Exploiting Contextual Information for Rank Aggregation

Daniel Carlos Guimarães Pedronette
Ricardo da S. Torres

RECOD Lab - Institute of Computing (IC)
University of Campinas (UNICAMP) - Brazil

Outline

- Introduction
- Contextual Rank Aggregation
  - Contextual Information Representation
  - Contextual Rank Aggregation Algorithm
- Experimental Evaluation
- Conclusions
- Future Work

Introduction

- Given a query image, a CBIR system aims at *retrieving the most similar images in a collection by taking into account image* visual properties
  - Shape, color, and texture
- Different descriptors leads to different results
  - Combining results aiming to improve the effectiveness
  - Traditional Rank Aggregation Approaches

Introduction

- In general, CBIR systems compute similarity considering only pair of images;
- User perception usually considers the query and query responses in a given *context*;
- Relationship among images and information encoded in ranked lists can be used for extracting contextual information;
  - **Contextual Rank Aggregation Algorithm**

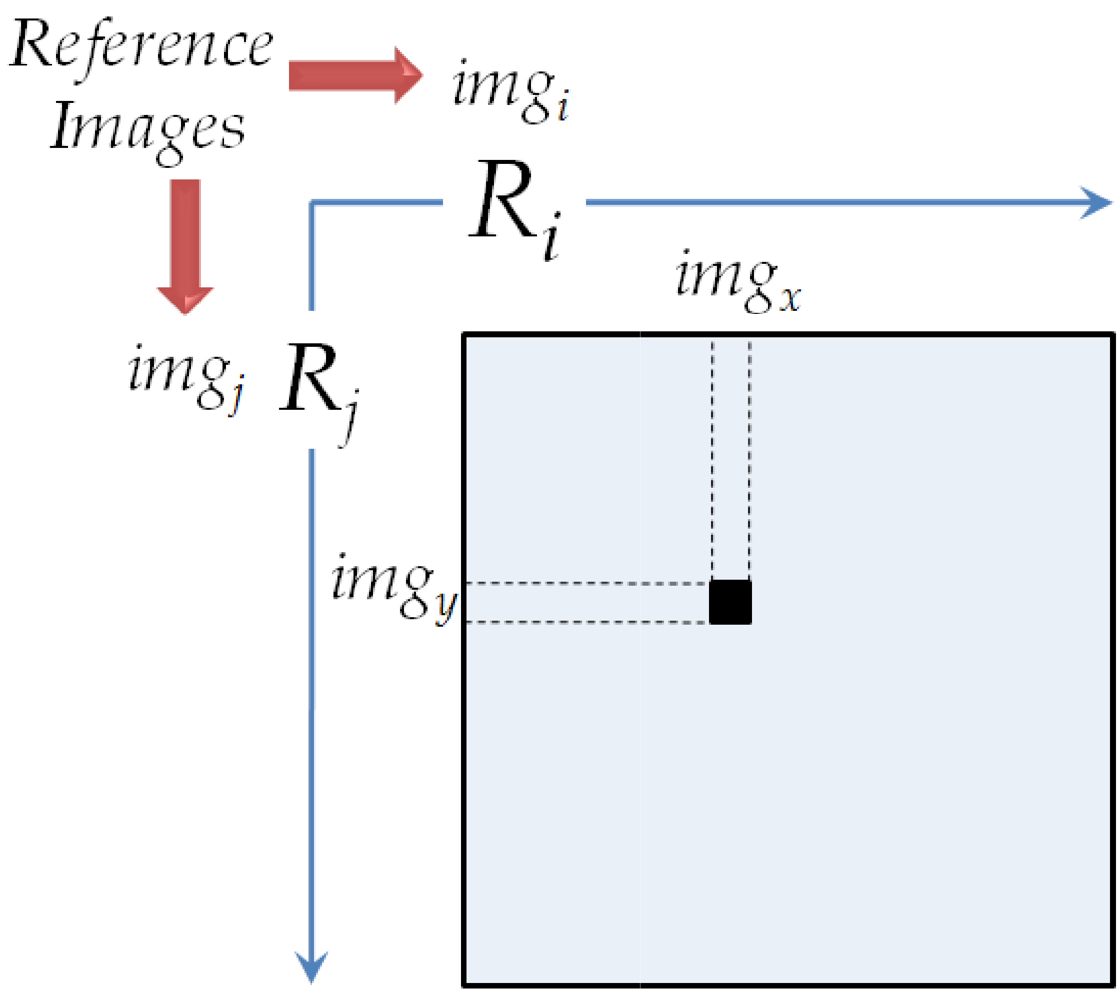
Rank Aggregation Mehtods

- Correlation between approaches to be combined:
  - Lowest error occurs when the approaches are independent and non-correlated
- Learning to rank approaches
  - SVM, GP
- Semi-supervised approaches
  - Co-Transduction
- In general, approaches does not consider *relationship* among images.

