A MODIFIED FEATURE RELEVANCE ESTIMATION APPROACH TO RELEVANCE FEEDBACK IN CONTENT-BASED IMAGE RETRIEVAL SYSTEMS

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ABSTRACT

This paper proposes a new approach for relevance feedback in content-based image retrieval systems. The proposed approaches combined the classical Rocchio relevance feedback with the Feature Relevance Estimation method. As such, according to the relevance feedback provided by the user, the algorithm performs a simultaneous query modification and a assignment of weights to all the components of the image description vector. We show that the Modified Feature Relevance Estimation outperforms classical RF methods for both natural and specialized image databases.

Keywords: *relevance feedback, content-based image retrieval, feature relevance*

1. INTRODUCTION

Content-based image retrieval (CBIR) became a must in the last two decades [1], [2]. Powered by the explosive development of the Internet, Web and the continuously cheaper digital imagining devices and technologies, applications such as digital libraries, image archives, video-on-demand and specific image databases emerge as a real-life fact. The basic idea of the CBIR process is to compactly describe an image by a digital signature and then match the query image to the most resembling image, within the database, according to the similarity of their signatures. Many low-level features have been researched, using color, texture and shape image attributes, but these cannot remove the semantic gap problem [1], [3]. Various techniques have been proposed in last years using relevance feedback algorithms: query modification, neural network based classification, Bayesian frameworks or nature-inspired algorithms.

This paper proposes a new approach for relevance feedback in CBIR systems, based on the innovative combination of well-known, classical RF methods. The proposed approach will be denoted as hierarchical clustering relevance feedback (HCRF) and we will show that it outperforms some of the classical relevance feedback methods.

The remainder of the paper is organized as follows: we describe in Section 2 the classic CBIR system framework, including a discussion on the classical relevance feedback algorithms; in Section 3 we present the new modified feature relevance estimation algorithm for relevance feedback (MFRE). The experiments are presented in Section 4 and the paper ends with some conclusions gathered in Section 5.

2. RELEVANCE FEEDBACK IN CBIR SYSTEMS

The most popular CBIR paradigm is the query by example; figure 1 schematically synthesizes the architecture of such a system.

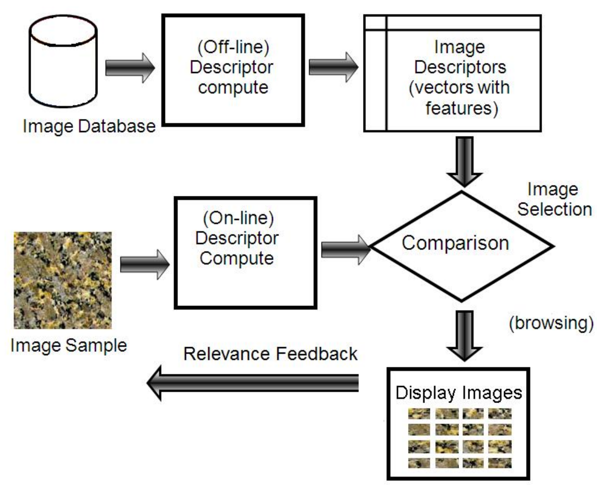

Figure 1: *Example of classical query by example CBIR system*.

The CBIR database stores all offline computed image descriptors and then the system calculates the top k nearest images. Traditional CBIR systems don't achieve high performance on general image databases mainly due to several specific problems, the two most important being:
- the difference between the high level features and the low level features, known as the semantic gap. In few cases the assumption that high-level feature concepts have mapped to low-level concepts is correct (e.g. yellow pears have their own color and shape description), but in most cases this is not true (complicated scenes, object with different features).

- the human perception which makes that humans can perceive the same visual content in many, often different circumstances.

Since human perception of image similarity is both subjective and task-dependent, the main method to reduce the semantic gap is the relevance feedback (RF). Relevance feedback is an essential component of a CBIR system and means the immediate and explicit assessment of the appropriateness of the original query results by the user. The CBIR integrates then the user feedback by means of the modification of the query feature vector or of the similarity distance.

