NEIGHBORHOOD-BASED FEATURE WEIGHTING FOR RELEVANCE FEEDBACK IN CONTENT-BASED RETRIEVAL

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ABSTRACT

High retrieval precision in content-based image retrieval can be attained by adopting relevance feedback mechanisms. In this paper we propose a weighted similarity measure based on the nearest-neighbor relevance feedback technique proposed by the authors. Each image is ranked according to a relevance score depending on nearest-neighbor distances from relevant and non-relevant images. Distances are computed by a weighted measure, the weights being related to the capability of feature spaces of representing relevant images as nearest-neighbors. This approach is proposed to weights individual features, feature subsets, and also to weight relevance scores computed from different feature spaces. Reported results show that the proposed weighting scheme improves the performances with respect to unweighed distances, and to other weighting schemes.

1. INTRODUCTION

The automatic extraction of the semantic content of images is still an open problem, which requires both low-level image analysis, and high-level image annotation. Content-based queries are often expressed by visual examples in order to retrieve from the database all images that are similar to the examples. It is easy to see that the effectiveness of CBIR techniques strongly depends on the choice of the set of visual features, and on the choice of the metric used to model the users perception of image similarity. However, no matter how suitably for the task at hand the features and the similarity metric have been designed, the set of retrieved images often fits the users needs only partly. Relevance feedback has been widely studied as a tool to allow users refining the retrieval results by marking the images retrieved with a given query as relevant or non-relevant [1, 2]. A number of relevance feedback techniques have been proposed in the literature to date [2]. Early works on relevance feedback have been formulated in terms of the optimization of one or more CBIR components, e.g., the formulation of a new query and/or the modification of the similarity metric to take into account the relevance of each feature to the user query [3, 4, 5, 6]. More recently, relevance feedback has been formulated in terms of a classification problem. In particular, the authors proposed a relevance feedback mechanism based on the nearest-neighbor paradigm [7]. In this paper we will further exploit neighborhood relations to weight feature subsets according to their relevance to user's needs. The basic idea behind the proposed weighting mechanism is that the feedback from the user implicitly defines which images should be considered as neighbors of each other (i.e., the relevant images), and which images should not (i.e., non-relevant images should not be in the neighborhood of relevant images). To this end, we propose different weighted similarity measures where the weights associated to a given feature space reflect the capability of representing nearest neighbors relations according to the user's choices. The formulation of the relevance feedback problem in terms of nearest neighbor relations arises from two considerations: i) non-relevant images clearly belong to multiple classes, and ii) the class of relevant images may be actually made up of distinct clusters of images in the considered feature spaces. Thus, first the "relevance" of different feature space is estimated in terms of their capability of representing relevant images as nearest neighbors, then the relevance of an image is estimated according to the relevant and non-relevant images in its nearest neighborhood.

This paper is organized as follows. In Section 2, the relevance feedback mechanism based on the nearest-neighbor paradigm is briefly reviewed. Section 3 presents the scenarios we considered for weighting different feature subsets, i.e., the measurement level, the feature level, and the similarity-measure level. The proposed weighting mechanism based on nearest-neighbor relations is proposed in Section 4. Experimental results on an image dataset are reported in Section 5, where some other weighting mechanisms proposed in the literature are also recalled for comparison.

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2. NEAREST-NEIGHBOR BASED RELEVANCE ESTIMATION

Relevance feedback based on the nearest-neighbor technique has been proposed by the authors in [7]. It is based on the assumption that the degree of relevance of an image depends on its similarity to the nearest relevant image and its dissimilarity to the nearest non-relevant image. As this assumption may only hold in some of the considered feature spaces, techniques for estimating the relevance of feature space are proposed in this paper, and described in Section 4. The degree of relevance of an image I can be computed as follows, according to [7]:

$$rel_{NN}(I) = P\left(relevant|I\right) = \frac{p_{NN}^{r}\left(I\right)}{p_{NN}^{r}\left(I\right)+p_{NN}^{nr}\left(I\right)} = \\ = \frac{\left\|I-NN^{nr}\left(I\right)\right\|}{\left\|I-NN^{r}\left(I\right)\right\|+\left\|I-NN^{nr}\left(I\right)\right\|} \tag{1}$$

where p_{NN} is defined as follows

$$p_{NN}\left(I\right) = \frac{1/C}{V\left(\left\|I-NN\left(I\right)\right\|\right)} \tag{2}$$

where C is the number of images, $NN(I)$ denotes the nearest neighbor of I, $\|\cdot\|$ is the metric defined in the feature space at hand, and V is the volume of the minimal hypersphere centered in I that contains $NN(I)$. The volume $V(r)$ in a d-dimensional space can be expressed as $V(r) = V_d \cdot r^d$ The relevance score computed according to equation (1) is then used to rank the images and the first k are presented to the user. It is worth noting that as the number of relevant and non-relevant images is usually small, the use of the first nearest neighbor can hardly be considered a reliable estimation of the local density, and the k-th distance can be used instead.

