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Relevance Feedback within CBIR Systems

Mawloud Mosbah, Bachir Boucheham

***Abstract*—**We present here the results for a comparative study of some techniques, available in the literature, related to the relevance feedback mechanism in the case of a short-term learning. Only one method among those considered here is belonging to the data mining field which is the K-nearest neighbors algorithm (KNN) while the rest of the methods is related purely to the information retrieval field and they fall under the purview of the following three major axes: Shifting query, Feature Weighting and the optimization of the parameters of similarity metric. As a contribution, and in addition to the comparative purpose, we propose a new version of the KNN algorithm referred to as an incremental KNN which is distinct from the original version in the sense that besides the influence of the seeds, the rate of the actual target image is influenced also by the images already rated. The results presented here have been obtained after experiments conducted on the Wang database for one iteration and utilizing color moments on the RGB space. This compact descriptor, Color Moments, is adequate for the efficiency purposes needed in the case of interactive systems. The results obtained allow us to claim that the proposed algorithm proves good results; it even outperforms a wide range of techniques available in the literature.

***Keywords*—**CBIR, Category Search, Relevance Feedback (RFB), Query Point Movement, Standard Rocchio's Formula, Adaptive Shifting Query, Feature Weighting, Optimization of the Parameters of Similarity Metric, Original KNN, Incremental KNN.

I. Introduction

DESPITE the effort put up ton now on the CBIR field, the results achieved still far from those desired by the user. In order to improve the results of a CBIR system, a lot of attempts have been made. These attempts touch broadly the three parts of a system namely: the query representation, the indexation stage and the comparison process. For the both first processes, we can find many signatures even within the same feature. For color feature [1] for example, there are: global Histogram [2], local histogram [3], CCV (Color Coherent Vector) [4] and color moments [5]. For the comparison process, we can find many distances and similarity formulas like: Euclidean distance, squared distance and histograms intersection [2].

The availability of all these signatures and distances makes difficult the selection of the adequate signature and distance for building a CBIR system. Generally, the fusion [6], [7] may achieve better results but even with the fusion, a natural question to rise is how to weight the combined signatures.

The failing in the CBIR domain originates mostly from the non-comprehension of the user need expressed generally in such system as alone image query. Indeed, a bad query can produce no better results. CBIR systems with multi queries [8] have come for encountering this limitation.

A common way to overcome the both cited problems is to make a CBIR system interactive through integration of relevance feedback mechanism [9]. This scheme aims at improving the results by involvement of the user via his or her judgment of the first returned images. This additional information of judgment, which helps to adapt the CBIR system, consists of selecting subset relevant images from the first set returned by the system. In light of this judgment, the system proceeds to better re-rank the rest of the images collection.

The rest of this paper is organized as follows: in Section II, we provide an overview on some techniques for relevance feedback mechanism; Section II is devoted to taking a closer look on the techniques under experimentation. The experimental results have been shown in Section IV. Discussion and some drawn conclusions have been given in Section V.

It is worth noting that we consider only here the case of short-term-learning where the user feedback is used only within the user's query context [10], [11], in other words, what the system learn over a certain query will not be utilized with the future queries.

II. Related Works

Relevance feedback is not new mechanism but it is a scheme applied in the last few years on the CBIR field [12]. Like other techniques, it comes from documentary information retrieval [13], [14]. This mechanism, which is fast applicable to images than to text, consists of providing additional information from the user. This information is simply a judgment of some displayed images. Based on this judgment, the system can better re-rank the results and reducing the semantic gap by eliminating the noise being available during the initial research. Consulting the literature, we can find a lot of approaches for exploiting the feedback. The first approach consists of shifting the query in a way that basing on the new query the images qualified as relevant by the user will be better ranked while the images judged as non-relevant will be ranked on the bottom. Query Point Movement [15], Standard Rocchio's Formula [16] and Adaptive Shifting Query [17] are three alternatives that fall into the purview of this approach. Another approach known as Feature weighting [18] touches the fusion of features. It answers the question how to weight features in order to get better results. How weighting features will be get then based on the relevance feedback provided by the user. The optimization of the parameters of the similarity metrics [19], [20] is another manner to exploit feedback coming from the user by proceeding to re-define the weights

Mawloud Mosbah and Bachir Boucheham are with the Department of Informatics, 20 Août 1955 of Skikda, Algeria (e-mail: mos_nasa@hotmail.fr, bachir_boucheham@yahoo.fr).

of the factors of the utilized similarity metric. As a last approach considered here, the relevance feedback can provide the system with the seeds necessary for launching the KNN classification algorithm [23]. Out of considering the research problem as a biased Discriminant classification [24], the classification considered here is a binary classification with only two classes namely: the class of relevant images and the class of non-relevant ones.

III. Experimented Techniques

A. Query Point Movement

Query point 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 [15]. Such technique needs only that the user selects the relevant images without selecting the non-relevant ones. The centroid is given by the following formula:

$$C = \frac{\sum_{i=1}^{n} W_i E_i}{\sum_{i=1}^{n} W_i} \tag{1}$$

where: E_1, E_2, …, E_i,…, E_n denote the n objects marked relevant by the user; W, W_2, …, W_i,…, W_n are the corresponding levels of relevance.

