Distances Correlation for Re-Ranking in Content-Based Image Retrieval

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Outline

- Distance Optimization Algorithm
  - The Algorithm
  - Clustering Approach
- Distances Correlation
  - Bidimensional Space
  - Distances Updating
- Evaluation
  - Shape, Color, Texture
- Conclusions

Distance Optimization Algorithm

- Basic Idea: Similarity of Ranked lists
  - If two images are similar, their ranked lists should be similar too.
- Distance Optimization Algorithm
  - Create clusters:
    - by exploring information of ranked lists
  - Update distances:
    - distances among images of a same cluster are decreased

Distance Optimization Algorithm

- Convergence
  - Process (make clusters and update distances) is repeated until the quality of clusters does not improve.
- Cohesion for measuring quality of ranked lists
  - Quantity of references among ranked lists of images on the same cluster (references in first positions of ranked lists have greater weights)

Distance Optimization Algorithm

Algorithm 1 Distance Optimization Algorithm [7]

Require: Distance matrix W

Ensure: Optimized distance matrix W_o

$lastCohesion \leftarrow 0$

$currentCohesion \leftarrow computeCohesion(W)$

while $curCohesion > lastCohesion$ **do**

  $Cls \leftarrow createClusters(W)$

  W $\leftarrow$ ***updateDistances(W,Cls)***

  $lastCohesion \leftarrow currentCohesion$

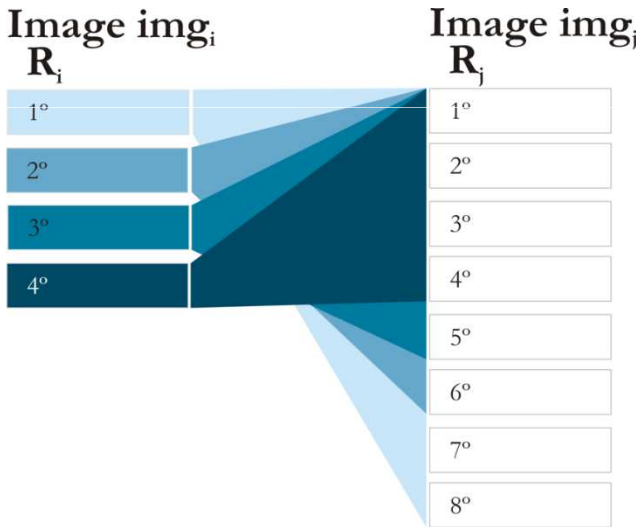
  $currentCohesion \leftarrow computeCohesion(W)$

end while

$W_o \leftarrow W$

Clustering Approach

- Graph-based clustering using ranked lists
  - Two images are assigned to the same cluster if they are cluster-similar
  - Basically, two images are cluster-similar if they refer to each other at the first positions of their ranked lists



