



Feature Mining for Effective Subspace Detection of Hyperspectral Image Classification

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Outline

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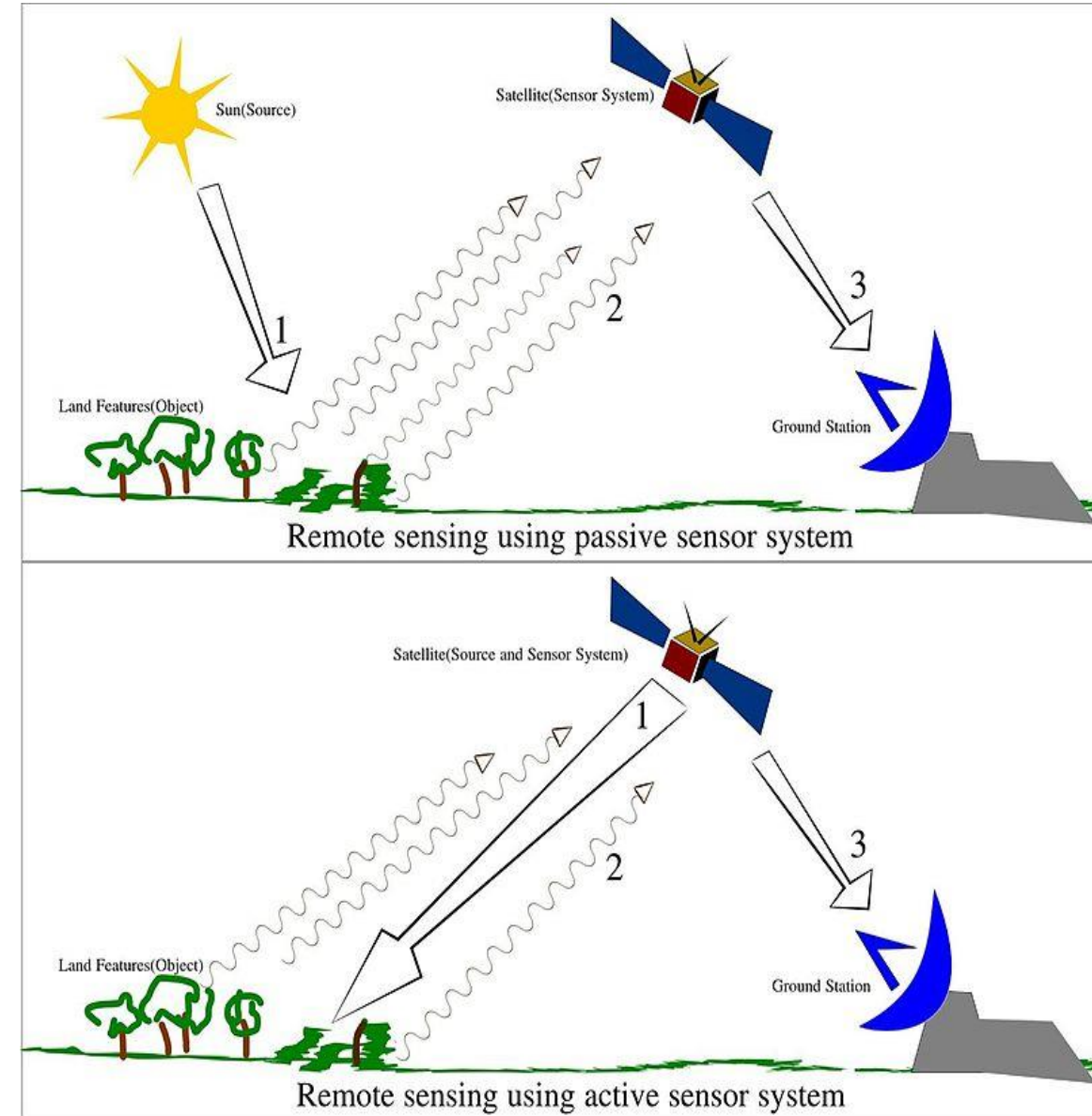
Remote Sensing

❖ What is remote sensing?

- ❖ Acquisition of information about an object without making physical contact with the object
- ❖ Used in geography, land surveying, military, intelligence and planning

❑ Types:

- ❑ Passive Remote Sensing
- ❑ Active Remote Sensing



Remote Sensing(Con't)

