Supplementary Material for the paper *Spectral-Spatial and Superpixelwise PCA for Unsupervised Feature Extraction of Hyperspectral Imagery*

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In this supplementary material, we will discuss the influence of different dimensions of the low-dimensional feature space for all the DR models. Especially for the proposed S^3-PCA, as we conduct three PCA models in SuperPCA, global PCA and feature fusion with the same dimension setting $d = 30$ corresponding to the dimensions of the low-dimensional feature space, it is necessary to testify the influence of different dimensions settings in the algorithm. Also, we provide data visualization in 2D and 3D space for the two HSIs data used in our experiments to subjectively compare SuperPCA and the proposed S^3-PCA.

I. Influence of the dimensions settings for three PCA models in S^3-PCA

In the proposed S^3-PCA, there are three PCA models, where PCA in SuperPCA is used to obtain the local features, PCA for global HSIs feature reduction is adopted to extract the global features and the concatenated global-local features from SuperPCA and global PCA are projected to the low-dimensional space also by PCA. For the experiments in our manuscript, we simply set the reduced dimensions $d = 30$ corresponding to the three PCA models. Obviously the performance of S^3-PCA will be affected if we choose different dimensions for the three PCA models.

In this section, we will discuss the influence of different dimensions settings for the three PCA models in S^3-PCA. Fig.S5-S6 show the OAs when the concatenated global-local features are reduced to $\{5, 10, 15, 20, 25, 30\}$ and PCA is not used to reduce the global-local features as well. For all the following experiments on Indian Pines and University of Pavia data, the number of training samples from each class is 30 ($T = 30$) where S_dim represents the dimension of SuperPCA, G_dim represents the dimension of global PCA and C_dim represents the dimension of the concatenated global-local features.

From Fig.S5-S6 we can find that when S_dim=15, G_dim=10, C_dim=10 in Indian Pines, and S_dim=15, G_dim=30, C_dim=30 in the University of Pavia, the proposed S^3-PCA can get the best OAs= 95.94% and 96.25%, respectively, which improve 0.13% and 0.01% compared to the experimental results in our manuscript where the dimensions of all the three PCA models are set to 30. However, it should be highlighted that the improvements are at the cost of the introduction of two new parameters (S_dim and G_dim) which makes the parameters tuning difficult. Therefore, we recommend that the dimensions of the three PCA models in the proposed S^3-PCA are simply set to 30.

II. Confusion Matrix of SuperPCA based Models

In this section, we will show the confusion matrices from the SuperPCA based feature extraction models (SuperPCA, CSuperPCA, RSuperPCA and S^3-PCA) with the classifier SVM.

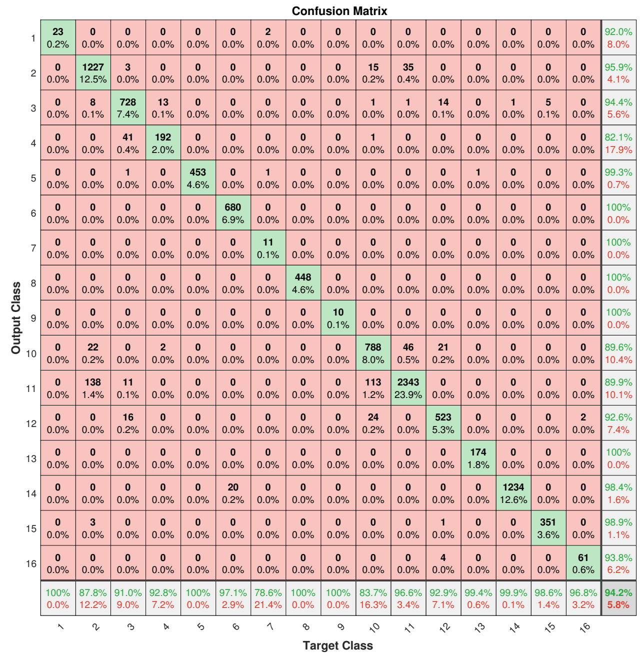
Fig. S1-S2 respectively show the confusion matrices of the classification results from different SuperPCA based models on the Indian Pines and the University of Pavia datasets when $T = 30$ and Fig. S3-S4 show the confusion matrices when $T = 5$.

