Combining Re-Ranking and Rank Aggregation Methods

Daniel Carlos Guimarães Pedronette and Ricardo da S. Torres

Recod Lab - Institute of Computing
University of Campinas
Campinas, Brazil

Abstract. Content-Based Image Retrieval (CBIR) aims at retrieving the most similar images in a collection by taking into account image visual properties. In this scenario, accurately ranking collection images is of great relevance. Aiming at improving the effectiveness of CBIR systems, *re-ranking* and *rank aggregation* algorithms have been proposed. However, different re-ranking and rank aggregation approaches produce different image rankings. These rankings are complementary and, therefore, can be further combined aiming at obtaining more effective results. This paper presents novel approaches for combining re-ranking and rank aggregation methods aiming at improving the effectiveness of CBIR systems. Several experiments were conducted involving shape, color, and texture descriptors. Experimental results demonstrate that our approaches can improve the effectiveness of CBIR systems.

1 Introduction

Given a query image, a Content-Based Image Retrieval (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). CBIR systems use visual similarity for judging semantic similarity, which may be problematic due to the *semantic gap* related to the mismatch between low-level features and higher-level concepts. In order to reduce the semantic gap, several approaches have been proposed, as *re-ranking* and *rank aggregation* algorithms.

In general, CBIR systems consider only pairwise image analysis, that is, compute similarity measures considering only pairs of images, ignoring the rich information encoded in the relations among several images. In the past few years, there has been considerable research on exploiting *contextual information* for improving the distance measures and *re-ranking images* in CBIR systems [9,15,16,18,25,26]. Another approach for improving CBIR systems is based on using *rank aggregation* techniques [2,5]. Basically, rank aggregation techniques aim at combining different and complementary rankings in order to obtain a more accurate one.

Although a lot of efforts have been employed to develop new re-ranking and rank aggregation methods, few initiatives aim at combining existing approaches. Different re-ranking and rank aggregation methods produce different and complementary rankings, and therefore, can also be combined to obtain more effective results. Considering this scenario, we propose three novel approaches for

L. Alvarez et al. (Eds.): CIARP 2012, LNCS 7441, pp. 170–178, 2012.

combining re-ranking and rank aggregation methods aiming at improving the effectiveness of CBIR systems. This paper presents new approaches to combine *(i)* re-ranking algorithms; *(ii)* rank aggregation algorithms, and both *(iii)* re-ranking and rank aggregation algorithms. A large evaluation protocol was conducted involving shape, color, and texture descriptors, different datasets and comparisons with baseline methods. Experimental results demonstrate that our combination approaches can further improve the effectiveness of CBIR systems.

2 Combining Re-Ranking and Rank Aggregation

2.1 Problem Definition

Let $\mathcal{C}$=$\{img_1, img_2, \ldots, img_N\}$ be an *image collection*. Let $\mathcal{D}$ be an *image descriptor*, which defines a distance measure $\rho(img_i,img_j)$ between two given images. The distance $\rho(img_i,img_j)$ among all images $img_i,img_j \in \mathcal{C}$ can be computed to obtain an $N \times N$ distance matrix A, such that $A_{ij} = \rho(img_i,img_j)$. Given an image query img_q, we can compute a ranked list R_q=$\{img_1, img_2, \ldots, img_N\}$ in response to the query, based on distance matrix A. We also can take every image $img_i \in \mathcal{C}$ as an image query img_q, in order to obtain a set $\mathcal{R} = \{R_1, R_2, \ldots, R_N\}$ of ranked lists for each image of the collection $\mathcal{C}$.

We can formally define a *re-ranking* method as a function f_r that takes as input the distance matrix A and the set of ranked lists $\mathcal{R}$ for computing a new and more effective distance matrix $\hat{A}$, such that $\hat{A} = f_r(A, \mathcal{R})$.

