

>>> Classification of Hyperspectral Images

>>> GRSS Summer School

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Date: [2017-04-26 Wed 13:30]–[2017-04-26 Wed 16:30]

1. Motivations

2. Introductory examples

Influence of the number of samples

Influence of the number of features

Comparison of state of the art classifier

Comparison spectral feature extraction

3. Spatial-spectral Classification

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Data fusion

Spatial post-regularization

Composite kernel

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>>> Classification of hyperspectral image is a challenging problem

\* Remember *Introduction*: High dimensional data

- ★ High number of features
- ★ Large volume of pixels
- ★ Low number of labelled pixels

\* Practical issues:

- ★ Intra-class spectral variability
- ★ Non-linear pre-processing (atmospheric/geometric corrections)
- ★ Noise in the data



- ★ Reference data ?
  - ★ Supervised
  - ★ Unsupervised
  - ★ Semi-supervised
- ★  $p(\mathbf{x}, y) \sim ?:$ 
  - ★ Parametric models
  - ★ Non parameterics models
- ★ Number of classes ?
  - ★ Multiclass
  - ★ One-class / detection
  - ★ Unknown



>>> Data sets used



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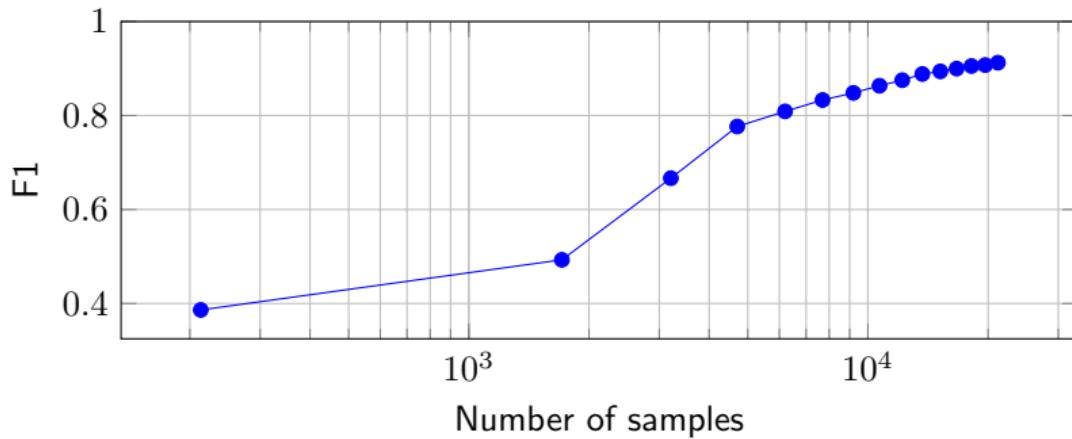
```
>>> Experimental set-up
```

```
import scipy as sp
import rasterTools as rt
from sklearn.model_selection import train_test_split
from sklearn.discriminant_analysis import QuadraticDiscriminantAnalysis
from sklearn.metrics import f1_score

# Load data set
X,y=rt.get_samples_from_roi('..../Data/university.tif','..../Data/university_gt.tif')

# Split the data
X_, X_test, y_, y_test = train_test_split(X, y, train_size=0.50,random_state=0,stratify=y)

# Try differents size of the training set
SPLIT = sp.linspace(0.01,0.99,15)
F1,NS = sp.zeros_like(SPLIT),sp.zeros_like(SPLIT)
for i,split in enumerate(SPLIT):
    # Split the data
    X_train, _, y_train, _ = train_test_split(X_, y_, train_size=split,random_state=0,stratify=y_)
    # Learn the classifier
    clf = QuadraticDiscriminantAnalysis()
    clf.fit(X_train,y_train)
    # Predict the classes
    yp = clf.predict(X_test)
    #Compute the F1
    F1[i],NS[i] = f1_score(y_test,yp,average='weighted'),y_train.size
```



- ★ Dimension of the data:  $d = 103$
- ★ Number of parameters to estimate: 49139

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```
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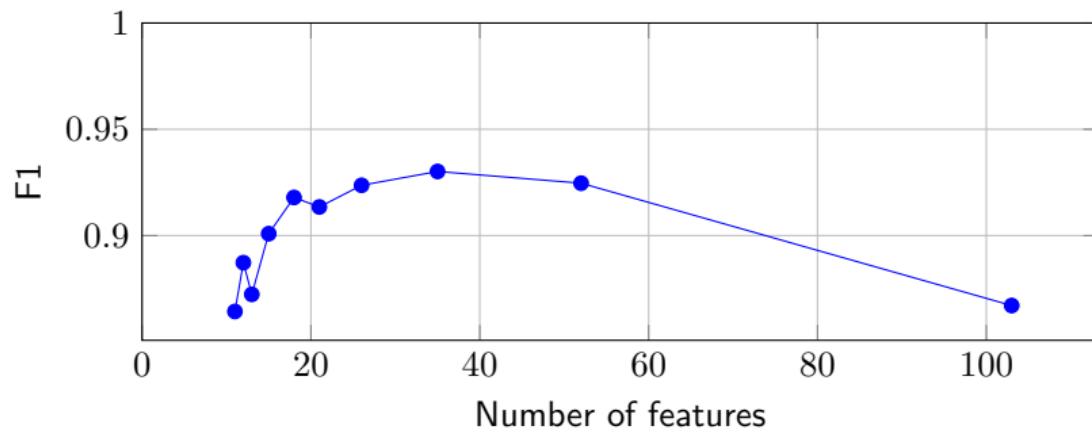
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import scipy as sp
import rasterTools as rt
from sklearn.model_selection import train_test_split
from sklearn.discriminant_analysis import QuadraticDiscriminantAnalysis
from sklearn.metrics import f1_score

# Load data set
X,y=rt.get_samples_from_roi('..../Data/university.tif','..../Data/university_gt.tif')

# Split the data
X_, X_test, y_train, y_test = train_test_split(X, y, train_size=0.25,random_state=0,stratify=y)

# Try differents size of the training set
SKIP = sorted(range(1,11),reverse=True)
FS,NF = sp.zeros_like(SKIP,dtype='float'),sp.zeros_like(SKIP)
for i,skip in enumerate(SKIP):
    # Skip some variables
    X_train = X_[:,::skip]
    # Learn the classifier
    clf = QuadraticDiscriminantAnalysis()
    clf.fit(X_train,y_train)
    # Predict the classes
    yp = clf.predict(X_test[:,::skip])
    #Compute the FS
    FS[i], NF[i] = f1_score(y_test,yp,average='weighted'), X_train.shape[1]
```

>>> Results



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>>> Experimental set-up

```
if __name__ == '__main__':
    # Load data set
    X,y=rt.get_samples_from_roi('../Data/university.tif','../Data/university_gt.tif')
    sc = StandardScaler()
    X = sc.fit_transform(X)

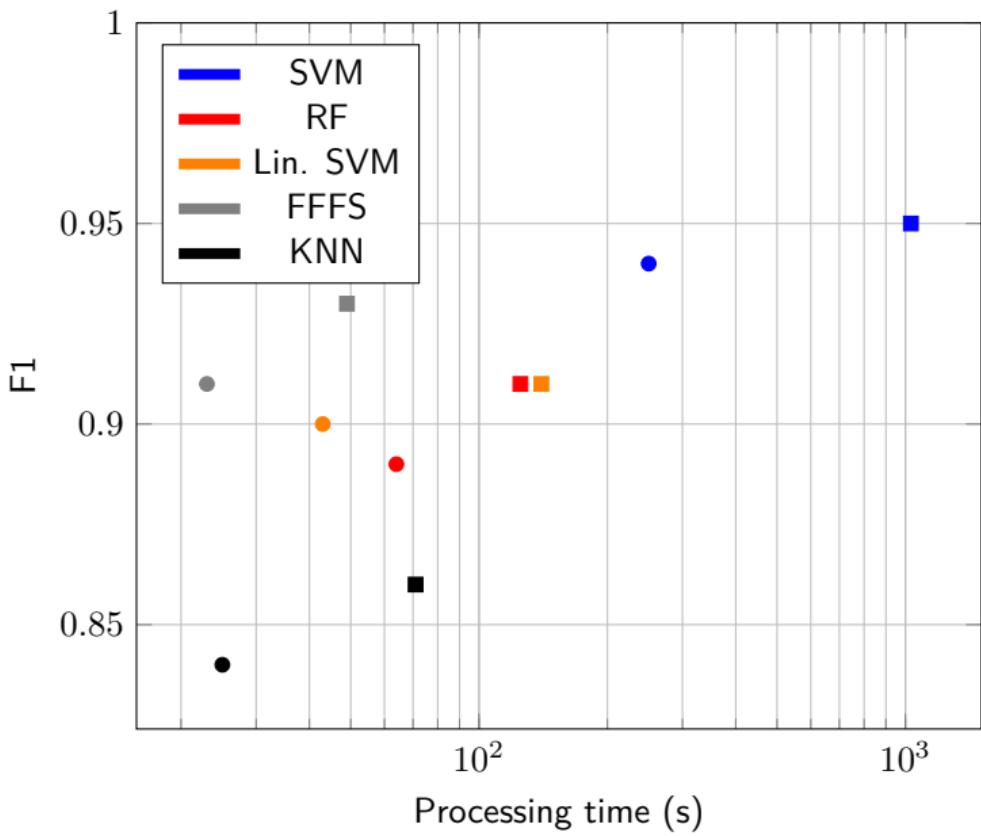
    # Split the data
    X_train, X_test, y_train, y_test = train_test_split(X, y, train_size=0.1,random_state=0,stratify=y)