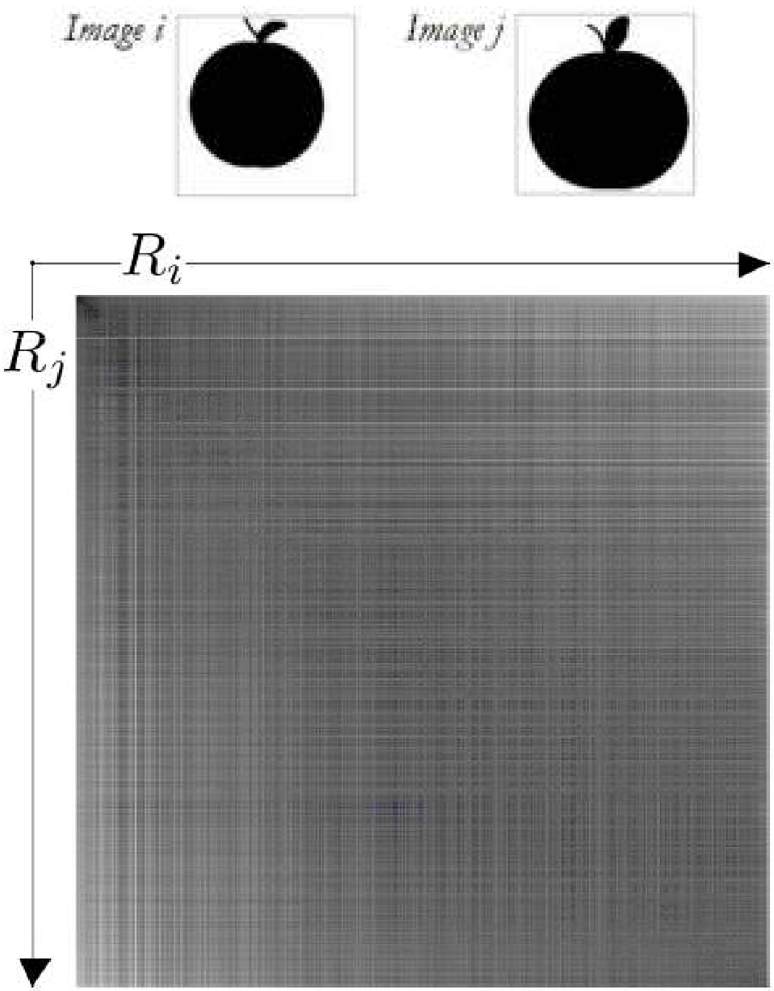
Contextual Rank Aggregation

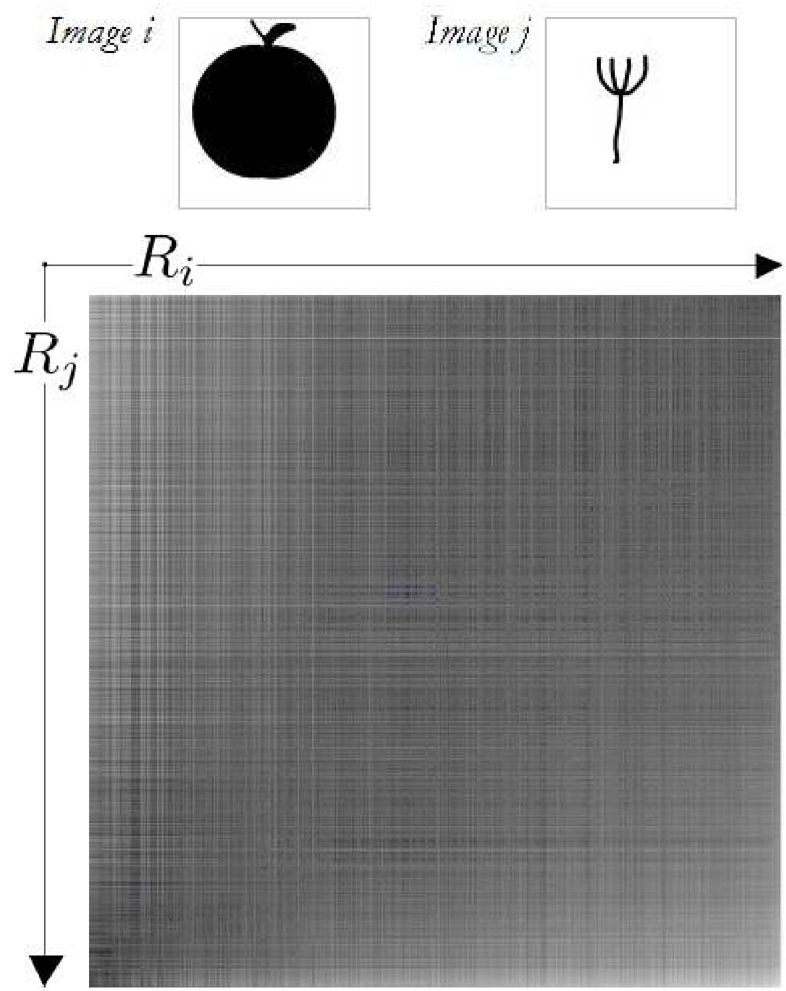
- Method that combine rankings taking into account *contextual information*;
- *Image processing* techniques for contextual information representation and processing;
- Objective: given two reference images, to construct a *Context Image* for exploiting contextual information;
- Context Image: a gray scale image which axis are ordered according to ranked lists of reference images and pixels represent distance between images

Contextual Information Representation