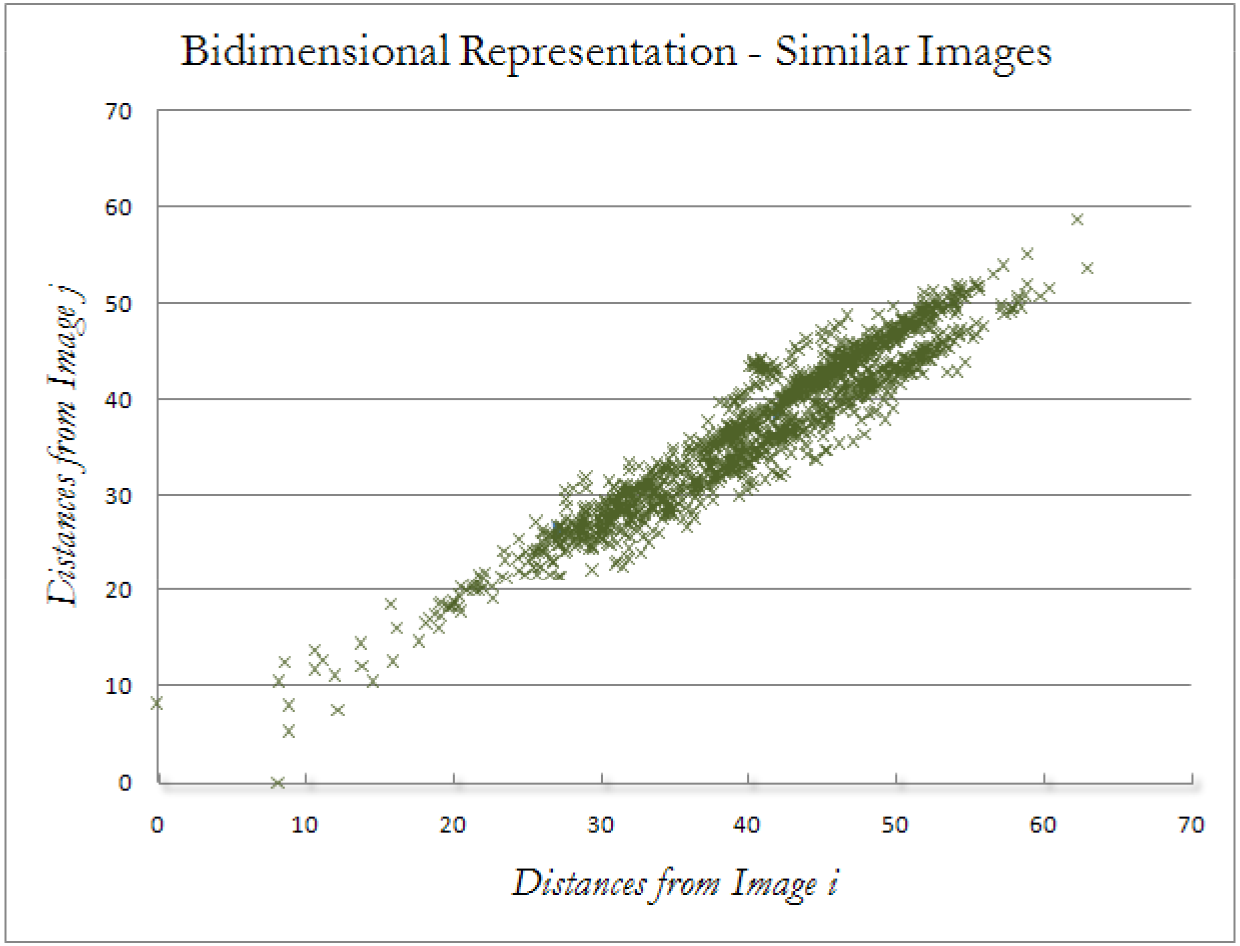
Distances Updating

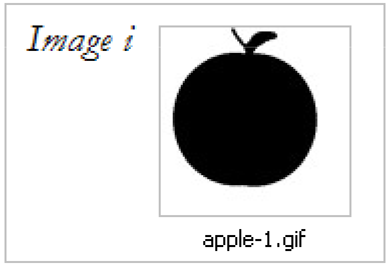
- Considering only clusters information:
  - If two images were assigned to the same cluster, the distance between them is decreased
    - Multiplied by a constant $\lambda < 1$
- Ignoring other information encoded in the relations among images
- A new approach to update distances in an adaptative way
  - Distances Correlation

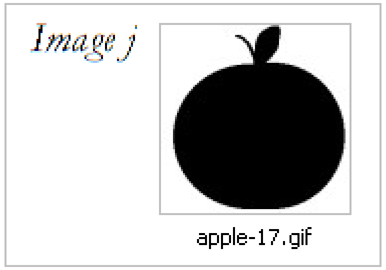
Distances Correlation

- Bidimensional Space
  - *Image space R^2 defined by the image collection $C=\{img_1, img_2, \ldots, img_n\}$ and a distance function $\rho : C \times C \rightarrow R$, where R denotes real numbers.*
  - Given two reference images img_i and img_j:
    - X axis represents the distances of collection images with regard to img_i.
    - Y axis represents the distances of collection images with regard to img_j.

