EXTENDING IMAGE RETRIEVAL WITH GROUP-ORIENTED INTERFACE

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ABSTRACT

ImageGrouper is a new user interface for digital image search and organization. It is group-oriented in that image search, annotation and organizing are done by grouping images on the workspace. This enables faster and flexible text annotation on a large number of images as well as effective image organization. In addition, this interface improves and extends Content-Based Image Retrieval (CBIR) as well. First, finding good combinations of query examples is essential for successful retrieval. Query-by-Groups concept allows the user to try different combinations of query examples quickly and easily. Second, because of semantic gap between the user's concept and extracted visual features, it may be difficult to represent the user's request by only one class of query examples. We propose a new feature-weighting scheme where the user's request can be expressed in multiple positive classes.

1. INTRODUCTION

In Content-based Image Retrieval (CBIR) [3][6][7][11], *Query-by-Example* is commonly used. In this method, the users select example images (as positive or negative) and ask the system to retrieve visually similar images. The similarity between images is computed based on extracted visual features such as color [10] and texture [9]. In addition, in order to improve the retrieval, CBIR systems often employ *relevance feedback* [6][11], in which the users refine the search incrementally by giving feedback to the result of the previous query.

We are developing a new tool for digital image search and organization, named *ImageGrouper* [5]. *ImageGrouper* is a *group-oriented* interface in that every operation is based on group configurations. The users search, annotate and organize images by creating groups of images. In this paper, we describe how the design of our new system addresses problems in the traditional image retrieval systems. We propose a new feature-weighting scheme that can handle the user's request as multiple positive and multiple negative classes problems.

In the next section, the basic concepts of *ImageGrouper* are briefly introduced. In Section 3 and Section 4, we describe how our system improves and extends content-based image retrieval.

2. THE IMAGEGROUPE

In this section, we briefly introduce the basic concepts of *ImageGrouper*: *Query-by-Groups*, *Annotate-by-Groups* and *Organize-by-Groups*.

2.1. Query-by-Groups

In *ImageGrouper*, a new concept *Query-by-Groups* is introduced to content-based image retrieval. This is an extension to Query-by-Example method that is commonly used in image retrieval [6][11]. The major difference is that while Query-by-Example handles the images individually, a group of images is considered as the basic unit of the query in Query-by-Group.

Figure 1. shows interface of the *ImageGrouper*. The display is divided into two panes. The left pane is the *ResultView* that displays the results of both content-based and keyword-based search. The right pane is the *GroupPalette*, in which the user manipulates image groups directly. In order to create an image group, the user first drags images from the *ResultView* to *GroupPalette*, then

Figure 1. ImageGrouper Interface (annotated)

encloses the images by drawing a box as we draw rectangles in an illustrating application. The user can create any number of groups within the palette. For each group, the user can specify it as relevant, irrelevant or neutral. Neutral groups do not contribute to the search at the moment and can be used for another query later. The properties of the groups can be easily changed from the popup menu. The box colors change accordingly. Moreover, the user can move images from one group to another at any moment. In addition, these groups can be overlapped to each other, allowing images to belong multiple groups.

When the user presses the “Query” button, the system retrieves images that are similar to positive group images while avoiding images similar to negative group images. The results are displayed in the *ResultView*. The user can refine the query further by dragging the new images into groups in the palette.

2.2. Annotating and Organizing Images by Groups

The concept of “groups” is also used for text annotation and image organization.

No wonder keyword-based image search is a very powerful method. The problem is that it works only when all images are annotated with textual information. Annotating a large number of images is, however, a tedious task. *ImageGrouper* introduces *Annotation-by-Groups* method where keywords are annotated not on individual images, but on groups. Because the users can simultaneously annotate the same keywords on a number of images, annotation becomes much faster and less error prone. Furthermore, when groups are overlapped, images in the overlapped region are associated with keywords of both groups. By creating a group within an existing group, hierarchical annotation is possible.

Once images are annotated, they can be used for keyword-based search. In *ImageGrouper*, keyword-based search and content-based search are closely related and complementary to each other. Content-based retrieval by *Query-by-Groups* is used to collect images to annotate. Conversely, keyword-based search can be used to find a starting point for content-based retrieval.

