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A Parameter Adjustment Method for Relevance Feedback

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Abstract: **Various relevance feedback techniques have been applied in Content-Based Image Retrieval (CBIR). By using relevance feedback, CBIR allows the user to progressively refine the system's response to a query. In this paper, after analyzing the feature distributions of positive and negative feedbacks, a new parameter adjustment method for iteratively improving the query vector and adjusting the weights is proposed. Experimental results demonstrate the effectiveness of this method.**

I INTRODUCTION

The rapid development of multimedia computing and communicating technology has led to increased demands for multimedia information. Since the1990s, Content-based Image Retrieval (CBIR) has attracted significant research attention [1-9]. Early research focused on finding the "best" representation for image content and the "best" measurement for image similarity. However, it has turned out that image feature or "content" has an objective statistic and character, which can not easily understood by human beings and furthermore, the perceptual "similarity" of images depends on the application, the person and the context of usage.

To better determine the user's intention it is helpful to involve the user in the retrieval loop. The interactive mechanism allows the user to submit a coarse initial query and iteratively refine the query information through relevance feedback. Currently the relevance feedback algorithms reported in the literature [1-7] can be grouped into two classes: weight adjustment and machine learning. The common idea of the latter is to apply some machine-learning algorithm (such as SVM, Bayesian, etc) to learn positive and negative feedbacks [2][7]. It classifies candidate images according to the low-level features, into relevant and non-relevant categories. In practice its performance greatly depends on the number of training samples. Moreover, if the image database is very large, training will be very time-consuming.

II RELATED WORK AND MOTIVATIONS

In 1997, relevance feedback was first introduced in CBIR by Yong Rui [1]. He proposed a relevance feedback algorithm based on parameter adjustment, including query vector movement and weight adjustment. MARS [1] use weighted Euclidian distance $d_{q,x} = (\vec{q} - \vec{x})^T \Lambda (\vec{q} - \vec{x})$ to measure image similarity. Here Λ is a diagonal matrix $diag(w_1, w_2, ..., w_M)$, while the diagonal element w_i denotes the degree of importance the i-th component of the feature vector $\vec{x}$.

In 1998 Ishikawa et al [6] proposed a generalized Euclidian distance $d_{q,x} = (\vec{q} - \vec{x})^T W (\vec{q} - \vec{x})$ could be used. Here the weight matrix W is an ordinary full matrix. Ishikawa[6] defines an optimal function for feedback that minimizes the sum of the distances between positive images and the query image, and obtains the weight matrix by solving an optimization problem, while the optimal query vector is the weighted average among positive feedbacks.

In 2000, based on [1][6], Yong Rui[5] proposed an optimizing learning algorithm. By using the method of Lagrange multiplier he derived the optimal solution for the query vectors and the weights. In addition Selim Aksoy[3] improved the weight adjustment algorithm by setting the weights to be the ratios of the standard deviations of feature components.

However, these algorithms only take positive feedbacks into consideration [1][3][5][6] and require the user to provide preference weights for relevant images [1][5] which is unreasonable. Motivated by these criticisms, we propose a novel parameter adjustment method for relevance feedback. While adjusting the query vector we take into account the influence of negative feedbacks; and after analyzing the different distribution characters of positive feedback and negative feedback we present an improved strategy to adjust the weights.

III A NOVEL SCHEME FOR PARAMETER ADJUSTMENT

Suppose $D' = D'_R \cup D'_N$ is the feedback image set. D'_R is the positive set, D'_N is the negative set. A general scheme [1] for query vector movement is:

$$Q' = \alpha Q + \beta \left(\frac{1}{N_{R'}} \sum_{i \in D'_R} D_i \right) - \gamma \left(\frac{1}{N_{N'}} \sum_{i \in D'_N} D_i \right) \quad (1)$$

Here Q is the original query vector; α, β, γ are predefined constants; $N_{R'}$ and $N_{N'}$ are the number of components in D'_R and D'_N, respectively.

According to most recent results obtained by Ishikawa[6] and Yong Rui[5] we know that the ideal query vector should be the weighted average of positive feedbacks. However such an approach requires the user to provide preference weights for the relevant images [1][5]. Moreover the original query information [9] is lost. The formula below captures our scheme:

$$Q' = \alpha Q + (1-\alpha)\left(\frac{1}{N_{R'}}\sum_{i \in D'_R} D_i\right) \tag{2}$$

Formula (2) does not take negative feedback into account because, in feature space, positive samples ordinarily are adjacent or relevant, while negative samples are not similar or adjacent to the query vector. Even negative samples themselves are not similar. Negative samples are usually scattered, so the concepts denoted by formula (1) are unreasonable, because the center of the negative vectors may not exist at all, as shown in Figure 1.

