



Improvements to Expectation-Maximization Approach for Unsupervised Classification of Remote Sensing Data

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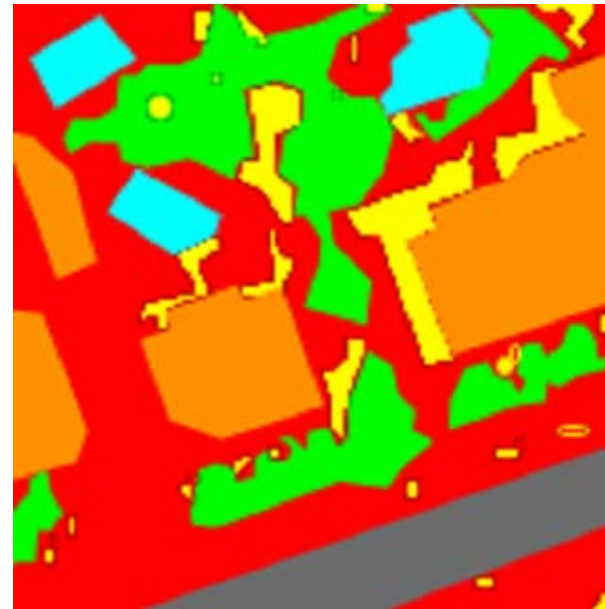
and

Luciano Dutra, Leila Fonseca

Guaraci Erthal, Felipe Silva

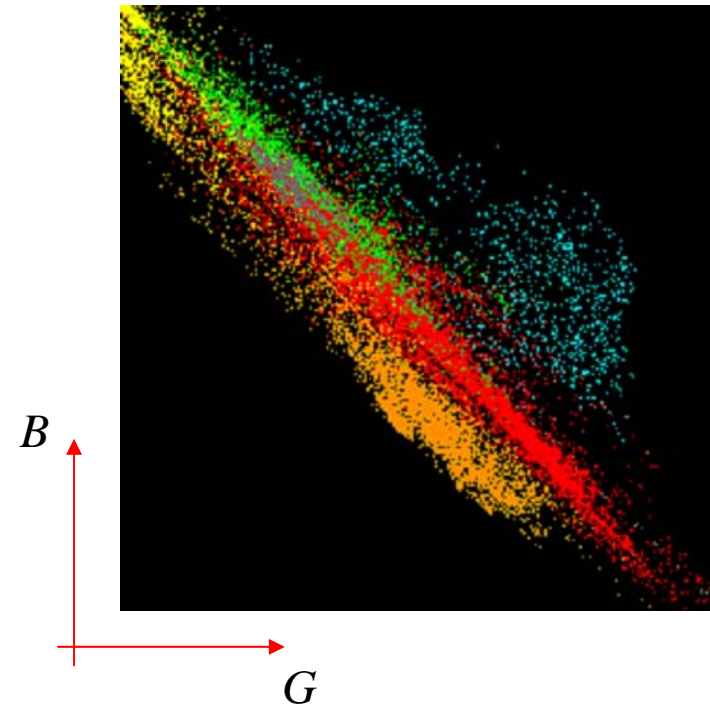
Introduction

- Color compositions of remote sensing imagery changes gradually according (x, y) axis



