Spatial and Spectral Methods for the Classification of Urban Hyperspectral Data

Mathieu Fauvel

mathieu.fauvel@gipsa-lab.inpg.fr

gipsa-lab/DIS, Grenoble National Polytechnical Institute - INPG - FRANCE
Department of Electrical and Computer Engineering, University of Iceland - ICELAND

INRIA Rhône-Alpes - Team MISTIS

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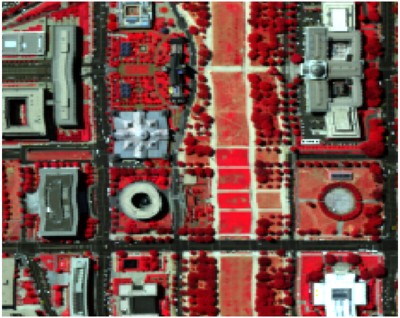
Very high resolution urban remote sensing data:

- Spatial resolution: 0.75 to 2.5 meter by pixel
- Spectral resolution: 1 to more than 200 spectral bands

Panchromatic

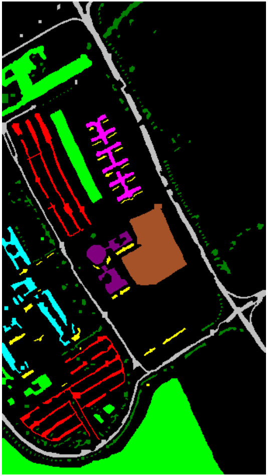


Hyperspectral

Classification: a pattern recognition approach

1. Feature extraction: one vector of attributes extracted for every pixel
2. Pattern recognition algorithms: Maximum Likelihood, Neural Network ...

Original Data



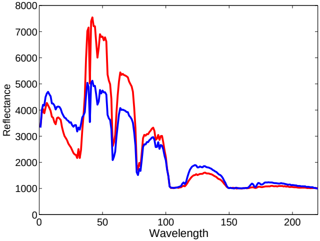
Ground-truth

Thematic Map

Data Set: *University Area*, Pavia, Italy. $[610 \times 340 \times 103]$, 1.5 m/pixel, 9 classes.

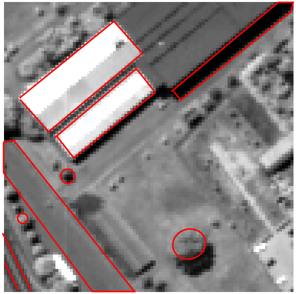
High resolution spectral information:

- ↗ Fine physical description
- ↗ Directly accessible
- ∽ Curse of dimensionality
- ↘ No contextual information



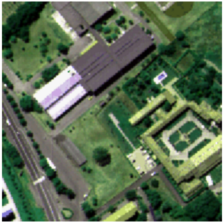
High resolution spatial information:

- ↗ Fine description of structure
- ∽ Not Directly accessible
- ↘ No spectral information

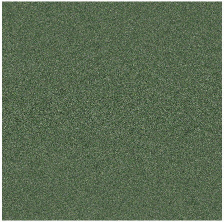


Combine the different types of information for the classification

Why?



⟶ Random permutation ⟶



Spectral classification ⟶ ⟵ Spectral classification

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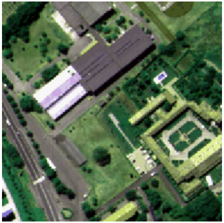

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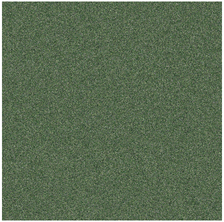

Spectral classification ⟶ Same classification !! ⟵ Spectral classification

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Need to incorporate information from the spatial domain

Combine the different types of information for the classification

How?