III. Influence of dimensions of the low-dimensional feature space

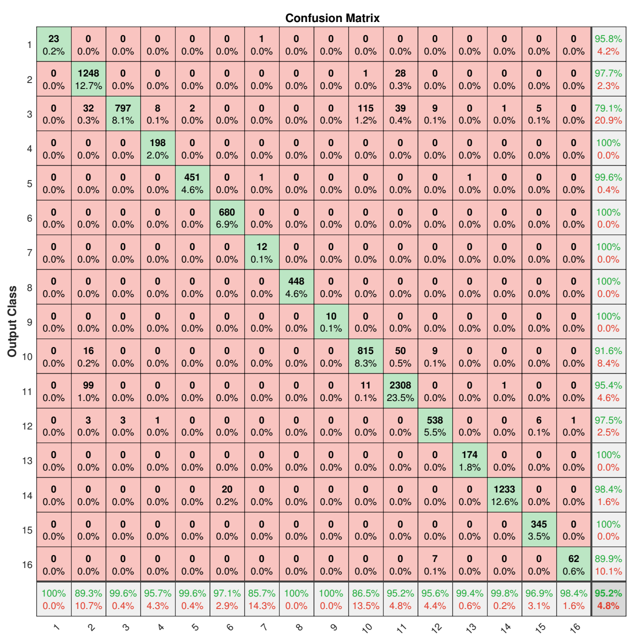
For all the experiments in the manuscript the dimensions of the low-dimensional feature space d is 30 for all DR models, such as PCA, LPP, NPE, LPNPE, LNSPE, SuperPCA, NWFE, LFDA and the proposed S^3-PCA where d corresponds to the dimension of the concatenated global-local features. Here we will conduct experiments to compare all the DR algorithms as the dimension of the low-dimensional feature space changes.

Fig. S7 shows the OAs based on SVM when the reduced dimension in the range $\{5, 10, 15, 20, 25, 30\}$ for all the DR methods on Indian Pines and University of Pavia data with the number of training samples from each class $T = 30$. As can be seen from Fig. S7 that S^3-PCA outperforms other models in terms of OAs and with the increase of dimensions the accuracy of all algorithms tend to be rising and then keeping stable. Compared to other DR models, SuperPCA and the proposed S^3-PCA can obtain high accuracy even when the dimension of the low-dimensional feature space is low. Based on the experimental results we can conclude that the optimal dimension of the low-dimensional feature space for all the DR models is 30.