Let $\mathcal{D} = \{D_1, D_2, \ldots, D_m\}$ be a set of m image descriptors. The set of descriptors $\mathcal{D}$ can be used for computing a set of distances matrices $\mathcal{A} = \{A_1, A_2, \ldots, A_m\}$ (and associated set of ranked lists $\mathcal{R}_\mathcal{A}$). The objective of *rank aggregation* methods is to use the sets $\mathcal{A}$ and $\mathcal{R}_\mathcal{A}$ as input for computing a new (and more effective) distance matrix $\hat{A}_c$, such that $\hat{A}_c = f_a(\mathcal{A}, \mathcal{R}_\mathcal{A})$.

2.2 Cascading Re-Ranking

Both input and output of a re-ranking method defined by a function f_r is a distance matrix (the set of ranked lists $\mathcal{R}$ can be computed based on the distance matrix). In this way, an output matrix obtained from a given function f_{r_1}, implemented by a re-ranking algorithm can be used as input of other re-ranking algorithm f_{r_2}, aiming at further improving its effectiveness. We call this combination approach as "*cascading re-ranking*", as it can be applied to a chain of re-ranking algorithms. The main motivation of this approach is based on two facts: *(i)* different re-ranking algorithms exploit contextual information in different ways and can be complementary (one algorithm can improve the quality of ranked lists that others did not); *(ii)* the second re-ranking algorithm can take advantage of improvements obtained by the first one. Figure 1 illustrates this combination approach, considering two re-ranking algorithms.

2.3 Re-Ranking with Rank Aggregation Combination

A single image descriptor can be submitted to different re-ranking algorithms, defined by a set of functions $\{f_{r_1}, f_{r_2}, \ldots, f_{r_m}\}$. In this scenario, a different

distance matrix is produced for each re-ranking algorithm. However, the results can be complementary (one re-ranking can exploit contextual information that others did not). In this way, a rank aggregation method can combine the results of different re-ranking algorithms in order to obtain a single, and more effective distance matrix. Figure 2 illustrates this process, considering the use of two re-ranking methods followed by a rank aggregation step.

2.4 Agglomerative Rank Aggregation

The two previous combination approaches consider that only one image descriptor is available. This sections presents the "*agglomerative rank aggregation*" approach that uses several image descriptors as input. Given a set of image descriptors, different rank aggregation methods can be employed for combining them. However, each rank aggregation method produces a different output. In this way, another rank aggregation method can be used for combining the results of the first rank aggregation methods. This combination approach uses a hierarchical agglomerative method, in which the rank aggregation approaches are divided into layers. Figure 3 illustrates our approach for a two-layer rank aggregation scenario.

Fig. 1. Cascading Re-Ranking

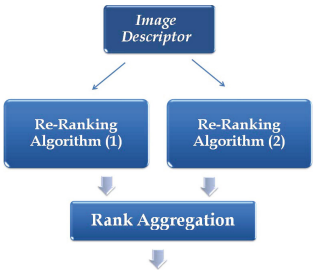

Fig. 2. Re-Ranking with Rank Aggregation

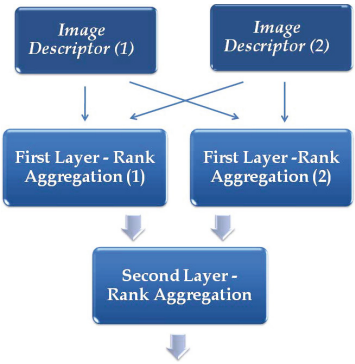

Fig. 3. Aglomerative Rank Aggregation

3 Used Re-Ranking and Rank Aggregation Methods

This section briefly describes the re-ranking and rank aggregation methods considered for combination in our experimental evaluation.

3.1 Re-Ranking Methods

• **Contextual Re-Ranking:** The Contextual Re-Ranking (CRR) [15] algorithm re-ranks images by taking into account *contextual information* encoded in

ranked lists and distance among images. The algorithm uses a *gray scale image* representation of distance matrices computed by CBIR descriptors, referenced as *context image*. The context image is constructed for the k-nearest neighbors of a query image and analyzed using image processing techniques.

• **RL-Sim Re-Ranking Algorithm:** The RL-Sim Re-Ranking [18] algorithm is based on the conjecture that *contextual information encoded in the similarity between ranked lists can provide resources for improving effectiveness of CBIR descriptors*. An iterative approach is used for improving the effectiveness of ranked lists.