B. Standard Rocchio's Formula

The Standard Rocchio's Formula [16] is coming from the documentary information retrieval. Unlike to the query point movement, this method requires that the user selects from the displayed images some relevant images and some non-relevant ones. It is given by the following formula:

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

where: Q_0 is the query issued by the user, subscript R is for « relevant documents » while subscript N-R is for « non-relevant » documents. Q_1 is the new query.

C. Adaptive Shifting Query

The Adaptive Shifting Query has been proposed in [17], to be applied on the narrow domain databases where there is a little variability between images. This method needs that the user marks the first images as relevant or non-relevant. Based on this approach, the new query is given by the following formula:

$$Q_{new} = \mu_R \left(\frac{1}{2} + \frac{k_{N-R}}{k}\right) \frac{\alpha D_{max}}{\|\mu_R - \mu_{N-R}\|} (\mu_R - \mu_{N-R}) \tag{3}$$

$$D_{max} = max_{I_{n \in N(Q)}} \|Q - I_n\| \tag{4}$$

$$\mu_R = \frac{1}{k_R}\sum_{I \in I_R} I,\ \mu_{N-R} = \frac{1}{k_{N-R}}\sum_{I \in I_{N-R}} I \tag{5}$$

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 $\mu_{N-R}$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).

D. Feature Weighting

In Feature Weighting approach [18] which aims to tackle the problem of weighting in the case of combining features, we proceed to increase the weight of relevant features. The relevant features are those that enable to better rank the images deemed relevant by the user.

E. Optimization of the Parameters of the Similarity Metric

This method known as "Optimization of the Parameters of the Similarity Metric" [19], [20] consists of optimizing the parameters in the case of many similarities or distances. It helps then to find the adequate formula which encloses many similarity or distance formulas and so based on the relevance feedback input coming from the user. The parameters that make the rate of images labeled as relevant by the user better than the rate of images labeled as non-relevant are the best configuration to search.

F. Original and Incremental K-Nearest Neighbors (KNN)

A lot of learning algorithms have been applied to re-ranking images in the context of CBIR, the majority of them is clustering algorithms adopting unsupervised learning and used generally as a post-research operation prior to visualize the results for the user. K-means and HACM (Hierarchical Algorithm Clustering Method) [21], [22] are some of them.

K-nearest neighbor (KNN) [23] is a supervised learning algorithm where the result of new instance query is classified based on majority [25] of K-nearest neighbor category. The purpose of this algorithm is to classify a new object based on attributes and training samples. Given an image point, we find K number of objects closest to the query point.

A lot of work has been done, in the CBIR field, either utilizing KNN algorithm or tending to ameliorate the results by introducing a new version of this algorithm. References [26]-[29] are some examples of these works.

The new version, introduced here as a contribution and referred to as an *Incremental KNN* is given by the following 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) Initialization:
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.

IV. Experimental Results

In order to test the 6 techniques of relevance feedback considered here, we have built a CBIR system which works on the Wang database [30] and utilizing the color moments, a fast indexing method which produces a reduced stored data, as signature on the RGB color space and the Euclidean distance as a matching measure. The color moments is a vector composed of three compounds that are the three low order moments: the mean, the variance and the skewness given respectively by the following formulas:

A. The Mean

$$\grave{u}_i = \frac{1}{N}\sum_{j=1}^{N} f_{ij} \tag{6}$$

where: N is the number of pixels in the image. f_{ij} is the value of the pixel of i^{th} row and j^{th} column.

B. The Variance

$$\sigma_i = \sqrt{\frac{1}{N}\sum_{j=1}^{N}\left(f_{ij} - \grave{u}_i\right)^2} \tag{7}$$

C. The Skewness

$$£_i = \left(\frac{1}{N}\sum_{j=1}^{M}\left(f_{ij} - \grave{u}_i\right)^3\right)^{1/3} \tag{8}$$

To compare between the techniques considered here, we construct the Precision/Recall plots. The precision and recall values have been computed using the following formulas [31]:

$$Precision = \frac{Number\ of\ relevant\ images\ retrieved}{Total\ number\ of\ images\ retrieved} \tag{9}$$

$$Recall = \frac{Number\ of\ relevant\ images\ retrieved}{Total\ number\ of\ relevant\ images\ in\ the\ Database} \tag{10}$$

Figs. 1 and 2 present respectively a screen snapshot of the built system and the obtained curves.

