Selection of Relevance Feedback Technique in the Context of CBIR

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Abstract: *in this paper, we address the relevance feedback mechanism in the context of CBIR. Review of literature shows that there exists many techniques for re-ranking using relevance feedback information. We propose then a CBIR prototype that selects the appropriate technique for a given submitted query and relevance feedback information. Experiments conducted on Wang database (COREL1K), using color moments as signature and Euclidean distance as matching formula, show the clear superiority of the results achieved adopting the selection process.*

Keywords: *CBIR, Relevance Feedback, Selection, Precision, Recall.*

1. Introduction

A CBIR system aims at visualizing a subset of relevant images from an asked images collection using images features. Review of literature shows that there exist many features and descriptors: for color, for instance, there are global color histogram [1], local color histogram [2], correlogram[3] and CCV [4]. Unfortunately, there is no effective feature that outperforms others in terms of performance. In order to encounter this reality, two approaches have been proposed: combining features [5] and features selection [6]. Relevance feedback [7] is a mechanism coming from information retrieval field that helps to reduce angle between system relevance and user relevance. There are many techniques adopted to exploit relevance feedback information.

The purpose of this paper is to answer the question which relevance feedback technique to adopt for a given query and relevance feedback information. We incur then the selection in the context of relevance feedback techniques.

The rest of this paper is organized as follows: section 2 is devoted to techniques of literature adopted to exploit relevance feedback information. Section 3 looks at the algorithm used for selecting the adequate relevance feedback technique. We conclude the paper by some experimental results and showing the high effectiveness achieved.

2. Relevance Feedback Techniques

2.1. Query Point Movement

Query Point Movement approach allows only a single object per feature as a query. When the user uses multiple examples to construct the query, the centroid is used as the single point query [8]. Such techniques needs only that the user marks the relevant images without marking the non-relevant ones. The centroid is given by the following formula:

$$C = \frac{\sum_{i=1}^{n} W_i E_i}{\sum_{i=1}^{n} W_i} \quad (1)$$

2.2. Standard Rocchio's Formula

This method is coming from the documentary information retrieval. Unlike to the Query Point Movement, the *Standard Rocchio's Formula* [9] requires that the user selects, from the displayed images, some relevant and non-relevant images. According to this method, the new query is computed as follows:

$$Q_1 = \alpha Q_0 + \beta\left(\frac{1}{n_R}\sum_{D_m \in D_R}\frac{D_m}{|D_m|}\right) - \gamma\left(\frac{1}{n_{N-R}}\sum_{D_m \in D_{N-R}}\frac{D_m}{|D_m|}\right) \quad (2)$$

Where Q_0 is the query issued by the user, subscript R is for "Relevant images" while subscript N-R is for "non-relevant images". $Q_1$is the new query.

2.3. Bayesian Relevance Feedback

This method [10] utilizes the Bayesian decision to estimate the boundary between relevant and non-relevant images. A new query is then computed whose neighborhood is likely to fall in a region of the feature space containing relevant images. The new query is given by the following formula:

$$m_R^{(1)} = m_R^{(0)} + \frac{\sigma^2}{\left\| m_R^{(0)} - m_N^{(0)} \right\|^2} * \left(1 - \frac{k_R^0 - k_N^0}{\max\left(k_R^{(0)}, k_N^{(0)}\right)}\right)\left(m_R^{(0)} - m_N^{(0)}\right) (3)$$

$$\sigma^2 = s_W . s_B \ (4)$$

$$s_W^2 = \frac{k_R}{k} . \frac{\sum_{I \in I_R(Q_0)} (I - m_R)^t . (I - m_R)}{k_R - 1} + \frac{k_N}{k} . \frac{\sum_{I \in I_N(Q_0)} (I - m_N)^t . (I - m_N)}{k_N - 1} \quad (5)$$

$$s_B^2 = (m_R - m_N)^t . (m_R - m_N) \ (6)$$

$$m_R = \frac{1}{k_R} \sum_{I \in I_R(Q_0)} I \ (7)$$

$$m_N = \frac{1}{k_N} \sum_{I \in I_N(Q_0)} I \ (8)$$

Where I is a feature vector representing an image in a d-dimensional feature space. Q_0 is the initial query, $N(Q_0)$ are the neighborhoods of Q_0, $I_{R(Q0)}$ and $I_{N(Q0)}$ are respectively sets of relevant and non-relevant images contained in $N(Q_0)$. m_R and m_N are respectively the means vectors of relevant and non-relevant images.