In addition, when very few relevant images are found during the first steps of iterative retrievals, the images ranked in the top positions are those whose relevance is just below 0.5, i.e. those images that are far from both relevant and non-relevant images. To handle the cases of few relevant images, we proposed to moderate the relevance computed by equation (1) by a term related to the distance of image I from the region of relevant images. In particular, we proposed to use the distance of image I from a modified query vector computed according to the Bayes decision theory (Bayes Query Shifting, BQS) [8]:

$$Q_{BQS} = \mathbf{m}_R + \frac{\sigma}{\|\mathbf{m}_R-\mathbf{m}_N\|}\left(1-\frac{k_R-k_N}{\max(k_R,k_N)}\right)(\mathbf{m}_R-\mathbf{m}_N) \tag{3}$$

where m_R and m_N are the mean vectors of relevant and non-relevant images respectively, σ is the standard deviation of the images belonging to the neighborhood of the original query, and k_R and k_N are the number of relevant and non relevant images, respectively. In order to combine this distance with the relevance score, a transformation of the distance into a score in [0,1] is needed:

$$rel_{BQS}(I) = \frac{1-e^{1-d_{BQS}(I)\big/\max\limits_{I} d_{BQS}(I)}}{1-e} \tag{4}$$

where d_{BQS} is the distance of image I from Q_{BQS}. We then proposed to compute the combined score as follows:

$$rel(I)_{stab} = \left(\frac{n/k}{1+n/k}\right)\cdot rel_{BQS}(I) + \left(\frac{1}{1+n/k}\right)\cdot rel_{NN}(I) \tag{5}$$

where r and n are the number of relevant and non-relevant images retrieved after the latter iteration, respectively. It is easy to see that the weights of $rel_{BQS}(I)$ are in reverse relation to the number of relevant images.

3. WEIGHTED METRICS

An image I can be represented as $I = I(F)$, where F is a set of low level features f_i, such as color, texture, etc. Each feature f_i can be modelled by several representations f_{ij}, e.g. color histogram and color moments are representations of the color feature. Each representation f_{ij} is itself a vector with multiple components

$$f_{ij} = \left[f_{ij1},\ldots,f_{ijh},\ldots,f_{ijk},\ldots,f_{ijL}\right], \tag{6}$$

where L is the vector length. For each level f_i, f_{ij} and f_{ijk} it is possible to associate a set of weights denoted with w_i, w_{ij} and w_{ijk}, aimed at representing the effectiveness of each feature to the query at hand. For example, for a given feature representation f_{ij}, the similarity between the images can be computed by the "weighted" Minkowski metric [4]:

$$S\left(f_{ij}\right) = \left(\sum_{k=1}^{L} w_{ijk}|I_A(f_{ijk})-I_B(f_{ijk})|^p\right)^{1/p} \tag{7}$$

with $p \geq 1$. Weights can also be assigned to "groups" of components of f_{ij} in accordance with their meaning. For example, an image in the Color Histogram Layout representation is subdivided into G sub-images ($G/4$ horizontal splits and $G/4$ vertical splits), and, for each sub-image, the Color Histogram representation is computed. Therefore equation (6) can be rewritten as:

$f_{ij} = \left[g_{ij1},\ldots,g_{ijk},\ldots,g_{ijG}\right]$, and

$$g_{ij1} = \left[f_{ij1},\ldots,f_{ijh}\right],\ldots,g_{ijG} = \left[f_{ijk},\ldots,f_{ijL}\right]. \tag{8}$$

Consequently, weights w_g can be assigned to the sets of components $g = 1\ldots G$, and equation (7) can be modified as follows:

$$S\left(f_{ij}\right) = \sum_{g=1}^{G} w_g \cdot d_p^g\left(I_A, I_B\right), \tag{9}$$

where $d_p^g\left(I_A, I_B\right)$ is the distance between I_A and I_B in the g sub-space. Finally, we also propose to weight the relevance of different feature spaces by combining the related relevance scores computed according to equation (5):

$$rel\left(I(f_{ij})\right)=\sum_{k=1}^{L} w_{ijk}\cdot rel\left(I(f_{ijk})\right), \qquad (10)$$

$$rel\left(I(f_{ij})\right)=\sum_{g=1}^{G} w_{g}\cdot rel\left(I(g_{ijg})\right), \qquad (11)$$

The weights in equations (7) - (10) can be computed in a number of ways [4, 5, 6, 3]. In the following section, we propose a weighting scheme specifically tailored to the nearest-neighbor relevance feedback technique.