3.2 Rank Aggregation Methods

• **Contextual Rank Aggregation:** The *Contextual Rank Aggregation (CRA)* [17] algorithm combines the results of different descriptors. The main idea consists in applying the Contextual Re-Ranking [15] algorithm, but using the affinity matrix W for accumulating updates of different descriptors at the first iteration. In this way, different matrices $A_d \in \mathcal{A}$ of different descriptors are combined.

• **RL-Sim Rank Aggregation:** Let $\mathcal{C}$ be an image collection and let $\mathcal{D} = \{D_1, \ldots, D_m\}$ be a set of descriptors. We use the set of descriptors $\mathcal{D}$ for computing a set of distances matrices $\mathcal{A} = \{A_1, \ldots, A_m\}$. The approach used by the RL-Sim Algorithm [18] combines the set $\mathcal{A}$ in a unique matrix A_c. For the matrices combination a multiplicative approach is used. Each position (i, j) of the matrix is computed as follows: $A_c[i, j] = (1 + A_1[i, j]) \times (1 + A_2[i, j]) \times \ldots (1 + A_m[i, j])$.

• **Set Rank Aggregation:** we propose a simple rank aggregation method to be used in the *second layer* of the agglomerative approach combination. We call this method as *Set Rank Aggregation (SetRA)* . We consider the strategy of modelling the ranked lists as *sets* of different sizes, also used by the RL-Sim [18] algorithm. We use the function ψ to compute the similarity between ranked lists. The objective of function ψ, based on the intersection metric [6], is to compute a more effective distance between two images considering the contextual information encoded in the first K positions of their ranked lists. The function ψ computes the intersection between the subsets of two ranked lists considering different values of k, such that $k \leq K$, as follows ψ: $\psi(R_x, R_y, K) = \frac{\sum_{k=1}^{K} |KNN(R_x,k) \cap KNN(R_y,k)|}{K}$. The main idea is to compute the similarity between ranked lists considering each descriptor being combined, and add this similarity scores in order to obtain a new combined score. Let m be the number of matrices being combined and R_{i_x} be the ranked list produced by matrix A_i for image img_x and R_{i_y} for image img_y, the new combined similarity score ψ_c is computed as follows: $\psi_c(img_x, img_y, K) = \sum_{i=1}^{m} \psi(R_{i_x}, R_{i_y}, K)$.

4 Experimental Evaluation

This section presents conducted experiments for assessing the effectiveness of the three proposed combination approaches. We analysed our approaches under several aspects and compared our results with baselines from the literature. Three

datasets and twelve descriptors (six shape descriptors, three color descriptors and three texture descriptors) are considered. We briefly describe the datasets in the following:

• **MPEG-7:** the MPEG-7 dataset [11] is a well-known shape dataset, commonly used for re-ranking and post-processing methods evaluation and comparison. The dataset is composed by 1400 shapes divided into 70 classes.

• **Brodatz:** the Brodatz [4] dataset is a popular dataset for texture descriptors evaluation. The Brodatz dataset are composed of 111 different textures. Each texture is divided into 16 blocks, such that 1776 images are considered.

• **Soccer:** the Soccer dataset [24] is composed by images from 7 soccer teams, containing 40 images per class.

As effectiveness measures, we use the Mean Average Precision (*MAP*). In addition to MAP, we consider the bullseye score (*Recall@40*) for the MPEG-7 dataset, which counts all matching objects within the 40 most similar candidates. Since each class consists of 20 objects, the retrieved score is normalized with the highest possible number of hits.

4.1 Cascading Re-Ranking

The evaluation of the *Cascade Re-Ranking* approach considers the MPEG-7 dataset and four different re-ranking methods: the Distance Optimization Algorithm (DOA) [16], the Mutual kNN Graph [9], the Contextual Re-Ranking [15], and RL-Sim [18] algorithms. We also considered the Contextual Re-Ranking [15] and RL-Sim [18] combined with all algorithms. Table 1 presents the results for *Recall@40* measure. We can observe that the gains are positives for all combinations, ranging from +0.11% to +1.99%. Those results demonstrate that, even with contextual information already exploited by the first re-ranking employed, the second re-ranking can further improve the effectiveness when combined by our cascading approach.