Prior studies: 2 steps approach

1. Feature extraction: Morphological processing
2. Classification: Neural Network, Fuzzy Logic

Contribution:

1. Feature extraction: Extraction of
   - Contextual information (self-complementary filter)
   - Spectral feature (KPCA)
2. Classification:
   - Support Vector Machines
   - Transferability of the hyperplane
3. Data Fusion:
   - at data level
   - at decision level

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Outline:

Supervised classification

Learn from samples:

- Generated from an unknown $\mathcal{P}(\mathbf{x}, y)$

$$\mathcal{S} = \{(\mathbf{x}^1, y_1), \dots, (\mathbf{x}^\ell, y_\ell)\} \in \mathbb{R}^n \times \{-1; 1\}$$

- Find $f(\mathbf{x})$ minimizing:

$$R(f) = \int_{\mathcal{S}} l(f(\mathbf{x}), y) d\mathcal{P}(\mathbf{x}, y)$$

- $\mathcal{P}(\mathbf{x}, y)$ unknown!!

$$R_{emp}(f) = \frac{1}{\ell} \sum_{i=1}^{\ell} l(f(\mathbf{x}^i), y_i)$$

Convergence? $\ell \rightarrow +\infty$

- $\forall f,\ R_{emp}(f) \rightarrow R(f)$
- f_1 min R_{emp} and f_2 min R

$$R_{emp}(f_1) \rightarrow R(f_1) \text{ but } R(f_1) \nrightarrow R(f_2)$$

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Restriction on f

Bayesian approach: Distribution *a priori* $P(f)$ over the class $\mathcal{F}$ of function f

---

Statistical Learning Theory: Control the capacity of $\mathcal{F}$

VC Dimension h: Number of points that can be learn by a class $\mathcal{F}$ of functions f.

VC Theory: V. Vapnik and A. Chervonenkis[1]

$$R(f) \leq R_{emp}(f) + \sqrt{\frac{h\left(\log\left(2\ell/h+1\right)\right) - \log(\eta/4)}{\ell}}$$

[1] V. Vapnik and A. Chervonenkis, *The necessary and sufficient conditions for consistency in the empirical risk minimization method*, Pattern recognition and Image Analysis 1(3):283-305, 1991.

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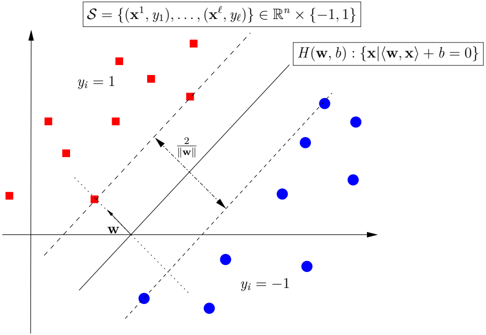
$$\boxed{\mathcal{F} = \left\{ f \middle| f(\mathbf{x}) = \langle \mathbf{x}, \mathbf{w} \rangle + b \right\} \Longrightarrow h \leq \|\mathbf{w}\|^2 \mathcal{R}^2 + 1}$$

[1] V. Vapnik and A. Chervonenkis, *The necessary and sufficient conditions for consistency in the empirical risk minimization method*, Pattern recognition and Image Analysis 1(3):283-305, 1991.

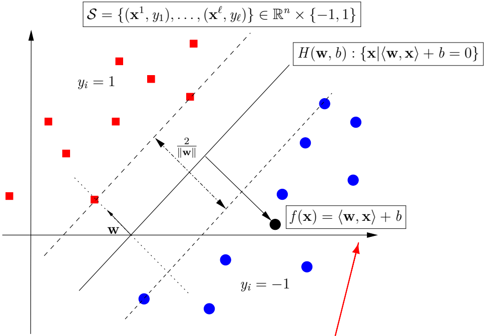


Optimal separating hyperplane[2]:

$$R(f) \leq R_{emp}(f) + \sqrt{\frac{h(\log(2\ell/h+1)) - \log(\eta/4)}{\ell}}$$

- $\min R_{emp}(f)$: Minimize training errors over $\mathcal{S}$
- $\min h$: Maximize the margin $\Longleftrightarrow$ minimize $\|\mathbf{w}\|^2$

[2] V. Vapnik, *Statistical Learning Theory*, Wiley, New York 1998.



$$\mathbf{w} = \sum \alpha_i y_i \mathbf{x}^i$$

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Decision: $g(\mathbf{x}) = \text{sgn}\left(f\left(\mathbf{x}\right)\right) = \text{sgn}\left(\sum_{i=1}^{\ell} \alpha_i y_i \langle \mathbf{x}^i, \mathbf{x}\rangle + b\right)$

[2] V. Vapnik, *Statistical Learning Theory*, Wiley, New York 1998.

