Content-Based Image/Video Retrieval

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How can I access image/video in database over networks?
1. Content List

a. Query Concept Specification

b. Similarity-Based Matching

c. Query Result Display and Evaluation

d. Relevance Feedback for Result Updating

e. Open Issues
2. Query Concept Specification

- Query By Examples

<table>
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<tr>
<th>Query example</th>
<th>Ranked Results</th>
</tr>
</thead>
<tbody>
<tr>
<td><img src="image1.png" alt="Query Example 1" /></td>
<td><img src="image2.png" alt="Ranked Result 1" /></td>
</tr>
<tr>
<td><img src="image3.png" alt="Query Example 2" /></td>
<td><img src="image4.png" alt="Ranked Result 2" /></td>
</tr>
<tr>
<td><img src="image5.png" alt="Query Example 3" /></td>
<td><img src="image6.png" alt="Ranked Result 3" /></td>
</tr>
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</table>
2. Query Concept Specification

- Query By Examples

How to get initial examples? *Page Zero problem*
2. Query Concept Specification

- Query By Examples

Random Sampling from Large-Scale Image Collections
2. Query Concept Specification

- Query By Examples

**Image Example Browsing and Selection**

*Sample*

*Similarity Search*
2. Query Concept Specification

- Query By Examples

System Response and User Evaluation
2. Query Concept Specification

- Query By Examples

More Users’ Inputs over time
2. Query Concept Specification

- Query By Examples

More Relevant Response

Sample

Similarity Search
2. Query Concept Specification

- Problems for Query-By-Example

a. We may not know users’ queries, how can we prepare examples for them? If the pool of users is very large and their queries could be diverse, the sample images could be another big database?!

b. Random sampling is one reasonable solution, but how random is real random? How can we believe random sampling can obtain good enough and large enough set of representative images? If they are not representative, how they can help us?
2. Query Concept Specification

- Query-By-Keywords
2. Query Concept Specification

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- Query-By-Keywords
2. Query Concept Specification

- Query-By-Keywords
2. Query Concept Specification

Problem of Query-By-Keywords

a. Keywords may not be good enough to interpret the details of image semantics—*one picture is more than one thousand words!*  

b. It is hard to obtain automatic annotation of large set of images. If users are allowed to annotate their images when they share, the human annotation could be biased and noisy, such human annotation may further mislead search engine---This is why we can lots of *junk images* in Google Images.
2. Query Concept Specification

- Browsing of Image Collections
2. Query Concept Specification

- Browsing of Image Collections

**Add details:**

**math_obs-v03.png**

**Thumbnail:** 200 x 150 px, 41.45 kB  
**Full size:** 1600 x 1200 px, 1010.67 kB (Show)

- How to include?
  - Thumb with link to full size
  - Thumb only
  - Full size only
  - Link to thumb
  - Link to full size

- Description:

```
Mathematical objects over checkered plane
```

- Get the code

Back | Close window
2. Query Concept Specification

- Browsing of Image Collections
2. Query Concept Specification

- Problems of Browsing

  a. There is **no good solution** for summarizing large-scale image collections with huge diversity of semantics and visual principles----The summaries should be good enough to represent the details of large-scale images at different levels!

  b. There is **no good structure** to organize such hierarchical image summaries at different levels of details. Such structure for summary organization should be semantic to human being!
2. Query Concept Specification

- Problems
  
a. Individually, they cannot support effective query concept specification because the users’ needs may be interpreted by multi-modal features!

b. We need more intuitive interfaces to enable more effective and precise query concept specification!

c. We also need new image display tools, so that users can assess the image similarity easily!
2. Query Concept Specification

- Hyperbolic Visualization as Solution
2. Query Concept Specification

- Hyperbolic Visualization as Solution

a. Let users see the summaries and the semantic organization structure at the first glance!

b. Let users change the visualization details dynamically according to their query interest!