2.4. Adaptive Shifting Query

The *Adaptive Shifting Query* has been introduced in [11], to be applied on the narrow domain databases where there is a little variability between images. This method needs that the user labels the first images as relevant or non-relevant. According to this approach, the new query is calculated by the following equation:

$$Q_{new} = \mu_R \left(\frac{1}{2} + \frac{k_N - R}{k} \right) \frac{\alpha D_{\max}}{\left\| \mu_R - \mu_{NR} \right\|} (\mu_R - \mu_{NR})$$
(9)

$$D_{\max} = \max_{i_{n \in N(Q)}} \left\| Q - I_n \right\| \ (10)$$

$$\mu_R = \frac{1}{k_R} \sum_{I \in I_R} I \ (11)$$

$$\mu_{N-R} = \frac{1}{k_{N-R}} \sum_{I \in I_{N-R}} I \ (12)$$

Where k_R and K_{N-R} are the number of relevant and non-relevant images respectively. And k is the sum of them. $\mu_R$and μ_{N-R} are the mean of the feature vectors of relevant and non-relevant images respectively. D_{max} is the maximum distance between the query and the images belonging to the neighborhood of Q, N(Q).

2.5. Feature Weighting

In *Feature Weighting method* [12] which aims to tackle the problem of weighting in the case of combining features, we proceeds to increase the weight of relevant features at the cost of non-relevant features. The relevant features are those that enable to better rank the images marked as relevant by the user.

2.6. Optimization of The Parameters of The Similarity Metrics

This method known as *Optimization of Parameters of the similarity metrics* [13], [14] consists of optimizing the parameters in the case of many (di) similarities. It helps then to find the adequate formula which encloses (di) similarities and so based on the relevance feedback input coming from the user. The parameters that make the rate of images deemed as relevant by the user better than the rate of images marked as non-relevant are the best configuration to consider.

2.7. Original K-Nearest Neighbor

K-nearest neighbor (KNN) [15] is a supervised learning algorithm where the result of new instance query is classified based on majority of k-nearest neighbor category [16]. The purpose of this algorithm is to classify a new object based on attributes and training samples. Given an image point, we find the k closest objects to the query point. Note that the search problem can be considered as a biased discrimination issue [17] or simply a binary classification with only two classes: the class of relevant images and the class of non-relevant ones. Images belonging to the relevant class will be rated first followed by the images of the other classes.

2.8. Incremental K-Nearest Neighbor

A lot of work has be done, in the CBIR field, either utilizing KNN algorithm or tending to ameliorate the results by introducing new versions of this algorithm [18], [19], [20], [21]. A new version of the k-nearest algorithm, known as *Incremental KNN*, has been introduced in [22]. This new version differs from the original one in the sense that besides the influence of the seeds, given by the user as relevance feedback, the classification of the actual target image is affected also by the images already classified. The pseudo code of *Incremental KNN* is given as follows:

Incremental KNN Algorithm:

Let N: the number of the first returned images.

C: the number of images labeled as relevant or non-relevant by the user.

F: a constant $<C$ which designs the number of the nearest images utilized to label non labeled image.

1) Initialisation :

Re-ranking set=Φ.

Images={*Im1, Im2, …, ImN*} (The First Returned Images)

Relevant-Images={*RIm1, RIm2, …, RImC*}(the images labeled as relevant)

Non-Relevant-Images={*NRIm1, NRIm2, …, NRImC*} (the images labeled as non relevant)

2) For each image *Im* which belongs to *Images* do :

- Compute the distances between the image *Im* being classified and the images of the both classes: *Relevant-Images* and *Non-Relevant-Images*.
- Rate the images of the both classes based on their distances with the image *Im* being classified.
- Classify the image *Im* either to Relevant-Images or to Non-Relevant-Images according to the *F* first images.
- Images=Images ***minus*** image *Im*.

3) *Re-ranking set=Relevant-Images***plus***Non-Relevant-Images.*

4) *END.*

3. Selection Algorithm

This algorithm enables to select the adequate relevance feedback technique. The pseudo code of this algorithm is given as follows:

Selection Algorithm

Input: images ranked by the different Relevance Feedback techniques
Output: the Selected Technique

S_r ← 0; // sum of rate for images marked as relevant by the user.

S_{nr}←0; // sum of Rate for images marked as non-relevant by the user.

For Each Technique
Compute S_r and S_{nr}.
S←$S_r$minusS_{nr};

Technique whos S is the least S is the selected Technique

END.

4. Experimental Results

In this paper, we have investigated eight relevance feedback techniques cited earlier. Experimentations have been conducted on the Wang database (COREL1K) [23] and using three first color moments [24] as signature and Euclidean distance as matching formula.