(a) SuperPCA



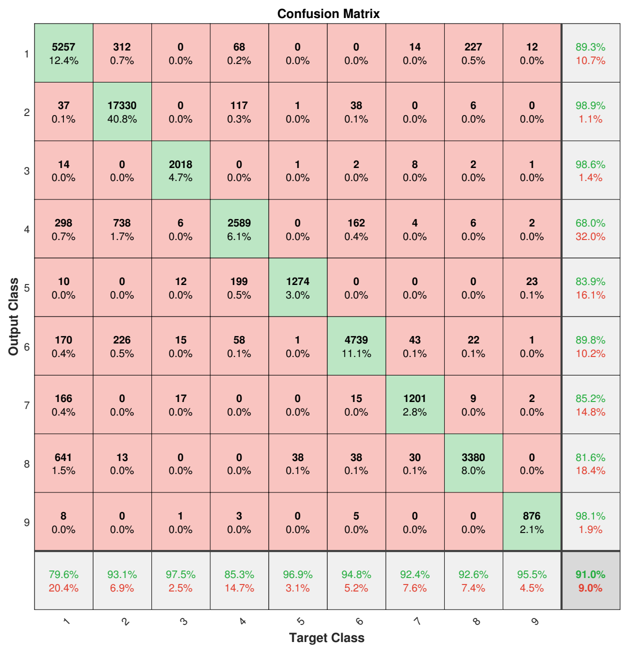
(b) CSuperPCA



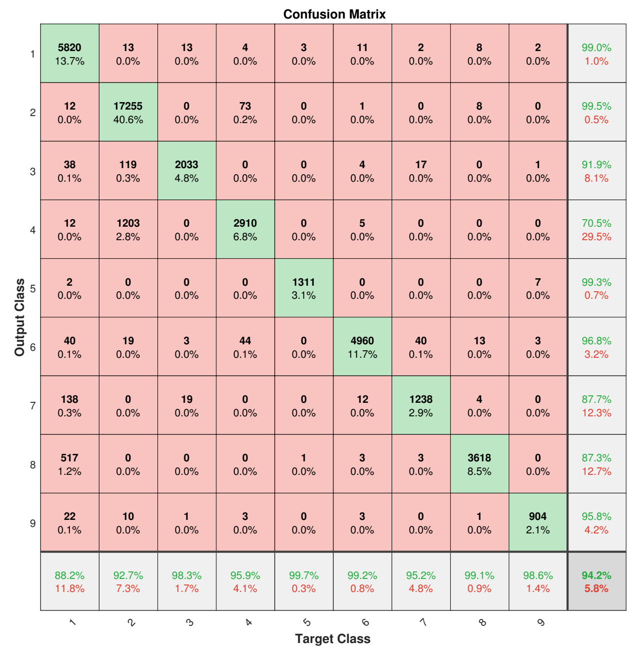
(c) RSuperPCA

(d) S^3-PCA

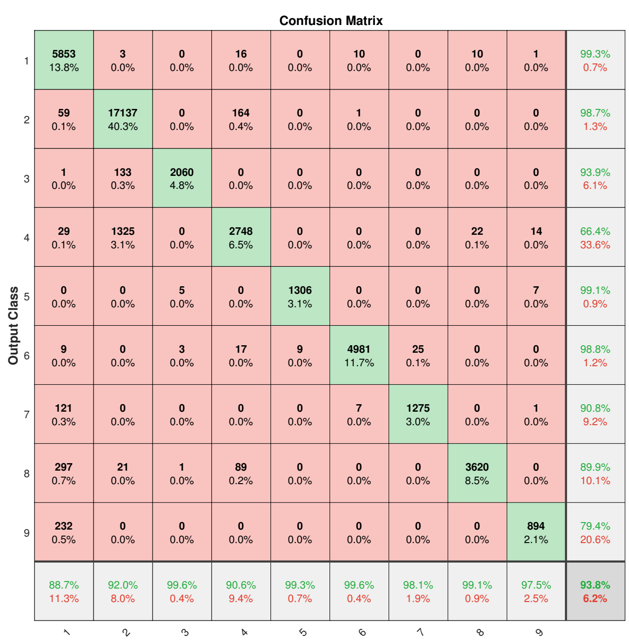
Fig. S1. The confusion matrix of SuperPCA based models on Indian Pines when $T = 30$.



