A Novel Spatial-Spectral Framework for the Classification of Hyperspectral Satellite Imagery

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Outline

- Motivation
- Related Work
- Datasets
- Proposed Approach
- Results & Discussion
- Conclusions
- References

Motivation

- Hyperspectral Satellite Imagery (HSI) - high resolution images
- Applications of HSI- disaster prediction and terrain feature classification
- Conventional spectral classification techniques process each pixel independently
- Possibility of using spatially adjacent pixels having similar spectral features
- Need for a computationally efficient classification of hyperspectral imagery

RELATED WORK

Pixel wise classification approaches:

- Ahmad et al. [1] - Use of a GML classifier when there exists a distinct separation between the classes in the decision space
- Makantasis et al. [2] - Combination of CNN for feature extraction + MLP for classification
- Ma et al. [3] use RNNs for HSI classification

Segmentation combined approaches:

- Tarabalka et al. [4] - SVM classifier with a Watershed segmentation method
- Qing et al. [5] use an MRF-based loopy belief propagation technique

[1] Ahmad et al.: Analysis of maximum likelihood classification on multi-spectral data. Applied Mathematical Sciences, 6425–6436 (2012)
[2] Makantasis et al.: Deep supervised learning for hyperspectral data classification through convolutional neural networks. In: IGARSS, pp. 4959–4962. (2015)
[3] Ma et al.: Hyperspectral image classification using similarity measurements-based deep recurrent neural networks. Remote Sens. 11(2), (2019)
[4] Tarabalka et al.: Spectral-spatial classification of hyperspectral imagery based on partitional clustering techniques. IEEE Trans. Geosci. Remote Sens. 2973–2987 (2009)
[5] Qing et al..: Spatial-spectral classification of hyperspectral images: a deep learning framework with markov random fields based modelling. IET Image Process. (2018)

DATASETS

Indian Pines Dataset [6]:

- Consists of 145 x 145 pixels and 224 spectral reflectance bands
- Gathered by the 220-band AVIRIS sensor over the test site in North-western Indiana
- Ground truth designated into sixteen classes with two-thirds agriculture + one-third forest + other natural perennial vegetation

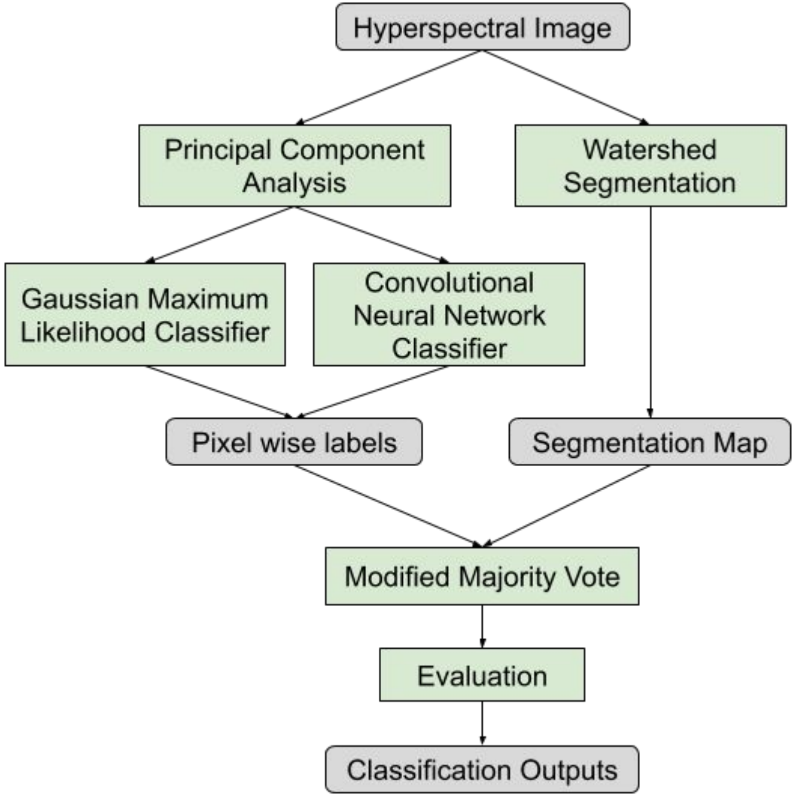
Pavia University Dataset [7]:

- Acquired by the 103-band ROSIS sensor over Pavia, northern Italy
- Dimensions of 610 x 610 pixels and 103 spectral bands
- Ground truth designated into nine classes
- Some samples contain no information - depicted using broad black strips

[6] Landgrebe et al..: Aviris nw indiana's indian pines data set (1992). https://engineering.purdue.edu/biehl/MultiSpec/hyperspectral.html
[7] Gamba, P.: Pavia university scene (2001). http://www.ehu.eus/ccwintco/index.php/

PROPOSED APPROACH

A brief overview of the proposed methodology:



Pre-Processing:

- First, over sample the weak classes then standardize - subtract the mean pixel value and scale to unit variance
- Principal Component Analysis (PCA) - transforms original high-dimensional data into a low-dimensional space

Pixel-wise Classification:

CNN based method:

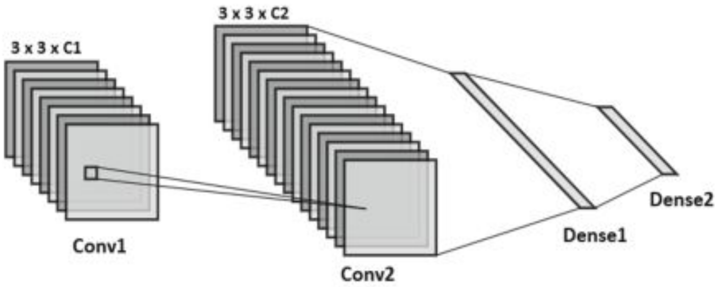


Fig. 1. An overall architecture of the CNN

GML based method:

$$P(C|\theta) = P(C)\frac{P(\theta|C)}{P(\theta)}$$

Watershed Segmentation

Fig. 2. (a) Overlaps (b) Distances and the (c) Separated objects for Indian Pines data

Fig. 3. (a) Overlaps (b) Distances and the (c) Separated objects for the Pavia dataset

Modified Majority Vote

```
uni_labels = unique values (labels in segmentation map)
final_map = 0
for i in uni_labels do
    arr ← []
    height ← height of segmentation map
    width ← width of segmentation map
    for j = 0 to j = height  do
        for k = 0 to k = width  do
            find all pixels in the segmentation map having label i
            append their pixel-wise classification labels to arr

   max_freq_label ← most frequent label in arr
   for j = 0 to j = height do
      for k = 0 to k = width do
         find all pixels in the segmentation map having label i
         assign max_freq_label as the label for these pixels in the final_map
```

RESULTS & DISCUSSION

Accuracies (%) on the Indian Pines Dataset

Category	GML	GML-W	CNN	CNN-W
Alfalfa	100.0	100.0	100.0	100.0
Corn-notill	0.00	100.0	80.11	0.00
Corn-mintill	94.74	82.35	89.90	100.0
Corn	97.83	88.19	96.61	93.37
Grass-pasture	100	100.0	95.04	100.0
Grass-trees	99.79	96.89	98.90	96.89
Grass-pasture-mowed	99.72	100.0	100.0	100.0
Hay-windrowed	0.00	100.0	100.0	0.00
Oats	100.0	100.0	100.0	100.0
Soybean-notill	0.00	100.0	88.06	0.00
Soybean-mintill	99.48	99.48	72.14	99.48
Soybean-clean	90.59	98.20	87.83	98.28
Wheat	99.32	100.0	100.0	100.0
Woods	100.0	100.0	98.41	100.0
Buildings-Grass-Trees	99.60	99.20	93.81	99.84
Stone-Steel-Towers	98.96	87.56	100.0	87.04
Average accuracy	93.80	96.99	80.10	91.76
Overall accuracy	97.46	98.31	87.08	97.7

