Image Re-Ranking and Rank Aggregation based on Similarity of Ranked Lists

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Abstract. We present a novel approach for redefining distances and later re-ranking images aiming to improve the effectiveness of CBIR tasks. In our approach, distance among images are redefined based on the similarity of their ranked lists. Conducted experiments involving shape, color, and texture descriptors demonstrate the effectiveness of our method.

1. 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 (such as, shape, color, and texture).

In this work, we present the *RL-Sim Re-Ranking Algorithm*, a new post-processing method that considers *ranked lists similarities for taking into account contextual information*.

We propose a **novel approach for computing new distances among images based on the similarity of their ranked lists**. Each ranked list is modeled as sets and set operations are used for computing the similarity between two ranked lists.

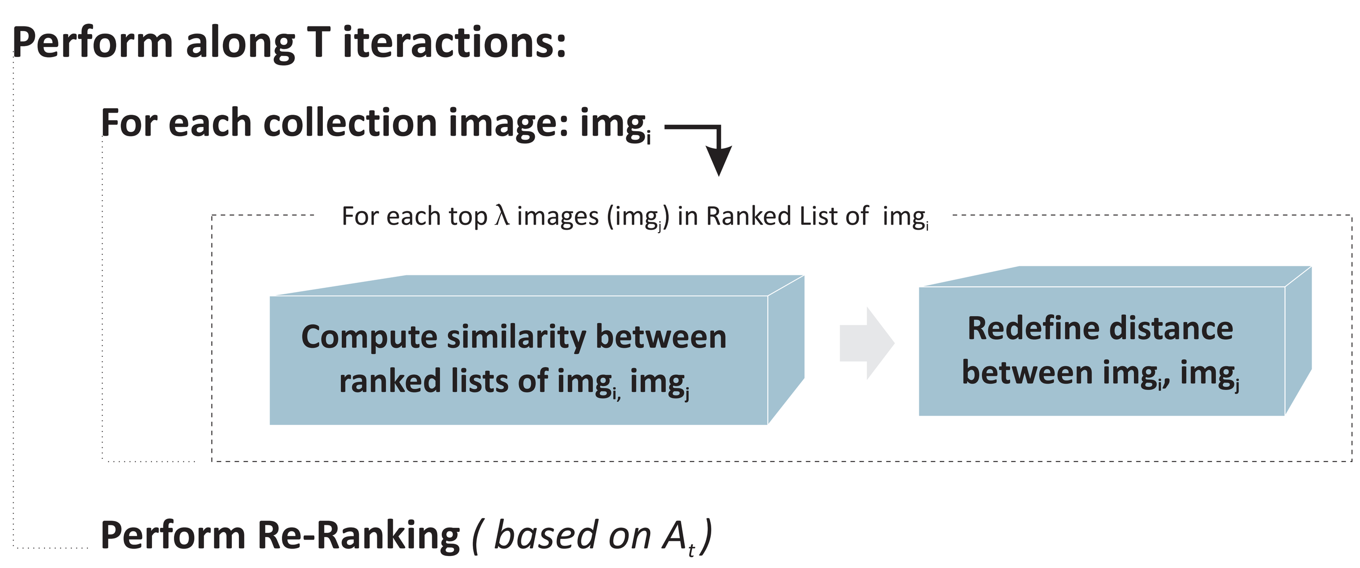
2. RL-Sim Re-Ranking Algorithm

The main motivation of RL-Sim Re-Ranking algorithm relies on two conjectures:

(i) the contextual information encoded in ranked lists can be used for improving effectiveness of CBIR descriptors;

(ii) by analysing the similarity/distance between ranked lists a more effective distance between images can be computed.