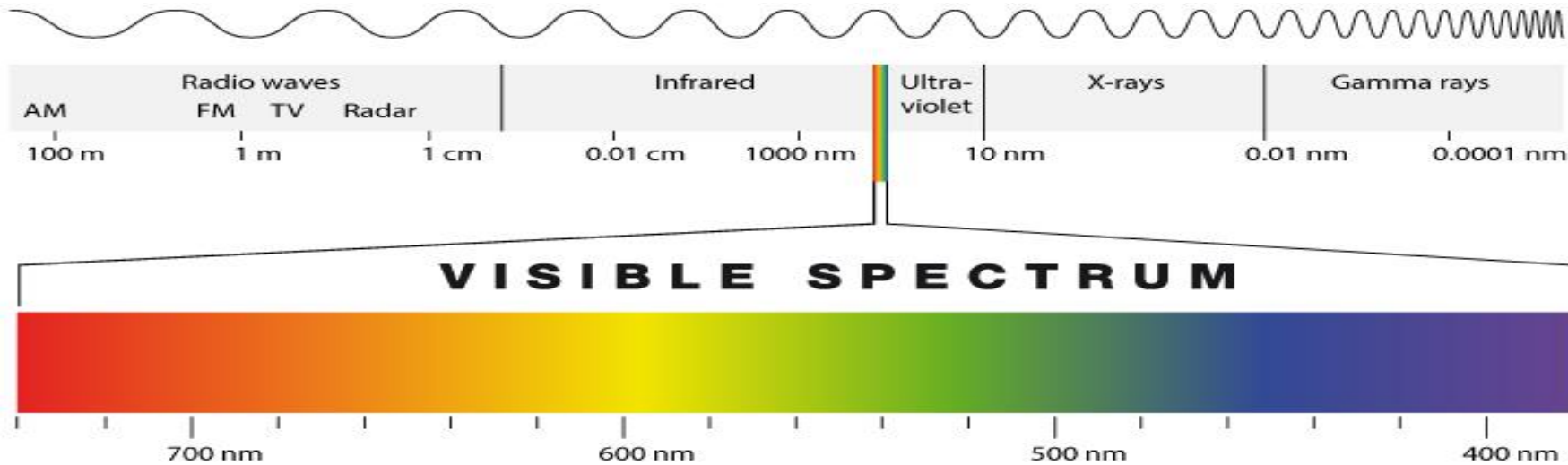


Figure: Electromagnetic Spectrum

- ❖ Visible and infrared range of wavelengths represents only part of the story in remote sensing
- ❖ Can also image the earth in microwave range