Meanwhile, these groups can be used to organize pictures as “photo albums [4]” When the user points a group and choose “Iconfify” from the popup menu, images in the group are shrunk into *Album icons* (shown in the lower right of Figure 1.) These icons can be moved anywhere in the *GroupPalette*. The user can expand an icon back into an image group where images are surrounded by a rectangle. In addition, album icons themselves can be used as query example for additional query. To this end, the user selects query property (positive, negative, neutral) of the icon from the popup

menu. Based on this property, the color of the album changes.

In the following sections, we describe how *ImageGrouper* improves and extends content-based image retrieval.

3. SUPPORTING FAST EXPERIMENTAL QUERY

ImageGrouper addresses several drawbacks in traditional user interfaces of CBIR systems that employ Query-by-Example. First, the traditional CBIR systems assume that *the more query examples are available, the better result we can get*. Therefore, the users are supposed to search images only by adding new example images incrementally from the previous query results. When no additional example is found in the result set, the search is considered to have converged. However, this assumption is not necessarily true. There are cases where additional examples may contain undesired features and degenerate the retrieval performance. In [5], Nakazato et al. showed that finding good combinations of query examples is essential for successful image retrieval. Unfortunately, this task was difficult or inefficient in the traditional interfaces.

Second, the traditional systems do not allow the user to put aside the query results for later uses. This type of interaction is desired because the users of CBIR are not necessarily looking for only one type of images. The users’ interest may change during retrieval. This behavior is known as *berry picking* and have been observed for text document retrieval [1]. Moreover, because of *semantic gap* [8] between the high-level concept in the user’s mind and the extracted low-level image features, the users often need to make more than one query to satisfy their need. Therefore, support for *trial-and-error* query (or experimental query) is desirable.

Compared with the traditional GUI, *ImageGrouper* is much easier to try different combinations of query examples. Images can easily enter or leave a group by mouse drags. Thus, the user can quickly explore different combinations of query examples by dragging images into or out of the box on the *GroupPalette*. It is shown that with the *trial-and-error* query, retrieval performance is improved even if relevance feedback algorithm is identical [5]. Therefore, *ImageGrouper* can achieve better retrieval (higher recall) without any modification to relevance feedback algorithm. In the next section, however, we will extend relevance feedback algorithm itself so that we can further take advantage of *Query-by-Group* interaction.

Moreover, the system provides storage area for images that are not used for query at the moment. They can be used for another query later. In addition, the user can create new groups within an existing group (*Group in a group*). Thus, the user can begin with collecting relatively generic images first, then narrow down the

search to more specific images. For example, assume the user is looking for “red car” images. S/he can initially collect “cars with any colors.” Once s/he found enough number of images, s/he can divide them into two groups: *red cars* and *other cars*. Then the user can specify red car group as relevant, and other cars as irrelevant. This narrowing down search was not possible with the conventional interfaces.

4. EXTENDING FEATURE DISTANCE METRIC

In interactive content-based image retrieval, the system needs to re-calculate distance metric (or feature weighting) based on the user’s feedback (*relevance feedback* [7][11].) This problem is reduced into online calculation of *feature space transformation matrix*.

4.1. Related Work

4.1.1. Traditional approaches

When negative image examples are not considered, the simplest way is to calculate the variance of each feature among the query examples. Then, the inverse of variance becomes the weight of the feature [6]. This gives higher weights to features in which example images are similar. If the number of example images is high, it is known that the *whitening transform* is the optimal choice [7].

Next, when negative examples are introduced, the problems can be addressed as *two-class* (positive and negative) problems. One solution is to use the *Fisher’s discriminant analysis* (FDA) [11]. This approach, however, introduces undesirable side effects because it tries to cluster negative examples into one class. In the actual scenario, negative examples can be any types of images in the database other than the positive class.

4.1.2. Image retrieval as a $(1+x)$ -class problem

Zhou et al.[11] proposed a new relevance feedback algorithm, which effectively takes negative examples into account. They consider the relevance feedback problem as $(1+x)$ -class (one positive and multiple negative classes) problem. In this scheme, it is assumed the negative examples are coming from an uncertain number of classes, while the positive can be clustered into one class. Their algorithm, named *Biased Discriminant Analysis* (BDA) is characterized by the following objective function,

$$W = \operatorname{argmax}_W \left| \frac{W^T S_{bias} W}{W^T S_W W} \right| \quad (1)$$

where,

$$S_W = \sum_{x \in C} (x - m)(x - m)^T \quad (2)$$

$$S_{bias} = \sum_{y \in D} (y - m)(y - m)^T \quad (3)$$

C is a set of positive examples and D is a set of negative examples. In short, BDA tries to minimize *within-class scatter matrix* S_W of the positive example, while S_{bias} is

Figure 2. White flowers and Red flowers. In *ImageGrouper*, users can separate them into two positive groups.

keeping the negative examples away from the positive examples.

