IEEE

ICIP abu dhabi 2024

IEEE International Conference on Image Processing

27 - 30 October 2024, Abu Dhabi, UAE

IEEE Signal Processing Society — CELEBRATING 75 YEARS

Semi-Supervised Graphical Deep Dictionary Learning for Hyperspectral Image Classification from Limited Samples

Anurag Goel, Delhi Technological University, New Delhi, India

Angshul Majumdar, IAI, TCG Crest, Kolkata, India

Background

- In Hyperspectral Image Classification (HSI), the typical process involves manually labeling a subset of the acquired image samples to create the training set to predict the labels for the remaining unlabeled samples in the testing set.
- Since manual labeling is a labor-intensive and time-consuming task requiring expert knowledge, it is desirable to minimize the number of samples that need to be manually labeled. Therefore, practical hyperspectral imaging always strives for accurate classification from the fewest possible labeled samples.
- In this work, we aim to reach the high classification rates of current deep learning methods with the training data requirement of shallow learning techniques.
- Another unique aspect of hyperspectral imaging is that the samples are spatially correlated; i.e. contiguous locations are likely to belong to the same class unless they are along the edges.

Objectives

- In this work, we propose a unified semi-supervised feature learning framework that jointly learns the features for both the labeled and unlabeled samples in such a fashion that features are spatially correlated via a graph structure.
- The generated features are input to a third-party classifier for final classification.
- Our work is based on the framework of Deep Dictionary Learning (DDL) and Deep Transform Learning (DTL) [14].
- In DDL, X is the input data, D_1, D_2, D_3 are three layers of dictionaries and Z is the coefficient / representation.
- In DTL, T_1, T_2, T_3 are three layers of transforms and Z is the coefficient/ representation.

Deep Dictionary Learning (DDL)

$$\min_{D_1,D_2,D_3,Z} \left\| X - D_1D_2D_3Z \right\|_F^2$$
$$s.t.\ D_2D_3Z \geq 0, D_3Z \geq 0 \text{ and } Z \geq 0$$

Deep Transform Learning (DTL)

$$\min_{T_1,T_2,T_3,Z} \left\| T_3T_2T_1X - Z \right\|_F^2 + \lambda \sum_{i=1}^{3} \left(\left\| T_i \right\|_F^2 - \log\det(T_i) \right)$$
$$s.t.\ T_2T_1Z \geq 0, T_1X \geq 0 \text{ and } Z \geq 0$$

Methodology

DDL based Formulation: Synthesis Version

$$\min_{D_1,D_2,D_3,Z} \left\| \left[X_S \mid X_U \right] - D_1D_2D_3 \left[Z_S \mid Z_U \right] \right\|_F^2$$
$$+\mu \sum_{i=1}^{2} Trace\left(ZL_iZ^T \right) + \gamma \sum_{c} \left\| \bar{Z}_c - Z_c \right\|_F^2$$
$$s.t.\ D_2D_3Z \geq 0, D_3Z \geq 0 \text{ and } Z \geq 0$$

Solution via Alternating Minimization

$$\min_{D_1} \left\| X - D_1D_2D_3Z \right\|_F^2 \qquad D_1 = X\left(D_2D_3Z\right)^{\dagger}$$
$$\min_{D_2} \left\| X - D_1D_2D_3Z \right\|_F^2 \quad \Rightarrow \quad D_2 = \left(D_1\right)^{\dagger} X \left(D_3Z\right)^{\dagger}$$
$$\min_{D_3} \left\| X - D_1D_2D_3Z \right\|_F^2 \qquad D_3 = \left(D_1D_2\right)^{\dagger} X \left(Z\right)^{\dagger}$$

$$\min_{Z_U} \left\| X_U - D_1D_2D_3Z_U \right\|_F^2 + \mu Trace\left(Z_SL_iZ_S^T \right)$$
$$\Downarrow$$
$$\left(D_1D_2D_3\right)^T D_1D_2D_3Z_U + \lambda Z_U\left(L_1+L_2\right)$$
$$= \left(D_1D_2D_3\right)^T X$$

$$\min_{Z_c} \left\| X_c - D_1D_2D_3Z_c \right\|_F^2$$
$$+\mu Trace\left(Z_cL_iZ_c^T \right) + \gamma \left\| \bar{Z}_c - Z_c \right\|_F^2$$
$$\Downarrow$$
$$\left[\left(D_1D_2D_3\right)^T D_1D_2D_3 + \gamma I \right] Z_c + \lambda Z_c \left(L_1+L_2\right)$$
$$= \left(D_1D_2D_3\right)^T X + \bar{Z}_c$$