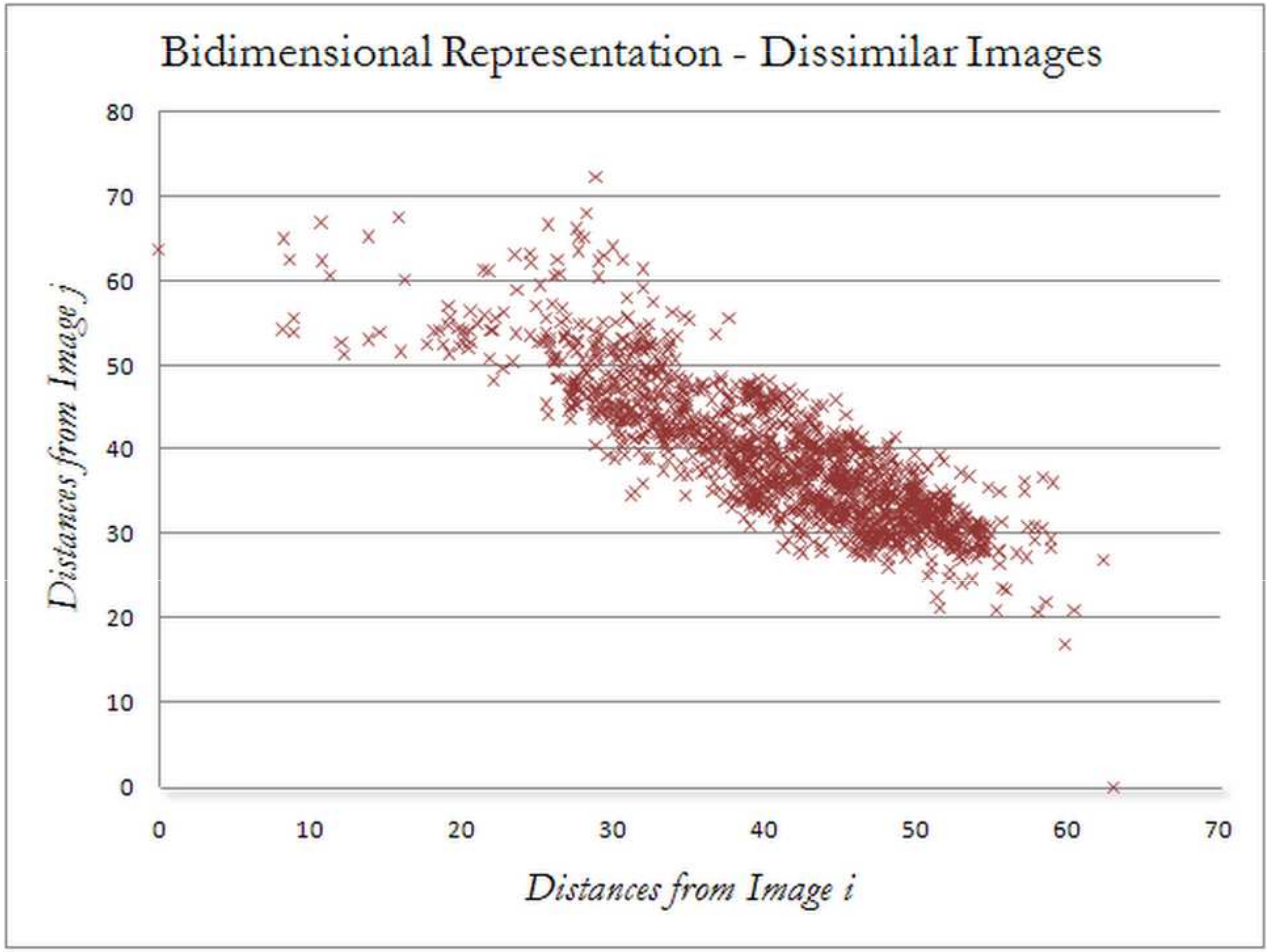
Distances Correlation

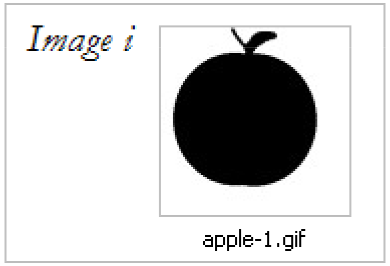


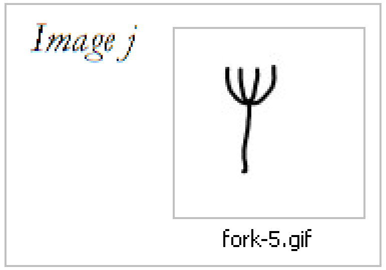




Distances Correlation







Distances Correlation

- Statistical measures to characterize the images distribution:
  - Magnitude of a relationship among variables
  - Pearson's Correlation Coefficient:

$$r = \frac{\sum_{i=1}^{n}(X_i - \overline{X})(Y_i - \overline{Y})}{\sqrt{\sum_{i=1}^{n}(X_i - \overline{X})^2}\sqrt{\sum_{i=1}^{n}(Y_i - \overline{Y})^2}}$$