Algorithm:

$$\begin{aligned} \text{minimize} \quad & \frac{\langle \mathbf{w}, \mathbf{w} \rangle_{\mathbb{R}^n}}{2} + C \sum_{i=1}^{\ell} \xi_i \\ \text{subject to} \quad & y_i \left(\langle \mathbf{w}, \mathbf{x}^i \rangle_{\mathbb{R}^n} + b \right) \geq 1 - \xi_i, \ \forall i \in 1, \dots, \ell \\ & \xi_i \geq 0, \ \forall i \in 1, \dots, \ell \end{aligned}$$

Lagrangian: $\alpha_i > 0$ et $\beta_i > 0$ Lagrange coefficients[3] .

$$L(\mathbf{w}, b, \boldsymbol{\xi}, \boldsymbol{\alpha}, \boldsymbol{\beta}) = \frac{\langle \mathbf{w}, \mathbf{w} \rangle_{\mathbb{R}^n}}{2} + \sum_{i=1}^{\ell} \alpha_i \left(1 - \xi_i - y_i \left(\langle \mathbf{w}, \mathbf{x}^i \rangle + b \right) \right) - \sum_{i=1}^{\ell} \beta_i \xi_i + C \sum_{i=1}^{\ell} \xi_i$$

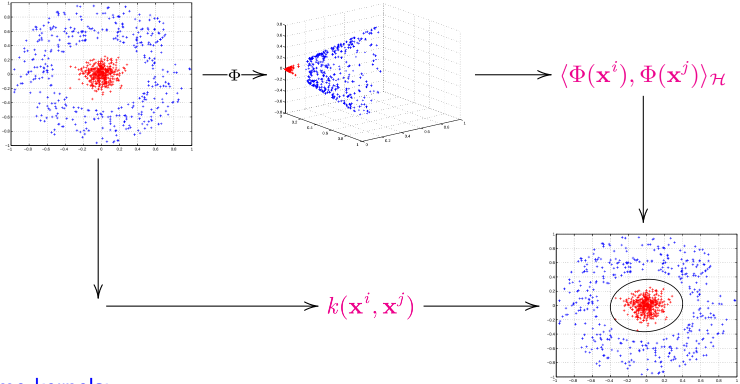
Dual formulation :

$$\begin{aligned} \max_{\alpha} \ g(\alpha) \quad &= \quad \sum_{i=1}^{\ell} \alpha_i - \frac{1}{2} \sum_{i,j=1}^{\ell} \alpha_i \alpha_j y_i y_j \langle \mathbf{x}^i, \mathbf{x}^j \rangle_{\mathbb{R}^n} \\ \text{subject to} \quad & \quad 0 \leq \alpha_i \leq C \\ & \quad \textstyle\sum_{i=1}^{\ell} \alpha_i y_i = 0 \end{aligned}$$

[3] S. Boyd and L. Vandenberghe. *Convex Optimization*, Cambridge University press, 2006.

Kernel methods: Use kernel function k (positive semi-definite)

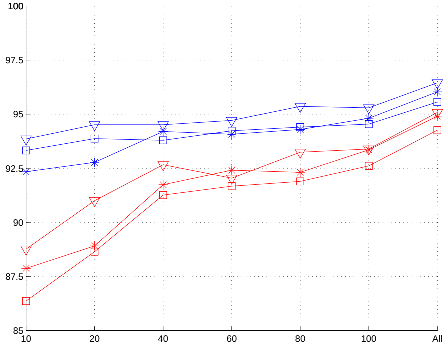
$$k(\mathbf{x}^i, \mathbf{x}^j) = \langle \Phi(\mathbf{x}^i), \Phi(\mathbf{x}^j) \rangle_{\mathcal{H}}$$



Some kernels:

$$\begin{aligned}
\text{Polynomial kernel:} \quad k(\mathbf{x}^i, \mathbf{x}^j) &= \left(\langle \mathbf{x}^i, \mathbf{x}^j \rangle + q\right)^p \\
\text{Gaussian kernel:} \quad k(\mathbf{x}^i, \mathbf{x}^j) &= \exp\left(-\gamma \|\mathbf{x}^i - \mathbf{x}^j\|^2\right) \\
\text{Spectral kernel:} \quad k(\mathbf{x}^i, \mathbf{x}^j) &= \exp\left(-\gamma \arccos\left(\frac{\langle \mathbf{x}^i, \mathbf{x}^j \rangle}{\|\mathbf{x}^i\| \|\mathbf{x}^j\|}\right)^2\right)
\end{aligned}$$

Training set: 10 to 100 samples by class. Testing set: 103.504 samples.