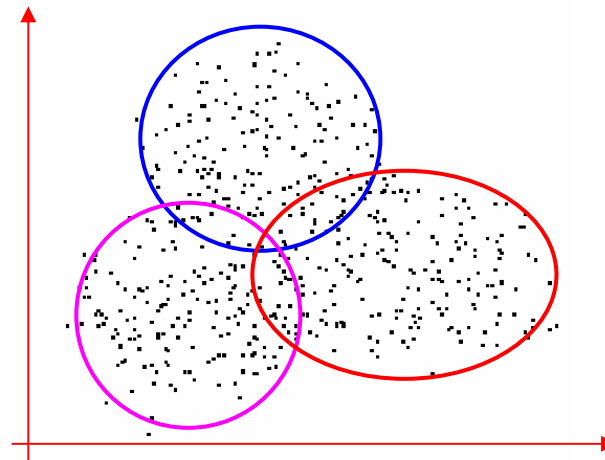
Introduction

- Linear classification is not enough



Introduction

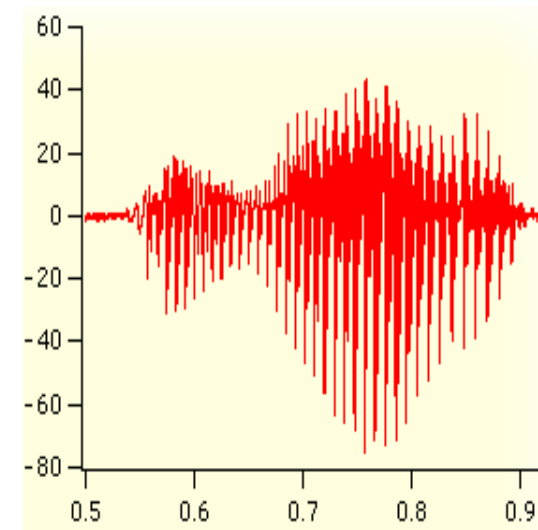
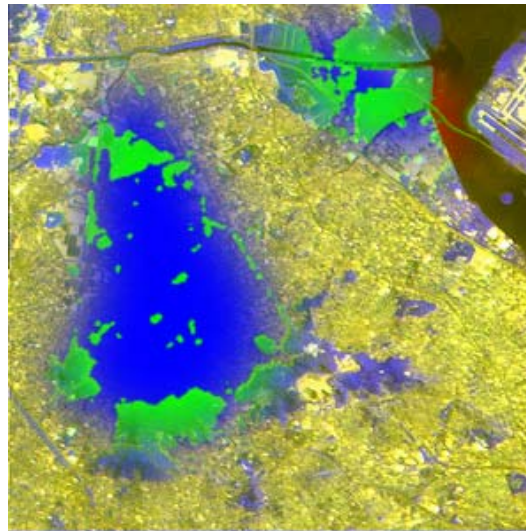
- Data points have membership in one data distribution → firstly unknown
- *Expectation-Maximization* (EM) algorithm



The EM algorithm

- EM is an iterative procedure, that estimates the probabilities from a set of clusters
- Input formed by the image pixels
- The parameters are the *mean* and *variance*

EM applications



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The standard EM

- Each class is characterized by mean and variance of pixels
- Based on the Bayesian theory
 - Input data is composed by N vectors

$$\mathbf{x}_k, k = 1, \dots, N$$

- Aims to estimate M clusters

$$C_j, j = 1, \dots, M$$

- Calculates probabilities

$$P(C_j | \mathbf{x}_k)$$

Computing EM

- Successive parameter estimation

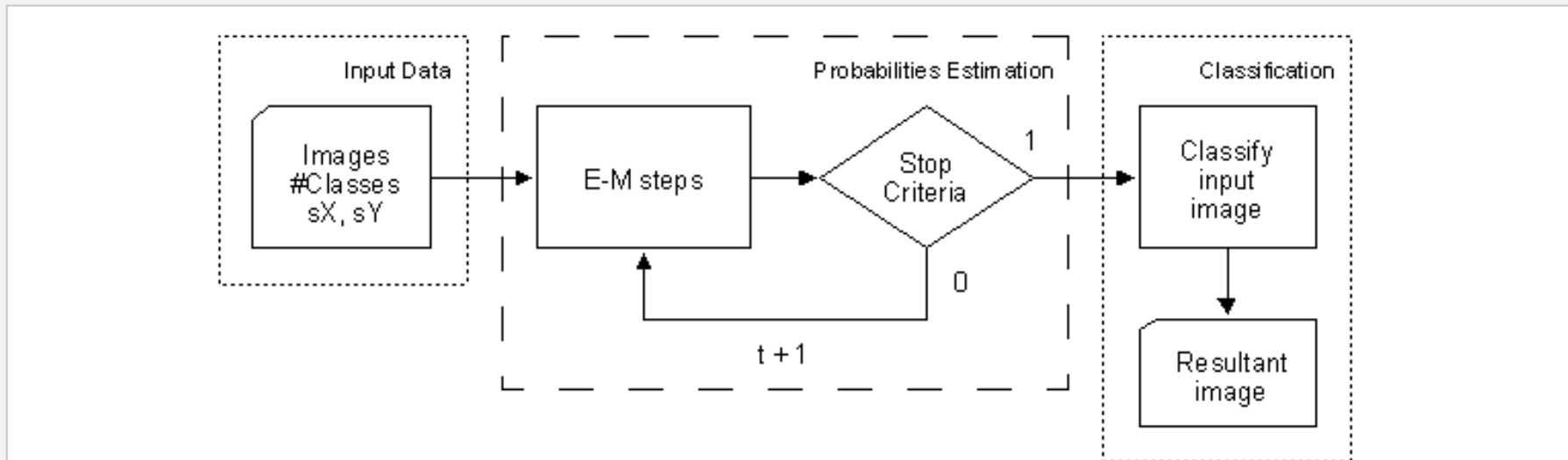
$$\hat{\theta}(t) = \{\mu_j(t), \Sigma_j(t)\}$$

