same is valid for the respective data generated by SVD, as observed in figure 3. The conclusion seems to be valid for all the selected texture measures in both DR cases.

Regarding the transformed components, the results achieved after texture analysis on PCA_proj1 and PCA_proj3 indicate that the classification accuracies observed are comparable to the ones of PCA_1/4, notably lower than the results of QB (figure 2). This outcome does not contradict common sense, since, on the one hand, the transformed features are not used for classification directly, but as proxies for the extraction of new features, involving also topological relations among them (texture analysis) and, on the other hand, PCA is not, in general, optimised with respect to class separability, therefore, it does not necessarily lead to maximum separability in the lower dimensional subspace [11]. The same observations and conclusions apply to SVD, as seen in figure 3.

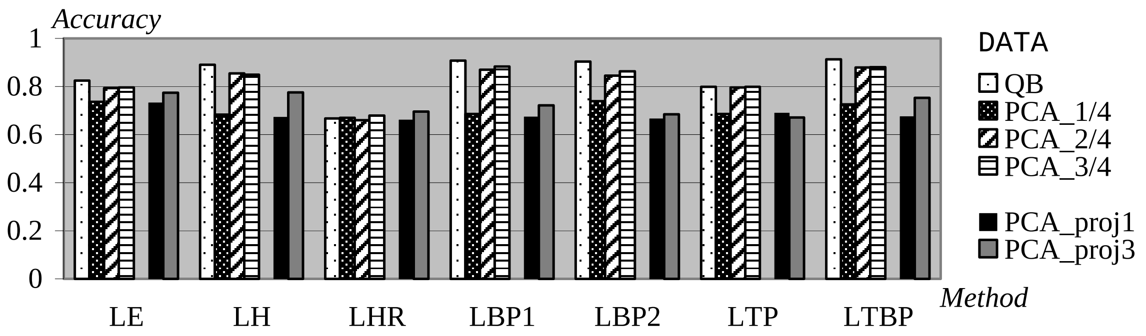

Figure 2. Classification comparison of Quickbird (QB) green band with PCA approximations of the original image (transformation inverse procedure) using the first *i* (*i*=1,2,3) principal components (PCA_*i*/4), as well as the 1st (PCA_proj1) and 3rd (PCA_proj3) PCA transformed components.

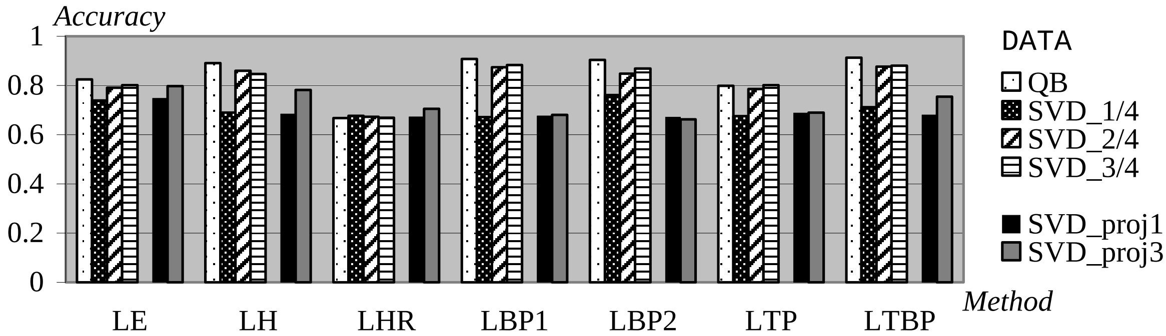

Figure 3. Classification comparison of Quickbird (QB) green band with SVD approximations of the original image (transformation inverse procedure) using the largest *i* (*i*=1,2,3) singular values (SVD_*i*/4), as well as the 1st (SVD_proj1) and 3rd (SVD_proj3) SVD transformed components.

5. Conclusions and future work

In this paper, dimensionality reduction was performed on a multispectral Quickbird image, used to derive vegetation height information through texture analysis. After transforming the original data using PCA and SVD analyses, reconstruction of the data was attempted using only some of the principal components and singular values identified. Contrary to the transformed data themselves, approximated images provided high classification results, showing that the applied DR methods can remove redundant information in the initial image and significantly reduce the amount of stored data, without compromising the achieved height classification accuracy, thus making the application of texture analysis in multispectral imagery even more appealing and computationally cost effective. Further improvements in information packing may be achieved through the use of more adjustable non-linear DR approaches. In addition, DR may also be applied to the final texture values, to combine their characteristics and potentially improve the height classification results. In general, the results achieved encourage future research in texture analysis methods as alternatives in vegetation height estimation. This may reduce the cost of land cover and habitat mapping, through the use of easily accessible data, and facilitate ecological monitoring and environmental sustainability planning.

6. Acknowledgments

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