Hidden Markov Models Applied in Agricultural Crops Classification

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Hidden Markov Models Applied in Agricultural Crops Classification
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Introduction
Who is growing what and where?
Reliable, up-to-date information about agricultural activities:
- Support (global and local) strategic decisions
- Development of commercial plans
- Decisions regarding subsidies
- Regulation of internal stocks
- Price formation
- …

Introduction
How can RS and OBIA be used to classify crops?
Basic problems
- Different crops may look similar in a RS image.
- The same crop may look different in different parts of the year.

Proposed approach
- Object based image analysis – segments instead of pixels.
- Multitemporal analysis – images of the same region at different points in time.
- Classification model explores knowledge of phenological cycles.
- Probabilistic tool: Hidden Markov Model.
Objectives

General
- Evaluate the potential of Hidden Markov Models for classification of agricultural crops from RS temporal image sequences.

Specific
- Develop an HMM-based method to identify different agricultural crops.
- Evaluate the proposed method with a sequence of medium resolution satellite images.

Plant Phenology

- The study of periodic plant life cycle events

Plant Phenology

- Plant phenology describes the life cycles of different species.
- Can be used to differentiate crops:
  - Some crops take longer to grow or to achieve maturity;
  - Some crops have short cycles: annual crops (corn, soybean);
  - Some crops are semi-perennial (sugar-cane).
- Plant life cycles can be divided into phenological stages.

Markov Models

Markov Models
- Memoryless processes (Markov property): given the present state, future states are independent of the past states.
  \[ \Pr(X_{t+1} = x \mid X_1 = x_1, X_2 = x_2, ..., X_t = x_t) = \Pr(X_{t+1} = x \mid X_t = x_t) \]
- Markov Chain
  - Probability of going from one state to another is given by transition probabilities.
    \[ \Pr(X_{t+1} = S_j \mid X_t = S_i) = a_{ij} \]
Markov Models

Markov Models
- Memoryless processes (Markov property): given the present state, future states are independent of the past states.

\[
\Pr(X_{t+1} = x | X_t = x_t, X_{t-1} = x_{t-1}, \ldots, X_0 = x_0) = \Pr(X_{t+1} = x | X_t = x_t)
\]

Markov Chain
- Probability of going from one state to another is given by transition probabilities.

\[
A = \begin{bmatrix}
0 & a_{12} & a_{13} & a_{14} \\
a_{21} & 0 & a_{23} & a_{24} \\
a_{31} & a_{32} & 0 & a_{34} \\
a_{41} & a_{42} & a_{43} & 0
\end{bmatrix}
\]

Markov Models

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Markov Chain
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A = \begin{bmatrix}
0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 \\
a_{41} & 0 & 0 & 0
\end{bmatrix}
\]

Markov Models

Hidden Markov Model (HMM)
- States are not directly observable: they emit symbols with \( b_k \) probabilities.

\[
S_i \rightarrow \text{State} \\
b_{ij} \rightarrow \text{Transition probability} \\
b_j \rightarrow \text{Symbol emission probability} \\
v_k \rightarrow \text{Possible observation}
\]

- A Hidden Markov Model is defined as \( \lambda = (A, B, \pi) \), where \( \pi \) is the a-priori probability that the system is in a given state \( S_i \) at the initial time instant.

Methodology

General Model
- Each crop class has its own model.
- States correspond to phenological stages:

- sugarcane
- soybean
- corn
- riparian forest
- pasture

- Observable symbols are vectors with the digital numbers of each spectral band plus the NDVI.
Methodology

Problem deviates from basic HMM description
- Images not available for all epochs – observations are not made at regular intervals.
- Each crop has preferential months for sowing – a-priori probability distribution ($\pi$) is not constant along the year.
- Symbol emission probabilities ($b_j$) depend on seasonal effects that cannot be fully compensated in the image pre-processing phase.

Methodology

Fitting the Model to the Application
- $A$, $B$, $\pi$ are estimated for each pair of images.
- We assumed a Gaussian distribution for the symbol emission probabilities.

Methodology

Emission probability density of a symbol $x$ (a vector consisting of the spectral bands and NDVI):

$$ p = \frac{1}{(2\pi)^{d/2}|\Sigma|^{1/2}} \exp \left(-\frac{1}{2} (x - \mu)^T \Sigma^{-1} (x - \mu) \right) $$

Where $\mu_{cs}$ and $\Sigma_{cs}$ denote the mean vector and the covariance matrix for crop $c$ and state $S_i$, and $d$ is the dimension of $x$.

Methodology

Classification

<table>
<thead>
<tr>
<th>Image Sequence</th>
<th>Segmentation</th>
<th>Feature Extraction</th>
<th>Reference Classification</th>
<th>HMM</th>
</tr>
</thead>
<tbody>
<tr>
<td>Crop Class $c$</td>
<td></td>
<td></td>
<td></td>
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</tbody>
</table>

HMM parameters estimation

<table>
<thead>
<tr>
<th>Image Sequence</th>
<th>Segmentation</th>
<th>Feature Extraction</th>
<th>HMM parameters Estimation</th>
<th>Reference Classification</th>
</tr>
</thead>
<tbody>
<tr>
<td>Crop Class $c$</td>
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</tbody>
</table>
Experiments

Study Area: Northern São Paulo State (Brazil)

Reference data: visual interpretation plus two field works

- Classification of segments enclosing reference points.

Image Sequence: 12 Landsat 5/7 images

Results

- Classification of segments enclosing reference points.
- Using mean DN and NDVI of pixels inside segments for HMM parameter estimation.

<table>
<thead>
<tr>
<th>States Classification</th>
<th>Rates (%)</th>
<th>Confusion Matrix (States)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Adult phase (AD)</td>
<td>80</td>
<td></td>
</tr>
<tr>
<td>Prepared soil (PS)</td>
<td>90</td>
<td></td>
</tr>
<tr>
<td>Riparian forest (RF)</td>
<td>80</td>
<td></td>
</tr>
<tr>
<td>Sugarcane (SC)</td>
<td>80</td>
<td></td>
</tr>
</tbody>
</table>

<table>
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<tr>
<th>Crops Classification</th>
<th>Rates (%)</th>
<th>Confusion Matrix (Crops)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Corn (CO)</td>
<td>77</td>
<td></td>
</tr>
<tr>
<td>Soybeans (SB)</td>
<td>77</td>
<td></td>
</tr>
<tr>
<td>Pasture (PA)</td>
<td>54</td>
<td></td>
</tr>
<tr>
<td>Sugarcane (SC)</td>
<td>77</td>
<td></td>
</tr>
</tbody>
</table>

Average class accuracy 77
Overall accuracy 75
Conclusions

- Remarkable superiority of the HMM-based method over a monotemporal maximum likelihood classification approach.
- The performance of the approach was impacted by the scarcity of training samples of some crop types.
- The approach also performed well with respect to recognition of phenological stages.
  - The exception was the Growth-Phase – symbol vectors used to characterize this stage should also take into account the variation of spectral values through time.
- Only sequences of data associated to one crop type were considered. An analysis of the behaviour of the method considering sequences with more than one crop type is planned for future.

The End

Thank you!

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