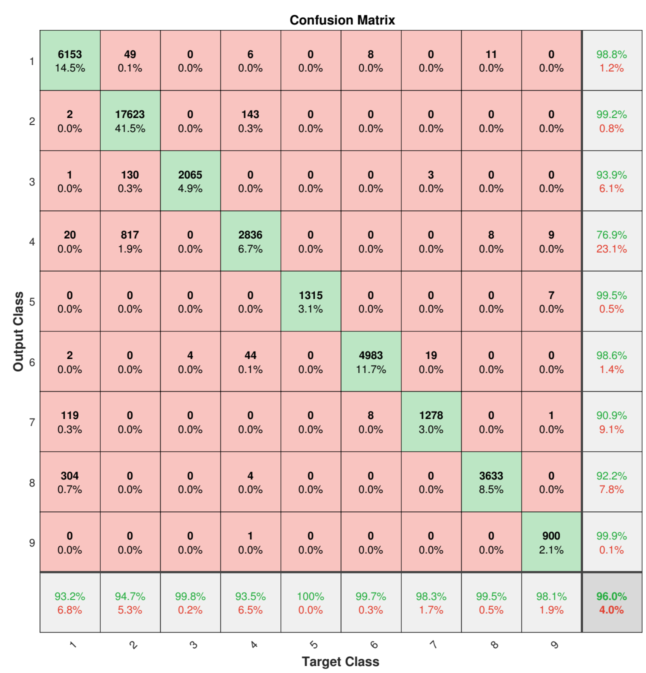
(a) SuperPCA



(b) CSuperPCA

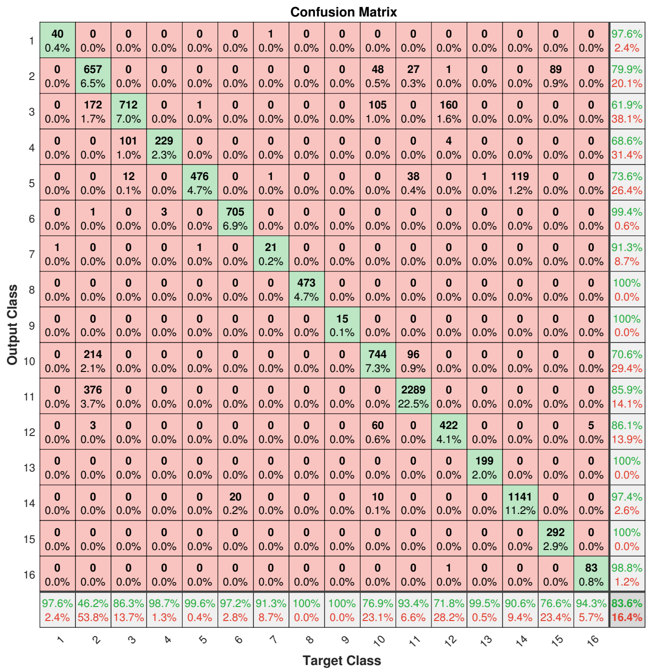


(c) RSuperPCA



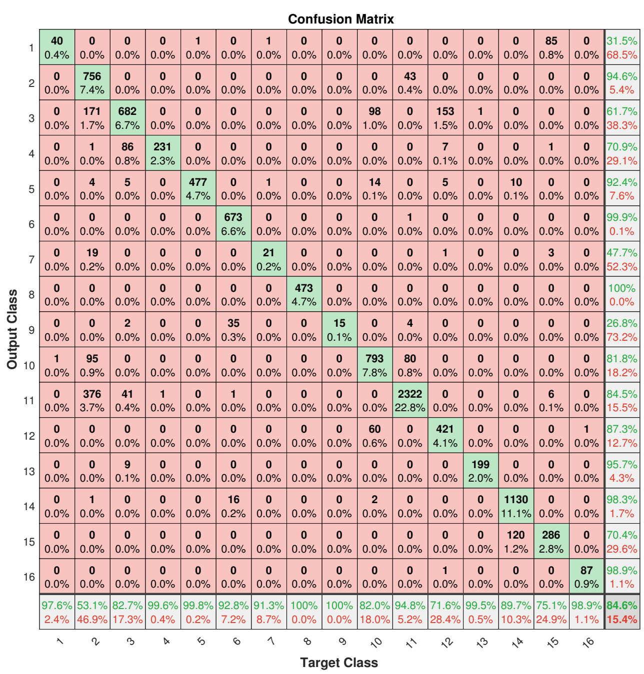
(d) S^3-PCA

Fig. S2. The confusion matrix of SuperPCA based models on the University of PaviaU when $T = 30$.