  - KNNs of img_i and img_j for composition of X and Y

Distances Correlation

– Pearson's Correlation Coefficient:

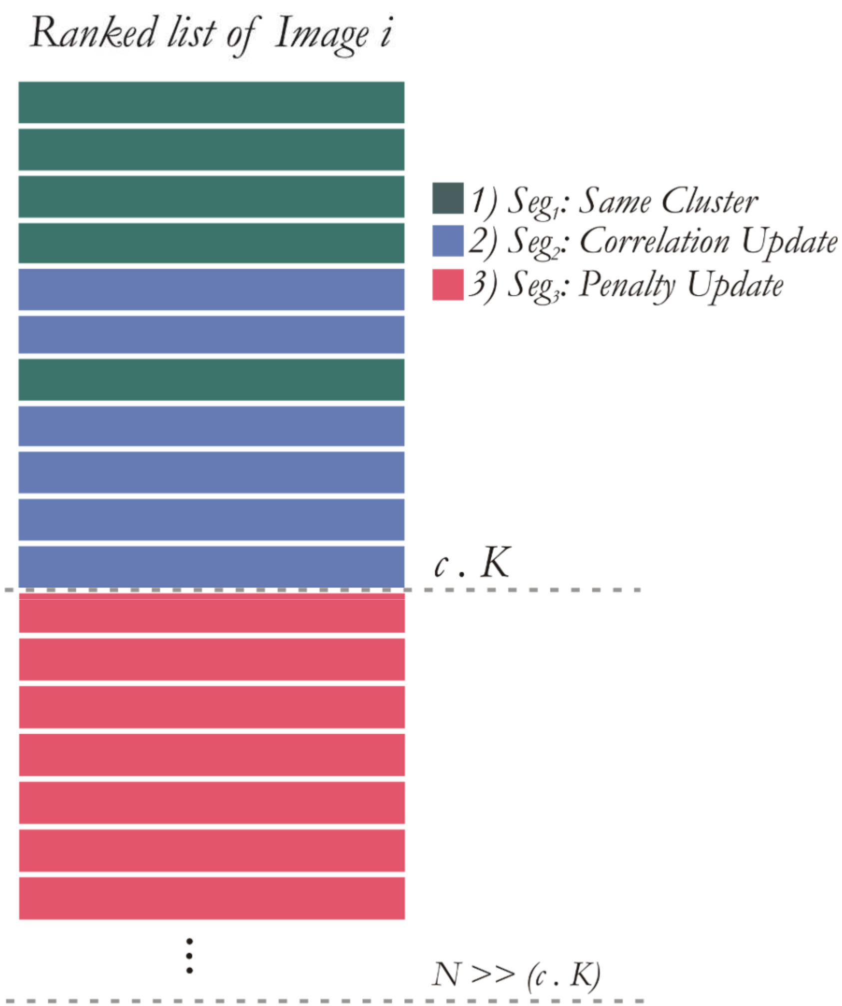
- r in the interval [-1,1];
- $\overline{r}$ in the interval [0,1];

  1: Perfect correlation

– Central Idea:

- Using cluster and correlation information for distances updating

Distances Updating

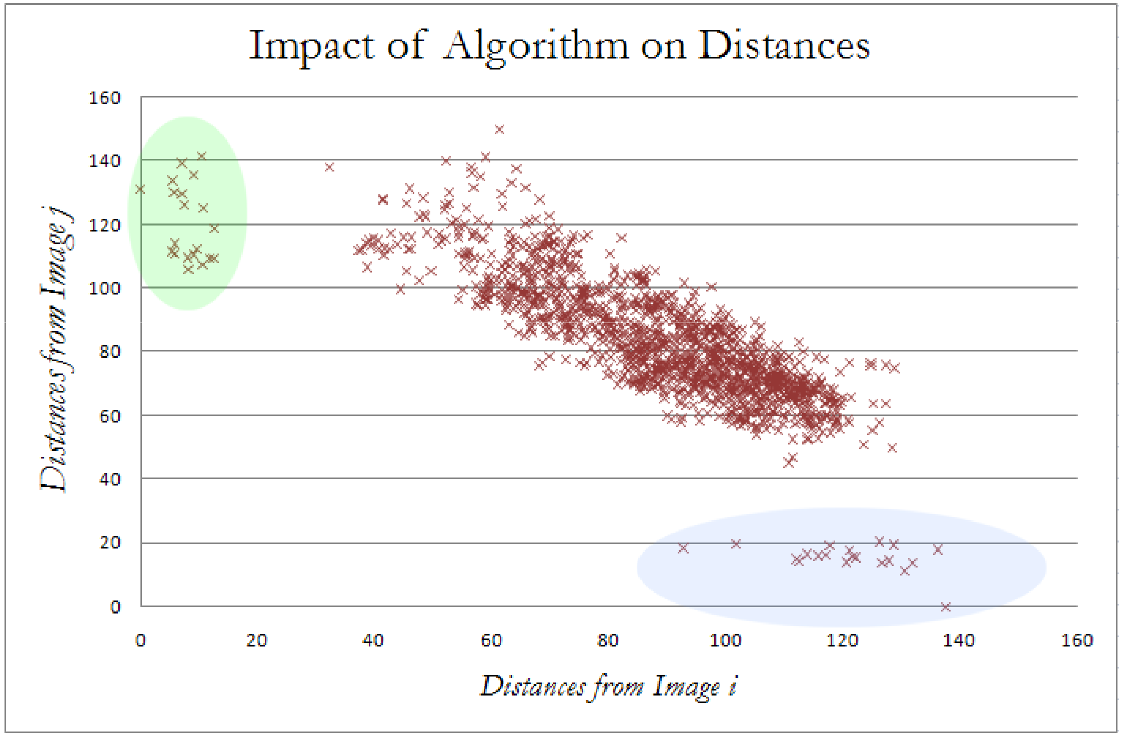


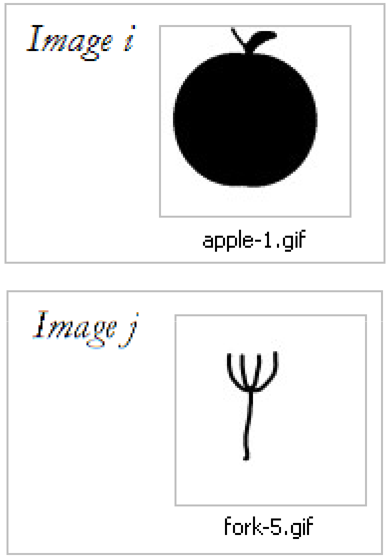
New Distances Computation: $\widehat{\rho}(i, j)$

- Seg_1: $\widehat{\rho}(i,j) = \rho(i,j) \cdot \lambda$
- Seg_2: $\widehat{\rho}(i,j) = \rho(i,j) \cdot (1 + [(1-\lambda) \cdot (1-\overline{r})])$
- Seg_3: $\widehat{\rho}(i,j) = \rho(i,j) \cdot [1 + (1-\lambda)]$

Experimental Analysis

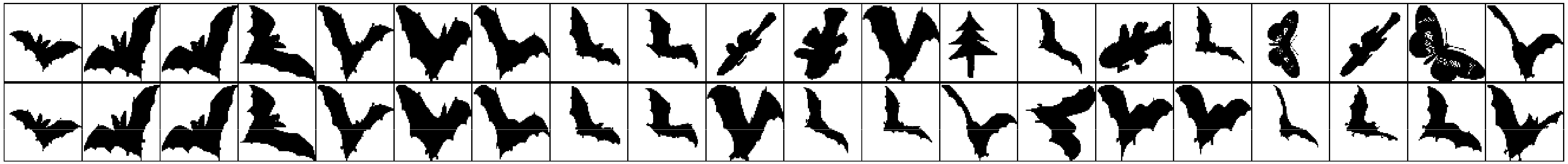
- Impact of algorithm on Distances
  - (considering non-similar reference images)





Evaluation

- **Shape**
  - Shape Descriptors:
    - CFD[7], IDSC[14], BAS[16], SS[15]
  - MPEG-7 Dataset (70 shapes, 20 each class)



  - <u>First row: </u>retrieval results for the CFD Shape Descriptor[7] (**first image as a query**).
  - <u>Second row: </u>retrieval results for the same shape descriptor after **distance optimization**.

