A NOVEL GENERALIZED ASSIGNMENT FRAMEWORK FOR THE CLASSIFICATION OF HYPERSPECTRAL IMAGE

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Abstract

With an insight on the mechanism of sparse representation (SR), this work treats the SR coefficients as a kind of soft assignments of the sample label, where the position of the nonzero entry and the associated magnitude indicate the possibility the sample belongs to the class of the respective dictionary atom. With this treatment, multiple samples and/or multiple features can be viewed as independent instances to estimate the likelihood distribution of the sample labels. As such, multi-sample and multi-feature classification are unified into the same framework. The proposed method has the following advantages:

- Multiple samples and multiple features can be easily fused for collaborative classification by assignment accumulation.
- With the assumption that the SR coefficients of similar samples and/or multiple features of a sample follow a similar distribution, assignment accumulation can exploit the diversity of multiple samples and/or the complementarity of multiple features automatically, which could greatly simplify the algorithm design.
- From a statistic perspective, assignment accumulation could also boost the robustness of the model to possible outliers.

Experiments on the hyperspectral image (HSI) classification demonstrate that the proposed method noticeably outperforms several state-of-the-art approaches.

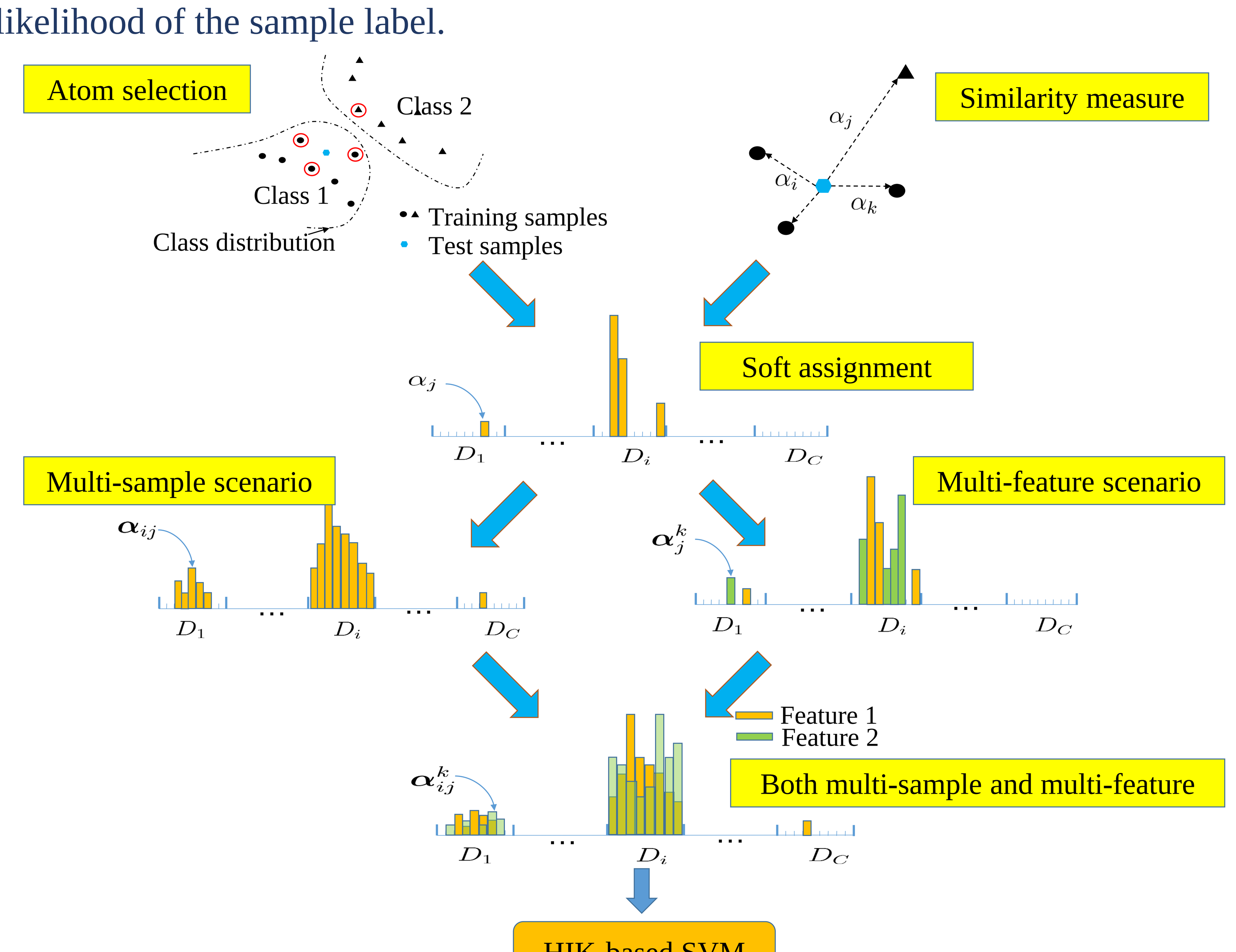
Proposed Method

Insight on sparse representation

Sparse representation with L1-norm:

$$\hat{\boldsymbol{\alpha}} = \arg\min_{\boldsymbol{\alpha}} \frac{1}{2}\|\boldsymbol{x} - D\boldsymbol{\alpha}\|_2^2 + \lambda\|\boldsymbol{\alpha}\|_1$$

where $D = [D_1, D_2, \cdots, D_C] \in \mathbb{R}^{d\times N}$ is the dictionary consisting of the training samples from all classes. L1-norm induced representation coefficients manifest two important characteristics: dictionary atom selection, and sample similarity measure. Then, the SR coefficients can be viewed as a kind of soft assignment on the likelihood of the sample label.



Generalization to multi-sample and/or multi-feature scenarios

- Since the soft assignment is class-dependent according to the subspace assumption, the accumulated assignments of multiple samples from the same class would be an estimate of their class distribution, from a statistic perspective.
- It is also applicable to the multi-feature scenario, with the assumption that the SR coefficients of different features follow a similar distribution pattern.
- Whatever multi-sample or multi-feature, the assignment accumulation is to estimate the assignment distribution of the sample. Therefore, they can be directly fused to boost the estimation.

The fused result would also be class-specific and hence discriminative, based on which the subsequent classification can be done.

Application to HSI classification

Multi-sample classification: spatially neighboring pixels

Multi-feature classification: spectral-spatial features (e.g. EMPs, EMAPs, etc.)

