Mutual Information based Spectrally Segmented Stacked Autoencoder Approach for Spectral-Spatial Classification of Land Use Land Cover Using Hyperspectral Data

Subir Paul [a] (*agsubir@gmail.com*), D. Nagesh Kumar [a]

[a] Department of Civil Engineering, Indian Institute of Science, Bengaluru 560012, India

AGU 100 FALL MEETING San Francisco, CA | 9–13 December 2019

Paper Number: B31K-2421

INTRODUCTION

- ✓ Hyperspectral (HS) data comprises of large number of continuous spectral bands (~ 100–250) with very fine bandwidths (~ 5–10 nm).
- ✓ Though HS data are very resourceful for classification studies, these have few limitations like data redundancy and curse of dimensionality.
- ✓ Feature extraction techniques are employed on the HS data to deal with the data redundancy issue.

OBJECTIVES

- ✓ Spectral segmentation of HS bands based on Mutual Information (MI) and extraction of local nonlinear spectral features from each spectral segments using Auto-Encoder (AE) or Stacked AE (SAE).
- ✓ Use of Segmented SAE (S-SAE) features for creating Extended Morphological Profiles (EMPs) to be considered as spatial features.
- ✓ Spectral-spatial Classification of HS data using Support Vector Machine (SVM) and Random Forest (RF) classifier.

METHODOLOGY

Hyperspectral Data

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Spectral Segmentation based on MI

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Feature Extraction from Each Segment using AE/SAE

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Creation of EMPs from Extracted Spectral Features

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Spectral-Spatial Classification using SVM/RF Classifier

Fig. 1. Flowchart of the proposed methodology.

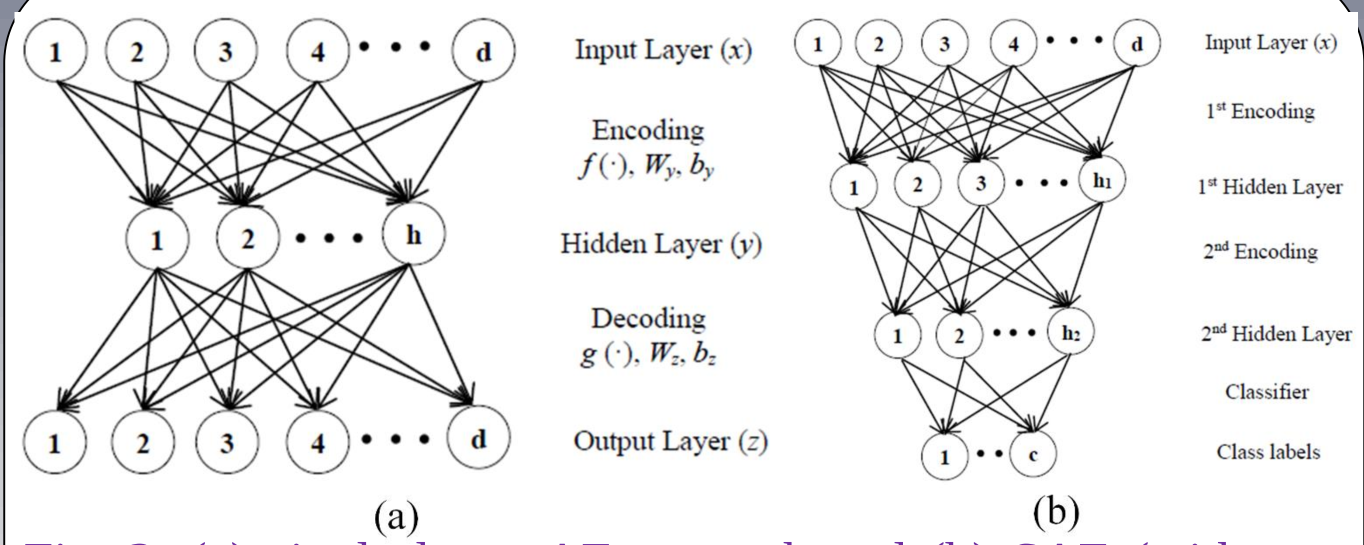

Fig. 2. (a) single layer AE network and (b) SAE (with two hidden layer) network with classifier.