Table 1. Cascading Re-Ranking Methods on the MPEG-7 dataset *(Recall@40)*

Descriptor	Score	Re-Ranking Algorithm 1	Score	Re-Ranking Algorithm 2	Cascade Score	Gain
CFD [16]	84.43%	Distance Optimization [16]	92.56%	Contextual Re-Ranking [15]	**93.39%**	+10.61%
CFD [16]	84.43%	Distance Optimization [16]	92.56%	RL-Sim Re-Ranking [18]	**94.40%**	+11.81%
IDSC [12]	85.40%	Mutual kNN Graph [9]	93.40%	Contextual Re-Ranking [15]	**93.68%**	+9.70%
IDSC [12]	85.40%	Mutual kNN Graph [9]	93.40%	RL-Sim Re-Ranking [18]	**94.09%**	+10.18%
CFD [16]	84.43%	RL-Sim Re-Ranking [18]	94.13%	Contextual Re-Ranking [15]	**94.23%**	+11.61%
CFD [16]	84.43%	Contextual Re-Ranking [15]	95.71%	RL-Sim Re-Ranking [18]	**95.94%**	+13.63%

4.2 Combining Re-Ranking Methods with Rank Aggregation

This section presents the evaluation of our approach for combining re-ranking with rank aggregation algorithms, considering three datasets and twelve descriptors, including shape, color, and texture descriptors. We consider the Contextual Re-Ranking (CRR) [15] and the RL-Sim [18] re-ranking algorithms, and the Set Rank Aggregation. Table 2 presents the MAP scores for RL-Sim [18] and Contextual Re-Ranking [15] algorithms in isolation (as baselines), and considering

our combination approach. As we can observe, for almost all descriptors our combination approach presents a higher MAP score than both baselines, with significant gains. Exceptions are the LBP [14] and LAS [22] descriptors, in which the RL-Sim [18] presents low gains. However, we should note that, even for those cases, our combination approach presents a MAP score higher than the worst re-ranking method. Our approach also presents a higher average score when compared with both re-ranking algorithms.

Table 2. Re-Ranking with Rank Aggregation Combination on CBIR Tasks *(MAP)*

Image Descriptor	**Type**	**Dataset**	**Score**	**Re-Ranking 1: *RL-Sim [18]***	**Re-Ranking 2: *CRR [15]***	**Rank Aggregation: *SetRA***	**Gain**
SS [19]	Shape	MPEG-7	37.67%	43.06%	44.79%	**47.33%**	+25.64%
BAS [1]	Shape	MPEG-7	71.52%	74.57%	76.60%	**78.31%**	+9.49%
IDSC [12]	Shape	MPEG-7	81.70%	86.75%	87.39%	**88.66%**	+8.52%
CFD [16]	Shape	MPEG-7	80.71%	88.97%	92.76%	**92.94%**	+15.15%
ASC [13]	Shape	MPEG-7	85.28%	88.81%	89.82%	**90.62%**	+6.26%
AIR [7]	Shape	MPEG-7	89.39%	93.54%	94.49%	**97.15%**	+8.68%
GCH [21]	Color	Soccer	32.24%	33.66%	33.02%	**33.78%**	+4.78%
ACC [8]	Color	Soccer	37.23%	43.54%	39.86%	**46.60%**	+25.17%
BIC [20]	Color	Soccer	39.26%	43.45%	43.04%	**47.27%**	+20.40%
LBP [14]	Texture	Brodatz	48.40%	47.77%	49.06%	**47.93%**	-0.97%
CCOM [10]	Texture	Brodatz	57.57%	62.01%	63.67%	**64.20%**	+11.52%
LAS [22]	Texture	Brodatz	75.15%	77.81%	78.48%	**77.89%**	+3.65%
Average			61.34%	65.32%	66.08%	**67.72%**	+11.52%