DTL based Formulation: Analysis Version

$$\min_{T_1,T_2,T_3,Z} \left\| T_3T_2T_1 \left[X_S \mid X_U \right] - \left[Z_S \mid Z_U \right] \right\|_F^2$$
$$+\lambda \sum_{i=1}^{3} \left(\left\| T_i \right\|_F^2 - \log\det(T_i) \right)$$
$$+\mu \sum_{i=1}^{2} Trace\left(ZL_iZ^T \right) + \gamma \sum_{c} \left\| \bar{Z}_c - Z_c \right\|_F^2$$
$$s.t.\ T_2T_1Z \geq 0, T_1X \geq 0 \text{ and } Z \geq 0$$

Proxy Variables

$$Z_3 = T_2T_1Z$$
$$Z_2 = T_1X$$

$$\min_{T_1,T_2,T_3,Z,Z_2,Z_3} \left\| T_3Z_3 - Z \right\|_F^2 + \alpha \left\| T_2Z_2 - Z_3 - A \right\|_F^2$$
$$+\beta \left\| T_1X - Z_2 - B \right\|_F^2 + \lambda \sum_{i=1}^{3} \left(\left\| T_i \right\|_F^2 - \log\det(T_i) \right)$$
$$+\mu \sum_{i=1}^{2} Trace\left(ZL_iZ^T \right) + \gamma \sum_{c} \left\| \bar{Z}_c - Z_c \right\|_F^2$$
$$s.t.\ Z_3 \geq 0, Z_2 \geq 0 \text{ and } Z \geq 0$$

Solution via Alternating Minimization

$$\min_{T_3} \left\| T_3Z_3 - Z \right\|_F^2 + \lambda \left(\left\| T_3 \right\|_F^2 - \log\det(T_3) \right)$$
$$\min_{T_2} \alpha \left\| T_2Z_2 - Z_3 - A \right\|_F^2 + \lambda \left(\left\| T_2 \right\|_F^2 - \log\det(T_2) \right)$$
$$\min_{T_1} \beta \left\| T_1X - Z_2 - B \right\|_F^2 + \lambda \left(\left\| T_1 \right\|_F^2 - \log\det(T_1) \right)$$
$$\min_{Z_3} \left\| T_3Z_3 - Z \right\|_F^2 + \alpha \left\| T_2Z_2 - Z_3 - A \right\|_F^2 \ s.t.\ Z_3 \geq 0$$
$$\min_{Z_2} \alpha \left\| T_2Z_2 - Z_3 - A \right\|_F^2 + \beta \left\| T_1X - Z_2 - B \right\|_F^2 \ s.t.\ Z_2 \geq 0$$
$$\min_{Z_U} \left\| T_3Z_3 - Z_U \right\|_F^2 + \mu \sum_{i=12}^{2} Trace\left(Z_UL_iZ_U^T \right) \ s.t.\ Z_U \geq 0$$
$$\min_{Z_S} \left\| T_3Z_3 - Z_S \right\|_F^2 + \mu \sum_{i=1}^{2} Trace\left(Z_SL_iZ_S^T \right)$$
$$+\gamma \sum_{c} \left\| \bar{Z}_c - Z_c \right\|_F^2 s.t.\ Z_S \geq 0$$

Update Step of Bregman Relaxation Variables

$$A \leftarrow T_2Z_2 - Z_3 - A \qquad B \leftarrow T_1X - Z_2 - B$$

Results

Dataset	Metric	AttentionNet	GANCap	DCN-T	ECR	Proposed Synthesis	Proposed Analysis
Pavia University	OA	80.09	82.02	88.91	86.24	**89.79**	88.67
	AA	80.26	82.69	88.48	87.41	**90.08**	88.11
	Kappa	.78	.80	.85	.84	**0.85**	0.85
Indian Pines	OA	70.36	73.32	77.38	75.85	**81.02**	78.02
	AA	70.95	74.07	77.91	76.30	**84.32**	79.42
	Kappa	.69	.72	.77	.75	**0.80**	0.78