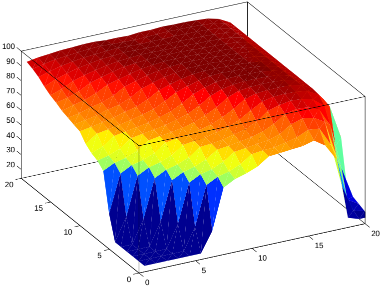
▽ Gaussian kernel, ∗ polynomial kernel and □ spectral kernel[4] .
Average accuracy | Overall accuracy

	Gaussian Kernel			
	SVM (90)	SVM (900)	SVM (5.536)	GML(5.536)
OA (%)	93,8	95,3	96,5	93,8
AA (%)	88,8	93,4	95,1	90,8

[4] M. Fauvel, J. Chanussot and J. A. Benediktsson *Classification of hyperspectral remote sensing images with support vectors machines*, in IEEE-ICASSP-06, May 2006, Toulouse.

Hyperparameters setting: Gaussian kernel $\Rightarrow \mathbf{p} = [\gamma, C]$

- Cross-validation: $-1 \leq \mathbf{x} \leq 1 \Rightarrow C \gg 1\ (\approx 200)$ and $\gamma \in \{0.5,\ 1,\ 2,\ 4\}$



- Error bound $\mathfrak{T}$ [5]: $R(f) \leq \mathfrak{T}(\mathbf{p})$

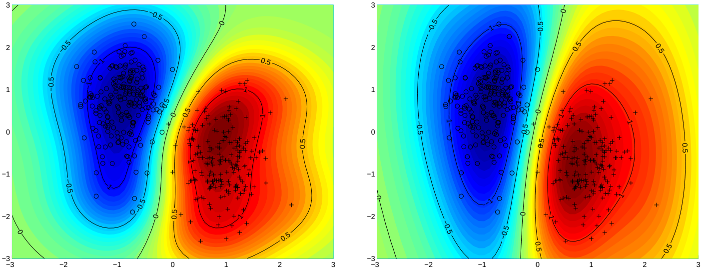
Radius-Margin Bound - $\mathfrak{T}(\mathbf{p}) := \|\mathbf{w}\|^2 \mathcal{R}^2$

$$\textbf{grad}\left(\mathfrak{T}(\mathbf{p})\right) = \begin{bmatrix} \frac{\partial \mathfrak{T}}{\partial C} \\ \frac{\partial \mathfrak{T}}{\partial \gamma} \end{bmatrix} = \begin{bmatrix} \frac{\partial \|\mathbf{w}\|^2}{\partial C}\mathcal{R}^2 + \frac{\partial \mathcal{R}^2}{\partial C}\|\mathbf{w}\|^2 \\ \frac{\partial \|\mathbf{w}\|^2}{\partial \gamma}\mathcal{R}^2 + \frac{\partial \mathcal{R}^2}{\partial \gamma}\|\mathbf{w}\|^2 \end{bmatrix}$$

[5] O. Chapelle, V. Vapnik, O. Bousquet and S. Mukherjee, *Choosing Multiple Parameters for Support Vector Machines*, Machine Learning 1(46):131-159, 2002.