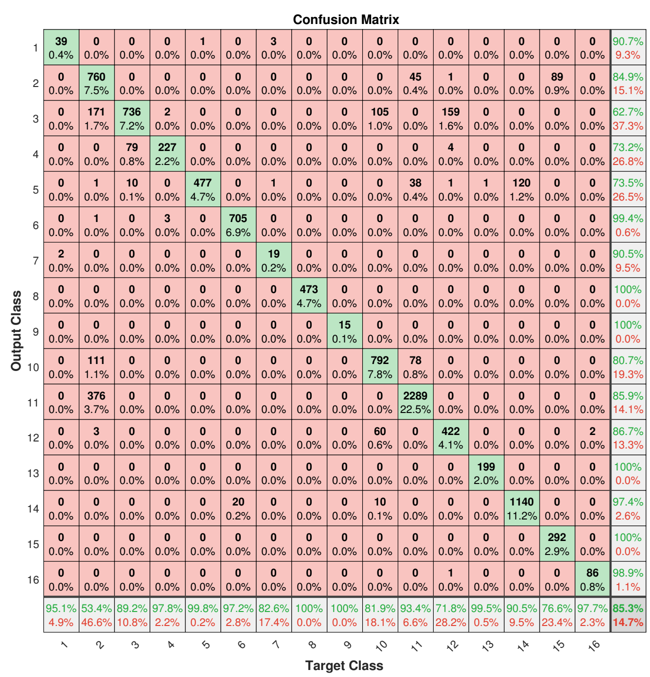


(a) SuperPCA

(b) CSuperPCA

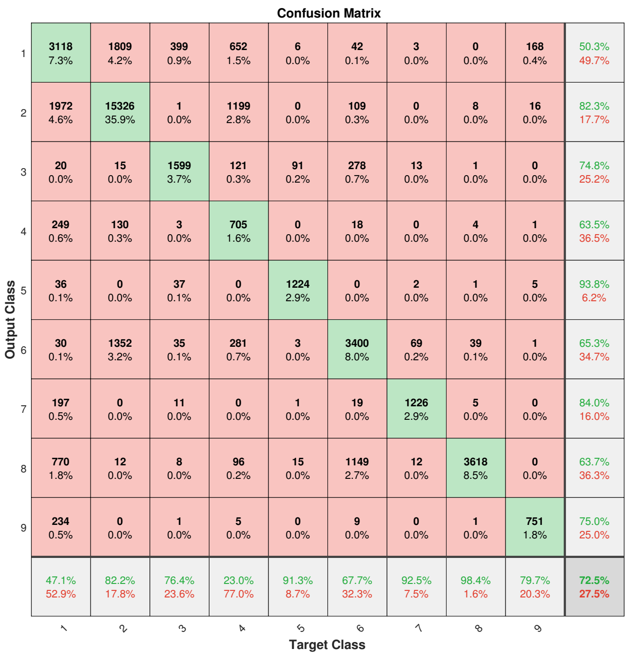


(c) RSuperPCA

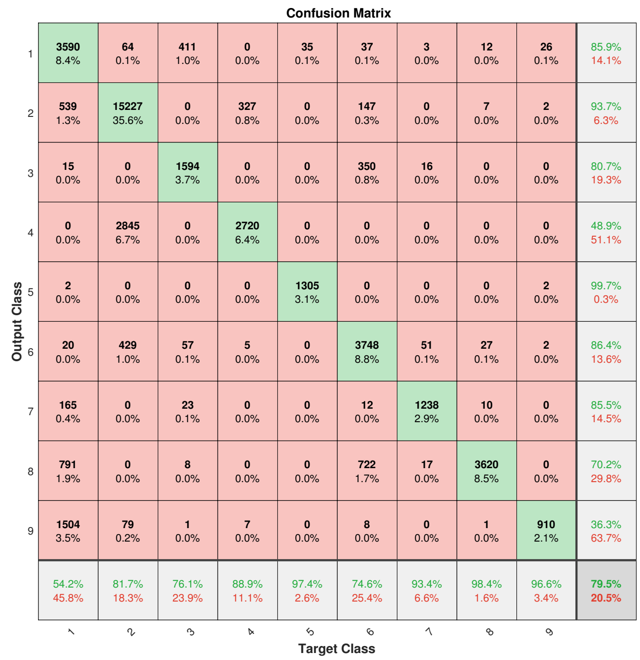


(d) S^3-PCA

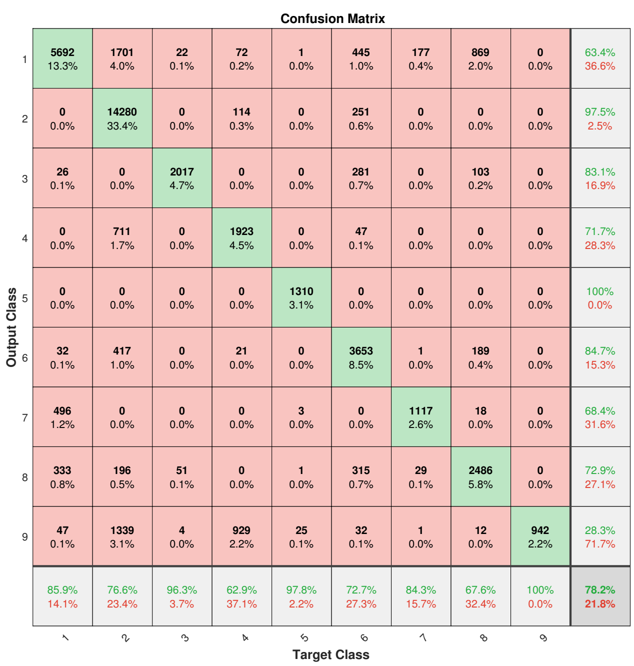
Fig. S3. The confusion matrix of SuperPCA based models on Indian Pines when $T = 5$.



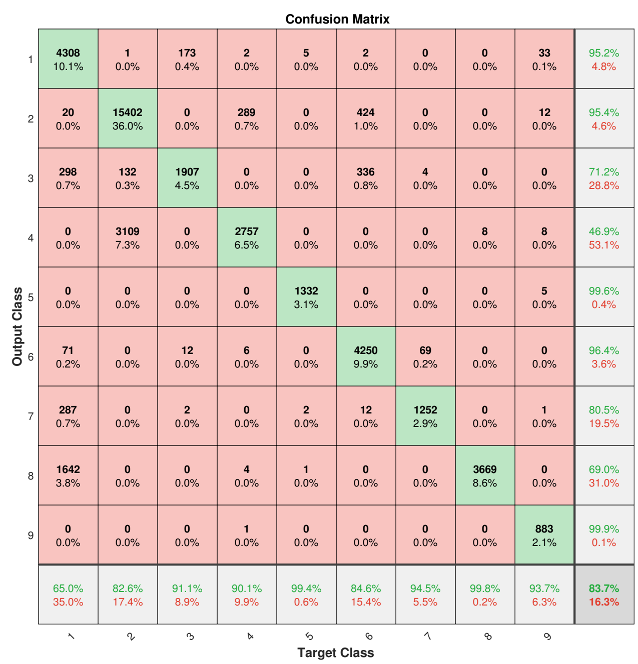
(a) SuperPCA



(b) CSuperPCA



(c) RSuperPCA



(d) S^3-PCA

Fig. S4. The confusion matrix of SuperPCA based models on the University of PaviaU when $T = 5$.