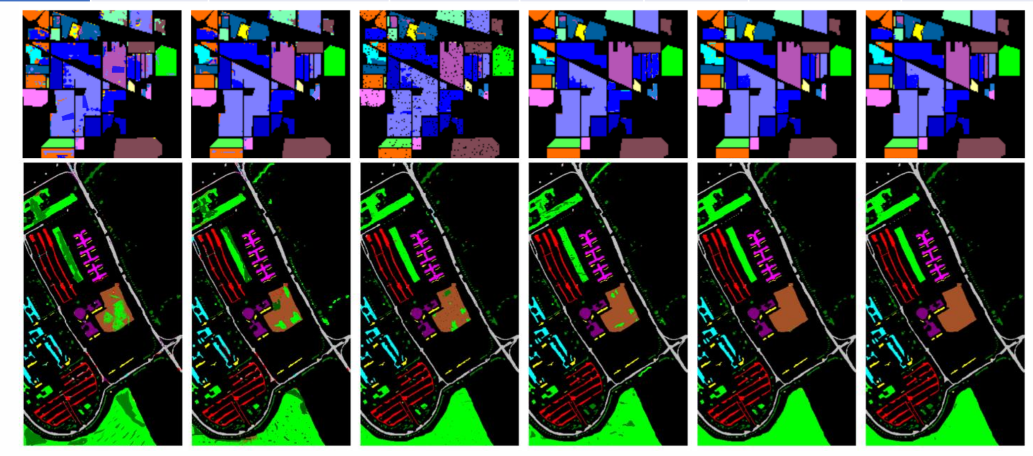

Fig. 1. Pictorial view of classification. Top – Indian Pines. Bottom – Pavia. Left to Right – AttentionNet, GANCap, DCN-T, ECR, Proposed Synthesis, and Proposed Analysis

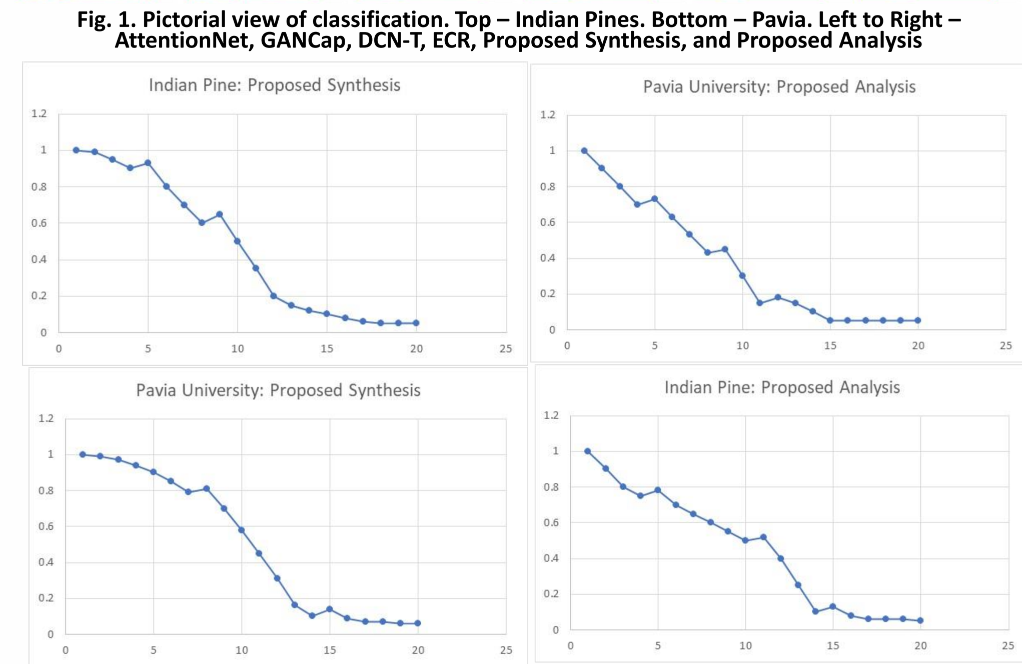

Fig. 2. Empirical Convergence. Y axis: Normalized Objective. X axis: Iteration Number