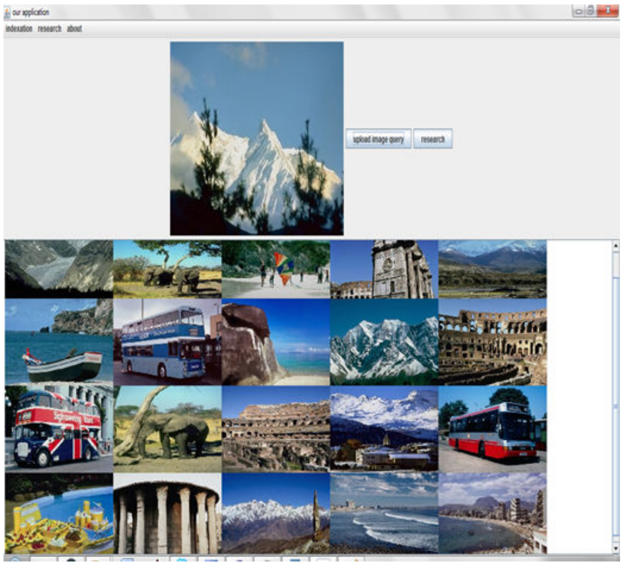

Fig. 1 (a) The returned images without RFB

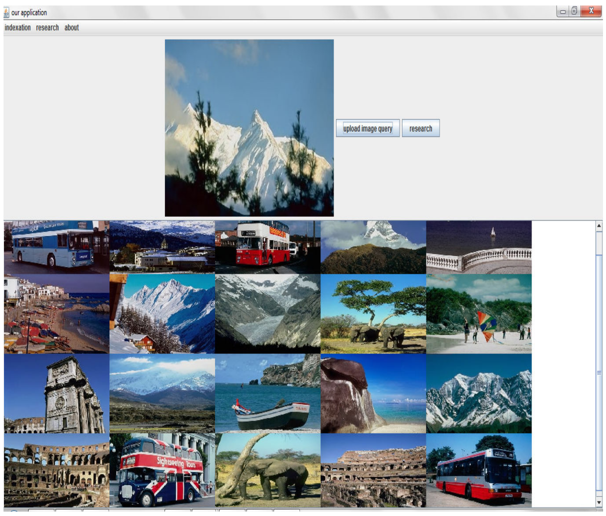

Fig. 1 (b) The returned images with RFB after the application of the *Original KNN*

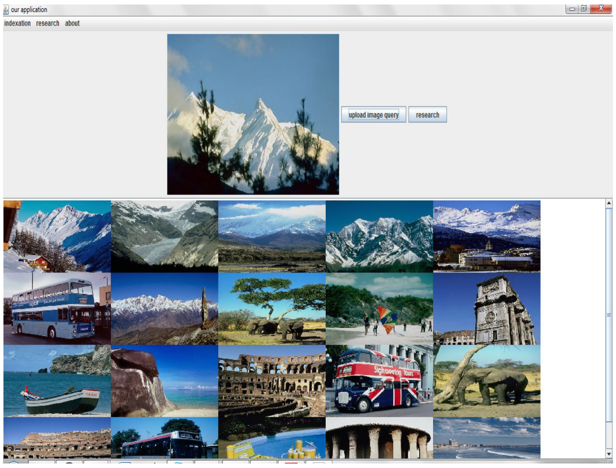

Fig. 1 (c) The returned images with RFB after the application of the *Incremental KNN*

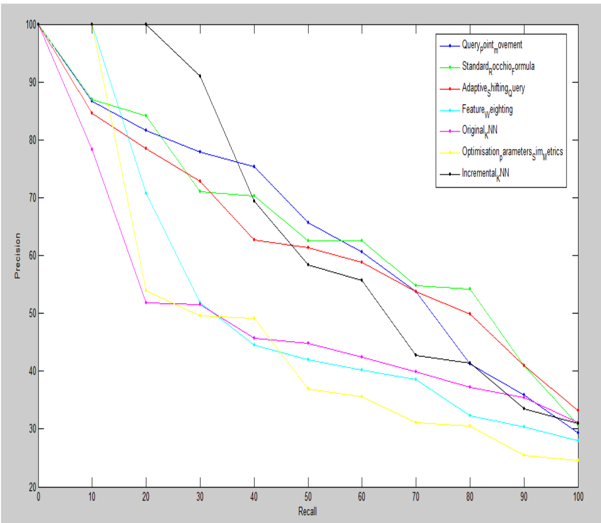

Fig. 2 The average Precision/Recall curves based on the experimented RFB techniques

In light of the results shown in Precision/Recall curves (Fig.2), we can claim that the proposal method (Incremental KNN) outperforms many techniques available in the literature such as: "Original KNN", "feature weighting" and "optimization of parameters of similarity metrics". For the other methods, our proposal method achieves better results partially (within the Recall's range of [0% 30%]). After 30% of Recall, "Query Point Movement", "Standard Rocchio's Formula" and "Adaptive Shifting Query" produce the best results.

V. Conclusion

In this paper, we have tested a lot of RFB methods in the case of CBIR system. We have also proposed a new version of the KNN algorithm. The results we obtained allow us to claim that the proposed algorithm proves good results; it even outperforms a large number of methods available in the literature. The experimentation performed here allows us also to rate the effectiveness of different RFB methods.

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