Table 3. Re-Ranking and Rank Aggregation Combination for Shape Descriptors

Shape Descriptor	**Score**	**Re-Ranking 1: *RL-Sim [18]***	**Re-Ranking 2: *CRR [15]***	**Rank Aggregation: *SetRA***	**Gain**
SS [19]	43.99%	53.15%	51.38%	**54.69%**	+24.32%
BAS [1]	75.20%	82.94%	82.43%	**83.51%**	+11.06%
IDSC [12]	85.40%	92.18%	91.84%	**92.16%**	+7.92%
CFD [16]	84.43%	94.13%	95.71%	**95.98%**	+13.67%
ASC [13]	88.39%	94.69%	93.07%	**93.80%**	+6.12%
AIR [7]	93.67%	99.90%	99.80%	**99.99%**	+6.75%
Average	78.51%	86.17%	85.71%	**86.69%**	+10.42%

We also considered the bullseye score (*Recall@40*) for shape descriptors on the MPEG-7 dataset. Table 3 presents the effectiveness results considering the *Recall@40* measure. Similar results to the use of the MAP measure are observed. Our combination approach also presents better average scores (86.69%) than both re-ranking algorithms.

4.3 Agglomerative Rank Aggregation

For the experimental evaluation of our proposed Agglomerative Rank Aggregation approach, we select two descriptors for each visual property (shape, color, and texture). Table 4 presents the MAP scores of our combination approach. We can observe that significant gains are obtained when compared with the results of the use of descriptors in isolation and of the first-layer rank aggregation method.

Table 4. Agglomerative Rank Aggregation Combination for CBIR Tasks *(MAP)*

Descriptor	Type	Dataset	First Layer - Rank Aggregation	Second Layer - Rank Aggregation	Score (MAP)
CFD [16]	Shape	MPEG-7	-	-	80.71%
ASC [13]	Shape	MPEG-7	-	-	85.28%
CFD [16] + ASC [13]	Shape	MPEG-7	RL-Sim [18]	-	98.75%
CFD [16] + ASC [13]	Shape	MPEG-7	CRA [17]	-	98.77%
CFD [16] + ASC [13]	**Shape**	**MPEG-7**	**RL-Sim + CRA**	**Set Rank Aggregation**	**99.41%**
ACC [8]	Color	Soccer	-	-	37.23%
BIC [20]	Color	Soccer	-	-	39.26%
BIC [20] + ACC [8]	Color	Soccer	RL-Sim [18]	-	44.49%
BIC [20] + ACC [8]	Color	Soccer	CRA [17]	-	42.14%
BIC [20] + ACC [8]	**Color**	**Soccer**	**RL-Sim + CRA**	**Set Rank Aggregation**	**49.00%**
CCOM [10]	Texture	Brodatz	-	-	57.57%
LAS [22]	Texture	Brodatz	-	-	75.15%
LAS [22] + CCOM [10]	Texture	Brodatz	RL-Sim [18]	-	80.26%
LAS [22] + CCOM [10]	Texture	Brodatz	CRA [17]	-	81.63%
LAS [22] + CCOM [10]	**Texture**	**Brodatz**	**RL-Sim +CRA**	**Set Rank Aggregation**	**83.70%**

4.4 Comparison with Other Approaches

We also evaluated our combination approaches in comparison with other state-of-the-art re-ranking an rank aggregation methods, applied to various shape descriptors. Table 5 presents the results of our approach in comparison with other methods. We consider the re-ranking with rank aggregation combination, using the RL-Sim [18] and Contextual Re-Ranking [15] for re-ranking and the Set Rank Aggregation method. We can observe that our combination approach achieves very high effectiveness performance, being comparable to the best scores reported in literature. Our methods are also compared with other rank aggregation approaches on the MPEG-7 dataset. Three baselines are considered: the traditional Borda Count method; the recently proposed Reciprocal Rank Fusion [5] method; and the Co-Transduction [2] method, recently proposed for CBIR applications. Our agglomerative approach were considered for comparison. We can observe that our method outperforms the considered baselines.