c. Inform the users what we have in database intuitively!
3. Similarity Matching

- Query-By-Example
3. Similarity Matching

- Query-By-Example

Query Example

Feature Extraction

Features for Indexing

Distance Function

Node Selection
3. Similarity Matching

- Query-By-Example

Query Example

- Feature Extraction
- Distance Function

Within-Node Nearest Neighbor Search

Top-K Results
3. Similarity Matching

- Query-By-Example: Query Result Evaluation

Users can easily assess their visually similarity intuitively!
3. Similarity Matching

- Query-By-Example: Query Result Evaluation
3. Similarity Matching

- Query-By-Keywords

```
Query Keyword
Distance Function
Matched Concept Node & Its Images
```

```
Concept Ontology
```

```
Query Keyword
```

```
Distance Function
```

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Matched Concept Node & Its Images
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Concept Ontology
```
3. Similarity Matching

- Query-By-Keywords: Query Result Evaluation

Query Results could be in large size, when query is in high level!
3. Similarity Matching

- Query-By-Keywords: Query Result Evaluation
3. Similarity Matching

- Query-By-Keywords: Zoom for Evaluation

Red Circle
3. Similarity Matching

- Query-By-Keywords: Zoom for Evaluation

Zoom into Images in Red Circle!
3. Similarity Matching

- Query-By-Browsing: Concept Tree Visualization
3. Similarity Matching

Query-By-Browsing: Concept Ontology Visualization
3. Similarity Matching

- Query-By-Browsing: Change of Focus
3. Similarity Matching

- Query-By-Browsing: Change of Focus
3. Similarity Matching

- Query-By-Browsing: Change of Focus
3. Similarity Matching

- Challenging Issues:
  
  a. **Distance Functions**: what kind of distance functions are good enough to characterize the underlying visual similarity between the images?

  b. **Semantic Gap**: there is a semantic gap between the image semantics and the low-level features? How can we bridge such gap in retrieval process?

  c. **Goal of Users**: what is the goal for users’ retrieval? How can we target this goal effectively?
4. Relevance Feedback

Why we need relevance feedback?

a. **Semantic Gap**: The feature-based matching may return large amounts of junk images!

b. **Query Intention**: The users may not be able to describe their query intention very precisely via examples, keywords, *when I see it, then I know it!*
4. Relevance Feedback

- **Distance Weighting Approach:**

\[ \phi = \log(L) = \sum_{i=1}^{I} \alpha_i (A_i - R_i) \]
4. Relevance Feedback

- Effectiveness of Feature Weighting

(a) Query image: Flower and vegetation

(b) Weights: $S = 0.33$, $C = 0.33$, $T = 0.33$.

(c) Weights: $S = 0.05$, $C = 0.05$, $T = 0.9$. 
4. Relevance Feedback

- Effectiveness of Feature Weighting:

Original Feature Space

Weighted Feature Space
4. Relevance Feedback

Two More Issues for Feature Weighting

a. **Informative Sample Generation**: what we should return to users, so that they can make good decision on relevance vs. irrelevance?

b. **Query Movement Control**: Through weighting the features, it is able for us to control the importance between the features for image similarity characterization. However, for image retrieval application, we also need to control the query point to move to target in the best way!
4. Relevance Feedback

- Query Point Movement Control

Where to go?

No Convergence

Initial Query Point

Target Image

Best Search Road

Potential Convergence Search Road
4. Relevance Feedback

- Query Updating

\[
\overline{Q}^{(k+1)} = \overline{Q}^{(k)} + \delta \sum_{i=1}^{N_{\text{rel}}} \overline{X}_{i}^{(k)} - \varepsilon \sum_{j=1}^{M_{\text{notrel}}} \overline{Y}_{j}^{(k)}
\]

- New Query Vector
