Mosaic-Based Relevance Feedback for Image Retrieval

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INTRODUCTION

A standard approach for content-based image retrieval (CBIR) is based on the extraction and comparison of features usually related to dominant colours, shapes, textures and layout (Del Bimbo, 1999). These features are a-priori defined and extracted, when the image is inserted into the database. At query time the user submits a similar sample image (query-by-sample-image) or draws a sketch (query-by-sketch) of the sought archived image. The similarity degree of the current query image and the target images is determined by calculation of a multidimensional distance between the corresponding features. The computed similarity values allow the creation of an image ranking, where the first k, usually k=32 or k=64, images are considered retrieval hits. These are chained in a list called ranking and then presented to the user. Each of these images can be used as a starting point for a refined search in order to improve the obtained results.

The assessment of the retrieval result is based on a subjective evaluation of whole images and their position in the ranking. An important disadvantage of the retrieval with content-based features and the presentation of the resulting images as ranking is that the user is usually not aware, why certain images are shown on the top positions and why certain images are ranked low or not presented at all. Furthermore, users are also interested which sketch properties are decisive for the consideration and rejection of the images, respectively. In case of primitive features like colour these questions can be often answered intuitively. Retrieval with complex features considering for example texture and layout creates rankings, where the similarity between the query and the target images is not always obvious. Thus, the user is not satisfied with the displayed results and would like to improve the query, but it is not clear to him/her, which parts of the querying sketch or the sample image should be modified and improved according to the desired targets. Therefore, a suitable feedback mechanism is necessary.

BACKGROUND

Relevance feedback techniques are often used in image databases in order to gain additional information about the sought image set (Rui, Huang, & Mehrotra, 1998). The user evaluates the retrieval results and selects for example positive and negative instances, thus in the subsequent retrieval steps the search parameters are optimised and the corresponding images/features are supplied with higher weights (Müller & Pun, 2000; Rui & Huang, 2000). Moreover, additional query images can be considered and allow a more detailed specification of the target image (Baudisch, 2001). However, the more complex is the learning model, the more difficult is the analysis and the evaluation of the retrieval results. Users – in particular those with limited expertise in image processing and retrieval – are not able to detect misleading areas in the image/sketch with respect to the applied retrieval algorithms and to modify the sample image/sketch appropriately. Consequently, an iterative search is often reduced to a random process of parameter optimisation.

The consideration of the existing user knowledge is the main objective of many feedback techniques. In case of user profiling (Cox, Miller, Minka, Papathomas, & Yianilos, 2000) the previously completed retrieval sessions are analysed in order to obtain additional information about user's preferences. Furthermore, the selection actions during the current session are monitored and images similar to those are given higher weights. A hierarchical approach named multi-feedback ranking separates the querying image in several regions and allows a more detailed search (Mirmehd & Perissamy, 2001).

Techniques for permanent feedback guide the user through the entire retrieval process. An example for this approach is implemented by the system Image Retro: based on a selected sample image a number of images are removed from the possible image set. By analysing these images, the user develops an intuition about promising starting points (Vendrig, Worring, & Smeulders, 2001). In case of the fast feedback, the user receives the

Figure 1. Compilation of a mosaic-based ranking

current ranking after every modification of the query sketch. The correspondence between the presented ranking and the last modification helps the user to identify sketch improvements leading in the desired retrieval directions and to undo inappropriate sketch drawings immediately (Veltkamp, Tanase, & Sent, 2001).

FEEDBACK METHOD FOR QUERY-BY-SKETCH

This section describes a feedback method, which helps the user to improve the query sketch and to receive the desired results. Subsequently, the query sketch is separated into regions and each area is compared with the corresponding subsection of all images in the database. The most similar sections are grouped in a mosaic, thus the user can detect well-defined and misleading areas of his/her query sketch quickly. The creation of a mosaic consisting of k areas with the most similar sections is shown in Figure 1.

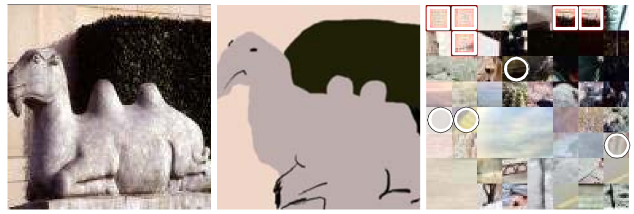
The corresponding pseudo-code algorithm for mosaic-based retrieval and ranking presentation is given in Algorithm 1.

The criterion c_m for the similarity computation of the corresponding sections can be identical with the main retrieval criterion ($c_m = c$) or be adapted to specific images or users ($c_m \neq c$). The size of the mosaic sections can also be selected by the user. Here grids consisting of 16×16 and 32×32 pixel blocks are evaluated.

Algorithm 1. Pseudo code of the mosaic build-up

```
procedure mosaic(sketch s, ranking R, criterion c_m, grid g)
begin
        divide s using a uniform grid g into k fields s_k
        initialise similarity[1 … k] = 0, image[1 … k]= none
        for each image i ∈ R
        begin
                scale i to i* with dim[i*] = dim[s]
                divide i* using grid g into k fields i_k
                for j=[1 … k] do
                if similarity[j] < c_m(s_j, i_j)
                        then similarity[j] = c_m(s_j, i_j), image[j] = i_j
                od
        end
        mosaic M =  j=1^k image[j]
    end
```

Figure 2. An example for a mosaic feedback



An example for the resulting mosaics is found in Figure 2. On the left hand side the sought image is shown, which was approximated by the user-defined sketch in the middle. On the right hand side the resulting 16×16 mosaic containing the best section hits of all images in the databases is presented. A manual post-processing of the mosaic clarifies the significance of individual mosaic blocks: Those sections, which are parts of the sought image, are framed with a white box. Furthermore, sections from images of the same category– in this case other pictures with animals – are marked with white circles.

An extension of the fixed grids is realised by adaptive mosaics, where neighbouring sections – depending on a given similarity threshold – are merged into larger, homogeneous areas, thus the user can evaluate individual sections more easily. Figure 3 shows a sample image and the corresponding mosaic-based ranking, which is gained using an adaptive grid.

In these manually post-processed cases additional information is provided to the user, which sketch regions are already sufficiently prepared (boxes) and which regions have the right direction but still need minor corrections (circles). Finally, all other regions do not satisfy the similarity criterions and have to be re-drawn. With this information the user can focus on the most promising areas and modify these in a suitable manner. For the usage of this feedback method in real-world applications it is necessary to evaluate, whether typical users are able to detect suitable and misleading regions intuitively and thus to improve the original sketch.

For the performance evaluation of the developed mosaic technique and measuring the retrieval quality we

Figure 3. Mosaic based on an adaptive grid