    # Parameters
    param_grid_svm = dict(gamma=2.0**sp.arange(-4,4), C=10.0**sp.arange(0,3)) # SVM
    param_grid_linear_svm = dict(C=10.0**sp.arange(-2,3)) # LinearSVM
    param_grid_rf = dict(n_estimators=sp.arange(10,150,10)) # RF
    param_grid_fffs = dict(maxvar=20,threshold=0.001) # FFFS
    param_grid_knn = dict(n_neighbors = sp.arange(1,50,5))
    F1,CT=[],[]

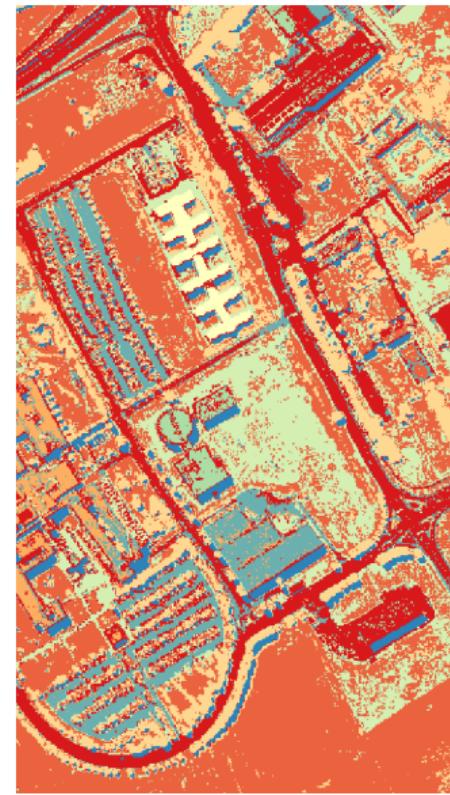
    # Start the classification: SVM
    ts=time.time()
    F1.append(compute_SVM(X_train,y_train,X_test,y_test,param_grid_svm))
    CT.append(time.time()-ts)

    # Start the classification: RF
    ts=time.time()
    F1.append(compute_RF(X_train,y_train,X_test,y_test,param_grid_rf))
    CT.append(time.time()-ts)
```

Class	•	■
1	663	1326
2	1865	3730
3	210	420
4	306	613
5	134	269
6	503	1006
7	133	266
8	368	736
9	95	189



>>> Classification Map



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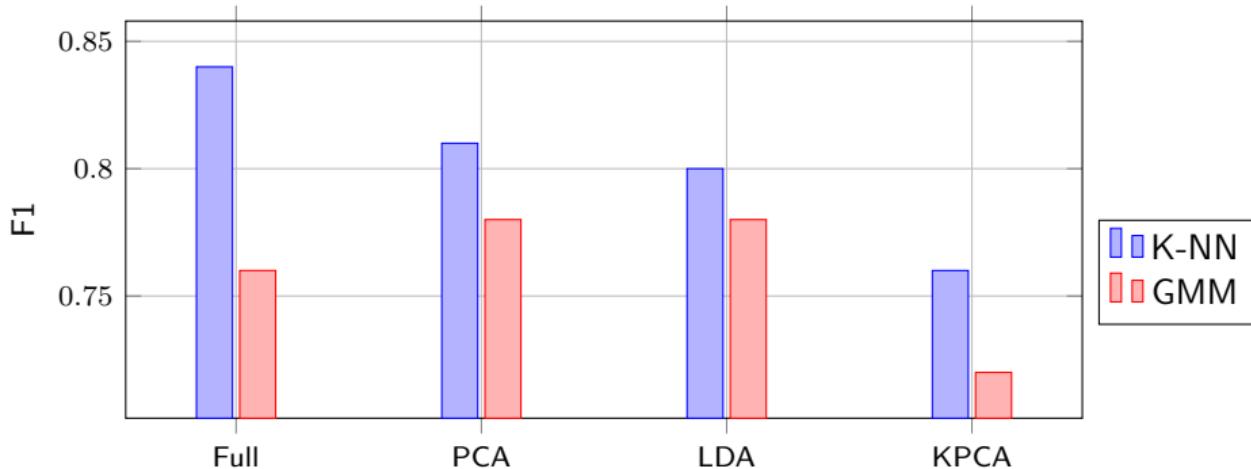
Composite kernel

## 4. References

```
>>> PCA, LDA and KPCA
```

```
DATA = ['../Data/university.tif', '../Data/pca_university.tif', '../Data/lda_university.tif',
        '../Data/kpca_university.tif']
GT = '../Data/university_gt.tif'

F1_knn,F1_gmm = [], []
for data in DATA:
    print data
    # Load data set
    X,y=rt.get_samples_from_roi(data,GT)
    sc = StandardScaler()
    X = sc.fit_transform(X)
```



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## Spatial inter-pixel dependency

- ★ Spatial feature extraction

- ★ Texture
- ★ Mathematical morphology
- ★ Convolution

- ★ Image Segmentation

- ★ kmeans
- ★ MeanShift

- ★ Markov Random Field

## Spatial inter-pixel dependency

- ★ Spatial feature extraction

- ★ Texture
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- ★ Image Segmentation

- ★ kmeans
- ★ MeanShift

- ★ Markov Random Field

## Joint use of spectral and spatial information

- ★ Data fusion

- ★ Input: Feature stacking,
- ★ Output: fusion of classifier outputs.

- ★ Post classification regularization

- ★ Majority vote,
- ★ Region growing from markers.

- ★ Spatial-spectral classifiers:

- ★ Composite kernel
- ★ MRF

>>> Question to solve

1. What kind of information is needed ?
2. How to extract it from the data ?
3. How to combine it with the spectral information ?

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- ★ Template filters
  - ★ Mean, variance, median, entropy, range, ...
- ★ Gabor features
- ★ Wavelet features [ML02]
- ★ Co-occurrence [HSD73]