Accuracies (%) on the Pavia Dataset

Category	GML	GML-W	CNN	CNN-W
Asphalt	100.0	100.0	98.13	100.0
Meadows	95.02	98.02	98.62	97.49
Gravel	94.98	96.02	89.33	96.02
Trees	92.42	96.56	99.73	91.47
Painted metal sheets	99.18	99.18	100.0	99.18
Bare soil	100.0	100.0	98.96	100.0
Bitumen	94.96	100.0	99.39	100.0
Self-blocking bricks	96.76	100.0	93.81	100.0
Shadows	92.85	99.10	100.0	98.66
Average accuracy	96.24	98.76	97.55	98.09
Overall accuracy	99.03	99.52	97.39	99.44

Comparison of our models

Classifiers	Indian Pines	Pavia Scene
GML	97.46%	99.03%
GML-W	98.31%	99.52%
CNN	87.08%	97.39%
CNN-W	97.7%	99.44%

Comparison with existing methods

Classifiers	Indian Pines	Pavia Scene
3D CNN [13]	99.07%	99.39%
CNN-MRF [14]	99.27%	99.55%
Ours (GML-W)	98.31%	99.52%

[13] Li, Y., Zhang, H., Shen, Q.: Spectral-spatial classification of hyperspectral imagery with 3D convolutional neural network. Remote Sens. 9(1), 67 (2017)
[14] Cao, X., Zhou, F., Xu, L., Meng, D., Xu, Z., Paisley, J.: Hyperspectral image classification with markov random fields and a convolutional neural network. IEEE Trans. Image Process. 27(5), 2354–2367 (2018)

Qualitative Analysis

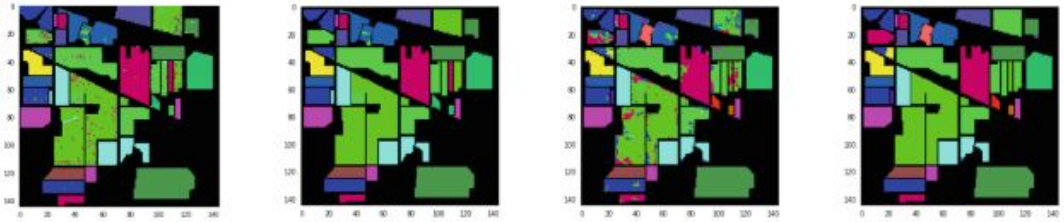


Fig. 4. Results of (a) GML (b) GML-W (c) CNN and (d) CNN-W on Indian Pines

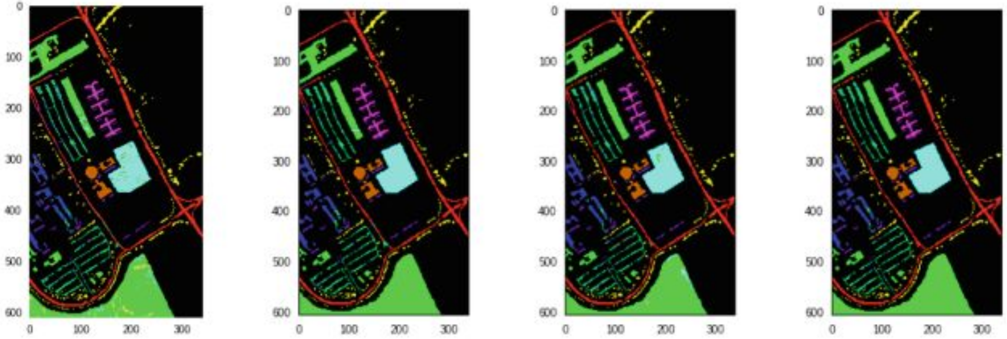


Fig. 5. Results of (a) GML (b) GML-W (c) CNN and (d) CNN-W on the Pavia dataset

Conclusions

- Overall accuracy of 99.52% on the Pavia dataset and up to 98.31% on Indian Pines
- Performs better than earlier approaches for HSI classification.
- Proposed GML based framework - No expensive training or learning procedures
- Achieves comparable performance to the state-of-the-art deep learning based methods and is a computationally efficient alternative

Future work

- Different feature extraction methods need to be investigated
- Proposed approaches to be verified on multispectral satellite image data to analyze robustness

THANK YOU

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