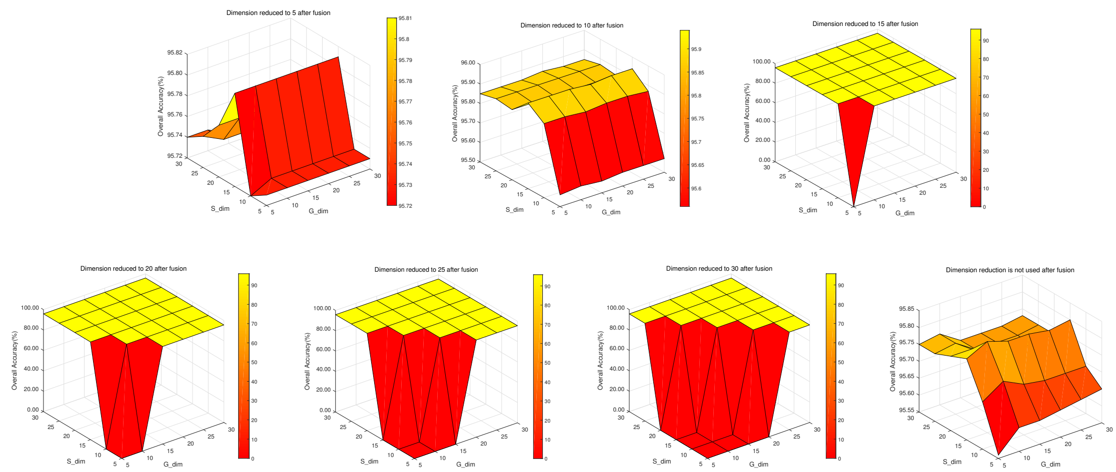


Fig. S5. The influence of reduced dimension in RSuperPCA, Global PCA and fusion in Indian Pines.