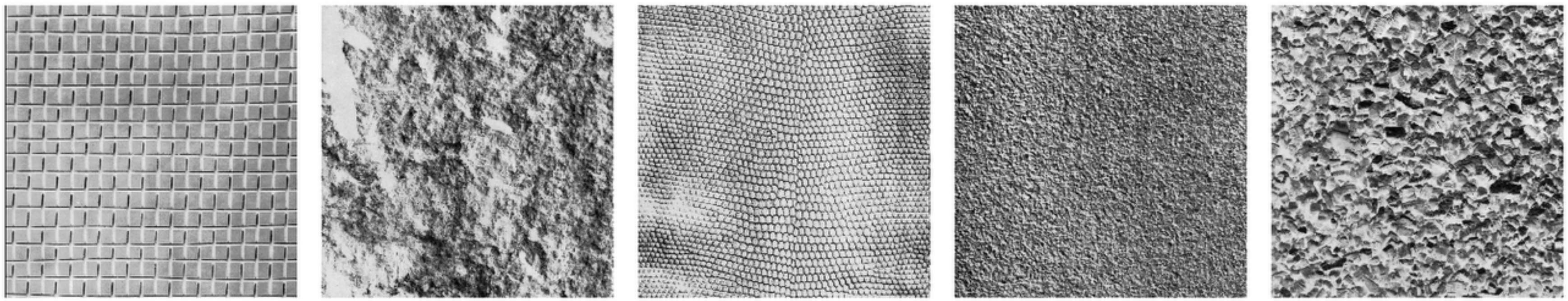
Evaluation

- **Color**
  - Color Descriptors:
    - ACC[17] , BIC[18],
  - Soccer Dataset [22]
    - 7 soccer teams, containing 40 images per class