Context Images





Contextual Rank Aggregation Algorithm

Perform along T iterations:

For each descriptor to be combined: D_l (only for the the first iteration)

For each collection image: img_i

For each KNN (img_i)

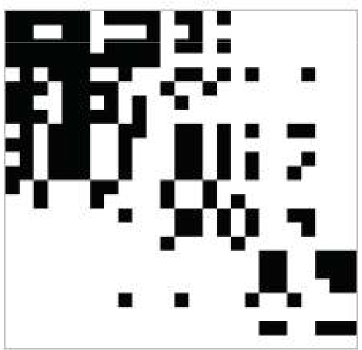
Create the Context Image $\hat{I}$ → **Process the Context Image $\hat{I}$** → **Increment Affinity Matrix W**

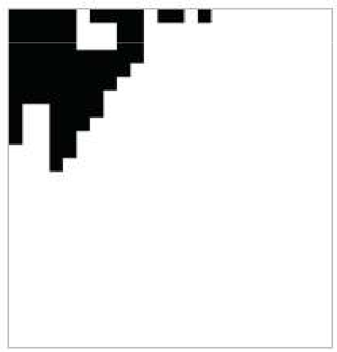
Compute Distance Matrix A_{t+1} *(from Affinity Matrix W)*

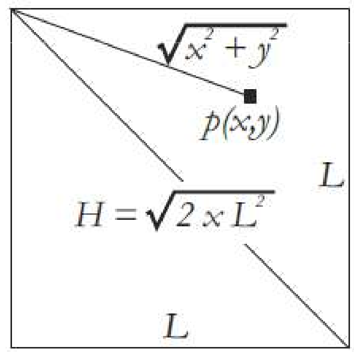
Perform Re-Ranking *(based on Matrix A_{t+1})*