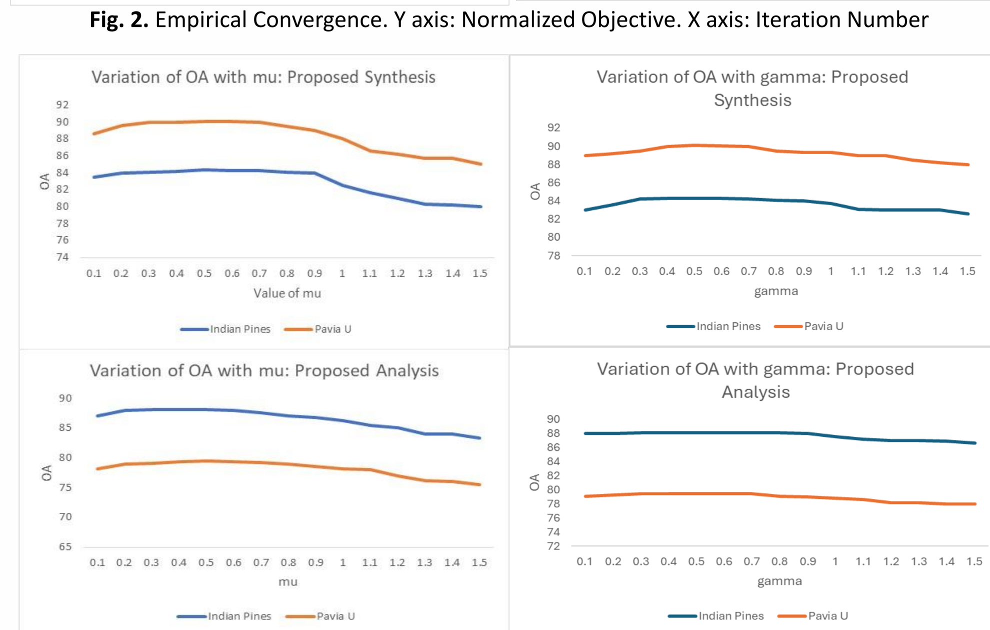

Fig. 3. Variation of Overall Accuracy (OA) with mu (μ) and gamma (γ)

Method	Time (in seconds rounded)	
	Pavia University	Indian Pines
AttentionNet	250	103
GANCap	304	129
DCN-T	327	112
ECR	571	206
Proposed Synthesis	418	177
Proposed Analysis	933	365

	Pavia University		Indian Pines	
	Proposed Synthesis	Proposed Analysis	Proposed Synthesis	Proposed Analysis
Layer: 1	87.87	86.29	77.18	76.13
Layers: 2	88.92	88.00	80.51	78.55
Layers: 3	**89.79**	**88.67**	**81.02**	**79.42**
Layers: 4	89.06	88.14	80.60	78.95
Layers: 5	86.15	86.45	78.83	77.68

Conclusion and References

The goal of this work was to propose a technique that can pragmatically solve hyperspectral image classification problems. It takes into account two unique aspects of hyperspectral image classification – 1. The total number of samples to be labeled is fixed; and 2. The samples are spatially correlated. The first aspect results in a semi-supervised formulation. The second aspect is modeled by graph regularization.

- Y. Dong, Q. Liu, B. Du and L. Zhang, "Weighted Feature Fusion of Convolutional Neural Network and Graph Attention Network for Hyperspectral Image Classification," in IEEE Transactions on Image Processing, vol. 31, pp. 1559-1572, 2022.
- J. Wang, S. Guo, R. Huang, L. Li, X. Zhang and L. Jiao, "Dual-Channel Capsule Generation Adversarial Network for Hyperspectral Image Classification," in IEEE Transactions on Geoscience and Remote Sensing, vol. 60, pp. 1-16, 2022.
- D. Wang, J. Zhang, B. Du, L. Zhang and D. Tao, "DCN-T: Dual Context Network With Transformer for Hyperspectral Image Classification," in IEEE Transactions on Image Processing, vol. 32, pp. 2536-2551, 2023.
- H. Liu, W. Li, X. -G. Xia, M. Zhang, C. -Z. Gao and R. Tao, "Central Attention Network for Hyperspectral Imagery Classification," in IEEE Transactions on Neural Networks and Learning Systems, vol. 34, no. 11, pp. 8989-9003, Nov. 2023.

DELTECH

tcg crest — Inventing Harmonious Future