Figure: Surveillance aircraft



Figure: Remote sensing satellite

Hyperspectral Images



Figure: Two dimensional projection of Hyperspectral cube

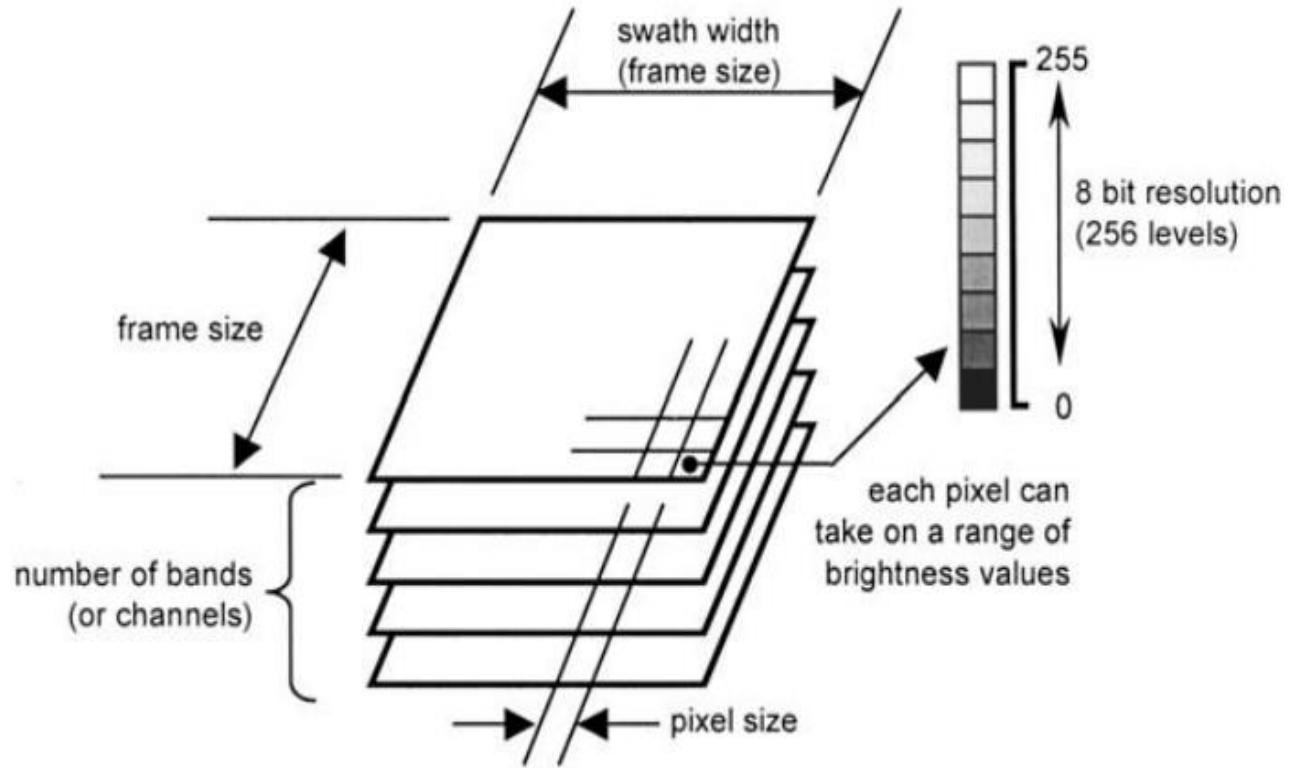


Figure: Technical characteristics of digital image data[2]

Challenges with Hyperspectral Images

- ❖ Curse of dimensionality
- ❖ High correlation among data
- ❖ All the feature are not equally important

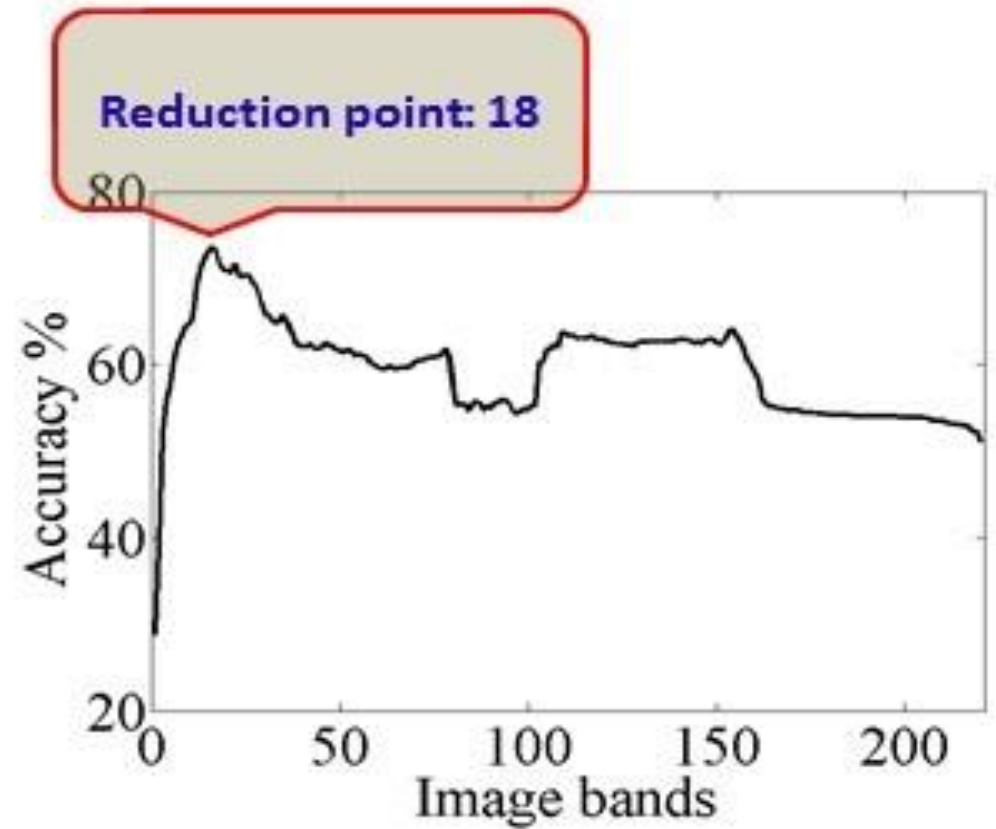


Figure: Curse of dimensionality [4]

Motivations and Objectives

- Extract only relevant features
- Address curse of dimensionality
- Improve classification accuracy

Proposed Method

Collaboration of feature mining and classification

- ❖ **Feature Extraction:**

 - Principal Component Analysis(PCA)

- ❖ **Feature Selection:**

 - Mutual Information(MI)

- ❖ **Classification:**

 - Support Vector Machine(SVM)

Data Set for Analysis

Data Set:

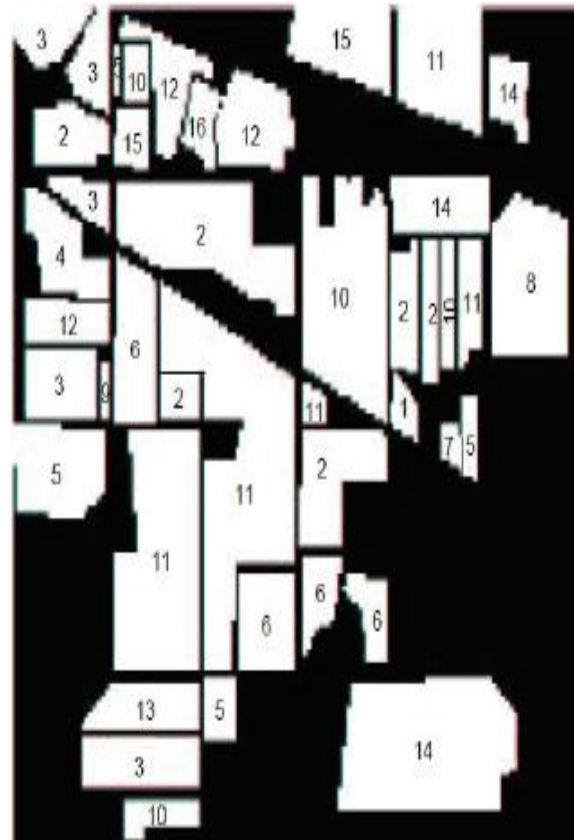
220 Band AVIRIS Hyperspectral Image

Date:

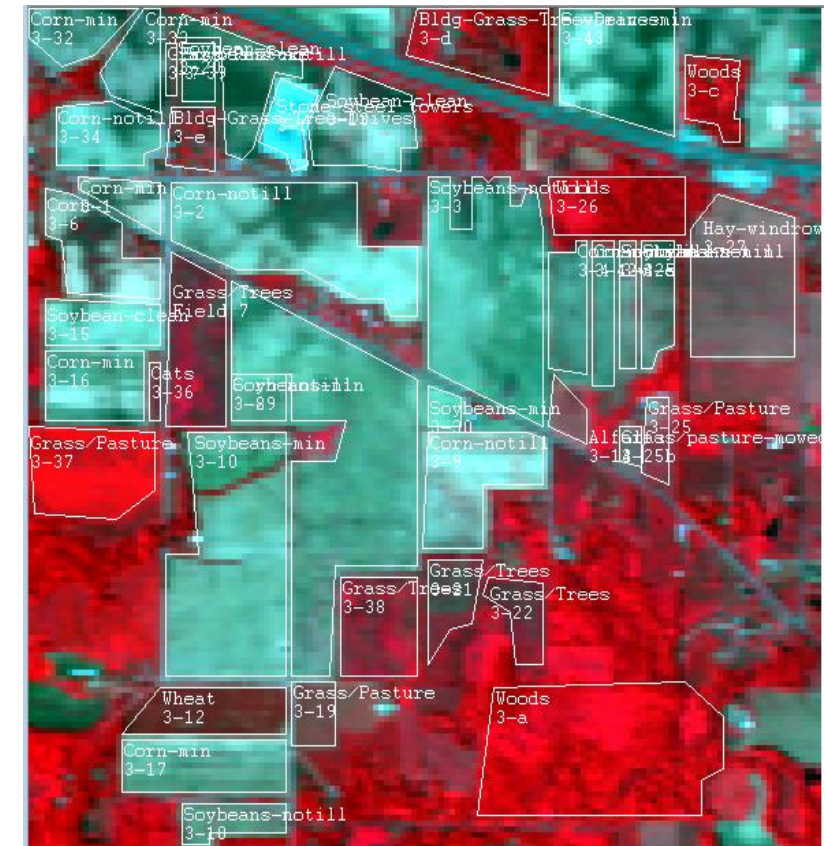
June 12, 1992 Indian Pine Test Site 3

Version 1.0

- ❖ Dataset: AVIRIS 92AV3C
- ❖ Spectral Resolution:
 $0.4\mu\text{m}$ - $2.5\mu\text{m}$
- ❖ Spatial Resolution: 30m
- ❖ Band: 220
- ❖ Classes:16
- ❖ Pixels: 145 x 145



1. Alfalfa
2. Corn-notill
3. Corn-min
4. Corn
5. Grass/Pasture
6. Grass/Trees
7. Grass/pasture-mowed
8. Hay-windrowed
9. Oats
10. Soybeans-notill
11. Soybeans-min
12. Soybean-clean
13. Wheat
14. Woods
15. Bldg-Grass-Tree-Drives
16. Stone-steel towers



Feature Extraction

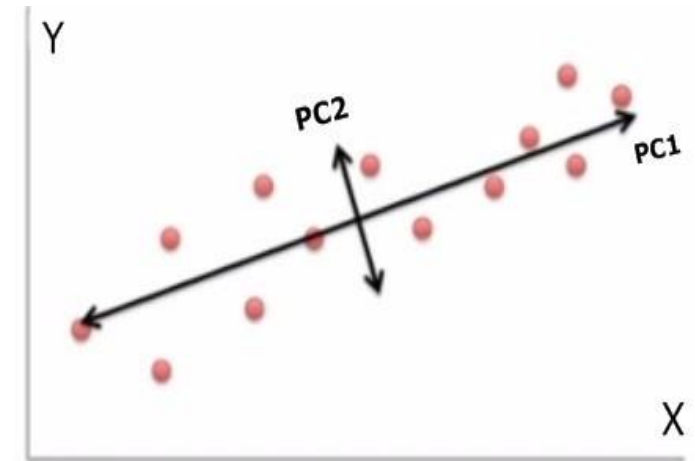
- Feature means unique measurable characteristics of an image/observed object.
- Feature extraction means creating new features which have the essence of original features.
- Feature extraction helps to obtain relevant information from large dataset.

