Query Decomposition: A Multiple Neighborhood Approach to Relevance Feedback Processing in Content-based Image Retrieval

Kien A. Hua, **Ning Yu**, Danzhou Liu

School of Electrical Engineering and Computer Science

University of Central Florida

Orlando, FL 32816

{kienhua, nyu, dzliu}@cs.ucf.edu

Relevance Feedback (RF)

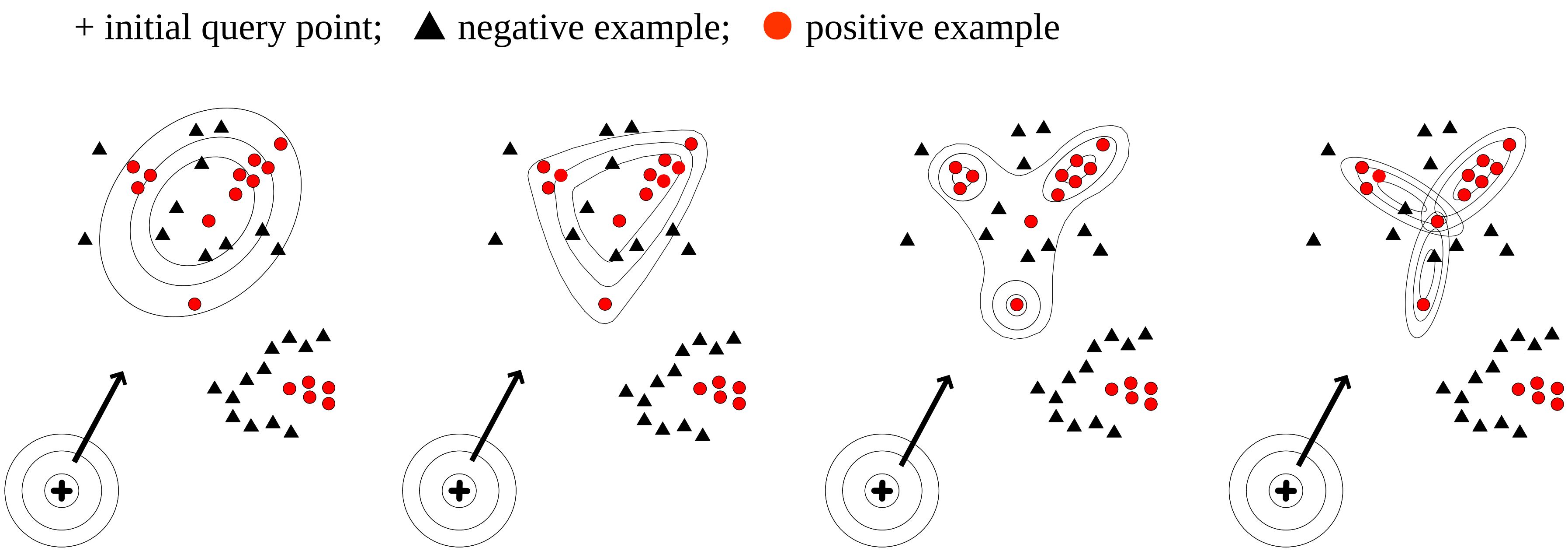
- Problem: Semantic gap between low-level visual features and the high-level concepts conveyed by the query images
- A Solution: User relevance feedback
  - User identifies relevant images within the returned set
  - System utilizes feedback to modify the query to retrieve better results in the next round
  - This process repeats until user is satisfied with the results

Existing RF Techniques

A query can be modified by:

- Query Point Movement (Ishikawa, VLDB '98)
- Multiple Queries (Porkaew, ACMMM '99)
- Qcluster (Kim, SIGMOD '03)
- Multiple Viewpoints (French, CIVR '04)