- **The Mean**

$$\grave{u}_i = \frac{1}{N}\sum_{j=1}^{N} f_{ij} \quad (13)$$

- **The Variance**

$$\sigma_i = \sqrt{\frac{1}{N}\sum_{j=1}^{N}\left(f_{ij}-\grave{u}_i\right)^2} \quad (14)$$

- **The Scenes**

$$£_i = \left(\frac{1}{N}\sum_{j=1}^{N}\left(f_{ij}-\grave{u}_i\right)^3\right)^{\frac{1}{3}} \quad (15)$$

- **Euclidean Distance**

$$L_2\left(V,V'\right)=\left(\sum_{m=1}^{M}\left(V_m-V'_m\right)^2\right)^{\frac{1}{2}} \quad (16)$$

For evaluating the considered relevance feedback methods, we employ Precision/Recall metrics computed as follows [25]:

$$\Pr ecision = \frac{NRIR}{TNIR} \quad (17)$$

$$\text{Re}\,call = \frac{NRIR}{TNRI} \quad (18)$$

Where NRIR: Number of relevant images retrieved, TNIR: Total number of images retrieved and TNRI: total number of relevant images in the database.

Even with precision/Recall curves, it is difficult to compare between the effectiveness of formulas. For this, Precision/Recall values will be changed to only one value using the Utility concept inspired from [26] as depicted by the following equation:

$$v=\sum_{s=0}^{1}P*(1-s) \quad (19)$$

Where: P is the *precision value* and s is a constant belongs to the range [0 1].

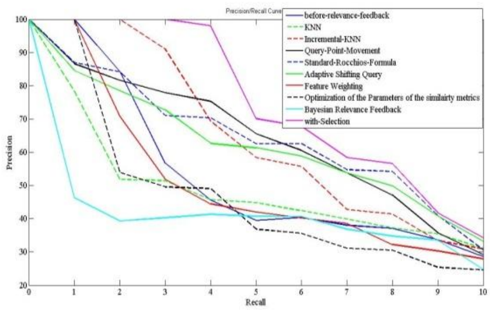

Fig.1 Average Precision/Recall of relevance feedback techniques against the approach with Selection

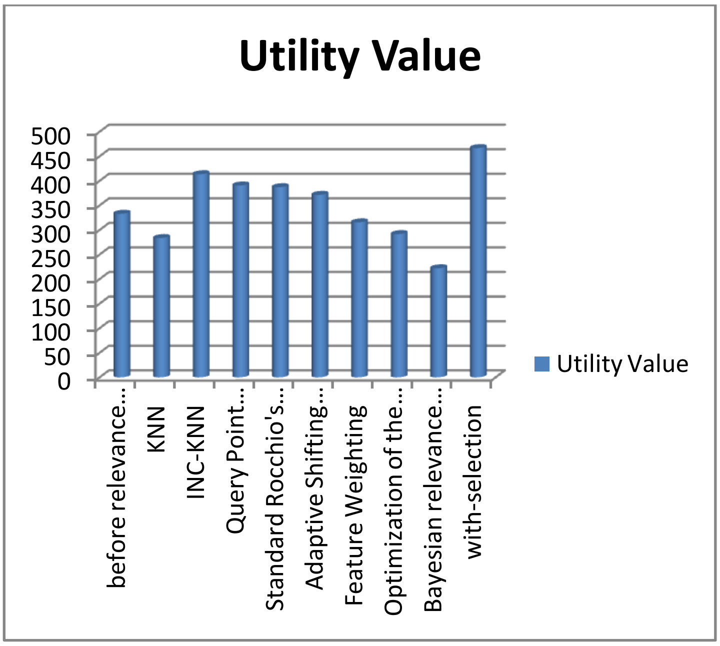

fig.2 Relevance Feedback Techniques against the approach with selection in terms of Utility Value.

According to Fig.1 and Fig.2, approach with selection outperforms on large scale the other relevance feedback techniques. Figures show also that some relevance feedback techniques such as: *KNN*, *Feature Weighting*, *optimization of the Parameters of Similarity Metrics* and *Bayesian Relevance Feedback* downgrade performances. However, techniques such as:*Incremental KNN*, *Query Point Movement*, *Standard Rocchio's Formula*, *Adaptive Shifting Query* upgrade, on different scale, effectiveness. Note that, the results depicted in Fig1 and Fig.2 are average results. This means that relevance feedback techniques, that downgrade performance, may be effective locally for a given query.

5. Conclusion

In this paper, we have introduced the selection of relevance feedback techniques in the context of CBIR. In light of the results achieved, this selection process upgrades highly performances. The paper also makes under light a comparison between wide ranges of relevance feedback techniques. As a perspective, the work can be extended to include other relevance feedback methods adopting other machine learning tools such as: SVM, neural networks and self-organizing map. In addition, combining between results returned by different relevance feedback techniques seems to be a good generalized idea of individual selection.

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