Principal Component Analysis(PCA)

- Only relevant features are obtained
- Dimensionality reduced
- Increase classification accuracy

Feature extraction using Principal Component Analysis(PCA)

- Principal Component Analysis (PCA) is a process of reduction input dimensionality.
- Transformed data is a set of orthogonal uncorrelated variables called principal components(PC)



Feature extraction using Principal Component Analysis(PCA)(Con't)

All the steps we need to perform Principal Component Analysis[1]:

- **Step 1:** Input the image
- **Step 2:** Subtract the mean
- **Step 3:** Calculate the covariance matrix
- **Step 4:** Calculate the eigenvectors and eigenvalues of the covariance matrix
- **Step 5:** Choose components and forming a feature vector
FeatureVector = (eig1 eig2 eig3...eign)
- **Step 6:** Derive the new data set
FinalData = RowFeatureVector x RowDataAdjust

Original Band

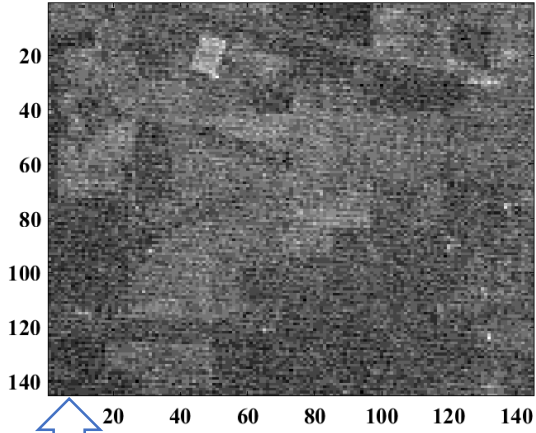
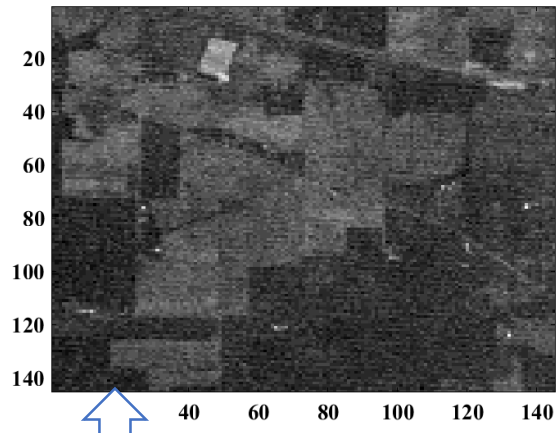
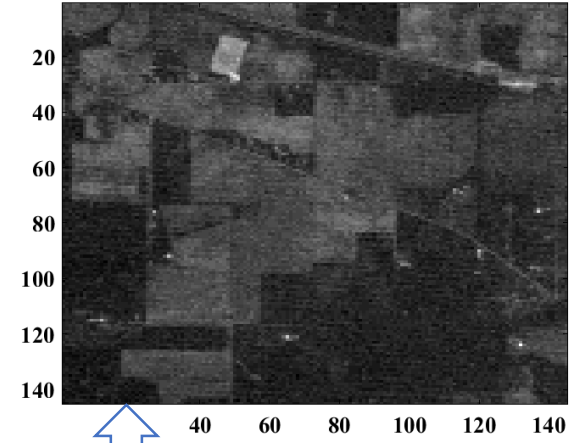