```
otbcli_HaralickTextureExtraction -in ../Data/pca_university.tif -channel 1 \
-out ../Data/university_haralick.tif -parameters.min 789 parameters.max 64897
```

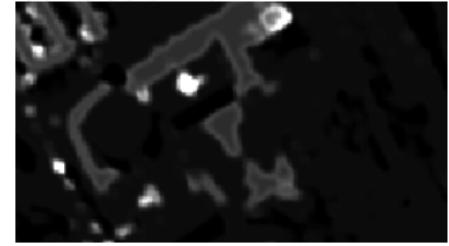
Color Image

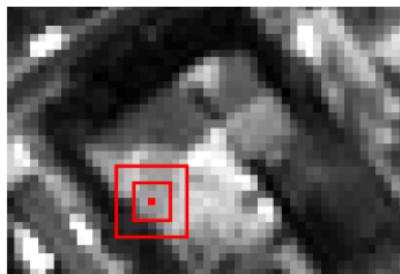


Energy for PC1



Correlation for PC1

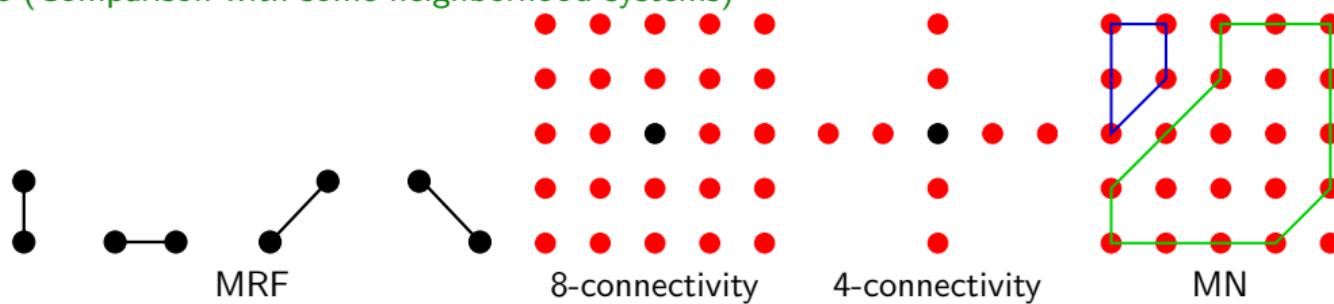




### Definition (Morphological neighborhood)

The Morphological Neighborhood of a pixel  $x$  is the set of pixels that belongs to the same spatial structure than  $x$ .

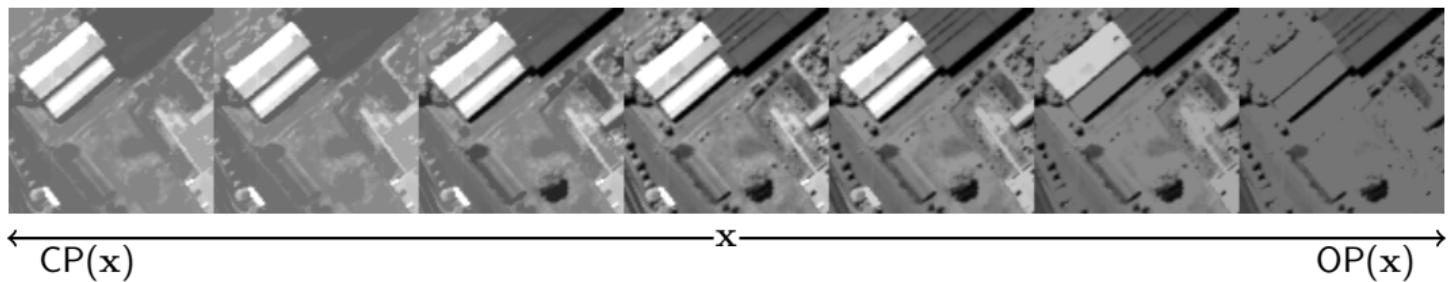
### Example (Comparison with some neighborhood systems)



### Definition (Morphological profile)

The Morphological Profile of size  $n$  is a  $(2n + 1)$ -dimensional vector such as:

$$\text{MP}(\mathbf{x}) = [\text{CP}_n(\mathbf{x}), f(\mathbf{x}), \text{OP}_n(\mathbf{x})].$$

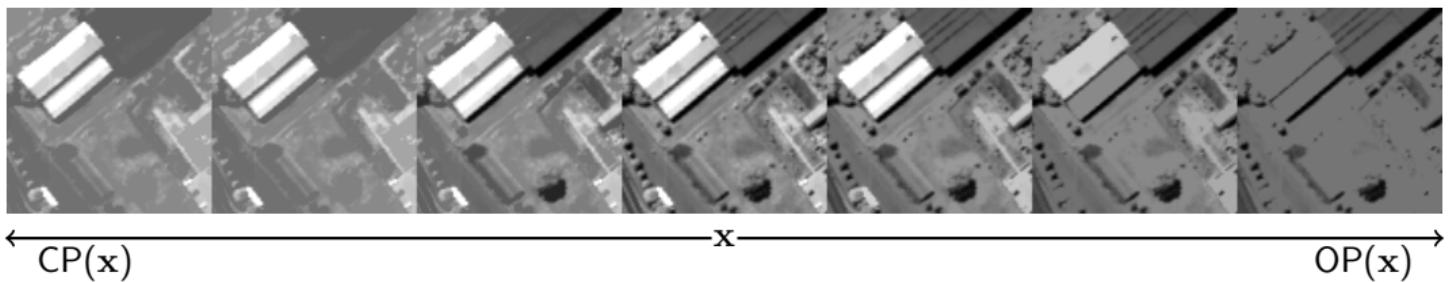


For a given pixel  $x$ , information include in the  $\text{MP}(x)$  are:

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The Morphological Profile of size  $n$  is a  $(2n + 1)$ -dimensional vector such as:

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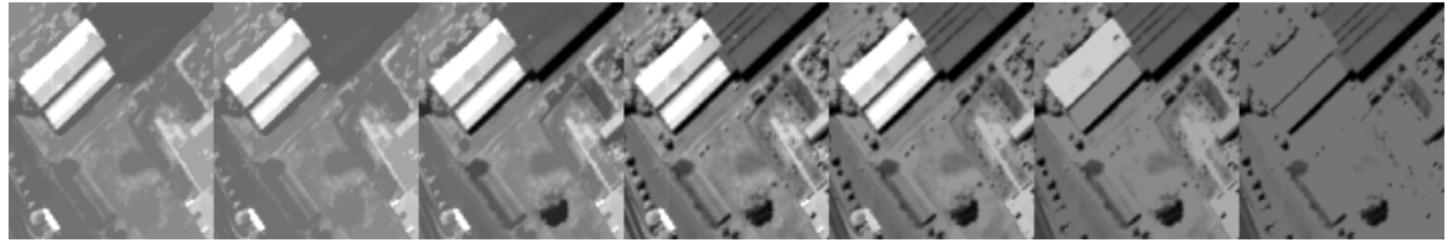
For a given pixel  $x$ , information included in the  $\text{MP}(x)$  are:

- ★ Contrast: Is the structure to which the pixel belongs darker or lighter than his surrounding neighbors?
- ★ Size: Is the structure to which the pixel belongs small or big compared to  $G$ ?

### Definition (Derivative of the morphological profile)

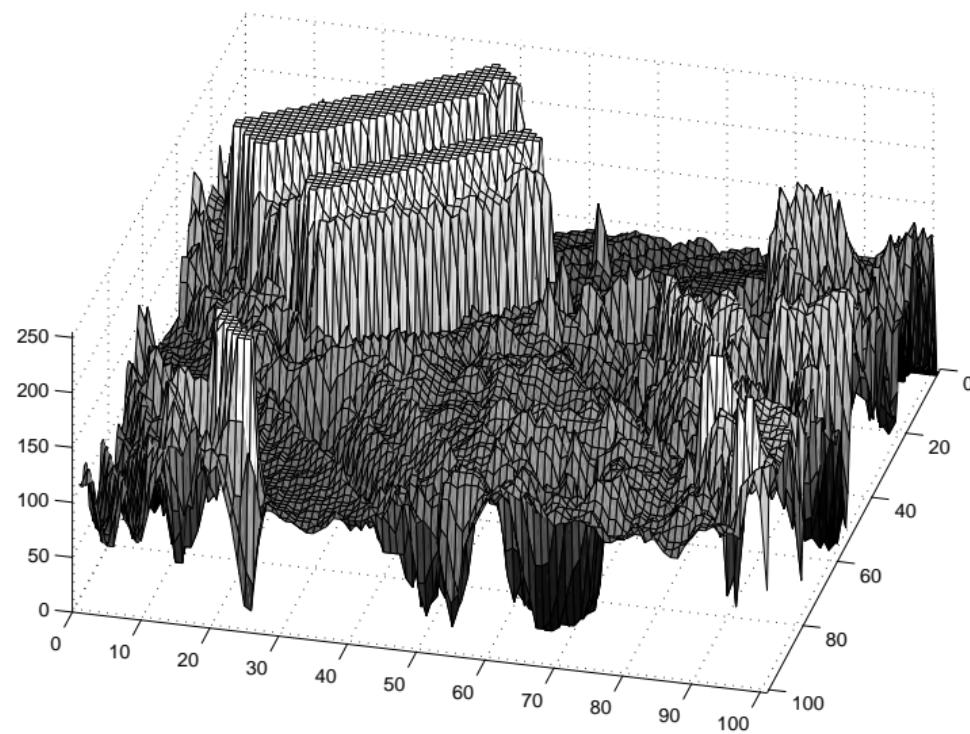
The Derivative of the Morphological Profile of size  $n$  is a  $(2n)$ -dimensional vector such as:

$$\text{DMP}(\mathbf{x}) = \left[ |\phi_n(\mathbf{x}) - \phi_{n-1}(\mathbf{x})|, \dots, |\gamma_{n-1}(\mathbf{x}) - \gamma_n(\mathbf{x})| \right].$$



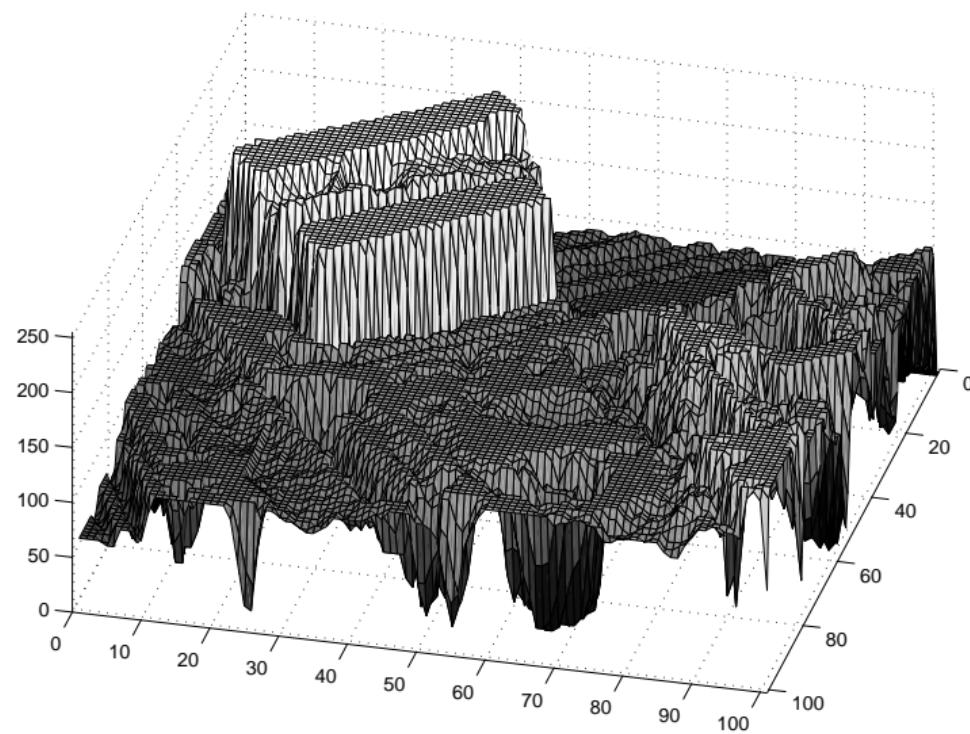
>>> Limits of the (D)MP

- ★ Geodesics filters only act on extrema structures

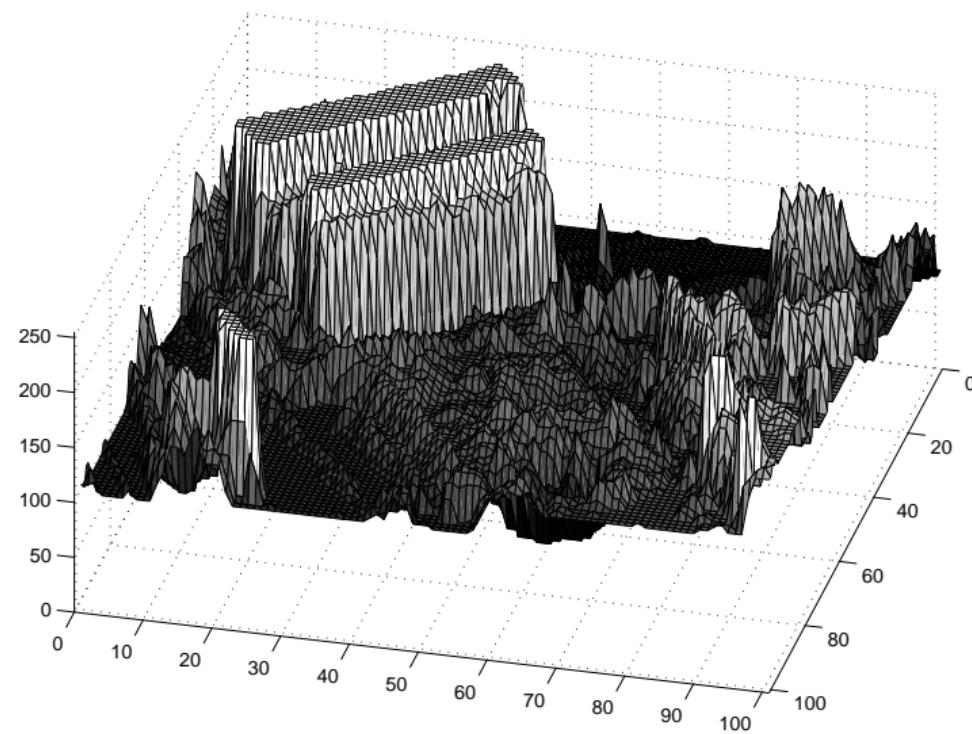


>>> Limits of the (D)MP

- ★ Geodesics filters only act on extrema structures

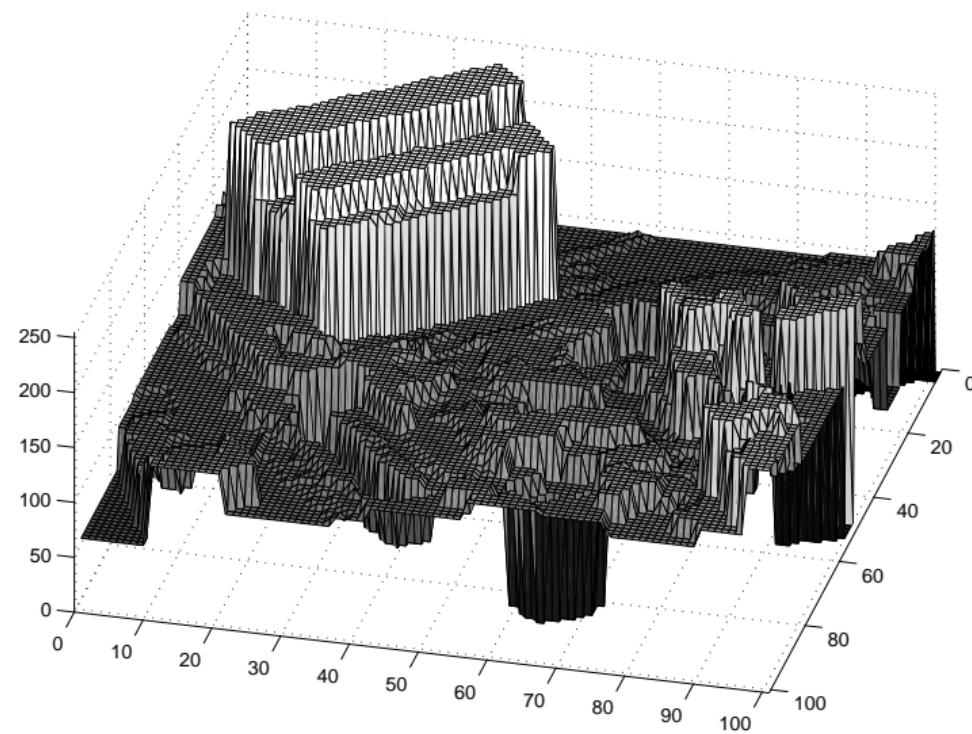


- ★ Geodesics filters only act on extrema structures

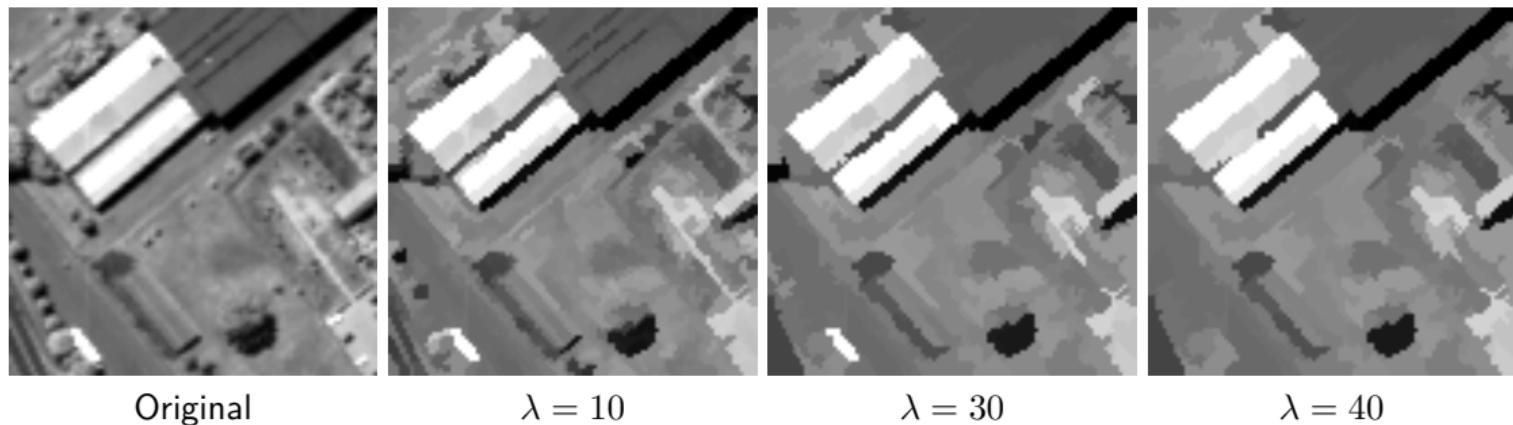


>>> Limits of the (D)MP

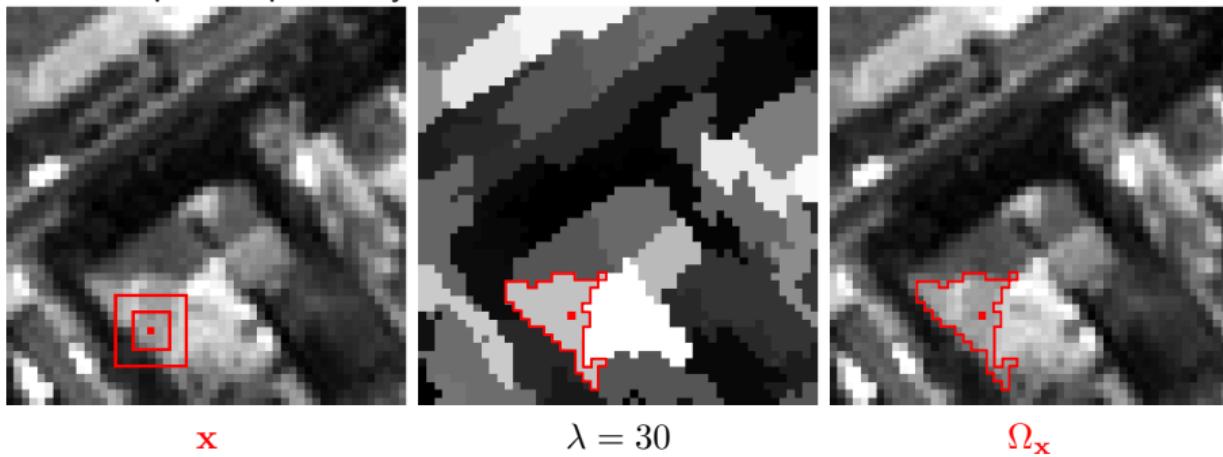
- ★ Geodesics filters only act on extrema structures
- ★ Self-complementary area filter



- ★ Self-complementarity:  $\Psi = \mathbf{C}\Psi \Rightarrow$  each structure is processed equally.
- ★ Area filter: Removes small structures (area = number of pixels).
- ★ Algorithm:
  1. Label all the flat zones that satisfy the area criterion  $\lambda$ ,
  2. Grow the labelled flat zones until a partition of the image is reached.



- ★ Extract the inter-pixel dependency  $\Upsilon$ :



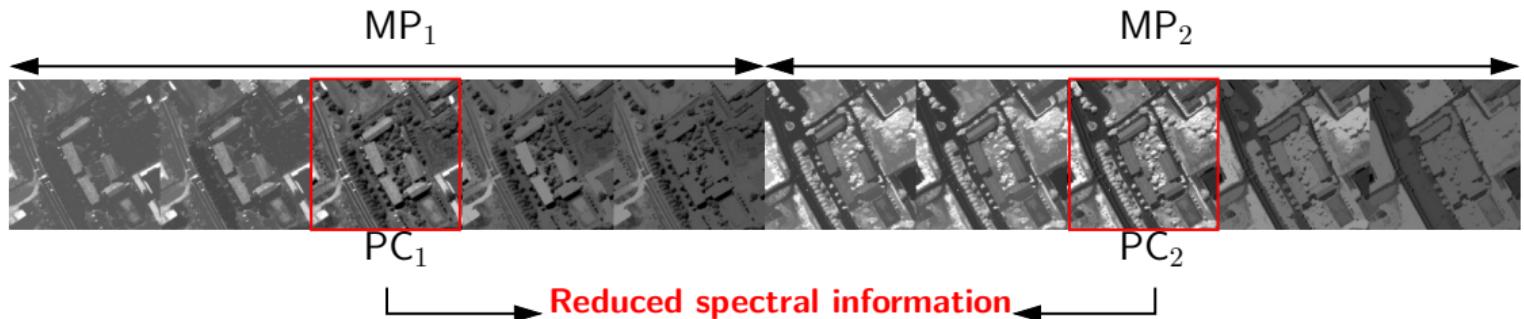
- ★  $\Upsilon_x = \text{median}(\Omega_x)$ :

- ★ Structure: What are the pixels related to  $x$ ?
- ★ Contrast: Local gray-level distribution

### Definition (Extended Morphological Profile)

The EMP of size  $n \times p$  is a  $(2n + 1)p$ -dimensional vector made of the MP build with the  $p$  first principal components:

$$\text{EMP}(\mathbf{x}) = [\text{MP}_1(\mathbf{x}), \dots, \text{MP}_p(\mathbf{x})].$$



- ★ Fusion of morphological and spectral features
- ★ PCA, FDA, Kernel-PCA ...
- ★ *Same methods for self-complementary area filter*

>>> Application case: Extended Morphological Profile