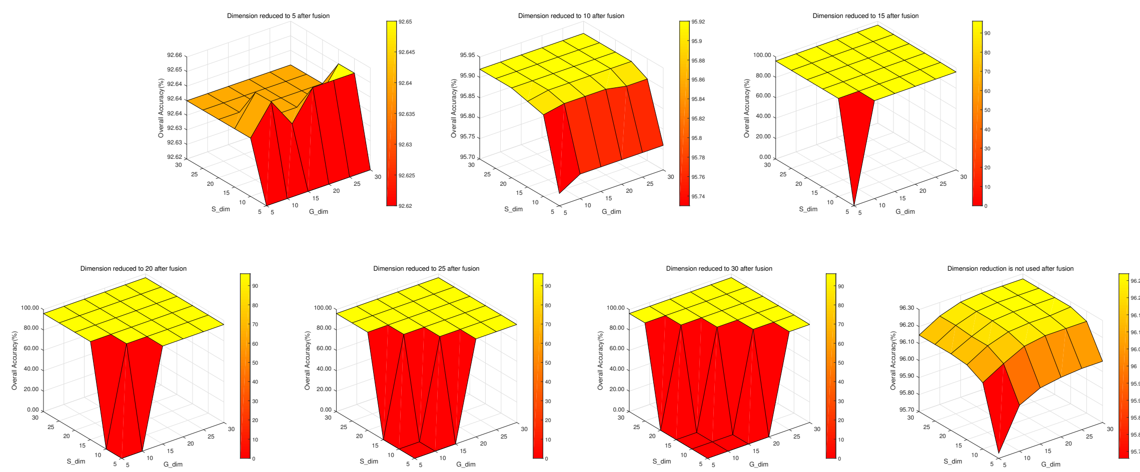
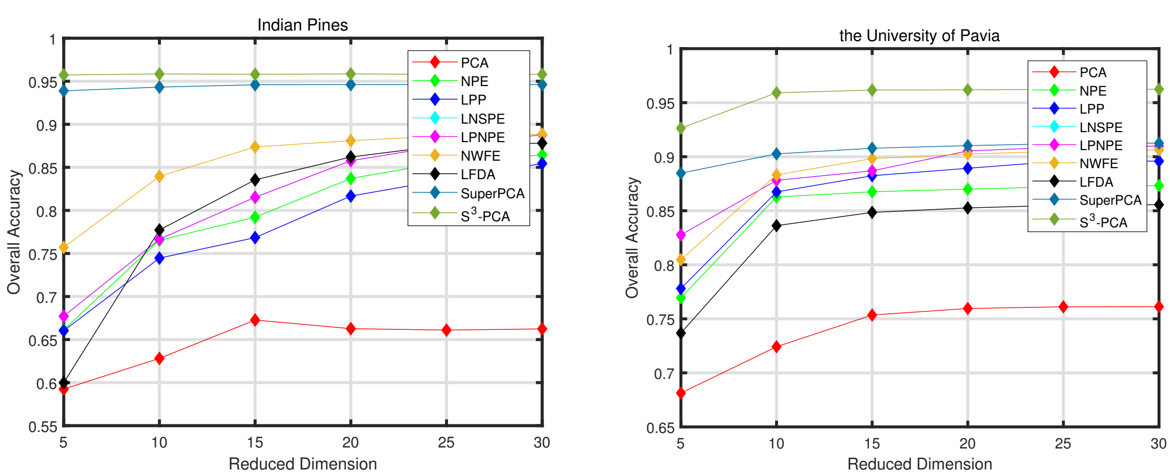
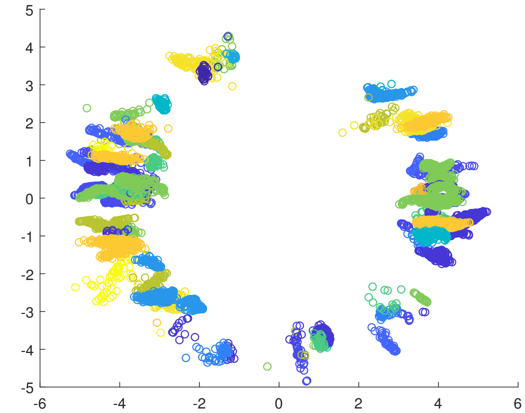


Fig. S6. The influence of reduced dimension in RSuperPCA, Global PCA and fusion in the University of Pavia.

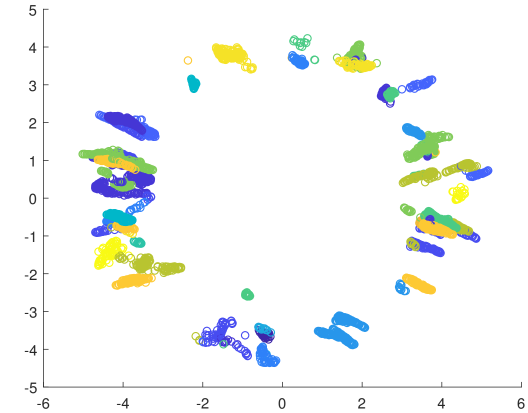


(a) (b)

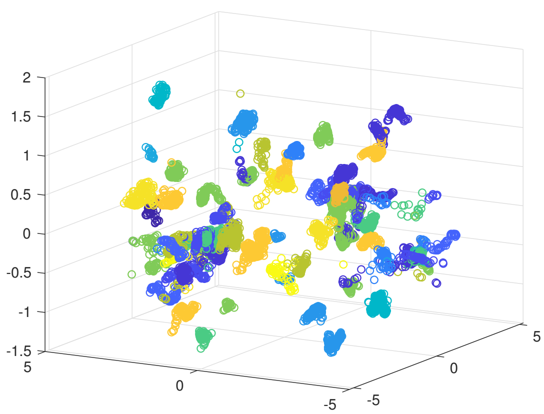
Fig. S7. OAs based on SVM for Indian Pines and the University of Pavia data when the dimensions of the low-dimensional feature space (d) changes in the range $\{5, 10, 15, 20, 25, 30\}$.