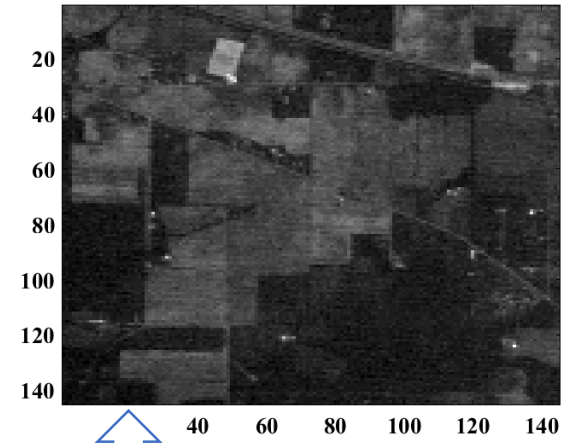
Image Band 1



Band 2

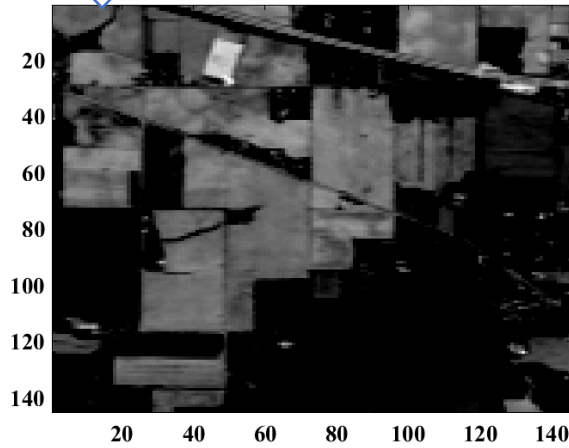


Band 3

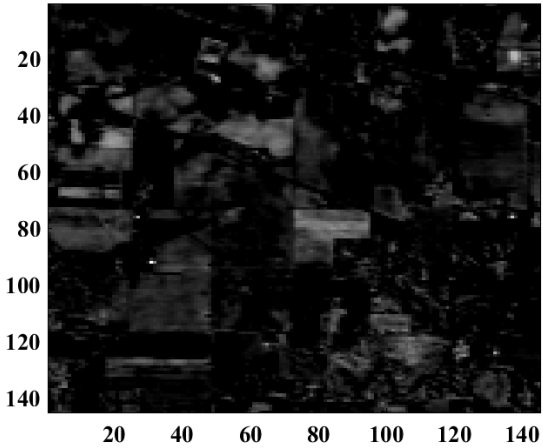


Band 4

PCA Band



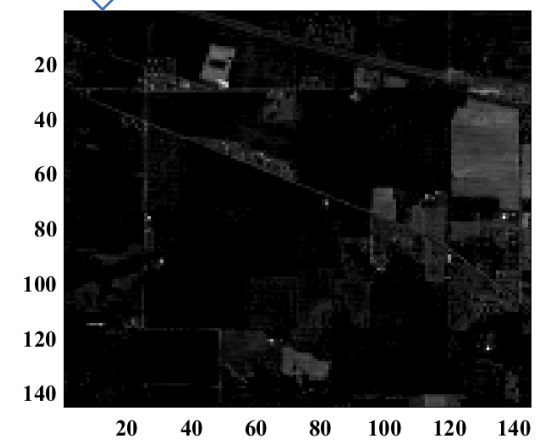
PC 1



PC 2

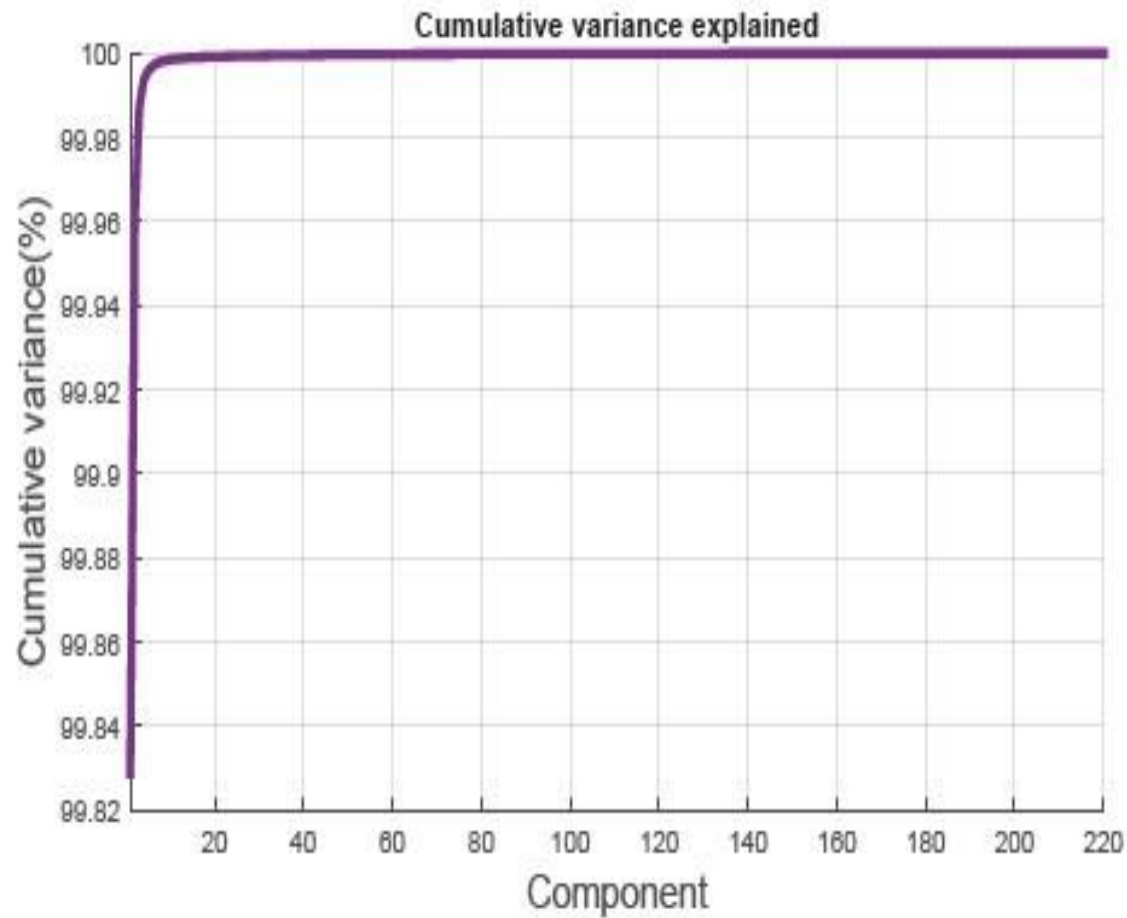


PC 3



PC 4

Result Principal Component Analysis(PCA)

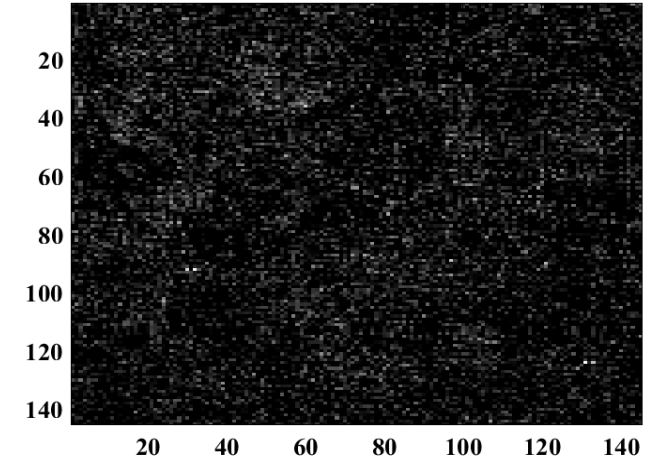


After principal component analysis first **14 band** or component has **99.80%** variance of the dataset.

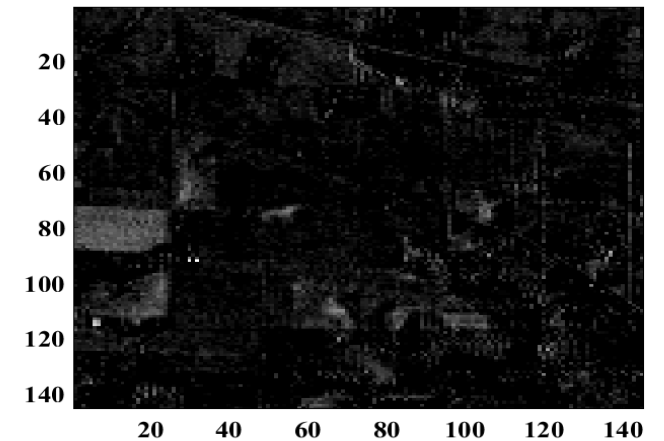
Figure: Cumulative variance

Limitations Principal Component Analysis(PCA)

- ❖ PCA assumes that data is normal distributed and high variance data contains more information.
- ❖ Here though PC 8 has high variance but it contains less information of image contents.
- ❖ On the other hand PC 9 has low variance but it contains more information of image contents.
- ❖ This is the problem that I want to address in my future work.



PC 8



PC 9

Classification

One-against-one support vector machine (SVM)[3]
classifier to classify 14 classes

Steps of classification:

Step 1: Get train and test data

Step 2: Scale data set into 0 to 1

Step 3: Calculate best c and γ for RBF
kernel of SVM

- 10 fold cross validation was used

Step 4: Train and Test SVM

- Radial basis function (RBF) kernel
was used

Class Name	Train	Test
Alfalfa	12	12
Corn-notill	42	36
Corn-min	49	42
Corn	30	30
Grass/Pasture	49	42
Grass/Trees	48	48
Hay-windrowed	77	88
Soybeans-notill	117	117
Soybeans-min	120	84
Soybean-clean	54	54
Wheat	54	60
Woods	120	96
Bldg-Grass-Tree-Drives	63	48
Stone-steel towers	25	24

Table: Data set

Conclusion

- ❖ 14 class is selected
- ❖ Selecting first 14 features after applying PCA gives 80.40% accuracy

Data set	C	g
Original Data	10	2.85
PCA Data	10	0.83

Data set	Classification Result (First 14 features only)
Original Data	51.08%
PCA Data	80.40%