```
# Start the computation
for i in xrange(no):
    # Structuring elements
    se = disk(radius+i*2)

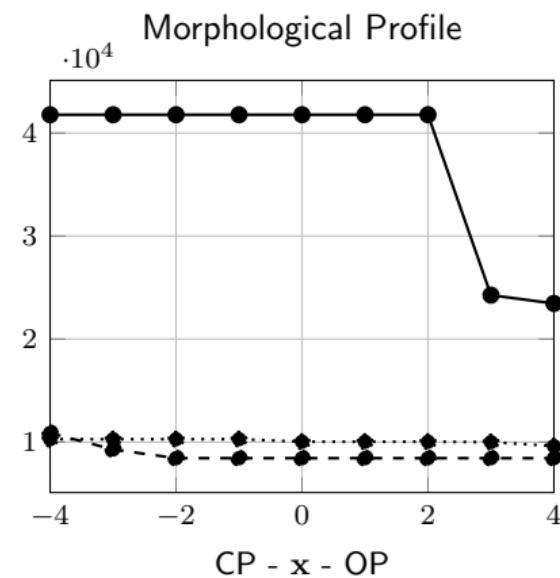
    # Compute opening per reconstruction
    temp = erosion(im,se)
    out[:, :, no+1+i] = reconstruction(temp,im,method='dilation')

    # Compute closing per reconstruction
    temp = dilation(im,se)
    out[:, :, no-1-i] = reconstruction(temp,im,method='erosion')

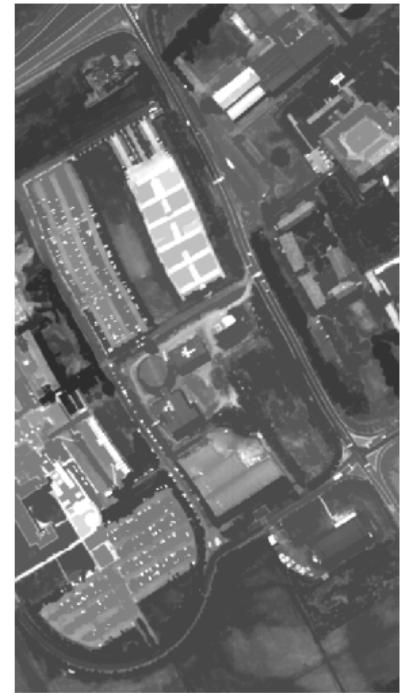
return out

if __name__ == '__main__':
    # Load image
    im,GeoT,Proj = rt.open_data('../Data/pca_university.tif')