$$j = 1, \dots, M$$

$$t = 0, 1, \dots$$

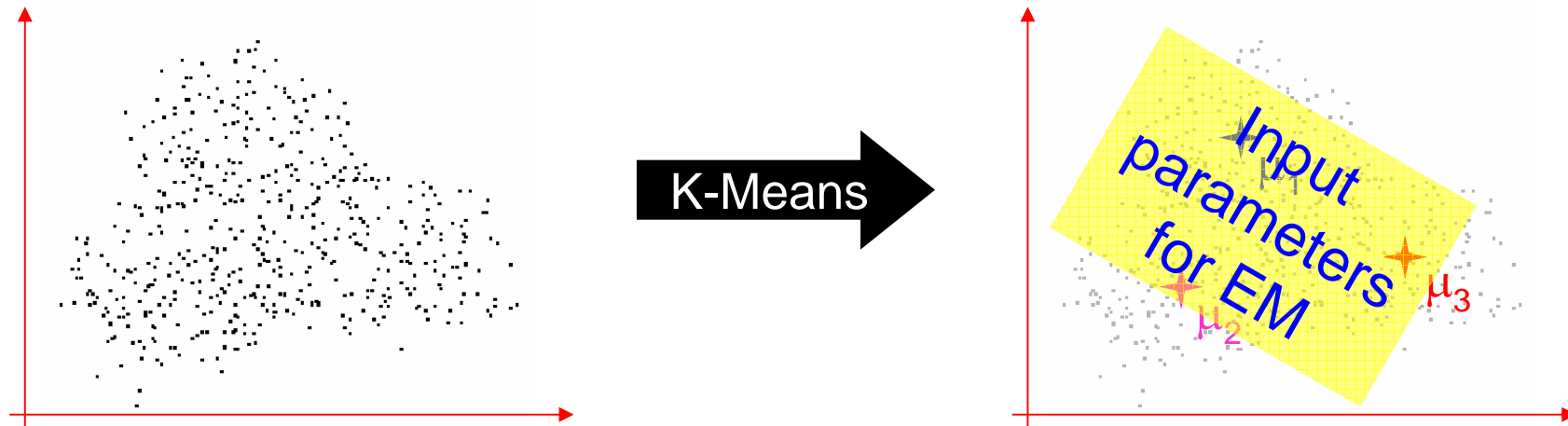
- E-step (Expectation)
 - Calculates *a posteriori* probabilities function
- M-step (Maximization)
 - Updates estimates of $\hat{\theta}(t)$