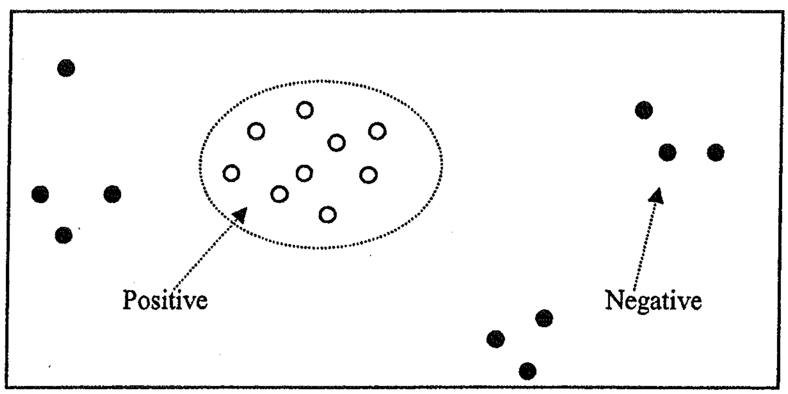

Fig. 1: In feature space, the similarity measure function tries to group positive vectors, while negative vectors may be scattered far away from the positive center

Assume the similarity of query image $\vec{q}$ and candidate image $\vec{x}$ is defined as

$$S(\vec{q},\vec{x}) = \sum_{i=1}^{F} u_i d(\vec{q}_i,\vec{x}_i) \tag{3}$$

Here, $i = 1,2,\ldots,F$ is the i-th feature of the image, representing such attributes as color and texture. $\vec{u}_i$ is the weight vector of i-th feature; $d(\vec{q}_i,\vec{x}_i)$ is the similarity, defined as the weighted Euclidian distance.

$$d(\vec{q}_i,\vec{x}_i) = (\vec{q}_i-\vec{x}_i)^T \Lambda_i (\vec{q}_i-\vec{x}_i) = \left(\sum_{j=1}^{K_i}[w_{i,j}(q_{i,j}-x_{i,j})]^2\right)^{1/2} \tag{4}$$

Here, $w_{i,j}$ is the weight of j-th component of i-th feature; K_i is the length of i-th feature. From (4), we know that once given query image $\overset{\omega}{q}$ and candidate image $\overset{\omega}{x}$, weight is the only factor which can influence $d(\overset{\omega}{q},\overset{\omega}{x})$. By adjusting the weights of feature components, relevance feedback can enhance efficient components and weaken inefficient ones. We believe that the standard deviations of effective components of relevant images should be smaller than these of the non-relevant images. Based on this, we propose a novel method to adjust the weights:

$$w_{i,j} = w_{i,j} + \frac{\sigma_{i,j}^{N}}{\sigma_{i,j}^{R}} \tag{5}$$

Where $\sigma_{i,j}^{R}$ is the standard deviation of the j-th component of the i-th feature for relevant images, $\sigma_{i,j}^{N}$ is that for non-relevant images.

According to the variance of $\sigma_{i,j}^{R}$ and $\sigma_{i,j}^{N}$, $w_{i,j}$ has four possible states. When $\sigma_{i,j}^{R}$ is large and $\sigma_{i,j}^{N}$ is small the variance of $w_{i,j}$ is small. This means that the j-th component of the i-th feature is not usually effective. It will tend to increase the distance between relevant images. When $\sigma_{i,j}^{R}$ is small and $\sigma_{i,j}^{N}$ is large the variance of $w_{i,j}$ is large. This means that the $j-th$ component of $i-th$ feature has good discriminative performance. Otherwise, when $\sigma_{i,j}^{R}$ and $\sigma_{i,j}^{N}$ are both large, or both small, this means the component has poor discriminative performance.

Our feedback algorithm implemented this idea, which can be briefly described as follows:

I. Initialize $u_i^0 \leftarrow 1/F$, $w_{i,j}^0 \leftarrow 1/K_i$, $k \leftarrow 1$.

Here k is the number of the iteration or feedback.

II. Search in the image database using weighted Euclidian distance and obtain an image set $D^k = D'_R \cup D'_N$. If finding the expected, goto VIII, else goto III.