    # Apply the Morphological profile on each PC
    EMP = []
    for i in xrange(3):
        EMP.append(morphological_profile(im[:, :, i]))
    EMP = sp.concatenate(EMP, axis=2)
    rt.write_data("../Data/emp_pca_university.tif",EMP,GeoT,Proj)
```



Where is the *closing* and the *opening* ?



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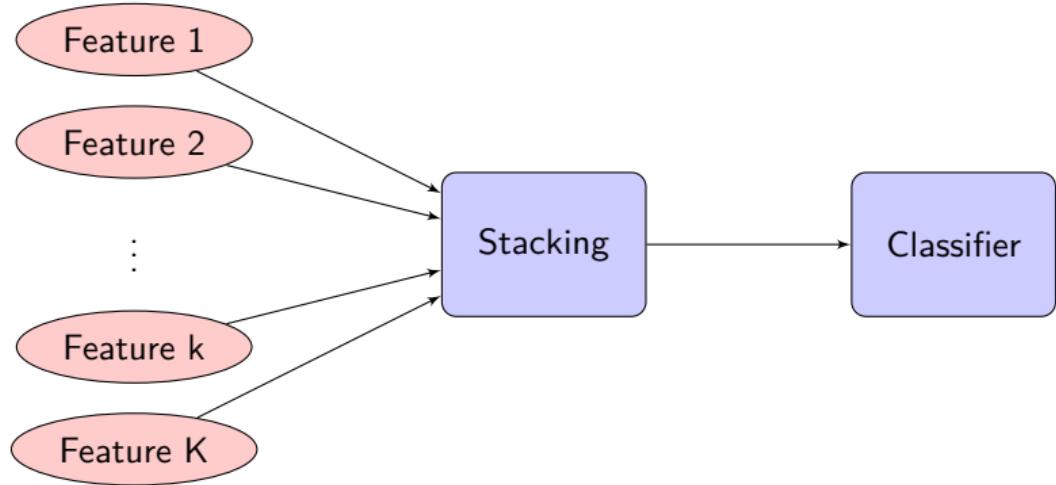
Data fusion

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Composite kernel

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>>> Feature fusion 1/2



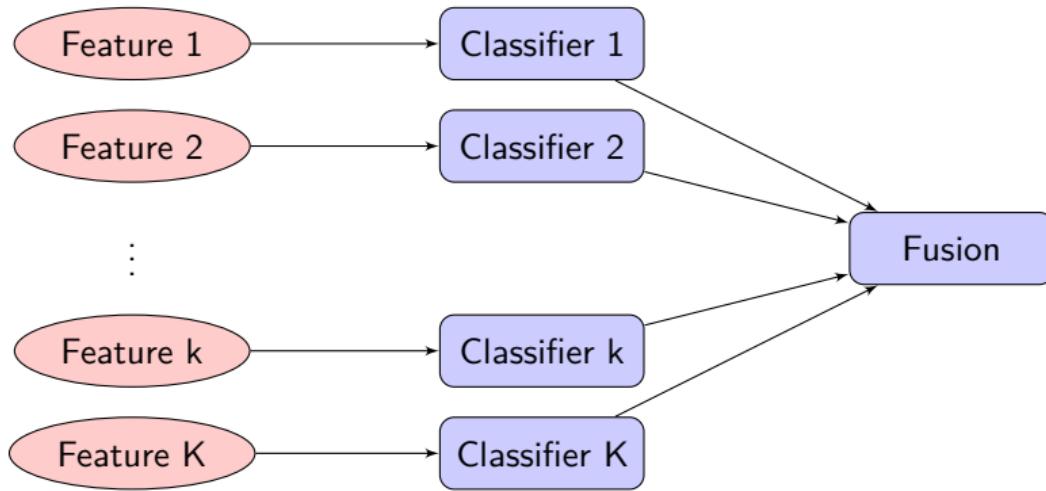
- ★ Extract several spatial descriptors
  - ★ EMP,
  - ★ Texture,
  - ★ Histogram of oriented gradients (HOG),
  - ★ ...
- ★ *Optional:* apply feature extraction
  - ★ Spectral features,
  - ★ Spatial features,
  - ★ Both
- ★ Stack all the features into a "big vector"

★ In [Fau+08]:

- ★ Extrat EMP
- ★ Apply PCA/LDA to the spectral and spatial features
- ★ Stack the first PCs of spectral/spatial feautres
- ★ Classification with SVM

Method	# Features	OA
Spectral	103	79.5
EMP	27	79.1
S+EMP	130	83.5
S-DBFE+EMP-DBFE	27+10	88.0

>>> Classifier fusion 1/2



## ★ Fusion of classifier outputs:

- ★ At the decision level

$$C_1 : \{y_1\};$$

$$C_2 : \{y_2\};$$

$$\vdots$$

$$C_K : \{y_K\}$$

- ★ At the membership level

$$C_1 : \{m_{11}, \dots, m_{1C}\};$$

$$C_2 : \{m_{21}, \dots, m_{2C}\};$$

$$\vdots$$

$$C_K : \{m_{K1}, \dots, m_{KC}\}$$

- ★ Decision level: Majority vote
- ★ Membership level: Probabilistics methods, fuzzy logic, Dempster-Shafer ...

- ★ In [FCB06]: Fusion of SVM
- ★ Use the distance to the hyperplane
- ★ *Absolute maximum* fusion rule
- ★ Two classifiers with different intput: Spectral and EMP

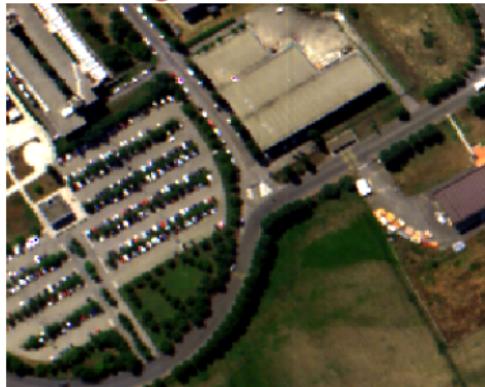
Feature	OA
Spectral	81.0
EMP	85.2
Output fusion	89.6

- ★ Simple to implement:

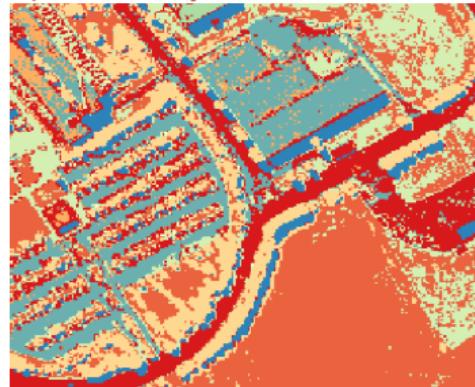
```
# Concatenate the spectral and spatial features and do scaling  
IM_EMP = sp.concatenate((im[:,::2],EMP.astype(im.dtype)),axis=1)
```

- ★ Good classification accuracy:  $F1 = 0.99$
- ★ spatial

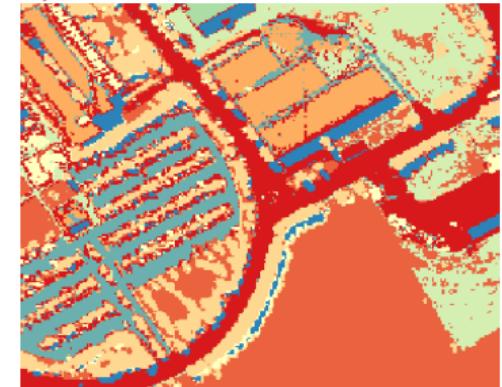
Color Image



Spectral only



Spectral + EMP



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★ Main ideas

- ★ Segmentation of the image: partition the image into non-overlapping homogeneous zones
- ★ Spatial regularization of the thematic map

★ Issues:

- ★ Segmentation of hyperspectral images is tricky !
- ★ Spatial regularization

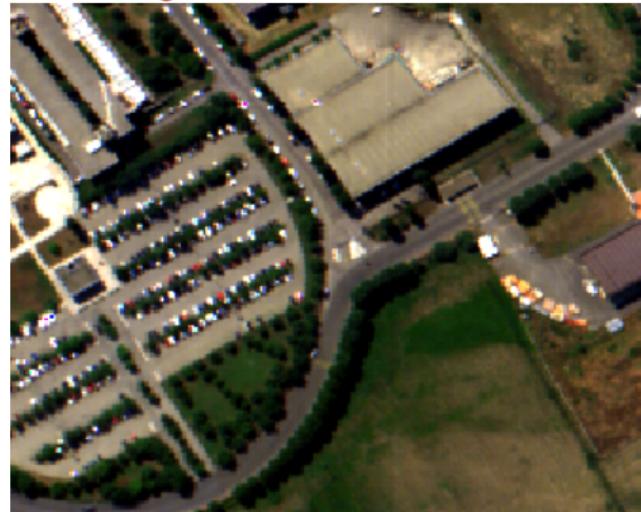
★ From [Fau+13]:

- ★ Segmentation:
  - ★ Image processing: Watershed, region growing, mean-shift, ...
  - ★ Statistical: GMM, K-means ...
- ★ Regularization:
  - ★ Majority voting,
  - ★ Region growing

# Using Mean Shift

```
otbcli_Segmentation -in ../Data/pca_university.tif -mode raster -mode.raster.out ../Data/mean_shift_unive  
-filter.meanshift.minsize 50
```

Color Image



Segmented



>>> Segmentation 3/4