Multiple hyperparameters setting: Gaussian kernel with adapted brandwith

$$k(\mathbf{x}^i, \mathbf{x}^j) = \exp\left(-\sum_{k=1}^{n} \gamma_k (x_k^i - x_k^j)^2\right)$$



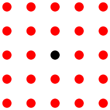
$\dim(\gamma) = 1$ $\dim(\gamma) = 2$

University data set:

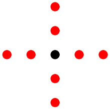
Model selection	CV	Gradient	
		$\dim(\gamma) = 1$	$\dim(\gamma) = 103$
OA(%)	95.58	94.19	93.87
N° Optim.	30	15	24

Markov Random Field [Lafarge-05]: fixed neighborhood (cliques)

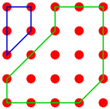
Contextual features [Camps-Valls-06; Bruzzone-06]: fixed neighborhood ($p \times p$ square)



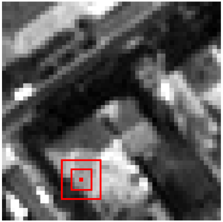
Texture features [Mercier-06] : two 1-D wavelets (on x and y)



Morphological processing [Benediktsson-03]: structures



Not well suited to urban area data: discontinuity (no stationarity)



Morphological Neighborhood: adapt the neighborhood to the structures

- Previous works: Granulometry with geodesic filters (Morphological profile and its derivative).

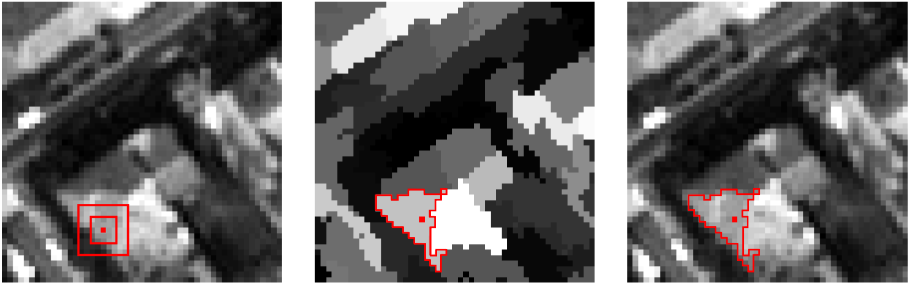
Acts only on extrema structures

- Proposed works: Self-complementary filters.

Acts on structures whatever their gray-level

Self-complementary area filter[6] : Remove all the structures that are smaller than a given area threshold

1. Labelling all the flat zones that satisfy the area criterion λ
2. Growing the labelled flat zones until an image partition is reached



[6] P. Soille, *Beyond self-duality in morphological image analysis*, Image and Vision Computing 2:249-257, 2005

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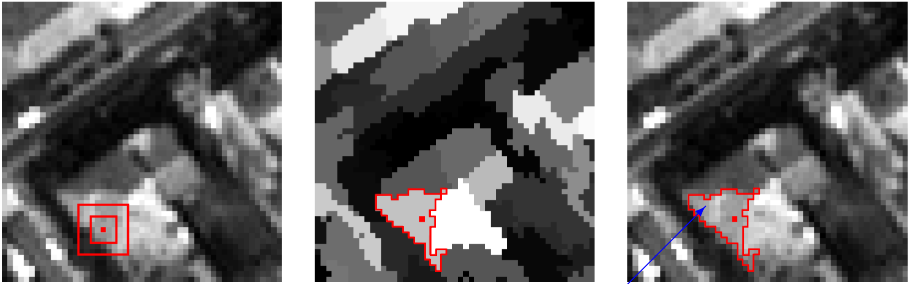

Extracting the inter-pixel dependency :

$$\Upsilon_{\mathbf{x}} = \text{med}(\Omega_{\mathbf{x}})$$

[6] P. Soille, *Beyond self-duality in morphological image analysis*, Image and Vision Computing 2:249-257, 2005

How to use conjointly the spatial and the spectral information?

- Kernel approach: mixture of kernels
- SVM classifier

Combination of kernels: Spatio-spectral kernel (SS kernel)

$$K = \mu k^{spect} + (1 - \mu) k^{spat}$$

- k^{spect} acts on the spectral information
- k^{spat} acts on the spatial information
- μ control the amount of each type of information

Extension to hyperspectral data?

Ordering relation for pixels is needed: does not exit.

- Marginal ordering $\Rightarrow$ by band filtering
- Total Pre-ordering $\Rightarrow h : \mathbb{R}^n \rightarrow \mathbb{R}^1$

Our approach: Dimension reduction with PCA[7].

