

Intelligent Indexing and Retrieval of Images

A Machine Learning Approach

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Outline

- Introduction
- Concept learning for image classification – learning sets of rules
- Cluster-based retrieval of images by unsupervised learning
- Conclusions and future work



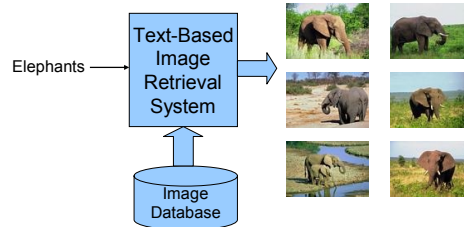
Image Retrieval

- The driving forces
 - Internet
 - Storage devices
 - Computing power
- Two approaches
 - Text-based approach
 - Content-based approach



Text-Based Approach

- Input keywords descriptions



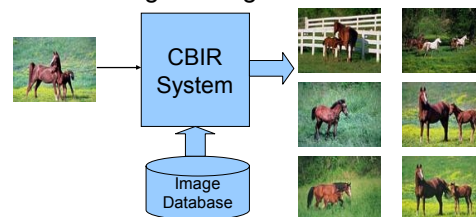
Text-Based Approach

- Index images using keywords (Google, Lycos, etc.)
 - Easy to implement
 - Fast retrieval
 - Web image search (surrounding text)
 - Manual annotation is not always available
 - A picture is worth a thousand words
 - Surrounding text may not describe the image



Content-Based Approach

- Index images using low-level features



Content-based image retrieval (CBIR): search pictures as pictures



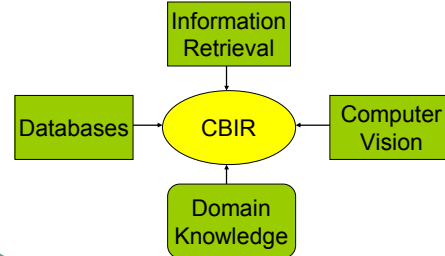
CBIR

- Applications
 - Commerce (fashion catalogue,)
 - Biomedicine (X-ray, CT,)
 - Crime prevention (security filtering,)
 - Cultural (art galleries, museums,)
 - Military (radar, aerial,)
 - Entertainment (personal album,)



CBIR

- A highly interdisciplinary research area

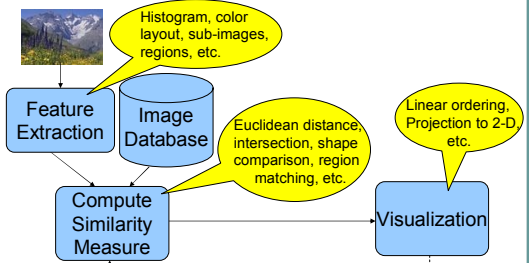


Previous Work on CBIR

- Starting from early 1990s
- General-purpose image search engines
 - IBM QBIC System and MIT Photobook System (two of the earliest systems)
 - VIRAGE System, Columbia VisualSEEK and WebSEEK Systems, UCSB NeTra System, UIUC MARS System, Stanford SIMPLicity System, NECI PicHunter System, Berkeley Blobworld System, etc.



A Data-Flow Diagram



Open Problem

- Nature of digital images: arrays of numbers
- Descriptions of images: high-level concepts
 - Sunset, mountain, dogs,
- Semantic gap: discrepancy between low-level features and high-level concepts
 - High feature similarity may not always correspond to semantic similarity
 - Different users at different time may give different interpretations for the same image



Richness of User Semantics



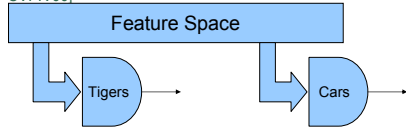
- What is this image?
 - Sunset scene
 - River or lake
 - Camping site
 - People
 - Kayak
 - Picnic
 - "National park" by Google



Narrowing the Semantic Gap

- Imagery features and similarity measure

- Select effective imagery features [Tieu et al., IEEE CVPR'00]



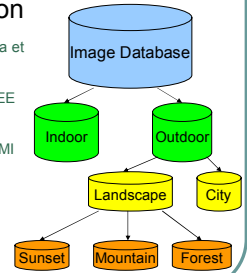
- Subjective experiments [Mojsilovic et al., IEEE Trans. IP 9(1)]