- Previous Query Vector
- Vectors for Positive Images
- Vectors for Negatives
4. Relevance Feedback

Problem for Feature Weighting Approach

a. **Cost-Sensitive**: It is very expensive to update the feature weights on real time!

b. **Semantic Gap**: The distance functions may not be able to characterize the underlying image similarity effectively!

c. **Visualization**: The underlying image display tools may separate similar images in different places, it is hard for users to evaluate the visual similarity (relevance) between the images!
4. Relevance Feedback

- Classification-Based Approach

\[ f(X) = \text{sign} \left( \sum_{l=1}^{M} \hat{\beta}_l Y_l K(X_l, X) + b \right) \]

- Relevant Images
- Irrelevant Images
- positive support vectors
- negative support vectors

margin
4. Relevance Feedback

- Classification-Based Approach

\[
f(X) = \text{sign} \left( \sum_{l=1}^{M} \beta_l Y_l K(X_l, X) + b \right)
\]

How can we capture users’ feedbacks to update SVM classifier?
4. Relevance Feedback

- Increment SVM Updating

\[ f_i(x_i) = \begin{cases} 
  x_i & x_i < u_i \\
  a \cdot (x_i - u_i) + u_i & x_i \in [u_i, v_i] \\
  x_i + (a - 1) \cdot (v_i - u_i) & x_i > v_i
\end{cases} \]

Piece-wise updating of kernel function by using users selected images!
4. Relevance Feedback

- Hyperbolic Visualization
4. Relevance Feedback

- Hyperbolic Visualization
4. Relevance Feedback

- Hyperbolic Visualization
4. Relevance Feedback

- Hyperbolic Visualization
4. Relevance Feedback

- Traditional Image Visualization
4. Relevance Feedback

- Challenging Issues

a. **Convergence**: It is very important to guarantee the algorithm for kernel updating is converged!

b. **Cost Reduction**: It is very important to reduce the cost for kernel updating!

C. **Semantic Gap**: The underlying kernels should be able to characterize the diverse visual similarity between the images!
5. Open Issues for CBIR

- More Representative Feature Extraction

Image Structure or Context Detection and Representation!
5. Open Issues for CBIR

- Distance Functions vs. Human Perception

\[ \phi = \log(L) = \sum_{i=1}^{I} \alpha_i (A_i - R_i) \]

Does feature weighting can indicate human perception effectively?

If not, what else we can do now?
5. Open Issues for CBIR

- Kernel Function vs. Human Perception

\[ \hat{K}(x, y) = \sum_{i=1}^{\kappa} \alpha_i K_i(x, y), \quad \sum_{i=1}^{\kappa} \alpha_i = 1 \]

\[ D(x, y) = \| \phi(x) - \phi(y) \| = \sqrt{K(x, x) + K(z, z) - 2K(x, z)} \]

Kernel function is more suitable for visual similarity characterization? Why?
5. Open Issues for CBIR

- Query Result Display and Evaluation

Visualization should be able to represent the underlying visual similarity between images!
5. Open Issues for CBIR

- Multi-Kernel Classifier Training

The visual principles between the images are diverse, and thus multiple kernels with different capabilities should be used!

a. Histogram kernel

\[ \chi^2(u, v) = \frac{1}{2} \sum_{i=1}^{16} \frac{(u_i - v_i)^2}{u_i + v_i} \]

b. Wavelet Kernel

\[ K(x, y) = \prod_{i=1}^{m} e^{-\chi_i^2(h_i(x), h_i(y))/\alpha_i} \]

c. Key-point matching kernel

\[ D(Q, P) = \frac{\sum_{i=1}^{M_Q} \sum_{j=1}^{N_P} \beta_{ij} d(q_i, p_j)}{\sum_{i=1}^{M_Q} \sum_{j=1}^{N_P} \beta_{ij}} \]
5. Open Issues for CBIR

- Multi-Modal Visualization for Query Specification
5. Open Issues for CBIR

Query Result Fusion & Junk Image Filtering

![Diagram]

- Query By Example
- Query By Keywords
- Final Results

Join
5. Open Issues for CBIR

Localized Similarity-Oriented Image Indexing

- Similarity-Based Image Hashing & Projection
- Images in Database
- Localized Image Buckets
5. Open Issues for CBIR

- Image Transmission over Internet & Concurrence Access Control