Table 5. Re-Ranking methods comparison on MPEG-7 dataset

Algorithm	Descriptor	Score	Gain
Shape Descriptors			
CFD [16]	-	84.43%	-
IDSC [12]	-	85.40%	-
ASC [13]	-	88.39%	-
AIR [7]	-	93.67%	-
Re-Ranking Methods			
DOA [16]	CFD [16]	92.56%	+9.63%
LCDP [25]	IDSC [12]	93.32%	+9.27%
Mutual kNN [9]	IDSC [12]	93.40%	+9.37%
RL-Sim [18]	CFD [16]	94.13%	+7.13%
CRR [15]	CFD [16]	95.71%	+13.36%
LCDP [25]	ASC [13]	95.96%	+8.56%
SetRA (CRR+RL-Sim)	**CFD [16]**	**95.98%**	**+13.68%**
CRR [15]	AIR [7]	99.80%	+6.54%
RL-Sim [18]	AIR [7]	99.90%	+6.66%
TPG [25]	AIR [7]	99.99%	+6.75%
SetRA (CRR+RL-Sim)	**AIR [7]**	**99.99%**	**+6.75%**

Table 6. Rank aggregation comparison on the MPEG-7 dataset

Shape Descriptor	Rank Aggregation	Score [%]
Shape Descriptors		
DDGM [23]	-	80.03%
CFD [16]	-	84.43%
IDSC [12]	-	85.40%
SC [3]	-	86.80%
ASC [13]	-	88.39%
Rank Aggregation Methods		
CFD [16]+IDSC [12]	Borda Count	91.92%
CFD [16]+ASC [13]	Borda Count	93.51%
CFD [16]+IDSC [12]	Reciprocal [5]	94.98%
CFD [16]+ASC [13]	Reciprocal [5]	96.25%
IDSC [12]+DDGM [23]	Co-Transduction [2]	97.31%
SC [3]+DDGM [23]	Co-Transduction [2]	97.45%
SC [3]+IDSC [12]	Co-Transduction [2]	97.72%
CFD [16]+ASC [13]	CRA [17]	99.38%
CFD [16]+ASC [13]	RL-Sim [18]	99.44%
CFD [16]+ASC [13]	**SetRA (RL-Sim + CRA)**	**99.50%**

5 Conclusions

We have presented novel combination approaches for re-ranking and rank aggregation methods. The main idea of the our work consists in exploiting complementary rankings obtained by different methods in order to obtain more effective results. We conducted a large set of experiments and experimental results demonstrate that our approaches can further improve the effectiveness of image retrieval tasks based on shape, color and texture descriptors. In future work, we intend to investigate the use of other re-ranking and rank aggregation methods in a iterative combination approach.

Acknowledgments. Authors thank AMD, CAPES, FAPESP, FAEPEX, and CNPq for financial support. Authors also thank DGA/UNICAMP for its support in this work.

References

1. Arica, N., Vural, F.T.Y.: Bas: a perceptual shape descriptor based on the beam angle statistics. Pattern Recognition Letters 24(9-10), 1627–1639 (2003)
2. Bai, X., Wang, B., Wang, X., Liu, W., Tu, Z.: Co-transduction for shape retrieval. In: Daniilidis, K. (ed.) ECCV 2010, Part III. LNCS, vol. 6313, pp. 328–341. Springer, Heidelberg (2010)
3. Belongie, S., Malik, J., Puzicha, J.: Shape matching and object recognition using shape contexts. PAMI 24(4), 509–522 (2002)
4. Brodatz, P.: Textures: A Photographic Album for Artists and Designers. Dover (1966)
5. Cormack, G.V., Clarke, C.L.A., Buettcher, S.: Reciprocal rank fusion outperforms condorcet and individual rank learning methods. In: SIGIR 2009, pp. 758–759 (2009)
6. Fagin, R., Kumar, R., Sivakumar, D.: Comparing top k lists. In: SODA 2003, pp. 28–36 (2003)
7. Gopalan, R., Turaga, P., Chellappa, R.: Articulation-invariant representation of non-planar shapes - supplementary material. In: Daniilidis, K. (ed.) ECCV 2010, Part III. LNCS, vol. 6313, pp. 286–299. Springer, Heidelberg (2010)
8. Huang, J., Kumar, S.R., Mitra, M., Zhu, W.J., Zabih, R.: Image indexing using color correlograms. In: CVPR 1997, p. 762 (1997)
9. Kontschieder, P., Donoser, M., Bischof, H.: Beyond Pairwise Shape Similarity Analysis. In: Zha, H., Taniguchi, R.-i., Maybank, S. (eds.) ACCV 2009, Part III. LNCS, vol. 5996, pp. 655–666. Springer, Heidelberg (2010)
10. Kovalev, V., Volmer, S.: Color co-occurence descriptors for querying-by-example. In: MMM 1998, p. 32 (1998)
11. Latecki, L.J., Lakmper, R., Eckhardt, U.: Shape descriptors for non-rigid shapes with a single closed contour. In: CVPR, pp. 424–429 (2000)
12. Ling, H., Jacobs, D.W.: Shape classification using the inner-distance. PAMI 29(2), 286–299 (2007)
13. Ling, H., Yang, X., Latecki, L.J.: Balancing Deformability and Discriminability for Shape Matching. In: Daniilidis, K. (ed.) ECCV 2010, Part III. LNCS, vol. 6313, pp. 411–424. Springer, Heidelberg (2010)

