Classification of Hyperspectral Data Using Support Vectors Machines and Data Fusion

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1. Hyperspectral Data
2. Support Vector Machines
3. Data Fusion
4. Experiment
5. Conclusions

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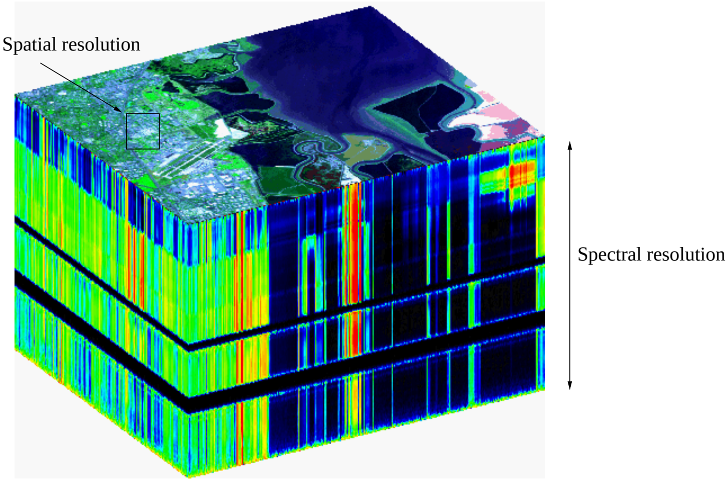

- Spatial resolution: up to 1m by pixel,
- Spectral resolution: up to 200 bands.

For a classification attempt:

- High spectral resolution: increases the separability of the classes
- Fine spatial resolution: allows a new definition of classes

but:

- Spatial features need to be extracted
- Curse of dimensionality: statistical estimation is difficult
- Hughes phenomenon
- How to use both the spatial *and* the spectral information?

Geometrical approach for the classification:

- Support Vector Machines (SVMs)
- Kernel Methods

Decision Fusion:

- Decision rule should use SVMs' output particularities
- Confidence of each classifier should drive the fusion

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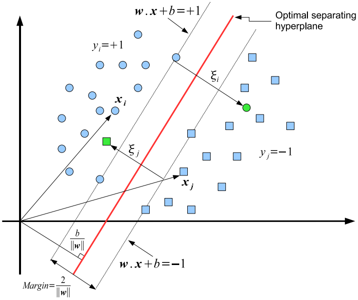
- Geometrical approach: *Find the optimal hyperplane which separates samples.*
- Hyperplane parameters: $(\mathbf{w}, b)$ which is found by solving,

$$\min \left[\frac{\|\mathbf{w}\|^2}{2} + C \sum_{i=1}^{N} \xi_i \right],$$

subject to $y_i(\langle \mathbf{w}, \mathbf{x}_i \rangle + b) \geq 1 - \xi_i,\ \xi_i \geq 0,\ \forall i \in [1, \ldots, N]$.

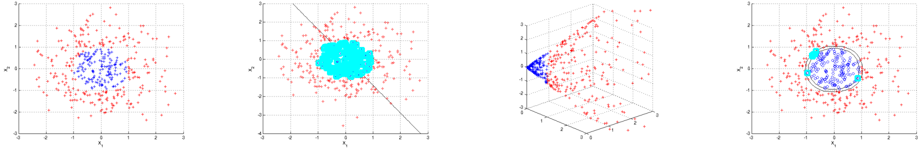


- The resulting classification rule is:

$$y_u = sgn\left(\sum_{i=1}^{N} y_i \alpha_i \langle \mathbf{x}_i, \mathbf{x}_u \rangle + b\right)$$

- Multiclass problems are solved by combining several binary classifiers
- Kernel methods increase the classification capability:

$$\langle \Phi(\mathbf{x}_i), \Phi(\mathbf{x}_j) \rangle = k(\mathbf{x}_i, \mathbf{x}_j)$$



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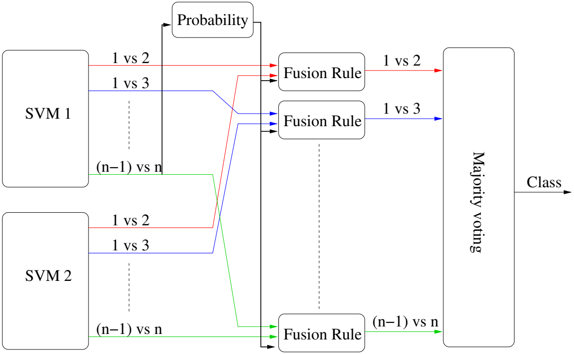
Decision rules should take into account:

- the SVMs' output characteristics (distance to the hyperplane):
  - signed numbers
  - not bounded
- the agreement of the classifier:
  - seen as a probability



Absolute maximum decision fusion rule:

$$d_{ij}^{f} = AbsMax(d_{ij}^{1}, d_{ij}^{2})$$

where *AbsMax* is the set of logical rules:

$$\begin{array}{rcl} \textbf{if}(|d_{ij}^{1}| > |d_{ij}^{2}|) & \textbf{then} & d_{ij}^{1} \\ \textbf{else if}(|d_{ij}^{2}| > |d_{ij}^{1}|) & \textbf{then} & d_{ij}^{2} \end{array}$$

The probability is computed by:

$$p_i^1 = \frac{2}{m(m-1)} \sum_{j=0, j\neq i}^{m} I(d_{ij}^{1})$$

Final fusion rule:

$$d_{ij}^{f} = AbsMax\left(\max(p_i^1, p_j^1)d_{ij}^{1}, \max(p_i^2, p_j^2)d_{ij}^{2}\right)$$

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Real hyperspectral data (ROSIS sensor):

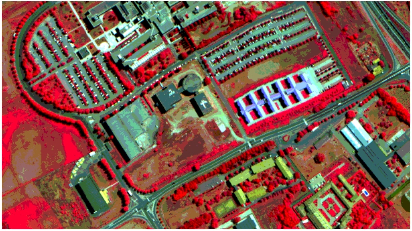
- Spectral data, 103 bands
- Extended morphological profile, 63 bands

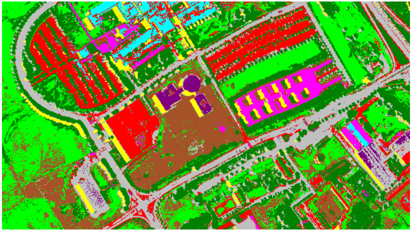
Three combination scheme were investigated:

- Our proposed fusion rule
- The *AbsMax* rule, without probability
- Majority voting

Classification accuracies:

	Spect.	PCA+EMP	Abs. Max.	A.M.+Prob.	Maj. Vot.
OA	80.99	85.22	89.56	**89.65**	86.07
AA	88.28	90.76	93.61	**93.70**	88.49
Kappa	76.16	80.86	86.57	**86.68**	81.77





Classes description: asphalt, meadow, gravel, tree, metal sheet, bare soil, bitumen, brick, shadow.

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Some Conclusions:

- Decision fusion for SVMs classifier has been discussed
- The absolute maximum perform well
- Unsupervised fusion scheme

Some perspectives:

- Test the method on other data
- Include some information about the generalization ability of the SVMs classifiers

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