DATASETS

Table 1 Land use land cover details of HS datasets

Dataset	Indian Pines		Pavia University		Botswana	
Sl. No.	Class name	Samples	Class name	Samples	Class name	Samples
1	Alfalfa	46	Asphalt	6631	Water	270
2	Corn-notill	1428	Meadows	18649	Hippo grass	101
3	Corn-mintill	830	Gravel	2099	Floodplain grasses 1	251
4	Corn	237	Trees	3064	Floodplain grasses 2	215
5	Grass-pasture	483	Painted metal sheets	1345	Reeds	269
6	Grass-trees	730	Bare Soil	5029	Riparian	269
7	Grass-pasture-mowed	28	Bitumen	1330	Firecar	259
8	Hay-windrowed	478	Self-Blocking Bricks	3682	Island interior	203
9	Oats	20	Shadows	947	Acacia woodlands	314
10	Soybean-notill	972			Acacia shrublands	248
11	Soybean-mintill	2455			Acacia grasslands	305
12	Soybean-clean	593			Short mopane	181
13	Wheat	205			mixed mopane	268
14	Woods	1265			Exposed soils	95
15	Buildings-Grass-Trees-Drives	386				
16	Stone-Steel-Towers	93				
Total Samples		10249		42776		3248

RESULTS

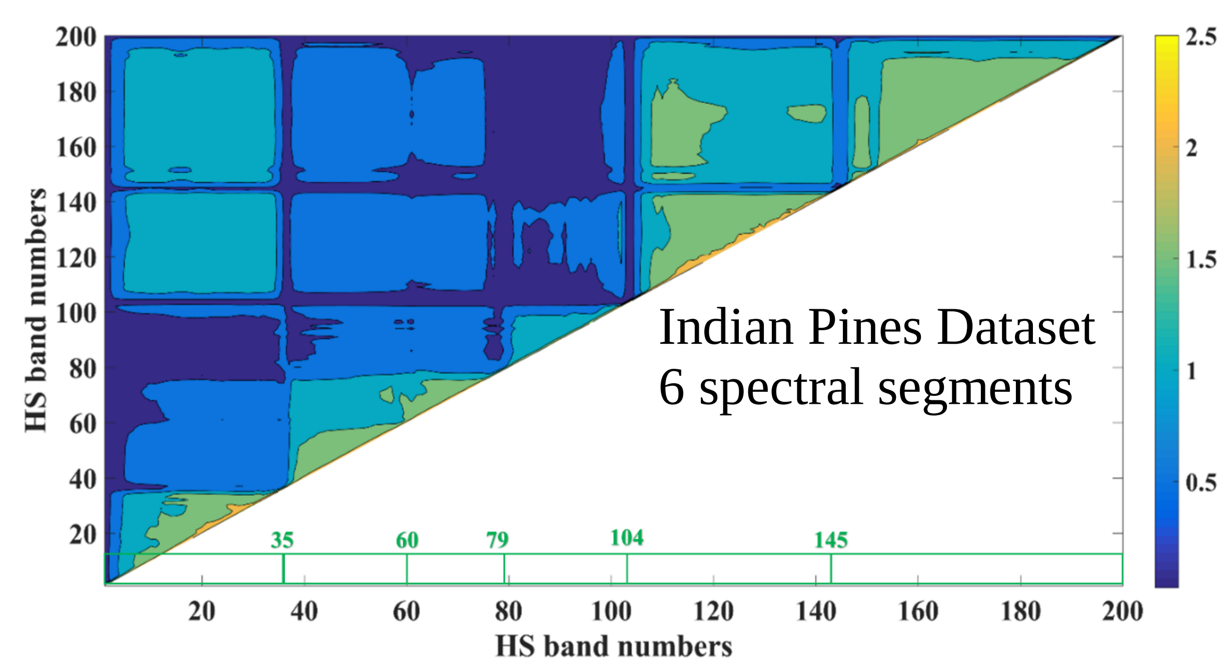

Fig. 3. Spectral segmentation based on inter-band MI.