Improving the approach

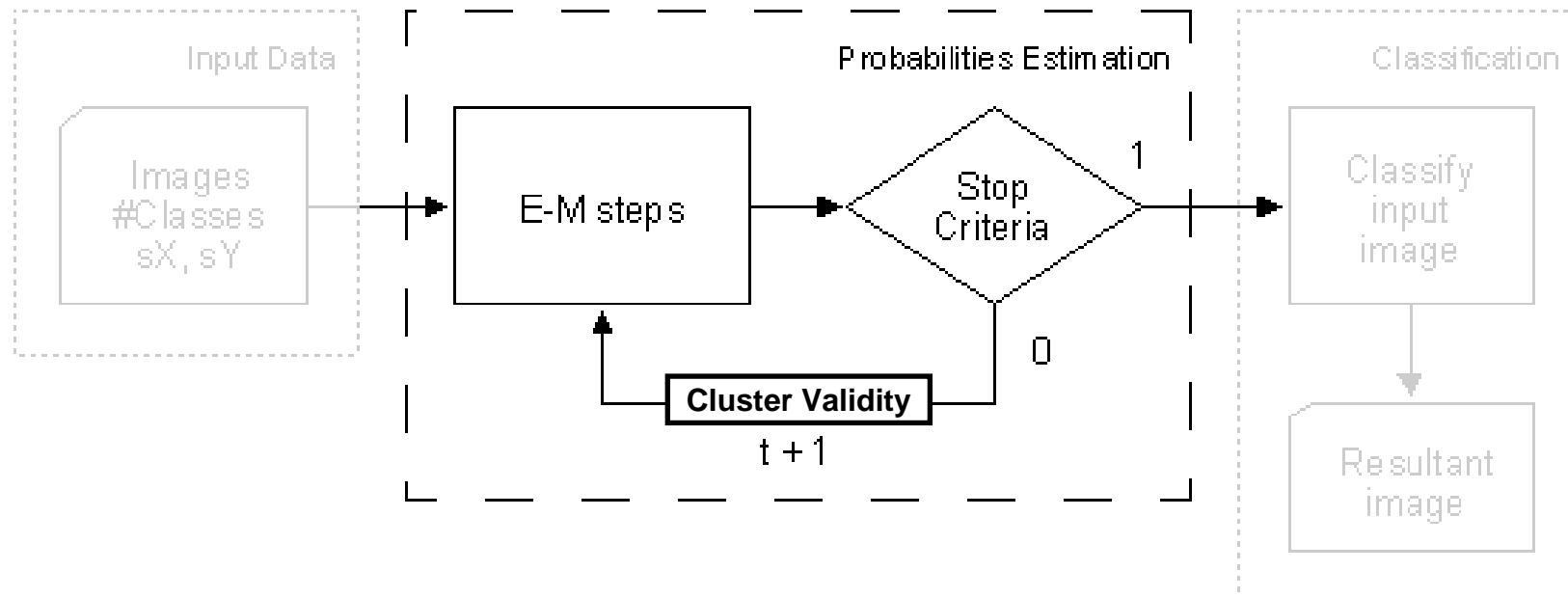


- Drawbacks
 - Random initial parameters
 - Iterative procedure can be time consuming
 - Local *minima* may prejudice results

Improving the approach – Hypothesis



Improving the approach – Cluster validity



Cluster Validity

- Performed at each iteration
- If two clusters are *close* to each other
 - Randomly modifies one of them
- If some cluster has *low* probability
 - Exclude cluster
- Thresholds (*close* and *low*) provided by the user

Results – 0

- Manual classification used as reference
- Three methods compared
 - Improved EM
 - K-Means
 - Maximum Likelihood