Processing Context Images

- **Processing Context Image:**
  1. Limiarization
  2. Median Filter
  3. Incrementing Affinity Matrix W







- Incrementing Affinity Matrix W:

$$W[imgj_x, imgi_y] = W[imgi_x, imgi_y] + [(K - k)(H / \sqrt{x^2 + y^2})]$$

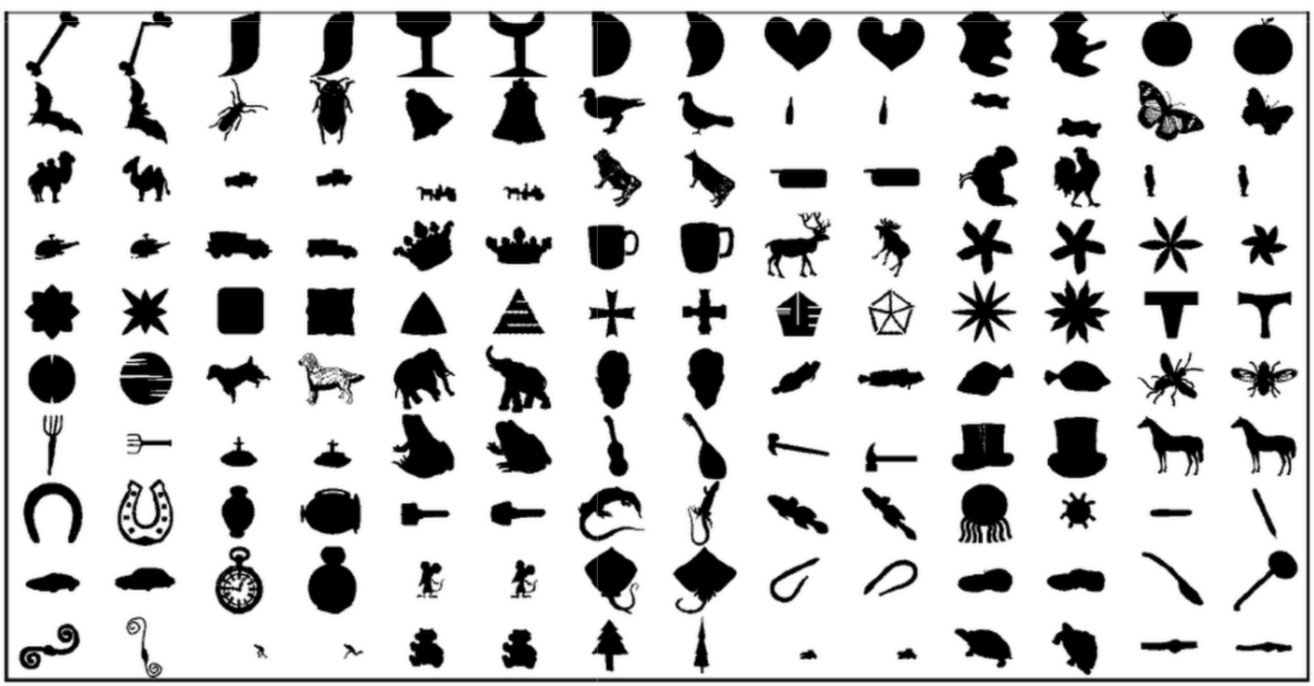
where (x,y) represents the pixel posistion, k the current neighbor, K the number of neighbors to be considered and H the diagonal size of top left region of context image being processed.

Experimental Evaluation

- Descriptors:
  - Shape : Inner Distance Shape Context (IDSC), Contour Features Descriptor (CFD), and Aspect Shape Context (ASC);
  - Color: Border/Interior Pixel Classication (BIC), Auto Color Correlograms (ACC), and Global Color Histogram(GCH);
  - Texture: Local Binary Patterns (LBP), Color Co-Occurrence Matrix (CCOM), and Local Activity Spectrum (LAS).