1. Projection on the first PC
2. Area filtering and generalization of the neighborhood mask for each band
3. Spatial feature extraction
4. Classification with SS SVM

$$\begin{array}{rcl} h : \mathbb{R}^n & \rightarrow & \mathbb{R}^1 \\ \mathbf{x} & \mapsto & x = \langle \mathbf{x}, \mathbf{v}_p^1 \rangle_{\mathbb{R}^n} \end{array}$$

[7] M. Fauvel, J. Chanussot and J. A. Benediktsson *Adaptive pixel neighborhood definition for the classification of hyperspectral images with support vector machines and composite kernels*, in IEEE-ICIP-08, October 2008, San Diego.

Classification using spectral and spatial information:

Spectral EMP SS SVM

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

Classification accuracies:

%	SVM	EMP	SS SVM
Overall Accuracy	80	80	**86**
Average Accuracy	88	85	**92**
Kappa coefficient	75	74	**82**
Asphalt	80	**93**	84
Meadow	68	73	**78**
Gravel	74	52	**84**
Bare soil	**95**	62	**95**

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$\Downarrow$

Data Fusion

Spatial information is helpful

Benefits

- Adaptive neighborhood definition
- Kernel formulation
- Performance for peri-urban area

Drawbacks

- Parameters λ (area threshold) and μ (weight in SS kernel)
- Statistical spatial information only
- Extension to multi- or hyperspectral data

Some results

Pavia Center $[1096 \times 610 \times 102]$

Original

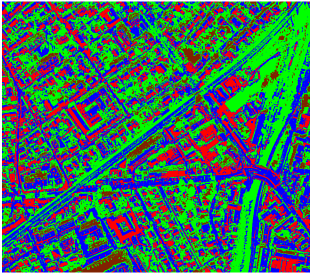
SVM (98.06%)

SS SVM(98.43%)

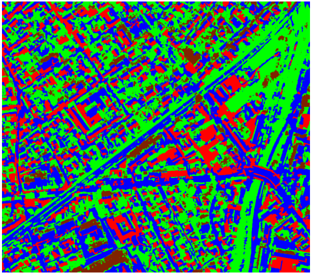
Some results

Toulouse $[886 \times 780 \times 1]$

Original



SVM (76.99%)



SS SVM (82.25%)

Support Vector Machines
- Optimal Separating Hyperplane
- Hyperparameters Selection
- Using spatial information with SVM

Multiple Classifiers - Fusion of SVM
- Problem formulation
- Fuzzy Fusion: application to SVM
- Multisource Markov Fusion

Conclusions and Perspectives

Different classifiers:

- Statistic Theory: Gaussian Maximum Likelihood, Fisher Discriminant Analysis...
- Machine learning Theory: Neural Network, Support Vector Machines...
- Fuzzy Set Theory: Fuzzy NN, Fuzzy model...

Different sources:

- Panchromatic and multispectral data
- Multi-valued data
- Multi-temporal data
- Extracted data: texture or geometrical features

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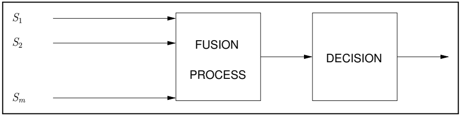
Complementary information

Decision fusion scheme (for classification):

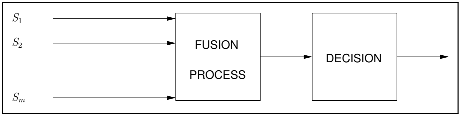


Problems:[8]

- Sources of different natures
- Sources of different reliabilities
- Conflicting situations

[8] M. Fauvel, J. Chanussot and J. A. Benediktsson *Decision fusion for the classification of urban remote sensing images*, in IEEE-Trans. Geosci. Remote Sens., Vol. 44, N$^{\circ}$ 10,October 2006.

Decision fusion scheme (for classification):



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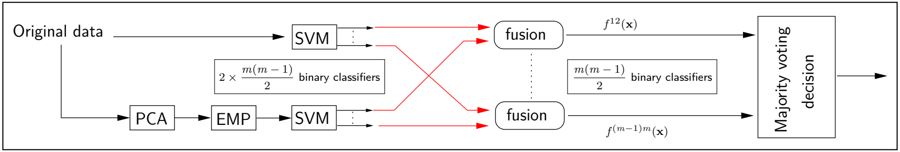
SVM fusion scheme:



SVM output: distance to the hyperplane $f(\mathbf{x})$

- sign numbers
- not bounded

[9] M. Fauvel, J. Chanussot and J. A. Benediktsson *A Joint Spatial and Spectral SVMs Classification of Panchromatic Images*, in IEEE-IGARSS, July 2007, Barcelona.