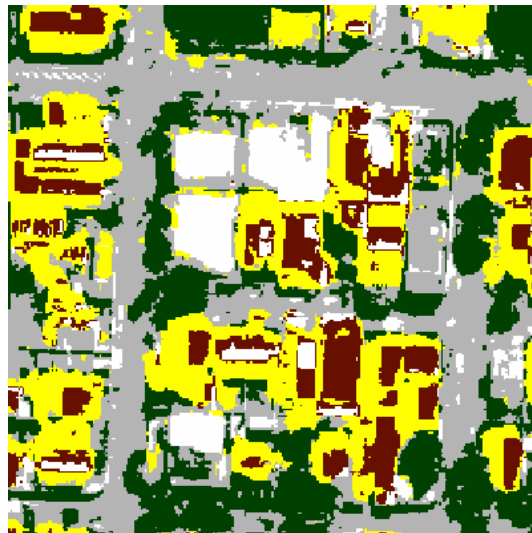
Results – 1

- Urban area of São José dos Campos

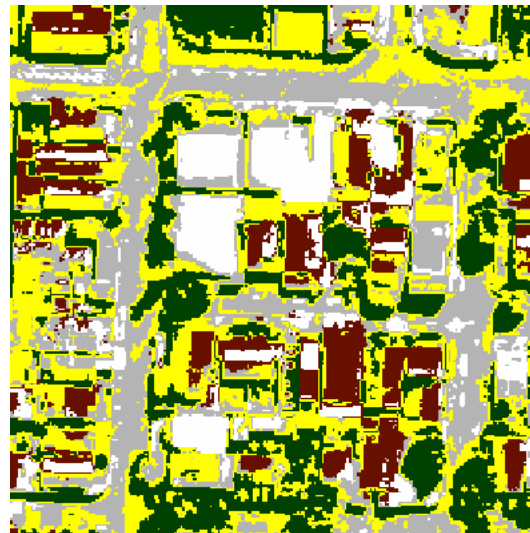


Comparison – Other approaches

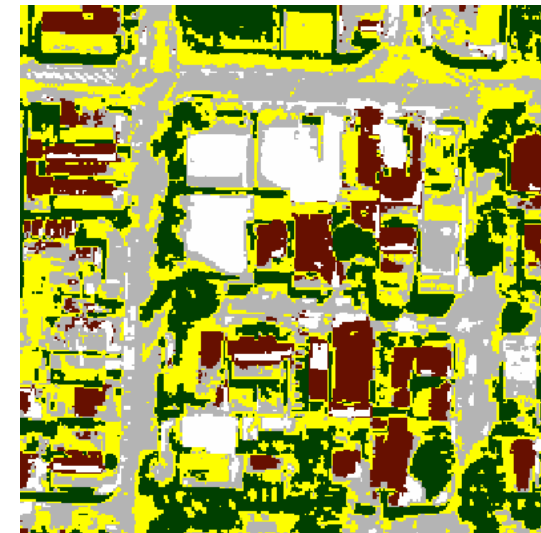
Improved EM



K-Means



ML



Comparison – Original x Improved

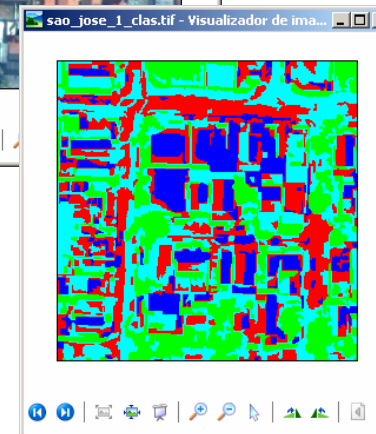
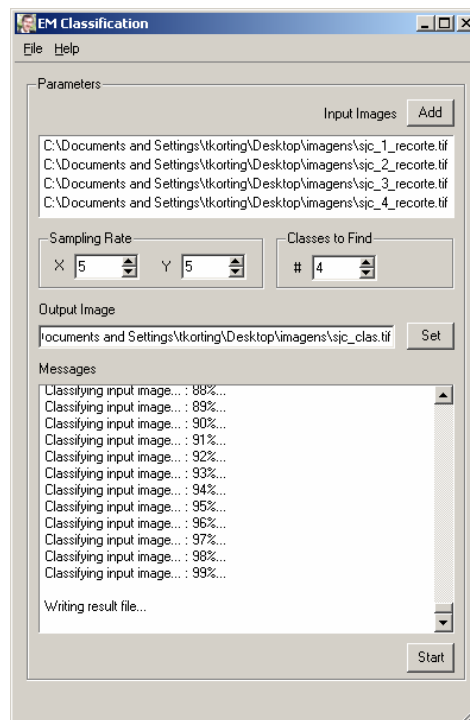
	Image1	Image2	Image3	Image4	Image5
Image size	512 × 512	512 × 512	200 × 200	512 × 384	264 × 377
# of classes	4	4	5	6	5
Δt_1 original EM	467s	467s	103s	402s	202s
Δt_2 improved EM	140s	148s	29s	105s	70s
$\Delta t_1/\Delta t_2$	3.335	3.155	3.551	3.828	2.885

Conclusion

- Improved EM approach presented
 - Uses K-Means results as input
 - Performs Cluster Validation
 - Runs ~3x faster than original EM
- EM has smooth convergence
 - Invulnerable to instabilities
 - Wrong initial parameters can decrease performance

Conclusion

- Implementation using TerraLib (3.2.0 RC1)
- GUI → <http://www.dpi.inpe.br/~tkorting>





END

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