4. NEIGHBORHOOD BASED METRIC WEIGHTING

The aim of the proposed weighting mechanism is to modify the distance metric through appropriate weights so that the distance between relevant images is smaller than the distance between relevant and non-relevant images. The rationale behind this proposal is the same behind the nearest-neighbor relevance computation. Let us estimate the relevance of feature f_x according to

$$rel_{NN}(f_x)=\frac{p_{NN}^{r}\left(f_x\right)}{p_{NN}^{r}\left(f_x\right)+p_{NN}^{nr}\left(f_x\right)} \qquad (12)$$

where we estimate $p_{NN}^{r}\left(f_x\right)$ and $p_{NN}^{nr}\left(f_x\right)$ as follows

$$p_{NN}^{r}\left(f_x\right)=\frac{1/C}{V_{NN}^{r}\left(f_x\right)} \qquad p_{NN}^{nr}\left(f_x\right)=\frac{1/C}{V_{NN}^{nr}\left(f_x\right)} \qquad (13)$$

where C is the number of images. The volume $V_{NN}^{r}\left(f_x\right)$ can be estimated as the average volume around relevant images which contains its nearest relevant image, and $V_{NN}^{nr}\left(f_x\right)$ as the average volume around relevant images which contains its nearest non-relevant image

$$V_{NN}^{r}\left(f_x\right)=\frac{1}{card\left(R\right)}\sum_{i\in R} d_{min}^{f_x}\left(I_i,R\right) \qquad (14)$$

$$V_{NN}^{nr}\left(f_x\right)=\frac{1}{card\left(R\right)}\sum_{i\in R} d_{min}^{f_x}\left(I_i,N\right) \qquad (15)$$

where R and N are respectively the set of the relevant and non-relevant images. and $d_{min}^{f_x}\left(\cdot\right)$ is a function that returns the minimum distance between an image and a set of images. This distance is computed as

$$d_{min}^{f_x}\left(I_i,M\right)=\min\left[d_{p}^{f_x}\left(I_i,I_k\right)\right]\forall I_k\in M, \qquad (16)$$

where M represents a set of images. Summing up, the weights associated to each feature f_x can be computed as follows:

$$w_{f_x}=rel_{NN}(f_x)=\frac{\sum_{i\in R} d_{min}^{f_x}\left(I_i,R\right)}{\sum_{i\in R} d_{min}^{f_x}\left(I_i,R\right)+\sum_{i\in R} d_{min}^{f_x}\left(I_i,N\right)} \qquad (17)$$

The above reasoning can also be used to compute the weights in equation (9). Equation (17) can thus be formulated as

$$w_{g}=rel_{NN}(g)=\frac{\sum_{i\in R} d_{min}^{g}\left(I_i,R\right)}{\sum_{i\in R} d_{min}^{g}\left(I_i,R\right)+\sum_{i\in R} d_{min}^{g}\left(I_i,N\right)} \qquad (18)$$

where, $d_{min}^{g}\left(\cdot\right)$ is a function that returns the minimal distance between two images measured in the g-th feature set of a certain feature space. In such a way the more each relevant image is far from its closest non-relevant image, and close to the nearest relevant image, the larger the weight assigned to the feature (or features set) used to evaluate the distance.

