Automated Classification of Bitmap Images Using Decision Trees

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Bitmap Classification

- the task is to automatically classify bitmap images into predefined classes
- finite set of bitmap images \( J \)
- finite set of classification classes \( K \)
- for each \( t \in K \) a characterization \( d(D) \) of the class \( t \) in the natural language is given (example: „image depicting landscape“)
- the correct classification of the set of images \( J \) is defined with respect to a fixed user using a function \( c: c: J \to 2^K \) such that \( W(t) = \{d(D) | d(D) \in d(J) \land d(D) \text{ characterizes } t \} \)
- we need to learn \( c: J \to 2^K \) such that it gives the same answer as \( c \) on as many as possible images
- the condition cannot be checked for all the images
- training/testing sets are used

Selected Attributes

- attributes based on color information
  - number of colors
  - color palette
  - important for distinguishing photographs and drawings
- attributes based on edge information
  - occurrence of straight lines
  - occurrence of right angles
  - important for buildings
- three stage transformation of the image
  1. edge detection at bitmap level
  2. Hough transformation for obtaining lines expressed analytically: \( p = x \cdot \cos(\theta) + y \cdot \sin(\theta) \)
  3. segmentation of lines

Decision Trees

- the concept of decision tree is used as underlying technology
- it is crucial to propose a set of good characterizing attributes and attribute extraction techniques
- different classification classes have different important characteristics (example: straight lines are characteristic for images of buildings

Classification Classes

- drawings
- landscapes
- buildings
- photographs/not a photo
- macro objects

Experimental Evaluation

- photography
  - learning set: 115, 114, 98.15%
  - set A: 207, 243, 81.63%
  - set B: 406, 382, 74.66%
- buildings
  - color palette
  - number of local maxima in macro objects
  - histogram
- drawings
  - learning set: 104, 108, 100.00%
  - set A: 207, 251, 84.51%
  - set B: 405, 392, 83.72%

Conclusions

- modular and extensible method for image classification
- set of classification classes \( K \) can be extended
- accuracy can increased by extending the set of attributes
- software tool has been implemented
- future work
  1. run a classification system on-line
  2. allow users to give natural language descriptions

10th Mexican International Conference on Artificial Intelligence (MICAI 2011), November 2011, Puebla, Mexico