Narrowing the Semantic Gap

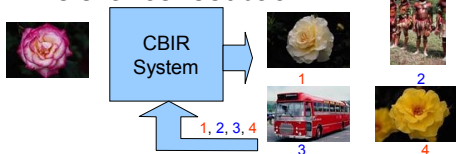
- Semantic Classification

- Vacation images [Vailaya et al., IEEE Trans. IP 10(1)]
- SIMPLIcity [Wang et al., IEEE Trans. PAMI 23(9)]
- ALIP [Li et al., IEEE Trans. PAMI 2003]



Narrowing the Semantic Gap

- Relevance feedback



- Adjusting similarity measure [Picard et al., IEEE ICIP'96], [Rui et al., IEEE CSVT 8(5)], [Cox et al., IEEE Trans. IP 9(1)]

- Support vector machine [Tong et al. ACM MM'01]



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Objects and Image Semantics

- Human visual system

- Sunset glow → Sunset
- Water → River or lake
- Tent → Camping site
- Persons → People
- Kayak → Kayak
- Smoke → Picnic



Objects and Image Semantics

- Image semantics may be related to objects in the image
- Semantically similar images may contain semantically similar objects
- Can a computer program learn semantic concepts about images based on objects?



Problem Formulation

- Binary classification

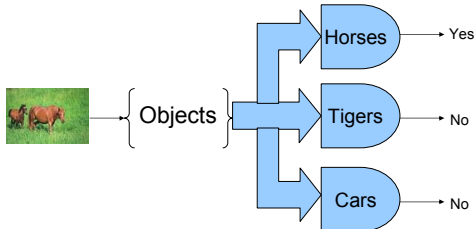
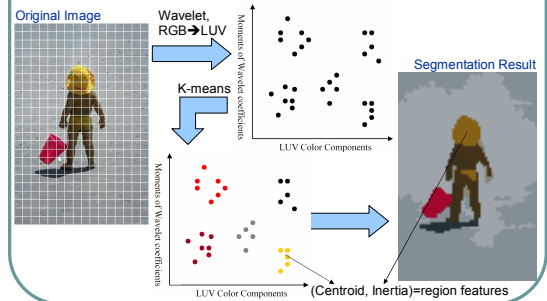


Image Segmentation



Learning

- Semantically similar images may contain semantically similar objects
 - Find similar objects (feature vectors) among "positive" images
 - At the same time they should be as distinct from all objects in "negative" images as possible
- Conceptual feature vector
 - Multiple-Instance Learning (MIL) using diverse density [Maron 1998], [Zhang et al., ICML'02]



Example



Example

- Three conceptual feature vectors
 - Water, rock, trees
- Rule description of a semantic concept
 - 1: **IF** one of the regions is similar to **water** **AND** one of the regions is similar to **rock** **THEN** it is a **waterfall** image, **OR**,
 - 2: **IF** one of the regions is similar to **water** **AND** one of the regions is similar to **trees** **THEN** it is a **waterfall** image



Learning

- Rule-based classification system and Support Vector Machine (SVM) [Chen et al., IEEE Trans. FS 2003]
- General learning scheme
 - Image segmentation
 - Learn a collection of conceptual feature vectors using MIL
 - Map images to a new feature space defined by conceptual feature vectors
 - Support vector learning

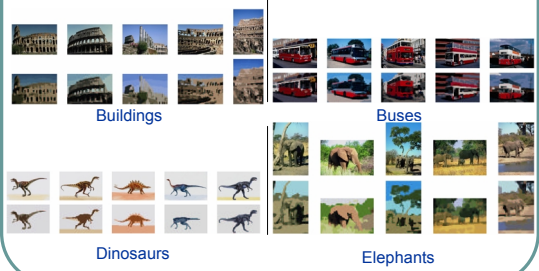


An Image Classification Example

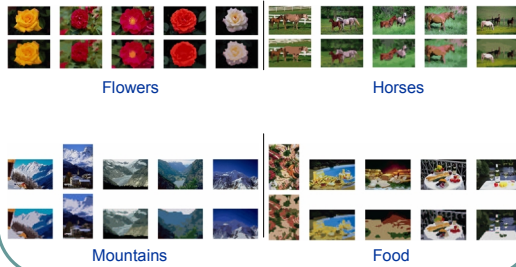
- 10 image categories each containing 100 images
 - Africa, beach, buildings, buses, dinosaurs, elephants, flowers, horses, mountains, and food (labels are provided by COREL)