Illustration of Existing Works

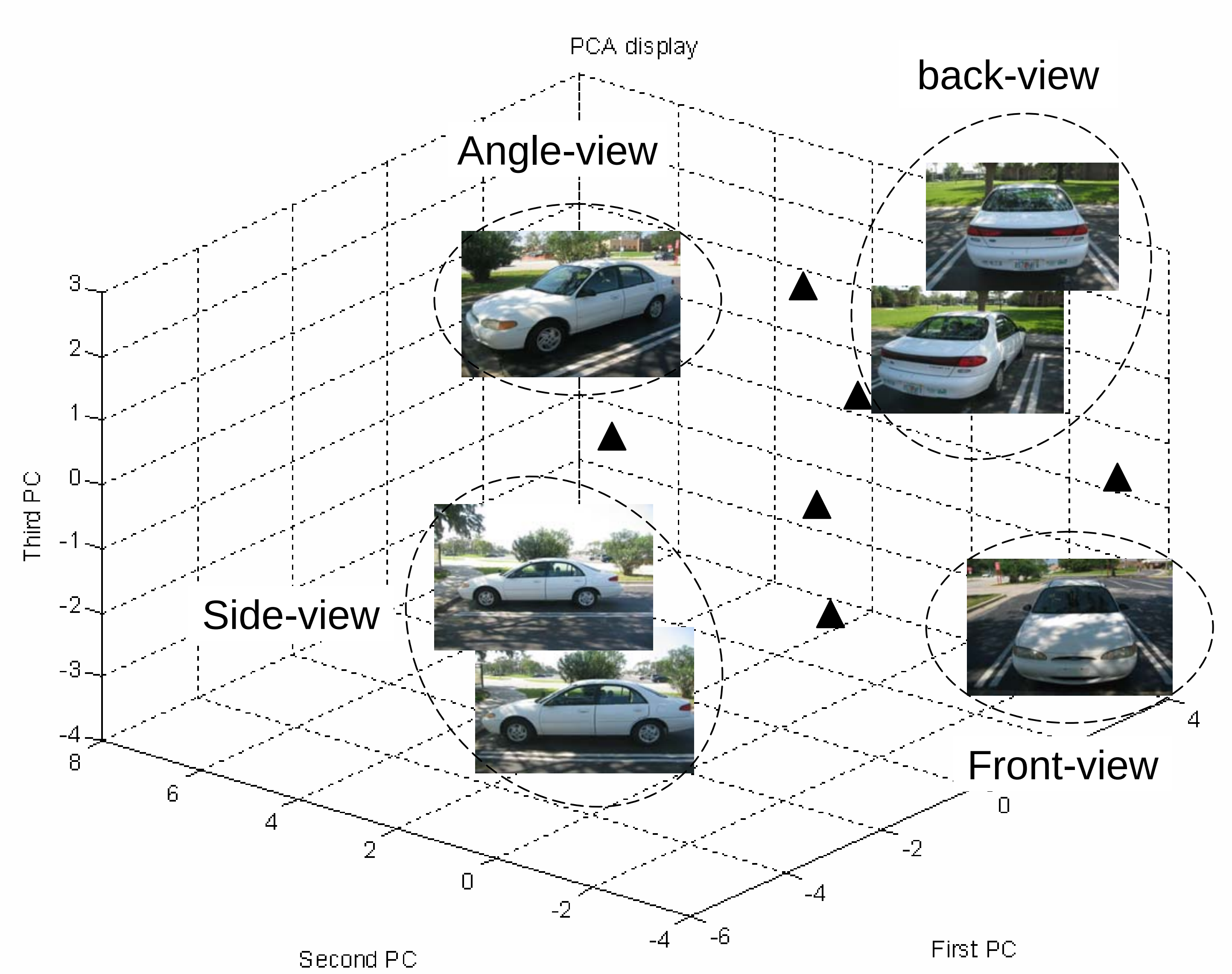


(a) Query Point Movement (b) Multipoint Query (c) QCluster (d) Multiple Viewpoints

Disadvantage: only retrieve images from single neighborhood

Limitation of Existing Techniques

- Assumption: Semantically similar images are located "close" to each other in the feature space, according to some distance measures.