Table 2 Classification performance of the S-SAE extracted spectral-spatial features of Indian Pines dataset

Spectrally segmented range of bands		S-SAE-C1-IP	S-SAE-C2-IP	S-SAE-C3-IP	S-SAE-C4-IP
		Units in 1st – 2nd hidden layer	Units in 1st – 2nd hidden layer	Units in 1st – 2nd hidden layer	Units in 1st – 2nd hidden layer
Band 1-35		10 – 2	10 – 3	10 – 4	15 –3
Band 36-60		10 – 2	10 – 2	10 – 1	15 – 2
Band 61-79		10 – 2	10 – 3	10 – 3	15 –3
Band 80-104		-	-	-	-
Band 105-145		10 – 2	10 – 1	10 – 1	15 – 1
Band 146-200		10 – 2	10 – 1	10 – 1	15 – 1
Total spectral features		10	10	10	10
Time required for FE		4.95 min	5.31 min	4.65 min	5.69 min
Spectral-spatial features		30	30	30	30
RBF-SVM classifier	OA (%)	92.14±0.62	93.08±0.74	91.69±0.74	91.72±1.19
	k	0.9104±0.0070	0.9211±0.0084	0.9052±0.0084	0.9055±0.0135
	AA (%)	93.53±1.81	94.28±1.23	91.58±1.80	93.36±2.33
RF classifier	OA (%)	95.81±0.75	96.52±0.54	96.42±0.37	**96.66±0.66**
	k	0.9521±0.0086	0.9603±0.0062	0.9591±0.0043	**0.9619±0.0076**
	AA (%)	96.06±0.91	97.49±0.40	97.18±0.55	**97.42±0.91**

Table 3 Optimal performances of different spectral and spectral-spatial classification approaches

Indian Pines dataset						
Approaches	Spectral classification		Spectral-spatial classification			
FE methods	AE	SAE	PCA	AE	S-AE	S-SAE
Classifier	RBF-SVM	RBF-SVM	RF	RF	RF	RF
OA (%)	80.46±0.73	80.16±0.63	94.77±0.70	95.63±0.62	96.07±0.60	**96.66±0.66**
k	0.776±0.008	0.773±0.007	0.940±0.008	0.950±0.007	0.955±0.007	**0.962±0.008**
AA (%)	79.63±2.71	80.53±2.77	95.92±0.73	95.93±1.53	97.03±0.79	**97.42±0.91**
Pavia University dataset						
Classifier	RBF-SVM	RBF-SVM	RBF-SVM	RBF-SVM	RBF-SVM	RBF-SVM
OA (%)	92.25±0.38	90.57±0.26	94.11±0.58	95.15±0.29	94.88±0.48	**96.66±0.28**
k	0.897±0.005	0.874±0.003	0.921±0.008	0.935±0.004	0.9320±0.006	**0.956±0.004**
AA (%)	90.96±0.65	89.90±0.41	94.60±0.76	95.30±0.47	94.75±0.72	**96.21±0.37**
Botswana dataset						
Classifier	RBF-SVM	RBF-SVM	RBF-SVM	RBF-SVM	RBF-SVM	RBF-SVM
OA (%)	91.77±0.71	91.72±0.95	96.42±0.81	97.15±0.72	97.28±0.74	**97.61±1.04**
k	0.911±0.008	0.910±0.010	0.961±0.009	0.969±0.008	0.970±0.008	**0.974±0.011**
AA (%)	92.43±0.74	92.41±0.88	96.74±0.60	97.42±0.58	97.17±0.80	**97.74±0.85**