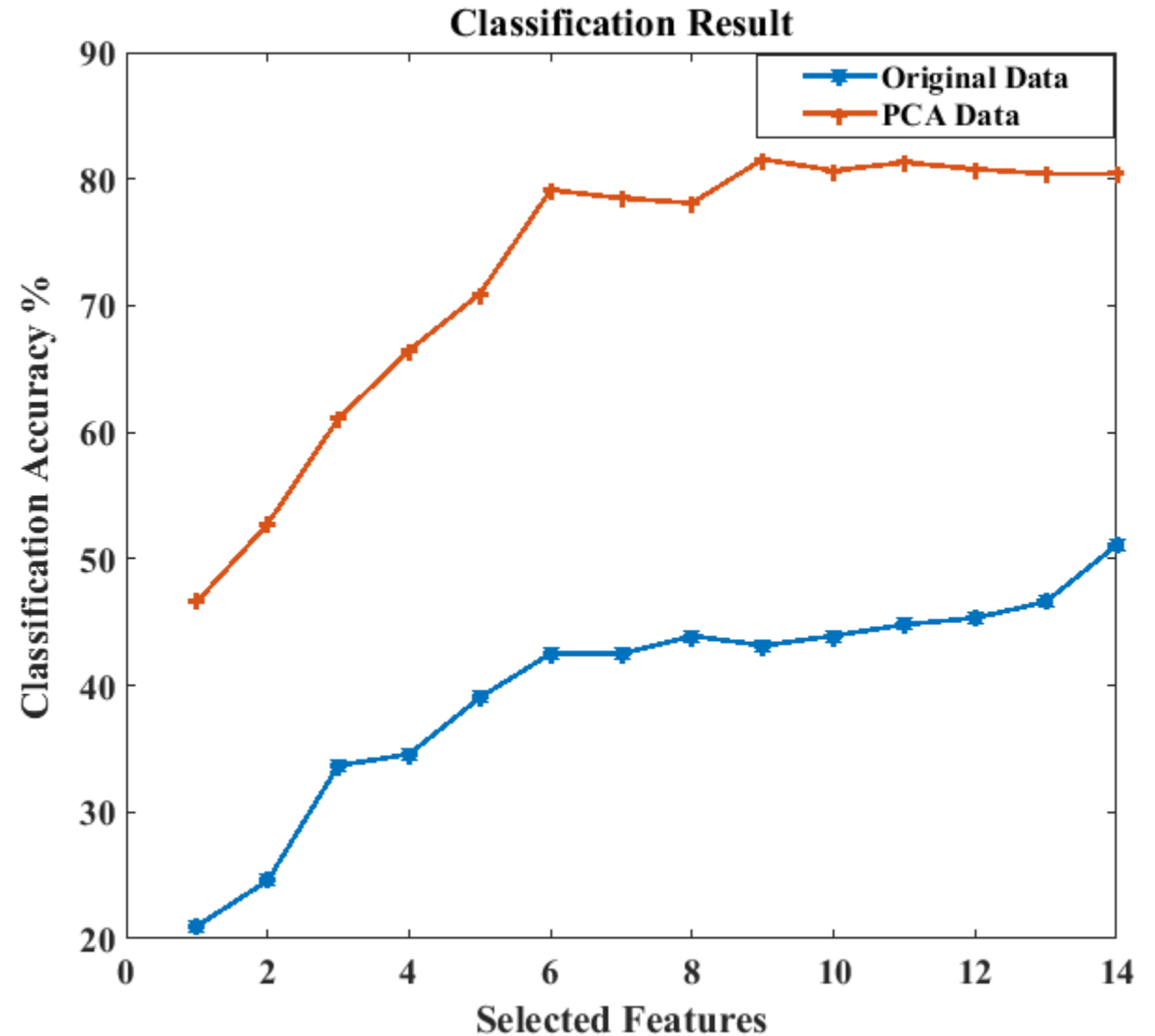


Figure: Comparison of classification result of original data and PCA data.

Future Work

- ❖ Subset features are selected after PCA
- ❖ Efficient feature selection technique can be applied for better classification accuracy like mutual information(MI)

Acknowledgement

Special thanks to
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References

- [1] Lindsay I Smith, “A tutorial on Principal Component Analysis”, February 26, 2002.
- [2] John A. Richards and Xiuping Jia, Remote Sensing Digital Image Analysis 4th edition, Verlag: Springer 2006.
- [3] Chih-Wei Hsu, Chih-Chung Chang, and Chih-Jen Lin, Department of Computer Science, National Taiwan University, Taipei 106, Taiwan, "A Practical Guide to Support Vector Classification", Initial version: 2003, Last updated: May 19, 2016.
- [4] Md. Ali Hossain, Xiuping Jia, Senior Member, IEEE, and Mark Pickering, Member, IEEE, "Subspace Detection Using a Mutual Information Measure for Hyperspectral Image Classification"

The End

Thank You