- Reality: Semantically similar images can look very different, and are therefore far apart in the feature space or sub-spaces.


PCA display
back-view
Angle-view
Side-view
Front-view
Third PC
Second PC
First PC
3
2
1
0
-1
-2
-3
-4
8
6
4
2
0
-2
-4
-6
-4
-2
0
4

Outline

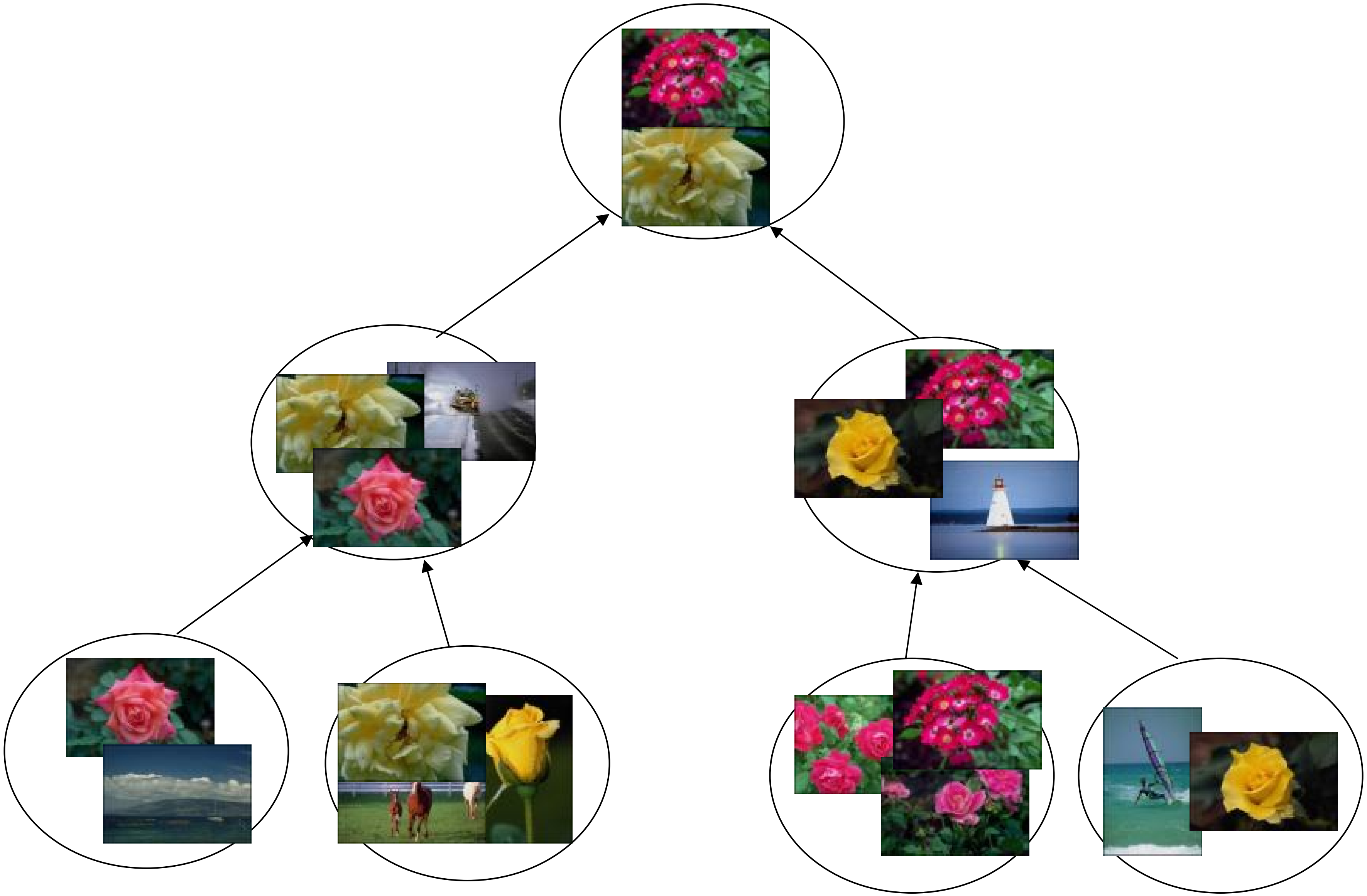
- Introduction
- Related Works
- Proposed System – Query Decomposition (QD)
- Prototype & Experimental Study
- Conclusions

