Hierarchical Classification of Diatom Images using Predictive Clustering Trees

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Outline



- Hierarchical multi-label classification system for diatom image classification
- Contour and feature extraction from images
- Predictive Clustering Trees
- Ensembles: Bagging and random forests
- Experimental Design
- Results and Discussion

Diatom image classification (1)



- Diatoms: large and ecologically important group of unicellular or colonial organisms (algae)
- Variety of uses: water quality monitoring, paleoecology and forensics



Diatom image classification (2)



- 200000 different diatom species, half of them still undiscovered
- Automatic diatom classification
 - image processing (feature extraction from images)
 - image classification (labels and groups the images)
- Labels can be organized in a hierarchy and an image can be labeled with more than one label
- Predict all different levels in the hierarchy of taxonomic ranks: genus, species, variety, and form
- Goal of the complete system: assist a taxonomist in identifying a wide range of different diatoms

Diatom image classification (3)



- Set of images with their visual descriptors and annotations
- Taxonomic rank with hierarchical structure



Contour extraction from images

- Pre-segmentation of an image
 - separate the diatom objects from dark or light debris
 - identify the regions with structured objects
 - merge nested regions
- Edge-based thresholding for contour extraction
 - locate the boundary between the objects and the background
 - produce a binary (black and white) image with the diatom contours
- Contour following
 - trace the region borders in the binary image

Feature extraction from images

- Simple geometric properties
 - length, width, size and the length-width ratio
- Simple shape descriptors
 - rectangularity, triangularity, compactness, ellipticity, and circularity
- Fourier descriptors
 - 30 coefficients
- SIFT histograms
 - Invariant to changes in illumination, image noise, rotation, scaling, and small changes in viewpoint

Predictive Clustering Trees (PCTs)

- Standard Top-Down Induction of DTs
- Hierarchy of clusters
- Distance measure: minimization of intra-cluster variance
- Instantiation of the variance for different tasks
 - Multiple targets, sequences, hierarchies



CLUS



9

- System where the PCTs framework is implemented (KULeuven & JSI)
- Available for download at
 <u>http://www.cs.kuleuven.be/~dtai/clus</u>
- The top-down induction algorithm for PCTs:

procedure $PCT(I)$ returns tree	procedure BestTest(I)
1: $(t^*, \mathcal{P}^*) = \text{BestTest}(I)$	1: $(t^*, h^*, \mathcal{P}^*) = (none, 0, \emptyset)$
2: if $t^* \neq none$ then	2: for each possible test t do
3: for each $I_k \in \mathcal{P}^*$ do	3: $\mathcal{P} = \text{partition induced by } t \text{ on } I$
4: $tree_k = PCT(I_k)$	4: $h = \operatorname{Var}(I) - \sum_{I_k \in \mathcal{P}} \frac{ I_k }{ I } \operatorname{Var}(I_k)$
5: return node $(t^*, \bigcup_k \{tree_k\})$	5: if $(h > h^*) \land \text{Acceptable}(t, \mathcal{P})$ then
6: else	6: $(t^*, h^*, \mathcal{P}^*) = (t, h, \mathcal{P})$
7: return leaf(Prototype(I))	7: return (t^*, \mathcal{P}^*)

• Selecting the tests: reduction in variance caused by partitioning the instances

PCTs for Hierarchical Multi-Label Classification



• HMLC: an example can be labeled with multiple labels that are organized in a hierarchy



PCTs for Hierarchical Multi-Label Classification



- Variance: average squared distance between each example's label and the set's mean label
- Weighted Euclidean distance: an error at the upper levels costs more than an error at the lower levels

$$Var(S) = \frac{\sum_{i}^{i} d(v_{i}, \overline{v})^{2}}{|S|} \qquad d(v_{1}, v_{2}) = \sqrt{\sum_{i}^{i} w(c_{i})(v_{1,i} - v_{2,i})^{2}}$$

Ensemble methods



• Ensembles are a set of predictive models

- Unstable base classifiers
- Voting schemes to combine the predictions into a single prediction
- Ensemble learning approaches
 - Modification of the data Bagging
 Modification of the algorithm

Random Forest



Image from van Assche, PhD Thesis, 2008



ADIAC diatom image database



- Three different subset of images:
 - 1099 images classified in 55 different taxa
 - 1020 images classified in 48 different taxa
 - 819 images classified in 37 different taxa
- The diatoms vary in shape and ornamentation

Experimental design – classifier



- Random Forests and Bagging of PCTs for HMLC:
 - Feature Subset Size: 10% of the number of descriptive attributes
 - Number of classifiers: 100 un-pruned trees
 - Combine the predictions output by the base classifiers: probability distribution vote

Results (1)



• Predictive performance of the feature extraction algorithms and their combination

			Overall recognition rate [%]		
Classifier	Descriptors	# features	55 diatom taxa	48 diatom taxa	37 diatom taxa
Bagging	Geometric and shape descriptors	9	76.3	76.7	77.2
	Fourier descriptors	30	86.7	88.1	88.6
	SIFT histograms	200	88.4	89.2	91.3
	Geometric and shape desc.+Fourier desc.+SIFT hist.	239	96.2	98.1	98.8
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	SIFT histograms	200	88.2	87.9	91.1
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Comparison of the performance of the ensembles of PCTs to the performance of the approaches from H. du Buf, M. M. Bayer (Eds.), Automatic diatom identification, World Scientific Publishing, 2002, pp. 245–257



Data # Images	a # Taxa	Descriptors	Classifier	Evaluation	Recognition Rate [%]
1099	55	geometric and shape; Fourier; SIFT	Bagging of predictive clustering trees	10-fold cross-validation	96.2
1020	48	geometric and shape; Fourier; SIFT	Bagging of predictive clustering trees	10-fold cross-validation	98.1
1009	48	contour profiling; Legendre polynomials	Decision trees; Neural networks; syntactical classifier	Random separation (50/50) to train and test set	82
808	38	geometric; shape; Fourier; image moments; ornamentation and morphological	Bagging of Decision Trees	Leave One Out	94.9
819	37	geometric and shape; Fourier; SIFT	Bagging of predictive clustering trees	10-fold cross-validation	98.8
781	37	contour; segment; global	nearest -mean classifier	set swaping (complex pseudo cross-validation)	82.9
781	37	Gabor; Legendre polynomials; ornamentation	Decision trees; Bayesian classifier	Random separation (50/50) to train and test set	88
781	37	contour; ornamentation	Bagging of Decision Trees	10 times random separation (75/25) train and test	89.6
781	37	Gabor; Legendre polynomials; ornamentation; contour; global; geometric; shape; Fourier; image moments; morphological	Bagging of Decision Trees	10 times random separation (75/25) train and test	96.9

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Results (2)



- The presented approach has very high predictive performance (ranging from 96.2% to 98.7%)
- Recognition rates of 100% for the majority of taxa
- Lower recognition rates are achieved for taxa that are very similar to each other and difficult to distinguish
 - Eunotia diatoms (presented on image), Fallacia diatoms



• Our results are better than the ones obtained from human annotators (63.3% recognition rate)

Conclusion



- Novel approach to taxonomic identification of taxa from microscopic images
- Different feature extraction approaches and hierarchical multi-label classification
- Very high predictive performance the best reported performance on this dataset