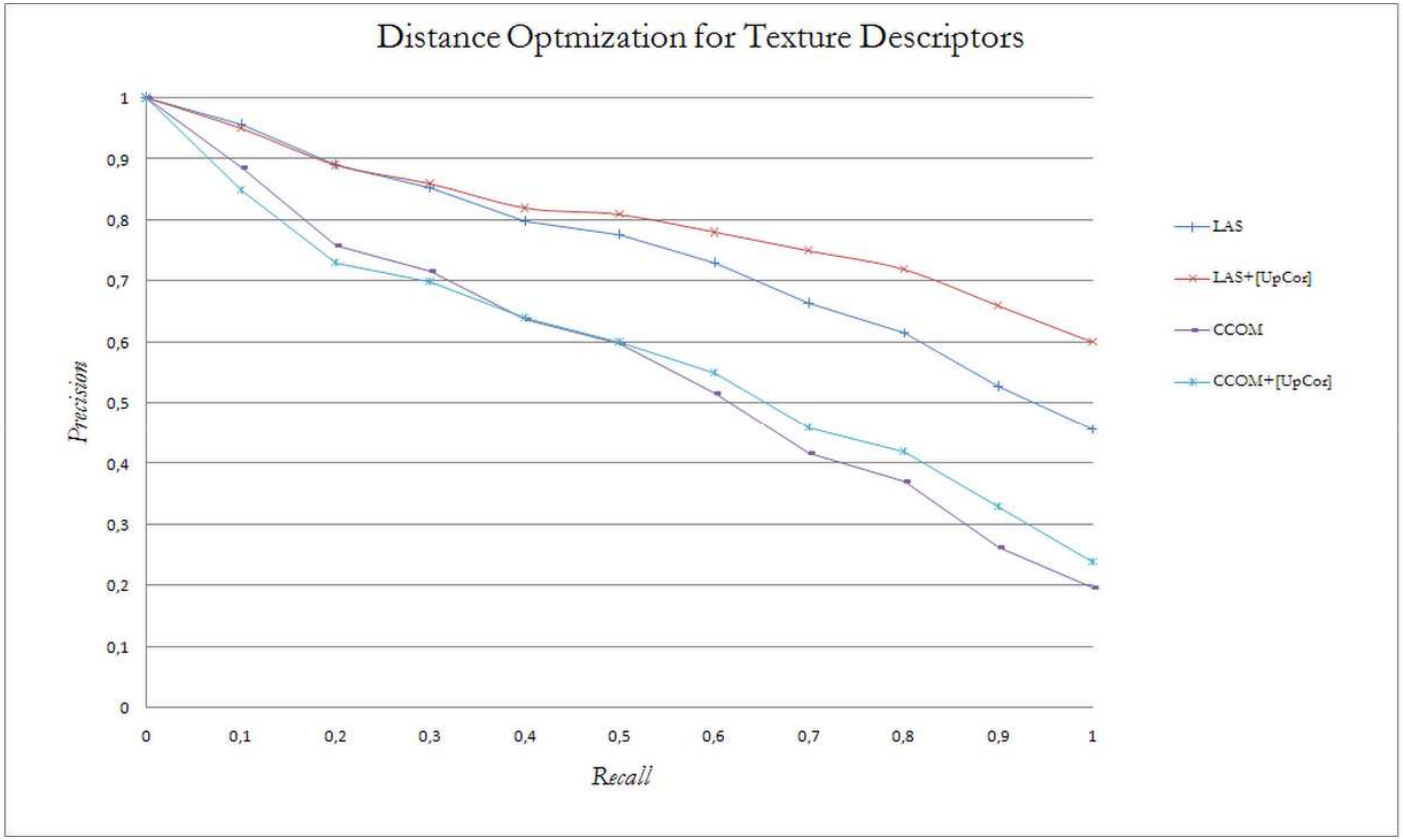

Evaluation

- **Texture**
  - Texture Descriptors
    - CCOM[19], LAS[20]
  - Brodatz Dataset [21]
    - 111 different texture classes



Experimental Results

- Example of *Precision x Recall* for Texture Descriptors:



Experimental Results

- General CBIR tasks:

Image Descriptor	Type	Dataset	Score [%] (MAP)	Distance Optimization + Update Correlation	Gain
SS [15]	Shape Descriptor	MPEG-7	37.67%	46.53%	+23.52%
BAS [16]	Shape Descriptor	MPEG-7	71.52%	81.05%	+13.32%
IDSC+DP [14]	Shape Descriptor	MPEG-7	81.70%	86.94%	+6.41%
CFD [7]	Shape Descriptor	MPEG-7	80.71%	91.79%	+13.73%
ACC [17]	Color Descriptor	Soccer Dataset	37.23%	42.46%	+14.05%
BIC [18]	Color Descriptor	Soccer Dataset	39.26%	38.16%	-2.80%
CCOM [19]	Texture Descriptor	Brodatz	57.57%	59.27%	+2.95%
LAS [20]	Texture Descriptor	Brodatz	75.15%	80.36%	+6.93%

Experimental Results

- Post-processing methods comparison on MPEG-7 (Recall@40)

Algorithm	Descriptor	Score	Gain
CFD [7]	-	84.43%	-
IDSC+DP [14]	-	85.40%	-
Graph Transduction [6]	IDSC+DP	91.00%	+6.56%
Distance Optmization [7]	CFD	92.56%	+9.63%
Constrained Diffusion Process [5]	IDSC+DP	93.32%	+9.27%
Mutual kNN Graph [4]	IDSC+DP	93.40%	+9.37%
DistOpt+UpCor	**CFD**	**93.62%**	**+10.88%**

Conclusions

- New concept of *'Distances Correlation'*
- New approach for a Re-Ranking method using this concept
- Experimental Evaluation
  – Shape, Color, Texture
  – Comparison to other post-processing methods
- Future Work
  – Application of method to other information retrieval tasks

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Cohesion Computation

- *Let $C = \{img_1, img_2, \ldots, img_n\}$ be a collection (or a cluster) of images, cohesion is defined as follows:*

$$cohesion(C) = \frac{\sum_{j=0}^{size} \sum_{i=0}^{topn} (top_n - i) \times (top_n / c) \times S(i)}{size^2}$$

where S is a function $S: i \rightarrow \{0,1\}$, that assumes value 1 if C contains the image at position i of ranked list and assumes value 0, otherwise.