2.1 The Rocchio algorithm

One of the earliest and most successful relevance feedback algorithms is the Rocchio algorithm, whose original description was published in 1965, and reprinted in 1971 [4]. The Rocchio algorithm uses a set R of relevant documents (containing |R| documents) and a set N of non-relevant documents (containing |N| documents), selected in the user relevance feedback phase, and updates the query features according to the following equation:

$$Q' = \alpha Q + \frac{\beta}{|R|}\sum_{R_i \in R} R_i - \frac{\gamma}{|N|}\sum_{N_i \in N} N_i \tag{1}$$

In equation (1) above, the new query Q' is obtained by adjusting the position of the original query Q in the feature space, according to the positive and negative examples and their associated importance factors (importance factor of positive feedback, β, importance factor of negative feedback, γ, and importance of the original query, α). All importance factors are within the [0, 1] range.

2.2 The feature relevance estimation algorithm

The feature relevance estimation (RFE) approach assumes, for a given query, that according to the users' subjective judgment, some specific features may be more important than other features [3]. Every feature will have an importance weight that will be computed as $W_i = 1/\sigma$, where σ denotes the variance of relevant retrievals, so that features with bigger variance have low importance than elements with low variations. The initial weights are equal to 1 and get updated as the user provides the feedback. After applying the relevance feedback, the distance between any two images becomes a weighted Euclidian distance within their associated feature vectors X and Y:

$$Dist(X,Y) = \sqrt{\sum_{i=1}^{d} W_i (X_i - Y_i)^2 \Big/ \sum_{i=1}^{d} W_i} \tag{2}$$

The modification of the weights associated to the individual features describing the image content means that, in the feature space, the shape of the query selection can be modified from the original sphere to an ellipsoid.

2.3 The Robertson-Sparck-Jones algorithm

In the Robertson/Sparck-Jones model of information retrieval [5], the terms in a corpus are all assigned relevance weights, which are updated for any particular query. For positive feedback, the relevance weights will be very small (and the distance between the query image and the target images will be 0); for negative feedback, the relevance weights will be significant. Initially, all the weights are equal to 1, later being updated according to the users feedback. After user's feedback the distance between two images will become

$$Dist(X,Y) = W_i \sqrt{\sum_{i=1}^{d} (X_i - Y_i)^2} \tag{3}$$

3. THE MODIFIED FEATURE RELEVANCE ESTIMATION APPROACH

In the Feature Relevance Estimation algorithm the W_i weights reflect each feature's relevance in describing the searched image's class. Intuitively, if all the relevant objects have similar values for the descriptor's components, it means that the components are a good indicator of the user's information need. On the other hand, if the component's values vary too much from one object to another, this means they are not to be taken into consideration as good indicators. Based on this analysis, Rui and Huang [3] use the inverse of the standard deviation to estimate the W weights of the components.

The main problem of this algorithm is that it doesn't use negative feedback. If a certain feature had a similar distribution and values for two different classes, the algorithm wouldn't be able to separate the two classes. Due to this fact the algorithm should be able to apply penalties based on negative feedback.

Supposing that each feature represents a random value with normal distribution, moving the query point to the center of the centroid would increase the probability to retrieve positive images. Although this algorithm has its starting point in the Rocchio algorithm, we only use positive feedback unlike the original one.