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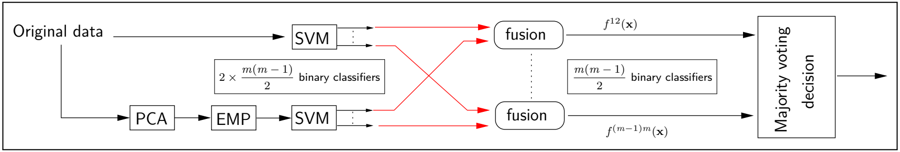

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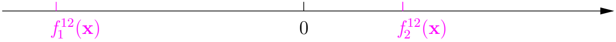
Fusion rule:[9]

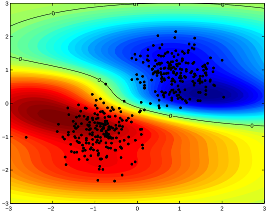
The greater the distance to the hyperplane, the more reliable the source

$$f^{ij}(\mathbf{x}) = \text{maxabs}\left(f_1^{ij}(\mathbf{x}), f_2^{ij}(\mathbf{x})\right)$$

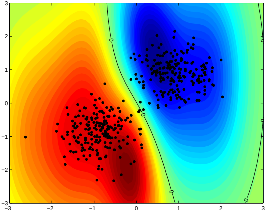


[9] M. Fauvel, J. Chanussot and J. A. Benediktsson *A Joint Spatial and Spectral SVMs Classification of Panchromatic Images*, in IEEE-IGARSS, July 2007, Barcelona.

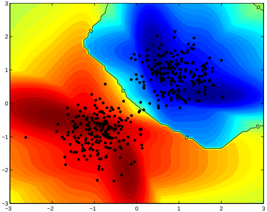
Fusion - Toy example:



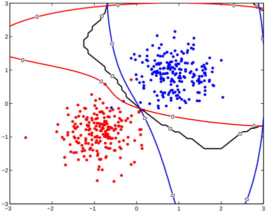
$f_1^{ij}(\mathbf{x})$



$f_2^{ij}(\mathbf{x})$



$f^{ij}(\mathbf{x})$



Fusion - real example:

	SVM	EMP	Decision fusion	Majority Voting
Overall Accuracy	81	85	**90**	86
Average Accuracy	88	91	**94**	88
Kappa coefficient	76	81	**87**	82
Asphalt	84	**95**	93	94
Meadow	70	80	84	**85**
Gravel	70	**88**	82	65
Bare soil	**92**	64	91	62

SVM

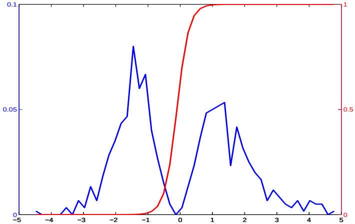
EMP

Decision fusion

Still spatial aberration : regularization

- $f(\mathbf{x}) \longrightarrow p(y=1|\mathbf{x}) = \dfrac{1}{1+\exp(Af(\mathbf{x})+B)}$
- Potts model: $\mathcal{U}(y|\mathbf{x}) = \sum_s \log\left(p\left(y_s=1|\mathbf{x}_s\right)\right) + \beta \sum_{s,t} \phi(y_s, y_t)$
- Gibbs sampler with temperature: simulated annealing

$$P_T(Y=y) = \frac{1}{Z(T)} \exp\left(-\frac{\mathcal{U}(y|\mathbf{x})}{T}\right)$$



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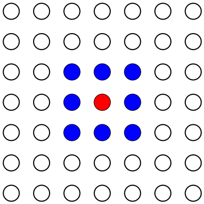