Overview of QD

- Decompose an initial query into localized subqueries based on user relevance feedback
- Subqueries are processed independently
- Their local results are merged into a single ranked list to form the final result
- Two key components of QD
  - Relevance Feedback Support (RFS) Structure
  - Localized k-NN Computation

RFS Structure

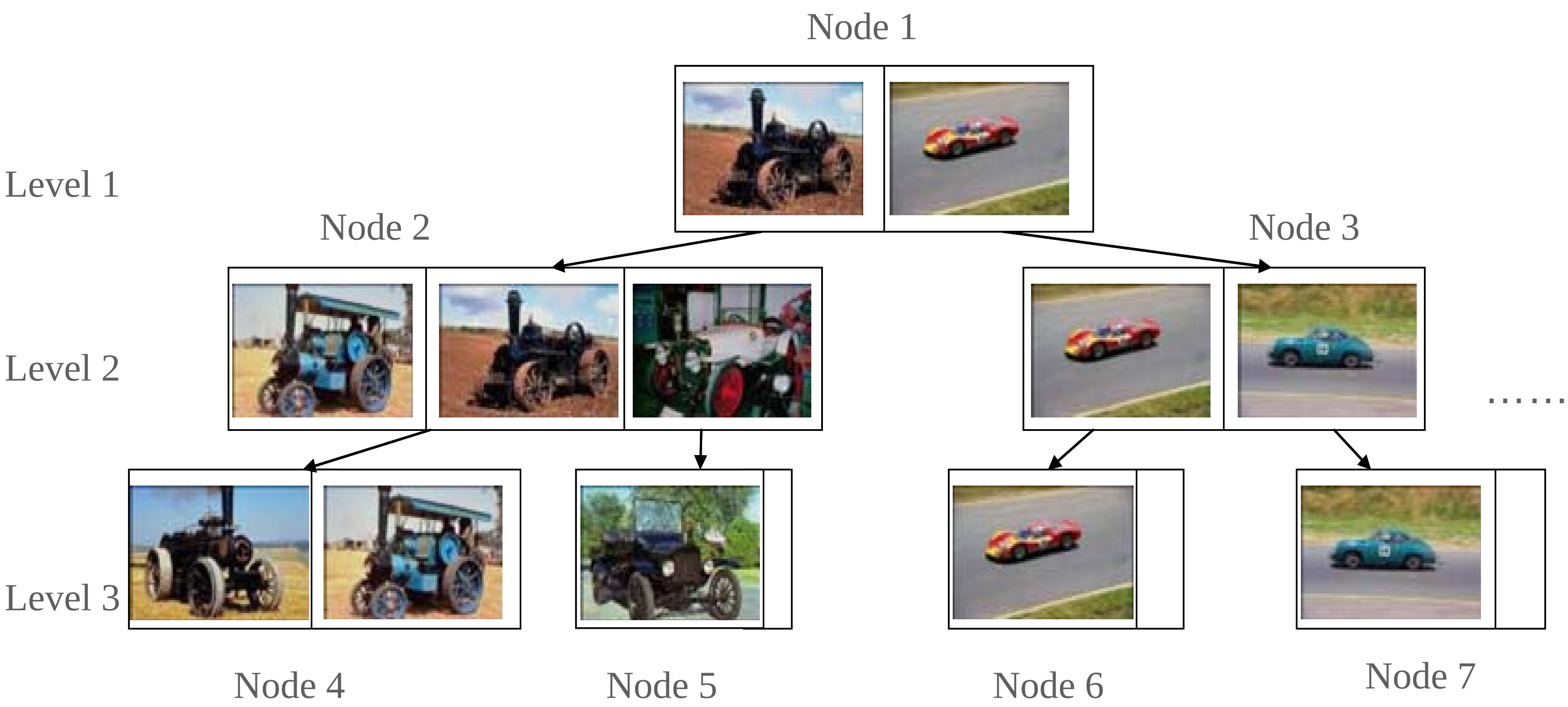
- Hierarchically clustered database images into a tree structure.
- Representative images are selected for each cluster in the in a bottom-up fashion