As such, we propose a modified feature relevance estimation algorithm combined with Rocchio algorithm. The query point is moved to the center of positive samples, while weights are computed according to new formulas:

$$w_i = \frac{\sigma^2_{negative}}{\sigma^2_{positive}} \tag{4}$$

$$Q' = \overline{Q} \tag{5}$$

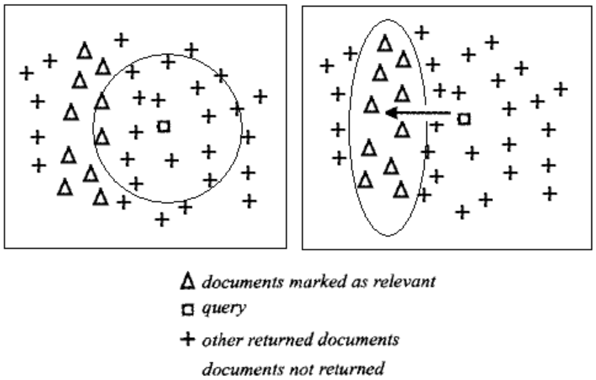

Figure 2: *Schematic illustration of the modified RFE algorithm.*

4. EXPERIMENTS

We tested the effectiveness of the proposed relevance feedback algorithm on two image databases. A first, generalist image database contains 2700 usual, everyday life pictures. This database includes various categories: seasons, buildings, ocean, dessert, concerts, children, portraits, paintings, famous cities (London, Paris, etc.), people, sports, cars, animals, food, for a total of 100 classes with 27 images per class. A second database contains 100 texture classes with 9 images per class, selected from the classical Vistex database. Figure 3 presents a selection of images from the testing databases.

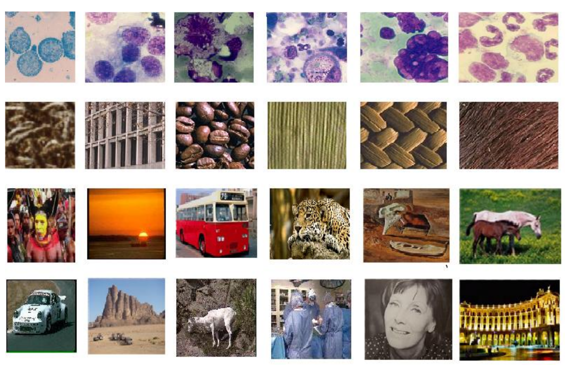

Figure 3: *Sample images from the databases used in experiments (first two rows: textures, last two rows: general color images).*

The visual image content description is implemented using the simplest MPEG-7 descriptor: the Color Histogram Descriptor (CHD) [8], [9]. This choice is justified by the need of comparing the learning speed and the performance increase of the relevance feedback algorithms and not the feature performance. The CHD is implemented in the HSV color space with a 16-4-4 (Hue – Saturation - Value) quantization [8]. Figure 4 shows a typical example of relevance feedback according to the proposed MFRE approach, with one feedback iteration.

Figure 4: *Example of system responses after a session of feedback with natural images using the proposed MFRE approach for (Aborigines class)*

Since the correct class membership is known for any image within the database, we evaluate the quantitative, objective retrieval performance of the proposed methods via the classical precision-recall curves [1], [2]. The next figures present the performance of the proposed RF algorithm, compared with classical RF methods. Figure 6 present the precision-recall curves for the tested image databases. Figures 5 and 6 present the variation of the average retrieval rate with respect to the number of relevance feedback iterations.

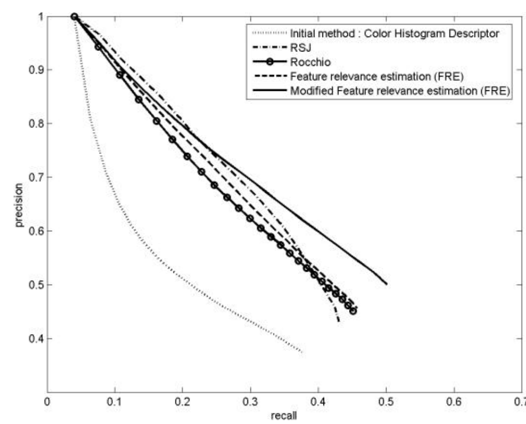

Figure 5: *Precision-recall curves for the natural images test database, showing the behavior of RF methods after one RF iteration. The plot shows the original CHD (dotted line), Robertson Spark Jones RF (dash-dotted line), FRE RF (dashed line), Rocchio RF (continuous line with circle marks) and the proposed Modified FRE (upper continuous line).*

Figures 7 and 8 show the performance of the proposed RF method after several feedback iterations.

