Data Dependant Adaptation for Improved Classification of Hyperspectral Imagery

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Hyperspectral sensors acquire data (reflectance values) corresponding to a wide range of wavelengths at fine spectral resolutions. Thus, the information present in the hyperspectral signatures is typically of very high dimensionality due to the presence of hundreds of continuous narrow spectral bands. This high dimensional data with the narrow spectral bands is expected to provide better classification accuracies compared to lower dimensional data, such as multispectral or panchromatic imagery. However, the high dimensionality of hyperspectral data presents key challenges when using such data for classification tasks. One key challenge is over-dimensionality, which is associated with the problem of over-fitting (Hughe's phenomenon). Hence, dimensionality reduction schemes and feature extraction and optimization algorithms like Principal Component Analysis (PCA), Linear Discriminant Analysis (LDA), Stepwise-LDA (S-LDA) are commonly employed [1]. Algorithms such as LDA and S-LDA reduce the dimensionality of the feature space by projecting the data onto a lower dimensional subspace, simultaneously maximizing an appropriate class separation metric in the projected space. However, in small training sample size situations (training data) these algorithms often fail. [2], [3]. An alternate way of overcoming these problems was recently proposed in [4]. In this Multi-Classifier Decision Fusion (MCDF) algorithm, the authors used a divide-and-conquer approach to overcome the small-sample-size problem by dividing the high dimensional data into subgroups, performed feature optimization and classification in each group separately, and finally, combined classification results from each group using a decision fusion mechanism.

In this paper, we propose an adaptation strategy for existing classification methods described above. Figure 1 describes a typical flow for the proposed approach. For a single classifier system, the adaptation process helps identify additional features that better separate the most "confused" class pairs in the dataset. A similar modification is also proposed for the recently devloped MCDF system. Results with experimental hyperspectral data demonstrate the benefits of this data dependant adaptation for land-cover classification. Both single and multiple classifier systems perform significantly better with this adaptation. Figure 2 shows example results for two datasets: (i) hyperspectral signatures collected with a handheld spectroradiometer (ASD™) and (ii) airborne hyperspectral imagery (SpecTIR™). Both datasets are from a very challenging agricultural application, where the goal is detect chemical stress on corn crops and create a ground cover map of 8 levels of stress depending on the concentration of chemical applied to the crop. Figure 3 shows results of a sensitivity study, where the proposed adaption process is shown to be less sensitive to small amounts of available ground-truthed training data as compared to conventional classifiers.

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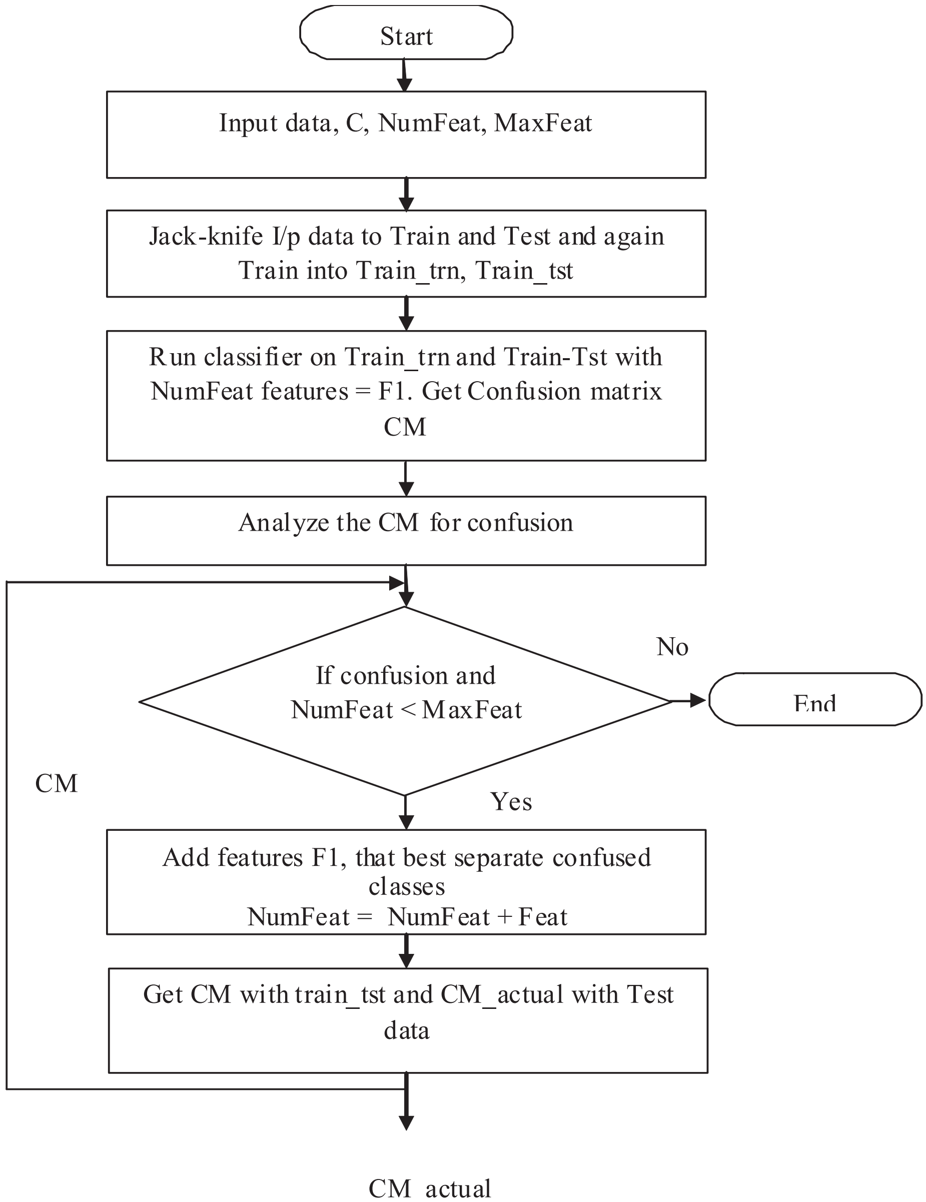

Figure 1. Flowchart of the proposed adaptation strategy for robust classification of hyperspectral data. NumFeat is the number of features selected prior to the adaptation process. MaxFeat is the maximum allowable dimensionality of the feature space (relative to the amount of available ground-truth / training-data). CM is confusion matrix resulting from training data.