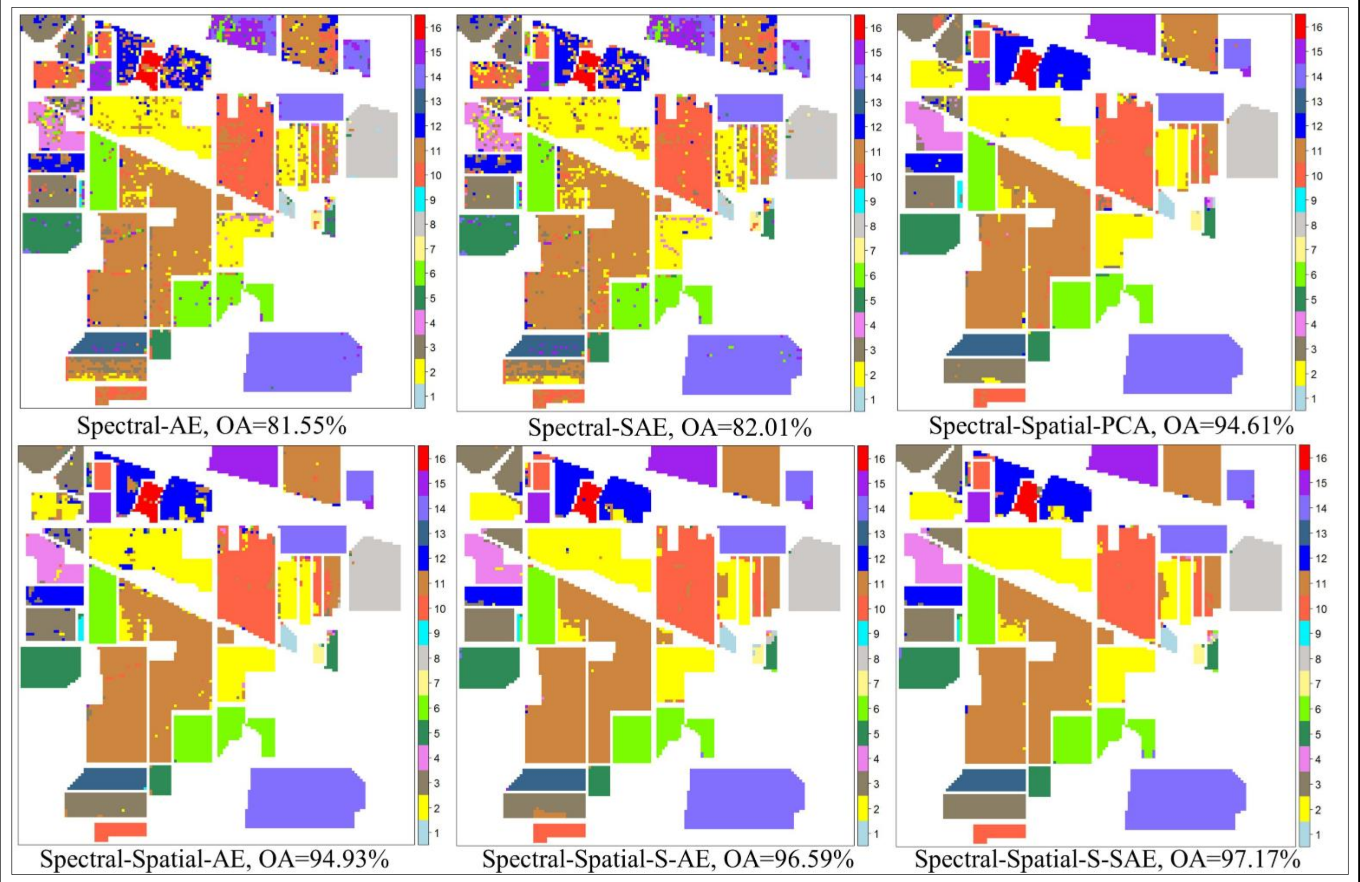

Fig. 4. Classified maps and corresponding OA for the Indian Pines dataset.

CONCLUSIONS

- ✓ Nonparametric dependency measure MI based S-SAE approach is proposed for spectral-spatial classification of the HS data.
- ✓ Spectral segmentation contributes in reducing the computation time for feature extraction.
- ✓ S-SAE extracts most apt representative deep nonlinear local features from the data, which contributes in improved classification accuracy.
- ✓ RF classifier is performing better with Indian Pines dataset, whereas RBF-SVM is performing better with other two datasets.
- ✓ The improvements in performance measures with the proposed approach are proven to be statistically significant.

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ACKNOWLEDGMENTS

- ✓ Travel is supported by the **Tata Trusts**.
- ✓ AGU Fall Meeting General Student Travel Grant.
- ✓ Financial Support from IISc GARP Funding.