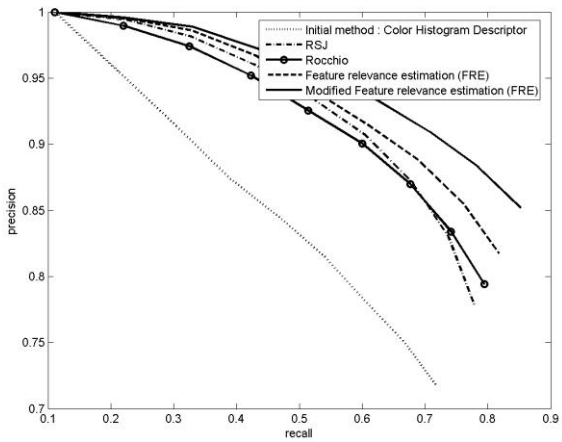

Figure 6: *Precision-recall curves for the texture images test database, showing the behavior of RF methods after one RF iteration. The plot shows the original CHD (dotted line), Robertson Spark Jones RF (dash-dotted line), FRE RF (dashed line), Rocchio RF (continuous line with circle marks) and the proposed Modified FRE (upper continuous line).*

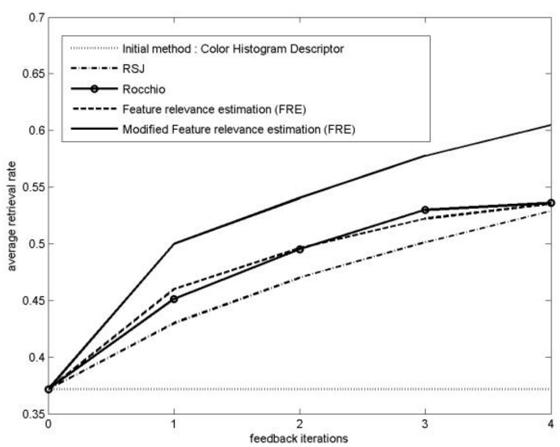

Figure 7: *Average retrieval rate vs. the number of RF iterations for the texture test database, showing the behavior of RF methods after several RF iterations. The plot shows the original CHD (dotted line), Robertson Spark Jones RF (dash-dotted line), FRE RF (dashed line), Rocchio RF (continuous line with circle marks) and the proposed Modified FRE (upper continuous line).*

5. CONCLUSIONS

In this paper we have presented an effective new relevance feedback algorithm based on the combination of feature relevance estimation and Rocchio methods. The proposed modified feature relevance estimation (MFRE) outperforms classical RF algorithms (such as Rocchio or RFE) for both generalist and specialized image databases.

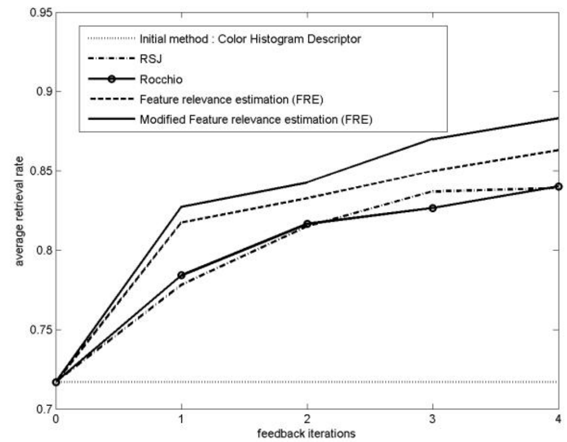

Figure 8: *Average retrieval rate vs. the number of RF iterations for the natural images test database, showing the behavior of RF methods after several iterations. The plot shows the original CHD (dotted line), Robertson Spark Jones RF (dash-dotted line), FRE RF (dashed line), Rocchio RF (continuous line with circle marks) and the proposed Modified FRE (upper continuous line).*

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