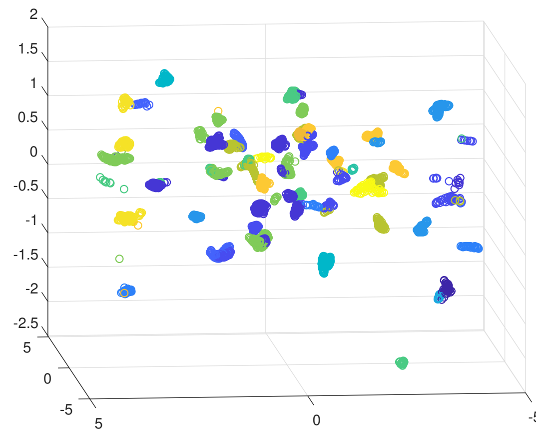
(a) 2D embedding based on SuperPCA



(b) 2D embedding based on S^3-PCA



(c) 3D embedding based on SuperPCA

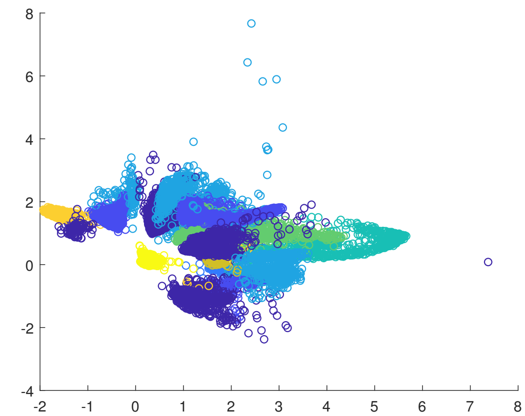


(d) 3D embedding based on S^3-PCA

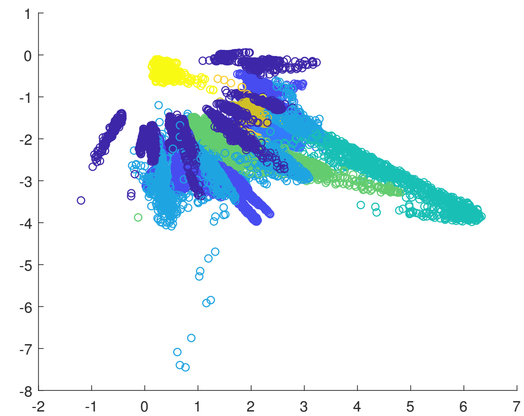
Fig. S8. 2D and 3D data visualization based on SuperPCA and S^3-PCA for Indian Pines data.

IV. Data Visualization

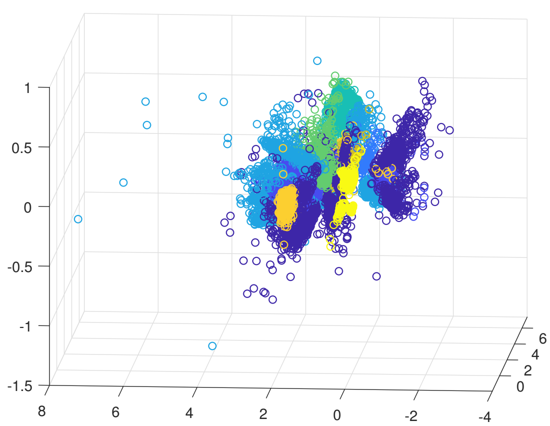
To further compare SuperPCA and the proposed S^3-PCA, we reduce the dimensions of the low-dimensional feature space to 2 and 3 based on the two algorithms in Indian Pines and University of Pavia data with the 2D and 3D data visualization in Fig.S8-S9. As can be seen from the figures that the proposed S^3-PCA outperforms SuperPCA because samples from different classes are more discriminating in the low-dimensional space learnt by S^3-PCA, which subjectively demonstrate the effectiveness of the proposed model.



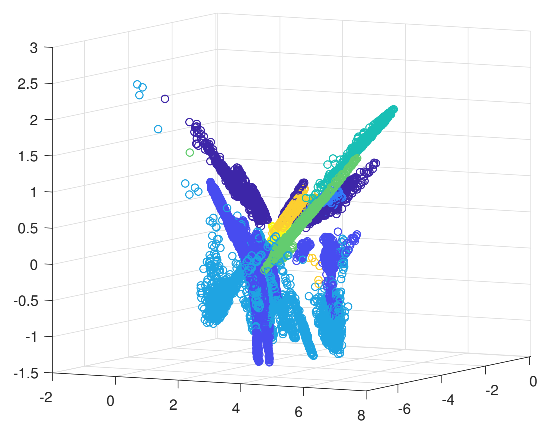
(a) 2D embedding based on SuperPCA



(b) 2D embedding based on S^3-PCA



(c) 3D embedding based on SuperPCA



(d) 3D embedding based on S^3-PCA

Fig. S9. 2D and 3D data visualization based on SuperPCA and S^3-PCA for the University of Pavia data.