```
import rasterTools as rt
import scipy as sp
from scipy.stats import mode

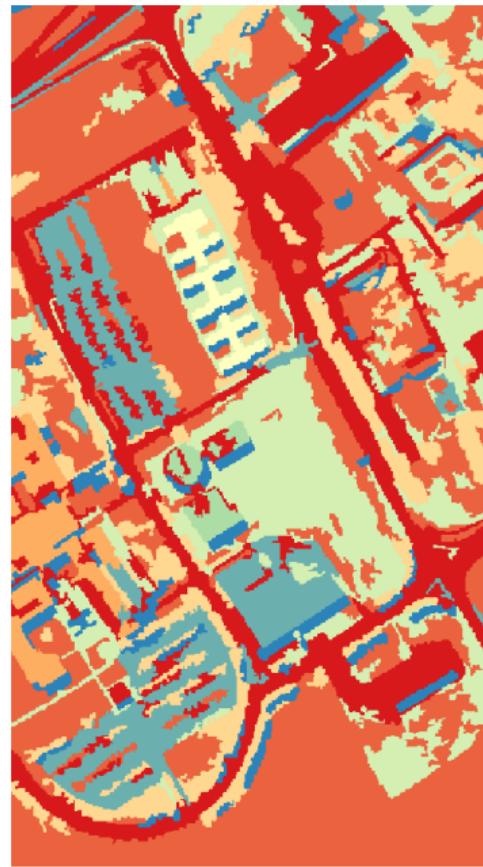
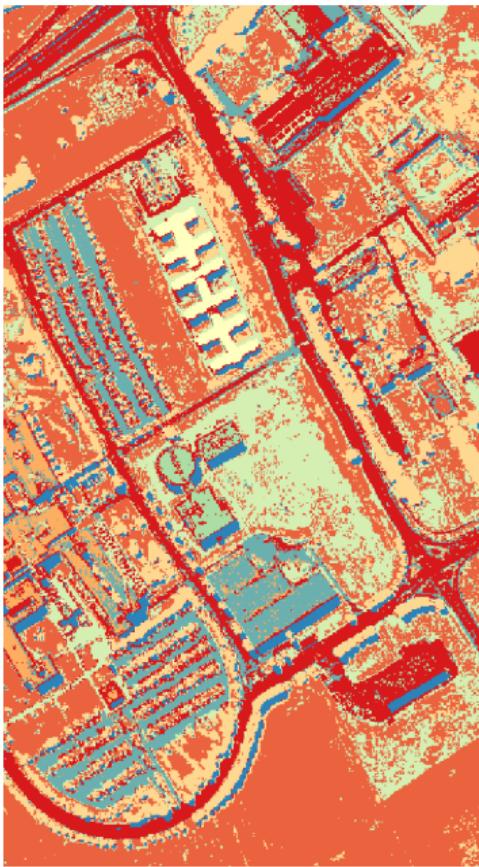
# Load Thematic Map
im,GeoT,Proj = rt.open_data('../Data/tm_university_svm.tif')
out = sp.empty_like(im)

# Load segmented image
segmented,GeoT,Proj = rt.open_data('../Data/mean_shift_university.tif')

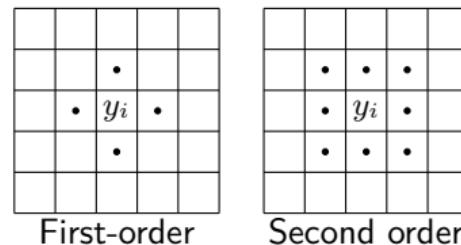
# Do the majority vote
for l in sp.unique(segmented):
    t = sp.where(segmented==l)
    y = im[t]
    out[t] = mode(y, axis=None)[0][0]

# Write the new image
rt.write_data("../Data/tm_university_fusion_mv.tif",out,GeoT,Proj)
```

>>> Segmentation 4/4



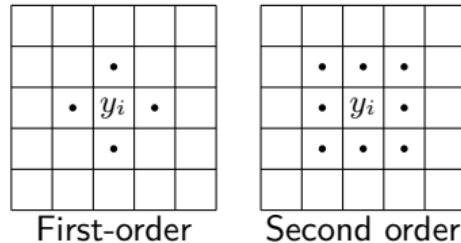
- ★ Markovian hypothesis/condition [MSB13]:  $p(y_i = c | \mathbf{x}_i, \mathcal{N}_i)$
- ★  $\mathcal{N}_i$ : neighborhood of pixel  $i$



- ★ When  $Y$  is a Markov Random Field:
  - ★  $P(Y|\mathbf{X}) \propto \exp(-U(Y|\mathbf{X}))$
  - ★  $U(Y|\mathbf{X}) = \sum_{i=1}^n U(y_i|\mathbf{x}_i, \mathcal{N}_i)$
  - ★  $U(y_i|\mathbf{x}_i, \mathcal{N}_i) = \Omega(\mathbf{x}_i, y_i) + \beta \mathcal{E}(y_i, \mathcal{N}_i)$
- ★ Spectral term:  $\Omega(\mathbf{x}_i, y_i) = -\log[p(\mathbf{x}_i|y_i)]$
- ★ Spatial term (*Potts model*):  $\mathcal{E}(y_i, \mathcal{N}_i) = \sum_{j \in \mathcal{N}_i} [1 - \delta(y_i, y_j)]$

## >>> Markov Random Field 1/2

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- ★ Spatial term (*Potts model*):  $\mathcal{E}(y_i, \mathcal{N}_i) = \sum_{j \in \mathcal{N}_i} [1 - \delta(y_i, y_j)]$
- ★ Function to be optimized

$$U(Y|\mathbf{X}) = \sum_{i=1}^n \left\{ -\log[p(\mathbf{x}_i|y_i)] + \beta \sum_{j \in \mathcal{N}_i} [1 - \delta(y_i, y_j)] \right\}$$

- ★ Global optimization is not tractable [Li09]: iteration of local optimization on

$$-\log[p(\mathbf{x}_i|y_i)] + \beta \sum_{j \in \mathcal{N}_i} [1 - \delta(y_i, y_j)]$$

- ★ Iterated conditional mode:

- ★ Scan all the pixels: change the label to maximize the local energy
  - ★ Stop when convergences is reached

- ★ Advanced algorithms

- ★ Simulated annealing [Tar+10]
  - ★ Graph-cut [MSB13]

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- ★ Advanced algorithms
  - ★ Simulated annealing [Tar+10]
  - ★ Graph-cut [MSB13]
- ★ For hyperspectral images: needs classification algorithms robust to the dimensionality!

```
>>> MRF in action 1/3
```

- ★ ICM main loop:

```
# Iterate until convergence
while (diff[-1] > th) and (niter < 100):
    old_labels= labels.copy() # Make a copy of the old labels
    for i in xrange(1,nl-1): # Scan each line
        for j in xrange(1,nc-1): # Scan each column
            energy = []
            labels_ = old_labels[i-1:i+2,j-1:j+2].copy()
            for c in xrange(C): # Compute the energy for the different classes
                labels_[1,1] = c+1
                energy.append(compute_energy(proba[i,j,c],labels_,beta))
            arg = sp.argmax(energy) # Get the maximum energy term for the local configuration
            labels[i,j] = arg + 1
    diff.append(1 - sp.sum(old_labels == labels ).astype(float)/nc/nl) # Compute the changes
    niter += 1
# Clean data
del old_labels
return diff
```

- ★ Ask SVM for probability outputs

```
clf.probability= True
clf.fit(X_train,y_train)