Example illustration

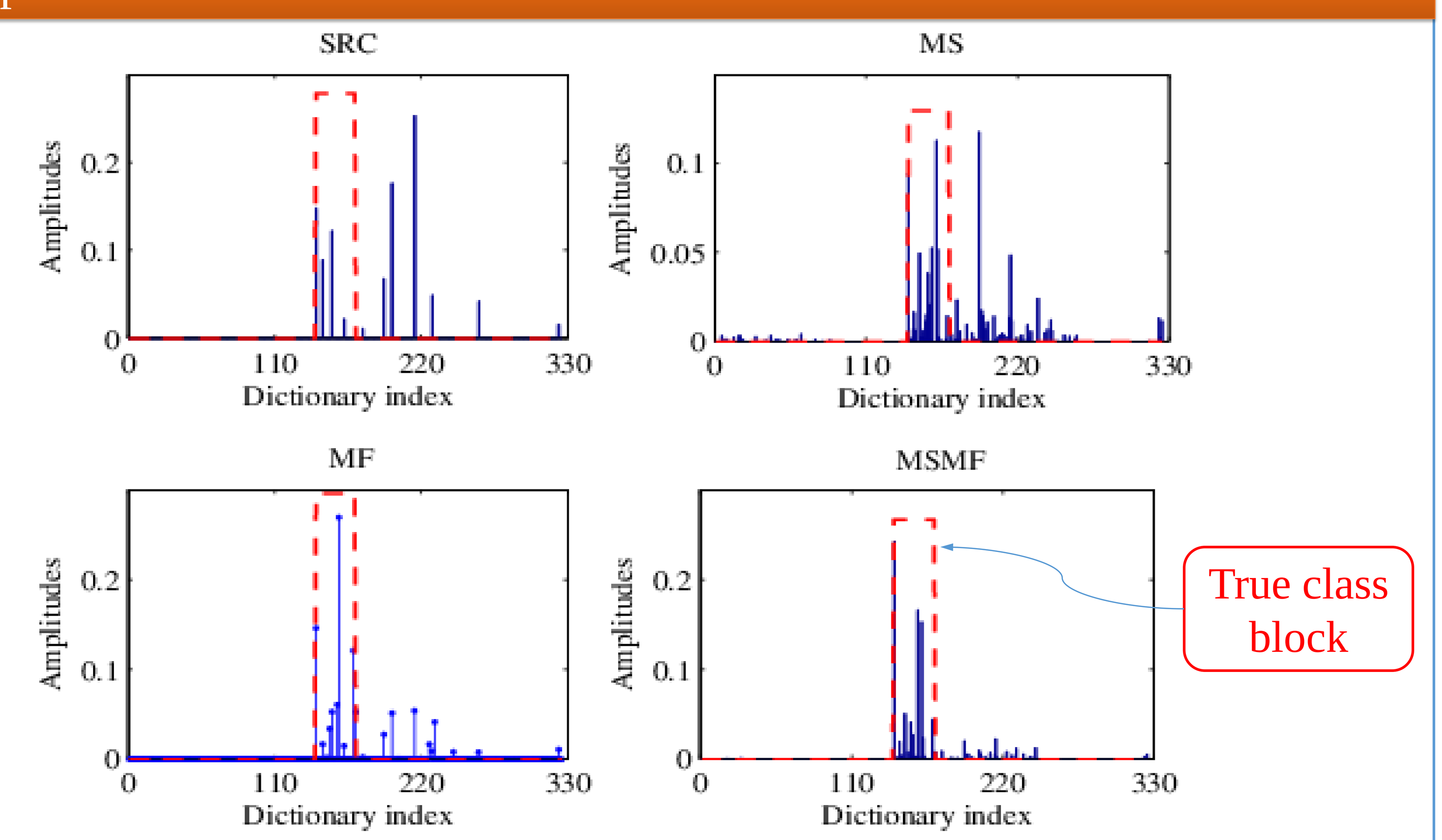
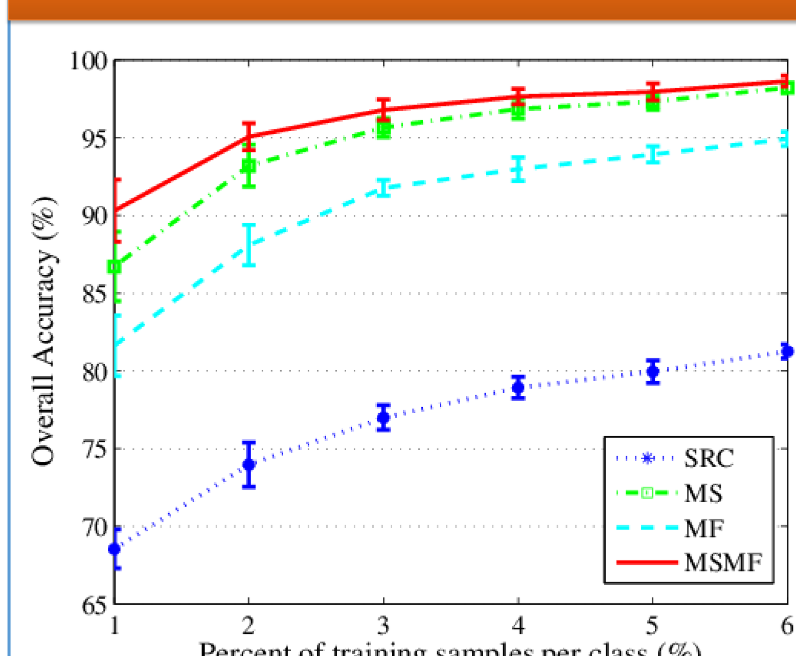
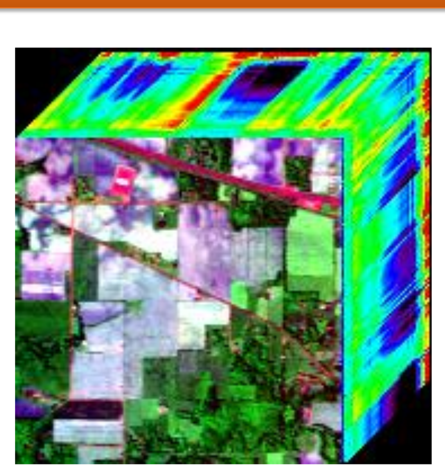


Fig. 2 The details of the assignments of a real test sample from the Indian Pines dataset, using 3% training samples per class.

Experimental results

Indian Pines dataset





Indian Pines dataset

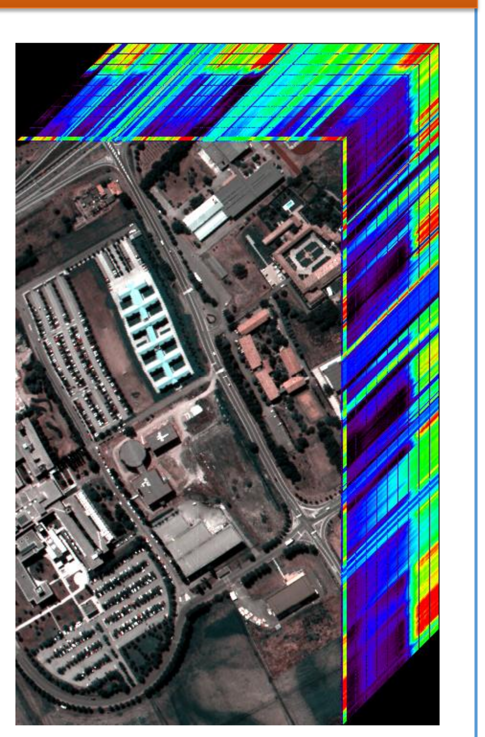


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Table 1. Classification accuracy (%) for the Indian Pines data set using 3% training samples per class