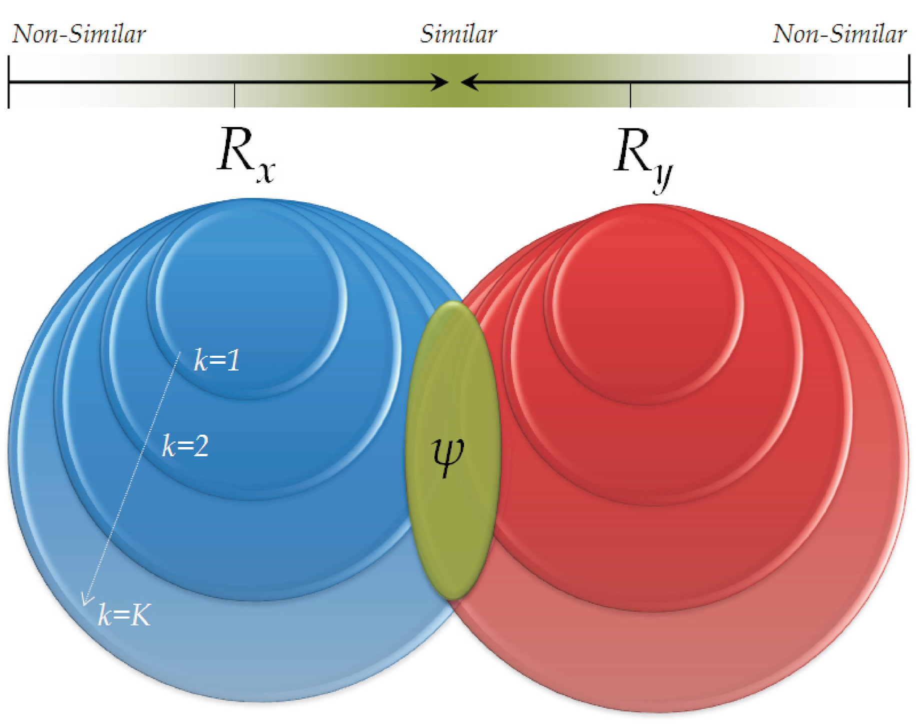
An iterative algorithm is proposed based on these conjectures:



3. Similarity Between Ranked Lists

A function ψ, inspired in the intersection metric, computes the similarity between two ranked lists considering their top K positions. It considers the intersection between the subsets of two ranked lists considering different values of k, such that $k \leq K$.

$$\psi(R_x, R_y, K) = \frac{\sum_{k=1}^{K} |KNN(R_x,k) \cap KNN(R_y,k)|}{K}$$

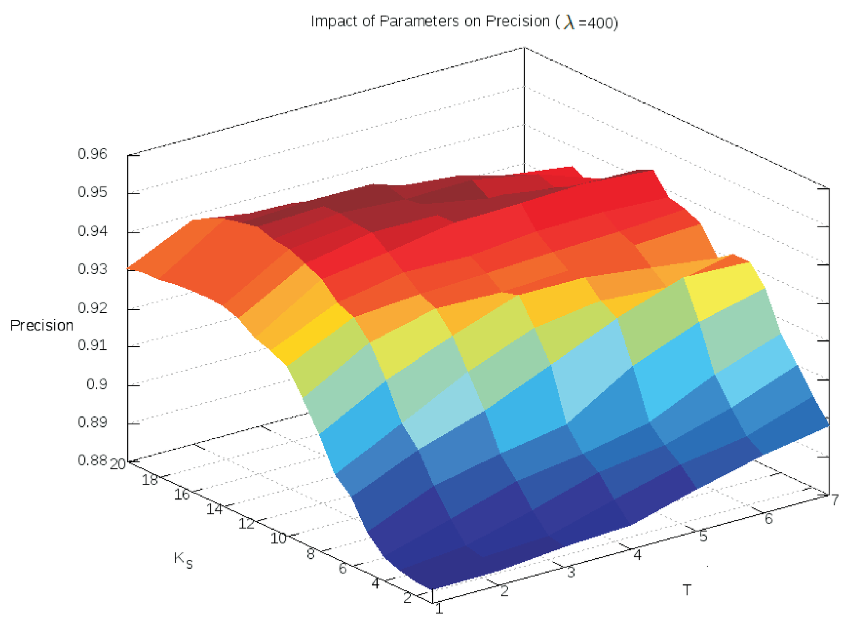


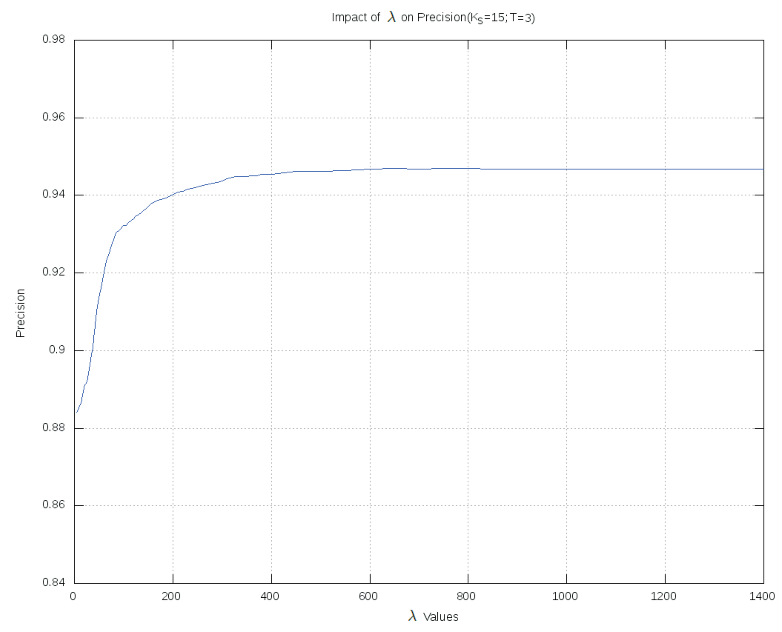
- Rank Aggregation:

$$A_c[i,j] = A_1[i,j] \times A_2[i,j] \times \dots \times A_m[i,j]$$

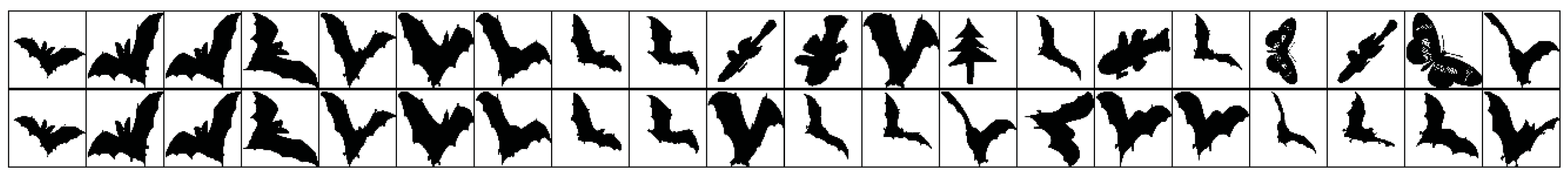
4. Experimental Results

- **Impact of Parameters:** K_s, T, and λ



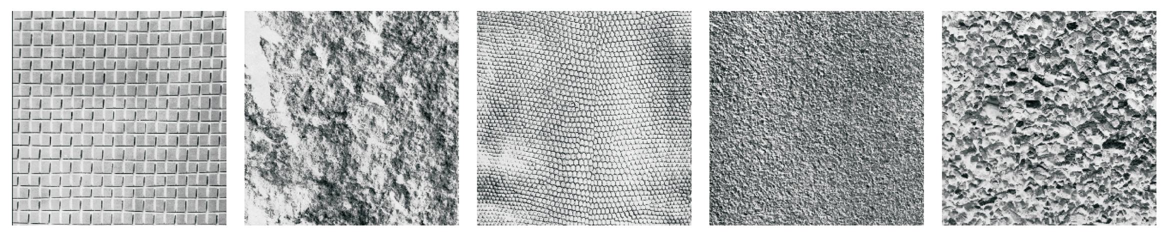


- **Shape Descriptors:** MPEG-7 Dataset



- **Color Descriptors:** Soccer Dataset

- **Texture Descriptors:** Brodatz Dataset



- **Results** *(MAP)*:

Descritor	Type	Dataset	Score[%]	Contextual Spaces	Gain
SS	Shape	MPEG-7	37.67%	43.06%	**+14.31%**
BAS	Shape	MPEG-7	71.52%	74.57%	**+4.25%**
IDSC	Shape	MPEG-7	81.70%	86.75%	**+6.18%**
CFD	Shape	MPEG-7	80.71%	88.97%	**+10.23%**
ASC	Shape	MPEG-7	85.28%	88.81%	**+4.14%**
GCH	Color	Soccer Dataset	32.24%	33.66%	**+4.40%**
ACC	Color	Soccer Dataset	37.23%	43.54%	**+16.95%**
BIC	Color	Soccer Dataset	39.26%	43.45%	**+10.67%**
LBP	Texture	Brodatz	48.40%	47.77%	**-1.30%**
CCOM	Texture	Brodatz	57.57%	62.01%	**+7.72%**
LAS	Texture	Brodatz	75.15%	77.81%	**+3.54%**

5. Conclusions

Contributions:
- A new re-ranking method based on ranked lists similarities;
- Applicability of the method to several image retrieval tasks based on shape, color and texture descriptors.

Future Work:
- Investigation of other distance functions between ranked lists ;
- Use of our approach in multimodal searches involving visual and textual descriptions associated with images.

6. Acknowledgment

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