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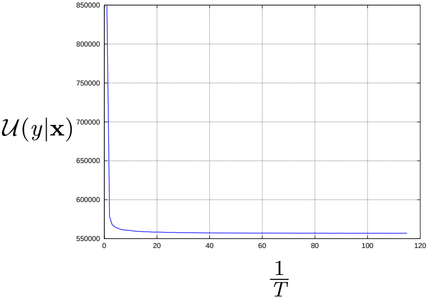
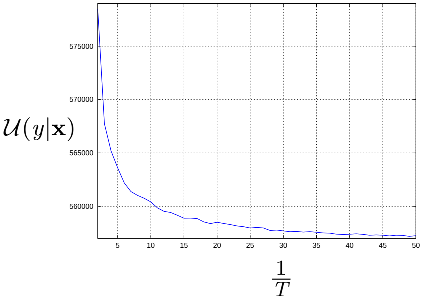
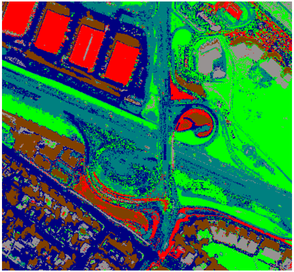
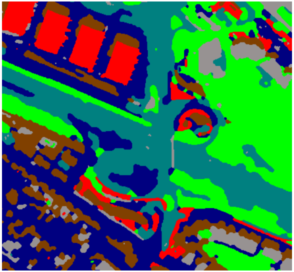


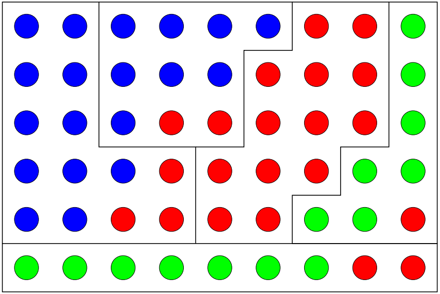


OA	80 %	83 %
AA	88 %	89 %
κ	75 %	79 %





OA	77 %	82 %
AA	78 %	84 %
κ	72 %	78 %



- Multi-scale model: $\mathcal{U}(\text{within connected set}) + \mathcal{U}(\text{between connected set})$
- Optimization algorithm and parameters setting?

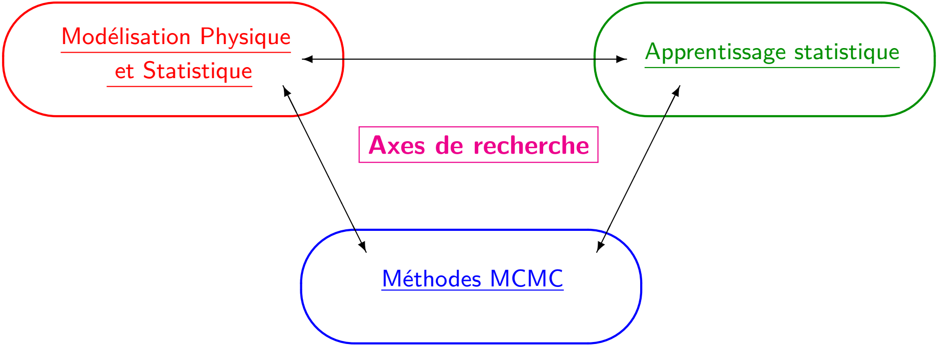
Classification of hyperspectral urban data

- High dimensional space: Support Vectors Machines
- Spatial and Spectral information:
  1. Neighbors definition
  2. Mixture of kernels
- Fusion of complementary classifiers
  1. Estimation of the reliability
  2. Appropriate fusion scheme

Ongoing works

- Spatial information:
  - Geometric and textural feature
  - Segmentation and regularization
- Definition of new kernel
  - Kernel for hyperspectral data
  - Use of semi-supervised SVM
- Errors bound estimation (Radius Margin Bound)
- Markov regularization on primitive graph: multi-scale approach

Traitement des signaux multicomposantes et multicapteurs à très grande dimension



Applications: Images et signaux vectoriels, séparation de sources, classification, apprentissage semi-supervisé, extraction de caractéristiques, réseau et coopération multicapteurs.

Spatial and Spectral Methods for the Classification of Urban Hyperspectral Data

Mathieu Fauvel

mathieu.fauvel@gipsa-lab.inpg.fr

gipsa-lab/DIS, Grenoble National Polytechnical Institute - INPG - FRANCE
Department of Electrical and Computer Engineering, University of Iceland - ICELAND

INRIA Rhône-Alpes - Team MISTIS

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