Localized k-NN Computation

- A localized *k*-NN computation is done independently over the corresponding relevant cluster at a leave node
- If a query point is sufficiently distant from the center of its cluster, compute the *k*-NN query over the parent node in the RFS structure

QD Illustration



Hiding Complexity

- User is not aware of the internal query decomposition process
- Subqueries and their results are maintained internally without the knowledge of the user
- User is presented a single list of ranked image for each round of RF

Outline

- Introduction
- Related Works
- Proposed System – Query Decomposition
- Prototype & Experimental Study
- Conclusions

PROTOTYPE

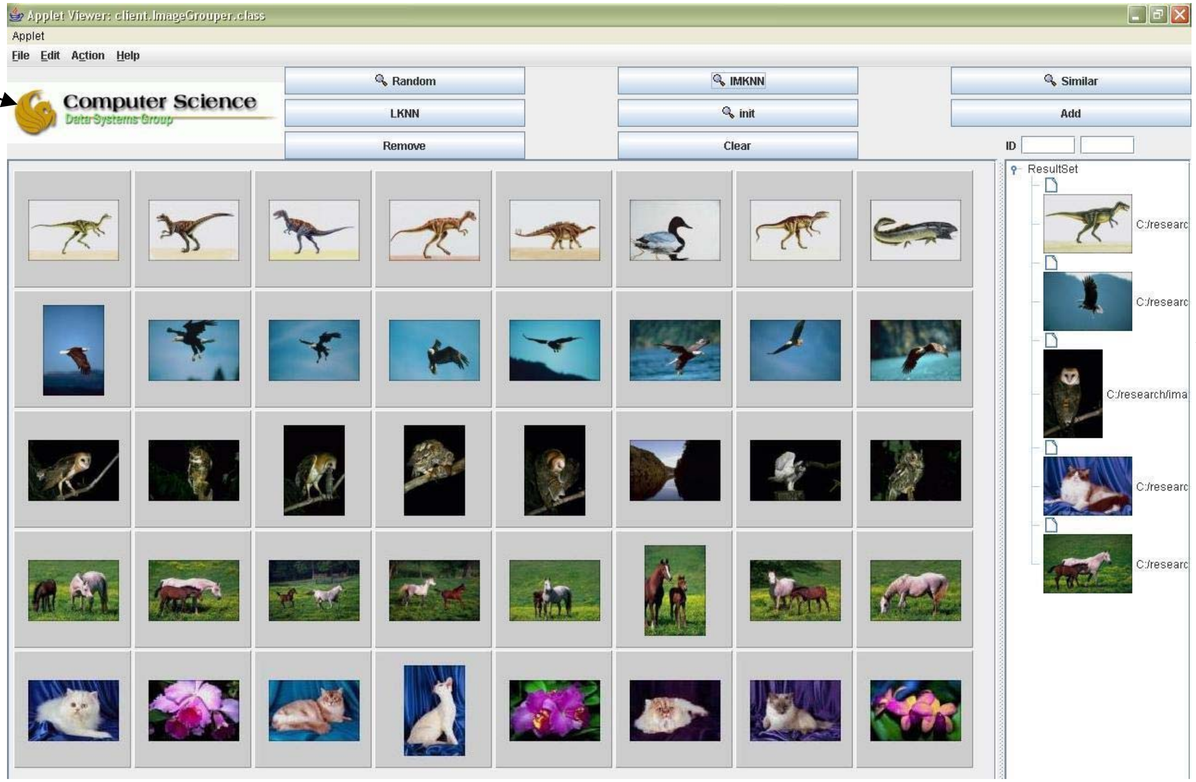
- 37 Features:
  - 9 color moments,
  - 10 Wavelet-based Texture, and
  - 18 edge-based structural features.
- RFS Structure:
  - Three levels deep
  - Each node contains 70 to 100 images
- User Interface
  - Results are shown in groups

Presentation of Final Results

- Intra-cluster Ranking: Relevant images are ranked according to their own localized *k*-NN computation
- Inter-cluster Ranking: The matching score for each *result group*, due to a localized *k*-NN computation, is the sum of the scores of its top *k* matches

