FEATURE REDUCTION OF HYPERSPECTRAL DATA USING AUTOASSOCIATIVE NEURAL NETWORKS ALGORITHMS

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ABSTRACT

Hyperspectral sensors provide a rich amount of information that, if appropriately used, may provide innovative procedures for qualitative and quantitative remote sensing of land cover parameters. However, high number of spectral samples exhibit high correlation, adding a redundancy that may obscure information relevant for the inversion task thus degrading the accuracy of final products. Therefore, dimensionality reduction may become a key parameter to obtain a good performance. As can be found in literature, classical techniques for feature reduction can be applied to the measured hyperspectral signatures. Mainly these include feature selection algorithms and feature extraction algorithms. As compared to feature extraction, feature selection is a more simple and direct approach, and the resulting reduced set of features is easier to interpret. On the other hand, extraction methods can be expected to be more effective [1], [2].

In this paper we present a novel feature extraction procedure based on neural networks. Although neural networks are recognized to represent a rather competitive family of algorithms for the analysis of remote sensing data, their potential for feature reduction in hyperspectral data has not been fully investigated yet. In particular we consider the autoassociative neural networks as a features extraction approach [3]. The autoassociative neural networks can be seen as a method to generate nonlinear features from the data under analysis. The networks are of a conventional type, featuring feedforward connections and linear or sigmoidal nodal transfer functions, trained by backpropagation or similar algorithms. The particular network architecture used employs three hidden layers, including an internal "bottleneck" layer of smaller dimension than either input or output. The network is trained to perform the identity mapping, where the input is approximated at the output layer. Since there are fewer units in the bottleneck layer than the output, the bottleneck nodes must represent or encode the information in the inputs for the subsequent layers to reconstruct the input. If network training finds an acceptable solution, a good representation of the input must exist in the bottleneck layer. This implies that data compression caused by the network bottleneck may force hidden units to represent significant features in data. The concept of using a neural network with a bottleneck to concentrate information has been originally introduced in [4] and it has been already positively applied in the retrieval of atmospheric variables from microwave radiometry [5].

The assessment of the presented methodology with respect to the currently most advanced and traditional features extraction approaches has been carried out for very different sets of hyperspectral data collected from sensors such as AVIRIS, ROSIS and CHRIS-PROBA. The results have been evaluated and critically analysed either in terms of their capability of representing the hyperspectral data with a reduced number of components or in terms of the accuracy obtained on the final derived products. These latters consist of land cover classification maps obtained over test areas for which an extensive ground-truth was available. As far as CHRIS-PROBA data are concerned, an additional issue has been addressed by including in the analysis the multi-angular acquisitions characterizing this sensor [6].

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