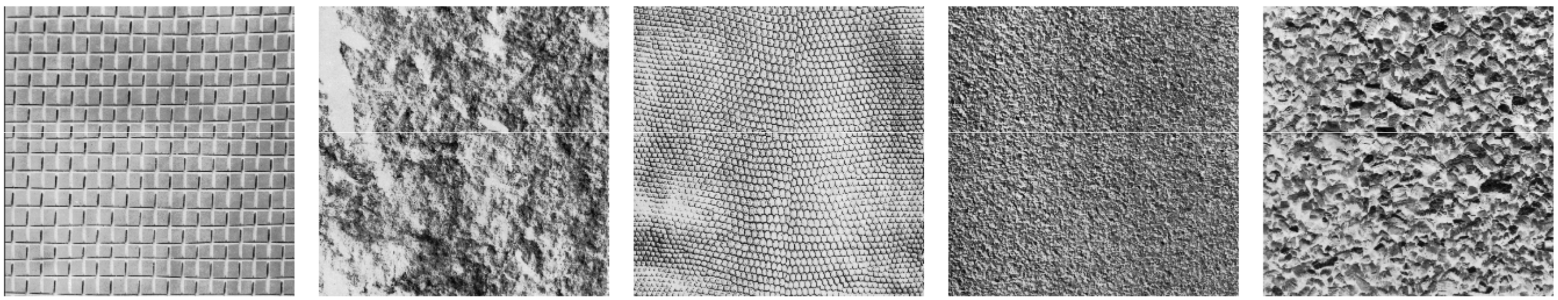
Experimental Evaluation

- Datasets
  - MPEG-7: 1400 binary images divided into 70 shape classes of 20 images each.



Experimental Evaluation

- Datasets
  - Brodatz: composed of 111 different textures. Each texture is divided into 16 blocks, such that 1776 images are considered.



  - Soccer Dataset: images from 7 soccer teams, containing 40 images per class.

Experimental Results: General CBIR Tasks

Image Descriptor	Type	Dataset	Score (MAP)
CFD	Shape	MPEG-7	80.71%
IDSC	Shape	MPEG-7	81.70%
ASC	Shape	MPEG-7	85.28%
IDSC+ASC	**Shape**	**MPEG-7**	**88.34%**
CFD+IDSC	**Shape**	**MPEG-7**	**98.11%**
CFD+ASC	**Shape**	**MPEG-7**	**98.61%**
ACC	Color	Soccer	37.23%
BIC	Color	Soccer	39.26%
ACC+BIC	**Color**	**Soccer**	**41.80%**
CCOM	Texture	Brodatz	57.57%
LAS	Texture	Brodatz	75.15%
CCOM+LAS	**Texture**	**Brodatz**	**81.25%**

Experimental Results: Comparison to other Rank Aggregation approaches

Algorithm	Score (Recall@40)
Data Driven Generative Models (DDGM)	*80.03%*
Contour Features Descritpor (CFD)	*84.43%*
Inner Distance Shape Context (IDSC)	*85.40%*
Shape Context (SC)	*86.80%*
Aspect Shape Context (ASC)	*88.39%*
IDSC + ASC + Contextual Rank Aggregation	**91.51%**
IDSC + DDGM + Co-Transduction	97.31%
SC + DDGM + Co-Transduction	97.45%
SC + IDSC + Co-Transduction	97.72%
CFD + IDSC + Contextual Rank Aggregation	**99.05%**
CFD + ASC + Contextual Rank Aggregation	**99.24%**

Conclusions

- Rank Aggregation method that exploits *contextual information* considering gray scale image representations of distances;
- Applicability to several CBIR tasks based on shape, color, and texture;
- High effectiveness performance when compared with state-of-the-art methods on the well-known MPEG-7 dataset.

Future Work

- Exploiting more contextual information
  - How to exploit relationship among pixels in context images?
- Other image processing techniques
  - Dynamic thresholding
  - Other filtering approaches
- Efficiency analysis and improvements

Exploiting Contextual Information for Rank Aggregation

Daniel Carlos Guimarães Pedronette
Ricardo da S. Torres

RECOD Lab - Institute of Computing (IC)
University of Campinas (UNICAMP) - Brazil