An Image Classification Example



An Image Classification Example



An Image Classification Example

- Confusion matrix

%	Africa	Beach	Buildings	Buses	Dinosaurs	Elephants	Flowers	Horses	Mountains	Food
Africa	72	2	4	2	0	12	2	0	0	6
Beach	0	54	8	6	0	2	0	0	26	2
Buildings	4	0	84	2	0	6	0	0	2	2
Buses	0	4	0	94	0	0	0	0	0	2
Dinosaurs	0	0	0	0	100	0	0	0	0	0
Elephants	14	0	6	0	0	74	0	4	0	2
Flowers	2	0	0	0	0	0	92	0	0	6
Horses	2	2	0	0	0	0	0	96	0	0
Mountains	0	8	12	4	0	4	0	0	72	0
Food	4	2	0	2	0	0	4	0	0	88

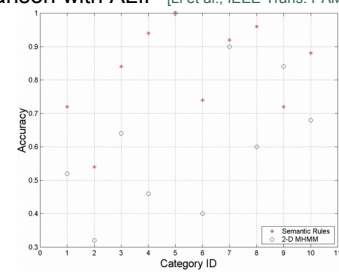


Beach vs. Mountains



An Image Classification Example

- Comparison with ALIP [Li et al., IEEE Trans. PAMI, 2003]



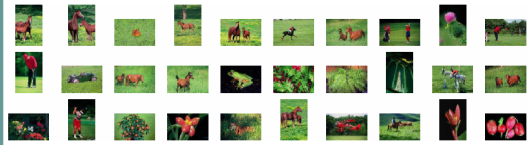
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CLUE: CLUsters-based rETrieval of images by unsupervised learning

- Motivation



Horses (11 out of 29), flowers (7 out of 29), golfer player (4 out of 29)



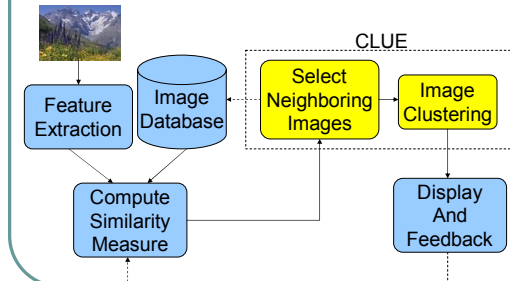
CLUE

- Hypothesis
 - In the “vicinity” of a query image, images tend to be semantically clustered
- CLUE attempts to capture high-level semantic concepts by learning the way that images of the same semantics are similar



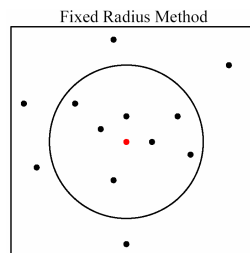
System Overview

A general diagram of a CBIR system using the CLUE



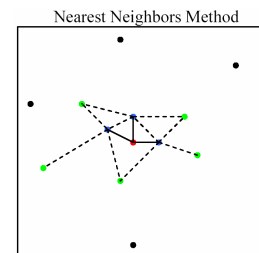
Neighboring Images Selection

- Fixed radius method
 - Take all target images within some fixed radius with respect to the query



Neighboring Images Selection

- Nearest neighbors method
 - Pick k nearest neighbors of the query as seeds
 - Find r nearest neighbors for each seed
 - Take all distinct images as neighboring images

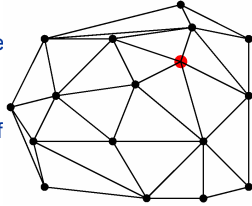


$k=3, r=4$



Weighted Graph Representation

- Geometric representation
- Graph representation
 - Vertices denote image
 - Edges are formed between vertices
 - Nonnegative weight of an edge indicates the similarity between two vertices