Screenshot of QD system

Control Panel

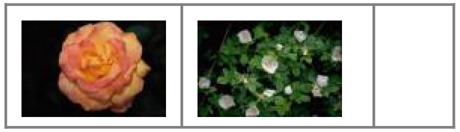


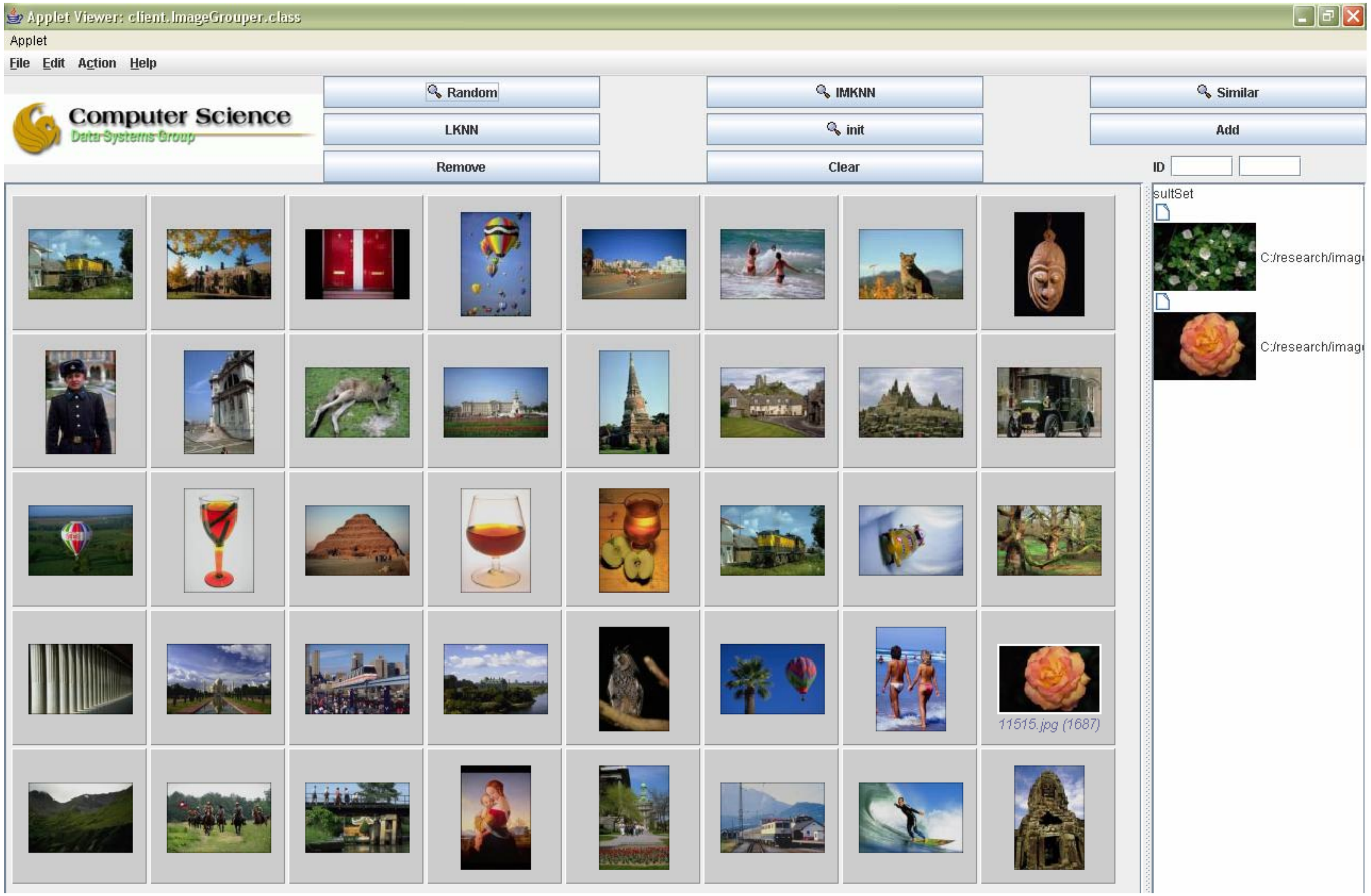
Example image panel

Result Panel

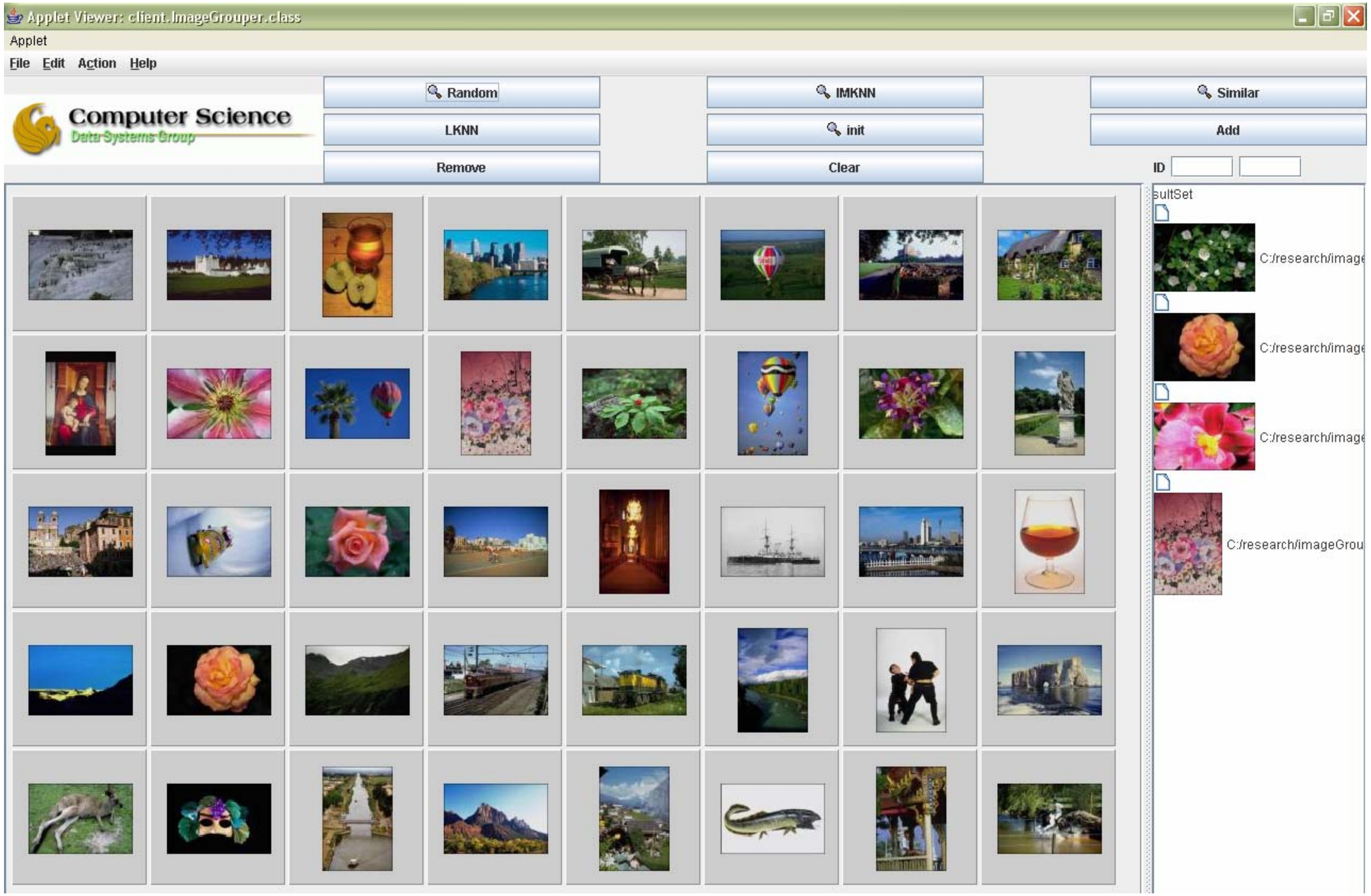
The localized sub-queries are “dinosaur,” “eagle,” “Owe,” “Cat,” and “Horse.” Query results are presented in the left panel.