5. EXPERIMENTAL RESULTS

A subset of the Corel dataset obtained from the UCI KDD repository[1] has been used. It consists of 19511 images that have been manually subdivided into 42 semantic classes [8]. Experiments have ben performed using all the four features vectors available at the UCI web site. In this paper, due to the lack of space, only results related to *Color Histogram* are reported. Performances are evaluated in terms of retrieval precision, recall and the F-measure. According to Section 3, we have split the Color Histogram feature vectors into 4 subsets, each subset made up of 8 components, as Color Histogram measures the density of colors in the entire image using the HSV color space (8 ranges for H and 4 ranges for S). The nearest-neighbor relevance feedback technique (equation (5)) has been tested using the 2^{nd}-NN, and the features weights proposed in Sections 3 and 4. The proposed *Feature-Relevance Nearest Neighbor* (FR-NN) weighting technique has been tested using both the weighted distance measure in equation (7), where weights are assigned to each feature component, and the weighted distance in equation (9) where weights are assigned to each feature subset (FR-NN SubFeat). Finally, the performances of FR-NN when used to weight relevance scores computed in different feature subspaces (equation (11)), are also shown. Reported results clearly show that the weighting scheme is effective when used to compute weighted similarities, rather than to combine relevance scores. It is worth noting that reported experiments are related to the combination of relevance scores computed over each feature component. Thus, the poor performances simply reflect the fact that individual feature components are not effective for computing relevance scores. On the other hand, we are currently investigating the combination of relevance scores computed over different image representations. Retrieval performances have also been compared with other weighting schemes, namely the PFRL [3], and std-dev [4], which weights feature according to the inverse of the standard deviation of feature values estimated from the images in the

[1] http://kdd.ics.uci.edu/databases/CorelFeatures/CorelFeatures.html

dataset. We also show the performances attained by *Support Vector Machines* (SVM) because it is currently used by many researchers to perform relevance feedback in CBIR. Figure 1 clearly shows that the use of a weighted distance measure in the framework of the nearest-neighbor relevance feedback improve the performances of the “pure” nearest-neighbor technique. In particular, the average retrieval precision of the proposed FR-NN weighting technique depends on the weighting scheme adopted. When weights are assigned to individual features, the performances decrease w.r.t. the use of unweighted distance measures. On the other hand, the computation of a distance measure as a weighted combination of distances in different feature subsets, allows attaining the best performances till the eighth iteration. Thus it can be concluded that the proposed weighted distance metric allows improving the performances of nearest-neighbor relevance feedback technique, when feature components are grouped according to their meaning. The results in terms of the Recall measure confirm the effectiveness of the proposed weighted scheme. Finally, the graphs reporting the F-measure, which takes into in account both the recall and the precision, clearly show that: i) performances of the nearest-neighbor relevance feedback can be improved by computing the relevance of different feature subspaces, and adopting a weighted distance measure accordingly; ii) the proposed technique for estimating the weights of the distance measure can provide better results w.r.t. other weighting schemes.

6. REFERENCES

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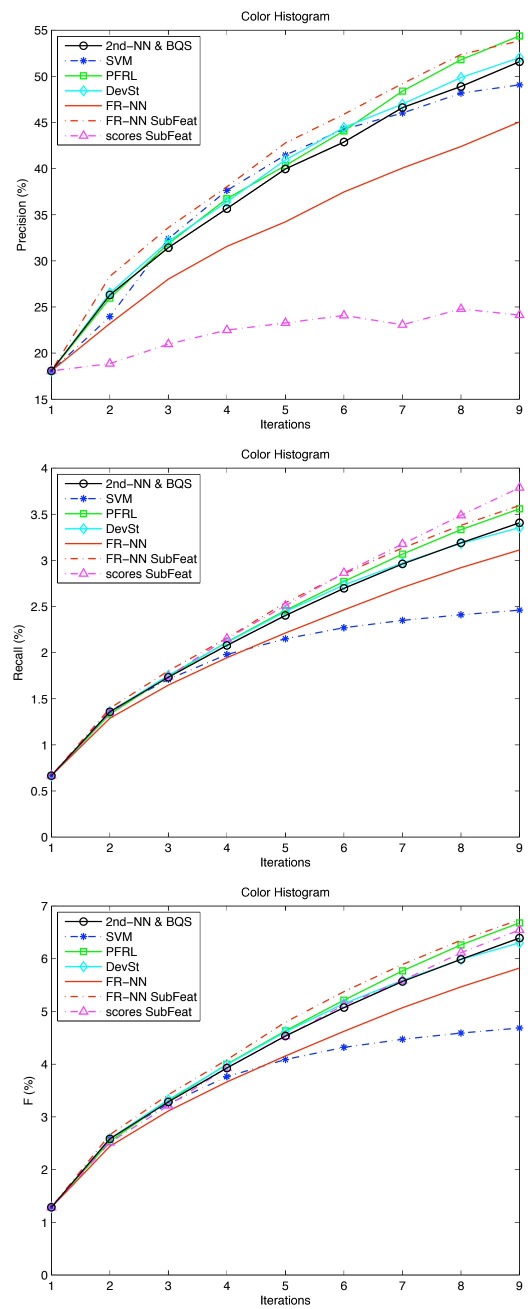

Fig. 1. Precision, Recall and F-measure - Color Histogram