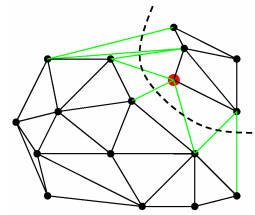
Clustering

- Graph partitioning and cut

$$cut(A, B) = \sum_{i \in A, j \in B} w_{ij}$$

- Normalized cut (Ncut) [Shi et al., IEEE Trans. PAMI 22(8)]

$$Ncut(A, B) = \frac{cut(A, B)}{assoc(A, V)} + \frac{cut(A, B)}{assoc(B, V)}$$



An Experimental System

- Similarity measure
 - UFM [Chen et al. IEEE PAMI 24(9)]
- Database
 - COREL
 - 60,000
- Computer
 - Pentium III 700MHz PC, Linux



User Interface

Option 1 → Image ID or URL: Option 2 → Random Option 3 → Click an image to see images in the cluster



(a) Thumbnails of image clusters.



(b) Images in Cluster 1.



Query Examples

- Query Examples from 60,000-image COREL Database

Bird, car, food, historical buildings, and soccer game



Query Examples



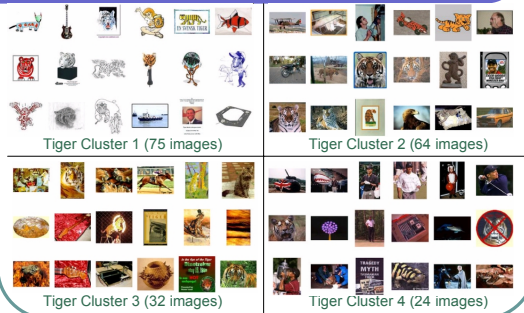
Query Examples



Clustering WWW Images

- Google Image Search
 - Keywords: tiger, Beijing
 - Top 200 returns
 - 4 largest clusters
 - Top 18 images within each cluster

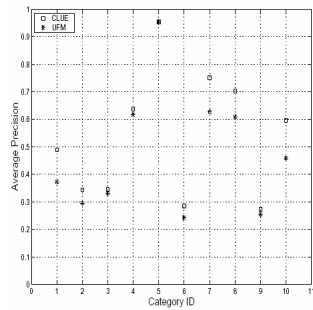
Clustering WWW Images



Clustering WWW Images



Retrieval Accuracy



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Conclusions

- Two approaches to tackle the “semantic gap” problem
 - Learning semantic concepts about images based on regions (objects)
 - Retrieving image clusters by unsupervised learning

Tested using 60,000 images from COREL and images from WWW



Related Publications

- Journal Publications
 - [IEEE Trans. PAMI, 2002], computer vision & soft computing
 - [IEEE Trans. FS, 2003], machine learning theory & soft computing
- Refereed Conference Publications
 - [ACM MM'01], computer vision & soft computing
 - [FUZZ-IEEE'03], machine learning theory & soft computing
 - [FUZZ-IEEE'03, invited], computer vision & soft computing



Other Contributions

- Robotics and control (University of Wyoming)
 - Modeling and identification of payload (in collaboration with Prof. McInroy)
 - [IEEE Trans. AC, 2002], [ICRA'02], control
 - Decoupled control algorithms (in collaboration with Prof. McInroy)
 - [IEEE Trans. CST, 2003], [ICRA'00], control
 - Motion planning (in collaboration with Prof. McInroy)
 - [IEEE Trans. RA, 2003], [ACC'03], robotics
 - Fault-tolerant kinematics analysis (in collaboration with Prof. McInroy and Yong Yi)
 - [IEEE Trans. RA, 2003], [ISSM'02], robotics



Future Work

- Continue to make contributions to the areas of
 - machine learning theories
 - robotics and automatic control
 - computer vision
 - soft computing



Future Work

- Apply theories to real world problems
 - Internet
 - Digital libraries
 - Robot vision systems
 - Sensor, imaging and video systems
 - Biomedicine
 - Autonomous intelligent agents
 - Homeland security



Potential Funding Sources

- NSF
 - Information Technology Research
 - SENSORS
 - Digital Libraries
 - Information and Data Management
 - Knowledge and Cognitive Systems
- NIH
- Office of Naval Research
- DARPA
- DOE
- Industrial funding



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 - Professor Jia Li, STAT
 - Professor Donald Richards, STAT
- NEC Research Institute
 - Dr. Robert Krovetz



More Information

- Papers in PDF, 60,000-image DB, demonstrations, etc.

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