# Predict the whole image and the probability map
labels = clf.predict(im).reshape(h,w)
proba = -clf.predict_log_proba(im).reshape(h,w,y.max())
```

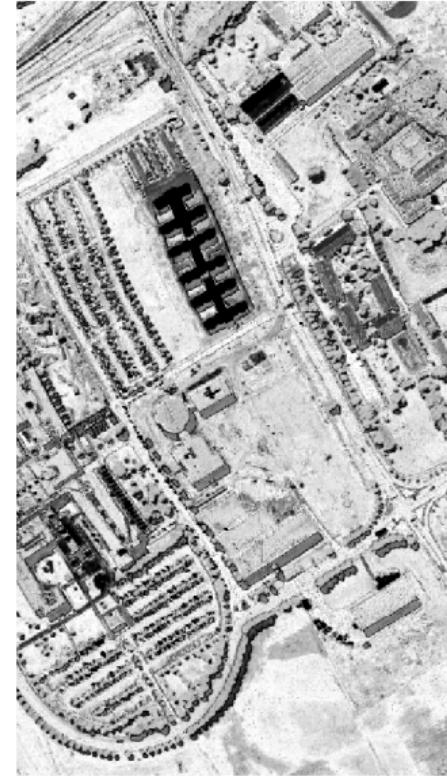
Asphalt



Tree

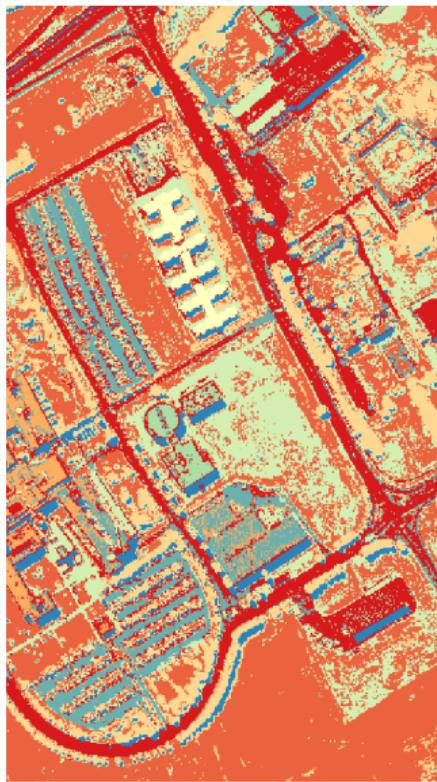


Metal sheet

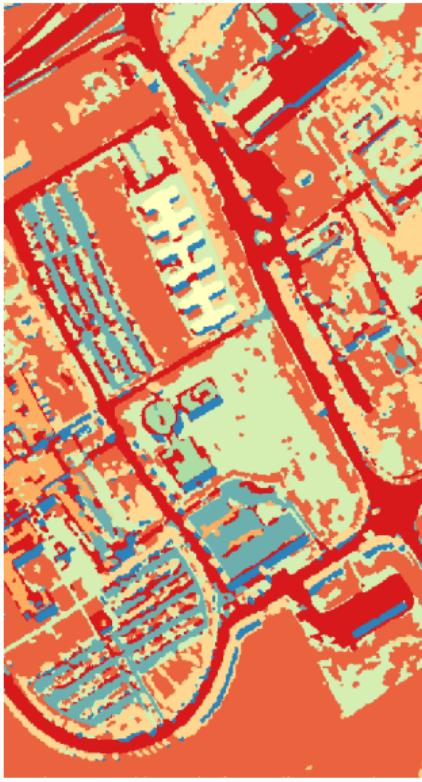


>>> MRF in action 3/3

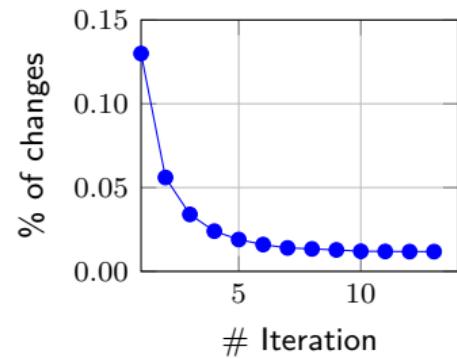
Spectral only



MRF



Iteration



## 1. Motivations

## 2. Introductory examples

Influence of the number of samples

Influence of the number of features

Comparison of state of the art classifier

Comparison spectral feature extraction

## 3. Spatial-spectral Classification

Introduction

Spatial filter

Data fusion

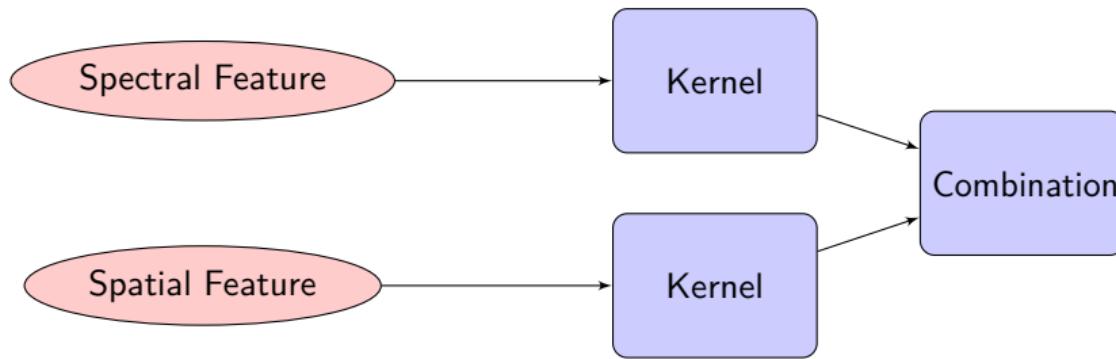
Spatial post-regularization

Composite kernel

## 4. References

- ★ Let  $k_1$  and  $k_2$  be positive semi-definite, and  $\lambda_{1,2} > 0$  then:
  1.  $\lambda_1 k_1$  is a valid kernel
  2.  $\lambda_1 k_1 + \lambda_2 k_2$  is positive semi-definite.
  3.  $k_1 k_2$  is positive semi-definite.
  4.  $\exp(k_1)$  is positive semi-definite.
  5.  $g(\mathbf{x}_i)g(\mathbf{x}_j)$  is positive semi-definite, with  $g : \mathbb{R}^d \rightarrow \mathbb{R}$ .
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- ★ A kernel is usually seen as a measure of similarity between two samples. It reflects in some sense, how two samples are similar.
- ★ In image classification. It is possible to build kernels that includes information from the spatial domain.
  - ★ Local correlation
  - ★ Spatial position
  - ★ Morphological feature,
  - ★ ...



- ★ From [Cam+06]:
  - ★ Feature fusion:  $k_{\text{spatial+spectral}}$
  - ★ Direct summation:  $k_{\text{spatial}} + k_{\text{spectral}}$
  - ★ Weighted summation:  $\mu k_{\text{spatial}} + (1 - \mu)k_{\text{spectral}}, 0 \leq \mu \leq 1$
- ★ Can be extended to more than two kernels: *multiple kernel learning* (tricky)

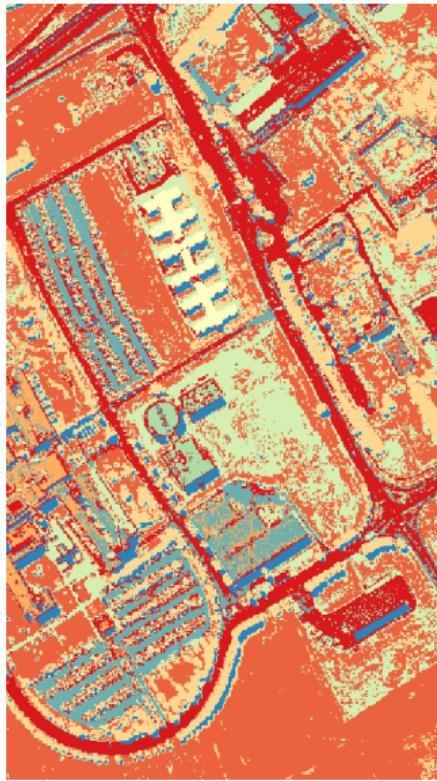
- ★ Combination of
  - ★ Spectral bands
  - ★ Spatial features: local median computed on a moving window
- ★ Weighted summation kernel + SVM

```
# Create a pipeline
pipe = Pipeline([
    ('CK',CompositeKernel()),
    ('SVM',SVC())
])

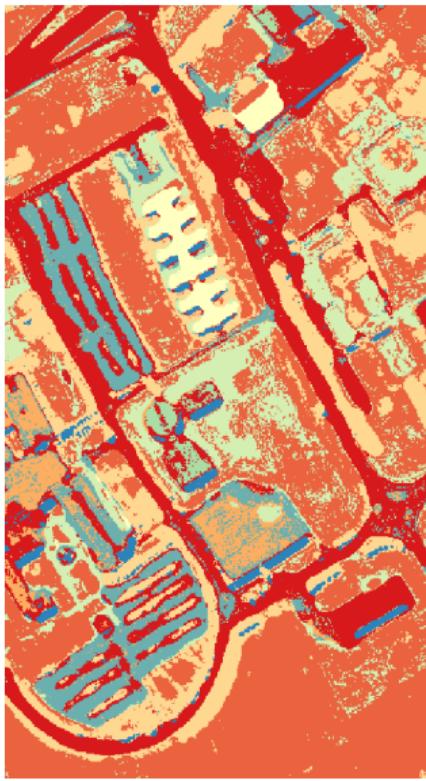
# Optimize parameters
cv_params = dict([
    ('CK__gamma', 2.0**sp.arange(-3,3)),
    ('CK__mu', sp.linspace(0,1,num=11)),
    ('SVM__kernel', ['precomputed']),
])

```

Spectral only



Composite kernel



Parameters

- \*  $F_1 = 0.89$
- \*  $\mu = 0.8$

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4. References

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