Example - Level 1

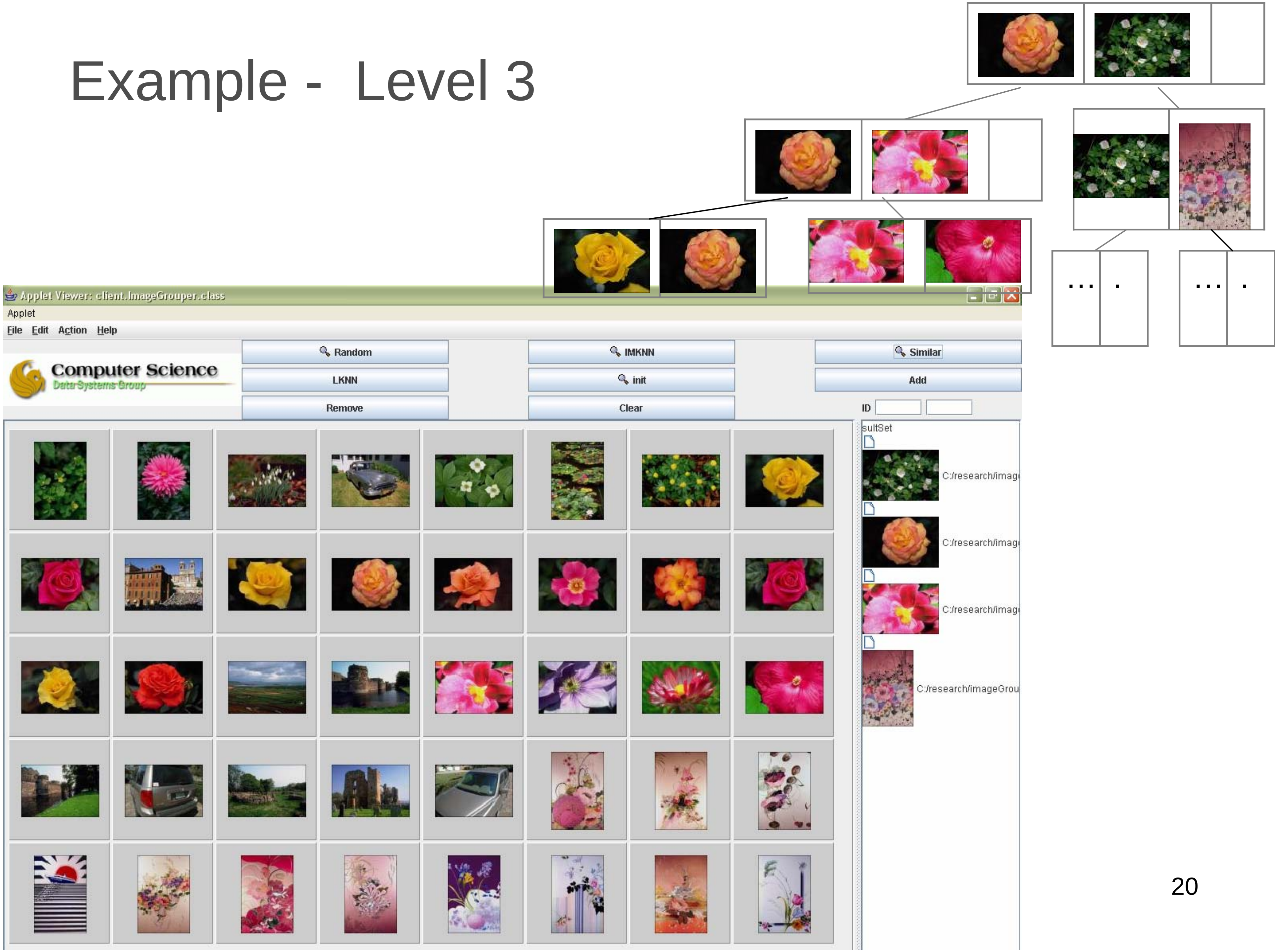




Example - Level 2

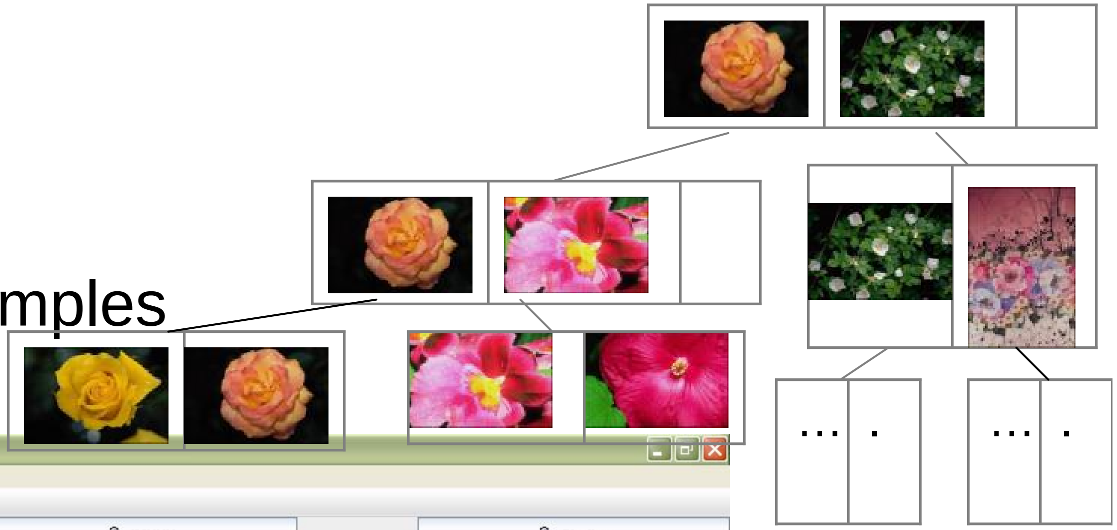


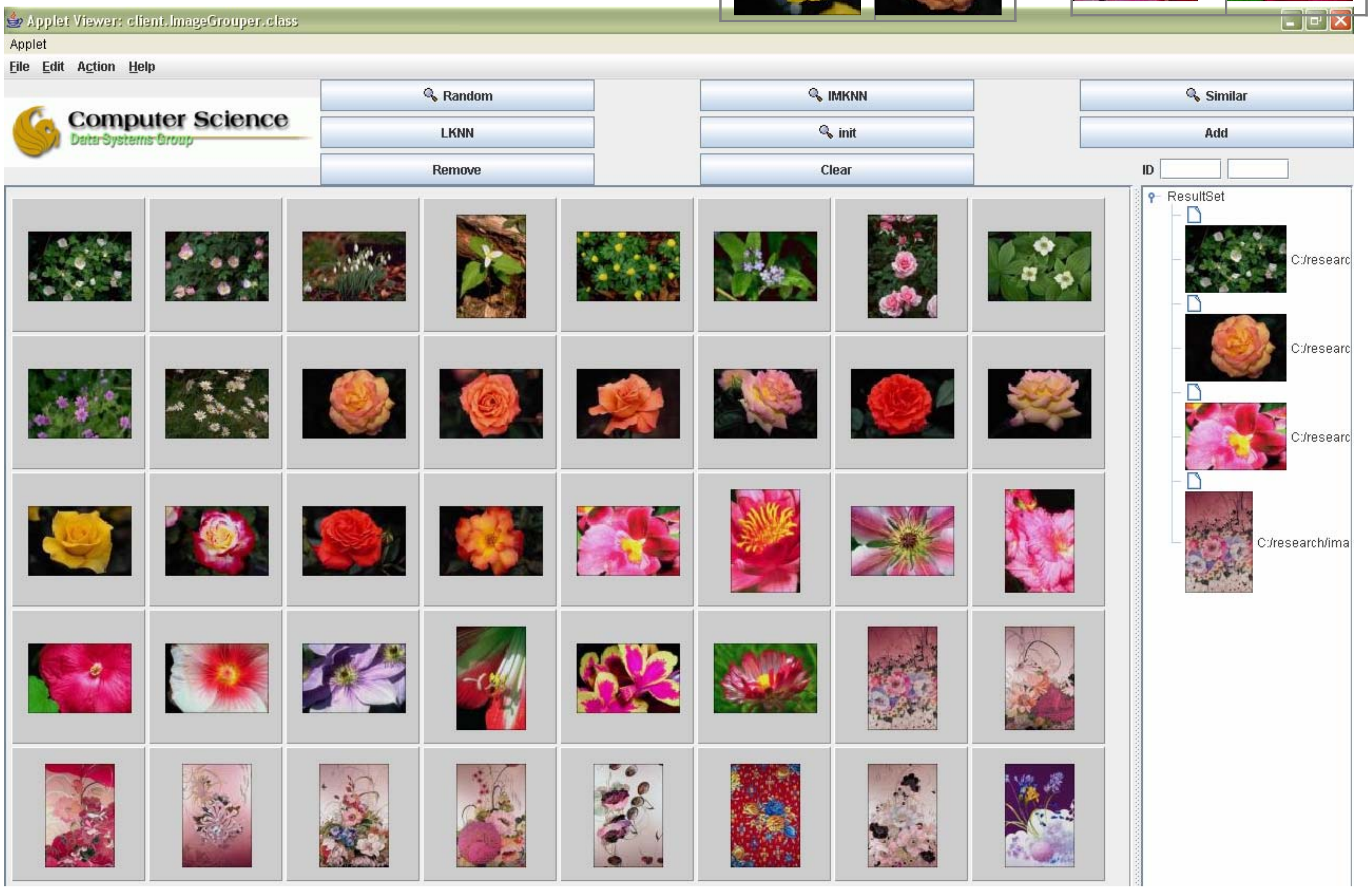
Example - Level 3



Final Result

Four groups of results corresponding to the examples





Experimental study

- Dataset has 20,000 images from COREL
- Compared to Multiple Viewpoints
- Performance Metrics

RET = The set of images retrieved for a query

RETREL = The set of the retrieved relevant images

GTIR: Ground Truth Inclusion Ratio

Precision = |RETREL| / |RET|

GTIR = |Retrieved subconcepts| / |Total subconcepts in ground truth|

Various Queries in MV & QD

	MV		QD	
Query	Precision	GTIR	Precision	GTIR
A person (Hair-model, fitness, Kongfu)	**0.25**	**0.33**	**0.81**	**1**
Airplane (single, multiple)	**0.21**	**0.5**	**0.85**	**1**
Bird (eagle, owl, sparrow)	**0.23**	**0.33**	**0.61**	**1**
Car (modern sedan, antique car, steamed car)	**0.35**	**0.33**	**0.85**	**1**
Horse (polo, wild horse, race)	**0.37**	**0.67**	**0.72**	**1**
Mountain view (snow, with water)	**0.38**	**1**	**0.46**	**1**
Rose (yellow, red)	**0.22**	**1**	**0.71**	**1**
Water Sports (surfing, sailing)	**0.11**	**0.5**	**0.44**	**1**
Computer (server, desktop, laptop)	**0.42**	**0.5**	**0.86**	**1**