No	SRC	SVM	CSVM	LS	KOMPCK	JCRCMTL	MSMF
OA	76.34	77.90	91.53	86.13	93.68	94.76	**96.54**
AA	73.99	78.01	89.97	77.30	92.36	92.36	**96.12**
κ	72.84	74.80	90.35	84.04	92.79	94.03	**96.06**

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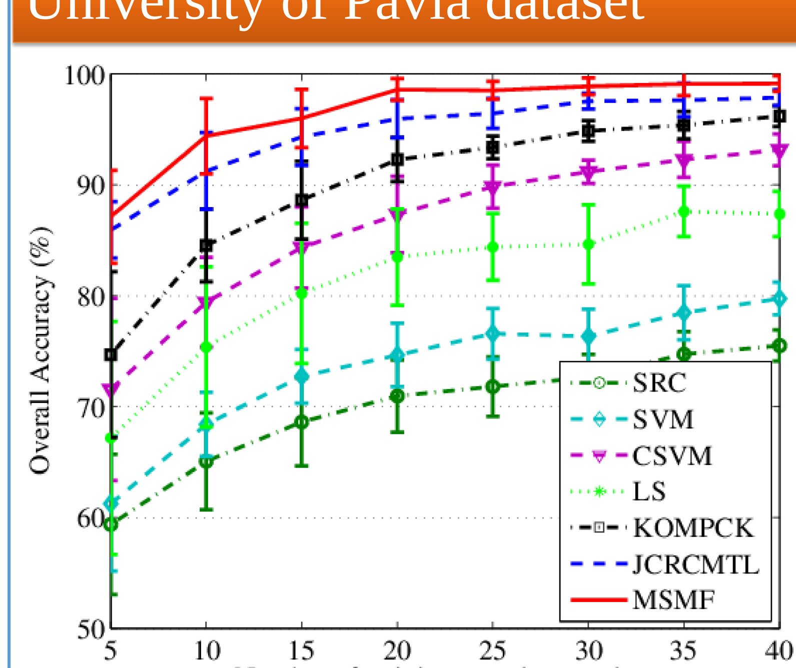

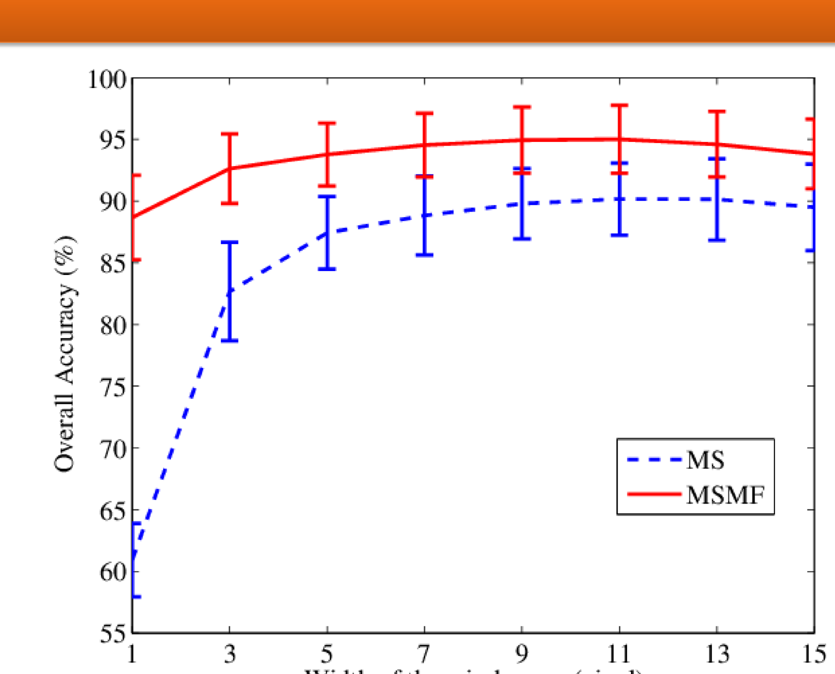

Conclusion

The SR coefficients can be view as a kind of soft assignments of the sample label. From this viewpoint, multi-sample and multi-feature classification can be unified into the same framework. As such, multi-sample and/or multi-feature collaborative classification can be realized by simple assignment accumulation. Accumulation trick could also make the model robust to few possible outliers from a statistic perspective. Experiments on HSI classification have demonstrated its superiority to other counterparts. We believe that it would also applicable to other multi-sample and/or multi-feature classification problems, such as image set based face recognition, multimodal biometrics recognition, etc. It is our future work to validate its effectiveness.