4.2. Extending to $(x+y)$ -class problem

In the first version [5] of *ImageGrouper*, when the user specifies more than one groups as positive, these groups are merged into one group for query. Thus, *biased discriminant analysis* described above was used, i.e. one positive group and multiple negative groups.

However, this approach is not taking full advantages of our group-oriented interface. When the user searches images, s/he may have high-level concept in her/his mind such as “beautiful flowers.” Such concept cannot be expressed by only one class of images. See Figure 2. Although white flowers and red flowers may have common visual features, they also have very different features, which is the color. If the system tries to consider them as one class of images, the color features have to be discarded. This is not desirable because these features may be beneficial to retrieve a specific color of flowers.

Even for the users, it is more intuitive if they can specify them as two different, but closely related positive classes. This fact motivated us to extend the relevance feedback problems to $(x+y)$ -class (multiple positive and multiple negative classes) problem.

In our new scheme, the objective function of the new approach becomes as follows,

$$W = \operatorname{argmax}_W \left| \frac{W^T S_{PN} W}{W^T S_W W} \right| \quad (4)$$

where S_W is the sum of the *within-class scatter matrix* [2] of the positive groups defined as follows,

$$S_W = \sum_{i=1}^c S_i \quad (5)$$

$$S_i = \sum_{x \in C_i} (x - m_i)(x - m_i)^T \quad (6)$$

m_i is the mean vector of i -th positive class C_i , c is the number of positive groups. S_{PN} is the *positive-to-negative scatter*, which is introduced in this paper as follows,

$$S_{PN} = \sum_{i=1}^c S_{Ni} \quad (7)$$

Figure 3. Concept of the new feature space transform. It minimizes the scatter of each positive class while maximizing the scatter between positive and negative samples.

$$S_{Ni} = \sum_{y \in D} (y - m_i)(y - m_i)^T \quad (8)$$

where, D is a set of negative examples.

Figure 3. visualizes the concept of our scheme. In short, this scheme tries to cluster each positive class while scatter the negative example away from the positive classes.

As in FDA and BDA described above, W is solved as the generalized eigenvector(s) associated with the largest eigenvalue(s) λ ,

$$S_{PN}w_i = \lambda_i S_W w_i \quad (9)$$

Finally, our *discriminating transformation matrix* [2] becomes,

$$A = \Phi \Lambda^{1/2} \quad (10)$$

Φ is the matrix whose columns are the eigenvectors, and Λ is the diagonal matrix of the corresponding eigenvalues. Once the transformation matrix is available, the distance between two images x and y is computed as follows.

$$\text{dist}(x, y) = (x - y)^T A (x - y) \quad (11)$$

In our current implementation, we compare the distance between images in the database and the mean of each positive group. Then, the database images are ordered according to those distances.

5. IMPLEMENTATION

ImageGrouper is implemented as a client-server system. The interface client is implemented as a Java2 applet so that the users can use the system through web browsers on various platforms. Computation of discriminating transformation matrix is done on the server side. It is implemented as a Java Servlet, which is written in Java and C++ with MATLAB C++ Math Library.

6. CONCLUSION

In this paper, we described how our new user interface *ImageGrouper* improves and extends relevance feedback

for content-based image retrieval. First, the system supports effective experimental query. The user can quickly try different combinations of query examples by dragging image on the workspace.

In addition, we introduced a new feature weighting scheme. In this method, the user's interest can be expressed as $(x+y)$ -class (multiple positive and multiple negative) problems. Our new user interface inspired this new scheme. In fact, there was no way to apply this scheme on the traditional interfaces because the user could not specify positive example as multiple classes.

Readers can try *ImageGrouper* demo online at <http://www.ifp.uiuc.edu/~nakazato/grouper/>

7. ACKNOWLEDGEMENT

This work was supported in part by National Science Foundation Grant CDA 96-24396.

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