Personal computer (desktop, laptop)	**0.44**	**0.5**	**0.69**	**1**
Laptop (with clear background, with complicated background)	**0.50**	**0.5**	**0.71**	**1**
Average	0.32	0.56	0.70	1

Compared to MV

We test the two system on 11 types of queries: the result of the first 3 rounds are reported

Quality Comparison				
Feed-back Round	Techniques			
	MV		QD	
	Precision	GTIR	Precision	GTIR
1	0.1	0.51	n/a	0.695
2	0.3	0.56	n/a	0.907
3	0.32	0.56	0.7	1

Result Comparison

“computer” result of MV

“computer” result of QD

QD – Concluding Remarks

- Better query result
  - Leverage user relevance feedback to more effectively address semantic gap;
  - Retrieve semantically similar images with different appearance.
- More efficient query processing
  - Only performs localized *k*-NN computation on very small subsets of the database (detailed result can be found in the full paper).
- More Scalable
  - RFS structure is small.

Query Decomposition: A Multiple Neighborhood Approach to Relevance Feedback Processing in Content-based Image Retrieval

Kien A. Hua, **Ning Yu**, Danzhou Liu
School of Electrical Engineering and Computer Science
University of Central Florida
Orlando, FL 32816
{kienhua, nyu, dzliu}@cs.ucf.edu