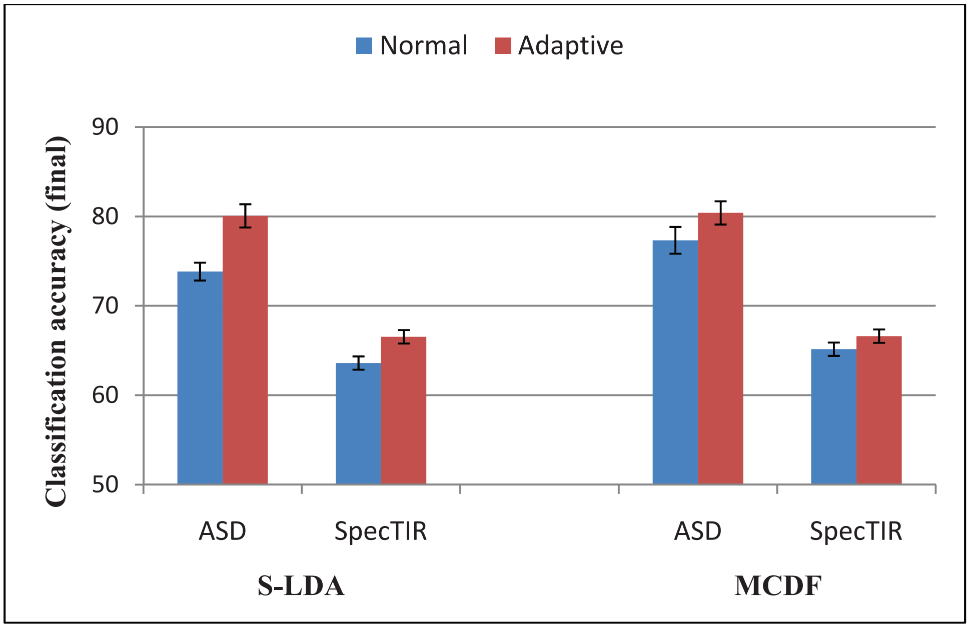

Figure 2. Overall 8-class classification accuracy using S-LDA and MCDF with the “normal” maximum likelihood classifier versus applying the proposed adaptive process to the maximum likelihood classifier.

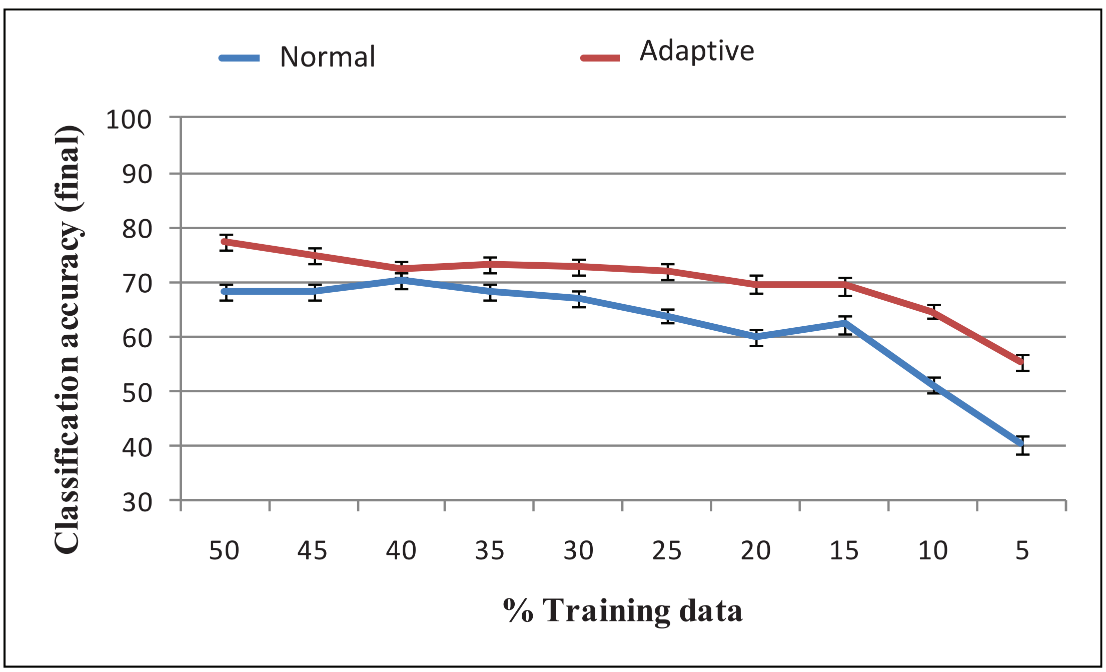

Figure 3. Overall 8-class classification accuracy using S-LDA with a “normal” maximum likelihood classifier versus applying the proposed adaptive process to the maximum likelihood classifier. The amount of available training data (ASD™) is reduced from 50% (jack knifing data) to 5% (more realistic scenario where limited ground truth data is available).