III. According to the feedback image set compute $\sigma_{i,j}^{R,k}$ and $\sigma_{i,j}^{N,k}$.

IV. Modify the query vector

$$Q = \alpha Q + (1-\alpha)\left(\frac{1}{N_{R'}}\sum_{i\in D'_R} D_i\right).$$

V. Compute $w_{i,j}^{k} = w_{i,j}^{k-1} + \dfrac{\sigma_{i,j}^{N,k}}{\sigma_{i,j}^{R,k}}$,

normalize $w_{i,j}^k$ using $w_{i,j}^k = w_{i,j}^k / \sum_{j=1}^{K_i} w_{i,j}^k$

$i = 1,2,\ldots,F$, $j = 1,2,\ldots,K_i$.

VI. Compute $u_i^k = u_i^{k-1} + \dfrac{|R^k|}{\sum_{x\in R^k} d(q_i, x_i)}$ and normalize

u_i^k using $u_i^k = u_i^k / \sum_{i=1}^{F} u_i^k$, $i = 1, 2, \ldots, F$.

VII. $k \leftarrow k+1$, go to II.

VIII. Finish.

IV EXPERIMENTAL RESULTS

In this section the proposed algorithms are tested on a natural image database. It contains more than 67,000 images, most of them come from "Corel Image Gallery" covering more than 450 categories. In the experiment we use a combined histogram of three visual features: color, texture and edge. For the color histogram we use the HSV color space because of its perceptual uniformity. According to human vision perception for color, the tri-color components (H, S, V) are mapped into 72 non-equal intervals [8]. We use texture and edge feature reported in [8], they are 256-D and 6-D vectors, respectively. The advantage of the combined histogram is: once histogram features are statistical and normalized, they do not belong to any metric space, so they can be integrated seamlessly.

Based on these visual features we have developed a CBIR system. Figure 2shows the user interface. The top left image is the query image and on the right are the return results. There are two image checkboxes associated with each image. A user uses them to give his positive or negative feedback to a system.

In order to demonstrate the performance of the proposed algorithm we randomly selected 30 images as query images from 6 image categories (summarized in Table 1), with 5 images from each categories. During each iteration of the retrieval process, the top 60 images are returned to the user. The statistic used to quantify accuracy in Table 2 is the average retrieval performance, defined as

$$\frac{\text{relevant ones retrieved}}{60} \times 100\%$$

Table 1: The test image categories in the experiment

	1	2	3	4	5	6
Category	Flower	Bird	Mountain	Tool	China painting	Building
Number	458	100	214	137	243	503

Fig. 3 compares the number of hits in top 60 returned images using our approach and that used in MARS, which uses positive feedback only. From Table 2 and Figure 3, when using our approach, after 3 iterations, the average accuracy improved from 0.721 to 0.795, a significant improvement over MARS[1].

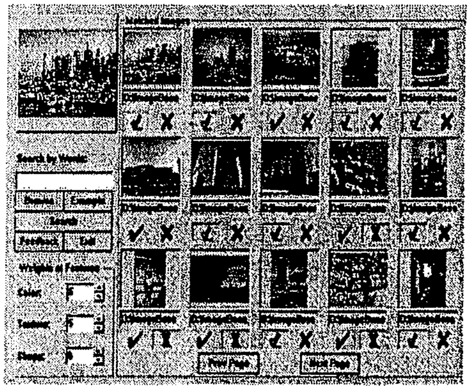

Fig. 2: The interface of the demo CBIR

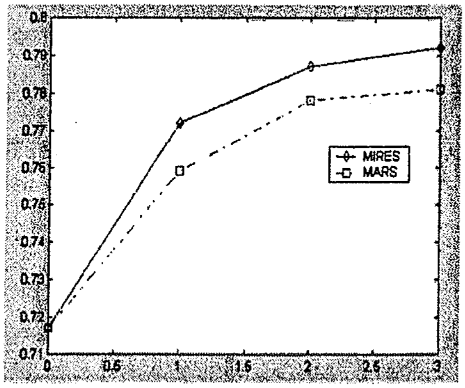

Fig. 3: Compare the proposed approach and that used in MARS

Table 2: Average retrieval performance for different image category

	0 RF	1 RF	2 RF	3 RF
Flower	71.1	75.9	75.8	75.1
Bird	61.2	69.7	71.6	72.6
Mountain	74.1	79.4	82.0	81.5
Tool	68.2	74.4	77.8	79.0
China Painting	81.8	82.0	80.7	83.6
Building	75.7	84.6	87.4	85.5

V CONCLUSIONS

In this paper, we have briefly reviewed the existing parameter adjustment-based relevance feedback algorithms. Emphasis is put on the analysis of the relation between the standard deviation and the image relevance. Based on these observations a new scheme for iteratively improving the query vector and adjusting the weights is proposed. In an experiment, results are obtained using the new method that outperforms the results obtained from a method that relies exclusively on positive feedback.

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