14. Ojala, T., Pietikäinen, M., Mäenpää, T.: Multiresolution gray-scale and rotation invariant texture classification with local binary patterns. PAMI 24(7), 971–987 (2002)
15. Pedronette, D.C.G., da S. Torres, R.: Exploiting Contextual Information for Image Re-ranking. In: Bloch, I., Cesar Jr., R.M. (eds.) CIARP 2010. LNCS, vol. 6419, pp. 541–548. Springer, Heidelberg (2010)
16. Pedronette, D.C.G., da, S., Torres, R.: Shape retrieval using contour features and distance optmization. In: VISAPP, vol. 1, pp. 197–202 (2010)
17. Pedronette, D.C.G., da, S., Torres, R.: Exploiting contextual information for rank aggregation. In: ICIP, pp. 97–100 (2011)
18. Guimarães Pedronette, D.C., da S. Torres, R.: Image Re-ranking and Rank Aggregation Based on Similarity of Ranked Lists. In: Real, P., Diaz-Pernil, D., Molina-Abril, H., Berciano, A., Kropatsch, W. (eds.) CAIP 2011, Part I. LNCS, vol. 6854, pp. 369–376. Springer, Heidelberg (2011)
19. da, S., Torres, R., Falcão, A.X.: Contour Salience Descriptors for Effective Image Retrieval and Analysis. Image and Vision Computing 25(1), 3–13 (2007)
20. Stehling, R.O., Nascimento, M.A., Falcão, A.X.: A compact and efficient image retrieval approach based on border/interior pixel classification. In: CIKM 2002, pp. 102–109 (2002)
21. Swain, M.J., Ballard, D.H.: Color indexing. IJCV 7(1), 11–32 (1991)
22. Tao, B., Dickinson, B.W.: Texture recognition and image retrieval using gradient indexing. JVCIR 11(3), 327–342 (2000)
23. Tu, Z., Yuille, A.L.: Shape Matching and Recognition – Using Generative Models and Informative Features. In: Pajdla, T., Matas, J(G.) (eds.) ECCV 2004, Part III. LNCS, vol. 3023, pp. 195–209. Springer, Heidelberg (2004)
24. van de Weijer, J., Schmid, C.: Coloring Local Feature Extraction. In: Leonardis, A., Bischof, H., Pinz, A. (eds.) ECCV 2006, Part II. LNCS, vol. 3952, pp. 334–348. Springer, Heidelberg (2006)
25. Yang, X., Koknar-Tezel, S., Latecki, L.J.: Locally constrained diffusion process on locally densified distance spaces with applications to shape retrieval. In: CVPR, pp. 357–364 (2009)
26. Yang, X., Latecki, L.J.: Affinity learning on a tensor product graph with applications to shape and image retrieval. In: CVPR, pp. 2369–2376 (2011)